Organizational Behavior and Human Decision Processes
Vol. 78, No. 3, June, pp. 204–231, 1999
Article ID obhd.1999.2830, available online at http://www.idealibrary.com on IDEAL®

# The Effects of Framing, Reflection, Probability, and Payoff on Risk Preference in Choice Tasks

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**A meta-analysis of Asian-disease-like studies is presented to identify the factors which determine risk preference. First the confoundings between probability levels, payoffs, and framing conditions are clarified in a task analysis. Then the role of framing, reflection, probability, type, and size of payoff is evaluated in a meta-analysis. It is shown that bidirectional framing effects exist for gains and for losses. Presenting outcomes as gains tends to induce risk aversion, while presenting outcomes as losses tends to induce risk seeking. Risk preference is also shown to depend on the size of the payoffs, on the probability levels, and on the type of good at stake (money/property vs human lives). In general, higher payoffs lead to increasing risk aversion. Higher probabilities lead to increasing risk aversion for gains and to increasing risk seeking for losses. These findings are confirmed by a subsequent empirical test. Shortcomings of existing formal theories, such as prospect theory, cumulative prospect theory, venture theory, and Markowitz's utility theory, are identified. It is shown that it is not probabilities or payoffs, but the framing condition, which explains most variance. These findings are interpreted as showing that no linear combination of formally relevant predictors is sufficient to capture the essence of the framing phenomenon.** 

*Key Words:* framing; reflection; risk; probability; payoff.

We thank two anonymous referees for helpful comments on earlier versions of this paper. This research was in part supported by the Austrian Fonds zur Forderung der Wissenschaftlichen Forschung, Grant P11397-SOZ, to the first and to the third author.

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0749-5978/99 $30.00

## INTRODUCTION

Tversky and Kahneman (1981) used the term *framing* for the finding that simple and unspectacular changes in the wording of decision problems can lead to different preferences. Drawing on prospect theory (Kahneman & Tversky, 1979), they argued that the different wording of formally identical problems makes people code the outcomes of identical options either as gains or as losses relative to a reference point. Those preference reversals are a striking deviation from widely accepted normative models that form the backbone of decision theory. A recent meta-analysis (Kuhberger, 1998) has identified about 150 empirical investigations and about 100 theoretical treatments of the framing effect. It shows that over all studies the effect is of small to moderate size ($d = 0.33$) and that some experimental procedures fail to show a framing effect. One interesting finding was that the larger the difference between a particular experimental procedure and the original Asian-disease procedure used by Tversky and Kahneman (1981), the smaller the framing effect in the new procedure.

While Kuhberger (1998) offers an analysis of all risky framing studies, the present analysis is more narrowly focused on the original Asian-disease procedure (Tversky & Kahneman, 1981; for defining features, see below). In particular, we focus on the role of framing, probabilities, and payoffs on risk preference. These are central concepts in most theories on risk preference but have hitherto not been systematically evaluated in a meta-analysis.

Tversky and Kahneman (1981) presented the following problem:

> Imagine that the United States is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimates of the consequences of the programs are as follows:
>
> If Program A is adopted, 200 people will be saved.
>
> If Program B is adopted, there is a 1/3 probability that 600 people will be saved and a 2/3 probability that nobody will be saved.
>
> Which of the two programs would you favor?
>
> Now consider this problem with a slightly different verbal description of the outcomes:
>
> If Program C is adopted, 400 people will die.
>
> If Program D is adopted, there is a 1/3 probability that nobody will die and a 2/3 probability that 600 people will die.
>
> Which of the two programs would you favor?

The example above clarifies the structure of the Asian-disease task: Participants have to choose one of two options, where one option offers a sure outcome (sure option) and the other option offers a risky outcome with identical expected value (risky option). The reference point is manipulated in such a way that the situation appears to incorporate either gains or losses. The probabilities (e.g., 1/3 for risky gain, 2/3 for risky loss) and the payoffs (e.g., 200 and 600 for gains, 400 and 600 for losses) are explicitly stated.

The general hypothesis of framing is that there is a tendency for risk aversion for positively framed problems and a tendency for risk seeking for negatively framed problems. This tendency is termed the framing effect. Unlike in Kuhberger (1998), however, we do not test the effect between framing conditions (unidirectional test; Wang, 1996). Rather, we are interested in bidirectional framing effects. That is, we test whether the choice proportions in each framing condition differ from the 50:50 proportion in the expected direction, i.e., whether risk aversion is predominant for gains (preference for sure option above 50%) and whether risk seeking is predominant for losses (preference for sure option below 50%). A further aim is to evaluate the role of probabilities and payoffs for risk preference. Many theories assume that risk preference (and the framing effect) is dependent on the probabilities used (cumulative prospect theory, venture theory, advantage model) and/or on whether the payoffs are large or small (Markowitz's utility theory, venture theory). These hypothesized effects of payoffs and probabilities are very variable (see Kuhberger, 1997).

## Task Analysis: Clarifying Confoundings

### *Framing Effect versus Reflection Effect*

We will distinguish between framing and reflection studies. In framing studies, the outcomes in both framing conditions are either both positive or both negative, objectively. In the Asian-disease problem, for instance, both framing conditions actually offer losses, since the status quo is that no one has yet died, and the sure option is that 400 people will be dead after having chosen this option (however, it is described as "200 will be saved"). The intention is to make losses seem like gains. Thus, in framing studies, both framing conditions offer identical outcomes with respect to final states.

In contrast, in reflection studies, the outcomes are different for gains and for losses (see Fagley, 1993). You either end up with more than you have now (or nothing gained) or end up with less than you have now (or nothing lost). Thus, in reflection studies the final outcomes are different in sign, while in framing studies they are equal in sign but look like being different. Table 1 shows this in more detail.

Table 1 shows that we have to distinguish two points of reference. One point is the status quo, how things are presently. In the Asian-disease problem this

**TABLE 1**

**Structure of Asian-Disease Task**

| Framing | Action | Status quo | Change | Final state |
|---|---|---|---|---|
| | Do nothing | 0 dead | 600 die | 600 dead |
| Gain | Option A (sure) | 0 dead | 200 saved | 200 saved (400 dead) |
| | Option B (risky) | 0 dead | 1/3 600 saved | 200 saved (400 dead) |
| Loss | Option C (sure) | 0 dead | 400 die | 400 dead (200 saved) |
| | Option D (risky) | 0 dead | 2/3 600 die | 400 dead (200 saved) |

state is given in the introductory paragraph, in which people learn that 600 people are expected to be killed. Presently, however, no one is dead. This is the status quo. If nothing is done, 600 people will die, resulting in a final state of 600 people dead. The sure and risky options then describe a change in the state of affairs; this change is framed either as a gain (200 saved) or as a loss (400 die) in the sure options, and in the risky options it is framed with the formally equivalent risky outcome. The change results in a final state of affairs, i.e., 200 of 600 saved or 400 of 600 dead. The framing manipulation is intended to make people adopt the reference point of "600 dead" in the gain condition; relative to this point, "200 saved" is a gain. In the loss condition, the framing manipulation is intended to make people adopt the "0 dead" reference point; relative to this point, "400 die" is a loss. This task analysis shows that the feature that distinguished framing from reflection tasks is whether or not a change occurs for the "do-nothing" option. If the do-nothing option does not result in a change, we have a reflection task, since final state and change are equal. Otherwise, if the do-nothing option results in a change, we have a framing task, where finals state and change are different.

Note that, irrespective of the framing condition, the final state of all options A to D in the Asian-disease task is that 400 people will be dead. Thus, all options are formally equal in final state. The question then is whether people do disregard the final state and do see only the change ("200 people saved are 200 saved") or whether they do consider the final state of affairs too ("200 people saved out of 600 in danger are in effect 400 people lost"). We will refer to the change as "subjective," or "framed," payoffs and will refer to the final state as "objective" payoffs. This distinction may be an important factor for understanding risk preference, since objective and subjective payoffs can be manipulated independently.

Through the distinction between change and final state, final losses can be presented to look like gains, and final gains can be presented to look like losses. An example will be helpful. Bazerman (1984) presented a scenario where a large car manufacturer had *to eliminate as many as 6000 jobs* because of recent economic losses. Highhouse and Paese (1996) reworded this to a threat and an opportunity version.[1] In the threat versions, two plans could result in either a sure saving of 2000 jobs (threat, positive frame, sure option) or a sure loss of 4000 jobs (threat, negative frame, sure option). Alternatively, in the opportunity versions, because of recent economic gains, the manufacturer could *create 6000 new jobs*. Two plans then could result in either a sure gain of 2000 of the 6000 possible jobs (opportunity, positive frame, sure option) or a sure loss of 4000 of the 6000 possible new jobs (opportunity, negative frame, sure option). In our terminology, the threat version entails final losses, and the opportunity version entails final gains, irrespective of the framing.

[1] The threat/opportunity distinction (Highhouse & Paese, 1996; Highhouse & Yuce, 1996) is related to subjective outcomes. We do not consider this distinction here because it cannot be coded unambiguously.

*Disentangling Probabilities and Payoffs*

In Asian-disease-type problems the task structure restricts the degrees of freedom for independently varying probabilities and payoffs. As an example, take the confoundings in a gambling task. Since the sure and risky option have to be equal in expected value (EV), the higher the risky gain, the smaller the probability of winning; e.g., for a sure gain of \$2, a risky gain of \$4 requires a probability of winning win of $p = .5$, whereas a risky gain of \$10 requires a probability of winning of $p = .2$. Conversely, for losses, the higher the risky loss, the higher the probability of losing; e.g., a high sure loss of \$8 (out of \$10, equivalent to the \$2-gain condition) requires a high probability of losing all \$10 of $p = 0.8$. This is true only for framing studies, since to make actual gains look like losses, one has to provide an initial endowment to lose from. This is not so in reflection studies. Thus, objective (final) and subjective (change) payoff conditions, levels of payoffs, and levels of probabilities are confounded.

## How Can Probabilities Influence Framing?

Probabilities can exert their influence on the framing effect via the following three ways:

1. Probabilities can be influential in a direct, unmediated way: the higher the probability of winning, the more attractive is the risky option for gains, and the higher the probability of losing the more unattractive is the risky loss. This would imply risk seeking with increasing probability for gains and risk aversion with increasing probability for losses.

2. The second, and related, way for probabilities to influence choices is by making the anticipation of winning or losing more or less salient. A high probability of winning may make it easier to imagine getting the gain than a low probability. The situation is similar for losses. The implication once more is risk seeking with increasing gain probability and risk aversion with increasing loss probability.

3. A third way for probabilities to influence choices is by the confoundings discussed above. Changes in probabilities result in proportional changes in payoffs and payoff differences. The higher the probability of a risky gain, the smaller the difference between sure and risky payoff. If the difference between risky and sure payoff is small it makes no sense to run the risk—increasing gain probabilities should therefore increase risk aversion. For losses the line of reasoning is the same, but the resulting preferences are different. The higher the probability of a risky loss, the smaller the difference between the sure and the risky payoff, and it makes sense to run the risk and to avoid the sure loss. After all, you cannot be much worse off if you run the risk. Therefore, increasing loss probabilities should lead to risk seeking. The predictions here are somewhat counterintuitive: with a higher probability of winning one is supposed to avoid the risk, while with a higher probability of losing one is supposed to take the risk.

## META-ANALYSIS

### *Data Collection and Procedure*

The database for the present meta-analysis is published Asian-disease-type experiments. In these experiments participants face decision tasks which offer two options. One option presents a sure payoff; the second option presents a risky payoff with probability $p$ and nothing with probability $1 - p$. The probability $p$ of the risky payoff is chosen so that both options have equal EV. Participants are asked to select their preferred option; reported is the proportion of risk-seeking or risk-aversive choices. The manipulation of framing is done by describing formally identical situations differently. This changes the reference point for the evaluation of the respective situation, so that (objectively or subjectively) identical situations are seen either as involving gains or as involving losses.

Because these features were used for inclusion, some experiments, though very similar to the Asian-disease task, had to be excluded. These similar, but excluded, experiments are those of Budescu and Weiss (1987); Cadet (1994); Erev and Wallsten (1993); Frisch (1993); Ganzach and Karsahi (1995); Neale and Bazerman (1985); O'Connor (1989); Paese, Bieser, and Tubbs (1993); Qualls and Puto (1989); Schoorman, Mayer, Douglas, and Hetrick (1994); Schurr (1987); and Sullivan and Kida (1995). These were excluded because they did not report choice proportions or were not recodable as a choice proportion. Miller and Fagley's (1991) experiment was excluded because they used seven different tasks with different payoff sizes and did not report the payoffs for each single task. Van Schie and Van der Pligt's (1990) experiment was excluded because they had only partial loss in the risky option. Kuhn's (1997) experiment was excluded because she did not exactly specify the probabilities used but tested the influence of ambiguous probabilities.

As the dependent variable we used the proportion of participants choosing the sure option. As independent variables we coded the following variables: (i) *objective payoff (final state)*. If you are equal or better off after the choice, as compared to the status quo, we coded this as an objective gain problem; if you are equal or worse off after the choice, as compared to the status quo, we coded this as an objective loss problem. (ii) *Framing*. This codes the subjective outcome (i.e., by means of the problem framing). Thus, objective and subjective payoffs can be studied independently. (iii) *Type of good* involved (human lives, money/property, other). Furthermore, we extracted the (iv) *levels of probabilities* and the (v) *size of payoffs* that were explicit in the problem description (i.e., sure (EV) and risky gain for gains, and sure and risky loss for losses).

To locate the relevant studies we used PsychINFO (this is the computerized version of Psychological Abstracts) and Medline. As keywords we used *framing, prospect theory, reflection, Tversky,* and *Kahneman*. Further studies were located by the ancestry approach, that is, by tracking the research cited in papers already obtained.

### *Results*

Using these criteria we came up with 43 different research reports. Most of these reports produced multiple choice proportions for gains as well as for losses, because a single research report may test either different cover stories, different probabilities, or different payoffs, and thus contributes a single proportion for each cover story, probability, or payoff. This resulted in 121 single choice proportions for objective gains and 271 choice proportions for objective losses. With respect to framing we found 200 positive and 192 negative framing proportions. A cross-tabulation of objective and subjective conditions showed that the cell frequencies were not independent ($\chi^2 = 21.6$; $p < .001$). From the 121 objective gains, 83 (68.6%) were positively framed and 38 (31.4%) were negatively framed; from the 271 objective losses, 117 (43.2%) were positively framed and 154 (56.8%) were negatively framed. Thus, objective and subjective payoffs tended to correspond.

The results for the proportions choosing the sure option are presented in Table 2.

In three of four conditions we found significant deviations from the 50:50 split. Framed gains led to risk aversion, irrespective of whether the payoffs were final gains or losses. In both cases the mean choice proportions were $P = .63$, and the 95% confidence limits do not include the value of $P = .50$. This shows a framing effect: positive framing conditions result in risk aversion. For framed losses, we found no effect for final gains ($P = .48$; the confidence limit includes the value of $P = .50$) but a clear framing effect for final losses ($P = .39$; the confidence limit is below the value of $P = .50$). This indicates risk seeking for losses only when the outcomes are also final losses. The counts of the instances of studies reporting choice proportions for the sure option of below, equal to, or above $P = .50$ mirror these findings.

**TABLE 2**

**Summary of Proportions Choosing the Sure Option**

| | Final gains | | Final losses | |
|---|---|---|---|---|
| | Framed gains | Framed losses | Framed gains | Framed losses |
| *k* | 83 | 38 | 117 | 154 |
| Mean *P* | 0.63 | 0.48 | 0.63 | 0.39 |
| *SD* | 0.20 | 0.19 | 0.17 | 0.15 |
| 95% Cl | [.59, .67] | [.42, .54] | [.60, .66] | [.36, .41] |
| Maximum *P* | 1.00 | 0.86 | 0.93 | 0.83 |
| Minimum *P* | 0.19 | 0.08 | 0.28 | 0.06 |
| Proportion $P < .50$ | 22.9% | 55.3% | 23.9% | 72.1% |
| Proportion $P = .50$ | 1.2% | 0.0% | 1.7% | 3.2% |
| Proportion $P > .50$ | 75.9% | 44.7% | 74.4% | 24.7% |

*Note. k* = number of proportions; *P* = proportion choosing sure option.

## Probabilities and Payoffs

### *Levels of Probabilities*

When we talk about levels of probabilities we mean the probability of the risky option yielding the maximal gain or the maximal loss, respectively. For instance, in the Asian disease this probability is $\frac{1}{3}$ for gains but $\frac{2}{3}$ for losses. Note that this is not the probability for the better outcome (which is $\frac{1}{3}$ for the loss too) but the explicitly mentioned probability.

The mean probability levels used for objective gains and losses were not different from each other; thus we collapsed the data over these two groups. Framed gains and losses, however, tended to differ. For gains, the mean probability level for the risky option was 0.39 and the median level was $\frac{1}{3}$, with a minimum of $p = .001$ and a maximum of $p = .99$. Probabilities ranged from very small up to $\frac{1}{4}$ in 23% of the cases, and from very small up to $\frac{1}{2}$ in 74% of the cases. Only 26% of the positive framing studies employed a probability level higher than $\frac{1}{2}$.

Losses conditions were run with higher probability levels. The mean probability level was 0.55; the median level was $\frac{2}{3}$. The minimum was $p = .001$ and the maximum was $p = 0.99$. Probabilities ranged from very small up to $\frac{1}{4}$ in 18% of the cases and from very small up to $\frac{1}{2}$ in 38%. In 62% of the cases, the studies used probabilities higher than $\frac{1}{2}$.

In sum, the explicitly presented probability levels are lower for gains than for losses. This may be seen as something like a perseverance effect: Tversky and Kahneman have introduced a level of $\frac{1}{3}$, and this served as the default level for the research to follow. This led to an unequal use of explicit probability levels for gains and for losses.

### *Levels of Payoffs and Types of Goods at Stake*

The analysis and comparison of payoffs across studies faces three problems. First, the range of payoffs is huge; it reaches from 0.1 items up to thousands of items. This problem can be solved by taking the logarithm of the payoffs.

Second, there are several payoffs to be considered: the expected value, the payoff of the sure option, the payoff of the risky option, and the difference in payoffs between sure and risky option. Since these values are mutually correlated, we decided to include only one of them. We included only the value of the risky payoff, since this value is explicitly stated and is equal for gains and losses. In contrast, the values of sure gain and sure loss are not equal for probabilities other than $\frac{1}{2}$; in the Asian-disease task, for instance, these are 200 saved and 400 lost. We included the absolute values of maximum gain/loss (i.e., without their formally correct positive or negative signs), since the signs are captured by the objective payoff and framing codes.

The third problem is: How can we compare amounts of money with human lives, or with animal lives, or with the number of jobs at stake? As a practical solution for this problem we coded the different types of goods as belonging to three subgroups: human lives, money or property (measured in dollars), and other goods (jobs, time, social qualities, etc.).

Note that the subgroups differ markedly in the magnitude of the risky payoffs used. Money/property experiments typically present very high payoffs (median = \$600.0, mean = \$29,047.4, minimum = \$0.11, maximum = \$1000,000.0, *SD* = 119,270.6). Human-lives experiments present smaller payoffs (median = 600.0 lives, mean = 4072.1 lives, minimum = 3 lives, maximum = 216,000 lives, *SD* = 24,507.1). The third subgroup, which contains other goods, uses the lowest values (median = 600.0, mean = 2285.5, minimum = 4.0, maximum = 12,000.0, *SD* = 3717.7). The choice proportions for the different subgroups are reported in Table 3.

Some points in Table 3 are noteworthy. First, for the money/property experiments, the final gains/framed gains cell has 72 entries, while the final gains/framed losses cell has only 24 entries. The reverse picture is found with final losses/framed gains (10 entries) and final losses/framed losses (51 entries). This is due to the fact that most money/property experiments are reflection tasks in the sense that final gains and losses, rather than framed gains and losses, are presented. Second, it appears that framing is much more influential on risk preference than the final payoff. This will be evaluated more thoroughly in the analyses to follow.

### *Variables Influencing Choices*

Which factor(s) in Asian-disease-like problems do significantly influence people's choices? To answer this question we ran different multiple regression analyses with the following independent variables: final outcome (gain, loss), framing condition (gain, loss), type of good at stake (human lives, money/property, other; these three groups were dummy coded), probability of risky payoff, and the natural logarithm of risky payoff. The dependent variable was the proportion choosing the sure option. Table 4 shows the intercorrelations among the variables.

Several features in Table 4 are noteworthy. First, the highest correlation

**TABLE 3**

**Proportions Choosing the Sure Option with Different Types of Goods.**

| Payoffs | | Human lives | | Money/property | | Other goods | |
|---|---|---|---|---|---|---|---|
| | | *k* | *P* | *k* | *P* | *k* | *P* |
| Final | Framed | [95% Cl] | | [95% Cl] | | [95% Cl] | |
| Gains | Gains | 4 | .60 | 72 | .63 | 7 | .64 |
| | | [.39, | .81] | [.59, | .68] | [.45, | .83] |
| | Losses | 4 | .41 | 24 | .42 | 10 | .65 |
| | | [.15, | .66] | [.35, | .49] | [.54, | .76] |
| Losses | Gains | 76 | .60 | 10 | .75 | 31 | .66 |
| | | [.56, | .64] | [.70, | .80] | [.59, | .73] |
| | Losses | 73 | .34 | 51 | .41 | 30 | .47 |
| | | [.31, | .37] | [.36, | .45] | [.41, | .52] |

*Note.* *k* = number of proportions; *P* = proportion choosing sure option.

**TABLE 4**

**Intercorrelations between Predictor and Dependent**

| | Final payoff | Framing condition | Probability | Risky payoff[a] | Stake Dummy1 | Stake Dummy2 |
|---|---|---|---|---|---|---|
| *P* (sure) | −.207** | −.547** | −.166** | −.284** | −.177** | .152** |
| Final payoff | | .235** | .061 | −.185** | .456** | .098 |
| Framing condition | | | .338** | −.290** | .001 | .023 |
| Probability | | | | .127* | .139** | .066 |
| Risky payoff | | | | | .183** | .141** |
| Stake dummy1 | | | | | | −.407** |

*Note*. *P* (sure) = mean proportion choosing the sure option.
[a]Transformed by the natural logarithm.
*$p < .05$ ($N = 392$).
**$p < .01$.

exists between risk preference and framing condition (gains are coded as 1; losses are coded as 2), indicating that framing will be the most important predictor in the regression. Second, risk preference is significantly correlated with all independent variables; this indicates that all variables may contribute to risk preference. Third, probability levels are positively correlated with framing condition. This reflects the fact noted earlier that higher probabilities tend to be used in the loss conditions of studies. Fourth, final payoff is highly correlated with one of the dummy variables of stake. This indicates that type of good at stake and final payoffs are not independent.

## *Regression Analysis*

We analyzed the data using hierarchical multiple regression. Since it is difficult to order the predictor variables in importance theoretically, and since most predictors are correlated, analyses with solo predictors cannot be interpreted unambiguously. Thus we conducted analyses in which we fit a regression equation with all predictors included simultaneously.[2]

We found a significant regression equation ($F(6, 385) = 36.6$, $p < .001$, multiple $R = .60$, adjusted $R^2 = .35$) with three significant predictors of risk preference: framing condition ($t = 10.8$, $p < .001$, semipartial $r = -.44$), risky payoff ($t = 3.4$, $p < .001$, semipartial $r = .14$), and type of good at stake ($t = 3.2$, $p = .001$, semipartial $r = .13$). Final payoff ($t = 0.5$, $p = .61$, semipartial $r = .02$) and level of probability ($t = 0.1$, $p = .89$, semipartial $r = .01$) were not significant.

In terms of the direction of the influence, the signs of the $\beta$'s are instructive: positive framing leads to more risk aversion (standardized $\beta = -.51$), higher risky payoffs lead to more risk aversion ($\beta = +.17$), and there are differences in risk attitude between types of good at stake.

[2] We also ran stepwise analyses which yielded similar results.

These results show that the framing condition is dominant for risk preference but that payoffs and the goods at stake have contributions too. It is possible, however, that the picture is different for each of the two objective and subjective payoff (framing) conditions. For instance, it is possible that probabilities have complementary effects for gains and for losses. Therefore we analyzed each condition separately.

## Subgroup Analysis

*Final gains/losses.* For final gains (i.e., irrespective of whether they were presented as gains or as losses) we found a significant regression equation ($F(5, 115) = 12.5$, $p < .001$, multiple $R = .59$, adjusted $R^2 = .32$), with framing condition ($t = 5.3$, $p < .001$, semipartial $r = -.40$), risky payoff ($t = 5.6$, $p < .001$, semipartial $r = .42$), type of good ($t = 3.3$, $p = .001$, semipartial $r = .25$), and probability ($t = 2.2$, $p = .05$, semipartial $r = .17$) as significant predictors of risk preference. For final losses the fit was significant too ($F(5, 265) = 37.8$, $p < .001$, multiple $R = .65$, adjusted $R^2 = .41$), with framing condition ($t = 10.9$, $p < .001$, semipartial $r = -.51$), risky payoff ($t = 2.4$, $p < .05$, semipartial $r = .11$), and type of good ($t = 3.7$, $p = .001$, semipartial $r = -.17$) as significant predictors.

*Framed gains/losses.* For framed gains (i.e., irrespective of whether they were actually objective gains or losses) we found a significant regression equation ($F(5, 194) = 15.7$, $p < .001$, multiple $R = .54$, adjusted $R^2 = .27$), with only risky payoff ($t = 7.3$, $p < .001$, semipartial $r = .45$) and probability ($t = 5.3$, $p < .001$, semipartial $r = .32$) as significant predictors of risk preference. For losses the fit was significant too ($F(5, 186) = 10.0$, $p < .001$, multiple $R = .46$, adjusted $R^2 = .19$), with probability ($t = 3.3$, $p = .001$, semipartial $r = -.22$), type of good ($t = 3.3$, $p = .001$, semipartial $r = .21$), and objective payoff ($t = 2.6$, $p < .01$, semipartial $r = -.17$) as significant predictors.

*Final gains/framed gains.* The subgroup analysis for final gains/framed gains yielded the following results. The fit was significant ($F(4, 78) = 12.2$, $p < .001$, multiple $R = .62$, adjusted $R^2 = .35$), with risky payoff ($t = 6.6$, $p < .001$, semipartial $r = .59$) and probability ($t = 3.4$, $p = .001$, semipartial $r = .30$) as significant predictors.

*Final gains/framed losses.* This subgroup analysis yielded an equation with $F(4, 33) = 4.0$, $p = .01$, multiple $R = .57$, adjusted $R^2 = .24$). Type of good at stake was the single significant predictor ($t = 3.2$, $p < .01$, semipartial $r = .46$).

*Final losses/framed gains.* The subgroup analysis for final losses framed as gains yielded a significant fit ($F(4, 112) = 9.8$, $p < .001$, multiple $R = .51$, adjusted $R^2 = .23$) with probability ($t = 4.6$, $p < .001$, semipartial $r = .37$), risky payoff ($t = 3.5$, $p = .001$, semipartial $r = .28$), and type of good ($t = 2.3$, $p < .05$, semipartial $r = -.19$).

*Final losses/framed losses.* This subgroup analysis yielded an equation with $F(4, 149) = 6.4$, $p < .001$, multiple $R = .38$, adjusted $R^2 = .12$. Probability was the single significant predictor ($t = 2.9$, $p < .01$, semipartial $r = -.22$).

A summary of the results is given in Table 5. Important points are the following: (i) Positive framing leads to risk aversion, irrespective of whether the payoffs are actually gains or losses. (ii) The picture for gains seems to be more consistent than that for losses. For gains, higher payoffs as well as higher probabilities lead to risk aversion. For losses, different factors contribute significantly in the different subgroups. Note that payoff size never matters for losses, while it always matters for gains. (iii) When probability is significant for losses, it fosters risk seeking.

The finding for probabilities is puzzling: for gains we found that a higher probability of a gain makes people avoid the gamble, and for losses we found that a higher probability of a loss makes people seek the gamble. However, if the probability of a gain is higher, one should be more inclined to take the gamble—the results indicate the opposite. For losses, if the probability of a loss is higher, one should be more inclined to avoid the gamble—again the results indicate the opposite. Such findings are understandable as a consequence of the confounding between probability levels and payoffs, however. High gain probabilities imply small differences between sure and risky gain;

**TABLE 5**

**Summary of Significant Predictor Variables**

| Source | Multiple adj. $R^2$ | Significant predictor variable(s) |
|---|---|---|
| Overall | .35 | Framing (−.44), payoff (+.14), type of good dummy1 (−.13) |
| Final gains | .32 | Framing (−.40), payoff (+.42), type of good dummy1 (+.25), probability (+.17) |
| Final losses | .41 | Framing (−.51), payoff (+.11), type of good dummy1 (−.17) |
| Framed gains | .27 | Payoff (+.45), probability (+.32) |
| Framed losses | .19 | Probability (−.22), type of good dummy2 (+.21), final payoff (−.17) |
| Gains/gains[a] | .35 | Payoff (+.59), probability (+.30) |
| Gains/losses | .24 | Type of good dummy2 (+.46) |
| Losses/gains | .23 | Probability (+.37), payoff (+.28), type of good dummy1 (−. 19) |
| Losses/losses | .12 | Probability (−.22) |
| Money/property & gains[b] | .41 | Payoff (+.60), probability (+.30) |
| Money/property & losses[b] | .09 | Probability (−.35) |
| Human lives & gains[b] | .10 | Probability (+.29), payoff (+.26) |
| Human lives & losses[b] | .04 | Payoff (+.25) |
| $p = 1/2$ & gains[b] | .57 | Payoff (+.70) |
| $p = 1/2$ & losses[b] | .60 | Final payoff (−40), type of good dummy2 (+.48) |

*Note.* Value of semipartial $R^2$ in parentheses. When appropriate, the sign indicates the direction of influence: + denotes “fosters risk aversion” and − denotes “fosters risk seeking.”

[a]To indicate final gains/framed gains; similarly for the three entries to follow.

[b]Gains/losses relate to the framing manipulation.

it makes no sense to run the risk, since you cannot earn much more. High loss probabilities imply small differences between sure and risky loss, and it thus makes sense to run the risk.

We tested this prediction directly by including the natural logarithm of the difference in payoffs as a predictor variable in the regression (this variable is not explicitly presented in the task). If the effects of probabilities are mediated largely by payoff differences, those differences should be included in the regression equation, while probabilities should be excluded. This resulted in a better fit of the overall regression equation ($F(7, 384) = 38.7$, $p < .001$, multiple $R = .64$, adjusted $R^2 = .40$), with four significant predictors of risk preference: framing condition ($t = 12.1$, $p < .001$, semipartial $r = -.47$), payoff difference ($t = 5.8$, $p < .001$, semipartial $r = .23$), type of good ($t = 2.5$, $p < .05$, semipartial $r = .10$), and probability ($t = 2.4$, $p < .05$, semipartial $r = .09$). Thus, two changes emerged with payoff differences included: the risky payoff now clearly failed to reach significance ($t = 0.1$), and level of probability was now included rather than excluded. This shows that the difference in payoffs may be more important than the absolute magnitude of the payoffs. The direction of the influence is instructive: the bigger the payoff difference, the more risk aversion. To understand this more deeply, we ran a regression on gains and losses separately. For gains we found that only the level of probability remained as a significant predictor ($t = 4.2$, $p < .001$, semipartial $r = .26$), while all other variables were excluded. Thus, the higher the probability of winning, the more risk aversion. For losses a different picture emerged. Type of good ($t = 3.7$, $p < .001$, semipartial $r = .24$), objective payoff ($t = 3.1$, $p < .01$, semipartial $r = -.20$), payoff difference ($t = 3.0$, $p < .01$, semipartial $r = .19$), and probability ($t = 2.3$, $p < .05$, semipartial $r = -.15$) were significant predictors. Thus the payoff difference is more important for losses than for gains. But it is not the differences in payoff alone that mediates the effects of probability, because even if the difference is in the equation, probability adds significantly to the fit in most cases.

## Test of Theories

Many theories of framing (cf. Kühberger, 1997) make explicit predictions about the effect of probabilities and payoffs on framing. Prospect theory (Kahneman & Tversky, 1979) and fuzzy-trace theory (Reyna & Brainerd, 1991) both predict risk aversion for gains and risk seeking for losses. This general prediction is supported by our meta-analysis. Security-potential/aspiration theory (Lopes, 1987) has a stronger motivational component and predicts risk aversion for gains and an inconsistent risk attitude for losses. Our findings can be interpreted to be evidence for this general prediction too, by pinpointing two results. First, for gains, but not for losses, we found that probabilities as well as payoffs were significantly related to risk preference. Second, and related, the percentage of variance explained was in both literatures higher for gains than for losses.

The theories discussed above make no exact predictions about effects of probability and payoff. Two theories incorporate probabilities explicitly in their predictions, but these predictions differ:

1. Cumulative prospect theory (Tversky & Kahneman, 1992) predicts risk aversion for gains/risk seeking for losses for moderate and high probabilities, but risk seeking for gains/risk aversion for losses for low probabilities. This prediction is not supported by our findings, which indicate that probabilities are linearly related to choice proportions in most analyses above. But, admittedly, we have not tested whether there are nonlinear relationships between probabilities and choices.

To test this prediction more specifically, we constructed two groups of studies based at the level of the probabilities used and calculated the choice proportions for low ($0 < p \leq \frac{1}{3}$) and high probabilities ($\frac{1}{3} < p < 1.0$). The critical value of $\frac{1}{3}$ was chosen because research has shown that the inflection point of the probability weighting function is above $p = .30$ and below $p = .40$, with a best estimate of $p = .34$ (Camerer & Ho, 1994; Tversky & Kahneman, 1992; Wu & Gonzalez, 1996). Since final payoffs have been shown to be of minor relevance for risk preference, we will collapse over the two levels. The results are depicted in Table 6.

For low probabilities we found weak risk aversion for gains ($P = .59$) and only a very weak tendency for risk seeking for losses ($P = .44$). For moderate to high probabilities we found considerable risk aversion for gains ($P = .69$) and medium risk seeking for losses ($P = .40$). These findings conform to the predictions of cumulative prospect theory only for high probabilities. For low probabilities, the predictions of cumulative prospect theory are wrong. What is clear from these findings is that there exists no fourfold pattern in risk preference in Asian-disease tasks. However, the tendency of gains to lead to risk aversion and the tendency of losses to lead to risk seeking are stronger for medium to high than for low probability levels.

2. Venture theory (Hogarth & Einhorn, 1990) predicts increasing risk aversion with increasing probability for gains and decreasing risk aversion with increasing probability for losses. This was already tested in the regression and was found to be true.

Two theories incorporate payoffs explicitly. These can be tested only in experiments with monetary payoffs in a meaningful way, since otherwise one would have to calculate the worth of a human's or animal's life or of a job.

3. Markowitz' utility theory (Markowitz, 1952) predicts risk aversion for

**TABLE 6**

**Proportions Choosing the Sure Option with Low and Medium to High Probabilities**

| | Gains | | | Losses | | |
|---|---|---|---|---|---|---|
| Probability | *k* | *P* | 95% Cl | *k* | *P* | 95% Cl |
| Low ($0 < p \leq 1/3$) | 127 | .59 | [.56, .62] | 38 | .44 | [.39, .49] |
| High ($1/3 < p < 1.0$) | 73 | .69 | [.66, .73] | 154 | .40 | [.37, .42] |

*Note.* P = proportion choosing sure option.

gains/risk seeking for losses with large payoffs, but risk seeking for gains/risk aversion for losses with small payoffs. Lacking a standard of how large a large payoff ought to be, we tested this prediction by excluding the middle third of payoffs and by analyzing only the small (payoffs $\leq$ \$100) vs large (payoffs $\geq$\$6000) risky payoffs groups. The results are depicted in Table 7.

Table 7 shows that small payoffs showed no reliable effects for gains but considerable risk seeking for losses. Large payoffs resulted in considerable risk aversion for gains and weak, but significant, risk seeking for losses. Thus, Markowitz's predictions of a fourfold pattern are not supported by our results.

4. For payoffs, venture theory (Hogarth & Einhorn, 1990) predicts increasing risk aversion with increasing payoffs/probabilities for gains and decreasing risk aversion with increasing absolute payoff/probability for losses. To test this, we ran a multiple regression on the subset of money/property studies. For gains we came up with risky gain ($t = 7.0$, $p < .001$, semipartial $r = .60$) and probability ($t = 3.5$, $p < .01$, semipartial $r = .30$) as significant predictors. The higher the gain and the higher the probability, the more risk aversion. For losses we found that only the probability of the loss predicted choices significantly ($t = 3.2$, $p < .01$, semipartial $r = -.35$). The higher the probability of a loss, the more risk seeking. This is only partially supporting evidence for venture theory.

In summary, none of the theories put forward is satisfactory in predicting the data. Furthermore, the findings show that risk preference is influenced by probabilities and by payoffs but in neither case strongly enough to result in a fourfold pattern of risk preference.

### Human-Lives Experiments

To provide an overall picture, we also ran a multiple regression analysis for the experiments on human lives. For gains the resulting model included probability ($t = 2.7$, $p < .01$, semipartial $r = .29$) and risky gain ($t = 2.4$, $p < .05$, semipartial $r = .26$). Higher probabilities and higher risky gains led to risk aversion. For losses the risky loss was the single significant predictor ($t = 2.2$, $p < .05$, semipartial $r = .25$): the higher the risky loss, the more risk aversion.

### *Disentangling Probabilities and Payoffs*

As introduced earlier, probabilities and payoffs are confounded in all cases where probability levels of $p \neq .5$ are used. Thus we analyzed only those cases

**TABLE 7**

**Proportions Choosing the Sure Option with Small and Large Risky Gains/Losses.**

| Magnitude of payoff | Gains | | | Losses | | |
|---|---|---|---|---|---|---|
| | *k* | *P* | 95% Cl | *k* | *P* | 95% Cl |
| Small (≤ \$100) | 25 | .49 | [.40, .58] | 23 | .35 | [.28, .42] |
| Large (≥ \$6000) | 25 | .76 | [.71, .80] | 23 | .43 | [.37, .49] |

*Note.* $P$ = proportion choosing sure option.

where $p = .5$. For gains, the multiple regression for experiments using a probability level of $p = .5$ produced a model including only risky gain ($t = 5.8$, $p < .001$, semipartial $r = .70$). For losses the model included final payoff ($t = 3.4$, $p < .01$, semipartial $r = -40$) and type of good ($t = 4.0$, $p < .001$, semipartial $r = .48$) as significant predictors. These findings show that with probabilities of $p = .5$, different variables are relevant for gains and for losses.

## *Discussion*

### Final and Framed Gains and Losses

The present meta-analysis found significant bidirectional framing effects. Presenting problems as gains leads participants to choose predominantly in a risk-aversive manner (about 60% of all participants chose the sure gain and only 40% chose the risky gain). With losses, risk seeking predominates (about 40% of the participants chose the sure loss, while 60% chose the risky loss). At a finer level, a distinction between final and framed payoffs was made. In final gain studies, all options are in effect gains, but some of them are presented so that they appear to be losses (see Fagley, 1993). In final loss studies, all options are in effect losses, irrespective of whether they are presented as gains or as losses. Framing, on the other hand, relates to the hedonic quality of the options irrespective of the final state of affairs. Which of these two is more influential for risk preference: the final or the framed payoff? Are there interactions? One could expect that an effect between framing conditions will be stronger when final and framed payoffs conform, since in framing it depends on a successful manipulation of the reference point to produce a feeling of a gain or loss.

Theoretically, it makes sense to distinguish between the final and the framed value of payoffs. Empirically, this distinction seems to be much less important. It appears that the framing manipulation is most influential for risk preference. At least for positive framing conditions it makes no difference whether these gains are actually gains or not, since risk aversion predominates uniformly. For losses, framed losses seem to foster risk seeking only if they are actually losses.

However, recall that final and framed payoffs tended to correspond. This is mainly due to gambling studies, where the final and framed payoffs are often identical. For these studies, which often come under the heading reflection effect studies, the influence of final and framed payoffs is not separable. Our results imply that the framed payoffs are more important in determining the choices, however.

On the other hand, it is not surprising that the final payoffs are shown to be of little influence. This is the very essence of framing: making things look better or worse by making some aspects of the situation more salient than others. Our results show that researchers are successful in emphasizing the values presented on the options in Asian-disease-like problems while deemphasizing the value which is presented in the problem description. Research that tries to equally emphasize all values in such tasks has a chance to clarify the conditions which make final payoffs an important factor for risk preference.

### *Framing Condition*

Framing was a significant predictor variable in all subgroup analyses and it explained most variance in the data. Thus, irrespective of the influence of probability, payoff, and type of good at stake, whether people believe they are dealing with gains or with losses is of major importance for their choices in risky contexts. We included payoffs and probabilities as predictor variables and not subjective utilities and subjective probabilities, but it is important to see that the influence of framing is independent of the probabilities and payoffs used. We take this as an indication that any theory that explains framing effects by reference to a value function defined over payoffs or by reference to a weighting function defined over probabilities must allow for a substantial amount of nonlinearity in payoffs and probabilities to capture the framing phenomenon adequately. A plausible interpretation of this finding is expressed by Schneider's (1992) conclusion that "the evidence suggests that risky choice is subject to a richer source of variation than just the psychophysical principles that relate objective quantities to subjective experience" (p. 1052).

Losses do not uniformly produce bigger effect sizes than gains, in contradiction to the notion that the psychological reaction to losses is stronger than the reaction to gains (e.g., Kahneman & Tversky, 1984; Tversky & Kahneman, 1991). This is also nicely shown in the studies using a probability level of $p = .5$, where we found no clear framing effect for losses (46% choices of risky option) but a clear effect for gains (69% choices of sure option). The evaluation of this difference is problematic, however, since it depends on the adequacy of the 50:50 proportion. To use the 50:50 proportion as a benchmark is to assume risk neutrality for a "neutral" framing condition. There is not much research on neutral framing, but Kuhberger (1995) showed that if you present a neutral framing condition (e.g., by stating both the number of people saved and the number of people not saved), the overall choices indicated risk neutrality, although there were differences between types of goods at stake.

### *A Genuine Influence of Probabilities*

For framing effects, probabilities per se were found to be always influential for gains but only incidentally so for losses. This differential influence of probabilities is difficult to interpret. We had hypothesized that probabilities could influence choices by making the outcome situation (winning or losing) more or less salient. For instance, a high probability of winning could lead one to imagine getting the gain more easily than could a low probability. The situation is similar for losses. This implies that probability levels are a significant predictor of choices. Well, they are, but only in a very restricted and unsystematic way. Research on the influence of probabilities suggests such an unsystematic picture, however. In one of the rare direct tests of probability, Miller and Fagley (1991) found that the greater the probability of success, the more people selected the risky option. However, the results of the present meta-analysis suggest the contrary. Hershey and Schoemaker (1980) reported that a reflection effect was most prevalent when extreme probabilities were involved. This would suggest a nonlinear relationship. In the domain of risky medical decision making, O'Connor (1989) found that probabilities were influential only for levels below $p = .50$; a similar finding was reported by Marteau (1989). With gambles, Wu and Gonzalez (1996) found irregularities of the probability weighting function at $p = .50$. Thus, we know that probabilities have an influence on risk preference in most cases, but it is unclear when and how this will be the case.

*Type of Good at Stake*

As indicated in Table 3, human-lives studies show a greater risk-seeking tendency than do money/property experiments. This is a somewhat surprising finding, since one would expect more cautious behavior in situations which have potentially more serious consequences. An idea put forward by Wang and Johnston (1995; Wang, 1996a, 1996b) may apply here: they state that, when the good at stake is very important (such as human lives), one may be urged to take the risk since the sure loss—even if it is small—is unbearable in any case. This may be part of the explanation, but we think it unlikely to be the whole story. Wang (1996a, 1996b) and Wang and Johnston (1995) offer a second idea on this topic. They tested the influence of payoff levels and found smaller payoff levels to be accompanied by disappearing framing effects. In fact, much of the data in the meta-analysis on small payoff levels are based on this work. Though he subscribes to a different view, Wang (1996a) discusses this finding under what he calls "diminishing sensitivity." "A diminishing sensitivity would result in a utility function in which 200/600 is greater than 2/6. In other words, 6 is valued nearly three times as much as 2, whereas 600 is valued less than three times as much as 200. This diminishing sensitivity hypothesis predicts risk-aversion for gains and risk-seeking for losses in the case of large numbers but not in the case of smaller numbers" (p. 39). We believe that this diminishing sensitivity also contributes to our findings.

A further factor may be found in the payoff sizes used. Money/property experiments generally present options worth hundreds or thousands of dollars. Human-lives experiments present options in the range of tens or hundreds of lives. Since we found that payoff size fosters risk aversion (see below), the higher risk-aversive tendency in money/property experiments may be due to the higher payoff values that are used in those experiments.

Another explanation is related to the context domain. Bless, Betsch, and Franzen (1998) have shown that framing effects tend to disappear if the task is embedded in a statistical context rather than in a disease context. Maybe the context makes people think more or less statistically or normatively. The context of money/property experiments is usually gambles, while the context of human-lives experiments is diseases. A gambling context may trigger normative reasoning more easily than such a rich context as fighting against disease. This would imply both less risk aversion for gains as well as less risk seeking for losses with gambles. However, the data in Table 3 indicate a general tendency to take the risk in human-lives experiments. But note the lack of objective-gains studies with human lives: we have only 8 cases of objective gains in human-lives experiments, but 149 cases of objective losses (see Table 3).

A different, and more qualitative, phenomenon may have contributed too. Imagine that you have a choice between $1 for sure, and $2 with $p = .50$ and nothing otherwise. In a sense, it makes no big difference whether you get $1, or $2, or even nothing; any outcome is not very impressive. Anyway, you have not much to win and can go for the risk. With small monetary payoffs this is a sensible strategy, and it resembles the processing which is assumed in fuzzy-trace theory (Reyna & Brainerd, 1991) to be relevant for framing.

The reasons for the finding that people are more inclined to take a risk with more important payoffs are not clear. Our meta-analysis has demonstrated the finding, and in light of the distinction between framing and reflection made here, the recent quest for replication (Fagley & Miller, 1997) is warranted. Fagley and Miller (1997) are correct in their evaluation of this finding: choice behavior involving human lives may be qualitatively different from choice behavior involving monetary outcomes. In a similar vein, Zickar and Highhouse (1998) demonstrated that the Asian-disease task showed an anomaly in an item response analysis when compared with other tasks not using human lives. Some reasons for this which may invite further research are given by Fagley and Miller (1997); these include different aspirations (Schneider, 1992) or different concerns about justifying decisions (Tetlock, 1992).

### *Payoff Size*

Concerning the size of the payoffs, the findings are surprising. In all regressions the risky gain entered as a significant predictor for gains, and the risky loss entered only once (human lives) for losses. Though the picture for the influence of payoffs is not uniform, one consequence is clear: one cannot adequately understand framing without incorporating payoffs into theory. We found a stronger influence for gains: higher gains lead to risk aversion. For losses we found only a weak indication (with human lives) that higher risky losses will lead to risk aversion.

To be sure, we analyzed the presented values of the payoffs. Prospect theory has a value function which transforms presented values in a nonlinear way. Thus, one could hold that prospect theory is not tested by the present analysis. But note that in prospect theory these transformed values are used to predict differences in risk preference between framing conditions, and not for the differences in risk preference which depend on the size of the payoffs.

### *Confoundings: Probabilities and Payoffs*

Probability levels are not evenly distributed over gains and losses. In framing studies, low probabilities are overrepresented in gains conditions and high probabilities are overrepresented in losses conditions. This has consequences for the payoffs used, since the payoffs cannot be manipulated independently of probabilities if the EVs have to be equal over framing conditions. Recall that the direction of the influence of probabilities was found to be counterintuitive: higher probabilities of a gain led to increased risk aversion, and higher probabilities of incurring a loss led to increased risk seeking for losses in most subset analyses. These findings are understandable only in the light of the confounding of probability and payoff difference. The higher the probability of the risky option, the smaller the difference between sure and risky payoff. The smaller this difference, the smaller the additional gain to be won, and the smaller the additional loss to be incurred. Risk aversion for high gain probabilities and risk seeking for high loss probabilities follows. Thus our findings indicate that, in addition to their unique contribution, probabilities are also influential via their corresponding payoff differences: often it is the payoff difference between sure and risky outcomes that matters, and not only the probability per se.

### *A Magical Value of 600*

We should also report the curious finding that the median payoff value of our database is 600, which is the value used in the original Asian-disease problem. It seems that this payoff value served more or less deliberately as reference anchor for most further studies.

## ***Summary***

The general message of the present meta-analysis is that risk preferences in Asian-disease-like tasks depend on framing, size and types of payoffs, and the probabilities used. The task structure implies that probability levels, payoff magnitudes, and framing conditions cannot be independently varied. Disentangling these factors shows a relatively complicated picture, where different variables are important.

Specifically, we want to turn attention to the finding that controlling for possible variables which are relevant for formal modeling (payoff, probability) does not make the framing condition superfluous as a predictor. Quite to the contrary, framing remains the most important predictor. Thus there is more to the framing effect than can be captured by the formal properties of tasks. This should be taken as an invitation to do more research on framing based on theories which incorporate factors such as cognitive and motivational processes (see Kuhberger, 1997). Fruitful lines of research may be those that try to uncover some common factors that make the framing effect disappear. There is some evidence what these factors may be. First, framing may be dependent on context (Bless et al., 1998; Goldstein & Weber, 1995). Second, implicit assumptions about relevance in a communication context may be important (Kuhberger, 1995). Third, individual differences may moderate the influence of framing (Fagley & Miller, 1990; Stanovich & West, 1998); in addition, more thorough thinking seems to lessen the framing effect (Sieck & Yates, 1997). The last finding and the present meta-analysis indicate that the characterization of the framing phenomenon as a “cognitive illusion” is misleading.

Meta-analysis is a technique that summarizes and organizes findings, and it should not be taken as a substitute for empirical proof. Interestingly, direct tests of probability levels and payoff levels on framing are rarely found in the literature. Two studies (Cohen, Jaffray, & Said, 1987; Hogarth & Einhorn, 1990) tested this and found main and interaction effects of probability and payoff for gains but no interaction effects for losses. In the following we present the results of a framing study where we experimentally manipulated framing, probability level, and size of monetary payoff in an attempt to clarify the role of probabilities and payoffs more directly.

## EXPERIMENT

### Method

*Participants*

Sixty-nine students in their final year of high school and of an evening engineering course (45 female, age = 19.2 years; 24 male, age = 22.7 years) volunteered to participate in a classroom experiment. Each subject had to fill in a booklet containing 12 hypothetical gambles (for a typical gamble see below). These gambles presented all 12 combinations of the two levels of *probability of winning/losing* (0.2 vs 0.8) and the six levels of *size of payoff* (EV of ATS 10, 100, 250, 500, 1000, and 2000; $1 ≅ ATS 10). In the loss conditions a hypothetical endowment was provided from which to lose. This is therefore a framing, rather than a reflection, task.

Each task was presented on a separate page of the booklet and participants were told to treat the gambles as independent. One half of participants received the gambles in order of increasing EV; the other half received the gambles in order of decreasing EV. Order of probability and presentation of payoff levels were counterbalanced. Participants were randomly assigned to one of the two framing conditions.

A typical task is shown below (positive framing condition, probability of winning = 0.2, payoff = 10 ATS):

Choose between the following two possibilities:

Either: You get 10 ATS.

Or: You play the following game: In a box are 10 balls (8 black balls and 2 white balls). After mixing the balls, one will be drawn at random. If this ball is white, you win 50 ATS. If the ball is black, you win nothing.

### Results

The proportions of choices of the sure option were analyzed by an ANOVA with probability level and size of payoff as within-subjects factors and with framing condition and presentation order (increasing vs decreasing EV) as between-subject factors. Since presentation order was not significant either as a main effect or in any interaction, data were lumped together for presentation orders. The results are depicted in Fig. 1.

There is clear evidence of a unidirectional framing effect between framing conditions ($F(1, 65) = 5.9$, $p < .02$). Positive framing led to more risk aversion than did negative framing. The two probability levels were also found to be influential ($F(1, 65) = 12.6$, $p < .001$). Recall that in framing studies positive and negative framing conditions have to have the same EV. For instance, if you win 10 with probability $p = .2$ or get 2 for sure (positive framing condition), this has to be paired with an initial endowment of 10 and then either give back 8 or run the risk and lose nothing, or lose all, with probability $p = .8$ (negative framing condition). That is, the gain probability of $p = .2$ is equivalent to the loss probability of $p = .8$.

Figure 1 validates the predictions from the meta-analysis: higher gain probabilities (and accordingly smaller differences between sure and risky gains) and higher loss probabilities lead to more risk aversion. The explanation for the loss finding lies in our coding of the probabilities of the loss: we coded the loss probabilities irrespective of their gain counterparts, as we did in the meta-analysis (e.g., if the probability of the loss was $p = .8$, we coded this as high probability; note, however, that the corresponding gain probability is $p = .2$, the low probability condition). That is, for framing, the corresponding condition for the high probability of gain condition is the low probability of loss condition. Exactly these two conditions show impressive bidirectional framing effects (proportions choosing the sure option in the high probability of gain condition are .50, .58, .58, .69, .78, and .75 for the six gambles with $p = .8$; proportions choosing the sure option in the low probability of loss condition are .11, .15, .24, .33, .48, and .48 for the six gambles with $p = .2$). Low probability of gain and high probability of loss condition did not produce a framing effect.

As predicted, payoff levels were significant too ($F(5, 325) = 16.7$, $p < .001$). Higher payoffs led to more risk aversion.

## Discussion

The predictions derived from the meta-analysis were confirmed. We replicated that framing effects are influenced by the size of the payoffs as well as by the probabilities. The condition with high probability of winning and the corresponding condition with low probability of losing produced uniform risk aversion and uniform risk seeking, respectively, over all payoff conditions. The low probability of winning and high probability of losing conditions produced no framing effect. Higher payoffs both for gains and for losses consistently resulted in increasing risk aversion.

For the present experimental manipulation the findings for losses are open to an alternative explanation to framing. This is the house-money effect (Thaler & Johnson, 1990). The only way to make the negative framing condition comparable to the positive one with respect to final outcome in a gambling task is to endow participants with money to play with and then to take this money away to induce the negative character of the task. This may not be truly negative, since participants have gotten the money from the house, so to say. There is convincing research (e.g., Thaler & Johnson, 1990) that such house money may

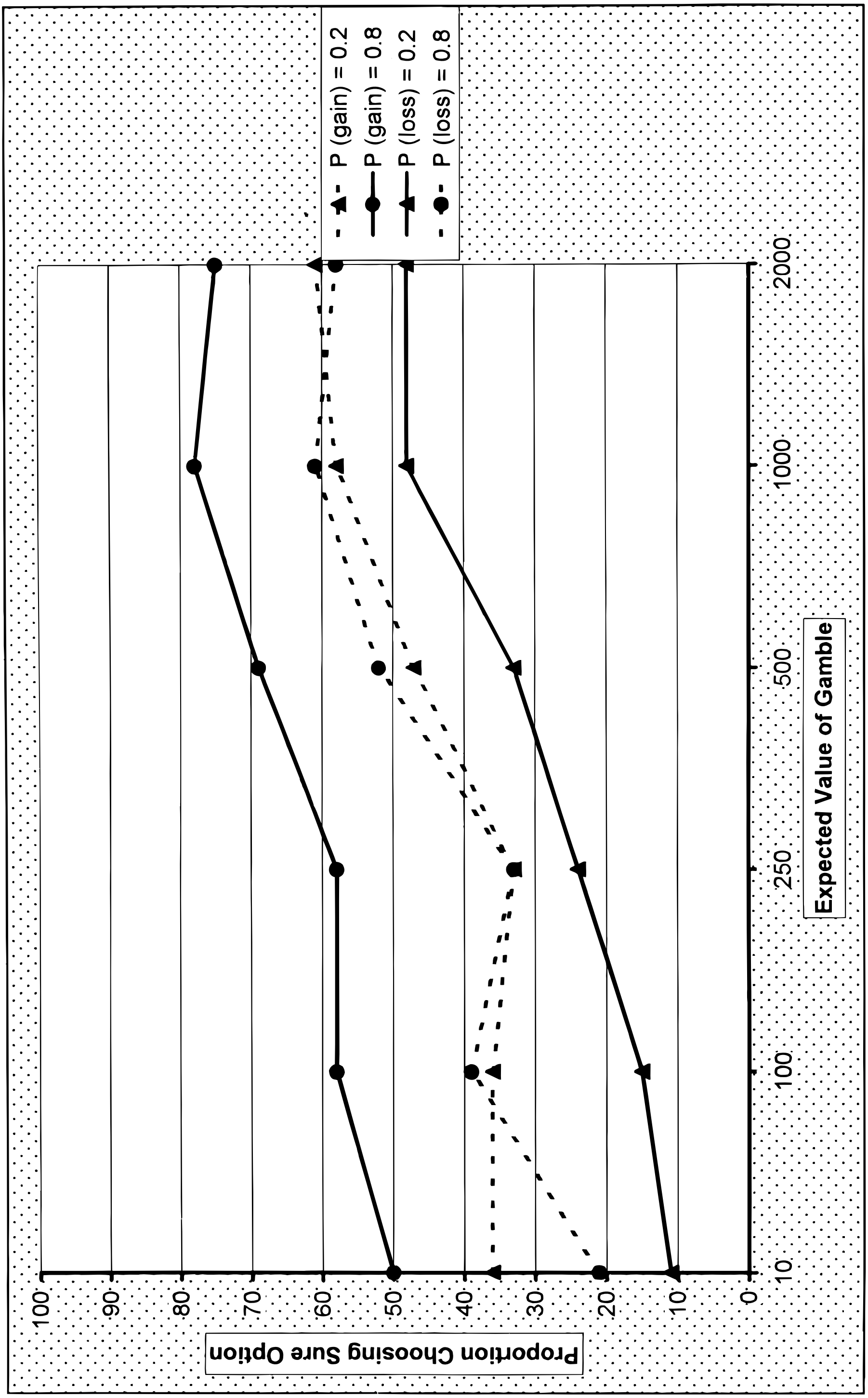


**FIG. 1.** Proportions choosing sure option for different framing conditions, EVs, and probability levels.

be treated as a gain rather than as a loss and that this may lead to increased risk seeking in gambling settings.

## SUMMARY AND CONCLUSIONS

The main findings of this paper can be summarized as follows:

Bidirectional framing effects exist in Asian-disease-like problems both for gains and for losses. Presenting outcomes as gains tends to induce risk-aversive choices, and presenting outcomes as losses tends to induce risk-seeking choices. This tendency is not stronger for losses than for gains. The risk preferences depend on the size and quality of the payoffs used. Larger payoffs induce risk aversion. Probabilities are influential, but the direction of influence makes it plausible that they work in part indirectly by their confounding with payoffs.

It is not possible to predict to a sufficient degree risk preferences from any linear combination of probability, payoff type, and payoff size. In the regressions, framing explains more variance than do any of the theoretically relevant variables probability, payoff, and type of good at stake. This leaves us with two possibilities: either (i) payoffs and/or probabilities have a significant additional nonlinear contribution that is not captured by the regression technique used here, or (ii) the essence of the framing phenomenon is not captured by reference to formal properties. Nonlinearity is a plausible explanation for payoffs when one considers the considerable curvature of the value function in prospect theory. Nonlinearity is much smaller in the curvature of the probability weighting function, however. Thus, trying to understand framing by using cognitive and motivational conceptions in addition to formal characteristics of tasks (Maule, 1995; Reyna & Brainerd, 1991: Schneider, 1992; Tykocinski, Higgins, & Chaiken, 1994) may be a more promising way to a better understanding of the framing phenomenon.

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Received June 9, 1998