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How Robust is the Common Consequence Effect?

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Abstract: An experiment and subjective Bayesian statistical methods are used to investigate how robust the common consequence effect is to changes in frame that make pure increases in risk transparent. We find that subjects avoid pure increases in risk when such risks are transparent, but not otherwise, and that there is no correlation between risk attitudes in frames that alternately mask and make transparent pure increases in risk. The common consequence effect is nearly frame independent, but no more predictable (marginally or jointly) than by chance in the sense of Laplace's law of succession.

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Introduction

Generalisations of the Allais paradox, known as the common consequence effect and the common ratio effect, have played a large part in undermining the descriptive validity of Expected Utility Theory (EUT) and in spawning the development of competing explanatory theories: Fanning Out (FO) or Fanning In hypotheses, Regret Theory, and Prospect Theory [1]. Framing effects have also proven to be important in understanding in a general way why violations of EUT occur, although few theories (barring prospect theory) systematically and explicitly incorporate framing effects. [2].Our research reports on an experiment designed to help understand the relationship between common consequence effects and framing effects.

Many of the examples of common consequence effects[3] in the literature involve choices between pairs of prospects which are almost, but not quite, *pure increases in risk* on one another in the sense of Rothschild and Stiglitz (1970). Yet the standard way of presenting or framing risky choices in experiments generating common consequence effects does not make the near pure increases in risk transparent. How robust is the common consequence effect to changes in frame that make such near increases in risk transparent? Will this effect be likely in frames where pure increases in risk are transparent? Moreover, Machina's FO hypothesis explains common consequence effects in terms of changing attitudes toward risk[4]. But are risk attitudes themselves sensitive to framing effects? If so, their use in FO theories as exogenous variables to explain common consequence effects is liable to be spurious.

In an attempt to answer these questions we designed an experiment which is a slight modification of one of Kahneman and Tversky's (1979) experiments. We find strong experimental evidence, shown by high posterior inferences (for a range of prior beliefs) , that people will choose to avoid pure increases in risk when the framing of alternatives makes it easy to detect such risks . Moreover, the degree of risk aversion exhibited by subjects in their choices is highly dependent on the frame in which the prospects are presented but there is little correlation between indices of risk aversion in alternative frames. However, by and large the original KT experimental results on the common consequence effect can be replicated in frames that both mask and make transparent near pure

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[1]Starmer (1992) presents an excellent overall discussion of the properties of many different theories operationalized for specific predictions concerning common consequence effects in a unit probability triangle; see also Appleby and Starmer (1987), Sugden (1987) , Machina (1987), Nielsen (1992), Tversky and Kahneman (1988) for general expositions of these theories.

[2]There are only a few accepted empirical generalisations about framing effects, see Tversky and Kahneman (1988).

[3]Allais' original example excepted.

[4]Explanations based on Regret Theory use the notion of correlation in the prize structure in conjunction with evaluation principles based on regret calculations while prospect theory uses explanations based on the form of the decision weights applied to probability assessments in order to explain common consequence effects. See Starmer (1992), Machina (1987), Sugden (1987), and Kahneman and Tversky (1988) for further explanations of and distinctions between different theoretical viewpoints. In our paper FO theories encompass any theory that predicts the common consequence effect.

increases in risk , i.e. the common consequence effect found by KT is independent of the framing effects we consider. But our results do create a strong posterior inference that the common consequence effect is unlikely when pure increases in risk are transparent and when the probabilities of prospects are changed only slightly to make some alternatives pure increases in risk on others.

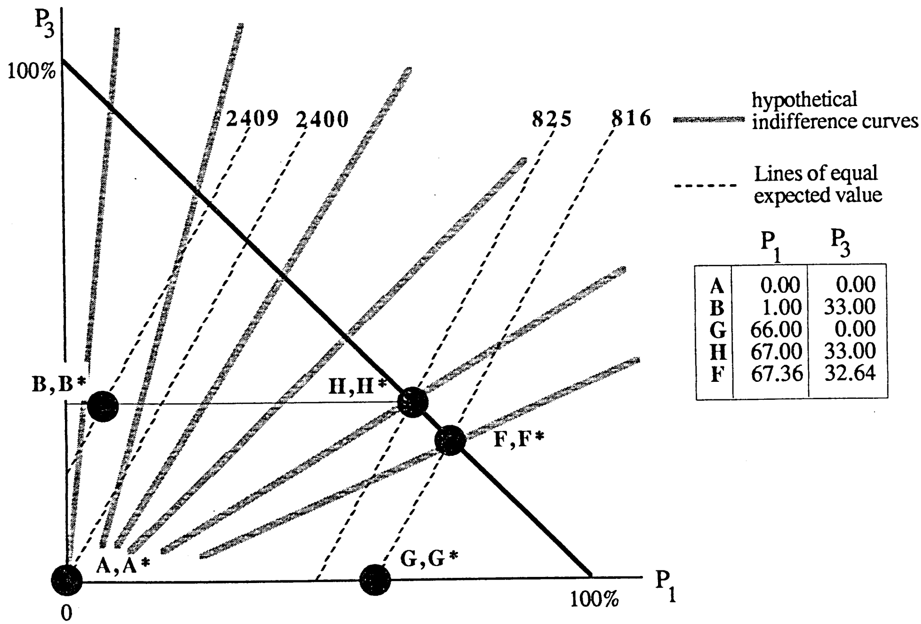
Although our experiment replicates the (marginal) patterns of common consequence effects observed in other experiments, we disagree strongly with the chorus of assertions in the literature that the observed patterns in our experiment (and other similar ones by implication) are systematic and predictable. Such assertions appear to be based on inferences derived from naive significance tests using marginal statistical analyses and a null hypothesis of EUT with i.i.d. errors. Of the three theories we assess, EUT, FO and a simple "Hit & Miss" theory based on a uniform prior and Bayesian updating, the Hit & Miss theory has better predictive ability than either of the other two theories. Taking the Hit & Miss theory as a benchmark, the KT common consequence effect, viewed marginally in one frame, or jointly in both frames, is no more predictable than "by chance" (suitably interpreted as starting out with a weakly held uniform prior and updating predictive probabilities according to Bayes rule).

The paper is divided into five sections. In the first we outline briefly how theoretical concepts are implemented in the experiment. The second section explains the operationally subjective Bayesian statistical methodology employed. The third section presents the experimental results and some theoretically interesting predictive distributions. The fourth section assesses alternative theories using the sequential log scoring rule for distribution functions and discusses some implications of our findings. The fifth section is a brief summary.

Conceptual Considerations

The original KT experiment on the common consequence effect asked subjects to choose between two prospects in two situations. All four prospects are different probability mixtures of the prizes 0£, 2400£ and 2500£. The first situation offered a choice between *A*, 2400 (Israeli £) with certainty, and *B*, a gamble giving 2500 with probability 0.33, 2400 with probability 0.66, and nothing with probability 0.01. The second situation offered a choice between *G*, a gamble giving 2400 with probability 0.34 and nothing with probability 0.66, and *H*, a gamble giving 2500 with probability 0.33 and nothing with probability 0.67. These four prospects are conveniently represented in Figure 1's unit probability triangle diagram[5].

Figure 1



	P_1	P_3
A	0.00	0.00
B	1.00	33.00
G	66.00	0.00
H	67.00	33.00
F	67.36	32.64

[5] In this diagram P_1 is the probability of receiving nothing and P_3 is the probability of receiving 2500; the probability of 2400 is implicit assuming probabilities sum to unity. Preference directions in the triangle are to the North (higher probability on the best prize) and to the West (lower probability on the worst prize). See Machina (1987) and Sugden (1987) for introductory analyses. The indifference curves shown in Figure 1 indicate risk averse preference in the choice of *A* over *B* and risk seeking preference in the choice of *H* over *G* (the gradient of the indifference curve becomes smaller than the gradient of the iso expected return lines towards the South East corner of the triangle). Note that subjects were not presented with prospects framed in the form of the unit probability triangle, but rather with verbal descriptions of each prospect as a probability distribution over prizes.

EUT implies linear and parallel indifference curves in (P_1,P_3) space. Since the four prospects ***A***, ***B***, ***G***, ***H*** form a parallelogram, if ***A*** is chosen in preference to ***B*** then ***G*** should also be chosen in preference to ***H*** according to EUT. In KT and other experiments many subjects chose ***A*** over ***B*** but also ***H*** over ***G***. These sorts of violations of EUT are in directions predicted by FO hypotheses. Figure 1 also illustrates the basic idea behind fanning out , taking a linear indifference curve case for simplicity. The gradient of the indifference curves in (P_1,P_3) space is an index of risk aversion, with steeper gradients indicating greater risk aversion[6]. Machina's FO hypothesis, for example, implies that the degree of (local) risk aversion will increase (or at least not decrease) as we move towards the North West in the unit probability triangle.

One characteristic of the KT experimental choice situations is how close each pair of alternatives is to a choice involving a pure increase in risk in the sense of a mean preserving spread. ***B*** offers a slight increase in expected return over ***A***, from 2400 to 2409. as does ***H*** (825) over ***G*** (816). ***H*** can be viewed as obtained from ***G*** by reducing the probability on the middle prize 2400 to zero and spreading the residual probability mass into the tails of the distribution ...33% to the top tail, 2500, and an extra 1% to the bottom tail, 0. To see just how close the change from ***G*** to ***H*** is to a pure increase in risk consider alternative ***F*** =(67.36, 32.64) in Figure 1. ***F*** is a pure increase in risk relative to ***G***, a mean preserving spread. In Euclidean distance in (P_1,P_3) space ***F*** is a mere 0.0051 away from ***H***, about one half a percentage point.

The verbal description of the alternatives in the original KT experiment is a choice of frame that does not make it easy for a subject to see that ***H*** is almost a pure increase in risk compared to ***G***. In our experiment subjects were presented with choices between all three pairs of prospects, ***A*** and ***B***, ***G*** and ***H***, and ***F*** and ***G*** from Figure 1 in two frames[7]. The choice between prospects ***G*** and ***F***, and the same prospects, ***G****** and ***F******, framed slightly differently, is shown as an example in Figure 2. The first frame is called the *standard prospect frame* because of it presents prospects as probability distributions of prizes. The second frame, called the *Mean Preserving Spread (MPS) transparent frame*, displays expected returns and the probability of receiving 0.

The two frames are logically equivalent representations of the same pairs of prospects. The standard prospect frame requires an explicit calculation in order to find the mean of prospects. The MPS transparent frame makes it easier to detect mean preserving spreads since it presents explicit information on the mean return and on how probability is changing in at least one tail (lower tail) of the distribution. Since each frame explicitly states the possible prizes in each prospect, reasonably intelligent subjects could in principle perform the necessary simple calculations to detect the logical equivalence of the pairs of prospects in alternative frames[8]. However, in accord with experience in

[6]Sugden (1987) pages 5, 9

[7]For reporting purposes we have used the symbol G and G* to denote the prospect G in standard and modified frames. In the actual experiment G* was denoted with a different alphabetical label.

[8]All of the students in the class were second year microeconomics students who had studied and done tutorial problems in expected utility theory.

other experiments involving framing effects (Tversky and Kahneman (1988)) we did not expect that subjects would in fact translate from one frame to another.

Figure 2
Experimental Frames

Standard Prospect Frame

Possible outcomes are $0, $2400, $2500	G	F
Probability of $0	66.00%	67.36%
Probability of $2400	34.00%	0.00%
Probability of $2500	0.00%	32.64%

MPS Transparent Frame

Possible outcomes are $0, $2400, $2500	G*	F*
Probability of $0	66.00%	67.36%
Expected Return	$816	$816

We conjectured that *G** would be chosen over *F** if subjects are risk averse, since the MPS frame makes it easy to detect that *F** is a pure increases in risk compared to *G**. In the standard prospect frame we expected to observe *F* chosen over *G* for two reasons. First, we expected to replicate the KT experimental results about the common consequence effect, namely *A* chosen over *B* and *H* chosen over *G*, and as we remarked above, *F* is so close to *H* as to be almost imperceptibly different. Our second reason is based on a hypothesis of Sugden's about a general evaluative strategy at work in the common consequence and common ratio effects:

> "In each case, people seem to be attracted to a certain gain rather than a gamble with a *slightly higher actuarial value*; but when it comes to a choice between two gambles in each of which the chance of winning anything is relatively small, they are attracted to the gamble with the larger prize" (Sugden 1987, 7 , italics added)

This notion suggests that *F* will be chosen over *G* since each prospect gives a relatively small chance at a positive prize, but *F* has the larger prize (2500 versus 2400 for *G*).

Given a sensitivity of risk attitudes (choices between *F* and *G*) to framing effects, we also conjectured that the common consequence effect is unlikely to occur in both frames jointly. That is, we expect to observe the original KT result, *A* chosen over *B*, and *H* chosen over *G*, but also to observe *A** chosen over *B**, and *G** chosen over *H**. The rationale for this conjecture is that in the choice between *A* and *B*, however framed, the certainty of 2400 with prospect *A* (or *A**) would be paramount. Moreover if *G** is chosen over *F**, according to our first conjecture, then *G** is likely to be chosen over H^*, since the difference between F and H is almost an imperceptible one half a per cent in the unit probability triangle.

Statistical Methodology

The data for this experiment was generated from a survey of 86 second year economics students at the University of Canterbury, Christchurch, New Zealand. Each student was presented with a booklet of cards depicting one of six pairings of the prospects shown in Figure 1 to choose between: A and B, G and H, F and G , A^* and B^*, G^* and H^*, and F^* and G^*, and asked to mark each card with their preferred selection. The students were not informed that some of the pairs of choices were alternative ways of presenting the same underlying prospect, but there was nothing in the experimental protocol to prevent them from comparing any two choice situations simultaneously and discovering this fact. As an incentive to truthful revelation of their own personal preferences they were advised that their names would go into a random draw to play a scaled down version of one of the prospects.

The data from each subject i, i=1,...86, in the experiment is thus a 6-tuple $X_i = (x_{i1},...,x_{i6})$ of observations, where $x_{ij} = 1$ or 0 according as the left hand member of the following six pairs is (or is not) selected by subject i: $j \in \{1=(A,B),\ 2=(G,H),\ 3=(F,G),\ 4=(A^*,B^*),\ 5=(G^*,H^*),\ 6=(F^*,G^*)\}$ For example, an X_i vector like (1,1 0,0,0,0) means subject i chose A over B, G over H, G *over* F, B^* over A^*, H^* over G^*, and G^* over F^*. We use the notation $X_N = \{X_1, X_2, ... X_N\}$ to describe a possible sequence of observations of an experiment involving N subjects.

Theories like EUT or fanning out and concepts like risk aversion predict patterns in the data $X_N = \{X_1, X_2, ... X_N\}$. For example, to be consistent with fanning out theory in both the standard prospect frame and the MPS frame, A should be chosen over B , H should be chosen over G, A^* should be chosen over B^*, and H^* should be chosen over G^*. This implies that an X_i vector should look like (1,0 0,1,0,0) or (1,0 0,1,0,1), (1,0 1,1,0,0), or (1,0 1,1,0,1), i.e. any data vector with 1's in the first and fourth places and 0's in the second and fifth places. Of course, observations X_i can be categorized in many different and theoretically interesting ways, such as whether or not they are consistent with expected utility theory, risk aversion, fanning out hypotheses, having preferences subject to framing effects, etc.. Table 1 identifies theoretically relevant categories for our experiment.

Table 1
Theoretically relevant categories

Theoretical Concept	Frame	Predicted Choice Pattern
Expected utility	standard prospect frame	{*A* over *B* and *G* over *H*} or {*B* over *A* and *H* over *G*}
	MPS transparent frame	{*A** over *B** and *G** over *H**} or {*B** over *A** and *H** over *G**}
Fanning out	standard prospect frame (KT replication)	{*A* over *B* and *H* over *G*}
	MPS transparent frame	{*A** over *B** and *H** over *G**}
Risk attitude	standard prospect frame	risk averse: *G* over *F* risk seeking: *F* over *G*
	MPS transparent frame	risk averse: *G** over *F** risk seeking: *F** over *G**

Suppose there are R categories or classifications of interest. The histogram, $s_j(X_N)$, j=1,2,...R corresponding to any observed sequence $X_N = \{X_1, X_2, ... X_N\}$ is defined in the natural way as the sum or count of the number of observations X_i in the sequence which are in category j. We will use the notation $s_1^*, s_2^*, ... s_R^*$ to denote the histograms derived from the sequence of actual observations $X_1, X_2, ... X_m$ in an experiment with m observations, and $s_1, s_2, ... s_R$ to denote category sums for yet to be observed sequences of observations $X_{N-m} = \{X_1, X_2, ... X_{N-m}\}$.

In this paper, and scientific activity generally[9] ,we are concerned with making an inference, a coherent conditional probability assessment, about yet to be observed sequences of observations $X_{N-m} = \{X_1, X_2, ... X_{N-m}\}$, or their associated histograms $s_1, s_2, ... s_R$, having observed other data sequences, summarised by their histograms $s_1^*, s_2^*, ... s_R^*$. We base our inferences on the theory of operational subjective statistical procedures (Lad (1992)), particularly on a fundamental representation theorem of de Finetti, a brief explanation of which follows.

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, $X_N = \{X_1, X_2 ... X_N\}$, *exchangeably.* Exchangeability is a restriction on one's personal probability assessment of sequences of possible experimental results $X_N = \{X_1, X_2 ... X_N\}$. It means that, if a particular sequence of experimental results $X'_N = \{X'_1, X'_2 ... X'_N\}$ yields a histogram $s_j(X'_N)$ j=1,2,...R, where R is the (finite) number of possible values each X'_i can take, one would assert equal probabilities to <u>any</u> individual sequence of experimental results $\{X_1, X_2 ... X_N\}$ yielding the same histogram. Exchangeability seems eminently

[9]see de Finetti, Ch 11

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 $X_N = \{X_1, X_2 ... X_N\}$. According to de Finetti's representation theorem, Lad (1992, Ch 5, pp 62-64)[10], if we regard the sequence $X_1, X_2 ... X_N$ 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 $X_1, X_2, ... X_m$ is a <u>sufficient statistic</u> for any coherent inference about the remaining N-m quantities in the sequence $X_1, X_2 ... X_N$.

B• One's personal probability distribution for an observable sequence $X_n = \{X_1, X_2 ... X_n\}$, for any choice of n observations from N, can be written as a mixture multinomial:

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

where $s_j(X_n)$ j=1,2,...R, is the histogram for X_n, $(\theta_1 \ldots \theta_{R-1})$ is a vector of parameters and $M((\theta_1 \ldots \theta_{R-1}))$ 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 (1), 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.

$$(2) \quad P[s_1, s_2, \ldots s_R \mid s_1^*, s_2^*, \ldots s_R^*] = \frac{(N-m)!}{s_1! s_2! \ldots s_R!} \frac{\Gamma[\sum_{j=1}^{R} \alpha_j + s_j^*] \cdot \prod_{j=1}^{R} \Gamma[\alpha_j + s_j]}{\Gamma[(N-m) + \sum_{j=1}^{R} \alpha_j + s_j^*] \cdot \prod_{j=1}^{R} \Gamma[\alpha_j + s_j^*]}$$

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 (1) and (2) permit us to distinguish between theoretical views that assess the probability of histograms of data differently through a choice of the mixing distribution M .

Equation (2) provides a useful way to think about the choice of parameters $(\alpha_1, \alpha_2, \ldots \alpha_R)$ for the Dirichlet mixing distribution. Notice that if we have no experimental evidence available (m=0), then all $s_j^*=0$ and the probability assessments $P(s_1, s_2 ... s_R \mid 0,0...0)$ for histograms of experimental data are completely determined by the parameters $\alpha_1, \alpha_2, \alpha_R$ of the Dirichlet density. For a given choice of parameters, $\alpha_1, \alpha_2, \ldots \alpha_R$, the probability assessments $P(s_1, s_2 ... s_R \mid 0,0...0)$ can be viewed as

[10]This theorem is discussed in Good (1975), Ch. 4

prior beliefs about possible histograms of data. As experimental evidence accumulates in the form of histograms ($s_1^*, s_2^* \ldots s_R^*$), coherent inferences based on the conditional probability assessments $P(s_1, s_2 \ldots s_R | s_1^*, s_2^* \ldots s_R^*)$, hereafter called the **predictive probabilities** , change at a rate determined by the size of the $\alpha_j + s_j^*$. Alternatively, we can hold $s_1^*, s_2^* \ldots s_R^*$ fixed, change $(\alpha_1, \alpha_2, \ldots \alpha_R)$, and note from equation (2) that $P(s_1, s_2 \ldots s_R | s_1^*, s_2^* \ldots s_R^*)$ changes at a rate also determined by the size of the $\alpha_j + s_j^*$. Viewed this way, changes in $(\alpha_1, \alpha_2, \ldots \alpha_R)$ have precisely the same (marginal) impact on predictive probabilities $P(s_1, s_2 \ldots s_R | s_1^*, s_2^* \ldots s_R^*)$ as do changes in observational data $s_1^*, s_2^* \ldots s_R^*$. The selection of parameters $(\alpha_1, \alpha_2, \ldots \alpha_R)$ can thus be calibrated in terms of "observational" equivalents in each category R.

The larger the size of α_k relative to other Dirichlet parameters, the relatively stronger is the prior assertion about events in category k being likely. Looking out one trial ahead prior to the experiment, with N=1 and m=0, the ratios $\alpha_k / \Sigma\alpha_i$ indicate the prior probability on category k of the first trial of the experiment. Inspection of the denominator of equation (2) also shows that the larger the overall sum of the parameters $\Sigma\alpha_i$ the slower will be the rate of change of the predictive distribution as observational data accumulates in any one category. Strongly held prior beliefs can thus be represented by large overall sums $\Sigma\alpha_i$. Accordingly, the number $\Sigma\alpha_i$ will be called the **strength** of the prior belief.

In this paper we will primarily be interested in making inferences "in the small", i.e., about the outcome of next trial of the experiment. Thus, for the theoretical concepts in Table 1, we report the predictive distribution $P(s_1, s_2 \ldots s_R | s_1^*, s_2^* \ldots s_R^*)$ of a relevant histogram on the *next trial of this experiment* (N-m=1), having seen a sequence of m experimental results. Our choice of parameters for the Dirichlet mixing distribution covers three representative possibilities, over a range of strength of beliefs between 1 and 100 observations: The Hit & Miss theory is incorporated as a benchmark. Surely theories like EUT or FO should be able to predict better than a uniform prior combined with simple Bayesian updating of predictive probabilities.

•**EUT symmetric**	Prior assertions are equivalent to 90% in support of EUT in either frame alone (ie taken marginally) with violations of EUT equally likely[11];
•**Fanning Out**	Prior assertions are equivalent to 90% in support of FO in either frame alone (ie taken marginally)[12];
•**(Uniform) Hit & Miss**	Prior beliefs assert an equal chance at any X_i vector;

One question raised in the previous section is whether there is a positive or negative *correlation* between aspects of subjects' choices like risk attitudes or common consequence effects in different frames. For our purposes, two events A and B are positively (negatively) correlated in a subjective probability assessment P if the probability of A given B exceeds (is smaller than) the probability of A. The more the ratio of conditional to unconditional probability differs from unity, the stronger is the degree of correlation between the relevant events. The probability distribution of equation (2), with an appropriate choice of categories, can be used to assess whether events are positively or negatively correlated. Correlations will be called predictive or prior according as predictive or prior probability assertions are used.

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[11]We assume the EUT theorist asserts 0.825 probability equally to the 8 possible X_i vectors with $\{A$ over B, G over H, A^* over B^*, G^* over $H^*\}$ or $\{B$ over A, H over G, B^* over A^*, H^* over $G^*\}$, i.e. 0.103125 each, and distributes the remaining probability equally between the rest of the 56 possible X_i vectors, i.e. 0.003125 each . This implies that the probability asserted for the following events (viewed marginally) is each 45%: A over B and G over H, A^* over B^* and G^* over H^* , B over A and H over G , B^* over A^* and H^* over G^*. In effect the EUT theory behind these assertions assumes that risk averse behaviour is just as likely as risk seeking behaviour.

[12]The Fanning Out theorist asserts a 90% chance of choosing A over B and H over G, in either frame. Since F and H are so close in the standard prospect frame we assume that the Fanning Out theorist will extend his original assertion to incorporate a 90% chance of choosing A over B and F over G, in either frame. There are many coherent ways to extend the original assertion of a 90% chance of choosing A over B and H over G using to the Fundamental Theorem of Prevision, Lad, Dickey and Rahman (1990). For simplicity we assume that for the modal outcome vector for FO, (1,0,1,1,0,1), meaning subject i chooses A over B, H over G, F over G, A^* over B^*, H^* over G^*,and F^* over G^*., a probability of z=0.86875 is asserted with the remaining probability mass 1-z distributed equally over the other 63 logically possible X_i vectors, i.e.0.00208 each. With this assertion the probability implicitly asserted for the following events (viewed marginally) is 90%: A over B and H over G, A over B and F over G, A^* over B^* and H^* over G^*, A^* over B^* and F^* over G^*. The conditional probability of the event of choosing A over B and F over G given the event of the common consequence effect, A over B and H over G in the standard prospect frame, is then implicitly asserted to be virtually certain, (0.86875 +5*0.00208)/.9, about 97.7%.

Experimental Results

Risk Attitudes

Our first conjecture, that subjects would avoid pure increases in risk that are transparent, is strongly supported by the experimental evidence. Histogram 1 shows how people in the experiment chose between a risky alternative (*F* in the standard prospect frame, *F** in the MPS transparent frame) that is a mean preserving spread of another, safer, alternative (*G* in the standard prospect frame, *G** in the MPS transparent frame). In the MPS transparent frame 80 out of 85 subjects display risk aversion (*G** chosen over *F**), while in the standard prospect frame the number revealing themselves risk averse (45) is almost equal to the number revealing themselves risk seeking (40). 42 subjects display risk aversion in both frames (choosing *G* over *F* and choosing *G** over *F**), but of the 40 subjects who display risk seeking attitudes in the standard prospect frame (*F* chosen over *G*), 38 out of 40 (95%), *switch to being risk averse in the MPS transparent frame*. The MPS transparent frame apparently makes it easier for such people to detect mean preserving spreads and, when they do, to reject them.

Histogram 1

Histogram for Risk Attitude

	G*	F*	total
G	42	3	45
F	38	2	40
total	80	5	85

Three predictive probability distributions based on the evidence in Histogram 1 are presented in Table 2. For each representative theory, predictive joint distributions for the outcomes of choices between *F* and *G* and between *F** and *G** on the next trial of the experiment are reported in full for four strengths of prior belief. The change in beliefs brought about by the experimental data is striking, especially for weak to moderately held prior beliefs. A Fanning Out theorist with moderately strong (10-50) prior beliefs asserting a 90% prior chance on *risk seeking* behaviour in both frames (choice of *F* and choice of *F**) changes his coherent probability assessments to predict *risk aversion* with between 65-88% probability. For a comparably committed theorist with more symmetrical prior beliefs about risk seeking and risk averting behaviour, the EUT symmetrical and Hit & Miss cases, the posterior predictive probability asserted for risk seeking in both frames drops from even odds to less than 10%.

Table 2
Predictive joint distribution for risk attitudes in MPS transparent (F^* vs G^*) and standard (F vs G) frames
[F is a mean preserving of G]

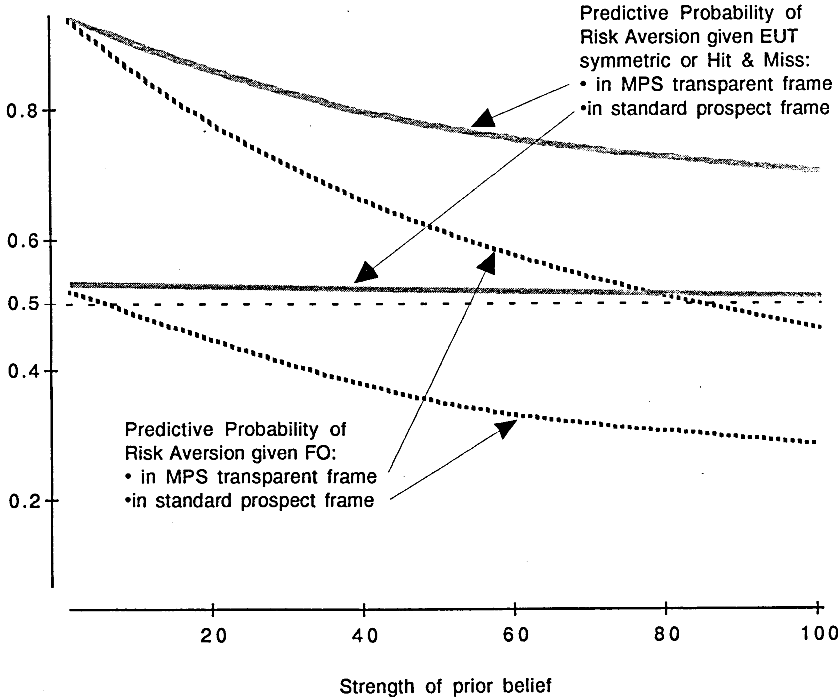
Strength of Prior Belief	Fanning Out				EUT symmetric & Hit and Miss			
	GG*	GF*	FG*	FF*	GG*	GF*	FG*	FF*
1	0.489	0.035	0.442	0.034	0.491	0.038	0.445	0.026
10	0.446	0.035	0.404	0.116	0.468	0.058	0.426	0.047
50	0.323	0.035	0.294	0.348	0.404	0.115	0.374	0.107
100	0.245	0.034	0.223	0.497	0.362	0.151	0.341	0.146
Prior	*0.033*	*0.033*	*0.033*	*0.9*	*0.25*	*0.25*	*0.25*	*0.25*

The joint distributions in Table 2 can be used to take a marginal view on risk attitudes by integrating over relevant events. Using row 2 of Table 2, for example, a FO theorist with moderately strong (10) initial beliefs asserting over 93% (=0.9+.033) prior probability on risk seeking behaviour in the MPS transparent frame (choosing F^* over G^*, irrespective of choices over F and G), changes this assessment to an 85% (=.404 +.446) predictive probability of observing risk averting behaviour in the MPS transparent frame on the next trial of the experiment[13]. In the standard prospect frame the 6.6% prior probability asserted for risk averting behaviour (choosing F over G) is increased to about 48%. A comparably committed (strength = 10) theorist with symmetrical initial views on risk attitudes revises his 50/50 prior beliefs substantially to assert a 90% predictive probability for risk aversion in the MPS transparent frame but hardly makes any revision at all to prior beliefs in asserting a 52% chance for risk aversion in the standard prospect frame.

Figure 3 plots the predictive probabilities for risk aversion in each frame for EUT symmetric and FO theories against strength of initial belief. Two elements of the diagram stand out . First, a theorist starting with EUT symmetric beliefs asserting even odds on observing risk averse or risk seeking choices essentially makes no revision in beliefs about the chances of risk aversion in the standard prospect frame, no matter what the strength of initial belief. In contrast, there is a substantial upward revision in beliefs about the chances of risk aversion in the MPS transparent frame. Second, no matter what your initial beliefs, whether in favour of FO or EUT or a simplistic Hit & Miss theory, and for all ranges of strength of belief we're looking at, the predictive probability of risk aversion in the MPS transparent frame is much higher than the predictive probability of risk aversion in the standard prospect frame.

[13] sum the probabilities in the cells for FF* and GF*

Fig 3
Predictive Probabilities for Risk Aversion



The inference that risk aversion in the MPS transparent frame is much more likely than risk aversion in the standard prospect frame is interesting, but perhaps not much of a worry if the two indices of risk aversion are correlated. However, the joint distribution in Table 2 can also be used to show that there is almost no correlation between risk aversion as indicated by choices in the MPS transparent and standard prospect frames. Table 3 presents the relevant predictive probability assertions. For example (row 2, columns 5 & 6), an EUT symmetric theorist or someone starting with a Hit & Miss theory with moderately strong initial beliefs asserts a predictive probability for risk aversion in the MPS transparent frame of 89% without knowledge of risk aversion in the standard prospect frame and asserts virtually the same predictive probability, 89.5%, for risk aversion in the MPS transparent frame conditional on knowledge that the person will be risk averse in the standard prospect frame. That is, knowledge that a person is risk averse in one frame makes very little difference to coherent predictive probability assessments derived from EUT symmetric or Hit & Miss theories that a person will be risk averse in the other frame. That this relationship between conditional and unconditional probability assertions is independent of strength of belief as indicated by the ratios in the last column of Table 3 being almost equal and very close to unity for all relevant strengths of initial belief. Similar inferences hold for predictive assertions based on FO theories held with moderate strength, except that as strength of belief increases the initially high and strongly held prior positive correlation[14] between indices of risk aversion in the two frames begins to dominate the influence of the experimental data.

Table 3
Correlations between risk aversion in the MPS transparent frame (choosing G^*) and risk aversion in the standard prospect frame (choosing G)

	FO prior			EUT symmetric & Hit and Miss Priors		
	Predictive probability			***Predictive probability***		
Strength	*Conditional* $G^*\mid G$	*Unconditional* G^*	ratio	*Conditional* $G^*\mid G$	*Unconditional* G^*	ratio
1	0.933	0.931	1.002	0.929	0.936	0.992
10	0.927	0.849	1.092	0.890	0.895	0.995
50	0.903	0.617	1.464	0.779	0.778	1.001
100	0.877	0.468	1.873	0.705	0.703	1.004
prior	*0.500*	*0.066*	*7.576*	*0.900*	*0.500*	*1.000*

In summary, there are two general points. First, the MPS transparent frame apparently induces people to take a much more conservative attitude towards pure increases in risk as revealed by their choices than the standard prospect frame does. Second, there is little or no correlation between behavioural indices of risk aversion in the MPS transparent frame and in the standard prospect frame.

Replicating the KT Common Consequence Effect

Our attempt to replicate the KT common consequence effect, A chosen over B and H chosen over G, in the standard prospect frame met with mixed success. As Histogram 2a indicates, approximately half of the subjects (42, along the diagonal) chose in accordance with EUT while approximately half (40) violated EUT in accordance with the fanning out hypothesis and the common consequence effect. KT's original experiment showed a slightly larger percentage, 61%, choosing in accord with the fanning out hypothesis; the proportion of subjects choosing H in our experiment (78%) is roughly the same as in KT's experiment (83%) but the proportion choosing A in our experiment (69%) is considerably less (KT's 82%),.

[14] According to our specification of FO theory, there is a 90% prior chance on risk seeking behaviour in both frames (both F and F* being chosen) when considering choices between F and G in either frame and inconsistencies with this modal outcome are considered equally likely. The initial probability asserted for risk aversion in either frame taken on its own is very low (0.066) , but knowledge that risk seeking is avoided in one frame implies that a FO violation is occurring, which creates prior even odds on risk aversion. The large increase in unconditional to conditional probability is what we mean by positive correlation.

Histogram 2:
The Common Consequence Effect (*A* and *H* or *A and *H**)**

Histogram 2a: standard prospect frame[15]

	A	B	total
G	17	1	18
H	40	25	65
total	57	26	83

Histogram 2b: MPS transparent frame

	A*	B*	total
G*	26	2	28
H*	47	10	57
total	73	12	85

Histogram 2b shows that more subjects exhibit the common consequence effect (choosing *A** and *H** or *A* and *H*) in the MPS transparent frame than in the standard prospect frame, contrary to our conjecture that KT's experimental results would not hold in the MPS transparent frame. While the MPS transparent frame did induce subjects more subjects to choose prospect *G** rather than *H** (28 out of 85 in the MPS frame versus 18 out of 83 in the standard prospect frame), as we had conjectured, the change in frame also had the effect of making the certainty prospect, *A**, more attractive (73 out of 85 in the MPS frame versus 57 out of 83 in the standard prospect frame).

Table 4
Predictive probability of the common consequence effect

	standard prospect frame			MPS transparent frame		
Strength	**FO**	**EUT symmetric**	**Hit & Miss**	**FO**	**EUT symmetric**	**Hit & Miss**
1	0.487	0.477	0.479	0.557	0.547	0.549
10	0.527	0.435	0.457	0.589	0.500	0.521
50	0.639	0.32	0.395	0.681	0.367	0.441
100	0.710	0.246	0.355	0.741	0.281	0.389
prior	*0.90*	*0.05*	*0.25*	*0.90*	*0.05*	*0.25*

The (marginal) coherent predictive probability assessments for observing the common consequence effect on the next trial of the experiment based on this data are shown in Table 4. A conspicuous feature in the table is that predictive probabilites for the common consequence effect (in either frame viewed marginally) of both EUT theorists and Hit & Miss theorists increase markedly relative to prior beliefs. For example, although prior to observing the experimental data a strongly committed EUT theorist asserts only a 5% probability of observing the common consequence effect in a trial, normal Bayesian updating will induce a coherent change in probability assessments to around a 1 in 4

[15]Counts in cells are for the number of subjects choosing the corresponding row element from the row choice (in this histogram G vs. H) and the corresponding column element from the column choice (in this case A vs. B). Row and column totals are presented for convenience.

chance. Even someone asserting strong Hit and Miss priors, giving an equal (25%) prior chance at any of the four cells in Histograms 2 or 3, would assess roughly a 40% predictive probability at the common consequence effect occurring after observing the data.

The marginal information in Histogram 2 is of limited interest. Histogram 3 below shows the numbers of experimental subjects who exhibit the common consequence effect in either frame alone or in both frames. Only 25 out of 86, 29%, actually demonstrate the common consequence effect in both frames, compared with 40 out of 83 (48%) and 47 out of 85 (55%) in each frame taken marginally. Unlike the case with risk attitudes, however, there is no asymmetry in the results: the numbers satisfying the common consequence effect in one frame and violating it in the other are roughly the same for both frames (24 out of 46 in the standard prospect frame and 22 out of 47 in the MPS transparent frame).

Histogram 3

Histogram for common consequence effects in both frames

		MPS transparent frame		
		Common consequence effect	Other	total
standard prospect frame	Common consequence effect	25	24	46
	Other	22	15	37
	total	47	39	86

Coherent predictive probability assertions derived from this data are shown below in Table 5[16]. and the associated correlations in Table 6. Table 5 indicates that someone holding a Hit and Miss prior revises beliefs slightly upwards towards the joint event of the common consequence effect in both frames (from 25% to 27-29% in cell YY*) and revises slightly downward beliefs about the event of completely avoiding the common consequence effect in both frames (from 25% to 17-22% in cell NN*). An EUT theorist revises beliefs about the common consequence effect in both frames upwards (from 5% to 27%-29%), but only to the levels associated with the Hit and Miss theory. A FO theorist with moderately strong beliefs will share this opinion, i.e., that there is roughly a 1 in 4 predictive probability of satisfying the common consequence effect in both frames. Even a FO theorist with

[16] From footnote 11 there are 8 outcome vectors (for a trial) agreeing with EUT having prior probability (for the first trial) 0.825 in total, with the remaining probability mass spread equally over the other 56 outcome vectors. The event of choosing H over G and A over B has 16 outcome vectors each with prior probability 0.175/56. The event H over G and B over A has 4 outcome vectors with prior probability 0.825/8 and 12 outcome vectors with prior probability 0.175/56. From footnote 12 the FO theorist asserts a prior probability of 0.86875 to the X_i vector (1,0,1,1,0,1), meaning subject i chooses *A* over *B*, *H* over *G*, *F* over *G*, *A** over *B**, *H** over *G**,and *F** over *G**.. There are 3 other outcome vectors, each with prior probability (1-0.86875)/63 with the property of the common consequence effect in both frames, for a total prior probability on this event of 0.875 For each theory the Dirichlet parameters for each category are the associated prior probabilities multiplied times the strength indicator.

strongly held prior beliefs cuts prior probability assertions of 87.5% for the joint event of a common consequence in both frames in half after seeing the experimental data.

Table 5
Predictive probabilities for the joint distribution of common consequence effects in MPS transparent and standard prospect frames

[The presence or absence of the common consequence effect is indicated by Y=yes N=no, with * denoting events in the MPS transparent frame]

	FO				*EUT symmetric*				*Hit & Miss*			
Strength	YY*	YN*	NY*	NN*	YY*	YN*	NY*	NN*	YY*	YN*	NY*	NN*
1	0.297	0.276	0.253	0.173	0.288	0.281	0.258	0.173	0.290	0.279	0.256	0.175
10	0.352	0.253	0.232	0.164	0.266	0.297	0.276	0.161	0.286	0.276	0.255	0.182
50	0.506	0.186	0.171	0.138	0.202	0.342	0.327	0.129	0.276	0.268	0.254	0.202
100	0.605	0.142	0.132	0.121	0.161	0.371	0.360	0.108	0.269	0.263	0.253	0.215
Prior	*0.875*	*0.025*	*0.025*	*0.075*	*0.050*	*0.450*	*0.450*	*0.050*	*0.25*	*0.25*	*0.25*	*0.25*

The inferences from the correlation assertions in Table 6 are just as revealing. All three theories assert virtually zero or indeed, slightly negative, predictive correlations between common consequence effects in both frames, with the lone exception of strongly held EUT theory, where the prior beliefs about a strong negative correlation between common consequences in both frames dominates the effect of the experimental data[17]. Essentially, knowledge that a common consequence effect is occurring in the MPS transparent frame either makes little or know difference to the coherent predictive probability these theorists would assert for common consequence effects in the standard prospect frame, or it slightly reduces that probability. Similar remarks hold for FO theorists, especially those with moderate prior beliefs.

[17]The way in which we specified beliefs consistent with FO theory simply assigned a high probability to one outcome (a modal outcome consistent with FO theory and the virtually imperceptible difference between F and H in prospect space) and equal probability to all other outcomes of a trial. It would be possible to introduce a prior positive correlation between the common consequence effects in the two frames to obtain a more refined assertion of FO theory, but the general conclusion from Tables 6 and 7 would remain the same - for moderately held beliefs the data indicates no correlation, while for strongly held beliefs the prior information dominates the effect of the data.

Table 6

Correlations between the common consequence effect in the MPS transparent frame and in the standard prospect frame

[The presence or absence of the common consequence effect is indicated by Y=yes N=no, with * denoting events in the MPS transparent frame]

	FO			*EUT symmetric*			Hit & Miss		
	Predictive Probability			Predictive Probability			Predictive Probability		
Strength	$Y \mid Y^*$[18]	Y	ratio	$Y \mid Y^*$	Y	ratio	$Y \mid Y^*$	Y	ratio
1	0.540	0.574	0.942	0.527	0.569	0.927	0.531	0.569	0.933
10	0.603	0.604	0.998	0.490	0.563	0.872	0.528	0.562	0.940
50	0.747	0.691	1.081	0.382	0.544	0.702	0.520	0.544	0.957
100	0.821	0.747	1.099	0.309	0.532	0.581	0.515	0.532	0.968
prior	*0.972*	*0.900*	*1.080*	*0.100*	*0.500*	*0.200*	*0.500*	*0.500*	*1.000*

In summary, framing effects are less pronounced for the common consequence effect than they are for risk attitudes. Apart from the cases of strongly held prior beliefs, predictive probabilities for common consequence effects in FO and EUT theories are very similar to what one would assert with a Hit & Miss theory - about a 1 in 4 chance of observing the common consequence in both frames and about a 50% chance of observing the common consequence effect in either frame taken marginally. Moreover there is either no predictive correlation between common consequence effects in both frames or a small negative predictive correlation.

[18] This notation means "Y given Y*", i.e. the common consequence effect in the standard prospect frame given knowledge of the common consequence effect in the MPS transparent frame.

Discussion and Further Implications

Our experiment and the analysis above suggests three further inferences, the first about claims that violations of EUT are systematically predictable by alternative theories, the second about the robustness of common consequence effects to parameter changes, and the third about the range of acceptable FO hypotheses.

How 'systematic' are violations of EUT?

While it is often claimed[19] that the common consequence effect shows that FO (or other) theories yield systematic and predictable violations of EUT theory, inferences based on our experimental results suggest this claim is exaggerated. Typically[20] researchers on the common consequence effect report histograms of observed choices and results of significance tests on a null hypotheses that the pattern of errors in EUT are i.i.d. This statistical methodology is generally inappropriate for drawing coherent inferences about the relative predictive power of alternative theories, and specifically inappropriate for the task of predicting outcomes over the entire outcome space using alternative theories. For example, when focusing attention on outcomes that are violations of EUT , it may well turn out that they tend to occur in directions predicted by FO theories. The null hypothesis that errors in EUT are i.i.d. will be rejected, and an inference drawn that something systematic is happening in the experiment in support of patterns predicted by FO (or some other) theories. But viewed as a conditional probability assertion, the claim that violations of EUT tend to occur in directions predicted by FO is quite consistent with another conditional probability assertion that violations of FO tend occur in directions predicted by EUT. Viewing this latter assertion as the hypothesis that errors in FO are i.i.d., it may well also be rejected at some significance level and an inference drawn that something systematic is happening in the experiment in support of patterns predicted by some other theory (here EUT).

Table 7 below illustrates this point .Each cell in the table is the predictive probability for the corresponding joint row and column event for an EUT theorist with moderately strong beliefs(=10) making predictions about the common consequence effect in the standard prospect frame. Conditional on a violation of a theory (either FO or EUT) the other theory does quite well in predicting the direction of error. For example when EUT fails, i.e. given the events HA and GB, the predictive probability of the violation being in directions consistent with FO, namely HA, is high: (0.435)/(0.435+0.016) = 0.965. But symmetrically, when FO fails, i.e. given the events GA, GB and HB, the predictive probability of the violation being in directions suggested by EUT, namely GA or HB, is also high: (0.231+0.317)/(0.231+0.317+0.016) = 0.972.

[19](Appleby and Starmer (1987), 26; Tversky and Kahneman (1987), 187), Machina (1987) 127,130,132), Starmer (1992), 813). In fact all of the surveys in footnote 1 use these adjectives to describe the empirical evidence

[20]Recent examples include Starmer(1992), Harless(1992); see also Hey (1991) Chapter 5.

Neither of the above two inferences about 'support ' for an alternative theory is warranted simply because the data indicates something systematic is going on in the experiment and a null hypothesis is rejected. The adjective systematic as applied to violations of EUT in this context means only *unlikely to have arisen by "chance" as specified in the null hypothesis*. It does not imply that these observations are systematically (methodically) predictable by some other theory, nor that they are even relatively more predictable by some other theory than according to the null hypothesis.

A more relevant assessment of the predictive power of two theories, EUT and FO, however, will compare unconditional predictive probability of 'successes' and 'failures' of two (or more) theories. Continuing to use Table 7 as an example, whether you start out as a FO theorist or as an EUT theorist, predictive probabilities for outcomes consistent with FO are 0.527 and 0.435 respectively and predictive probabilities for outcomes consistent with EUT are (0.186+0.272) = 0.458 and (0.231+0.317) = 0.548 respectively. These probabilities are, qualitatively speaking, all in the neighbourhood of 50%, which is to say that the predictive probability of success on the next trial of the experiment within either theory, EUT or FO, is about the same as getting a head on the toss of a fair coin. Viewed this way, the theories are hardly providing much systematic (methodical) predictive power![21]

Table 7

Predictive probabilities for choices over *A* vs*B*,*G* vs*H*

(moderate (strength=10) prior beliefs)

EUT

	A	B
G	*0.231*	*0.016*
H	*0.435*	*0.317*

Fanning Out

	A	B
G	*0.186*	*0.014*
H	*0.527*	*0.272*

The acid test of a theory is its ability to predict relative to other theories. While a comparison of the latest (next trial) predictive probability distribution for alternative theories is insightful, a more systematic way of assessing the predictive performance of theories on all previous 86 trials is provided by the operational subjective theory of proper scoring rules (Lad (1992, Ch.6)). The log scoring rule is particularly appropriate for our purposes. 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

[21]This proposition is conditional on our assumption that prior beliefs are held with only a moderate amount of conviction, i.e., about 10 observations worth. If either or both prior beliefs are "stronger" in the sense of equivalent to more "observations", the priors will dominate the effect of the data in formulating a coherent predictive probability of success and lead to larger probabilities being asserted for violations of the other theory.

distribution function $(Q_1,...Q_K)$ from the K dimensional unit simplex where Q_i is the probability of the event $(X=x_i)$. With the convention that $(X=x_i)=1$ if $X=x_i$ and 0 otherwise, the log scoring rule is given by:

$$(3) \qquad S(X,Q_1..Q_K) = \sum_{j=1}^{K} (X=x_j)*Ln(Q_j)$$

The sequential score "in the small" for a theory's predictive probability distribution is derived in the following way. 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. 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[22]. The predictive probability is then updated 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. If the theory predicted outcome y_2 with a high probability (now using $f_x(X_1=y_2 \mid X_1=y_1)$ it gets a high score, otherwise it gets a low score. Continuing in this way the score for a theory after a sequence of m observations $(y_1,y_2,...y_m)$ is:

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

The second equality holds because the log of the sum is the log of the product, and the product in this case is just one way of factoring a joint pdf into a product of conditional pdfs. Equation (4) makes it clear that the log scoring rule has a total score that is independent of the order in which the observations arrive[23]. Equation (2) can be used to calculate the coherent probability of a particular data sequence $(y_1,y_2,...y_m)$[24] for a particular theory.

Table 8 presents the Log scores for the three theoretical viewpoints we have been considering, starting with its application to common consequence effects in each frame taken alone (essentially two 2X2 tables), then for the 4X4 table of joint common consequence effects in both frames and finally over the whole outcome space. In all cases, a theory asserting a simple uniform prior that permits

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[22]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

[23]The log scoring rule is also a proper scoring rule. If an agent asserting a theory $(Q_1,...Q_K)$ personally holds $(P_1,...P_K)$ as his/her own probability assessments a proper scoring rule assures that the expected score viewed as a function of $(Q_1,...Q_K)$, where the expectation is taken with respect to $(P_1,...P_K)$, is maximized by choosing $(Q_1,...Q_K)=.(P_1,...P_K)$. A proper scoring rule encourages honest revelation of personal probability assessments if expected score matters to the agent. The log scoring rule is discussed in Buehler (1971) and Lad (1992) Ch. 6

[24]To assess scores over the entire outcome space. set R, in equation (2) the number of categories, equal to K, the number of possible outcomes, (in our case 64) and remove the multinomial coefficient. By exchangeability, all sequences with the same category sum are equally likely. The multinomial coefficient in equation (2) simply counts the number of such sequences.

Bayesian updating, our Hit & Miss theory, has a higher log score than EUT or FO, no matter what portion of the outcome space we evaluate the theories over. A notable feature of the table is that any strongly held theory (strength equal to 100 or 50) has lower scores than a weakly held theory (strength equal to 10). Recalling our interpretation of Equation (2) for predictive probabilities, weakly held theories permit the observed data to change prior predictive probabilities via Bayes rule faster than with strongly held theories. The evidence from Table 8 is that it's basically better for predicting if one just lets the data 'speak for themselves' via Bayes rule than through the medium of a strongly held formal model like EUT or FO. In our experiment, only for one situation, the common consequence effect in the MPS transparent frame, (A* vs B* and G* vs H*),Table 8b, and that situation considered only marginally (ie unconditionally on other responses), did the predictive ability of a highly sophisticated theoretical construct, FO theory, come close to that of the Hit & Miss theory (see Table 8b, row 3). The Hit & Miss theory appeals to the cynical economist who regard information revealed in experiments over hypothetical outcomes as dubious at best, but who is willing to update his predictive distributions according to Bayes rule. The Log scoring rule results we have demonstrated tend to vindicate that cynicism.

In a simple binary comparison of EUT with FO, EUT, in at least a mildly held version does better at predicting outcomes than FO over the whole outcome space (Table 8d), over the common consequence effect in both frames and in the standard prospect frame (Tables 8c,8a), but not as well as FO in the MPS transparent frame. In spite of the fact that the common consequence effect of KT has basically been replicated EUT still does a better job at predicting outcomes than FO in some, though not all, frames, taken marginally or jointly.

Table 8

Log Scores for various theories over different parts of the outcome space

8a:Log score for the Common Consequence effect in the Standard Prospect Frame (Avs B and G vs H)

Strength	EUT symmetric	FO	Hit & Miss	Max Score
1	-99.2285	-101.519	-97.6316	Hit & Miss
10	-98.6624	-99.9207	-97.6551	Hit & Miss
50	-108.962	-109.006	-103.529	Hit & Miss
100	-117.473	-116.746	-106.884	Hit & Miss

8b:Log score for the Common Consequence effect in the MPS transparent Frame (A*vs B* and G* vs H*)

Strength	EUT symmetric	FO	Hit & Miss	Max Score
1	-96.6014	-98.5618	-94.6982	Hit & Miss
10	-97.5356	-95.8747	-94.5735	Hit & Miss
50	-111.895	-101.923	-101.629	Hit & Miss
100	-123.183	-107.628	-106.058	Hit & Miss

8c:Log score for the Common Consequence effect in both frames (Avs B, G vs H, A*vs B* , and G* vs H*)

Strength	EUT symmetric	FO	Hit & Miss	Max Score
1	-201.877	-207.32	-193.494	Hit & Miss
10	-195.003	-196.072	-187.435	Hit & Miss
50	-213.534	-206.693	-197.86	Hit & Miss
100	-229.312	-218.109	-205.175	Hit & Miss

8d: Log score for all outcomes, both frames

Strength	EUT symmetric	FO	Hit & Miss	Max Score
1	-294.564	-312.843	-276.239	Hit & Miss
10	-276.418	-298.216	-258.75	Hit & Miss
50	-292.974	-323.465	-273.707	Hit & Miss
100	-309.646	-346.168	-286.888	Hit & Miss

Why does the simple Hit & Miss theory do better than the other theories? Histogram 4 below, for the two frame common consequence effect, is suggestive of an answer at one level. The highlighted rows are the patterns that are consistent with either EUT or FO. Notice that there are still many other observed patterns occurring , patterns which both EUT and FO will tend to predict with a relatively low probability (even after Bayesian updating). The Log scoring rule penalises these predictive errors and rewards the Hit & Miss theory for assigning higher probabilities to such outcomes[25]. Essentially, the Hit & Miss theory is the only one that gives any credence to framing effects, albeit crudely. The other two theories, FO and EUT, by assuming invariance of decisions to choice of frame, simply rule out (assign low probability to) framing effects.

Histogram 4

The common consequence effect in two frames

(Highlighted cells are predictions of FO and EUT; • indicates a missing value)

A vs B	*G vs H*	*A* vs B**	*G* vs H**		*Raw Count*
A	*G*	*A**	*G**		*9*
A	G	A*	H*		8
A	H	A*	G*		10
A	*H*	*A**	*H**		*25*
A	H	B*	G*		2
A	H	B*	H*		3
A	•	A*	G*		2
A	•	A*	H*		1
B	G	B*	H*		1
B	H	A*	G*		5
B	H	A*	H*		13
B	*H*	*B**	*H**		*6*
B	H	B*	•		1

The common consequence effect and parameter changes

Appleby and Starmer (1987 p 28) raise the question as to te robustness of the common consequence effect to parameter changes in experimental design. Our experiment shows that the combination of a change in frame with a very slight change in the alternatives presented in the KT experiment to mean preserving spreads of one another is, with reasonably high predictive probability, likely to avoid the common consequence effect, even though a change in frame alone will probably not produce this effect. Consider trying to produce a common consequence effect from the four alternatives A,C,F and G in Figure 4, framed in a manner that makes the pure increases in risk from A to C and from G to F

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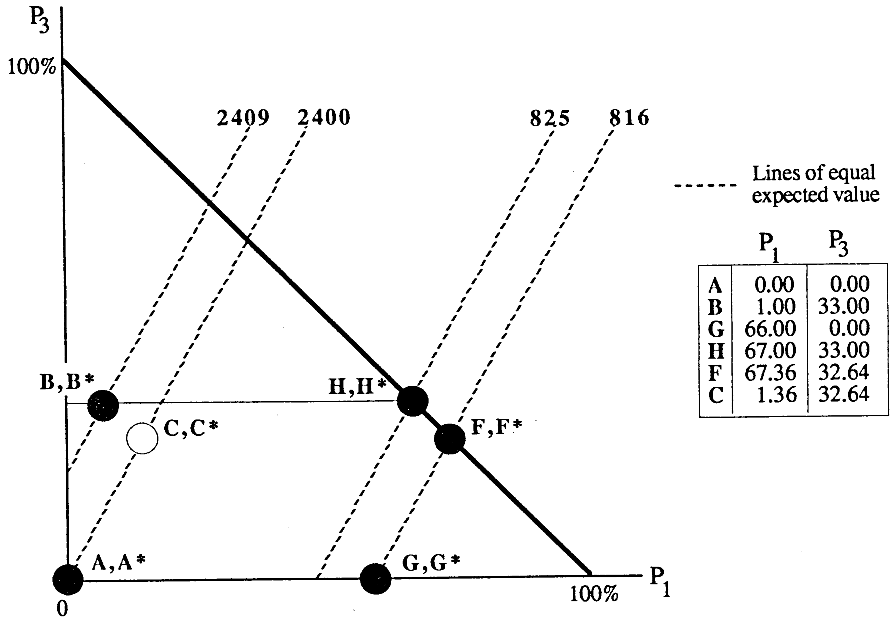
[25]Of course the Hit & Miss theory also pays a penalty for assigning higher probabilities (prior to Bayesian updating) to patterns which have not been observed experimentally, but overall, the penalties for these errors are apparently less than the rewards for its successes, at least relative to its competitors, FO and EUT.

transparent. We would still expect the certain alternative A to be chosen, no matter how framed. But, our experiment shows that there is about a 90% predictive probability that G will be chosen over F in the MPS transparent frame, avoiding the common consequence effect.

Figure 4



	P_1	P_3
A	0.00	0.00
B	1.00	33.00
G	66.00	0.00
H	67.00	33.00
F	67.36	32.64
C	1.36	32.64

FO theories relying on changing attitudes towards risk

Finally, one has to query a theory like Machina's that tries to explain common consequence effects in terms of stable personal characteristics, namely predictable changes in risk attitudes in various regions of the unit probability triangle. Indifference curves that appear to fan out strongly in a frame that masks relations of pure increase in risk, with subjects exhibiting a change from risk averting to risk seeking attitudes, are unlikely to fan out in another frame that makes pure increases in risk transparent (Table 2, above). Moreover, there is little correlation between the two indices of risk aversion.(Table 3), creating further doubt that there is a stable (frame independent) personal attitude towards risk that can be used to explain choice patterns. People *may* have underlying attitudes towards risk that are stable and consistently integrated across frames, but our evidence suggests otherwise.

Conclusions

The basic questions we set out to ask, and answer , were:

1• Does a frame that makes pure increases in risk transparent make any difference to choices over risky alternatives and to explanations of those choices that rely on predictable patterns of attitudes towards risk?

2• Will common consequence effects be predictable in frames where pure increases in risk are transparent?

Our answer to the first question is that the framing of information so that pure increases in risk can easily be detected does matter. Pure increases in risk will tend to be avoided when they are transparent, but not necessarily otherwise. In the two frames investigated in this paper there was no correlation between the risk attitudes observed in different frames. Our inference here concurs with the major finding of Tversky and Kahneman (1988, 185) that basic axioms of EUT like dominance and cancellation (independence) tend to be satisfied when they can be applied transparently but not generally otherwise . Concerning theoretical explanations that rely on changing attitudes towards risk, we find that risk aversion, as evidenced through choices, is not an exogenous underlying characteristic of decision makers, but endogenous and highly sensitive to the framing of alternatives.

Our answer to the second question is that it all depends on how close the four alternatives chosen for the common consequence effects are to pure increases in risk. With alternatives chosen that represent pure increases in risk on one another, the common consequence effect is very unlikely to be observed in an MPS transparent frame. However, a very slight increase in the expected value of the more risky prospect appears to be sufficient to make marginal inferences about the common consequence effect in one frame alone relatively independent of choice of frame in the sense that the predictive probability of the common consequence effect occurring in the MPS transparent frame is about the same size (about 50%) as the predictive probability of the common consequence effect occurring in the standard prospect frame. The predictive probability of a common consequence effect occurring in both frames, however, is about 1 in 4.

Viewed marginally or jointly, the common consequence effect is more predictable by FO theories than by *independent* chances, and in one sense of the word "chance" is therefore systematic (not happening just by "chance"). But the results of our scoring rule assessments show that the common consequence effect is no more predictable then by "chance" in the sense of a simple uniform prior and Bayesian updating - essentially Laplace's law of succession[26]. In this sense the common consequence effect is not systematically predictable by the current crop of FO theories. Some form of hybrid theory is necessary to adequately explain and predict experimental responses involving framing

[26]With r successes in n trials Laplace's law of succession says that the probability of a success on the next trial is (r+1)/(n+1)

framing effects. We suggest that either a theory asserting confidence in EUT with errors distributed according to FO rather than symmetrically, or a theory asserting a milder version of FO (reduced modal probability on joint occurrence of common consequence effects in both frames and increased probability of at least one occurrence of common consequence effects) with errors distributed according to EUT, with both theories recognising empirical regularities associated with framing effects, is likely to have better predictive power than EUT or FO theories in their "pure" form. This sort of formulation of a theory may sound *ad hoc*, but as Tversky and Kahneman (1988, 186) have pointed out, good predictive theories cannot afford to ignore framing considerations, yet the framing of decisions is highly dependent on context and language in the a choice situation. The development of formal (mathematical) theories incorporating framing considerations remains a challenge. The challenge will be successful when the new theories score better than Laplace's law of succession in predicting experimental outcomes.

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