Buying Insurance for Disaster-type Risks: Experimental Evidence

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We are grateful for the financial support of the United States Geological Survey in this project, and the valuable comments of Richard Bernknopf.

Abstract

This paper presents a series of experiments that confront subjects with low probability, high loss situations. A rich parameter set is examined and we find subjects respond to low probability, high loss risks in predictable ways. As loss events become more likely, or loss amounts get larger, or the cost of insurance falls, subjects are more likely to buy indemnifying insurance, even for the class of low probability risks that usually presents problems for standard expected utility theory. A novel application of Cameron's method to estimate willingness to pay from dichotomous choice responses allows us to estimate willingness to pay for insurance. We do not observe the bimodal distribution of bids found in other studies of similar risk situations.

Key words: experiments, risk, insurance.

JEL category: C91, D80

Introduction

There is evidence, both anecdotal and researched, that people's responses to very low probability events are not well understood. (Camerer and Kunreuther, 1989) When low probability events produce large losses, their decisions often seem confused and perverse. Camerer and Kunreuther (1989, p.568-570) reveal a dichotomy in perceptions, where some individuals downplay or dismiss the low probability (optimism and threshold biases), and others overestimate or exaggerate low probabilities (conjunction and availability biases). In a study of the risks of living near a landfill site, McClelland, Schulze and Hurd (1990) present evidence of this dichotomy, with some people dismissing the risk and concluding there was no hazard, while others placed a relatively high value on the risk. In a related experimental study of low probability risk response, McClelland, Schulze and Coursey (MSC, 1993) again found bimodality in the distribution of willingness to pay for insurance against low probability events. The divergence of subjective probability perceptions and objective probabilities is a constant source of concern to analysts and policy makers, but especially in the case of many natural disasters and environmental hazards where probabilities are low and potential losses high.

Even though natural disasters are inevitable, their timing and consequences are uncertain. Preparedness, mitigation and insurance all provide relief from natural disasters, yet many people fail to head warnings, remove themselves from harm's way, or purchase insurance against loss. Kunreuther (1978) identifies a number of low probability situations in which people fail to purchase insurance, even when it is available, promoted and subsidized.[1]

Standard expected utility theory predicts that all risk neutral or risk averse individuals would purchase insurance and undertake all relevant precautions to the extent that the extra benefits from such actions exceed the marginal costs, less some risk premium in the case of risk aversion. This model fails to explain actual decisions when people use an array of *ad hoc* rules to assess uncertainty and risk. (Camerer and Kunreuther, 1989) For example, more detailed events seem to be more likely, as people focus on the detail to make the events more plausible and believable. An abstract and ill-defined event, such as "global destruction by an errant meteor" is assigned a very low probability, while a very specific event, such as "the injury of a passenger on flight 123 from Chicago to Dallas on Tuesday evening" is considered a much more likely event. W. Kip Viscusi finds that smokers vastly overestimate the probabilities of disease associated with smoking, perhaps because these consequences are heavily promoted in anti-smoking campaigns. (Viscusi, 1990) People tend to down play a very unlikely event because "it can't happen to me," or they have a perception threshold below which very unlikely events are essentially impossible, or at least ignorable.

Which of these behaviors dominates to explain under-insurance for natural disaster risks is an open question, especially when empirical tests to identify and discriminate between alternative explanations are lacking. (Camerer and Kunreuther, 1989, p.586) Analysis of behavior and policy prescription would not be such a problem if low probability natural disasters had small consequences, but often these unlikely events cause severe losses, making the expected value of the outcome large relative to other insurable risks. When disasters involve the loss of property and life, the outcome is extreme for those who suffer the losses. The losses in natural disasters can often be so severe and large that they dominate people's assessment of the risk they face. Rather than calculate expected losses, they simply assess the event in terms of the absolute value of losses, not how they are distributed among individuals.

To decide how to act in risky situations, individuals must have beliefs about the probability distribution of outcomes as well as information on the possible losses involved. Herein lies a possible explanation for the bimodal distribution of risk attitudes, and corresponding bimodal distribution of the value of insurance found by McCelland, Schulze and Coursey (1993). When losses are real and large there could be a divergent focus among subjects. Some individuals focus upon the probability of the event, and take the very low value to indicate that it is so unlikely as to be overlooked, or perhaps it falls below a sensitivity threshold. They are unwilling to purchase insurance or pay anything to avoid the risk. Other individuals focus upon the loss, and even though the event is unlikely, the consequences are extremely serious and worth avoiding at some cost. These people will purchase insurance at prices above the actuarially fair premium. Our experiments shed some light on this interpretation in the later discussion.

Experimental evidence has played a major role in the study of natural disaster-type risks because of confounding effects in field data. (Camerer and Kunreuther, 1993 p. 7) These events occur infrequently and private decisions in the field are heavily influenced by institutions that sever the connection between event characteristics and perceived personal exposure (for example, natural disaster relief). The laboratory offers us the opportunity to expose subjects to this type of event repeatedly in a controlled institutional setting with none of the physical consequences. A large amount of data can be gathered in a relatively short time.

In the set of experiments reported in this paper we investigate the decision to purchase an insurance policy that indemnifies the subject against all losses from events that cause relatively high losses but occur with relatively small probabilities. In this regard our work addresses a similar issue to that of McCelland, Shulze and Coursey (1993), however there is much to distinguish our work from theirs.[2] Our main concern is to create in the laboratory a risk scenario with many features of real world natural disasters, for example earthquakes, floods, fires and hurricanes. These types of events occur with relatively low probability, and are modeled in the experiment by two events, conveniently distinguished by the terms periodic and episodic. Floods offer an illustrative example of this distinction: many rivers flood periodically, but every now and then a major flood of the river, or episode, occurs. Though flooding is a relatively infrequent occurrence, major floods are less likely than minor floods. Even when a disaster occurs, the consequences are not always uniform. Some unlucky souls suffer tremendously from even minor disasters, and while most people suffer something from a major incident, some lucky ones emerge relatively unscathed.[3]

To reflect these characteristics our experiments present subjects with two different low probability events, each with two possible outcomes, as well as the possibility that nothing occurs. Subjects face compound probabilities that range from 0.36 down to 0.001, with most below 0.1. Loss amounts are relatively large however. Each time the subject faces a decision to buy insurance, an income of 200 tokens, convertible into coin of the realm at a specified rate, is earned. With an average of 4.3 decisions for each set of parameters, wealth can rise to over 800 tokens by the end of the treatment. Losses from the events in the experiment range from 100 tokens to 1000 tokens, representing a substantial proportion of, and sometimes an amount exceeding, current wealth.

In another attempt to infuse the experiments with realism, the insurance policy costs are varied over a range from relatively inexpensive to a considerable proportion of period income. The lowest cost of 5 tokens makes the insurance premium only 2.5 percent of period income, but the highest premium of 99 tokens is almost 50 percent of period income.[4]

Our experiment, which is described in detail in the next section, allows us to investigate the relative importance of low probabilities and large loss amounts. While concentrating on very low probabilities, losses vary sufficiently to generate a relatively large range of expected losses. We use a complete, crossed-treatment design, with all probability and all loss amount combinations presented to the subjects. There are a total of 90 distinct treatments in our design. Our first research goal is to describe purchase behavior of subjects when faced with such a richly specified event space, and to more fully characterize the motives driving such behavior. Our second objective is to predict the distribution of willingness to pay for insurance against these particular types of risks. These predictions can be directly compared with those generated by McClelland, Schulze and Coursey (1993) to test for bimodality in the willingness to pay distribution.

1. Experimental design

1.1 Design

The experiment was designed to implement the game depicted in Figure 1. In each decision period, the subject has the option of purchasing the insurance policy at a stated cost. This policy indemnifies the subject completely against all losses, other than the cost of the policy, of course. Each subject is then exposed to a number of draws from a distribution containing three outcomes: nothing, a low probability event and a very low probability event. As mentioned earlier, the terms episodic and periodic are used as a convenient language to indicate to subjects the relative probabilities of each event. For example, one treatment has the events distributed with probabilities (0.89, 0.1, 0.01). We chose repeated draws to capture a particular feature of many insurance markets: policies are purchased at regular intervals, say annually, whereas exposure to the risk can occur multiple times during that period. If a loss event occurs, the subject then experiences one of two possible losses: small or large. In all there are 5 possible outcomes from any draw: no loss, a small periodic loss, a large periodic loss, a small episodic loss and a large episodic loss. Subjects are always provided with numeric information regarding the event and loss distributions. Though there is only one outcome distribution, each subject experiences a separate draw from the distribution.

Each treatment presents the subject with some particular combination of policy cost, event probabilities, loss probabilities and loss amounts chosen from the parameters values listed in Table 1. A total of 18 parameter combinations across 5 cost levels means 90 distinct parameter sets for the experiments. To contain experimental expenses while still paying subjects a reasonable expected hourly fee, the number of rounds (draws from the event distribution) and the number of periods (separate purchasing decisions) were randomly drawn from the following uniform distributions: rounds on the interval (1,4) and periods on the interval (1,9).[5] Hence, each subject has up to 9 opportunities (with a mean of 5) to purchase insurance for a given set of parameter values, and experiences up to 4 (with a mean of 2.5) draws from the event distribution for each period.

One significant contributor to the large number of treatments is the variation in the cost of the insurance policy. Costs vary in 5 levels from 5 tokens to 99 tokens, which represent a small fraction of period income (5/200) to a large fraction (99/200). All probability and loss parameter combinations are run for each policy cost. Since expected losses vary from a low of 1.8 tokens to a high of 68, we observe insurance purchase decisions over a range of cost-to-expected loss ratios as low as 0.07 (5/68) to as high as 55 (99/1.8).

As subjects have the choice of purchasing the insurance policy each period, they must have a source of income. Each period they are endowed with 200 tokens (redeemable at the end of the experiment at an advertised exchange rate.) Over the succession of periods wealth accumulates according to the following rule:

end of period wealth = MAX{0, last period's wealth + 200
- cost of policy * (buy)
- any losses during period * (not buy)}.

The subject's wealth is increased by 200 at the beginning of each period, but decreased during that period by the cost of the policy if purchased, and any losses incurred if insurance was not purchased. Since the subject faces up to 4 event draws each period, its is possible, although highly unlikely, for total losses to exceed the subject's wealth, leaving the subject with a negative balance. In this case, the subject is declared bankrupt. Bankruptcy zeros the subject's wealth, and the subject must sit out until the next period, beginning again with only the new income of 200.

1.2 Implementation

Subjects were recruited from the university student community as a whole, with little over-representation of economics students.[6] Experiment sessions lasted approximately one hour, and average payoffs were around $13. Since the laboratory has 20 stations, sessions were conducted with between 10 and 20 subjects. With the number of periods and the number of rounds per period randomly drawn, an average of 3 treatments could be run per session. Funds and time permitted us to run a total of just over 2 replications of all 90 treatments.

The experiment instructions are included as Appendix 1 to this paper. We conducted several practice rounds before the actual recorded rounds started. At the beginning of each period the subject is informed of the amount of wealth they have, all treatment parameters, the cost of the insurance policy and given the option of purchasing the insurance policy. After this decision, a random number of rounds, or draws from the event distribution, is experienced. These draws are displayed on the subject's monitor as a sequence of random digits between 0 and 99 flashed in a panel. Eventually the counter comes to rest, with the value indicating the resulting event. If a loss event is indicated another random digit counter engages to choose which of the losses, small or large, occurs. As each subject experiences a separate draw it is very unlikely for any two subjects to obtain the same counter value, although given the event probabilities, many subjects may have similar outcomes. At the end of a round, each subject presses the return key to acknowledge the experience, and another round begins, or the period end is announced and ending balances calculated.

Table 2 shows the actual observed frequency of events in the experiment compared to the theoretical frequencies predicted by the parameter values. Loss events occurred approximately as frequently as expected in the experiments. Subjects were never informed on actual event frequencies, other than the very small number of their own event experiences they directly observed, so they could only have made decisions based on predicted probabilities, subjective probabilities, their own limited experience, or randomly. This mirrors real life since natural hazards occur at such low frequencies that most people never experience them personally in a life time. For most people actual event frequencies are significantly lower than expected frequencies, and rationally should not base their decisions on their own experiences.

2. Empirical model

In these experiments subjects can purchase an insurance policy that fully indemnifies them against losses caused by any periodic or episodic event. Within each session there are multiple treatments, and within each treatment the subject may make the purchasing decision a number of times. The insurance policy is a private good, each subject acts independently of each other and the outcome of a random draw is private for each subject.

For a risk neutral subject, the decision to purchase the policy rests on the following comparison:

$$\textbf{BUY policy if Cost (C)} \leq \textbf{Expected Loss (EL)} \qquad \textbf{(1)}$$

And a risk averse subject would be prepared to pay more than the cost of the policy to avoid facing the gamble, i.e.

$$\textbf{BUY policy if C} \leq \textbf{EL} + \pi, \qquad \textbf{(2)}$$

where π is the risk premium that depends upon the subject's attitude to risk (**R**) and possibly wealth (**W**). The more risk averse the subject is, the greater π will be, and the more likely a subject will purchase insurance even when it costs more than the expected loss of the gamble.

In specifying the empirical model we assume there is some underlying probability of buying the policy that is a function of the cost of the policy, the expected loss faced, the subject's wealth **W**, and factors that determine the subject's attitude to risk **R**. That is:

$$\textbf{Prob (buy policy)} = f\textbf{(C, EL, W, R).} \qquad \textbf{(3)}$$

For any risk neutral or risk averse subject we can expect the following derivatives:

$$\partial \mathbf{buy}/\partial \mathbf{C} < 0, \qquad \partial \mathbf{buy}/\partial \mathbf{EL} > 0,$$

$$\partial \mathbf{buy}/\partial \mathbf{W} \; ? \; 0, \qquad \partial \mathbf{buy}/\partial \mathbf{R} \geq 0.$$

The effect of increased wealth on the probability of buying the policy is ambiguous. As the subject accumulates wealth, the cost of the policy becomes a smaller fraction of wealth, making it more likely to purchase insurance. But as wealth increases the potential losses represent a smaller share of wealth, insurance may become less attractive and subjects may choose to self-insure.[7]

The probability of buying the policy is a latent, unobserved variable, when the decision to buy insurance is a binary outcome variable. A simple binary choice model such as the probit or logit can be chosen to specify and estimate the parameters of the function $f(\cdot)$ in equation (3) above.

3. Data description and analysis

3.1 Data Description

Over a period of three months 449 subjects were recruited to participate in the experiment. The experiment generated 13,179 individual purchase decisions, with 90 separate parameter combinations. Some treatments were duplicated, and additional information on risk preferences was collected for a subset of 149 subjects. Each subject made an average of 4.3 purchase decisions under any particular set of parameters. Generally, the frequency with which insurance is purchased varies with expected loss and insurance cost. A review of the data leads to the following characterizations:

(i) Subjects are more likely to buy insurance as the expected loss they face increases.

(ii) The likelihood of buying insurance generally decreases as the cost of the insurance increases, holding the expected loss constant.

(iii) There is considerable "noise" in the relationship at very low expected loss values but the variance in buying probabilities at these low levels appears to be smaller for higher insurance premiums.

The raw data appear consistent with the basic theory presented above in a rather obvious, but reassuring, way: insurance is more likely to be purchased the larger the expected losses, and the less expensive it is to buy. We go on to investigate these relationships further using regression analysis in the section to follow.

3.2 Data Analysis

Using all 13,179 purchase decisions, a simple logit specification of equation (3) above can be estimated. The dependent variable is the binary decision to buy the insurance policy or not. Independent variables include the logarithm of the policy cost, chosen to allow us to directly compare our results with those of McClelland, Schulze and Coursey (1993) by employing Cameron's (1988) method of estimating willingness to pay from dichotomous choice data. The expected loss variable in equation (3) is broken into its components for estimation of individual treatment effects by using binary indicators for event probabilities, loss amount probabilities and loss amount. Also included as regressors is a wealth measure, and measures of experience with the loss events.

Table 3 presents the results of estimating models derived from equation (3) using the econometrics program Limdep. Estimates of the parameters of the logit model using all 13,179 observations are given in column (1) of the table. For each explanatory variable, the estimated coefficient indicates the sign of the effect of a change in that variable on the probability of buying the insurance policy, however since the model is non-linear, the coefficients are not marginal effects. The impact of a unit change in each independent variable on the likelihood of buying insurance is given in the column adjacent to the coefficient estimates.

As expected, increasing the policy cost reduces the probability of purchasing the policy, independent of the expected loss or other influences. The wealth variable has a negative coefficient, and a relatively large marginal effect given the size of the variable.[8] The sign of the wealth effect is consistent with decreasing absolute risk aversion and constant relative risk aversion. The negative estimated effect implies that as wealth increases, subjects are more likely to self-insure. Since expected losses range from a low of 1.8 to a high of 68 tokens, they are relatively small compared to period income of 200, and the mean wealth of 570 tokens. Self-insurance, or the failure to purchase insurance, against natural disaster type risks is common, for example, in the case of earthquakes in California, despite the relatively high incomes of property owners in that state. When confronted with very low probabilities of losses, and relatively low expected values for those losses even though the ex post losses are very large, subjects appear willing to forego the uncertain value of insurance rather than face the certain loss of the insurance premium.

The exposure index measures the number of draws from the event distribution. Its effect is positive, so the more subjects are exposed to the possibility of losses, the more likely they are to buy insurance. This may reflect a common risk fallacy in which people view independent events as not independent: just because a low probability event has not occurred yet makes it more likely to occur in the future. The experience index measures actual losses suffered (total uninsured losses rather than the total of all losses). Experiencing larger uninsured losses decreases the likelihood of purchasing insurance although with a relatively small marginal effect. Only those subjects not buying insurance experienced uninsured losses and they are less likely to buy insurance the larger the actual loss. Preference for self-insurance can explain why they continue not to buy insurance, but only another risk fallacy can explain why they fail to buy insurance as their losses mount. Subjects may believe that the very unlikely loss events are now even less likely since they have already occurred, and so insurance is unnecessary.[9] Alternately, having suffered a loss, subjects may expose themselves to the risk of further losses, and go uninsured, in order to regain their former wealth position. This explanation comes from Tversky and Kahneman's (1991) "reference-dependence" argument in which people are willing to accept more risk to regain former positions after suffering losses. Despite the possibility of bankruptcy, discussed in section 1.1 above, it almost never occurred during the experiments.[10] In some cases however, fear of insolvency may have caused subjects to forego buying insurance as their wealth fell.[11]

The coefficients on the loss amounts (called small loss and medium loss in the table) are not statistically significant at the 5 percent level or lower for the whole sample, although they are for the sub-sample of subjects, discussed below. The omitted category is the large loss treatment that doubles all the small loss values. Measured by the marginal effects, subject behavior appears relatively unresponsive to the size of the loss, but quite responsive to the event probabilities (labeled low event pr. and mid event pr. in the table). The omitted category is the high event probability that multiplies all low event probabilities by 10. Subjects are significantly less likely to insure against low probability events than high probability events. The estimated marginal effects are very large. Combining these two findings we can address the question posed in the introduction: what is the relative importance of probability verses loss amount in determining behavior toward low probability, high loss events? Our findings suggest a dominant role for the probabilities in situations of low probabilities and high losses: subjects in our experiments are significantly and substantially more responsive to the variation in probabilities than to the variation in loss amounts. Evidence of this relative sensitivity is provided by Kunreuther (1996), where he argues that despite growing losses from natural disasters, with probabilities and ambiguity constant, purchase of insurance has not increased accordingly.

To further investigate these findings, and to predict willingness to pay for insurance against this type of risk, additional regression analysis is presented. A subset of the subject pool was exposed to a further treatment, in which a subsequent experiment was conducted asking subjects to choose a preferred gamble from a set of gambles with a constant mean payoff, but increasing variance. (Brown and Stewart, 1998) This choice is used in the empirical model as an independent measure of risk preference. When included in the regression equation it also has the property of invariance for each subject, and so captures some fixed effect in the independent variable. This confronts an obvious criticism of the empirical model discussed above: that the error terms in the model are treated as independent, when in fact each subject generates an average of 29 observations. The solution is to estimate a fixed, or random, effects logit rather than the simple logit. A random effects specification was estimated for this sub-sample, and the random effects coefficient was found to be statistically no different from zero. A fixed effects specification can be obtained by including the risk preference index as it varies across individuals, but is constant for each individual.

Table 3 presents estimates of equation (3) for the sub-sample of 149 subjects exposed to the additional treatment, for direct comparison with the estimates presented in column (1). Variable means are also provided in Table 3 that show very little difference between the sub-sample and the whole sample. The smaller sample was exposed to slightly more low loss events and their loss experiences were consequently lower than for the larger sample. Consequently, coefficient estimates are very stable, with some notable exceptions. The subset of subjects appears more sensitive to the size of the loss than the entire sample, even though only the smallest loss amount becomes statistically significant. The positive coefficient indicates that subjects are more likely to insure against a given loss distribution when it is less likely, even though the marginal effect is relatively small. This may be an artifact caused by a limited variation in treatments across the smaller sample compared to the larger sample. Even though each treatment is represented in this data, not all combinations of probability and loss are observed. No other explanation for this finding suggests itself at present.

The estimates presented in column (3) of Table 3 come from the purchase decision model augmented by the addition of the risk preference index for the subset of 149 subjects for whom this measure was collected. These subjects generated 3330 separate purchase decisions, and the model performs better in terms of the likelihood ratio, and the percentage of actual decisions correctly predicted. The negative coefficient on the index is statistically significant, and the marginal effect implies an elasticity with respect to the risk measure of .50 measured at the means. Subjects with more preference for risk are less likely to buy insurance against losses, a finding consistent with expected utility theory. The inclusion of an independent measure of risk preference for each individual leaves all other coefficient estimates unchanged.

Predicted probabilities of buying insurance for selected treatments are given in Table 4 along with standard errors for these estimates. Purchase probabilities across the different loss amount distributions (columns) are not significantly different when tested using a simple difference of proportions test. When looking at event probabilities, three comparisons are noteworthy. Comparing the first and second rows shows how purchase behavior changes with an increase in the probability of the higher probability event, from .04 to .10, holding the lower probabilities constant. There is a statistically significant decline in the probability of buying insurance of approximately 23 percent. This could reflect the response of subjects to the relatively low loss amounts associated with the periodic event. However, increasing both probability events by ten from (.04, .01) to (.40, .10) raises the probability of buying insurance by approximately 80 percent. An explanation for this is that expected losses at these higher probabilities are quite a lot greater than for either of the lower probability treatments.

The estimates from model (3) can be used to predict the willingness to pay for the insurance policy using methods developed by environmental economists. In particular, the method of Cameron (1988) is directly applicable to the current situation. Her method allows us to estimate willingness to pay when the decision is binary (called a referendum procedure) and the threshold value (or bid amount) is an explicit variable appearing on the right hand side of the logit regression. The derivation of the willingness to pay for the insurance policy (***wtp***) is straightforward and described below. We model the decision to buy the insurance, $\boldsymbol{I} = 1$ if $\boldsymbol{wtp} > \boldsymbol{C}$, $\boldsymbol{I} = 0$ otherwise, where the unobserved willingness to pay is a linear function of experimental parameters $\boldsymbol{x}'b$ and a stochastic error term $\boldsymbol{u}$**.** The probability of buying insurance is

$$\Pr(I = 1) = 1 - \Pr(j < (C - x'b)/k)$$

in which j is the standard logistic random variable and k is a parameter of the distribution if $\boldsymbol{u}$ is assumed to be distributed logistically. In the model the coefficient on the cost variable, $\boldsymbol{C}$ is the reciprocal of k. Estimates of willingness to pay can then be calculated by taking the anti-log of $\boldsymbol{x}'b*$ where $b*$ is the vector of estimated coefficients divided by k. The predicted willingness to pay has a mean of 47 tokens, a median of 4.4, an inter-quartile range of 22.4 and a mode of 3.7 tokens.

Predicting willingness to pay allows us to directly compare our results with those of McClelland, Schulze and Coursey (MSC, 1993). In their experiment they directly elicit a bid from subjects for a limited set of probabilities and loss amounts, and present their main results in the form of histograms of the ratio of bid to expected loss for various probability treatments. The probabilities used in our experiments all compare with the low probability events in their experiments, the treatments that produce the bimodal distributions of bid/expected loss values. MSC use a pseudo-logarithmic scale for the ratio values in their histograms. To ensure comparability, our histograms use a similar horizontal scale.

Figures 2(a) through 2(d) show histograms of the ratio of the predicted willingness to pay for insurance to the expected loss covered by the policy. The two histograms 2(a) and 2(b) present distributions for the whole sample (2a) and the sub-sample for which the additional risk preference was elicited (2b). There is little evidence of the bimodality identified by MSC in any of these distributions, even when it is acknowledged that the horizontal pseudo-logarithmic scale tends to visually accentuate any mode at zero. The ratio 1.0 is a focal point of the distribution, since this is where the willingness to pay is just equal to the expected loss faced, an equilibrium for risk-neutral subjects. The largest number of predictions is observed for ratios between 0.75 to 1.5 for the whole sample, whereas the modal category for the smaller sample is for ratios in the range 1.5 to 3.0.

Figures 2(c) and 2(d) give the relative frequency histograms from the smaller sample for the subjects with the lowest risk preference index, and the highest risk preference index.[12] Predicted willingness to pay for the relatively risk averse subjects exceeds expected loss by large amounts with nearly all the mass of the distribution lying above 1.0. The distribution of the willingness to pay–expected loss ratio is substantially more even for subjects who are relatively risk preferring. The difference between these distributions is consistent with expected utility theory, even though many of the value–loss ratios imply much greater risk aversion than seems plausible. (McClelland, Schulze and Coursey, 1993, p.110) Again, these histograms show no bimodality.

What could explain the divergence between our findings and those of MSC? Either the subjects are different or the experiments and hence the data are different. Given that subjects in both cases are university students and chosen randomly with respect to any relevant experiment characteristics it is unlikely that differences in subject preferences or attitudes account for our findings. It is far more likely that the very different environments and decisions facing subjects can account for the observed divergence. In particular, subjects in the MSC experiments were bidding to purchase a fixed number of insurance policies in an auction. Bids were elicited for four insurance policies from eight subjects, with the four highest bidders buying policies at the 5th highest bid price. If the loss event was drawn, those with insurance suffered no loss, those without insurance a loss of 4. If no loss event was drawn all subjects received an income of 1. In contrast, our experiments present each subject with an individual choice of buying insurance at a fixed (treatment) cost. Since costs are always positive and responses are dichotomous (yes, no) actual willingness to pay is never observed. And subjects are not "competing" against each other, or having to act strategically, to purchase insurance.

In our experiments a bid of zero is not directly observable while it is in MSC's experiments since their elicitation mechanism calls for an open-ended bid. The implied frequency of actual zero bids in the MSC experiments is consistent with the number of zero bids observed in contingent valuation method (CVM) surveys using the open-ended bid elicitation mechanism, and is often interpreted in part an artifact of the mechanism. MSC do not address this issue in their discussion and do not appear to have taken any measures to protect against, or test for, protest zeros amongst the data, so whether this artifact is responsible for the mode at zero or not remains an open question.

4. Conclusion

The experiments reported here present subjects with a more complex decision setting than has previously been used to investigate insurance purchases for low probability, high loss events. We did this to give our experiments a greater degree of realism since real world natural disasters rarely treat all people equally. And in the real world many people facing the same risks display quite different behavior. Expected utility theory has often been invoked to explain the purchase of insurance, but it fails in very low probability situations by implying considerably higher risk aversion than seems plausible. Our objective in these experiments was twofold. The first was to employ the experimental laboratory to "break open" some of the factors that influence insurance purchase behavior when faced with natural disaster type risks. Using econometric models of the decision to buy an insurance policy to cover any losses from low probability, high loss events, many of our findings are consistent with expected utility theory. Insurance purchase is less likely when the cost of the insurance is high, when the expected loss is low, and as the individual becomes wealthier. But we find evidence of effects that remain to be explained, such as the negative effects of repeated exposure to events, and the relatively greater sensitivity to the probability of the loss than to the size of the potential loss.

Our second objective was to predict willingness to pay for insurance from referendum data of a kind similar to that collected using the contingent valuation method, currently used heavily in valuing environmental commodities. This also allows us to directly compare our results with those of McClelland, Schulze and Coursey (1993). We employ Cameron's (1988) method to calculate willingness to pay, and see no evidence of the bimodality in the distributions of the value – loss ratio found by McClelland, Schulze and Coursey. While there is still substantial over-valuation of insurance when faced with low probability losses to challenge the appropriateness of expected utility theory, much of the behavior observed in our experiments is predictable by the parameters of the loss event, and characteristics of the individual.

Some extensions of this research are worth mentioning. The experimental setting could be expanded to include an insurer of last resort, a feature that may explain why so little disaster insurance is purchased in areas such as California, even when the premiums are set at reasonable or bargain rates. Failure to purchase insurance for hurricanes, floods and earthquakes in the U.S. may be rational when FEMA assistance is almost guaranteed and there is much political reward to governors and presidents proclaiming states of emergency. Another extension would directly address the issue of subject behavior under alternative elicitation mechanisms, in particular open-ended verses dichotomous choice, to see if the zero mode is an artifact of the elicitation mechanism. There has been some research into this difference in the contingent valuation field, but not in our context of insurance purchase. Finally, an experiment may be designed to directly test hypotheses about expected utility theory against the alternatives of more generalized expected utility or other models such as prospect theory or regret theory. At present, our tests are such that rejecting predictions of the expected utility model does not provide any support for taking up any particular alternative theory.

REFERENCES

Brown, Paul and Steven Stewart (1998) "Risk Attitudes and Non-Compliance Penalties in Competition Between Firms," Working Paper, University of Tennessee

Camerer, Colin F. and Howard Kunreuther (1989) "Decision Processes for Low Probability Events: Policy Implications," *Journal of Policy Analysis and Management*, 8:4, 565-592.

Camerer, Colin F. and Howard Kunreuther (1993) "Making Decisions About Liability and Insurance: Editor's Comments," *Journal of Risk and Uncertainty* 7, 5-15.

Cameron, Trudy A. (1988) "A New Paradigm for Valuing Non-market Goods Using Referendum Data: Maximum Likelihood Estimation by Censored Logistic Regression," *Journal of Environmental Economics and Management* 15:3, 355-79.

Clotfelter, Charles T. and Philip J. Cook (1993) "The Gambler's Fallacy in Lottery Play" *Management Science* 39, 1521-25.

Kunreuther, Howard. (1978) *Disaster Insurance Protection: Public Policy Lessons* John Wiley and Sons: New York.

Kunreuther, Howard (1996) "Mitigating Disaster Losses through Insurance" *Journal of Risk and Uncertainty* 12:2, 171-187.

McClelland, Gary H., William D. Schulze, and Brian Hurd (1990) "The Effects of Risk Beliefs on Property Values: A Case Study of a Hazardous Waste Site," *Risk Analysis* 10, 485-97.

McClelland, Gary H., William D. Schulze, and Don L. Coursey (1993) "Insurance for Low-Probability Hazards: A Bimodal Response to Unlikely Events," *Journal of Risk and Uncertainty* 7, 95-116.

Palm, Risa I., Micheal E. Hodgson, R. Denise Blanchard and Donald I. Lyons (1990) *Earthquake Insurance in California* Westview Press: Boulder.

Tversky, A. and D. Kahneman (1991) "Loss Aversion in Riskless Choice: A Reference-dependent Model" *Quarterly Journal of Economics* 106, 1039-61.

Viscusi, W. Kip (1990) "Do Smokers Underestimate Risk?" *Journal of Political Economy* 98:6, 1253-69.

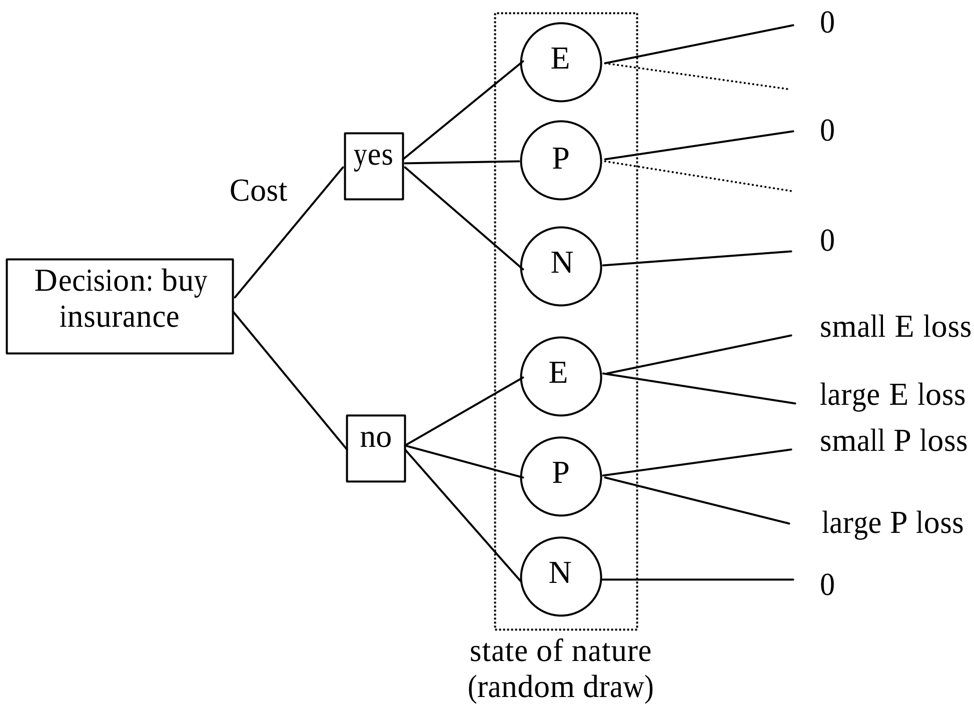


Figure 1 Extensive Form of Game

Table 1
Parameter Values in Experiment Design

PARAMETER	**No.**	**Values**
Costs	5	5, 10, 25, 50, 99
Event Probs (N, P, E)	3	(0.89, 0.1, 0.01) (0.95, 0.04, 0.01) (0.5, 0.4, 0.1)
Loss Probs (small, large)	2	(0.9, 0.1) (0.7, 0.3)
Losses (small P, large P, small E, large E)	3	(0, 100, 100, 500) (0, 200, 100, 500) (0, 200, 200, 1000)

Table 2
Actual verses Expected Event Occurrences

		small periodic		large periodic		small episodic		large episodic	
loss prob	event probs.	expect.	observ.	expect.	observ.	expect.	observ.	expect.	observ.
	.04/.01	.036	.018	.004	.002	.009	.000	.001	.000
low (.1)	.1/.01	.090	.070	.010	.009	.009	.000	.001	.000
	.4/.1	.360	.269	.040	.032	.090	.083	.010	.008
	.04/.01	.028	.013	.012	.006	.007	.000	.003	.000
high (.3)	.1/.01	.070	.060	.030	.032	.007	.000	.003	.000
	.4/.1	.280	.208	.120	.083	.070	.074	.030	.032

Table 3
Estimates of Logit models for Probability of Buying Insurance Policy[a]

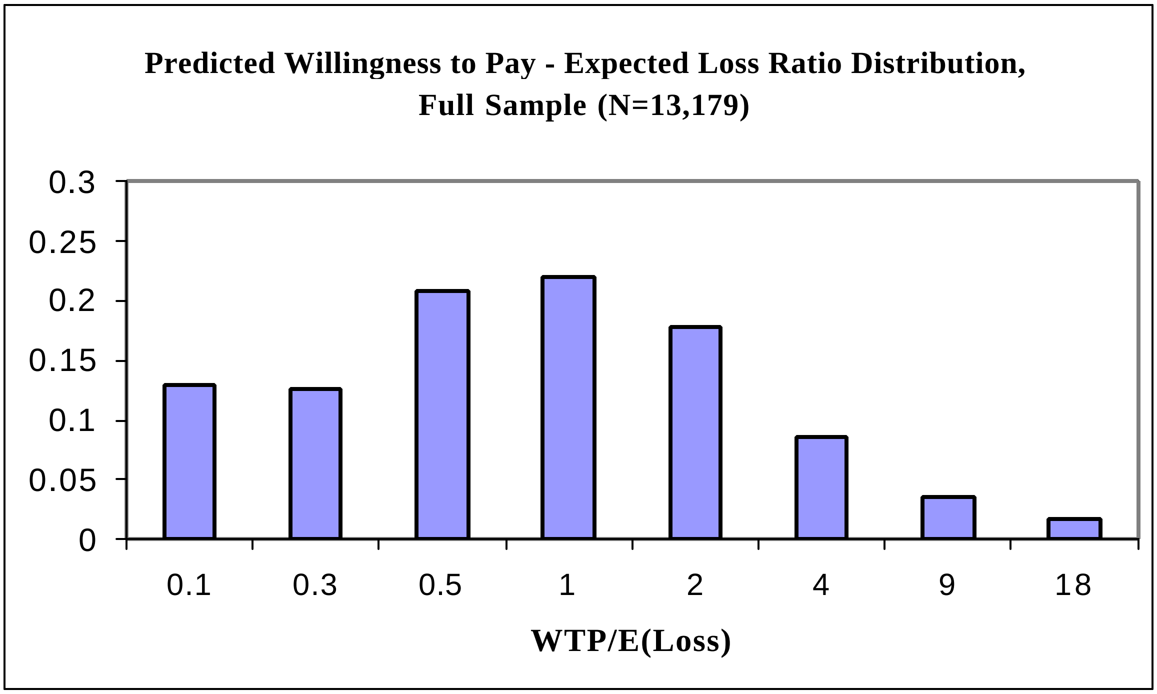
(Variable means given for large, small samples)	(1) All Decisions. Logit Coeff. (t-stat.)	(1) Marginal Effect	(2) Subset of Subjects Logit Coeff (t-stat.)	(2) Marginal Effect	(3) Risk Preference Included, Logit Coeff (t-stat.)	(3) Marginal Effect
Constant	2.16 (23.6)	.489	2.15 (10.4)	.506	3.11 (12.6)	.729
Ln(Cost) (mean=3.35, 3.22)	-.449 (-24.3)	-.102	-.518 (-14.3)	-.122	-.543 (-14.7)	-.127
Wealth (mean=567, 577 tokens)	-.003 (-21.6)	-.001	-.003 (-11.7)	-.001	-.003 (-11.6)	-.001
Exposure (mean=7.80, 7.90 rounds)	.228 (21.7)	.051	.207 (10.9)	.049	.207 (10.9)	.049
Experience (mean=48.5, 33.4 tokens)	-.005 (-22.3)	-.001	-.005 (-9.21)	-.001	-.005 (-8.94)	-.001
Small Loss =(100,100,500) (mean=.348, .328)	.071 (1.45)	.016	.209 (2.06)	.049	.208 (2.03)	.049
Med. Loss =(200,100,500) (mean=.296, .310)	.014 (.27)	.003	.062 (.623)	.015	.055 (.548)	.013
Low Event Pr. = (.04,.01) (mean=.292, .333)	-1.51 (-29.4)	-.341	-1.14 (-9.93)	-.269	-1.20 (-10.3)	-.282
Mid Event Pr. = (.1, .01) (mean=.338, .411)	-1.42 (-27.6)	-.322	-1.49 (-13.2)	-.350	-1.58 (-13.8)	-.372
Low Loss Pr. = (.1) (mean=.562, .674)	-.117 (-2.93)	-.027	.384 (4.23)	.090	.403 (4.39)	.095
Preference for risk index (range 1-6, mean=4.33)					-.194 (-7.76)	-.046
Log Likelihood	-7576		-1983		-1952	
Log Like (β=0)	-8689		-2242		-2242	
sample size	13179		3330		3330	
Correct Prediction:						
Actual (buy)	43%		52%		53%	
Actual (not buy)	87%		76%		78%	

Notes:
a. Dependent variable is binary purchase decision (buy=1) Mean for large sample = .371, mean for small sample = .401.

Table 4
Predicted Probability of Buying Insurance

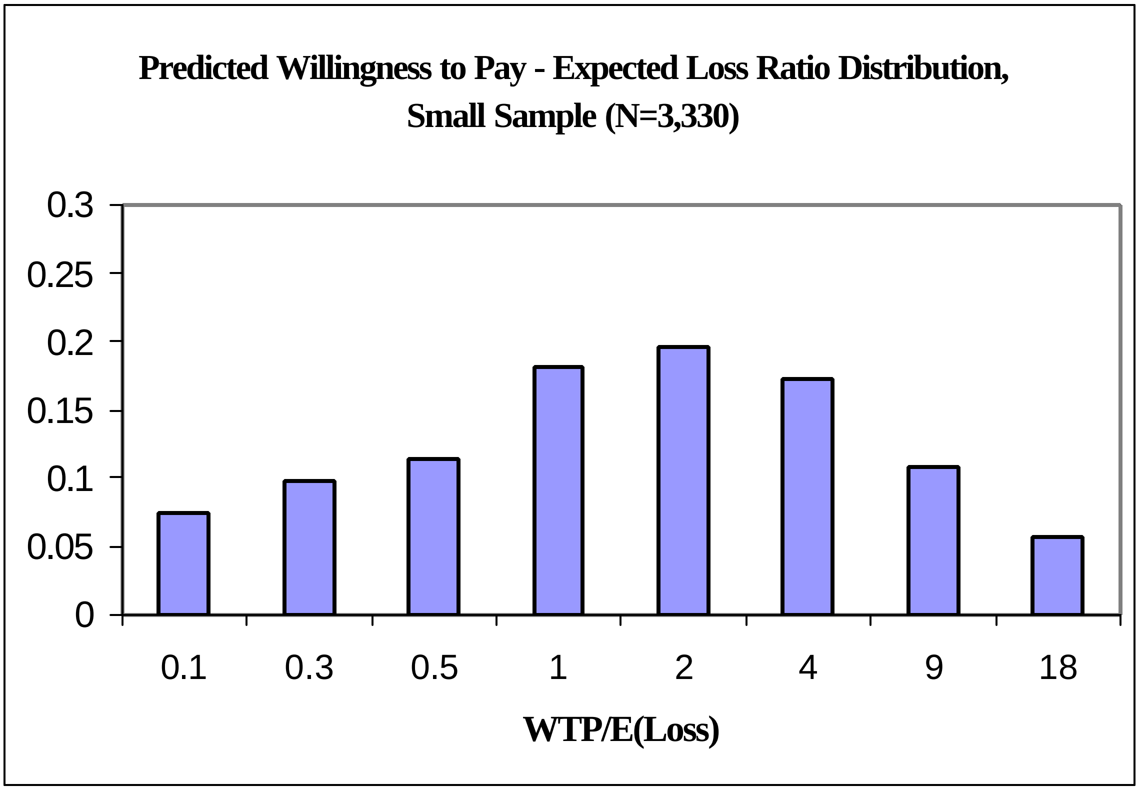
Event and Loss probabilities:	***Loss amounts***		
	low (Large P=100, Small E =100, Large E=500)	**medium** (Large P=200, Small E =100, Large E=500)	**high** (Large P=200, Small E =200, Large E=1000)
Pr(event P) = .04 Pr(event E) = .01 Pr(small loss) = .10	Pr(buy) = .400 (std. err. = .024)	.364 (.023)	.351 (.021)
Pr(event P) = .10 Pr(event E) = .01 Pr(small loss) = .10	.313 (.020)	.281 (.019)	.270 (.019)
Pr(event P) = .40 Pr(event E) = .10 Pr(small loss) = .10	.690 (.023)	.656 (.024)	.643 (.024)

Figure 2(a)



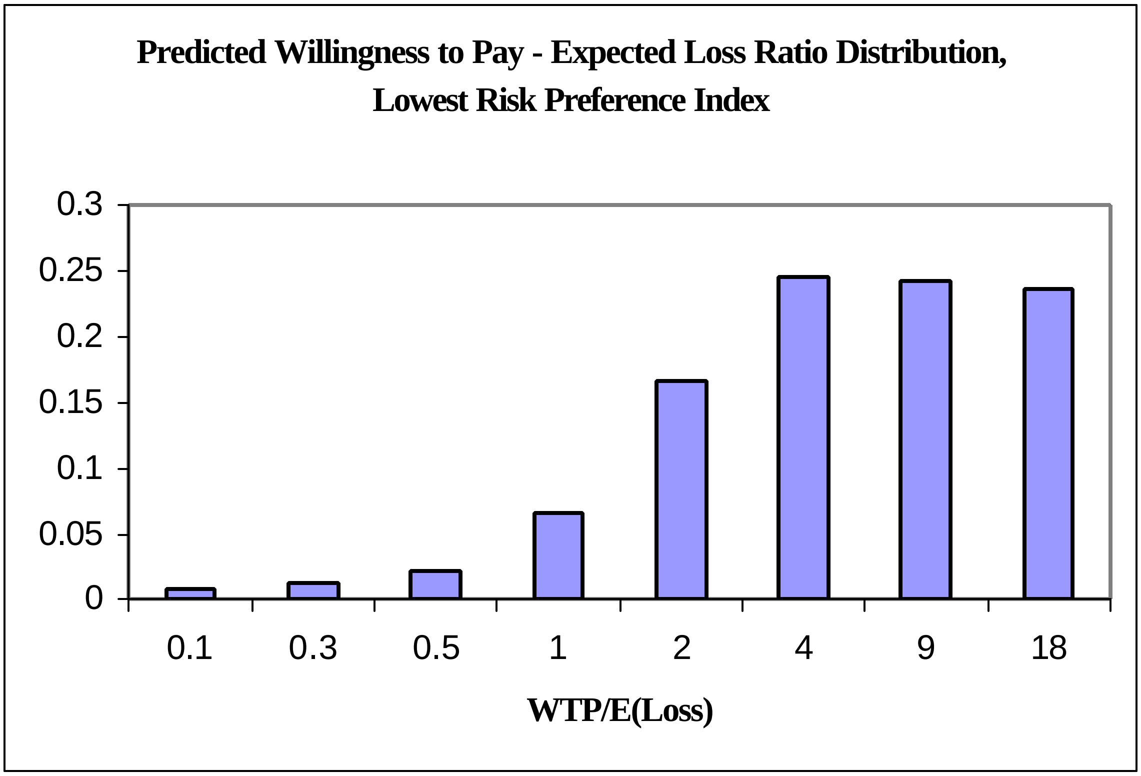
Mean WTP = 47.05
Median WTP=4.41
Mean Ratio = 2.09
Median Ratio=0.84

Figure 2(b)



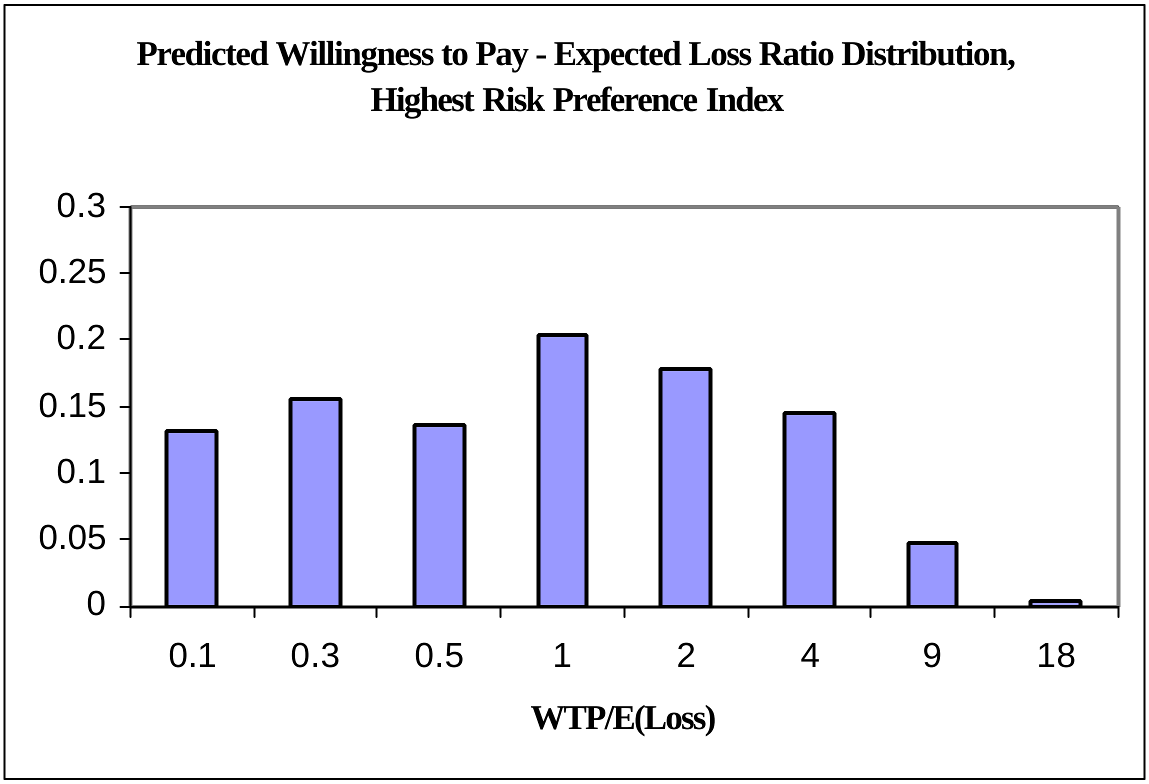
Mean WTP = 40.42
Median WTP = 8.58
Mean Ratio = 3.86
Median Ratio = 1.68

Figure 2(c)



Mean WTP = 38.16
Median WTP = 23.49
Mean Ratio = 11.07
Median Ratio = 6.30

Figure 2(d)



Mean WTP = 20.46
Median WTP = 4.17
Mean Ratio = 1.82
Median Ratio = 0.93

NOTES

[1] Palm, *et al* (1990) provide evidence from a survey of four counties in California that earthquake insurance is purchased by less than 50% of home owners. Data presented in their report also indicates that, on average, insurance premiums collected far exceed payouts for earthquake insurance, despite the often quoted claim by the insurance industry that natural disasters are an uninsurable risk.

[2] McClelland, Schulze and Coursey's focus is more limited than ours. Their main question is whether bids for insurance are different for low probabilities than for high probabilities, but they go on to identify the bimodal bid distribution for low probabilities. While our research does not look at high probability events, many of the issues addressed by MSC are a subset of our research agenda.

[3] Fires provide interesting, albeit scary, examples of this possibility. When fires are fueled by high winds they often display a patchy burn pattern, jumping some houses and consuming others. Hurricanes and tornadoes display this pattern less often.

[4] Due to an artifact of the software, the cost could not be set at 100 tokens.

[5] One of the drawbacks of having an established experimental laboratory at a university and drawing subjects from the student pool, is that over time word-of-mouth establishes payment benchmarks. At the time the experiments were held (1998) a reasonable expected hourly payoff was greater than $10 and nearer $15.

[6] The University has a distinctly varied student body, with a significant number of older, non-traditional students. The average age of students is 27 years. These experiments were conducted during the summer session, increasing the proportion of non-traditional students even further.

[7] A maintained hypothesis of constant relative risk aversion and decreasing absolute risk aversion would tilt the balance of these arguments toward less insurance purchases as wealth increase.

[8] The wealth variable has a mean of 567 tokens which explains the small size of the coefficient. However, a 10% change in wealth would reduce the probability of buying the insurance by about 5 percentage points.

[9] Lottery purchases and bingo choices seem to suffer from this effect, referred to as the gambler's fallacy. (Clotfelter and Cook, 1993)

[10] The 99th percentile for total period losses was 700 tokens.

[11] This explanation, and the reference-dependence explanation, was suggested by an anonymous reviewer.

[12] Those allocated the lowest index preferred a bet with mean of $1 and variance of $0 whereas those assigned the highest index value preferred a bet with a mean of $2 and a variance of $4.