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EXAGGERATED RISK: PROSPECT THEORY AND PROBABILITY
WEIGHTING IN RISKY CHOICE

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EXAGGERATED RISK: PROSPECT THEORY AND PROBABILITY WEIGHTING IN RISKY CHOICE

Abstract

In five experiments we studied precautionary decisions where participants decided whether or not to buy insurance with specified cost against an undesirable event with specified probability and cost. We compared the risks taken for precautionary decisions with those taken for equivalent monetary gambles. Fitting these data to Tversky and Kahneman's (1992) prospect theory we find that the weighting function required to model precautionary decisions differs from that required for monetary gambles. This result indicates a failure of the descriptive invariance axiom of expected utility theory. For precautionary decisions people overweighted small, medium-sized and moderately large probabilities - they exaggerated risks. This effect is not anticipated by prospect theory or experience-based decision research (Hertwig, Weber, Erev & Barron, 2004). We find evidence that exaggerated risk is caused by the accessibility of events in memory: the weighting function varies as a function of the accessibility of events. This suggests that people's experiences of events "leak" into decisions even when risk information is explicitly provided. Our findings highlight a need to investigate how variation in decision content produces variation in preferences for risk.

Keywords: probability, accessibility, risk exaggeration, frequency, precautionary decisions

A virtue of good theory is that it is general; theories that predict a wide range of events have obvious merit. Several prominent theories of decision-making achieve this objective by proposing that all decisions can be modeled with the same generic representation. So it is that the leading normative (e.g., von Neumann & Morgenstern, 1947) and descriptive psychological theories (e.g., Kahneman & Tversky, 1979; Tversky & Kahneman, 1992) of decision-making share a common representational assumption: people's risk preferences and decisions under risk and uncertainty are task-independent. For example, these theories assume that all decisions under risk or uncertainty can be represented as gambles with monetary amounts representing the outcomes. Although the nature of the content area being contemplated (e.g., decisions about health or money or jobs) may influence judgments of the degree of risk and benefit (cf. Slovic, 1987) most prominent decision theories assume that, once the basic input values for likelihoods and costs are determined, decision-making with risky prospects is not influenced by any factors associated with this content and is independent of the decision-task. For example, the decision whether or not to insure my luggage worth £500 for a cost of £5 where the risk of loss is 1% is identical to the decision to pay £5 or take a gamble where I have a 1% chance of losing £500.

Here, we investigate the validity of this assumption by studying the factors that affect people's reactions to presented probabilities in described real-world decision prospects. Research studying people's decisions under risk using choices between gambles implies that decision-makers weight the probability of risky events in characteristic ways that deviate from normative expected utility theory (axiomatized by von Neumann & Morgenstern, 1947). Specifically, when making risky decisions,

people overweight small probabilities and underweight moderate and large probabilities; breaching rational agents' rules, people's decisions weight probabilities non-linearly (Kahneman & Tversky, 1979; Tversky & Kahneman, 1992 - see also Abdellaoui, 2000; Gonzalez & Wu, 1999; Prelec, 1998; Tversky & Wakker, 1995; Wakker, 2003).

The nonlinear impact of probability on decisions is exemplified by the fourfold pattern of risk preferences predicted by Cumulative prospect theory (Tversky & Kahneman, 1992). Thus, because people overweight small probabilities, both low probability gains and low probability losses loom large relative to certain payoffs with the same expected value. This results in risk seeking for gains and risk aversion for losses at low probability - for example, people are tempted to buy lottery tickets (seeking unlikely gains) and insurance (attempting to avoid unlikely losses). Also, as people underweight moderate and large probabilities, they show a contrasting risk aversion for high probability gains and risk seeking for high probability losses compared to certain payoffs with the same expected value.

Risky Decision-Making and Precautions

Tversky & Kahneman's (1992) studies reporting under- and over-weighting of probability measured respondents' binary choices between monetary gambles. However, there is some reason to believe that people's choices about monetary gambles may not correspond with their preponderance for risk in situations where they need to consider decisions regarding other kinds of risks. Several studies have reported increased attractiveness of decision prospects when framed as insurance decisions; specifically, there is evidence for a context effect in which prospects presented in an insurance context are judged with greater risk aversion than mathematically identical choices presented as standard gambles (Connor, 1996;

Hershey & Schoemaker, 1980; Schoemaker & Kunreuther, 1979; Slovic, Fischhoff, Lichtenstein, Corrigan & Combs, 1977). This finding has prompted the suggestion that people have a relatively favorable attitude towards insurance because, unlike gambling, insurance is viewed as an investment as well as a means of risk reduction (Slovic, Fischhoff & Lichtenstein, 1987).

Given the suggestion that there may be differences in people's decision behavior as a function of the type of risks they may be contemplating, we propose that there is a need to be sensitive to possibly different psychological types of risky decision. Accordingly, we identify and define *precautionary* decisions and behavior as those occasions where people aim to minimize or avoid risks by taking protective actions and where the benefits of taking precautions exemplify risk-averse behavior (Baron et al., 2000; Hershey & Schoemaker, 1980). Protective behavior and decisions in the face of risk have been the subject of a number of studies (e.g., Baron, Hershey & Kunreuther, 2000; Huber & Huber, 2008; Johnson, Hershey, Meszaros & Kunreuther, 1993; Kunreuther, 2001; Slovic et al., 1987; Wakker, Thaler & Tversky, 1997) and yet, to our knowledge, no study has attempted to assess the probability-weighting function for precautionary decisions in the same way as has been done for choices with monetary gambles.

In this paper we present evidence for a dissimilarity between the pattern of risk preferences with precautionary decisions and risk preferences with monetary gambles indicating that the process of decision-making in the two cases may be very different. Apart from the empirical evidence there are - *a priori* - strong reasons to expect that there might be differences in the way people evaluate a choice between two monetary gambles and the way that they might consider adopting precautions against risks, such as whether to buy earthquake insurance. While a choice between monetary

gambles may present a real dilemma, the gambles themselves typically do not have any features that have any meaning for the decision maker - other than their essential structural properties (probability of winning/losing and amount to win/lose). By contrast, hazards that one might insure against have all sorts of other aspects associated with them other than the probability of winning/losing and the amount to win/lose. Decisions associated with insurance and gambling can be seen as qualitatively different from each other. For example, for insurance decisions - but not for monetary gambles - factors such as individual experience of real-world frequency (e.g., decisions made by analogy to previously encountered problems Gilboa & Schmeidler, 2001; Stewart, Chater & Brown, 2006), accessibility to particular information in memory (Koriat, 1993, 1995; Tulving & Pearlstone, 1966) and past subjective experience with anxiety or fear (Kunreuther, 2001; Viscusi & Chesson, 1999), arguably all result in support for precautionary action. Relevant to our concerns here, we suggest that the accessibility of information influences the decision to purchase or not purchase a particular insurance product. We see no evidence that the same factor applies to decisions about monetary gambles. The issue is of considerable importance because, to the extent that decisions made with monetary gambles differ from those made for insurance, the goal of studying monetary (gamble) decisions as a basis for explaining all varieties of human decisions is called into question.

Experiment 1

We assume that, because they are relatively abstract, monetary gamble tasks do not prompt the same history of experience and range of associations as typical real-world protective tasks (e.g., precautionary decisions). For instance, according to the normative theory, a set of simple binary gamble choices of the form “ p chance of x ,

otherwise y ” should evoke the same preference order across different decision domains. Accordingly, a 1% chance of losing £300 or a sure loss of £60 and a 1% chance of an insurable event of losing £300 or paying £60 for insurance are equivalent prospects. However, we believe that there are grounds to suspect that behavior in monetary gamble situations may not correspond with precautionary risk behavior. In particular, we suspect that people might be more risk averse when contemplating the probabilities and losses associated with options in precautionary decision-making. Accordingly, Experiment 1 was designed to compare the pattern of people’s risk preferences in protective (insurance) decision-making with the pattern exhibited for monetary gambles and also to see if insurance decision-making can be modeled within the classic framework of Tversky and Kahneman’s prospect theory (Kahneman & Tversky, 1979) and cumulative prospect theory (Tversky & Kahneman, 1992; Tversky & Fox, 1995).

Method

Participants.

Participants were 60 students (33 female, 27 male) from the University of Warwick. Mean age was 21 ($SD = 2.43$). They took part individually and received a payment of £5.

Stimuli and Equipment.

An interactive computer program for binary decision-making was used. Four types of binary decision-making situation (scenario), each corresponding with one of four experimental conditions, were included: gamble gain (monetary gamble with a sure gain versus a gain with a given probability), gamble loss (monetary gamble with a sure loss versus a loss with a given probability), insurance gain (a sure rebate - i.e. a refund on an insurance premium - versus a rebate with a given probability) and

insurance loss (insurance against loss of luggage versus a loss of luggage with a given probability).

In a first session, participants had to indicate a preference between a probabilistic outcome and a sure outcome in a series of 308 trials. The trials were created by combining 4 monetary amounts (£50, £100, £200, £400) for the probabilistic outcomes with 11 probabilities (.01, .05, .10, .25, .40, .50, .60, .75, .90, .95, .99) and each of these combinations was presented with one of 7 monetary amounts for the sure outcome (logarithmically spaced between £1 and the amount of the probabilistic outcome), producing $4 \times 11 \times 7 = 308$ combinations. Using a method similar to that used by Tversky and Kahneman (1992), binary-choice prospects (a choice between a probabilistic and a sure outcome) were presented. The following algorithm was used for each participant: (1) randomly select one of the four monetary amounts; (2) for this monetary amount randomly select a probability level; (3) randomly present each of the seven sure monetary amounts; (4) go back to (2) unless all probability levels have been sampled in which case go back to (1) and repeat until all prospects have been presented.

As in Tversky and Kahneman (1992), participants' certainty equivalent (CE) estimates were based on the sure outcomes chosen in the task: the midpoint between the lowest accepted value and the highest rejected value in the prospects. To obtain a more refined estimate of the CE, in a second session, values of people's preferences were linearly spaced between a value 25% higher than the lowest amount accepted in the first set (session) and a value 25% lower than the highest amount rejected. The CE of a prospect was estimated as the midpoint between the lowest accepted value of the sure outcome and the highest rejected value in the second set of choices.

Design and Procedure.

Previous research (Tversky & Kahneman, 1992) used a repeated measures design with loss and gain scenarios mixed in a single series (simultaneous within subjects design, Keppel, 1991). Results obtained under these conditions could be an artifact of the design. Specifically a *contrast effect* may result (Keppel 1991), that is either an effect becomes more pronounced compared to an independent measures design, or a spurious effect could occur, which would not occur with an independent measures design. In order to avoid this pitfall, we used a 2×2 between-subjects design, with the following independent variables: decision-making task (gamble, insurance) and decision-making domain (gain, loss). There were 15 participants in each experimental condition.

At the start of the program, task instructions and then an example scenario with illustrative choices were presented. On each trial, participants were asked to consider a presented scenario and choose one of two options, for example:

Insurance Loss Scenario:

A. 1% chance of losing your luggage which is worth £400

or

B. Buying insurance at a cost of £20 to insure against the loss of your luggage;

Gamble Loss Scenario:

A. 1% chance of losing £400

or

B. A sure loss of £20;

Insurance Gain Scenario:

A. 1% chance of winning a insurance rebate of £400

or

B. A guaranteed insurance rebate of £20;

Gamble Gain Scenario:

A. 1% chance of winning £400

or

B. A sure gain of £20

Participants completed a series of 308 trials of binary decisions with one of the four types of scenario within each of two sessions.

Results and Discussion

The results section is organized as follows: first we present an analysis of the risk preferences of the respondents. Next we present analysis of the CE measures and finally we present the result of our attempts to fit the observed decisions to the Prospect theory probability weighting function. All statistical tests reported in this paper used a significance level of .05 unless indicated otherwise.

Risk Preference

In both the insurance and gamble gain scenarios, rates of risk-seeking choices (where CE exceeds expected value) decreased from about 80% to about 10% as the probability of the risky prospect increased (see Table 1 and Figure 2). All participants in the gain conditions were predominantly risk averse. A two-way ANOVA confirmed this result for gain scenarios, with a significant effect of probability range ($= .01, \leq .1$ and $\geq .5$) on risk preference, $F(2, 56) = 149.39, p < .001$, very large effect size $\epsilon^2 = .77$, but the effect of task (gamble, insurance) and the interaction effect of range and task were not significant, both $F < 1$. In the insurance-loss condition there were fewer risk-seeking choices - ranging from 0% to 40% - across the different probabilities of prospects compared to the gamble-loss condition - where the

proportion of risk-seeking choices ranged from 10% to 83% (see Table 2 and Figure 2).

In the two loss scenarios, rates of risk-averse choices decreased with increasing probability of risky prospects, but more so for the gamble-loss scenario - from 90% to 17% - than for the insurance-loss scenario - from 100% to 60% (see Table 2 and Figure 2). A two-way ANOVA confirmed this result; there were significant effects on risk preference of both main effects of range, $F(2, 56) = 82.12, p < .001$, very large effect size $\epsilon^2 = .62$, and task, $F(1, 28) = 24.39, p < .001$, medium effect size $\epsilon^2 = .05$, as well as an interaction effect, $F(2, 56) = 6.60, p < .001$, medium effect size $\epsilon^2 = .05$, significant. Simple effect tests showed that the effect of range was significant for the gamble scenario, $F(2, 56) = 91.74, p < .001$, very large effect size $\epsilon^2 = .82$, and for the insurance scenario, $F(2, 56) = 15.73, p < .001$, very large effect size $\epsilon^2 = .48$.

Certainty Equivalent

The average CE estimation was based on respondents' decisions between sure outcomes and probabilistic outcomes. Seven sure outcomes logarithmically spaced between 1 and the amount of the probabilistic outcome (£50, £100, £200, £400), each presented with 11 probabilities (.01, .05, .10, .25, .40, .50, .60, .75, .90, .95, .99), were paired with 1 probabilistic outcome (£50, £100, £200 or £400). For the gain scenarios a trend of increasing CE with amount is discernible in Figure 3. In addition, CE is substantially higher for the insurance loss condition (about 0.6) than for the other three conditions (less than 0.4). These observations were confirmed by the results of statistical tests. A $2 \times 2 \times (4)$ ANOVA with independent variables task (insurance, gamble), type of decision domain (loss, gain), and probabilistic amount (£50, £100, £200, £400), showed that the following main- and interaction effects were significant: task, $F(1, 56) = 12.46$, medium effect size $\epsilon^2 = .05, p < .001$; domain, $F(1, 56) =$

23.20, medium to large effect size $\epsilon^2 = .10$, $p < .001$; probabilistic amount, $F(3, 168) = 6.04$, small to medium effect size $\epsilon^2 = .04$; task by domain, $F(1, 56) = 12.11$, medium effect size $\epsilon^2 = .05$, $p < .001$; amount by domain, $F(3, 168) = 2.64$, small effect size $\epsilon^2 = .02$; and amount by task by domain, $F(3, 168) = 3.64$, small to medium effect size $\epsilon^2 = .03$ (see also Figure 3). The interaction effect between amount and task, $F < 1$, was not significant. The three-way interaction precluded interpretation of main effects and two-way interactions therefore, 2x2 ANOVAs with independent variables task (insurance, gamble) and decision domain (loss, gain) were conducted as simple effect tests for each probabilistic amount (£50, £100, £200, £400). The effects of task, domain and the interaction effect were large and significant, with the largest effect size for the smallest probabilistic amount and the smallest effect size for the largest probabilistic amount (see Table 3 and Figure 3). These results demonstrate relatively high CE in the insurance loss condition, consistent with the notion that people are particularly risk averse for insurance losses.

The CE analysis mirrors the analysis of people's risk preferences: more risk-averse precautionary decisions than gambling decisions and higher precautionary CE than gambling CE. These results provide evidence for a greater propensity for precautionary action with insurance risks than would be inferred from responses to equivalent monetary gambles - what we term a *protective effect*.

Probability-Weighting Function

Numerous studies investigating preferences for monetary-prospects (e.g., Camerer & Ho, 1994; Fox & Tversky, 1998; Gonzalez & Wu, 1999; Tversky & Kahneman, 1992; Tversky & Fox, 1995) report evidence in favor of overweighting of small probabilities and underweighting of moderate and large probabilities - resulting in an inverse S-shaped probability-weighting function. However, there is reason to believe

that people's risky decisions across different sorts of decision are not consistent. For instance, a person may prefer to bet on sporting events rather than on the outcomes of political elections, even when the chance of winning is held constant (Heath & Tversky, 1991).

Using a non-linear regression procedure, judged probabilities were modeled using a variation (with no constant parameters) of Gonzalez and Wu's (1999) two-parameter probability-weighting function (1)

$$\omega^{+,-}(p) = \frac{\delta p^\beta}{\delta p^\beta + (1-p)^\beta}, \quad (1)$$

and a power utility function with one free parameter of the form $U(x) = x^\alpha$.

In the two parameter probability weighting function ω represents the decision weight given to probability p , where β represents *probability discriminability* (curvature of the function) and δ represents *attractiveness* (elevation of the function).

Probability-weighting functions were fitted for each participant in all four experimental conditions, replicating the method adopted by Tversky and Kahneman (1992). As indicated above, respondents' CEs were inferred from their choices between sure outcomes and probabilistic outcomes each presented at various levels of probability. In the modeling procedure we express the actual CEs as a function of probability, amount, and the model parameters. As in previous research (Tversky & Kahneman, 1992), for the gamble gain, gamble loss and insurance gain scenarios small probabilities were overweighted and medium-sized and large probabilities were underweighted. This was confirmed by the model's estimations of the probability weighting function (see Figures 1a, 1b, 1c). However, for the insurance-loss scenario, small, medium-sized and moderately large probabilities were overweighted and large probabilities were slightly underweighted (see Figure 1d).

We fitted the functions for each participant and then analyzed the effect of the independent variables on the model parameters and the error - in each case, minimizing the summed squared error between actual CEs and predicted CEs. Mean values (*SD*) of model parameters were < 1 for probability discriminability (β) [gamble gain: 0.60 (0.24); gamble loss: 0.72 (0.28); insurance gain: 0.63 (0.13)], < 1 for attractiveness (δ) [gamble gain: 0.49 (0.35); gamble loss: 0.79 (0.46); insurance gain: 0.63 (0.26)] and (almost) equal to 1 for the utility function parameter α [gamble gain: 1.02 (0.06); gamble loss: 1.03 (0.13); insurance gain: 1.00 (0.03)]. By contrast, for insurance losses mean values (*SD*) for β , δ and α were 0.69 (0.23), 1.60 (0.64) and 1.00 (0.02) respectively and the model reproduced the relationship between actual and weighted probabilities shown in Figure 1d.

A two-way ANOVA showed no significant effect of task (insurance, gamble), type of the decision domain (loss, gain) and their interaction on error, or the utility function parameter α , or probability discriminability (β). However, there were significant effects of task, $F(1, 56) = 16.34$, large effect size $\epsilon^2 = .14$, $p < .001$, domain, $F(1, 56) = 28.56$, very large effect size $\epsilon^2 = .25$, $p < .001$, and an interaction effect, $F(1, 56) = 8.11$, medium effect size $\epsilon^2 = .07$, $p < .01$, on attractiveness (δ). Multiple-comparison tests with Bonferroni correction demonstrated that in the domain of loss the effect of task on attractiveness (δ) was significant, $t(28) = 3.94$, large effect size $r = .60$, $p < .001$, but in the domain of gain the effect of task was not significant, $t(28) = 1.24$, $p > .05$. Furthermore, planned comparison tests with Bonferroni correction showed that attractiveness (δ) for the insurance loss condition was significantly different from that for each of the other three conditions, all $t(56) = 7.06$, large effect size $r = .59$, $p < .001$. The finding of a greater value for attractiveness in the insurance loss condition indicates that respondents overweighted

small and medium probabilities to a greater extent in that condition and is consistent with the notion that respondents show a protective effect for precautionary decisions.

Our results demonstrate that the independent variables task and domain did not affect the error of the model in predicting CE, or the utility function parameter α , or probability discriminability (β). Best fitting utility functions were approximately linear in each condition, with $\alpha \approx 1$. Thus the observed differences across conditions in the probability-weighting function are not compensated by any corresponding changes in the utility function across conditions.

The results of Experiment 1 demonstrated a different pattern of over- and underweighting of probabilities in the insurance-loss condition compared to the other conditions. A protective effect - exaggerated probability weights for insurance-loss decisions was observed. Existing normative and descriptive theories cannot account for the phenomenon found in Experiment 1, which can be modeled as a function of two psychologically autonomous properties of the probability-weighting function (cf. Gonzalez & Wu, 1999): β (the curvature) signifying probability discriminability and δ - attractiveness (the elevation). This finding suggests a need for models which differentiate between precautionary behavior and other types of decision-making under risk and uncertainty.

Cumulative prospect theory predicts a fourfold pattern of risk preferences (see Table 4) across gain and loss scenarios: people are predominantly risk seeking for low probability gains and high probability losses and predominantly risk averse for high probability gains and low probability losses. However, protective decision-making with described real-world prospects, as represented in Figure 1d, highly overweights small, moderate and even large probabilities and underweights only the most extreme high-probability options, in contrast to the function we (and Tversky

and Kahneman) observed for gambles and that is responsible for the fourfold pattern of risk preferences. All of Tversky and Kahneman's (1992) participants (25), were predominantly risk averse for gains and risk seeking for losses (see Table 4); we replicated this observation in respondents contemplating monetary gambles (see Tables 1 and 2). In contrast our insurance respondents, although predominantly risk averse for gains (see Table 1), were also predominantly risk averse for losses (see Table 2).

As we noted earlier, prominent decision theories - although differing in their approach - assume that all decisions can be represented as gambles with monetary amounts representing the outcomes. The present findings suggests that, counter to this assumption, decision-making with risky prospects is influenced by the nature of the issue being decided and is not independent of the decision-task.

Experiment 2

The protective effect (exaggerated probability weights) found in Experiment 1, if confirmed, creates difficulties for current descriptive theories of decision-making. This is why it is important to demonstrate the stability of the risk preferences found in Experiment 1. Accordingly, in Experiment 2 we sought to replicate the effect with the same participants, but leaving time to allow their memory of the specific trials of the experiment to decay (in Experiment 3 we again sought to replicate the effect using a different sample of respondents).

In Experiment 2 the stability over time of the protective effect (exaggerated probability weights) found in Experiment 1 was assessed. This experiment further explored people's precautionary preferences and the significance of the probability function's overweighting for protective loss, following Tversky and Kahneman (1992) and Tversky and Fox's (1995) theoretical framework.

Method

Ninety days after Experiment 1, the same 15 participants who were in the insurance loss condition in Experiment 1 took part again in the same experimental condition for a payment of £5. Materials and apparatus were the same as in Experiment 1.

Results and Discussion.

We fitted the two parameter-probability weighting function for each participant as in the previous experiment. Mean values (*SD*) were 0.67 (0.23) for probability discriminability (β), 1.43 (0.77) for attractiveness (δ) and 1.00 (0.03) for the utility function parameter α . The model produced the relationship between actual and weighted probabilities shown in Figure 1e; as can be seen, the shape of the function is very similar to that observed for insurance losses in Experiment 1 (cf. Figure 1d). In terms of the two-parameter model, decision-making was consistent within participants from Experiment 1 to Experiment 2, with intra-class correlations¹ (*ICC*) of .71 for β , $F(14, 14) = 3.56$, $p = .001$, and .87 for δ , $F(14, 14) = 14.31$, $p < .001$.

The pattern of risk-seeking preferences (proportions of total (*SD*) = .00 (.00), .11 (0.21) and .46 (0.29), for $p = .01$, $.01 < p \leq .1$ and $p \geq .5$ respectively) was very similar to that in the insurance loss condition in Experiment 1 (see Figure 2). This pattern was identical for the probability of .01 and consistent for probabilities $.01 < p \leq .10$, $ICC = .47$, $F(14, 14) = 2.77$, $p < .05$, and for probabilities $\geq .50$, $ICC = .91$, $F(14, 14) = 20.26$, $p < .001$. In conclusion, the stability of the protective effect identified in Experiment 1 was confirmed in Experiment 2.

Experiment 3

The protective effect found in Experiment 1 proved to be stable over time (Experiment 2). Experiment 3 investigated the generalizability of this effect under

different circumstances: (a) a different type of protective (insurance) scenario (home insurance), (b) a different monetary amount for the sure outcome and accordingly (c) a different set of monetary amounts for the probabilistic outcome were used, furthermore (d) participants took part in only one session.

Method

Participants.

One hundred and twenty-eight students (99 female, 29 male) from the University of Teesside participated individually as part of their course requirement, their mean age was 22 ($SD = 6.49$).

Stimuli and Equipment.

An interactive computer program for binary decision-making was employed. Four types of binary decision-making situation (scenario), each corresponding with one of four experimental conditions, were included: gamble gain (monetary gamble with a sure gain versus a gain with a given probability) ($n = 33$), gamble loss (monetary gamble with a sure loss versus a loss with a given probability) ($n = 34$), insurance gain (a sure rebate on an insurance premium versus a rebate with a given probability) ($n = 30$) and insurance loss (insurance against burglary versus loss of belongings as a result of burglary with a given probability) ($n = 31$).

Participants were required to indicate a preference between a probabilistic outcome and a sure outcome in a series of 231 trials. Using a method similar to that used by Tversky and Kahneman (1992) the trials were created by combining 1 monetary amount for the probabilistic outcome (£600) with each of 11 probabilities (.01, .05, .10, .25, .40, .50, .60, .75, .90, .95, .99), and each of these combinations was presented with one of 21 monetary amounts representing the sure outcomes (linearly spaced between £1 and £600), producing $1 \times 11 \times 21 = 231$. The 231 decisions were

presented in random order. The CE of a prospect was estimated as the midpoint between the lowest accepted value and the highest rejected value.

Design and Procedure.

A 2×2 between-subjects design was used, with independent variables task (gamble, insurance) and domain (gain, loss). At the start of the session, task instructions and then an example scenario with illustrative choices were presented. On each trial, participants were asked to consider a presented scenario and choose one of two options, for example:

Insurance Loss Scenario:

A. A 10% chance of losing your belongings which are worth £600

or

B. Buying insurance at a cost of £90 to insure against the loss of your belongings.

Participants completed a series of 231 trials of binary decisions with one of the four types of scenario.

Results and Discussion

Risk Preference

In both loss scenarios, rates of risk-seeking choices increased as the probability of the risky prospect increased (see Table 5 and Figure 5), but with more risk seeking in the gamble-loss scenario - ranging from 35% to 92% - than in the insurance-loss scenario - ranging from 10% to 46%, confirming the pattern of risk preferences found in Experiments 1 and 2. A two-way ANOVA investigating the effects of domain (gain, loss) and probability of risky prospect on risk preferences confirmed this result for the loss scenarios, with significant effects of probability ($= .01, \leq .1$ and $\geq .5$), $F(2, 126) = 39.30, p < .001$, large effect size ($\epsilon^2 = .20$), and task (gamble, insurance), $F(1, 63) = 39.96, p < .001$, large effect size ($\epsilon^2 = .17$), but the interaction effect of

probability and task was not significant, $F(2, 126) = 1.80, p > .05$. In the gain scenarios risk seeking decreased with probability, and gamble and insurance scenarios did not seem to differ (see Figure 5). A further two-way ANOVA investigating the effects of domain (gain, loss) and probability of risky prospect on risk preferences for the gain scenarios showed a significant effect of probability ($= .01, \leq .1$ and $\geq .5$), $F(2, 122) = 189.66, p < .001$, very large effect size ($\epsilon^2 = .58$), but the effect of task (gamble, insurance) $F(1, 61) = 2.01, p = .16$ and the interaction effect of probability and task, $F < 1$, were not significant.

Certainty Equivalent

The average CE estimation was based on 21 sure outcomes, each presented together with 11 probabilistic outcomes. As in Experiment 1, the average CE was higher for the insurance loss scenario (above 0.5) than for the other scenarios (below 0.4) (See Figure 6). A 2×2 analysis of variance (ANOVA) with independent variables task (insurance, gamble) and domain (loss, gain) showed that the main effects of domain, $F(1, 124) = 68.28$, very large effect size $\epsilon^2 = .29, p < .001$, and of task, $F(1, 124) = 26.95$, large effect size $\epsilon^2 = .11, p < .001$, as well as the interaction effect, $F(1, 124) = 15.76$, medium effect size $\epsilon^2 = .06, p < .001$, were significant (see also Figure 6). Simple effect tests with Bonferroni correction showed that the effect of domain was significant both in the gamble task, $t(65) = 3.07$, medium effect size $r = .36, p < .01$, and in the insurance task $t(59) = 8.59$, very large effect size $r = .75, p < .001$. The difference between the effect sizes was significant as well, $z = 3.26, p < .001$. Further simple effect tests with Bonferroni correction showed that the effect of task was significant in the domain of losses, $t(63) = 6.77$, large effect size $r = .65, p < .001$, but not in the domain of gains, $t < 1, r = .11$. The difference between the effect sizes was significant, $z = 3.69, p < .001$. These results demonstrate higher CE

judgments for the prospects within the insurance loss condition, in agreement with the results of risk preferences found in Experiments 1 and 2.

Probability-Weighting Function

Judged probabilities in the insurance loss scenario were modeled as in Experiment 1. The results from Experiment 3 confirmed our basic finding that with precautionary decisions people exaggerate risk. There were differences in the shape of the probability-weighting function in the different tasks (gambles and precautionary decisions); specifically probability weights were exaggerated in precautionary decisions in the domain of loss (Figure 4).

We fitted the function for all participants (see Figures 4a, 4b, 4c), minimizing the summed squared error between actual CEs and predicted CEs of all participants, and values of model parameters were < 1 for probability discriminability (β) (gamble gain: 0.48; gamble loss: 0.67; insurance gain: 0.56), < 1 for attractiveness (δ) (gamble gain: 0.37; gamble loss: 0.98; insurance gain: 0.45) and (almost) equal to 1 for the utility function parameter α (gamble gain: 0.98; gamble loss: 0.95; insurance gain: 0.98). In the insurance-loss scenario, small, medium-sized and moderately large probabilities were overweighted and large probabilities were slightly underweighted and values for β , δ and α were 0.55, 1.86 and 0.99 respectively.

One possible reason for the difference between gambles and precautionary decisions in the domain of loss is that, for precautionary decisions, experienced real-world risk frequencies are likely to influence decision-making about described recognizable prospects. We hypothesize that the probability-weighting function is affected by the accessibility of real-world events - instances of some described real-world precautionary prospects may be more accessible in our memory than any (less likely) corresponding traces that may exist for monetary gambles.

As in previous research, participants in the gamble-gain and insurance-gain conditions, overweighted very small probabilities and underweighted medium-sized and large probabilities (see Figures 4a, 4c). Similarly in the gamble-loss condition small to medium-sized probabilities were overweighted and the remaining probabilities underweighted. However, in the insurance-loss condition, small to medium-sized probabilities were massively overweighted, medium-sized to high probabilities somewhat overweighted and only very high probabilities underweighted (see Figures 4b and 4d). The results of Experiment 3, confirmed the distinctiveness of people's precautionary decisions, in particular a different pattern of over- and underweighting of probabilities compared to the gamble condition. Participants exaggerated (overweighted) the described protective risk and demonstrated a lack of risk-seeking preferences in protective decision-making compared to the monetary (gamble) condition, where risk-seeking preferences predominated (see Table 5).

Experiment 4

As discussed earlier, prior research has reported increased attractiveness of risk-averse options when presented in the context of insurance decisions (Hershey & Schoemaker, 1980; Schoemaker & Kunreuther, 1979; Slovic et al., 1977). When evaluating risks for insurance people do not usually use statistical evidence about the probability of risky events. Instead people may commonly rely on inferences based on what they remember hearing or observing about a particular risk (Hertwig, Pachur & Kurzenhäuser, 2005; Slovic, Fischhoff & Lichtenstein, 1979; Tversky & Kahneman, 1973). According to the accessibility framework (Kahneman, 2003; Koriat, 1993, 1995; Tulving & Pearlstone, 1966), people's judgments are based on the amount and intensity of the information accessed in the course of a particular task. Many instances of insurable events are encountered in everyday life more frequently

than others not only from personal experience but also via TV, newspapers, advertisements and conversations. Reliance on such sources may have some validity (cf. Hertwig, Pachur & Kurzenhäuser, 2005) but may induce erroneous feelings that some sorts of risk are more frequent than others (e.g., Lichtenstein, Slovic, Fischhoff, Layman & Combs, 1978). For instance, the *familiarity bias* reported by Fox and Levav (2000) showed that people typically judged more familiar events to be more probable than less familiar events, more often than they judged the *complement* of the same less familiar event to be more probable than the complement of the more familiar events. Thus when MBA students were asked to judge the comparative future performance of two investment funds, the proportion who judged that a familiar fund was more likely than an unfamiliar fund to perform well was greater than the proportion who judged that the unfamiliar fund was more likely than the familiar fund to perform poorly. Such results are assumed to occur partly because it is easier to recruit evidence supporting familiar events than unfamiliar events. Accordingly we hypothesized that more accessible events (e.g., high-frequency events) would be viewed with an increased perceived likelihood, whereas less accessible events (e.g., low-frequency events and monetary gambles) would not be.

In their studies, Koriat (1995) and Koriat and Levy-Sadot (2001) rated the accessibility of questions as high or low on the basis of the percentage of participants who provided an answer to each question regardless of whether the answers were correct or incorrect. We adapted this method for the present study where participants were first asked to recall any instances of the defined events and then rate their frequency (high- or low-frequency risks). We defined the accessibility of events in memory in terms of these subjective ratings of their frequency (high- or low-frequency risks). We then investigated whether the influence of accessibility would

be strong enough to have a measurable impact on the risky decisions that respondents made in the decision-making phase of the experiment. Accordingly, Experiment 4 examined the hypothesis that accessibility (measured by rated frequency) affects choice and risk preferences for risky decisions where we explicitly supplied - and independently varied - the precise probability of the risk. In particular, we predicted greater risk-averse behavior for more accessible risks. We also hypothesized that the certainty equivalents inferable from people's insurance decisions would reflect an apparent exaggeration of the supplied probability for judged high-frequency risks compared to low-frequency risks. Given our argument that monetary gambles provide few accessible features, risk aversion for monetary gambles should be less than, or, at most, at the same level as for the judged low-frequency risks.

In order to meet a possible criticism of the earlier experiments that they involved respondents repeatedly evaluating the same risky scenario (albeit with varying probabilities and amounts of loss), Experiment 4 presents a wide range of different risky scenarios to each respondent. All decisions required respondents to consider the risk of loss.

Method

Development of Materials.

A norming procedure was designed to produce two sets of risk and to allow the selection of high- and low-frequency risks to be used in Experiment 4. Eighty-four City University undergraduate and postgraduate students (52 female, 32 male) were recruited for a brief norming procedure. The participants were paid £3 and took part individually. Mean age was 19.17 ($SD = 2.26$). On the basis of our intuitive judgments, 24 risks with similar actuarial low probability were presented - 12 presumed to be perceived as low- and 12 presumed to be perceived as high-frequency

risks were included. Respondents rated each risk according to its frequency (participants were asked to refer to any instances of each risk that came to mind from any source of information) on a 10-point Likert scale ranging from *not frequent* to *very frequent*. In order to help respondents to focus on frequency independent of riskiness, respondents also rated the riskiness of these risks on a 10-point Likert scale from *not risky* to *very risky*. Participants were encouraged to use the full range of the scale (see Appendix).

At the start of the procedure, task instructions and then all 24 risks were presented before any of the ratings were elicited. Participants first had to judge the frequency of each of the presented risks and then - in a separate series - their riskiness.

Our intuitions were broadly confirmed; those items we selected as high frequency were rated significantly higher than those selected to represent low frequency. As expected, the estimated frequency of the average risks rated as high frequency (mean = 6.09, $CI_{.95}(\text{mean}) = [5.83; 6.35]$, $SD = 1.19$) was higher than that of the average risks rated as low frequency (mean = 4.27, $CI_{.95}(\text{mean}) = [4.03; 4.50]$, $SD = 1.08$), $t(83) = 14.16$, $p < .001$, $r = .84$, with high-frequency risks estimated 43% higher than low-frequency risks. The estimated frequency of risks correlated with the perceived riskiness of risks, $r = .64$, $p < .001$. The nine risks with the highest estimated frequency and the nine risks with the lowest estimated frequency were selected for inclusion in Experiment 4 (see Appendix). Across respondents, the mean judged frequency of the high-frequency risks was always greater than 5, whereas the mean judged frequency of the low-frequency risks was always less than 5.

Participants.

Ninety City University undergraduate and postgraduate students (36 male and 54 female) were recruited for a decision-making experiment. They were paid £5 and took part individually. Mean age was 19.17 ($SD = 2.26$).

Stimuli and Equipment.

As before, a computer-based experiment for binary decision-making was employed. On the basis of the results from the norming procedure, we constructed three types of binary decision-making situation (scenario), each corresponding with one of three experimental conditions: high-frequency risk (insurance against risks with a given probability that received a high estimated frequency in the norming procedure), low-frequency risk (insurance against risks with a given probability that received a low estimated frequency) and monetary-gamble risk (monetary gamble with a sure loss versus a loss with a given probability). Thirty participants were assigned to each experimental condition.

Participants in each condition were required to choose between a probabilistic outcome and a sure outcome in a series of 162 trials: on each trial the fixed monetary amount for the probabilistic outcome (£680) was paired with one of 9 probabilities (.01, .05, .10, .25, .50, .75, .90, .95, .99) with one of the risks (judged as either high or low frequency in the norming procedure) or a monetary gamble and each of these combinations was presented with one of 18 amounts for the sure outcomes (linearly spaced between £1 and £680), producing $1 \times 9 \times 18 = 162$ trials. The probability levels were presented in random order. As before, the CE of a prospect was estimated as the midpoint between the lowest accepted value and the highest rejected value.

Design and Procedure.

A 3 task (monetary-gamble risk, high-frequency insurance risk, low-frequency insurance risk) \times 9 probability levels (.01, .05, .10, .25, .50, .75, .90, .95, .99) design was used. Task was a between-groups factor and probability was a within-groups factor. All nine probabilities were used in each of the three task conditions. However, in order to maximize any effect of accessibility on risk aversion, in the high-frequency insurance risk condition we attached the highest-probability levels to those risks judged as more frequent in the norming procedure and, for the low-frequency insurance risk condition, we attached the highest-probability levels to those risks judged as less frequent in the norming procedure (see Appendix).

At the start of the computer-controlled experimental session, task instructions and then an example scenario with illustrative choices were presented. On each trial, participants were asked to consider a presented scenario and choose one of two prospects, for example:

A. A 10% chance of theft of your laptop computer worth £680

or

B. Buying insurance at a cost of £40 to insure against the theft of your laptop computer.

Participants completed a series of 162 trials each consisting of binary decisions with one of the three types of scenario.

*Results and Discussion**Risk Preference*

A plausible account for the difference between monetary gambles and precautionary decisions observed in our earlier experiments is that precautionary decisions invite respondents to refer to their experience and knowledge of the events

referred to while gambles do not. The results from Experiment 4 are consistent with this interpretation and moreover confirm our hypothesis regarding the differential accessibility of familiar and unfamiliar (judged high- and judged low-frequency) risks - risk aversion is greatest for the high-frequency decisions (59% overall), smaller for the low-frequency decisions (40% overall) and least for the monetary gambles (32% overall; see Table 6).

As in Experiments 1, 2 and 3, participants' choices in the monetary-gamble risk and low-frequency risk conditions revealed a preponderance of risk-averse behavior for prospects with small probabilities (see Table 6) and risk-seeking preferences for prospects with medium and large probabilities. Decisions in the high-frequency condition were more risk averse for small and medium probabilities and, unlike the low frequency and monetary gamble conditions, were even predominantly risk averse for probabilities as high as 50% (see Table 6). In all three conditions, rates of risk-seeking choices increased with probability of risky prospects, but with even more risk seeking in the monetary-gamble and low-frequency risks scenarios than in the high-frequency risks scenarios, confirming the pattern of risk preferences found in Experiments 1 and 3. A 3 (high-frequency risk; low-frequency risk; monetary gamble) \times 9 (probability level) ANOVA confirmed these results: the main effects of risk scenario, $F(8, 696) = 44.40, p < .001, \epsilon^2 = .27$, and probability level, $F(2, 87) = 20.62, p < .001, \epsilon^2 = .06$, were significant. The interaction effect was not significant, $F < 1$. Multiple comparison tests with Bonferroni correction confirmed that risk-seeking preferences were significantly lower for high-frequency risks than for low-frequency risks and monetary-gamble risks (both $p < .001$), but there was no significant difference between low-frequency- and monetary gamble risks ($p > .05$).

Certainty Equivalent

As in Experiment 3 we analyzed the average level of participants' CE in order to investigate the need for theory to differentiate protective decision-making from other types of decision-making. For each respondent the average CE estimation was based on 18 sure outcomes, each presented together with 9 probabilistic outcomes.

Consistent with the results for risk-preferences, risk scenario had an effect on CE; participants' CE for high-frequency risks were higher (overall 0.46) than these for low-frequency risks (overall 0.39) and monetary gambles (overall 0.40), indicating a greater propensity for precautionary decisions for high-frequency risks.

Unsurprisingly, CE increased with probability for all three types of risk (see Table 7).

A 3 (high-frequency risk; low-frequency risk; monetary gamble) \times 9 (probability level) ANOVA confirmed the significant main effects of risk scenario,

$F(8, 696) = 267.00, p < .001, \epsilon^2 = .68$, and probability level, $F(2, 87) = 4.64, p < .05$,

$\epsilon^2 = .01$, but the interaction effect was not significant ($F < 1$). Multiple comparison

tests with Bonferroni corrections confirmed that CE was significantly higher for high-

frequency risks than for low-frequency risks ($p < .05$) and the difference between

high-frequency risks and monetary-gamble risks was close to significance

($.05 < .p < .10$), but there was no significant difference between low-frequency- and

monetary gamble risks ($p > .05$).

Although there is no scope for any generic theory of risky choice to anticipate any difference between the responses given to low- and high-frequency risks where the supplied probabilities are matched, we do observe a difference: high-risk events evoke choices with higher CE than low-risk events. The most plausible basis for this discrepancy is the encoded frequency of these events in respondents' memory.

Inspection of Table 7 also indicates that the difference between the certainty equivalents for the low- and high-frequency risks increases as the probability of the

risky prospect increases. Recall that, in the choice task for the high-frequency insurance risk condition, we attached the highest-probability levels to those risks judged as more frequent in the norming procedure; however, for the low-frequency insurance risk condition, we attached the highest-probability levels to those risks judged as less frequent in the norming procedure. Accordingly, the increasing difference between the CEs for high- and low-frequency events can be attributed to the influence of the accessibility of memory representations for these events - also responsible for the increasing difference in the judged frequency of those events. Consistent with this interpretation, the correlation between the difference in judged frequency for high- and low-frequency events and the corresponding difference in CE is positive and significant ($r = .88, p = .002$).

Probability-Weighting Function

We attempted to obtain fits of the probability-weighting function for individual participants but, presumably due to noise in responses, were unable to obtain good fits. To reduce noise we attempted to fit the probability weighting function for triples of participants; respondent triples were formed based on the similarity of participants' CEs. Ten triples were created for each of the three conditions. We fitted the functions for each triple and then analyzed the effect of the independent variables on the model parameters - in each case, minimizing the summed squared error between actual CEs and predicted CEs. As in the previous experiments, the model parameters are estimated based on actual CEs, probabilities and monetary amounts of the certain options. We fitted the probability-weighting function successfully for eight of the ten triples in each of the high- and low-frequency conditions (the other four triples showed an inconsistent pattern of CE across probability levels, i.e. CE was not a

strictly increasing monotonic function of probability level) and for all participants in the monetary gamble condition.

For monetary gambles and low-frequency insurance risks the mean values (*SD*) of attractiveness (δ) were < 1 : for monetary gambles $\delta=0.77$ (0.39) and for low-frequency insurance risk $\delta=0.71$ (0.68). By contrast, for the high-frequency insurance risks condition mean values (*SD*) for δ was 1.47 (0.70). The finding of a greater value for attractiveness in the high-frequency insurance condition indicates that respondents overweighted probabilities to a greater extent in that condition and is consistent with the notion that respondents show a protective effect for (i.e. exaggerate risk for) decisions about more accessible risks.

ANOVA conformed that the effect of task on attractiveness (δ) was significant, $F(2, 23) = 4.11$, very large effect size $\epsilon^2 = .23$, $p < .05$. Planned comparison tests with Bonferroni corrections showed that attractiveness (δ) for the insurance loss condition with high-frequency risk was significantly larger than that for each of the other two conditions: $t(23) = 2.46$, large effect size $r = .46$, $p < .05$ for gamble loss, and $t(23) = 2.54$, large effect size $r = .47$, $p < .05$ for insurance with low-frequency risk. The model therefore exhibits a similar relationship between actual and weighted probabilities - exaggerated risk - to that shown in Experiments 1, 2 and 3.

Parameter values for the other variables (probability discriminability [β] and utility [α]) were more similar across tasks: for high-frequency risks $\beta=0.80$ (0.29), $\alpha=0.98$ (0.03); for low-frequency insurance risk $\beta=0.59$ (0.36), $\alpha=1.06$ (0.16); and for monetary gambles $\beta=0.67$ (0.26), $\alpha=0.99$ (0.03). As in the previous experiments, the independent variables *task* and *domain* did not affect the utility function parameter (α), or probability discriminability (β); ANOVA showed no significant effect of task,

on the utility function parameter α , $F(2, 23) = 3.14$, $p > .05$, or probability discriminability (β), $F(2, 23) = 1.04$, $p > .05$.

Together, the results from Experiment 4 suggest that participants' risky choices are influenced by the accessibility of events in memory even when these events are explicitly presented with probability information and the values of the possible outcomes. As with Experiments 1, 2 and 3, our results demonstrate the specificity of people's precautionary decisions: contemplating different referents of the risky choice " p chance of x , otherwise y " leads to different preferences, which, given the observed pattern, we attribute to respondents' familiarity with the particular events being considered.

The similar CE and pattern of risk aversion for low-frequency risks and monetary gambles and their differentiation from the high-frequency risks corroborate our view that the differences observed between monetary gambles and insurance risks in the earlier experiments were caused by differences in the accessibility of these prospects.

Experiment 5

The memory-based account presented in this paper assumes that the frequency of encounters with risky events in everyday life affects participants' preferences in characteristic ways not anticipated by most theories which assume that all risky choices are equivalent to monetary gambles. Our account implies that, when making risky decisions, human preferences are affected by decision content - specifically the accessibility of events in memory - even after outcome values and probabilities are known. We hypothesize that decisions about events rated as high-frequency differ from decisions about events rated as low-frequency and monetary gambles because the first cues accessible features in memory while the latter two do not.

Experiment 5 was designed to explore this issue further by investigating whether risky choices for the same events would vary systematically across respondents who had different perceptions of the frequency of those events. Studies have established that people in different countries have different views as to the riskiness of various events (e.g., Teigen, Brun & Slovic, 1988). We aimed to investigate if accessibility (measured by judged frequency) has a measurable impact on participants' risky preferences when we compare the risky choices made by UK participants and participants recruited in Japan who we expect to differ somewhat in their perceived frequency of some of the risky events. In particular, we predict an association between differences in accessibility and resulting differences in the patterns of risky preferences across the two participant populations.

Method

Materials and apparatus were the same as in Experiment 4 though all stimuli and instructions were translated into Japanese. Based on the norming procedure in Experiment 4, respondents were asked to rate each risk according to its frequency (participants were asked to refer to any instances of each risk that came to mind from any source of information) on a 10-point Likert scale ranging from *not frequent* to *very frequent*. Participants first judged the frequency of each of the presented risks and then they were randomly assigned to one of the three experimental risky choice conditions. For the risky choices, monetary amounts were in Japanese yen (¥) and equivalent in value to those used in Experiment 4.

Participants

Seventy-five University of Tokyo undergraduate and postgraduate students (49 male and 26 female) were recruited for a decision-making experiment. They were paid ¥700 and took part individually. Mean age was 20.67 ($SD = 3.11$).

Results and Discussion

As we expected, the Japanese respondents judged the frequency of the risky events somewhat differently to how the UK respondents (in Experiment 4) judged the same events - in some cases the differences were quite marked (see Appendix). As we predicted, across events, the differences between Japanese and UK (Experiment 4) respondents' mean judged frequency for each of the risky events corresponds to differences in their willingness to buy insurance for those events as measured by the CE measures used previously ($r = .62, p = .006$). A noteworthy aspect of this finding is that, unlike Experiment 4 which compared reactions to different high and low-frequency risks, it shows a difference in willingness to take risks for the same events as a function of differences in their perceived differential frequency. Consequently, the observed difference here cannot be attributed to any qualitative differences between the types of events.

As with the UK respondents in Experiment 4, for Japanese respondents the correlation (across nine levels of probability) between the difference in judged frequency for high- and low-frequency events and the corresponding difference in CE is positive and significant ($r = .78, p < .05$). This result replicates the finding that the frequency of events affects risky choices and further supports our claim that the accessibility of memory representations of events affects risky choices for these events.

Risk Preference

For both low-frequency insurance risks and monetary gambles more risk-seeking preferences were evident than for high-frequency insurance risks across most of the range of probabilities (see Table 8). The judged frequency of the four risks rated as highly frequent (above the midpoint of the scale) by both UK and Japanese

participants in Experiments 4 and 5 (high-high risks) and their four counterparts rated as low frequency (below the midpoint of the scale) by both UK and Japanese participants (low-low risk) were analyzed for Japanese participants. A 3 (task: low-frequency insurance task, high-frequency insurance task, and monetary gamble) \times 4 (probability level: .05, .25, .50, and .99) ANOVA showed that the main effects of task, $F(2, 72) = 13.94, p < .001, \epsilon^2 = .07$, and probability level, $F(3, 216) = 58.01, p < .001, \epsilon^2 = .33$, on risk preference were significant. The interaction effect was not significant, $F(3, 216) = 1.06, p > .05$. Multiple comparison tests with Bonferroni corrections confirmed that risk-seeking preferences were significantly lower for high-frequency risks than for low-frequency risks ($p = .001$) and monetary-gamble risks ($p < .001$), but there was no significant difference between low-frequency- and monetary gamble risks ($p > .05$).

The effects of both judged risk frequency and supplied probability on risky preferences (0 = risk-seeking, 1 = risk-averse) in the insurance conditions were investigated over all presented risky events and all probability levels using hierarchical logistic regression analysis. Independent variables were judged event frequency (per participant) and supplied probability (.01, .05, .10, .25, .50, .75, .90, .95, and .99), while controlling for the effect of participant (using criterion scaling, Pedhazur, 1997). The effects of judged frequency, $\chi^2(1) = 31.88$, odds ratio = 3.58, $p < .001$, and probability, $\chi^2(1) = 23.11$, odds ratio = 0.009, $p < .001$, and the interaction effect, $\chi^2(1) = 3.84$, odds ratio = 0.58, $p = .05$, were all statistically significant. The effects of judged frequency and probability confirm that both factors affect risky choice. Inspection of the interaction showed that judged frequency had a greater influence on decisions with lower probabilities resulting in more risk aversion than for higher probabilities though this may be due to a ceiling effect; for high

probabilities participants were risk seeking close to 100% of the time. Further testing showed that the effect of judged frequency was significant for both probabilities below the median value (.50), $\chi^2(1) = 23.45$, odds ratio = 3.12, $p < .001$, and for probabilities above the median value, $\chi^2(1) = 30.42$, odds ratio = 2.15, $p < .001$.

Certainty Equivalent

The judged frequency of the four risks rated as highly frequent in both Experiments 4 and 5 (high-high risks) and their counterparts (low-low risks) were analyzed. Analysis of the high-frequency insurance risks showed a higher CE than monetary gambles and low-frequency risks across the range of probabilities (see Table 9). A 3 (task: low-frequency insurance risk, high-frequency insurance risk, and monetary gamble) \times 4 (probability level: .05, .25, .50, and .99) ANOVA confirmed the main effects of task, $F(2, 72) = 21.98$, $p < .001$, $\epsilon^2 = .03$, and probability level, $F(3, 216) = 493.30$, $p < .001$, $\epsilon^2 = .80$, were significant. The interaction effect was not significant, $F(3, 216) = 1.30$, $p > .05$. Multiple comparison tests with Bonferroni correction confirmed that CE was significantly higher for high-frequency risks than for low-frequency risks and monetary-gamble risks (both $p < .001$), but there was no significant difference between low-frequency- and monetary gamble risks ($p > .05$).

The effects of both judged risk frequency and supplied probability on CE was investigated over all presented risks in the insurance conditions and all probability levels using hierarchical multiple regression analysis. Independent variables were judged risk frequency and probability (.01, .05, .10, .25, .50, .75, .09, .95, and .99), while controlling for the effect of participant (using criterion scaling - Pedhazur, 1997). The effects of judged frequency, $t(396) = 16.32$, $sr^2 = .06$, $p < .001$, and probability, $t(396) = 60.63$, $sr^2 = .86$, $p < .001$, and the interaction effect (judged frequency by probability), $t(396) = 3.34$, $sr^2 < .01$, $p < .001$, were significant.

Inspection of the interaction showed that, as with risk preferences, judged frequency had a greater influence on decisions with higher probabilities resulting in even higher CEs than for lower probabilities. Further testing showed that the effect of judged frequency was significant for both probabilities below the median value (.50), $t(197) = 6.31$, $sr^2 = .20$, $p < .001$, and for probabilities above the median value, $t(197) = 10.10$, $sr^2 = .35$, $p < .001$.

The effect of judged frequency from the norming procedure on CE and pattern of risk aversion are consistent with our view that the differences observed between monetary gambles and insurance risks in the earlier experiments were caused by differences in the accessibility of these prospects.

In summary, the results from Experiment 5 corroborate our earlier findings that decisions about subjectively more frequent events are different from those observed for equivalent choices between monetary gambles and judged low-frequency events. Japanese participants' risky judgments and corresponding preferences were different from those observed in the UK sample, but nonetheless maintained the same relationship to each other and thereby confirmed our hypothesis regarding the impact of differential accessibility of risks on choice.

General Discussion

Our research demonstrates that risky decisions vary as a function of the events being considered even after all required probabilities and outcome values have been specified. In five experiments we found and confirmed a *protective* effect - exemplified by exaggerated probability weights and greater risk aversion for precautionary decisions about more accessible (high frequency) events compared to less accessible (low frequency) events and monetary gambles. These findings establish that, contrary to the assumptions of normative theory and numerous

descriptive theories of decision making under risk and uncertainty (e.g., Birnbaum, 2008; Brandstätter, Gigerenzer & Hertwig, 2006; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992; von Neumann & Morgenstern, 1947), people's risk preferences and decisions under risk and uncertainty are *not* independent of problem content after all probabilities and outcome values are defined.

From the point of view of those theorists who assume that all risky decisions can be represented as monetary gambles the results can be viewed as a demonstration of the failure of *descriptive invariance* - one of the axioms of expected utility theory (Kahneman & Tversky, 1984). The descriptive invariance axiom states that equivalent formulations of a choice problem should give rise to the same preference order. However we found that varying referent events with the same decision-making prospects leads to different preference patterns.

Our result implies that the assumption that all decisions under risk or uncertainty can be effectively represented by monetary gambles, requires some revision. Precautionary decisions can still, in a general sense, be viewed as gambles - but with the critical proviso that decision makers make different decisions when contemplating precautions than when contemplating gambles with identical values.

The finding that people's risk preferences cannot be accurately specified from studies of their reactions to monetary gambles raises both practical and theoretical questions. To the extent that there is no generally stable set of risk attitudes then reliable predictions of risky decision making will not be possible across different decision-making domains. The experiments reported here found discrepancies between the risk attitudes for gambles and those for decisions regarding insurance against hazards - perhaps the most obvious practical application of risky decision-making.

We found that the probability-weighting function exhibits properties for precautionary decisions different to those observed for putatively identical choices between gambles. People's protective willingness (greater risk aversion for precautionary decisions under risk) is indicated by increases in the probability-weighting estimates for low, moderate and high probabilities of hazardous events. Overweighting of probability for precautionary decisions for moderate and high probabilities is a finding not anticipated by prospect theory or cumulative prospect theory - the most prominent descriptive theories for decisions under risk.

Our findings of exaggerated risk for small probabilities are also not anticipated by proponents of so-called *experience based decision making* who have argued that people underweight rather than overweight small probabilities when making decisions based on their experience of risky events rather than summary descriptions of their likelihoods (Hertwig, Weber, Erev, & Barron, 2004). In particular, experienced-based decision-making research finds that people's decisions about sequentially experienced events underweight low probability events (cf. Fox & Hadar, 2006; Jessup, Bishara & Busemeyer, 2008; Newell & Rakow, 2007; Ungemach, Chater & Stewart, 2009). Of course, our experiments were not specifically designed to investigate decisions based on experienced small probability events (we always supplied descriptions of likelihood of events). Nonetheless, when decisions involved real-world events that could relate to and draw on our participants' experience, overweighting of probability (or risk aversion for negative events) was observed for small probabilities - even for those events participants rated as low frequency experiences (Experiments 4 & 5).

The pattern of people's risk preferences found here is inconsistent with those of previous descriptive studies. Early studies of utility commonly assumed that people's

risk preferences are predominantly risk-averse (Pratt, 1964). However, risk seeking is also predictable under certain conditions. According to the well known fourfold pattern of risk attitudes established with gambles (Tversky & Kahneman, 1992; Tversky & Fox, 1995) people show risk aversion for gains and risk seeking for losses at high probability, and risk seeking for gains and risk aversion for losses at low probability. A similar prediction is made by Brandstätter et al. (2006) with their proposed *priority heuristic* - which produces a pattern of risk-averse and risk-seeking preferences based on rules (priority, stopping and decision rules) consistent with the fourfold pattern found by Tversky and Kahneman (1992) - see also Stewart et al. (2006).

By contrast, we demonstrate that people's risk preferences can be risk averse for precautionary decisions about high-frequency events for almost the whole range of probability, and yet with monetary gambles in the domain of loss and for precautionary decisions involving low-frequency events people are predominantly risk seeking. We find that, in precautionary decision-making, more accessible events in memory have a greater influence on decisions than less accessible events (e.g., monetary gambles and less familiar real-world events). Experiments 4 and 5 produced evidence that the accessibility of hazardous events affect people's decisions: instances of some protectable risks are judged to occur more frequently in everyday life than others and the former risks produced a greater protective effect. The results of all five experiments demonstrated that people exaggerate described real-world risky prospects consistent with the assumption that precautionary decisions are dependent on the accessibility of hazardous events in memory.

The idea presented in this paper that people's precautionary decisions might be affected by the accessibility of frequencies in memory is also supported by case-based

decision theory (Gilboa & Schmeidler, 2001), which assumes that decisions under uncertainty are made by analogy to previously-encountered problems. The theory postulates a similarity function over decision problems and a utility function on outcomes, such that acts are evaluated by a similarity-weighted sum of the utility they yielded in past cases in which they were chosen.

The finding of Experiment 5 that Japanese decision makers, who differed from UK participants in their perception of the relative frequency of risky events and altered their choices accordingly, strongly suggests that a memory-based assessment of events informs risky decisions. The strong positive correlation between the differences in rated frequencies and the differences in risky choices for the same set of events is a clear indication that memorial representations of the frequency of events affected decisions made about them.

Such ideas could possibly account for our findings that people's risk preferences vary across specific decision-task domains, which, as we have argued, can be linked to the differential accessibility of the events under consideration. In contemplating most real-world risks, people suffer from a lack of knowledge about the probabilities of hazardous events (e.g., natural disaster, health and safety risk). Where accessibility is a valid cue for likelihood then it should produce reasonably good decisions. However, problems will arise when people have information about likelihood that is corrupted via the accessibility of events "altering" the impact of the probability information. One could view this as akin to the Stroop effect (Stroop, 1935) where information in memory that conflicts with information present in the stimulus can disrupt decisions.

Other research has also shown differences in risky decisions as a function of decision content. Heath and Tversky (1991) found that decision makers under risk

were sensitive to aspects of content independent of probability and utility information. In their studies respondents exhibited a preference for betting on decisions about events on which they were knowledgeable rather than matched monetary gambles or events on which they were less knowledgeable. Although Heath and Tversky interpret their result in terms of attributions for credit and blame, it could also be interpreted in terms of accessibility. Rottenstreich and Hsee (2001) also found evidence for effects of decision content on risky choice. They report that the probability-weighting function may be influenced by affective reactions associated with potential outcomes of a risky prospect. As these authors point out, if the weight attached to an outcome depends on the nature of that outcome then it is not possible to specify separate functions to describe the evaluation of outcomes and the evaluation of probabilities.

Huber and Huber (2008) have argued that gambles are not good models for many real life risky decisions because in real life, if decision makers realize that an otherwise attractive alternative may produce a negative outcome, they search for a risk-defusing operator (RDO) to eliminate or reduce the risk involved. In everyday risky decision situations, they claim that RDOs are quite common. For example, people having to decide whether or not to travel to a region where infectious disease are prevalent, will inquire whether there is a vaccine against that disease instead of passively contemplating probabilities. A person wanting to buy a new car but uncertain whether she can meet the monthly instalments, may take out consumer credit repayment insurance. Huber (2007) claims that in many real life decisions - but not monetary gambles - many decision makers are not interested in probability information and instead actively search for RDOs. Evidence for the search for RDOs has been found in insurance decision making (Williamson, Ranyard & Cuthbert,

2000). However it is not clear how RDOs could explain our finding that people are more risk averse for insurance than for gambles. According to Huber (2008) if a decision maker finds an RDO or an RDO is available, he or she chooses the risky alternative in question much more often than without finding an RDO. While RDOs might be discovered in insurance scenarios, in choices among gambles (according to Huber) besides choosing one alternative, the decision maker cannot exert any control at all. Moreover, it is clear that our respondents are influenced by probabilities.

One possible objection to the claims made here is that the risky insurance loss is in fact objectively worse than the risky monetary loss, because the insurance loss involves an additional hassle factor (e.g., being deprived of possession's one likes, needing to go out and buy replacements). To the extent that the risky insurance losses are indeed more negative than the corresponding risky monetary losses, one might argue that it is not surprising that participants are more risk averse in the insurance domain.

In our view, for both conceptual and empirical reasons, the notion that the insurance loss is objectively worse than the risky monetary loss cannot account for our results. For respondents in the insurance scenario any envisaged “additional hassle factor” should not influence the insurance decision. Whether one is insured or not, loss of the luggage implies that one has to suffer being deprived of possessions one likes and the inconvenience of having to go out and buy replacements - if one has the money to be able to afford to go and buy replacements, as, assuredly (literally), in the insurance case one does. The point is that, in the insurance scenario, the option to buy insurance does not magic away any hassle or even reduce the likelihood of experiencing hassle (cf. Tykocinski, 2008) and hence does not justify greater risk aversion; indeed, one might even argue that there might be greater hassle in the

insurance case *if one buys insurance* as here one has the additional hassle of making an insurance claim.

In any event the idea that the insurance loss is objectively worse than the risky monetary loss was not a view held by our respondents as they were not, in terms of their willingness to suffer monetary losses to compensate them for loss of their luggage, risk averse for every level of probability of loss. As is shown in every experiment (e.g., see Figure 1d) respondents in the insurance loss condition were risk seeking at the highest level of probability of loss; had they valued loss of their luggage as worse than the loss of its corresponding expressed monetary value this would not have happened.

Moreover, the possibility that risky insurance loss is objectively worse than the risky monetary loss is also excluded by another aspect of the results of Experiments 4 and 5. In both of these experiments we report that, while risk-seeking preferences were significantly lower for high-frequency insurance risks than for low-frequency insurance risks and monetary gamble risks, there was no significant difference between low-frequency-insurance risks and monetary gamble risks; decisions were predominantly risk seeking for both sorts of risk - as predicted by cumulative prospect theory. Nevertheless the low-frequency insurance risks would still entail “hassles” of the sort envisaged by this argument and yet this does not appear to have been a factor for our respondents when considering such risks as “Damage to accommodation by burst pipes”, “Damage to laptop computers by fire (caused by a technical problem)” or “Damage to gardens by falling trees”. Although these hazards will undoubtedly involve “hassle” for a victim of these misfortunes, as we have explained, the hassle will present regardless of one’s decision to insure.

The effects we attribute to the accessibility of risky events should be tested further in future studies. For instance, one obvious next step is to see whether the effects can be measured when the accessibility of probability information is manipulated independently of subjective frequency beliefs. One possible way to achieve this, suggested to us by an anonymous reviewer of this paper, would be to develop a priming paradigm.

In sum, the evidence presented in this paper calls into question the assumption that decisions made with monetary gambles can be used as a methodology for evaluating domain-independent risk preferences. We suggest that this in turn should prompt further exploration of how what it is that people are deciding about produces variation in the risks people are prepared to take.

Over the years several authors have commented on the preeminence of monetary gambles in studies of risky choice. For example, Lopes (1983) commented that: “The simple static lottery or gamble is as indispensable to research on risk as is the fruitfly to genetics” (p.173). Goldstein and Weber (1997) in similar comparative vein argued that: “Simple gambles are as prevalent in decision research as nonsense syllables ever were in memory research” (p. 92).

It is understandable why researchers have found monetary gambles an attractive research vehicle. As Goldstein and Weber (1997) made clear it seems “...a poor trade to exchange familiar content free taxonomies of decision problems (e.g. decision making under risk, uncertainty and certainty) for an explosion of content-specific categories of decisions (e.g. career decisions; housing decisions; animal, mineral and vegetable decisions etc.), each of which may require a different theory” (p. 84). As these authors argue one can also be tempted to believe that in studying reactions to monetary gambles one is studying risky decision-making in its most “essential” form

permitting the widest possible generalizability. Although some take it as a basic premise that “Most decisions in life are gambles” (Fox & See, 2003, p. 273) our research indicates that for some decisions this attractive metaphor may be misleading.

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Appendix

Events	Judged frequency of event ^a (UK)		Judged riskiness of event ^a (UK)		Judged frequency of event ^a (Japan)		Probability presented with event ^{abb}
	Mean	<i>SD</i>	Mean	<i>SD</i>	Mean	<i>SD</i>	Percentage
Accidents using public transport (High) ^c	6.70	2.39	5.89	2.37	6.04	2.06	99
Credit-card fraud (identity fraud) (High)	6.42	2.22	7.05	2.26	2.79	1.51	95
Theft of laptop computers (High)	6.30	2.10	5.52	2.38	2.39	1.23	90
Home burglaries (High)	6.17	2.34	6.74	2.07	2.52	1.39	75
Loss of income as a result of redundancy (High)	6.08	2.61	6.42	2.09	5.00	1.52	50
Loss of luggage and personal belongings (High)	5.94	2.46	5.27	2.21	5.71	2.44	25
Accidents during football games (High)	5.85	2.40	5.65	2.26	4.11	1.70	10
Accidents using home appliances (Low) ^d	5.76	2.58	5.90	2.19	6.04	2.16	5
Theft of personal belongings inside cars (High)	5.67	2.29	5.61	1.91	2.81	1.36	1
Accidents during leisure time (Low)	4.57	2.16	5.70	1.88	5.91	1.77	1
Malicious damage to motorbikes (Low)	4.54	2.33	4.44	2.15	3.12	1.56	5
Damage to cars by storms (Low)	4.52	2.18	4.49	2.19	1.87	1.19	10
Damage to accommodation by burst pipes (Low)	4.44	2.32	4.95	2.30	3.24	1.61	25
Damage to laptop computers by fire (caused by a technical problem) (Low)	4.37	2.28	4.51	2.32	3.67	1.80	50
Damage to gardens by flood (Low)	4.35	2.45	3.48	2.13	2.63	1.67	75
Damage to gardens by falling trees (Low)	4.10	2.33	3.48	1.90	2.57	1.32	90
Accidents during golf games (Low)	3.88	2.19	3.19	1.91	4.63	1.70	95
Damage to property by aircraft or things falling from aircraft (Low)	3.63	2.22	3.99	2.43	2.12	1.14	99

^aNorming procedure ^bExperiment 4 ^cExperiment 5 ^dRisk chosen as high-accessibility stimulus for inclusion in the norming procedure (UK) ^dRisk chosen as low-accessibility for inclusion in the norming procedure (UK)

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Footnotes

¹ The intra-class correlation co-efficient is a measure of similarity taking into account both profile shape and profile elevation (Lorr, 1983) and expresses the between-subjects variability relative to other sources of variability (Howell, 1997).

Table 1

Percentage of risk preferences with gain (Experiment 1)

Risk preferences	Gamble gain			Insurance gain		
	$p = .01$	$.01 < p \leq .1$	$p \geq .5$	$p = .01$	$.01 < p \leq .1$	$p \geq .5$
Risk seeking	78%	59%	11%	77%	57%	9%
Risk averse	22%	41%	89%	23%	43%	91%

Note. Similarity between gain and insurance in risk seeking with gain. Percentages are mean values.

Table 2

Percentage of risk preferences with loss (Experiment 1)

Risk preferences	Gamble loss			Insurance loss		
	$p = .01$	$.01 < p \leq .1$	$p \geq .5$	$p = .01$	$.01 < p \leq .1$	$p \geq .5$
Risk seeking	10%	27%	83%	0%	7%	40%
Risk averse	90%	73%	17%	100%	93%	60%

Note. Inconsistency of risk seeking preferences with loss between gamble and insurance. Percentages are mean values.

Table 3

Summary of analysis of variance results for certainty equivalent preferences

(Experiment 1)

Probabilistic amount	Source	F	ϵ^2	p
£50	Task	8.13	0.08	0.024
	Domain	8.31	0.09	0.022
	Task \times domain	11.58	0.13	0.005
£100	Task	7.22	0.06	0.038
	Domain	29.77	0.27	0.000
	task \times domain	13.30	0.12	0.002
£200	Task	14.76	0.11	0.008
	Domain	35.19	0.13	0.004
	Task \times domain	27.82	0.09	0.020
£400	Task	10.06	0.10	0.010
	Domain	21.40	0.23	0.000
	Task \times domain	2.21	0.01	0.571

Notes. $df = 1, 56$ for all F ratios. Bonferroni correction applied to all p values.

Table 4

Percentage of risk preferences (Tversky & Kahneman, 1992)

Risk preferences	Gamble gain		Gamble loss	
	$p \leq .1$	$p \geq .5$	$p \leq .1$	$p \geq .5$
Risk seeking	78%	10%	20%	87%
Risk averse	10%	88%	80%	6%

Note. Values that correspond to the fourfold pattern (Tversky & Kahneman, 1992). Percentages are mean values.

Table 5

Percentage of risk preferences with loss (Experiment 3)

Risk preferences	Gamble loss			Insurance loss		
	$p = .01$	$.01 < p \leq .1$	$p \geq .5$	$p = .01$	$.01 < p \leq .1$	$p \geq .5$
Risk seeking	35%	56%	92%	10%	17%	46%
Risk averse	65%	44%	8%	90%	83%	54%

Note. Inconsistency of risk seeking preferences with loss between gamble and insurance prospects. Percentages are mean values.

Table 6

Mean proportion of risk-averse and risk-seeking preferences (Experiment 4)

Probability	High-frequency risk		Low-frequency risk		Monetary-gamble risk	
	Risk seeking ^a	Risk averse ^b	Risk seeking ^a	Risk averse ^b	Risk seeking ^a	Risk averse ^b
p =.01	0%	100%	17%	83%	20%	80%
p =.05	17%	83%	23%	77%	43%	57%
p =.10	23%	77%	43%	57%	53%	47%
p =.25	34%	76%	47%	53%	43%	57%
p =.50	33%	67%	60%	40%	80%	20%
p =.75	57%	43%	87%	13%	93%	7%
p =.90	63%	37%	83%	17%	93%	7%
p =.95	63%	37%	87%	13%	90%	10%
p =.99	77%	23%	90%	10%	100%	0%
Overall	41%	59%	60%	40%	68%	32%

^a[% of responses where CE > EV] ^b[% of responses where CE < EV]

Table 7

Means and Standard Deviations of certainty equivalents (Experiment 4)

Task	Probability of risky prospect																			
	1%		5%		10%		25%		50%		75%		90%		95%		99%		Average	
Monetary-gamble risk	.043	(.06)	.082	(.09)	.132	(.09)	.243	(.13)	.382	(.16)	.596	(.26)	.637	(.16)	.709	(.14)	.812	(.07)	.403	(.043)
High-frequency risk	.088	(.06)	.121	(.16)	.154	(.10)	.303	(.23)	.522	(.23)	.637	(.25)	.709	(.25)	.757	(.16)	.869	(.07)	.462	(.088)
Low-frequency risk	.059	(.05)	.096	(.73)	.122	(.14)	.251	(.22)	.432	(.26)	.549	(.34)	.581	(.33)	.651	(.31)	.749	(.14)	.388	(.059)
Overall	.063	(.06)	.100	(.20)	.137	(.12)	.266	(.20)	.446	(.22)	.594	(.29)	.641	(.26)	.706	(.22)	.810	(.10)	.418	(.063)

Note. Range is a proportion of £680. Values are means with (SD)

Table 8

Mean proportion of risk-averse and risk-seeking preferences (Experiment 5)

Probability	High-frequency risk ^a		Low-frequency risk ^b		Monetary-gamble risk	
	Risk seeking ^c	Risk averse ^d	Risk seeking ^c	Risk averse ^d	Risk seeking ^c	Risk averse ^d
p =.01	0%	100%	0%	100%	0%	100%
p =.05	16%	84%	28%	72%	40%	60%
p =.10	24%	76%	40%	60%	44%	56%
p =.25	4%	96%	28%	72%	32%	68%
p =.50	14%	86%	60%	40%	54%	44%
p =.75	88%	12%	80%	20%	88%	12%
p =.90	96%	4%	84%	16%	88%	12%
p =.95	100%	0%	44%	56%	96%	4%
p =.99	80%	20%	100%	0%	100%	0%
Overall	47%	53%	52%	48%	60%	40%

^{a,b}Stimuli identified as High and Low in Experiment 4 ^c[% of responses where CE > EV]^d[% of responses where CE < EV]

Table 9

Means and Standard Deviations of certainty equivalents (Experiment 5)

Task	Probability of risky prospect																			
	1%		5%		10%		25%		50%		75%		90%		95%		99%		Average	
Monetary-gamble risk	.042	(.04)	.070	(.04)	.141	(.10)	.288	(.17)	.449	(.19)	.667	(.14)	.747	(.18)	.771	(.17)	.845	(.11)	.447	(.127)
High-frequency risk ^a	.053	(.04)	.184	(.14)	.202	(.12)	.386	(.12)	.624	(.16)	.599	(.19)	.633	(.14)	.734	(.10)	.898	(.10)	.479	(.126)
Low-frequency risk ^b	.092	(.09)	.086	(.05)	.137	(.07)	.289	(.08)	.486	(.12)	.661	(.12)	.769	(.11)	.916	(.09)	.786	(.11)	.469	(.093)
Overall	.062	(.05)	.113	(.08)	.160	(.10)	.321	(.12)	.520	(.16)	.642	(.15)	.717	(.14)	.807	(.12)	.843	(.11)	.465	(.115)

Note. Range is a proportion of ¥136000. Values are means with (SD) ^{a,b}Stimuli identified as High and Low in Experiment 4

Figure Captions

Figure 1. Two-parameter probability-weighting functions based on mean estimates of probability discriminability (β) and attractiveness (δ) in equation (1) (Experiments 1 and 2).

Figure 2. Distribution of risk-seeking choices by probability (Experiment 1). Mean values are proportions. Error bars represent 95% confidence interval of mean.

Figure 3. Certainty equivalent proportions by monetary amount (Experiment 1). Mean values are proportions. Error bars represent 95% confidence interval of mean.

Figure 4. Two-parameter probability-weighting functions based on average estimates of participants' CE (Experiment 3).

Figure 5. Distribution of risk-seeking choices by probability (Experiment 3). Mean values are proportions. Error bars represent 95% confidence interval of mean.

Figure 6. Certainty equivalent proportions by experimental condition (Experiment 3). Mean values are proportions. A certainty equivalent of 1.0 corresponds with an amount of £600. Error bars represent 95% confidence interval of mean.

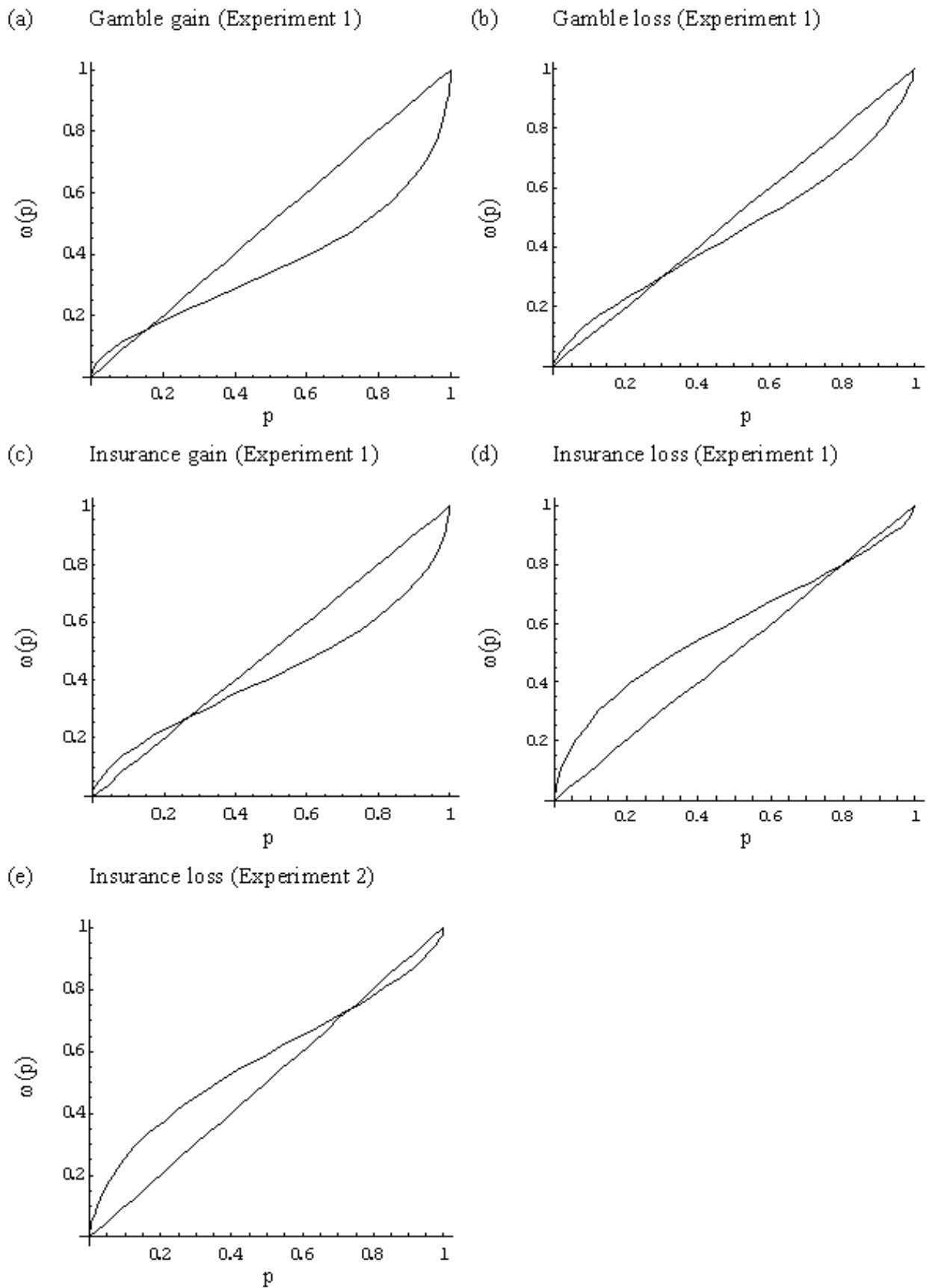


Figure 1.

Note. Median values. Two-parameter models.

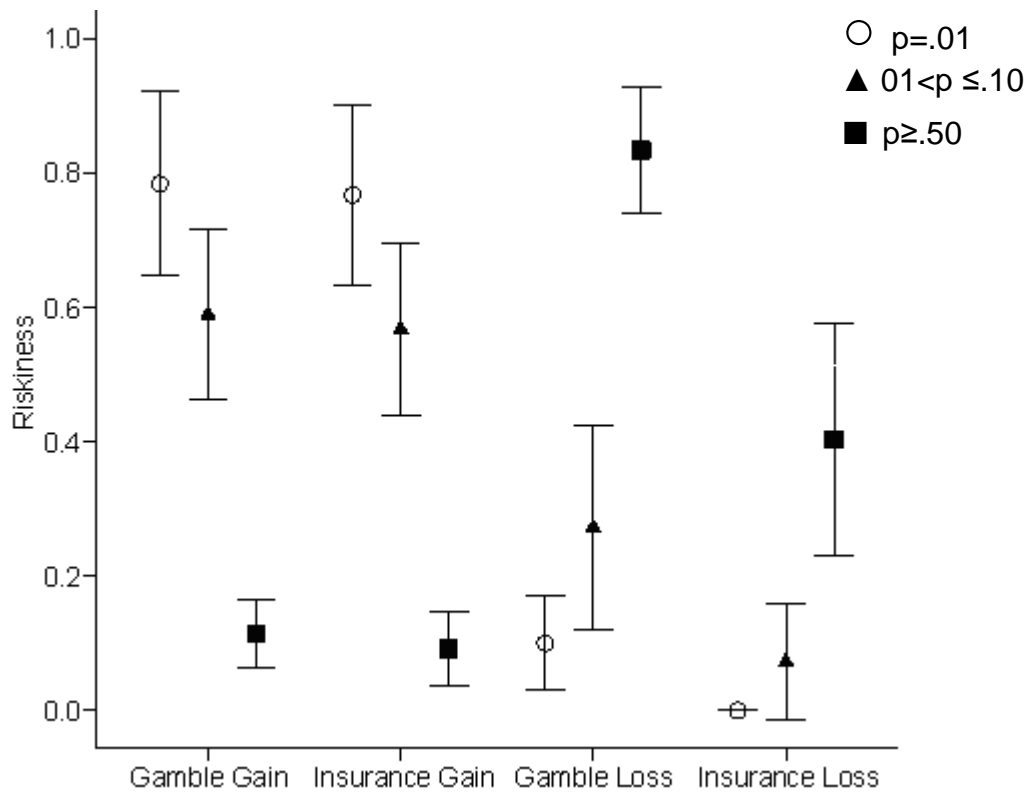


Figure 2.

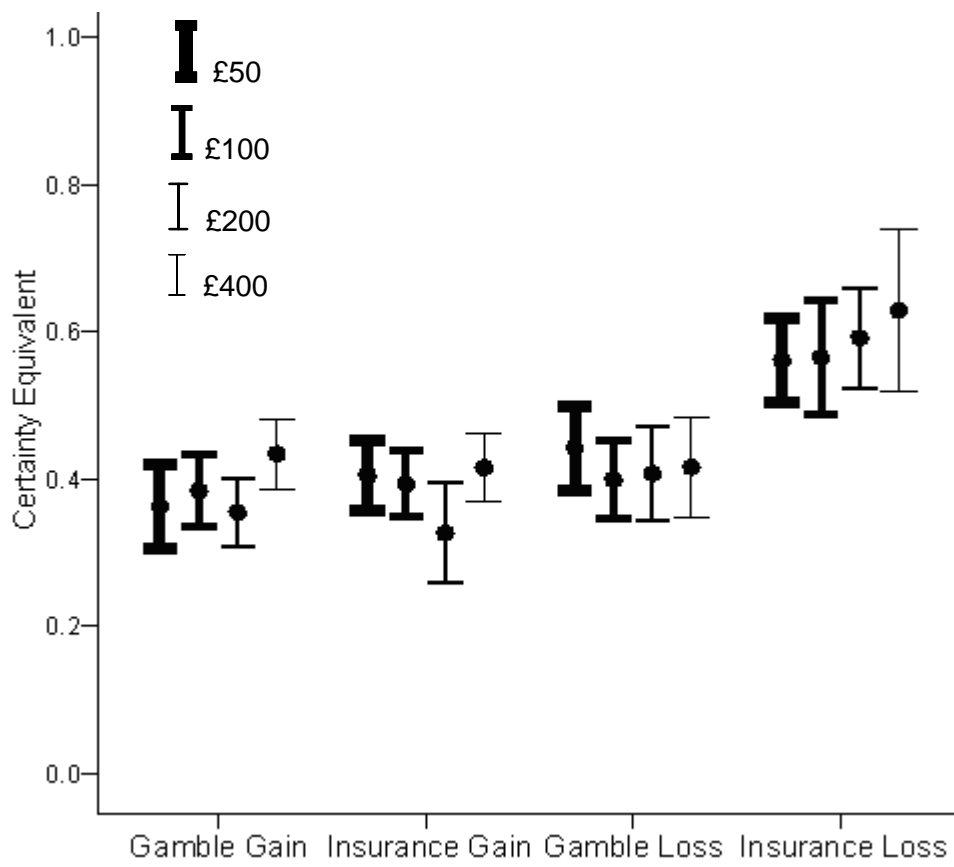
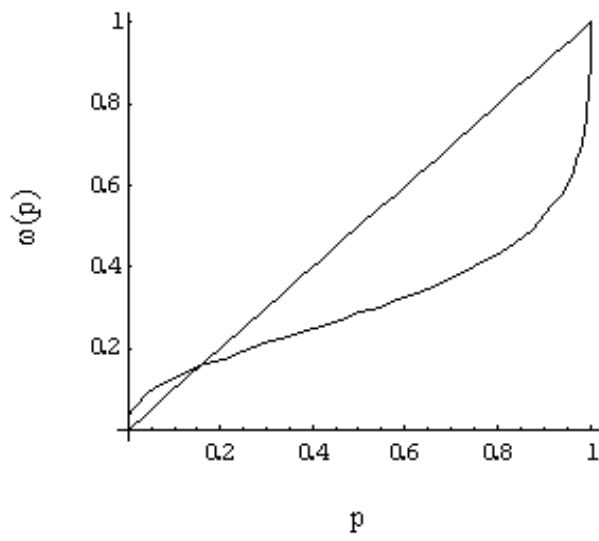
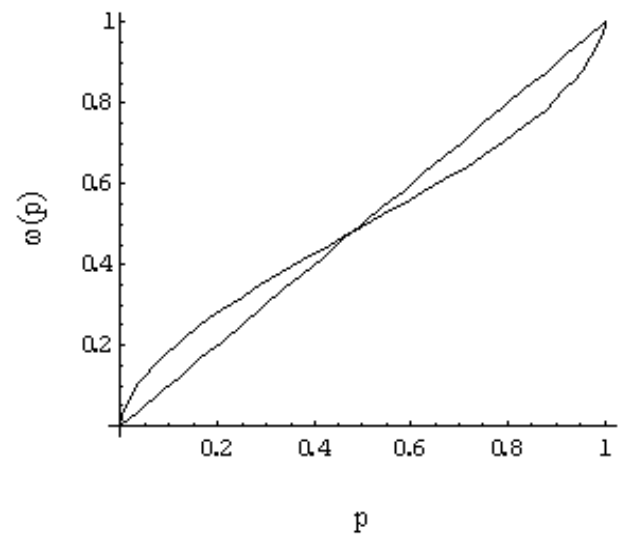


Figure 3.

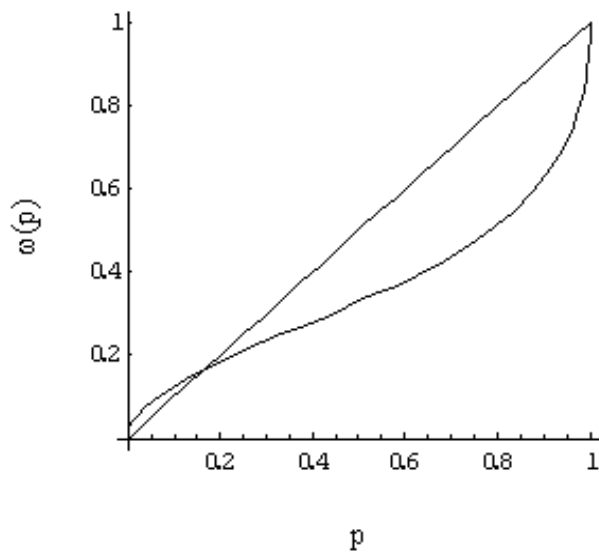
(a) Gamble gain (Experiment 3)



(b) Gamble loss (Experiment 3)



(c) Insurance gain (Experiment 3)



(d) Insurance loss (Experiment 3)

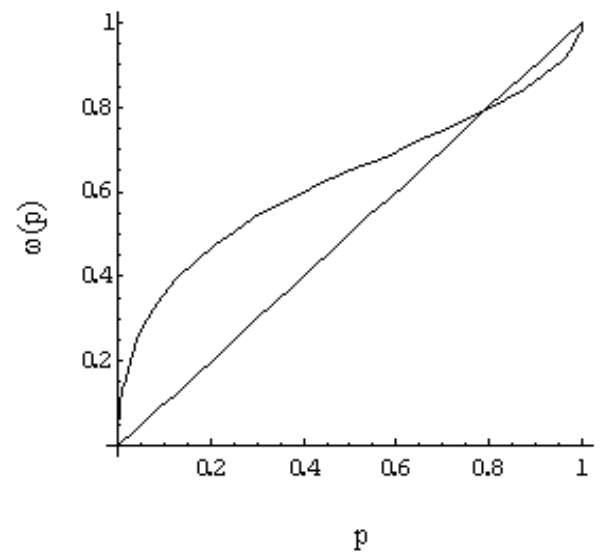


Figure 4.

Note. Median values. Two-parameter models.

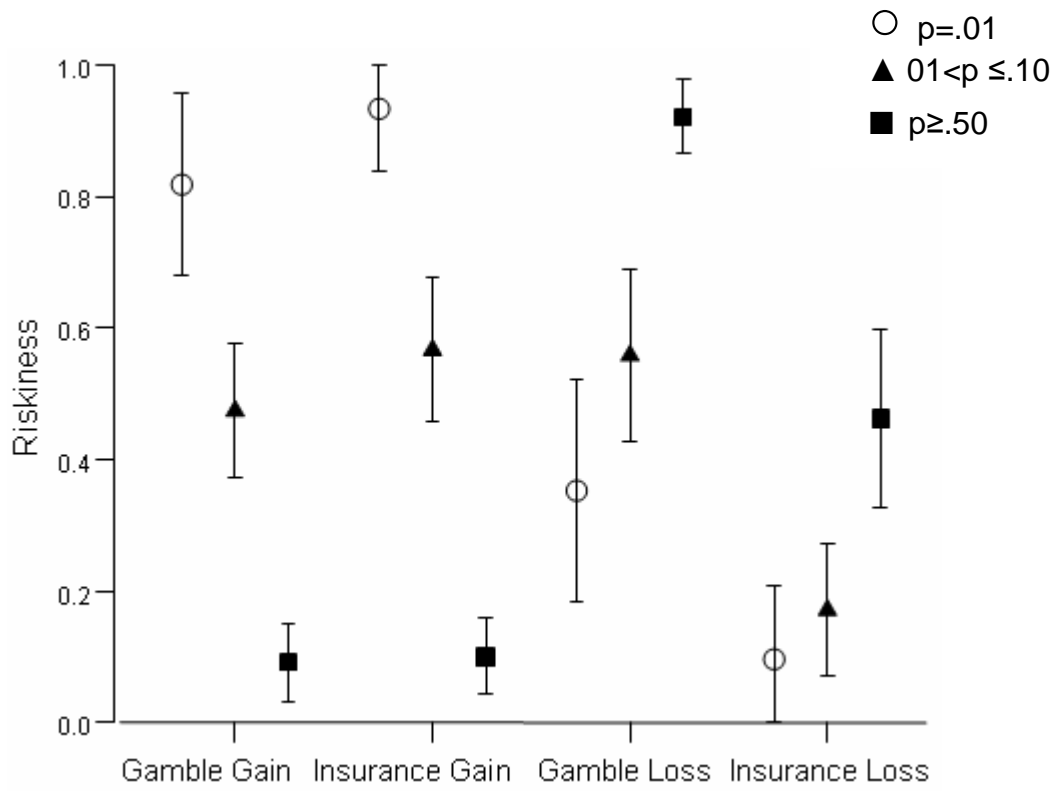


Figure 5.

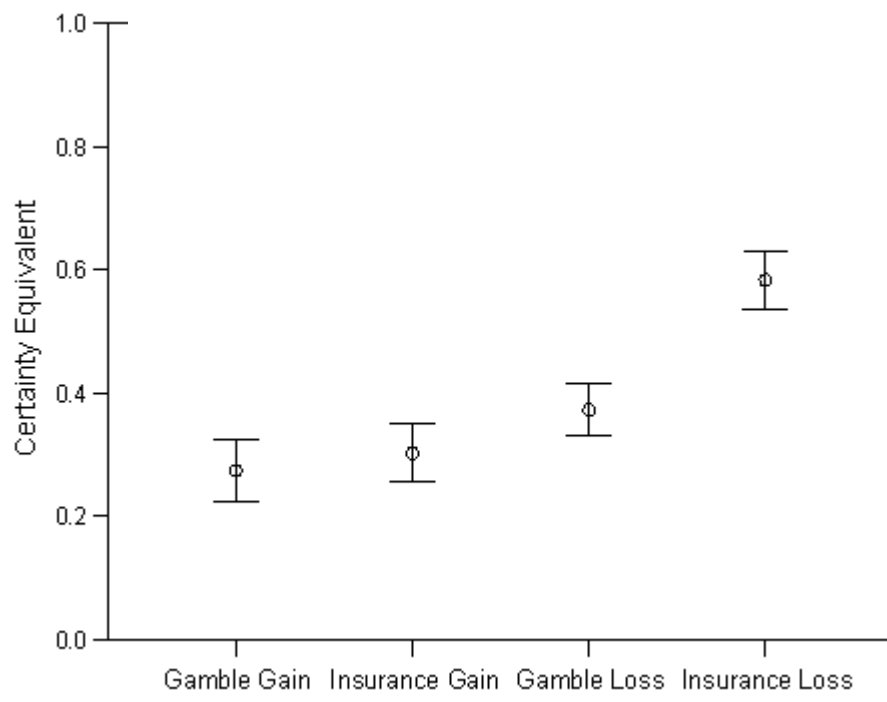


Figure 6.