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Inducing Risk Preferences

Intermediate article

John Dickhaut, University of Minnesota, Minneapolis, Minnesota, USA
Vesna Prasnikar, Carnegie Mellon University, Pittsburgh, Pennsylvania, USA

CONTENTS

Inducing preferences is a method of creating a laboratory commodity that enables tests of expected utility in both single-person and multi-person economic environments.

TESTING THE PREDICTIVE ABILITY OF ECONOMIC THEORIES

Economic theory attempts to explain the behavior of agents in an economy. There is no stipulation in the theory that these agents are economists, that these agents have been trained in mathematics, or that they have any conscious awareness of the forces that guide their behavior. Rather, agents are assumed to behave 'as if' the tenets of the theory guided their behavior, even though they may be unaware that such forces are at work. (For example, agents may not know their own utility functions.)

Since the 1950s, economics has moved towards being a formal science. Notable advances include the first laboratory demonstrations that the theory of competitive equilibrium, the theory of games, and theories of choice have predictive content (Smith, 1962; Roth and Malouf, 1979; Siegel and Goldstein, 1959). Since expected-utility theory remains a cornerstone of much theorizing, there is a continuing interest in how to test its exact predictions, specifically its predictions of individual choices and prices. The results, while contributing to our understanding of a theory when it performs well, also appear to bear on a related body of research on attention, according to which slight environmental changes (in this case levels of incentives) can alter subjects' attention and thus their decision-making performance.

EXPECTED-UTILITY THEORY

According to expected-utility theory, each economic agent is in a world of uncertainty. Any setting, no matter how simple or complex, can be viewed as consisting of lotteries from which the agent is choosing. The theory is especially useful for describing choices between lotteries with monetary pay-offs. In such cases, it is possible to make two important assessments. Firstly, it is possible to determine, for any two lotteries A and B, whether lottery A is preferred to lottery B; and secondly, it is possible to determine the maximum (or minimum) price at which the individual would buy (or sell) any lottery.

In theorizing about behavior, economists assume that the system of preferences over lotteries can be summarized by a function (the 'utility function') that describes an individual's attitudes towards pay-offs, and that the individual in effect maximizes the expectation of this function. Applying this assumption to knowledge about specific lotteries enables the economist in principle to assess choices and prices.

For example, suppose lottery A represents a 0.5 chance of winning \$5 and a 0.5 chance of winning \$15; and lottery B represents a 0.5 chance of winning \$1 and a 0.5 chance of winning \$20. Suppose that the subject's attitudes toward dollar pay-offs x can be summarized by the utility function $u(x) = \sqrt{x}$. For each gamble, the expected utility will be the sum of the probability-weighted utilities of the pay-offs. Specifically, the expected utility of A is $0.5 \times u(5) + 0.5 \times u(15) = 3.05$, and the expected utility of B is $0.5 \times u(1) + 0.5 \times u(20) = 2.74$. Given that the decision maker maximizes expected utility, lottery A would be chosen over lottery B.

The maximum (minimum) price at which the decision maker would buy (sell) the lottery would be the amount that yields the same utility as the lottery. For lottery A, this amount would be determined by solving the equation $u(x) = \sqrt{x} = 3.05$, i.e., \$9.33. Since the certainty equivalent to the decision maker of the lottery (\$9.33) is less than its expected pay-off (\$10 = 0.5 × \$5 + 0.5 × \$15), the individual is said to be 'risk-averse'. A certainty equivalent greater than \$10 would indicate a risk-preferring individual.

HOW TO INDUCE PREFERENCES

The method of inducing preferences (Berg *et al.*, 1986; Roth and Malouf, 1979) enables researchers to test in a laboratory virtually any individual choice or equilibrium prediction that derives from expected-utility theory. (In general, an economy is in equilibrium when no agent has an incentive to alter his or her action.) The particular advantage of the inducing technique is that, to predict any subject's choices and prices, the experimenter does not need to learn the subject's utility function.

We will show how, by constructing examples, inducing preferences solves the problem of predicting bids and prices of a subject. The technique requires no assumptions about the subject's utility function except that the subject prefers more money to less.

To predict subjects' choices and prices, we introduce a binary lottery to be played for cash (for definiteness, assume it pays \$0 or \$10), along with a new currency called the 'econo', and a function G, that converts econos to probabilities of winning the binary lottery.

Suppose the subject has to choose between a lottery with a 50 per cent chance of 5 econos and a 50 per cent chance of 15 econos, and a lottery with a 50 per cent chance of 1 econo and a 50 per cent chance of 20 econos. Also assume that the subject's conversion function is given by $G(x) = \sqrt{(x/50)}$, where x represents the number of econos that the subject has after the lottery is played. Figure 1 illustrates one way in which lotteries are presented to subjects using this technique.

Each lottery is presented as a wheel divided into two parts. The proportion of the wheel shaded in a given color is the probability of receiving the number of econos associated with that color.

Suppose the subject, with utility function u, considers lottery A. He or she would behave 'as if' going through the following computation. If red came up on the disk, the subject would have a $G(5)$probability of receiving \$10 and a $(1-G(5))$ probability of winning \$0. The expected utility would then be $G(5)u(\$10) + (1 - G(5))u(\$0)$. Similarly, the expected utility if yellow came up would be $G(15)u(\$10) + (1 - G(\$15))u(\$0)$. Therefore the expected utility of lottery A is $(0.5 \times G(5) + 0.5 \times G(15))u(\$10) + (1 - (0.5 \times G(5) + 0.5 \times G(15)))u(\$0) = 0.432 \times u(\$10) + 0.568 \times u(\$0)$.

A similar computation for lottery B yields $0.387 \times u(\$10) + 0.613 \times u(\$0)$.

Since more dollars are preferred to less, and since under lottery A there is a 0.432 chance of \$10 while in lottery B there is only a 0.387 chance, any individual who obeys expected-utility theory will prefer lottery A to lottery B. Note that this observation holds without the experimenter, or even the subject, knowing what u is.

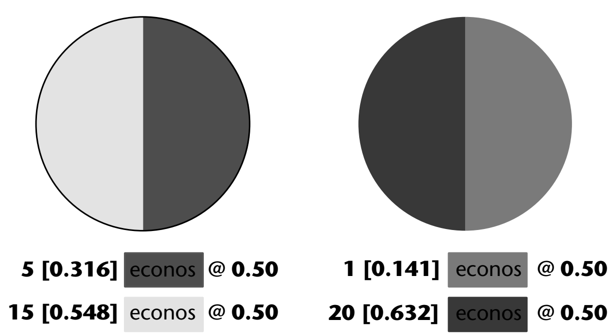

Figure 1. [*Figure is also reproduced in color section.*] A pair of lotteries as presented to subjects in the relative risk-averse condition.

PREDICTING BOUNDS ON ACCEPTABLE PRICES

Now consider the more difficult problem of predicting maximum (minimum) buying (selling) prices for a subject. (Again, for definiteness, assume that the binary lottery pays \$0 or \$10.) To price lottery A, the decision maker behaves 'as if' determining the price in econos (not dollars) of a lottery that pays off 5 econos with a 50 per cent chance and 15 econos with a 50 per cent chance.

Again, suppose the conversion function is $G(x) = \sqrt{(x/50)}$. The subject's expected utility is $0.432 \times u(\$10) + 0.568 \times u(\$0)$. The value x^* to the subject in econos of lottery A will be the number of econos that yields exactly the same probability of winning \$10 as when lottery A is played. Thus, $\sqrt{(x^*/50)} = 0.432$, or $x^* = 9.33$.

Without knowing the utility function of the subject, we are able to predict the price the subject will pay. Admittedly, the price is in econos; however, if our interest in studying behavior is the pricing process and not the price in dollars then it does not matter whether we are talking about dollars or econos. Since 9.33 is less than 10 (the expected number of econos), we can say that the subject is 'induced' to be risk-averse in econos.

EQUILIBRIUM BEHAVIOR

Much of economics is concerned with equilibrium behavior. By inducing preferences it becomes possible to unambiguously state what the equilibrium predictions are in a laboratory experiment. By rewarding subjects with the probability of winning a binary lottery, Roth and Malouf (1979) and Cooper *et al*. (1990, 1993) have been able to test the predictive ability of the Nash equilibrium. A Nash equilibrium is one in which no individual agent has an incentive to alter behavior given the actions of the other agents. By mapping outcome–action pairs to probabilities of winning a binary lottery, Berg *et al*. (1992) study how well incentives (getting agents to take desirable actions) are traded off for risk sharing (getting agents to bear risk). By inducing concave functions on econos, Srivastava and O'Brien (1991) are able to ask if laboratory security markets lead to optimal risk sharing. The inducing technique has found application in accounting (Sprinkle, 2000) and marketing (John, 2001).

PERFORMANCE OF THE INDUCING TECHNIQUE

Since its inception, the inducing technique (and slight modifications of it) have been subjected to numerous examinations. One series of studies focused on its applicability in first-price auctions. (In a first-price auction, the highest bidder for an object gets the object at the price he or she bid.) Based on subjects' bids, Cox *et al*. (1984) estimated subjects' utility functions. Usually, subjects are estimated to have convex utility functions (i.e., they are risk-averse) when being paid in dollars. Cox *et al*. found that if subjects were induced to be risk-neutral, the corresponding estimated utility functions were not risk-neutral, but rather risk-averse in econos. These findings have been vigorously debated by Rietz (1993) and by Cox and Oaxaca (1995). Rietz argues that with proper modifications there is some support for inducing, while Cox and Oaxaca contest the ability of the technique to induce risk-neutrality in a majority of subjects.

Several points emerge from these two papers. First, it appears that in assessing predicted auction prices, the induction technique does reasonably well. Second, since to fit many subjects' data Rietz needs to incorporate a constant term, the inducing technique appears not to work for all values that come up in the auction.

It appears that both sets of results are consistent with the idea that the inducing technique works best when subjects are likely to win the auction, or alternatively when the potential gains are higher.

When lotteries are presented as in Figure 1, choices, on average, reflect risk-aversion (risk-preferring) when risk-aversion (risk-preferring) is induced. In pricing tasks, the effect of the induction technique is more variable than in the choice task. In a review paper, Berg *et al*. (2003) show that the variance in the bidding task is highest when penalties from erroneously bidding are lowest.

Selten *et al*. (1999) tried to induce risk neutrality in a nonstrategic setting. Their design involves four experimental treatments that vary in two dimensions: pay-offs are made in econos or in money, and subjects are allowed to request statistical summaries (expected value and mean absolute deviation from expected value). The tasks test the ability of the inducing procedure to mitigate traditional choice biases (the common-ratio effect, the reference-point effect, the preference-reversal effect, and violations of stochastic dominance). Selten *et al*. found that the inducing technique does not mitigate traditional choice biases.

Selten *et al*. do not assess differences in the performance of the lottery technique associated with the differences in expected rewards. Their raw data reveal that there were only three lotteries with high reward conditions. In only three lottery choices was the difference in winning the preferred prize greater than 14 per cent. For these choices, on average only 9 per cent of subjects' choices deviated from the predicted choice. In 70 per cent of all choices in the Selten *et al*. experiment, the expected difference in the probability of winning between the predicted and alternative choice was less than 6 per cent. Thus their data appears consistent with the notion that the level of incentive affects the performance of the technique.

Loomes (1998) further explores the Selten *et al*. result that individuals process probabilistic pay-offs in the same way that they process monetary pay-offs. In the Loomes task, a subject sees a lottery that has a 13/20 chance of outcome A and a 7/20 chance of outcome B. In the monetary task, the subject picks the pay-offs in pounds that he wishes to assign to each outcome (A and B), with the proviso that the sum of the pay-offs be 20 pounds. In the probability task, the subject assigns the probability of winning 20 pounds to outcome A and the probability of winning 20 pounds to outcome B, with the proviso that the probabilities sum to one. In the probability task, the subject will maximize expected utility by assigning probability 1 to the A outcome. However, in the money task, the subject will assign 20 pounds only if he or she is risk-neutral. Given a reasonable distribution of risk types, the distribution should be different in the two tasks. Loomes finds that he cannot identify any difference between performances in the distribution of outcomes under this task. Like Selten *et al*., Loomes did not attempt to measure whether the performance of the inducing procedure improved with the level of pay-offs.

THE PRASNIKAR STUDY

Induced Utility Functions

Prasnikar's (2001) study examines what produces variations in performance of the inducing procedure, and shows, as do Berg *et al*., that conclusions about the inducing technique (paying off in probabilities) should be tempered by a consideration of the reward structure. Prasnikar attempted to induce one of three utility functions. One function reflected constant absolute risk-aversion, another reflected constant absolute risk-preferring, and the third, risk-neutrality. These functions were, respectively:

$$G(x) = \left(1 - e^{-0.07365x}\right)/\left(1 - e^{-0.35}\right) \tag{1}$$

$$G(x) = \left(-1 + e^{0.07365x}\right)/\left(-1 + e^{0.35}\right) \tag{2}$$

$$G(x) = x/50 \tag{3}$$

Estimation

For each induced utility function, Prasnikar asked if the observed responses deviated significantly from the coefficient of risk aversion she attempted to induce (the target). To assess the deviation, each subject's coefficient of risk aversion was estimated using probit analysis, assuming that the subject's utility function for econos was in the constant absolute risk-averse (preferring, relative risk) class. Then Prasnikar asked if the estimated coefficient was within a 95 per cent confidence interval around the target. The results are shown in Table 1. A total of 20 subjects were examined for each of the three utility functions. Estimated coefficients are stated, and the tests to determine if they are significantly different from prediction are presented, for each of the induced coefficients.

The Effect of Different Probabilities of Winning

Much of Prasnikar's study is concerned with determining the circumstances in which the induction technique does not predict. In the design, pairs of lotteries are selected so that the number of pairs of lotteries is evenly distributed from smaller to higher differences in expected rewards (i.e., absolute differences in expected probability between lottery A and lottery B). (In our example, the probability difference was $0.432 - 0.387 = 0.045$.) In Prasnikar's study, the differences in expected probabilities of winning for each choice pair are divided in increments of 5 per cent from 0 per cent to 35 per cent.

The data show a lower chance of making the predicted choice when the difference in expected probabilities between the choices is small. Even when the difference in expected probabilities is high, some subjects do make unpredicted choices. Figure 2 shows the percentage of correct predictions for each level of difference in expected probability of winning. The pattern, whereby predicted lotteries are selected more frequently at higher differences in expected probability than at lower differences, is observed in risk-neutral, risk-averse, and risk-preferring induction categories. For example, at 5 per cent difference in expected probability, subjects selected the predicted lottery in the risk-preferring sample only 37 per cent of the time, and 53 per cent of the time in the risk-averse and risk-neutral samples. The percentages did not change when Prasnikar compared the results of the lottery pair at 10 per cent minus 5 per cent and the lottery pair at 62 per cent minus 57 per

Table 1. Parameter estimates of induced behavior for each individual (Prasnikar, 2001). Numbers in parentheses are standard errors

Subject	*Constant absolute risk-averse induced behavior*			*Constant absolute risk-preferring induced behavior*			*Risk-neutral induced behavior*	
	Estimated coefficient of risk-aversion	*LR test (proximity to target)*	*LR test (linearity)*	*Estimated coefficient of risk-aversion*	*LR test (proximity to target)*	*LR test (linearity)*	*Estimated coefficient of risk-aversion*	*LR test (proximity to target)*
1	0.086[a] (0.030)	0.84	66.40[c]	0.068[a] (0.011)	0.02	16.08[c]	0.482[a] (0.188)	8.44[c]
2	0.006 (0.181)	16.56[c]	2.80	0.017[a] (0.006)	1.52	5.98[c]	0.625[a] (0.144)	1.98
3	0.076[b] (0.044)	0.00	14.56[c]	−0.021[a] (0.006)	6.64[c]	19.22[c]	2.732 (1.528)	0.18
4	0.053[a] (0.007)	0.14	43.06[c]	0.052[a] (0.017)	0.08	35.46[c]	0.925 (0.902)	0.66
5	0.140 (0.220)	3.42	41.48[c]	0.028[a] (0.009)	1.14	9.03[c]	0.696[a] (0.123)	7.78[c]
6	0.039[a] (0.013)	2.08	6.72[c]	0.071[a] (0.012)	0.00	8.36[c]	0.781[a] (0.135)	2.2
7	0.084[a] (0.001)	0.28	31.73[c]	−0.012 (0.034)	7.96[c]	3.60[c]	0.543[a] (0.074)	5.98[c]
8	0.019 (0.007)	4.06[c]	1.80	0.056[a] (0.008)	0.28	5.40[c]	1.79[a] (0.53)	18.14[c]
9	0.023 (0.058)	0.80	16.08[c]	0.050[a] (0.009)	0.38	28.32[c]	0.971[a] (0.307)	2.34
10	0.084[a] (0.031)	0.24	28.67[c]	−0.065[a] (0.029)	8.78[c]	12.90[c]	0.816[a] (0.400)	2.06
11	0.059[a] (0.006)	2.52	50.82[c]	−0.016[a] (0.004)	5.98[c]	20.40[c]	0.751[a] (0.248)	0.42
12	0.113[a] (0.019)	1.30	24.82[c]	0.022[a] (0.005)	2.26	34.50[c]	1.105[a] (0.059)	3.12
13	0.068[a] (0.009)	0.16	40.08[c]	−0.024 (0.065)	12.18[c]	3.28	1.754[a] (0.526)	14.08[c]
14	0.018 (0.068)	4.76[c]	0.62	−0.037 (0.059)	14.10[c]	3.56	0.821 (0.737)	0.50
15	0.035[a] (0.007)	6.92[c]	14.32[c]	0.222[a] (0.051)	2.58	5.00[c]	0.989[a] (0.219)	0.02
16	0.087[a] (0.030)	0.84	46.40[c]	0.080[a] (0.014)	0.04	6.24[c]	0.834[a] (0.393)	0.14
17	0.058[a] (0.007)	2.06	36.18[c]	0.107[a] (0.019)	0.50	8.62[c]	0.818[a] (0.148)	1.72
18	0.060[a] (0.012)	0.58	25.74[c]	0.051[a] (0.014)	0.14	11.93[c]	0.935[a] (0.213)	0.10
19	0.006[a] (0.003)	4.28[c]	0.58	0.173[a] (0.038)	0.88	7.54[c]	1.508[a] (0.537)	3.80
20	0.087[a] (0.030)	0.84	19.82[c]	0.026[a] (0.008)	1.42	28.66[c]	2.315[a] (0.261)	4.24[c]

[a]Estimate significantly different from 0 at 5 per cent test level.
[b]Estimate significantly different from 0 at 10 per cent test level.
[c]Estimate significantly different from the null hypothesis.

cent. When the difference in expected probabilities is greater than or equal to 15 per cent, the chance of selecting the predicted lottery is always above 80 per cent for the risk-averse induced preferences; and it increases to 88 per cent at 30 per cent difference. For the risk-preferring induced behavior, at 15 per cent difference in expected probabilities subjects select the predicted lottery 71 per cent of the

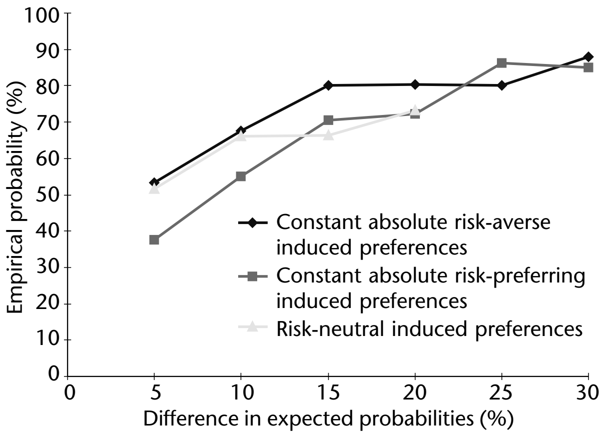

Figure 2. Empirical probability of making the predicted choice, as a function of the difference in expected probabilities (Prasnikar, 2001).

time, and if the difference is greater than 25 per cent, the predicted lottery is chosen 86 per cent of the time. Four subjects from the sample of 20 were making unpredicted choices when the difference was greater than or equal to 15 per cent, and when the difference was greater than or equal to 30 per cent there were two subjects who were making unpredicted choices for the risk-averse induced preferences. For the risk-preferring preferences, three subjects were making unpredicted choices for differences greater than 20 per cent.

The Effect of Different Knowledge Levels of Subjects

After completing all choices, each subject was tested to see whether they understood how to calculate the probability of winning the $10 prize in Prasnikar's experiment. (No instructions on computation of compound lotteries are given to subjects in the instructions before they finish the experiment.) This test question allows Prasnikar to distinguish subjects with good understanding of compound lotteries.

To identify whether unpredicted choices are related to the knowledge of how to compute the expected probability of winning, empirical frequencies were plotted separately for a sample of subjects who knew and for a sample who did not know how to calculate the expected probability. Figure 3 shows the empirical frequencies for each difference in expected probabilities.

Subjects who knew how to calculate the expected probability were making the predicted choices approximately 10 per cent more often than subjects who did not know how to calculate the expected probability, for risk-averse and risk-neutral induced preferences. At 30 per cent difference in expected probabilities, subjects who knew how to calculate the expected probability made the predicted choice 94 per cent of the time for the risk-averse induced preferences and 86 per cent of the time for risk-preferring induced preferences. Figures 2 and 3 show that the pattern of tendencies to make the predicted choice is similar for the induction of risk-aversion, risk-preference, and risk-neutrality.

The Effect of Natural Preferences

The design of the experiment also permits a test of the relationship of individuals' (natural) risk-aversion for money and the subjects' estimated risk coefficients (shown in Table 1). In theory, the natural risk-aversion for money should not affect the performance of the inducing technique. Prasnikar examines this hypothesis first by plotting the relationship between natural risk-aversion and the estimated coefficients of risk-aversion. Natural risk-aversion is assessed by asking a subject to answer a series of 19 questions in Table 2. Each question asks a subject to assess receiving $5 for sure versus a p chance of $10 and $1-p$ chance of $0, where p varies between 5 per cent and 95 per cent. The minimum p for which the lottery is chosen is an indication of risk-aversion. Higher p is assumed to reflect higher risk-aversion.

Figure 4 shows this relationship for the three induced conditions (risk-averse, risk-preferring, and risk-neutral) with subjects divided into four categories, according to whether they knew how to calculate expected probability and whether their estimated coefficient of risk-aversion is significantly different from the induced coefficient. The horizontal axis represents the values of natural risk-aversion, measured by minimum selected probability p, and the vertical axis represents the estimated coefficients of risk-aversion obtained from Table 1.

In the risk-neutral sample, we find that a subset of players (i.e., subjects whose estimated coefficient is significantly different from the induced coefficient) with lower values of natural risk-aversion have lower values of the estimated coefficient of risk-aversion, while players with higher values of natural risk-aversion have higher values of the estimated coefficient of risk-aversion. A positive relationship between natural risk-aversion and estimated coefficient is also observed for the risk-averse sample.

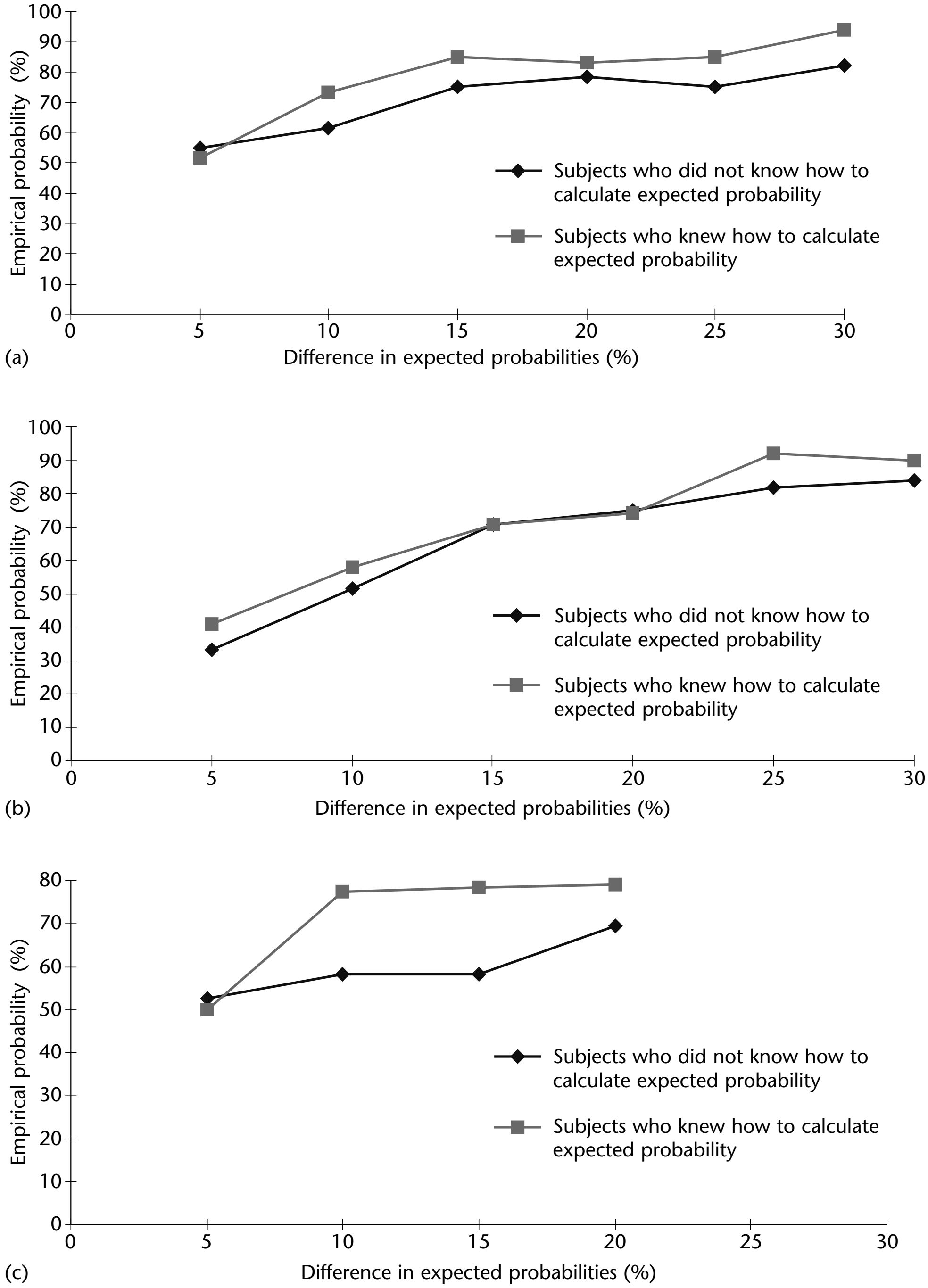

Figure 3. Empirical probability of making the predicted choice, as a function of the difference in expected probabilities for subjects who knew and subjects who did not know how to calculate the expected probability (Prasnikar, 2001). (a) Risk-averse induced preferences. (b) Risk-preferring induced preferences. (c) Risk-neutral induced preferences.

To test formally for such a relationship, Prasnikar estimated a probit function with the coefficient of risk-aversion β replaced by $\beta_0 + \beta_1 p$, where β_0 measures the effect of induced preferences, β_1 measures the effect of natural risk-aversion, and p is the minimum probability selected by subjects. See Table 3.

Columns 6 and 9 suggest that subjects' decisions were influenced by their natural risk-aversion, and not only by their induced preferences. The estimates of natural risk-aversion – $\beta_1 = -0.078$ for risk-preferring induced preferences, and $\beta_1 = -1.012$ for risk-neutral induced preferences – are statistically significant. The effect of natural risk-aversion

Table 2. The sequence of choices given to subjects to test their natural risk-aversion for money

\$5.00	for sure	< >	95 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	90 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	85 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	80 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	75 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	70 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	65 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	60 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	55 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	50 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	45 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	40 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	35 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	30 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	25 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	20 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	15 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	10 per cent	chance for	\$10.00	or	\$0.00
\$5.00	for sure	< >	5 per cent	chance for	\$10.00	or	\$0.00
		Done					

use ↑ and ↓ to move up and down
use ← to select \$5.00 for sure or → to select lottery

($\beta_1 = 0.081$) for the risk-averse induced preferences (column 3) is not statistically significant. Therefore the observed relationship between risk preferences and performance of the induction technique was positive; i.e., the higher a subject's natural risk-aversion, the higher was his or her estimated coefficient of risk-aversion for econos.

Interaction of Natural Risk Preferences and Knowledge Level

Next, Prasnikar addresses the question of whether this result represents the behavior of the whole sample, or only subjects who did not know how to calculate the expected probability (squares in Figure 4) or subjects who knew how to calculate the expected probability (circles in Figure 4). She examines these hypotheses by estimating the probit model of the form $\beta = \beta_0 + \beta_1 p$ separately for the subjects who did not know how to calculate the expected probability and the subjects who knew how to calculate the expected probability. The results are reported in Table 4.

For subjects who knew how to calculate the expected probability, Prasnikar finds no evidence that natural risk-aversion (as measured by the minimum probability p) influences the decision making. The estimated coefficient for the natural risk-aversion β_1 is never significantly different from zero for subjects who understand compound lotteries. For subjects who did not know how to calculate the expected probability, the estimates of natural risk-aversion become significant for the risk-preferring and risk-neutral samples. However, in the risk-averse sample the effect of natural risk-aversion is insignificant.

CONCLUSION

The research to date on inducing risk preferences is generally consistent with the hypothesis that the performance of the induction technique depends on the incentives. Simply stated, pay-offs matter. Knowledge of how to calculate joint probabilities affects the performance, but natural risk preferences seem to affect risk preferences only when knowledge of how to calculate joint probabilities is absent. When the differences between expected rewards are small, knowledge does not relate to performance (all subjects make a lot of mistakes). When the difference in expected rewards increases, everybody makes fewer mistakes, and subjects with computational knowledge perform better.

A related interpretation of the results can be based on research on attention. It is generally believed that there is no 'control homunculus', no central agent that allocates attention according to some rational principle; rather, attention can be easily diverted by slight environmental factors (Newell, 1980). Klien and Shore (2000) examined

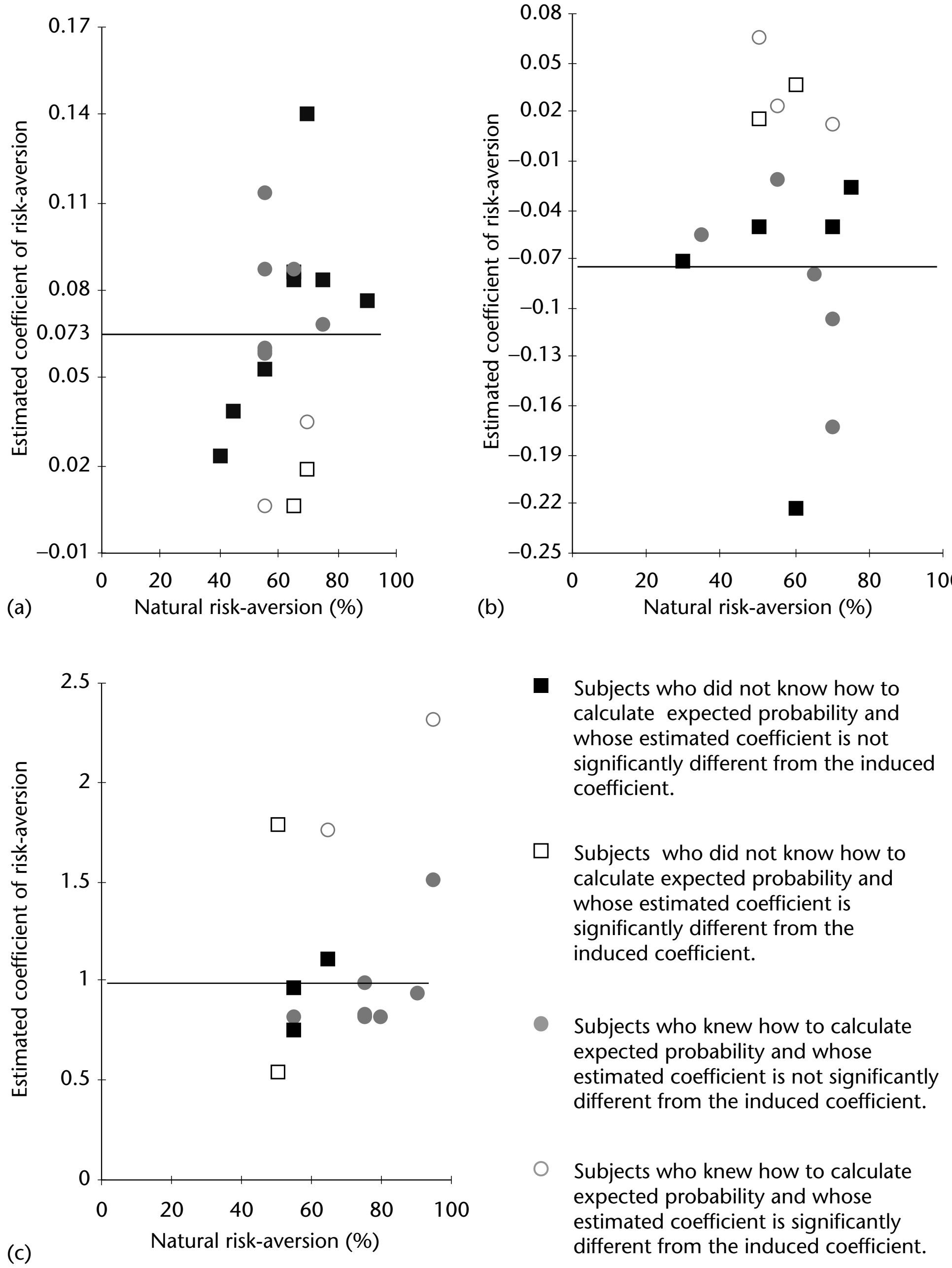

Figure 4. The relationship between the estimated coefficient of risk-aversion and natural risk-aversion for money (Prasnikar, 2001). (a) Risk-averse induced preferences. (b) Risk-preferring induced preferences. (c) Risk-neutral induced preferences.

this issue in terms of 'covert' versus 'overt' orienting.

From a rational perspective, the induction technique is independent of the level of incentives; yet by manipulating the incentives we can produce observed results much more consistent with the induction model. It seems reasonable to postulate that the level of incentives changes the orientation and/or attention of the subject.

From the standpoint of axiomatic choice, the critical assumption necessary to induce preferences is the compound-lottery axiom. As Luce (2000) points out, people's choices frequently violate this axiom. Camerer and Hogarth (1999) provide some understanding of incentive effects across studies, and suggest that incentives may very easily influence both mean and variance of performance levels. This may be the case with inducing preferences.

Table 3. Parameter estimates of the effect of induced preferences and natural risk-aversion (Prasnikar, 2001). Numbers in parentheses are standard errors

	Constant absolute risk-averse induced preferences			*Constant absolute risk-preferring induced preferences*			*Risk-neutral induced preferences*		
	(1)[c]	(2)[d]	(3)	(4)[c]	(5)[d]	(6)	(7)[c]	(8)[d]	(9)
α^e	-1.072^a	-0.157^a	-0.172^a	1.566^a	1.566^a	1.394^a	1.204^a	1.069^a	1.082^a
	(0.258)	(0.065)	(0.018)	(0.145)	(0.145)	(0.0383)	(0.198)	(0.227)	(0.221)
β_0	0.074^a	0.175^a	0.194^a	0.039^a	0.039^a	0.092^a	0.894^a	0.876^a	1.480^a
	(0.011)	(0.042)	(0.024)	(0.002)	(0.002)	(0.097)	(0.064)	(0.084)	(0.231)
β_1	—	—	0.081	—	—	-0.078^a	—	—	-1.012^a
			(0.084)			(0.024)			(0.399)
Log-likelihood	−659.03	−471.19	−470.55	−680.87	−680.87	−672.78	−742.12	−559.96	−556.18
N	1155	770	770	1100	1100	1100	1100	825	825

[a]Estimate significantly different from zero at the 5 per cent test level.
[b]Estimate significantly different from zero at the 10 per cent test level.
[c]The model with $\beta_1 = 0$ for the whole sample.
[d]The model with $\beta_1 = 0$ and the sample that includes only subjects with identifiable natural risk-aversion.
[e]The intercept.

Table 4. Parameter estimates of the effect of induced preferences and natural risk-aversion (Prasnikar, 2001). Numbers in parentheses are standard errors

		Constant absolute risk-averse induced preferences		*Constant absolute risk-preferring induced preferences*		*Risk-neutral induced preferences*	
		(1)[c]	(2)	(3)[c]	(4)	(5)[c]	(6)
Subjects who knew how to calculate the expected probability	α^d	-0.399^a	-0.329^a	1.692^a	1.499	1.208^a	1.215^a
		(0.045)	(0.178)	(0.613)	(0.515)	(0.453)	(0.442)
	β_0	0.087^a	0.160	0.047^a	0.104^a	1.004^a	1.561^a
		(0.023)	(0.087)	(0.010)	(0.028)	(0.145)	(0.413)
	β_1	—	0.009	—	−0.086	—	−0.891
			(0.074)		(0.067)		(0.636)
	Log-likelihood	−285.62	−285.54	−210.53	−209.87	−147.53	−146.06
	N	496	496	385	385	220	220
Subjects who did not know how to calculate the expected probability	α^d	-0.054^a	−0.275	1.142^a	1.483^a	1.031^a	1.045^a
		(0.012)	(0.362)	(0.517)	(0.600)	(0.264)	(0.253)
	β_0	0.054^a	−0.102	0.041^a	0.073^a	0.817^a	1.538^a
		(0.022)	(0.144)	(0.012)	(0.024)	(0.107)	(0.268)
	β_1	—	0.018	—	-0.058^a	—	-1.279^a
			(0.151)		(0.029)		(0.480)
	Log-likelihood	−184.43	−182.32	−460.67	−457.48	−411.63	−408.81
	N	275	275	715	715	605	605

[a]Estimate significantly different from zero at the 5 per cent test level.
[b]Estimate significantly different from zero at the 10 per cent test level.
[c]The model with $\beta_1 = 0$.
[d]The intercept.

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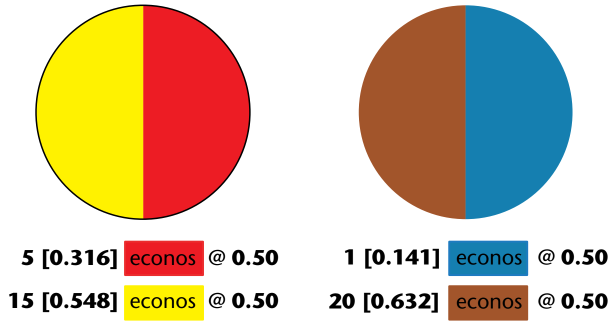

Plate 8 [Inducing Risk Preferences] A pair of lotteries as presented to subjects in the relative risk-averse condition.