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The Role of Geoscience Information in Reducing Catastrophic Loss Using a Web-Based Economics Experiment

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Executive Summary

What role can geoscience information play in the assessment of risk and the value of insurance, especially for natural hazard type risks? In an earlier, related paper Ganderton and others (2000) provided subjects with relatively simple geoscience information concerning natural hazard-type risks. Their research looked at how subjects purchase insurance when faced with relatively low probability but high loss risks of the kind that characterize natural hazards and now, increasingly, manmade disasters. They found evidence to support the expected utility theory (definitions of economics terms can be found in a glossary at the end of report), yet there remained the implication that subjects with excessive aversion to risk were willing to pay considerably more for insurance than the actuarially fair price plus any reasonable risk premium. Here, we report the results of additional experiments that provide further support for the basic postulates of expected utility theory. However, these new experiments add considerably to the decision environment facing subjects by offering an option to purchase geoscientific information that would assist them when calculating expected losses from hazards more accurately.

Using an Internet-based mechanism to present information and gather data in an experimental setting, this research provided subjects with considerable textual and graphical information, and time to process it. Over a period of three months, almost 400 subjects participated in on-line experiments that generated approximately 22,000 usable data points for the empirical analysis discussed in this report.

In the design of the experiment, we modeled the decisions to purchase (1) a detailed map giving subjects more information regarding the distribution of losses from a hazard and (2) insurance to indemnify them from any losses should they occur. On the basis of this design, we find strong evidence in support of the expected utility theory. Many of the findings reinforce those found in the early, similar study (Ganderton and others, 2000). However, this research also finds interactions between the decision to become better informed and the decision to insure. We chose an empirical framework that allows for both explicit and implicit (unobservable) correlations between the two decisions. The results suggest that at the end of the computer game subjects recognize the benefits of greater geoscience information. They take advantage of it, but are sensitive to its cost. When subjects use the more detailed information, they are more likely to purchase insurance when it offers a net benefit.

The Role of Geoscience Information in Reducing Catastrophic Loss Using a Web-Based Economics Experiment

By Richard L. Bernknopf[1], David S. Brookshire[2], and Philip T. Ganderton[3]

Introduction

Natural hazards present both organizations responsible for protecting public safety and organizations that protect private individuals with the most serious risk-management problems. Nature is often seen as a random force, and although considerable progress has been made to model and predict natural hazard and disaster risk, events such as earthquakes, tornadoes, fires, and floods continue to wreak havoc on an increasingly dense and resource-rich social and economic environment (Kunreuther and others, 1999).

Risk management is most generally a set of policies and practices designed to assess and affect risk to human life, social and economic activities, and the natural environment (Carnegie Commission, 1993). The risks from natural hazards (as well as other, manmade hazards) have the following elements:

(1) A probability distribution for the natural event defined over intensity, severity, duration, magnitude, or other measures;
(2) A probability distribution for the event defined over time;
(3) Some process that converts natural hazard events into actions that impact human life and activity (for example, an engineering relationship that links ground movement with building collapse or rainfall and local geography with landslides and subsidence); and
(4) A geographic distribution of human and economic losses attributable to the natural hazard event (Platt, 1999).

The two main mechanisms for addressing the problems of natural hazards are mitigation and insurance. Insurance is most effective when the probability distribution of the event is well known, when linkage to loss is direct, and loss is well specified. Some examples are auto insurance, homeowner's insurance, and life insurance. Insurance is least effective when the calculations required to assess the net benefits accruing from insurance coverage are difficult or impossible to make. Natural-hazard insurance is relatively uncommon because of difficulty in describing the event probability distribution over space and time. This problem is exacerbated by the great variance in the losses experienced across both dimensions from a single natural disaster and the relatively high premiums that insurance companies must charge given the low take-up rates for this type of insurance.

This report presents the findings of a research project designed to study the role improved geoscience information might play in the assessment of risk and the value of insurance, especially for natural-hazard-type risks. Earlier, we investigated the response of subjects to relatively low probability but high-loss risks of the kind that characterize natural hazards (Ganderton and others, 2000). Those experiments provided evidence for support of the theory that subjects are making decisions to maximize expected utility. Results from experiments reported here provide further support for the postulates of expected utility theory. In addition, the richer choice environment provided to subjects in the experimental setting allows more detailed study of the factors influencing risk assessment and insurance purchase.

The research reported does not consider the decision to invest in mitigation rather than purchase insurance.[4] However, it does investigate a mechanism by which people can make better decisions regarding insurance purchases by utilizing detailed information on the probability distribution of hazardous events and losses. In this sense, obtaining better information using detailed maps of either probabilities of loss or size of loss plays a complimentary role to insurance just as mitigation can.

Elements of the Program

The research program contains 5 basic elements:

(1) The use of maps to provide varying types of information,
(2) The use of a web interface to provide and collect data,
(3) The use of experimental-economics games to create scenarios and value,
(4) Investigation of the choices of mitigation and insurance, and
(5) Variation of treatments to allow econometric analysis of data.

The current study implements elements 1, 2, 3, and 5.

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[4] The logical next step for this research would be to study the affect of better geoscience information on the choices between insurance and mitigation.

It is essential for organizations such as the U.S. Geological Survey (USGS) to provide geoscience information that passes a reasonable benefit-cost test. To do this the USGS needs to assess the value placed on its geoscience information (Bernknopf and others, 2001; Bernknopf and others, 1997; Bernknopf and others, 1988). To further this agenda, the research reported here explicitly includes geoscientific information concerning the probability distribution and size of losses in a decision model of insuring against property risks.

Traditionally, experimental economists have employed laboratory settings for their experiments (Hagel and Roth, 1995). Even the nomenclature encourages subjects to consider themselves part of an experiment. Despite the greater control over the environment provided by real-time laboratory settings, many administrative and organizational difficulties limit the size of the subject pool and the amount of data collected in a reasonable time.

There is an increasing need to provide subjects with an experimental interface that is interactive, maintains their interest, gives them flexibility, and provides them control over elements of the experiment they can access. Subjects are loath to sit in laboratories waiting for slow computers to provide them with inadequate information to do the experiment properly. Although researchers must give up a certain level of control over subjects, the Internet provides a wonderful interface for supplying subjects with considerable information and it allows them to participate at their own pace, obtaining information in a controlled way, as they require it. Our experiments also suggest that the Internet is a very cost effective means of data collection.

The natural progression from previous work looking at the purchase of insurance against natural-hazard-type risks with no spatial reference to the hazard is one that includes geoscience information in the decision environment of subjects. Ultimately, this information not only helps with the decision to purchase insurance, it also assists with the decision to invest in mitigation activities. Further experiments will continue this progression by adding a mitigation option to the current map and insurance setting.

Many observations are required to provide a statistical basis for drawing conclusions from any empirical analysis. Because of our desire to model a relatively large number of treatments in order to provide a reasonable variation in explanatory factors for the econometric analysis, and to investigate a wider range of questions, we needed to collect a large number of data points. Our results support the use of Web-based experiments as a cost-effective time-efficient mechanism for gathering large amounts of data.

Experiment Design

We gathered data for this analysis using the web-based experiment discussed above. The structure of the website is given below:

(1) Login, or register and login.
(2) Questionnaire regarding insurance use and simple demographics.
(3) Miniexperiment designed to elicit independent measure of subject's risk aversion.
(4) Main experiment generating data on insurance and information purchase.
(5) Generate claim check and exit from experiment.

Appendix A provides screen captures from the Web site. Included are many of the introductory and welcome pages as well as the main decision page providing all relevant information to the subject. Given the nature of the Internet and people's experience and practice with websites, the experiment was set up such that subjects were able to exit and reenter the experiment at any time, their progress through the experiment monitored to prevent retaking any previously completed section, and completion of the experiment was required to generate a claim check for payment.[5]

The main experiment implements the study design to confront subjects with a risky scenario in which they can purchase a more detailed risk map and purchase full indemnity insurance if they choose. Subjects face the same kind of risk repeatedly, but with differing loss probabilities and loss amounts. A detailed flow chart of the design of the main experiment appears in appendix B, and table 1 provides a summary.

We fixed the number of games at 15 and subjects are told this in advance. Within each game there are a random number of periods. This is chosen at the beginning of each game, as are certain parameters used as treatments in the experiment. These include the cost of the map, one from a set of two values: 10 tokens and 20 tokens, representing 5 percent and 10 percent of period income. The insurance premium is also chosen from a set of two values representing, 10 percent and 20 percent of period income. In addition, the maps shown to the subject are variable; two sets were available. The subject's location on the map was chosen at random from a possible 36 sites on the map and indicated by a dot in the center of a cell. The hazard level at that location is implied in the coarse map and displayed in the detailed map (more on this later). Each period the subject receives a constant income of 200 tokens. Appendix B gives the text of the introduction provided to subjects.

There are a random number of rounds within each period, ranging between 2 and 4. The subjects are decision makers within these rounds, deciding on the purchase of a more detailed map than the one shown initially. The coarse map in figure 1 shows four large cells of equal size. Each cell is colored uniformly with the color of the dominant cells that lie within that larger cell (fig. 1*A*).

Each large cell actually contains 9 smaller cells, each colored one of three colors to indicate the amount that would be lost were a hazardous event to occur (fig. 1*B*). For example, there may be 5 red cells of highest loss, and 4 orange cells

[5] This feature introduces an interesting, although subsidiary, treatment to this experiment, where some subjects completed the experiment but did not claim their payment, while others did. In real-time laboratory experiments, all participating subjects are generally paid as they leave the experimental session.

Table 1. Experiment Structure.

GAME	PERIOD (within each game)	ROUND (within each game)
15 games	*between 2 and 6 periods*	*between 2 and 4 rounds*
Following values set: map cost (2) insurance premium (2) map (2) location on map (36)	loss probability (3) loss amount (2) Income increased each period by constant amount	Subject can choose to buy map or insurance, both, or neither

of moderate loss. The subject may be located in an orange cell. If the subject only sees the coarse map they will get the false impression that they are in a red cell, since red is the dominant color of the cells contained within. If the subject purchases the detailed map, it remains in effect for the entire game, since the subject's location is chosen at the start of each game, and remains fixed for that game.

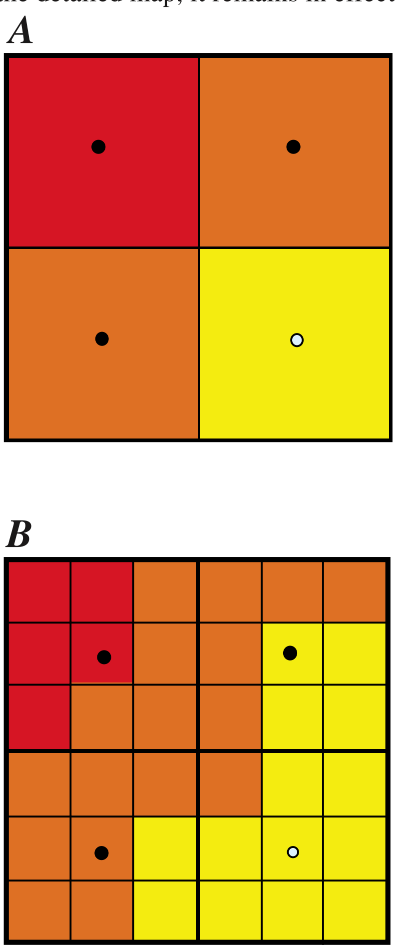

Figure 1. Maps of a natural hazard and severity of loss at two scales. Color of zone is determined by modal hazard in that zone, yellow corresponds to low loss, orange to medium loss, and red to high loss. Highlighted point indicates subject location. This map determines actual losses in experiment.

The subject can also purchase insurance. This insurance fully compensates the subject in the case of a loss. Insurance covers the entire period and can be purchased during any round within that period. Having purchased both the detailed map and insurance, the subject can make no more decisions that period, and the experiment progresses through the remaining rounds in the period automatically, stopping each period to inform the subject of any event that may have occurred that round, and requiring a mouse click to proceed with the experiment.

Each round, the computer program draws a random number from an integer set determined by the event probability. For example, if the probability of a hazardous event occurring is 0.01, the program chooses a random number from the uniform distribution U[0,99], and if the number equals a prechosen and fixed integer, say 11, the event occurred, otherwise no hazardous event occurred. The program shows the results of the draw to the subject each round, and the subject must click to continue (see appendix E for a screen capture of this page).

The subject proceeds through the experiment accumulating income each period, and spending it on map purchases or insurance premia or self-insurance. Losses without insurance can be quite large relative to both period and accumulated income. Although the probability of a hazardous event is the same for every location within a round, each location is identified in the map as having a potential loss amount of small (yellow), moderate (orange), or large (red.) The two alternative loss amount distributions are {10, 100, 1,000} and {100, 1,000, 10,000}. With event probabilities for each time period of (0.1, 0.01, 0.001), the expected loss can range from 0.01 token to 1,000 tokens, and actual losses can range from 10 to 10,000 tokens making bankruptcy a possibility.[6] The maximum possible accumulated income for a subject is 18,000 tokens at the end of the experiment, so uninsured losses of 1,000 or 10,000 can represent a considerable proportion of the subject's accumulated income during the experiment.

[6] A subject who goes bankrupt during a period is required to sit out the remaining rounds and continues the experiment with the next round income of 200 tokens. All previous income is lost.

The subject's accumulated income at the end of any round is calculated using the following equation:

New balance = max{0, old balance + NEWPER *200 – BUYMAP*MCOST – BUYINS*ICOST – (1-BUYINS)*L*
[(RED)*High Loss value (for example, 10,000) +
(ORANGE)*Med Loss value (for example, 1,000) +
(YELLOW)*Low Loss value (for example, 100)]}

where
NEWPER = 1 if beginning of a new period
BUYMAP = 1 if purchased detailed map this round
BUYINS = 1 if purchased insurance this round
MCOST = cost of map
ICOST = insurance premium
L = 1 if hazardous event occurred
RED = 1 if subject located in red cell
ORANGE = 1 if subject located in orange cell
YELLOW = 1 if subject located in yellow cell

Code on the website writes a comprehensive set of data to a database each round, including all parameters, subject decisions, and outcomes. Values from previous rounds are stored and used in calculations provided to the subjects in following rounds, even if the subject exits the experiment midway through and returns to the website later.

The relatively complex scenario faced by the subjects has two important features. The first is that the experiment attempts to create a decision environment with complexity approaching that of the real world environment modeled. We can think of each game as a person's lifetime, each period a year within that life, and each round a day within that year. Natural hazards are infrequent events (even 1/1,000 is a relatively high probability of occurrence for some hazards), but losses are often very large (and cause death or economic hardship akin to bankruptcy). The second feature of the experiment is a relatively rich treatment specification to be estimated econometrically. There are 48 possible treatment combinations in the experiment. Additionally, subjects have two decisions to make at any time during each game—(1) to purchase the detailed map and (2) to purchase insurance. In the next section, we investigate the empirical model that provides a link between the risk-event parameters and the subject's insurance decisions.

The experimental design and the website operation were extensively pretested using subjects invited into a live laboratory session. Testers received a flat fee to compensate them for their time and were asked to login to the website and play the game. The timing of certain events was recorded in a log, and testers were asked to answer some post-experiment debriefing questions. An open discussion with the researchers followed the experiment. An exchange rate providing adequate compensation for a subject's time was chosen using results from the pretests.

The Empirical Model

In these experiments, each subject acts independently, attempting to maximize the earnings from the experiment as a return on the investment of time and effort at the website. The subject faces two decisions each round, but the consequences of each decision remain with the subject for subsequent rounds within periods or games. Having purchased insurance, it cannot be purchased again until the current period is finished. Having purchased the detailed map, it cannot be purchased again until the current game is finished.

The decision to purchase insurance is based on the following comparison for a risk neutral subject:

BUY policy if Cost (C) $\leq$ Expected Loss (EL), (1)
and a risk averse subject would be prepared to pay more than the cost of the policy to avoid facing the gamble, that is

BUY policy if $C \leq EL + \pi(R, W)$, (2)
where π is the risk premium that depends upon the subject's attitude to risk (R) and possible wealth (W). The more risk averse the subject is, the greater π will be, and the more likely a subject will be to purchase insurance even when it costs more than the expected loss of the gamble.

The expected loss (EL) is the probability of loss multiplied by the amount of the loss. In most cases, the decision maker does not know these two elements, particularly the probability distribution associated with the loss-causing event. For some risks, the loss is well specified, such as personal property, but for others even the loss is poorly defined, such as injury in an accident or economic losses in a flood. Consequently, the calculation of expected loss when faced with a risk is determined in large part by the information available regarding the losses and probability distribution of loss. The expected loss calculation is predicated on sufficient information regarding the components required to perform the calculation, otherwise the expected loss is at best an educated guess. In the current experiment, the probability of the loss event is well defined, but the loss is ill defined when the subject can only observe the coarse map (fig. 1*A*). The subject can draw quite incorrect conclusions from the coarse map. For example, if the location dot is inside a large RED cell, the subject may conclude that expected losses are Pr(loss) × Loss(RED), where Pr is probability, a relatively large value when compared to the actual expected loss. The actual expected loss is Pr(loss) × Loss(YELLOW) after purchasing the detailed map and seeing that the location was in a smaller YELLOW cell (fig. 2*B*). The decision to purchase the detailed map is therefore based on the potential benefits a subject expects from greater information about the spatial distribution of loss amounts and location within that space. The subject will compare the cost of purchasing the map with the benefits of a potentially more accurate calculation of expected losses from the hazard.

The empirical model entails two equations, one to explain the decision to purchase a map, the other the decision to purchase insurance. What is the proper way to model the interaction between these two decisions? If the decisions are alternatives, then a random utility model (RUM) framework would seem appropriate. However, they are essentially complementary, not substitute, decisions. The more detailed map aids in making the insurance decision. The decisions are not independent, but they are not alternatives, hence modeling them as simultaneous equations with possibly correlated errors seems more appropriate. Greene (2003) outlines the methodology for estimating a Bivariate probit model, and STATA (2001) allows the estimation of two alternative forms of the model, one in which both decisions are functions of the same set of variables, and another using the seemingly unrelated regression form allowing for different sets of regressors for each decision. We can also perform a Wald test for the hypothesis that the decisions are unrelated.

We model each decision as a function of the variables specifying (1) the cost of the decision, (2) the expected loss from the hazard, (3) the potential for over- or under-estimation of the risk, (4) historical decisions and outcomes, and (5) a measure of the wealth of the subject at the time of the decision. Expected utility theory would suggest the following impacts of these factors on the decision to purchase insurance: (1) higher premiums should decrease the probability of purchasing insurance and (2) higher loss amounts or higher loss probabilities should increase the probability of buying insurance. Having a map that indicates a higher loss amount than is actually the case at the location should increase the probability of buying insurance. While not explicitly indicated by the expected utility theory, other factors may play a part in determining the insurance purchase decision, such as past behavior. If subjects display adaptive behavior or base their decisions on past behavior, past insurance purchases should increase current insurance purchases. The wealth of the subject may affect insurance purchase if self-insurance is more likely as wealth increases. Additionally, other factors linked to the subject's attitudes to risk may impact the decision. We include some of these factors as measured in the survey in the empirical analysis. The decision to purchase the detailed map should be positively related to lower map costs, to a higher expected loss, and to experience because these factors raise the expected net benefit from the detailed map on the expected loss calculation.

Data Analysis and Interpretation

Over a period of three months approximately 398 subjects registered for the experiment, and 362 completed the main experiment, generating 23,099 observations. We paid a total of $2,800 to 268 subjects before the experiment website was closed down. Each subject contributed an average of 58 observations to the dataset. Because each subject played 15 games, there was an average of 3.87 periods per game. As there are no decisions made at the level of rounds within periods, the data were collapsed to the period level even though a total of 66,221 draws of the random hazardous event were made during the experiment.[7]

Table 2 lists the variables used in the empirical analysis and provides definitions for these variables. The first set of variables gives some descriptive statistics for the sample of subjects participating in the experiment. More than half were female (56.7 percent) and nearly one-third were 30 years or older (29.8 percent). Slightly more than half of the subjects held health insurance (51.5 percent), 35.7 percent had either home owner's or renter's insurance and nearly two-thirds had auto insurance (66.5 percent).[8] Just less than 3 percent of subjects had any form of hazard insurance, which includes flood insurance, a requirement for a mortgage in areas in or near arroyos in the desert southwest.

Table 2 also gives other statistics for the experiment. The actual occurrence of hazardous events matches the mean probability of a hazardous event occurring in the model (0.037). Bankruptcy was a relatively rare event (0.006). The detailed map was purchased more frequently than was insurance (0.626 verses 0.471). By comparison, the rate of purchasing insurance in a previous experiment with similar parameters (Ganderton and others, 2000) when the detailed map was not available was between 0.371 and 0.401.

As discussed above, a bivariate probit model was chosen to model the decision to purchase the detailed map and purchase insurance against loss. The results of alternative specifications appear in table 3. The preferred model based on statistical inference is shown in column (1) of the table, with other specifications provided for comparison. There are two basic specifications of the bivariate probit model—(1) the BiProbit (BP) where both decisions are considered functions of the same set of explanatory variables, and (2) the Seemingly Unrelated BP, where each decision equation can be specified with separate sets of explanatory variables.

For most models, we give two estimates—one named Cluster, the other No Cluster. Because each subject generates more than one observation for the analysis, there is potential for nonindependent observations and correlated errors.

The coefficient estimates for the Cluster and No Cluster models are identical, but the standard errors are considerably smaller for the Cluster estimates. This suggests that explicitly modeling the within-subject error correlations results in more efficient estimates of the coefficients. Despite this, the parameter estimates are quite robust to the No Clustering/Clustering specification.

Estimates for rho, the correlation of errors between the two equations, are provided in the tables. There are statistically significant correlations between the errors of the map

[7] A statistic testifying to the power of the Internet as a mechanism for conducting experiments. It would take a considerable effort to generate more than 66,000 draws from a bingo cage in a laboratory experiment, especially with student subjects.

[8] This is in a state in which auto insurance is mandatory, but the sample mean is slightly above the State mean of 60 percent of drivers that have auto insurance.

Table 2. Definitions and summary statistics for variables used in analysis.

Variable name	Variable description	mean[1]	std dev[2]
Idnum	subject identifier		
Status	indicates section of web completed		
Payout	indicates if subject collected payment	0.675	
Healthins	indicates if health insurance held	0.515	
Houseins	indicates if home or contents insurance held	0.357	
Cairns	indicates if auto insurance held	0.665	
Hazins	indicates if hazard (including flood) insurance held	0.028	
Insscore	count of insurances held (range 0-6)	2.05	0.081
q5	indicates if subject is female	0.567	
over30	indicates if subject aged 30 or older	0.298	
Number	count of periods in each game	4.47	0.017
Mapcost	cost of purchasing detailed map	15.1	0.073
insurancecost	cost of purchasing insurance (premium)	29.9	0.148
totalbalance	balance of account	5234	51.7
Mapb	indicates map A shown (rather than map B)	0.491	
Lossamt	potential loss at location	1855	64.5
Outcome	hazardous event occurred	0.037	0.003
lossprobability		0.037	0.001
Bankrupt		0.006	0.001
mapbought	1=yes	0.626	0.020
insurancebought	1=yes	0.471	0.014
maphloss	actual loss is higher than coarse map shows	0.021	0.002
Maplloss	actual loss is lower than coarse map shows	0.110	0.007

[1]Mean not provided for ID type variables.

[2]Standard deviation not given for binary variables.

purchase and insurance purchase decisions in all model specifications except for the preferred model (table 3, column 1). Note, however, that this is quite consistent with the proposition that insurance purchase is dependent in part on map purchase. The test is for the correlation between factors influencing the two decisions, but not included as explanatory variables in the two equations. Equation 1 includes a sufficiently rich set of explanatory variables for the two decisions that no unexplained correlation remains between the two equations.

A simple specification for the two decisions is provided in column 5 of tables 3. This provides a set of explanatory variables based on a strict interpretation of the expected utility theory. Only decision costs and expected loss variables are included. The occurrence of misleading information in the coarse map is also included in the equations as this directly affects the accuracy of the expected value calculations. The equation for the decision to purchase a detailed map shows that map cost or insurance cost has no impact on buying a map. A map is more likely to be bought the higher the probability of a loss and the lower the loss amount. Potential errors from using only the coarse map (for example, by reading the map and concluding the loss is higher or lower than it actually is) reduce the likelihood of buying a detailed map. There is some difficulty in interpreting this variable, as the subject cannot know if the coarse map is revealing the true loss amount or not, and once the detailed map is purchased, the issue of any error in loss reporting in the coarse map is of no importance to the subject's decision to purchase the map. It is therefore not surprising that the results of these variables in the map purchase equation are mixed.

Map information and interpretation errors have more significance in the insurance purchase decision. Considering the insurance purchase decision (table 3*B*, column 5) we observed that although the map cost is not important, the higher the cost of insurance the less likely subjects are to buy coverage. The higher the probability of loss the more likely is the purchase of insurance, as it is when the amount of the loss is greater. The potential map errors are statistically significant in this equation, and when the actual loss is lower than what is shown by the coarse map, the subject is likely to overestimate the probability of a loss and more likely to purchase insurance (coefficient estimate is +0.182). When the actual loss is higher than what is shown by the coarse map, the subject is likely to underestimate the probability of a loss and less likely to purchase insurance (coefficient estimate is –0.259). In summary, the simple models in column 5 of each table perform reasonably well as explanations of the decisions and are consistent with the predictions of the expected utility theory.

Columns 3 and 4 present estimates of a BiProbit model with and without correction for the panel nature of the data gathering process. This adds to the simple model a richer specification of the decision environment facing the subjects. In particular there are variables indicating past decisions by subjects, and some demographic variables are included. Map cost is important in determining whether a subject purchases the map, and the sign of the coefficient is consistent with expectations. Once accounted for, clustering makes the cost of insurance insignificant. The higher the probability of loss the more likely is the purchase of the detailed map. The effect of uncertainty from the coarse map remains in these models of the map purchase decision. Subjects display some habitual behavior in that they are more likely to buy a map this game if they purchased one last game and more likely to buy a detailed map if they bought insurance last period. Past losses and bankruptcies are not statistically significant factors in map purchase, nor are factors indicating if the subject holds insurance policies outside the experiment. Age does not appear to be a factor in map purchase, but females are less likely to buy maps than males. The coefficient on the wealth variable (the natural log of accumulated experiment wealth) is negative and statistically significant. Although this result may be interpreted as evidence for less need of map information as subjects get wealthier, wealth is more likely a proxy for experience with the game, because for most subjects in this experiment, wealth increases as the game progresses. Interpreted this way, the negative coefficient indicates that subjects are less likely to buy the map the more they play the game because they see it offering little marginal benefit. This behavior may also be a reflection of increasing confidence leading to overconfidence as the game progresses and nears completion.

Table 3B presents estimates for the BiProbit model for insurance purchase in columns 3 and 4. Although map cost is not important in determining the decision to purchase insurance, the cost of insurance is negative and statistically significant. Whereas higher premiums decrease the probability of buying insurance, higher losses and more likely losses increase the probability of buying insurance. All these impacts are consistent with the expected utility theory. As was the case with the simple model, decision errors based on the coarse map are consistent with subjects buying more insurance when they overestimate the size of the loss and buying less insurance when they underestimate the size of the actual loss. Insurance purchase displays some habitual behavior, while past losses and bankruptcies are not statistically important factors. Insurance coverage outside the experiment, as a measure of the subject's risk aversion, shows a statistically significant positive impact on the decision to buy insurance in the experiment. Age does not influence insurance purchase but in contrast with the map buying decision, females are more likely to buy insurance. Could it be that females are more confident in interpreting the map information and therefore do not need the detailed map, but are more risk averse than males and hence more likely to buy insurance?[9] Also in contrast to the impact on the map purchase decision, the wealth variable has a statistically significant but positive effect on the decision to buy insurance. In previous experiments of a similar nature, Ganderton and others (2000) found wealth to exert a negative effect on insurance purchase. Here, the subjects have better information on which to base their insurance decision in the form of the detailed map, and they do not self-insure as they become wealthier, nor do they assess the risks as being lower as their confidence builds with experience playing the game. On average, a map costs half what insurance costs, so maps could be showing an inferior income effect, whereas insurance shows a normal income effect.

As stated earlier, the preferred model is shown in column 1. The model in column 2 is the same specification but does not account for within-subject correlations that are reflected in excessively large standard errors. This model finds no statistical correlation between the errors in the map and insurance purchase decisions. Variables measuring map errors have been omitted from the map purchase equation since they really have no relevance as argued above. Results for these variables are mixed in this equation, and the interpretation of their impact is unclear at best. The lack of any significance for the variables indicating insurance activity outside the experiment recommends omitting these variables from the map buying equation. Column 1 of table 3*A* shows map purchase to be less likely at higher map cost, and insensitive to insurance cost and loss amount. A subject is more likely to purchase the detailed map when the probability of a loss is high. Those who previously bought maps and insurance are more likely to purchase maps.

Using equation 1 for both map purchase and insurance purchase, table 4 presents estimates of the marginal effects of each variable on the joint probabilities of buying the map and insurance. Table 4, column 1 shows the influence of each variable on the joint probability of buying both the detailed map and insurance. Increases in both the cost of the map and insurance decrease this probability, but by far the strongest impact on the joint probability is the probability of loss. Increases in the size of the potential loss also increase the joint probability of purchasing the map-insurance bundle, but the effect is substantially smaller than for changes in the probability of loss.

[9] Or could this be evidence that females appreciate maps less than males?

Table 3*A*. Bivariate probit analysis of decision to buy detailed map (simultaneous estimation)[1].

	Seemingly Unrelated Bivariate Probit		Bivariate Probit		
	Cluster[2]	No Cluster	Cluster	No Cluster	Cluster
Equation Variable	(1)	(2)	(3)	(4)	(5)
Buy Map					
Constant	**–0.442**[3] (–2.69)	**–0.442** (–5.63)	0.129 (0.72)	0.129 (1.44)	**0.781** (7.02)
Map cost	**–0.017** (–3.85)	**–0.017** (–8.70)	**–0.014** (–2.69)	**–0.014** (–6.07)	–0.005 (–1.11)
Insurance cost	0.004 (0.00)	**0.004** (4.06)	0.004 (0.03)	**0.004** (3.55)	0.003 (1.43)
Log(loss amount)	–0.001 (–0.11)	–0.001 (–0.23)	**–0.050** (–4.70)	**–0.050** (–8.92)	**–0.043** (–4.12)
Loss probability	**1.02** (4.37)	**1.02** (4.56)	**0.872** (3.41)	**0.872** (3.48)	**0.870** (3.93)
Actual loss lower than coarse map shows			**–8.58** (–139)	–8.58 (0.0)	**–7.49** (–153)
Actual loss is higher than coarse map shows			**–8.76** (–45.7)	–8.76 (0.0)	**–7.32** (–139)
Buy map last game	**1.87** (28.7)	**1.87** (92.5)	**1.84** (26.5)	**1.84** (81.2)	
Buy insurance. Last period	**0.137** (3.37)	**0.137** (6.72)	**0.177** (4.15)	**0.177** (7.71)	
Suffer loss last period	0.062 (1.16)	0.062 (1.26)	0.084 (1.40)	0.084 (1.48)	
Bankrupt last period	–0.252 (–1.59)	–0.252 (–1.59)	–0.292 (–1.69)	–0.292 (–1.70)	
Log(total a/c balance)	**–0.031** (–2.57)	**–0.031** (–4.56)	**–0.041** (–3.05)	**–0.041** (–5.51)	
Insurance score			0.005 (0.20)	0.005 (0.56)	
has hazard insurance			–0.016 (–0.09)	–0.016 (–0.23)	
Female	**–0.141** (–2.17)	**–0.141** (–6.97)	**–0.164** (–2.43)	**–0.164** (–7.16)	
Age 30 or older	0.082 (1.16)	**0.082** (3.75)	0.078 (0.98)	**0.078** (2.80)	

[1] Estimates are full information maximum likelihood.

[2] Clustering allows for correlated errors within observations from the same subject, but none across subjects.

[3] Coefficients in bold are statistically significant at the 5 percent level. The number in parenthesis is the t-statistic for significance that is estimated as the coefficient/standard deviation of the coefficient.

Table 3*B*. Bivariate probit analysis of decision to buy insurance (simultaneous estimation).

	Seemingly Unrelated Bivariate Probit		Bivariate Probit		
	Cluster	No Cluster	Cluster	No Cluster	Cluster
Equation Variable	(1)	(2)	(3)	(4)	(5)
Buy Insurance					
Constant	**–2.28**[1] (–20.7)	**–2.28** (–33.6)	**–2.62** (–20.9)	**–2.62** (–33.3)	**–1.39** (–13.3)
Map cost	0.004 (1.58)	**0.004** (2.00)	0.003 (1.24)	0.003 (1.56)	0.005 (1.53)
Insurance cost	**–0.004** (–3.16)	**–0.004** (–3.96)	**–0.003** (–2.99)	**–0.003** (–3.73)	**–0.004** (–2.68)
Log(loss amount)	**0.187** (18.4)	**0.187** (37.9)	**0.185** (18.0)	**0.185** (37.6)	**0.198** (16.7)
loss prob.	**9.34** (19.2)	**9.34** (43.3)	**9.38** (19.3)	**9.38** (43.6)	**8.16** (17.7)
Actual loss lower than coarse map shows	**0.322** (7.32)	**0.322** (9.40)	**0.243** (5.23)	**0.243** (7.69)	**0.182** (2.53)
Actual loss is higher than coarse map shows	–0.075 (–1.00)	–0.075 (–1.15)	**–0.152** (–2.09)	**–0.152** (–2.37)	**–0.259** (–2.63)
Bought map	**0.241** (3.48)	**0.241** (7.56)			
Buy map last game			**0.135** (3.22)	**0.135** (6.66)	
Insured last period	**1.113** (23.41)	**1.113** (58.4)	**1.12** (23.7)	**1.12** (59.1)	
Suffered loss last period	–0.066 (–1.34)	–0.066 (–1.45)	–0.063 (–1.26)	–0.063 (–1.37)	
Bankrupt last period	0.289 (1.83)	**0.289** (2.01)	0.273 (1.71)	0.273 (1.90)	
Log(total a/c balance)	**0.058** (6.98)	**0.058** (9.13)	**0.056** (6.63)	**0.056** (8.83)	
Insurance score	**0.041** (2.08)	**0.041** (5.96)	**0.042** (2.08)	**0.042** (5.99)	
Has hazard insurance	–0.100 (–0.50)	–0.100 (–1.71)	–0.099 (–0.49)	–0.099 (–1.70)	
Female	**0.183** (3.24)	**0.183** (9.59)	**0.175** (3.10)	**0.175** (9.23)	
Aged 30 or older	–0.117 (–1.75)	**–0.117** (–5.08)	–0.113 (–1.69)	**–0.113** (–4.92)	
Rho	–0.043	**–0.043**	**0.086**	**0.086**	0.144
Wald test for rho=0	2.13	4.01	13.56	30.43	13.58
Sample size	22981	22981	22981	22981	22981
Wald test	**3000**	**14923**	**51438**	**12912**	**31453**

[1] Figures in bold are statistically significant at the 5 percent level.

Table 4. Marginal effect of explanatory variables on joint probabilities.

	Impact on joint probability:			
	(1)	(2)	(3)	(4)
Variable	buy map and buy insurance	buy map, do not buy insurance	do not buy map, buy insurance	buy neither map nor insurance
Average probability	0.334	0.320	0.186	0.159
Cost of map	–0.003[1]	–0.004	0.004	0.003
Cost of insurance	–0.0002	0.002	–0.001	–0.0002
Log(loss amount)	0.049	–0.049	0.026	–0.025
Probability of loss	2.64	–2.26	1.08	–1.46
Log(wealth)	0.009	–0.021	0.014	–0.003
Loss lower than map	0.083	–0.083	0.043	–0.043
Loss higher than map	–0.020	0.020	–0.010	0.010
Bought map	0.063	–0.063	0.033	–0.033
Insurance score	0.011	–0.011	0.006	–0.006
Female	0.021	–0.073	0.052	–0.0001
Age 30 and older	–0.015	0.045	–0.031	0.001

[1] The numbers in the table are the change in probability due to the impact of each explanatory variable from the regression equations.

Just as was found in the previous research (Ganderton and others, 2000) subjects appear to be far more sensitive to changes in the probability of loss than changes in the loss amount. This is somewhat surprising given the general view that people have difficulty dealing with small probabilities of the order considered here (1/10, 1/100, 1/1,000). However, that view relates more to the tendency for people to either exaggerate or discount small probabilities than their sensitivity to marginal changes in these small probabilities.

In summary, the results of data analysis provide strong evidence of rational behavior by subjects consistent with the expected utility theory. Subjects are less likely to purchase additional information (the map) the higher the cost of the map, but are insensitive to the cost of insurance in map purchase. Similarly, insurance against loss is less likely to be purchased the higher the premium but is insensitive to the cost of the map. Map purchase is more likely with an increase in the probability of loss, but is insensitive to the amount of the loss, but the decision to purchase insurance is positively impacted by both elements determining expected loss. The relationship between the two decisions is relatively strong and positive—subjects who bought a map are more likely to buy insurance, and those who bought insurance are more likely to buy a map both now and in the future. While past decisions influence current decisions, past outcomes are not statistically significant determinants of current decisions.

There is some evidence that those subjects who rely on less information, in the form of a coarse map, and forego the additional information contained in the detailed map, are more likely to purchase insurance when they overestimate the size of the loss as indicated by the coarse map. Subjects are basing their insurance decision on the information provided in the coarse map, even though it is erroneous. In the case of the hazard modeled in this experiment, it is only when subjects purchase the detailed map that they realize they were overestimating the size of the loss, calculating an exaggerated expected loss, and buying too much insurance. Clearly, subjects are aware of the benefits that arise from the more detailed geoscience information contained in the detailed maps. In the case of this experiment, the benefit is that insurance costs to the subject can be lowered, but in the real world application the benefit would just as likely be that the subject might realize that they are underinsured.

As subjects accumulate earnings over the duration of the experiment, they are less likely to purchase a detailed map, but more likely to purchase insurance. Although there is no theoretical expectation regarding the marginal effect of wealth on these decisions, it could be that two distinct factors are at work. In the case of the map purchase decision, increasing wealth could be a proxy for experience with the game, and as subjects increase their experience they value the additional map information less. In the case of buying insurance, subjects may be suffering from the common gambling fallacy that as the game nears its end a hazardous event is more likely to occur. It could also be that as subjects become richer they can afford more insurance as the pre mium represents a smaller fraction of total wealth. Further investigation is required to identify the true motivations for these observed behaviors.

Finally, subjects who hold insurance outside the experiment are more likely to buy insurance, but this behavior has no influence on their decision to buy a detailed map. Because the detailed map provides a higher level of risk-relevant information on which to base insurance purchase decisions, this suggests that subjects have little or no experience with such options in their everyday lives. Also requiring further investigation is the curious observation that females are more likely than males to purchase insurance, but less likely to purchase the additional information contained in the detailed map.

Program Potential

The results of this experiment suggest considerable potential for the research program of which it was a major part. The experiment demonstrates the use of the Internet as a mechanism for conducting experiments, especially of the kind requiring the delivery of considerable geoscience information of a graphical nature. The Web-based experiment is not limited geographically or temporally. Once a payment mechanism with a corresponding reach that also conforms with both the needs of human subjects and confidentiality and financial requirements that control research work is developed, we could modify existing methods employed for on-line commerce to work in this case.

Future work would entail providing maps that are more realistic to selected groups such as policy makers and stakeholders in regional organizations both public and private. Extending the coverage across the county and overseas is also a simple extension of the current work. A major extension of the current experiment would provide subjects with a mitigation alternative. This would allow us to determine the impact of geoscience information on the choice between mitigation and insurance, as well as study the interaction between mitigation and insurance for these types of low-probability, high loss risks.

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Glossary

Expected utility theory Expected utility theory is a normative theory for decision making under risk. Von Neumann and Morganstern axiomated expected utility theory by showing that alternative actions can be ranked by their expected utilities. The expected utility of an alternative action is the weighted average of the utilities of the possible outcomes where the weights are the objective probabilities of each outcome.

Moral hazard Moral hazard is a phenomenon that occurs in insurance markets caused by an asymmetry of information between the consumer and the insurance provider. When an insurance company has a stake in the action taken by a consumer, such as self-protection (for example, maintenance of a vehicle), but the insurance company cannot observe the consumer's action, the situation involves moral hazard. Moral hazard can be partly overcome with insurance deductibles.

Adverse selection Adverse selection is a phenomenon that occurs in insurance markets that is caused by an asymmetry of information between the consumer and the insurance provider. In markets for insurance, the basic asymmetry of information is that the purchasers of insurance may well have a better idea of the relevant risks than does the insurance company.

Treatment specification Treatments are experimental controls used to condition responses or behaviors. The method of estimation must identify them explicitly in the model specification to remove, or control, for their effect in the experiment. With sufficient sample observations, the treatment effect can be identified and measured.

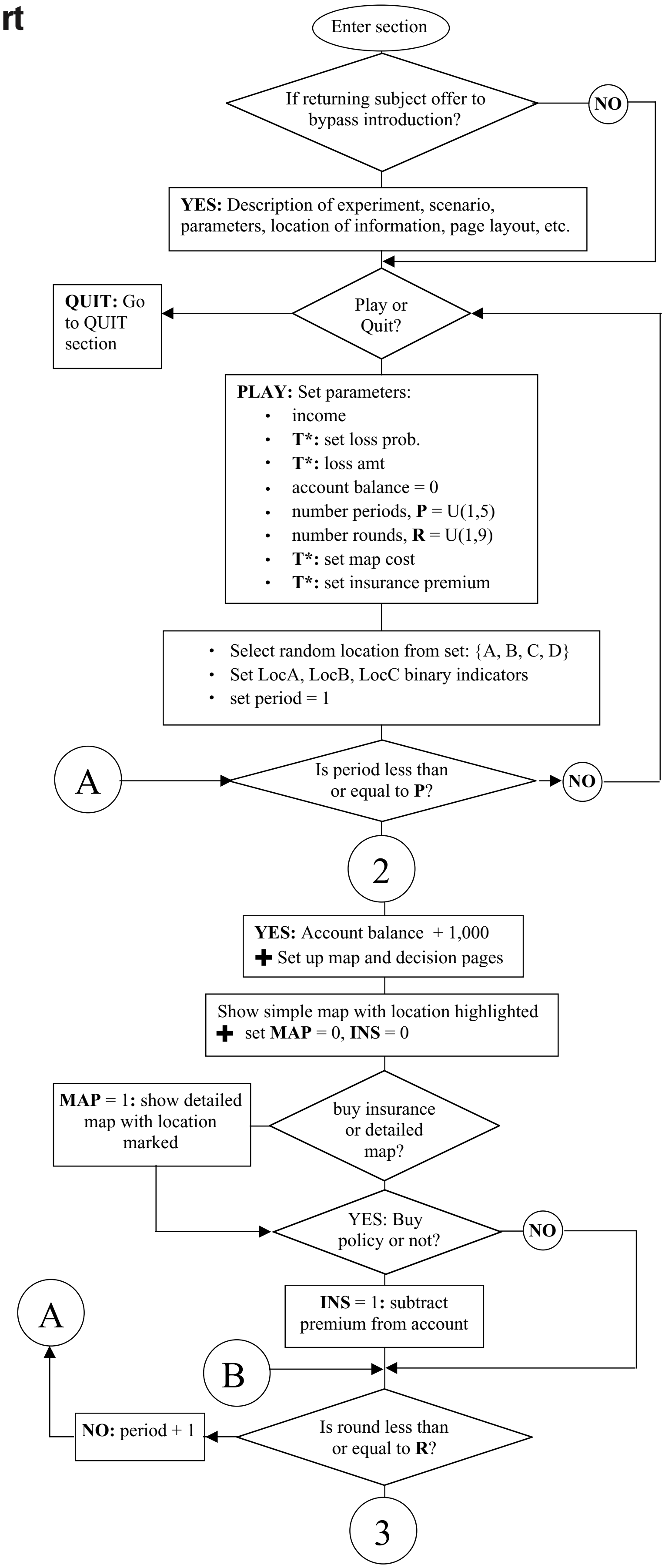
Treatment combination The number of alternative treatment values when all possible values are allowed. If one treatment has two possible values and another three, then combined there are 6 combinations of the two treatments. To estimate treatment effects we must determine the appropriate sample size for each combination of treatment values.

Wald test The Wald test is based upon the restriction imposed by the null hypothesis. If true then a specific quadratic form of the parameter and its mean under the null will be distributed chi-squared. This test statistic is used to test a whole range of hypotheses concerning both individual parameters and sets of parameter restrictions.

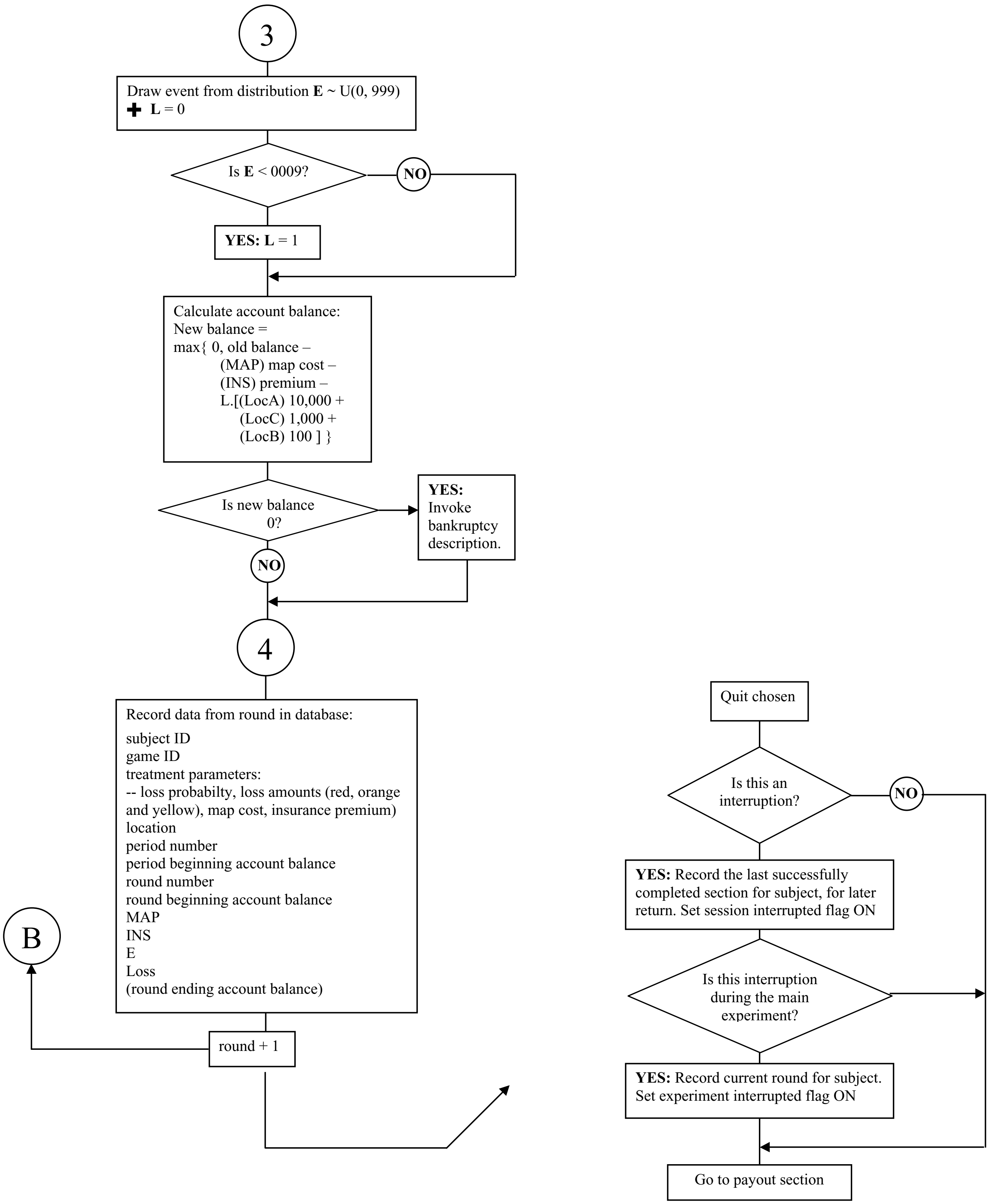
Bivariate probit (BiProbit) model The bivariate probit model is a qualitative response regression model in which the dependent variable assumes discrete values. The simplest of these models is that in which the dependent variable is binary (it can assume only two values which can be denoted by 0 and 1). The bivariate probit is the case where observed values of the dependent variable are realizations of a binomial process with probabilities given by $\Pr(y = 1) = 1 - F(-\beta' x)$ and varying from trial to trial depending on x_i, where Pr is probability, y is the dependent variable, F is the cumulative normal probability distribution, b is a regression coefficient, x is an independent variable, and i observations, $i = 1,\ldots,I$.

Income effect The income effect is a consumer's reaction with respect to purchases of a commodity to changes in their income, prices remaining constant.

Appendix A. Experiment Flow Chart



Appendix A. Experiment Flow Chart—Continued



Appendix B. Game Explanation Text

New Main Game introductory text:

You are about to enter the main experiment. The general structure of the game is outlined below.

- You play a number of **GAMES.**
- Within each game there is a random number of **PERIODS.**
- Each period you earn game **income** of 200 tokens.
- Within each period there is a random number of **ROUNDS.**
- Each round you are exposed to a potential **loss** event.
- You either suffer a loss, or not.
- The size and likelihood of loss depends on your **location.**
- You know how often these losses occur, but not when.

The sequence above is repeated with certain experimental parameters changing each period and each game.

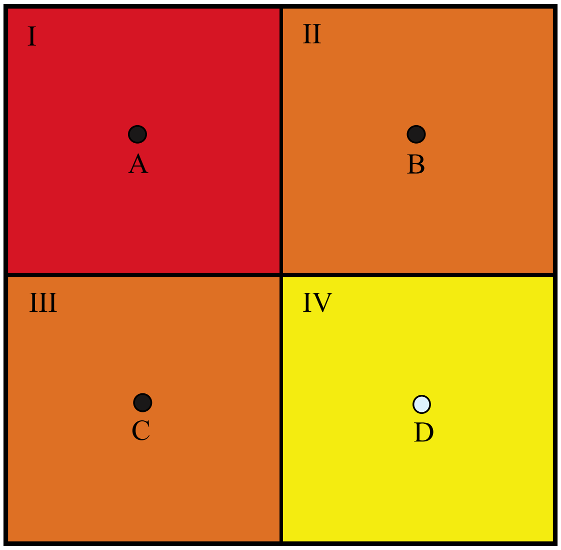
You face the following decision each period:

- Buy **insurance** to offset any potential losses.
- Buy a more **detailed map** of your location to help in your decision making.
- You can buy either, or both, or none at all.
- At all times you will know the **probability** of suffering a loss, the **size** of that loss, and your **location** on either a coarse, or detailed, map.
- You will know how many games tokens you have and the **cost** of buying a map and (or) buying insurance.
- Once you buy insurance you have coverage for the whole period, but not for the next period.
- Insurance covers any losses you may suffer during the period.
- If you lose more tokens than you own, you are declared bankrupt, and must wait until the start of the next period to get more tokens.

As you go through the experiment you will earn income and may spend it to buy maps and insurance. You may lose income if you suffer an uninsured loss. At the end of the experiment your accumulated earnings in tokens will be converted to U.S. dollars and a claim check will be issued for you to print.

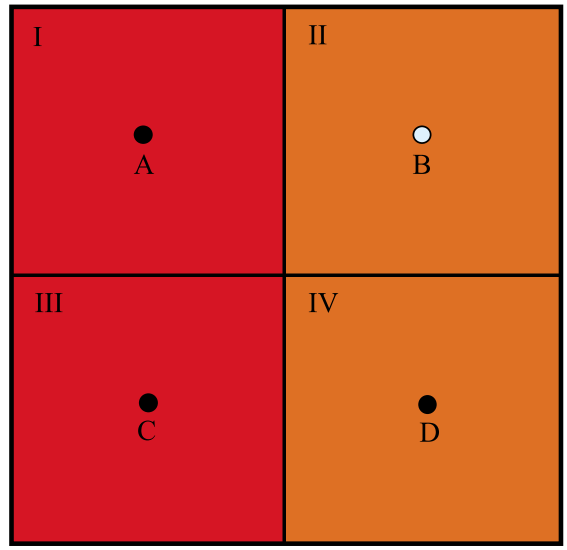
Appendix C. Maps

MAPGEO = A Course Map
with point D highlighted to show subject location.



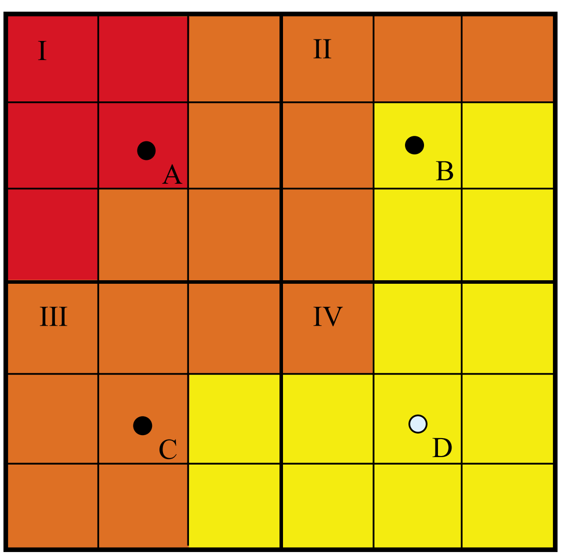
Notes: (i) Color of zone is determined by modal hazard in zone. (ii) Location A appears to have the highest loss, B and C have medium loss, and D has lowest loss.

MAPGEO = B Course Map
with point B highlighted to show subject location



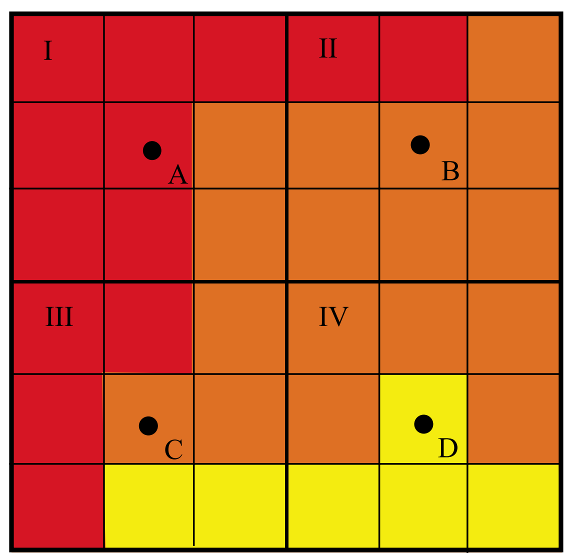
Notes: (i) Color of zone is determined by modal hazard in zone. (ii) Locations A and C appear to have highest loss, B and D have medium loss and no location has lowest loss.

Fine Map



Note: (i) Now location A has highest loss, C has medium loss and B and D have lowest loss. This map determines actual losses in experiment.

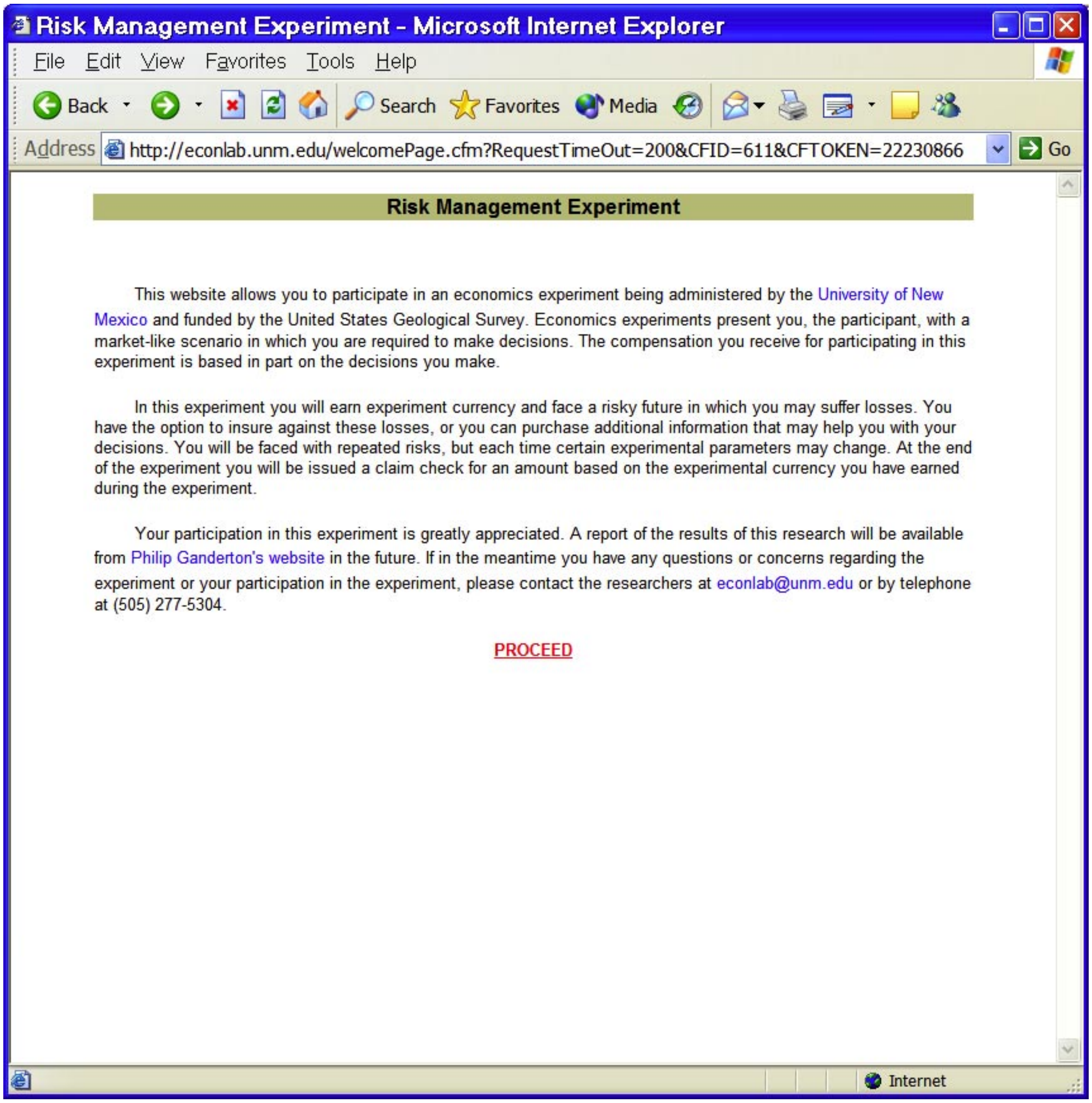
Fine Map



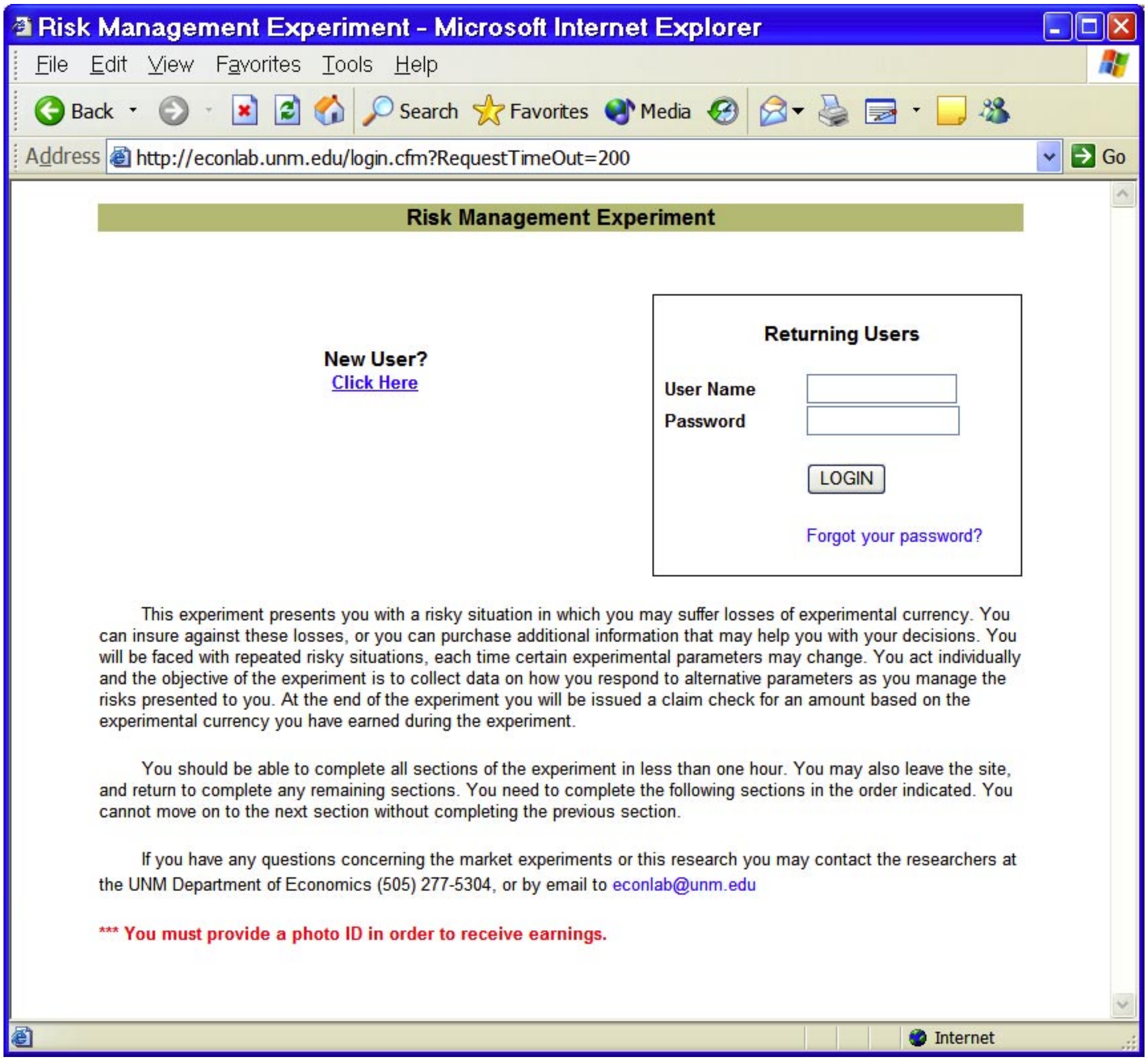
Note: (i) Now location A has highest loss, B and C have medium loss, and D has lowest loss. Actual losses in experiment are determined by this map.

Appendix D. Screen Captures

Welcome Screen Capture From Website

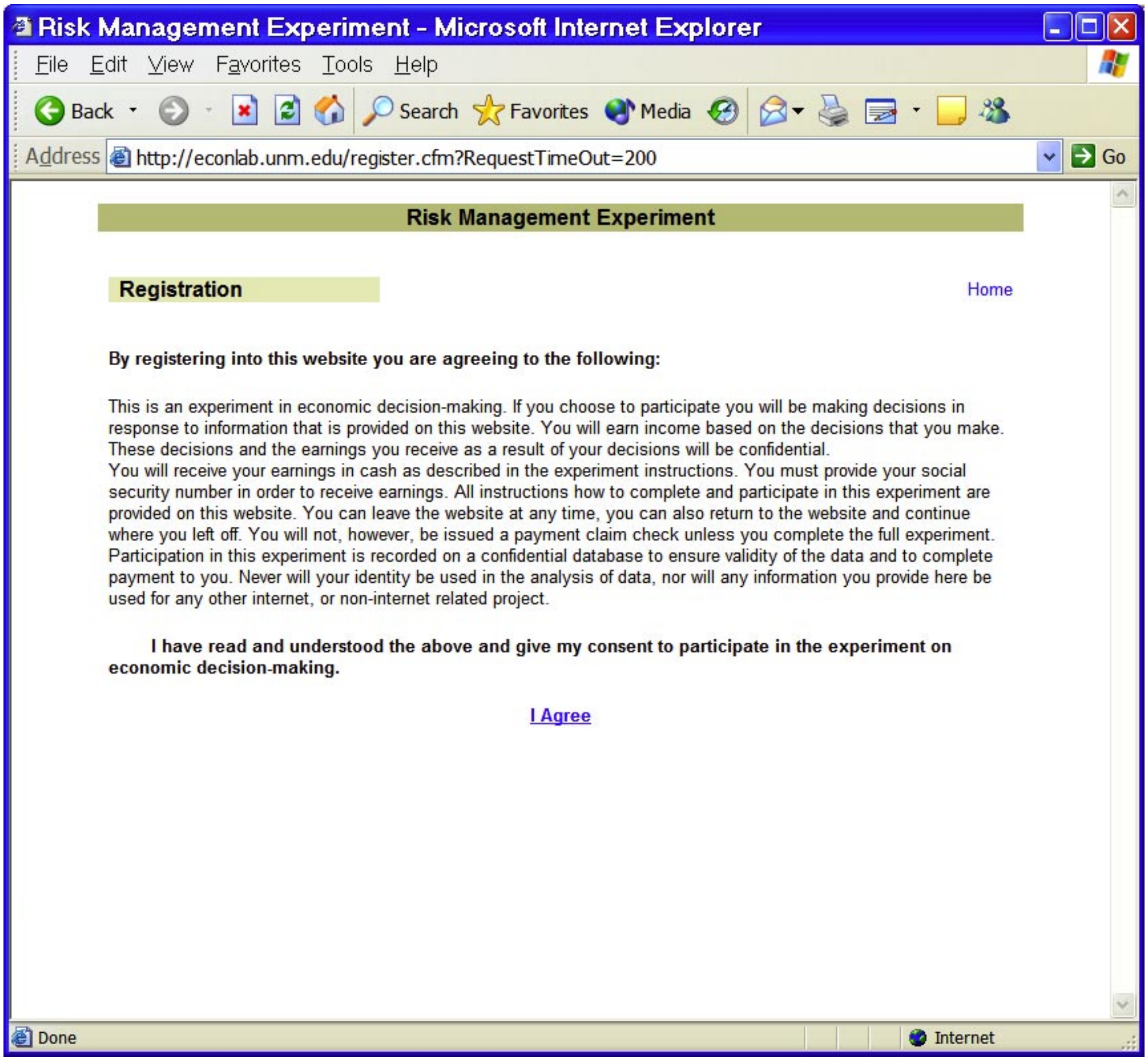


Appendix D. Screen Captures—Continued
Logon Screen Capture

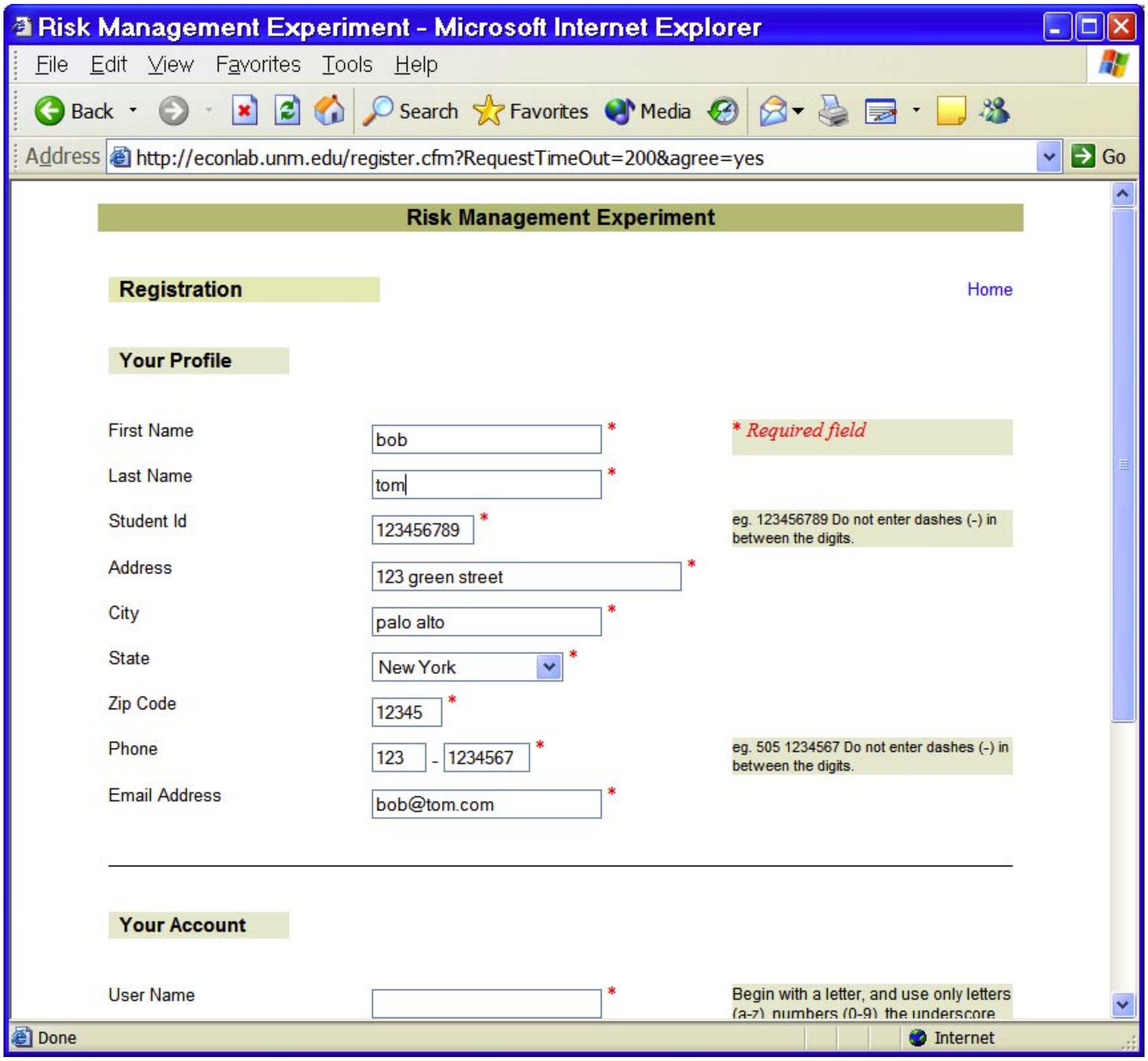


Appendix D. Screen Captures—Continued

Registration Welcome Screen Capture

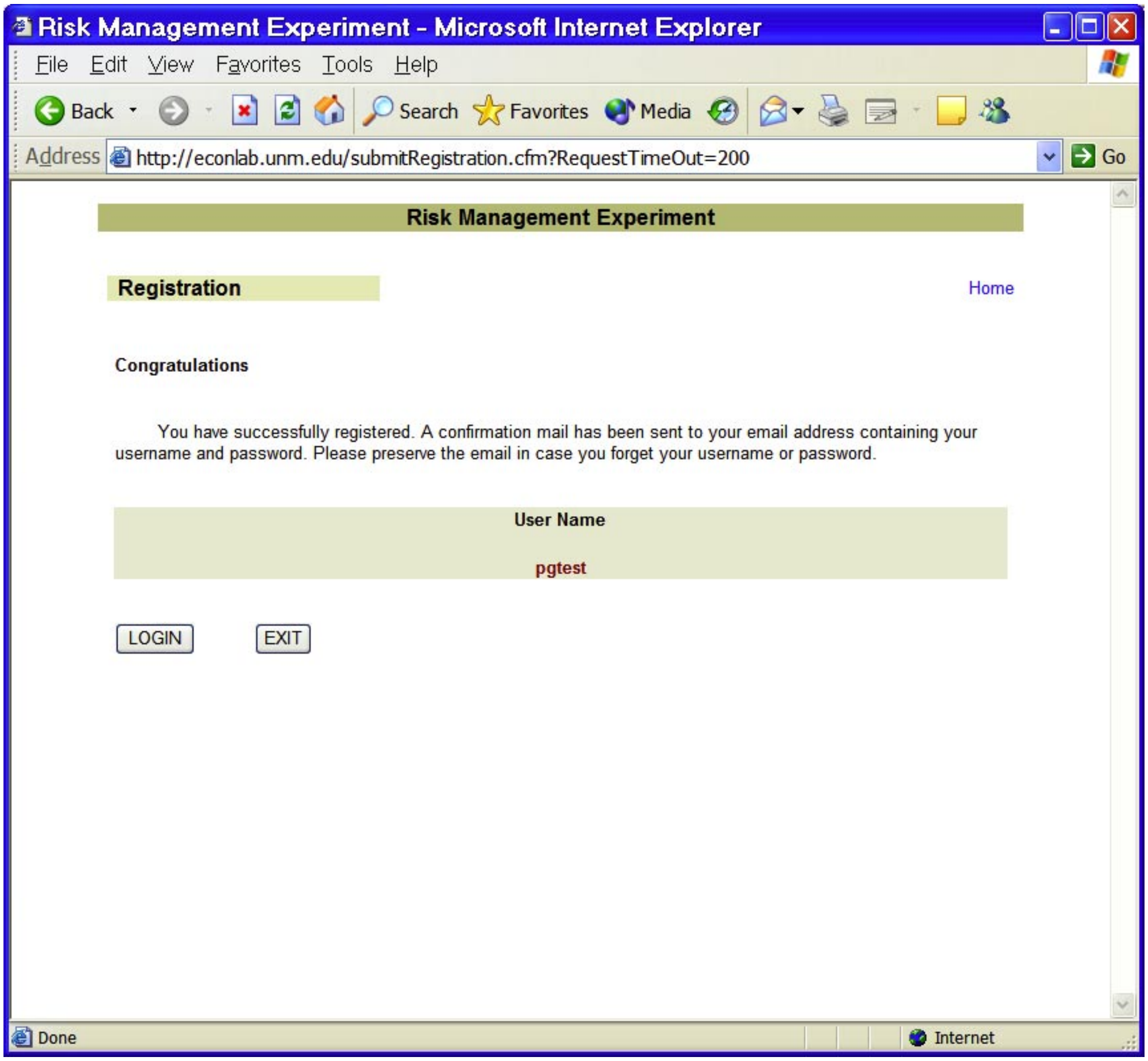


Appendix D. Screen Captures—Continued
Registration Screen Capture



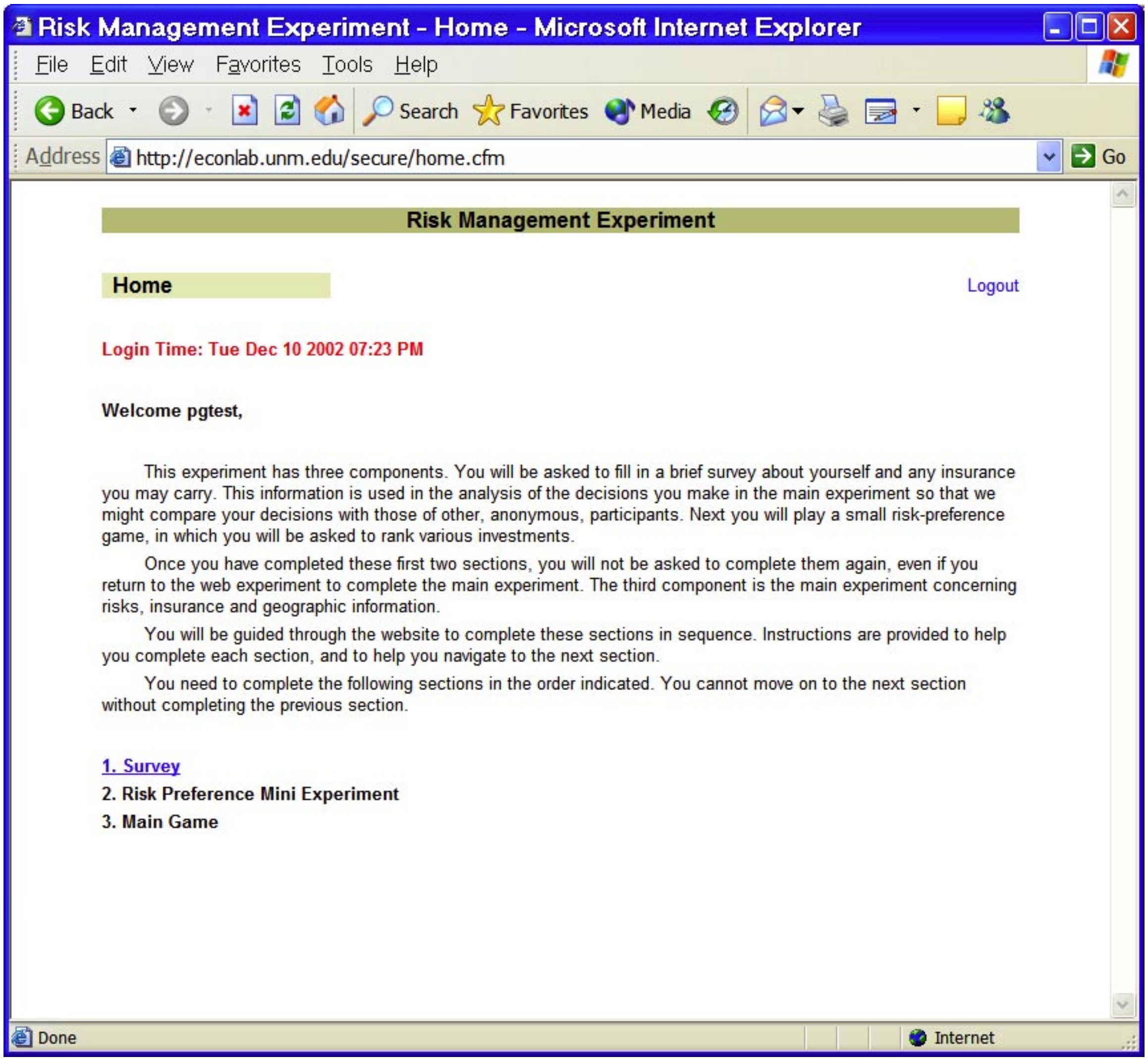
Appendix D. Screen Captures—Continued

Registration Complete Screen Capture

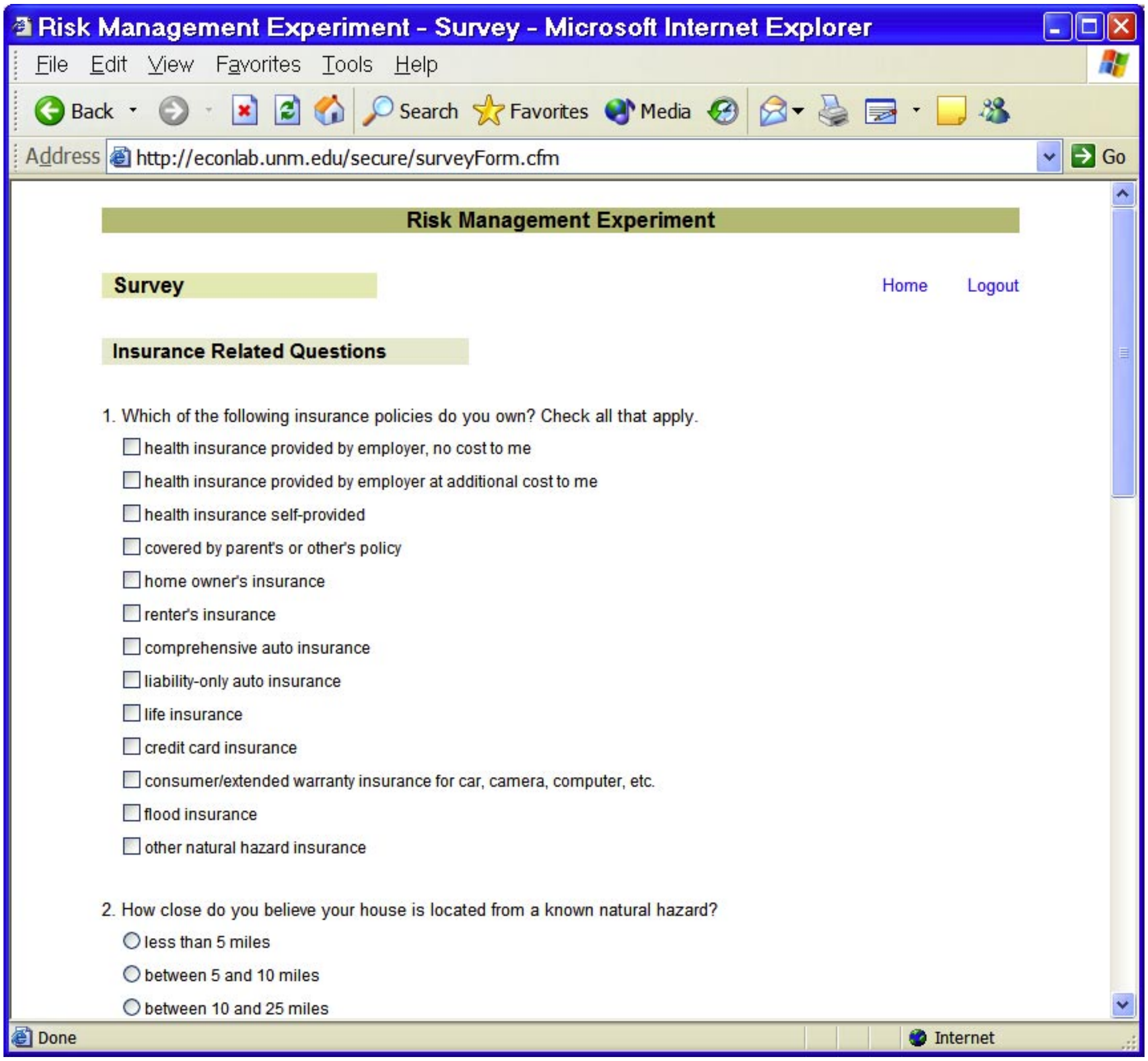


Appendix D. Screen Captures—Continued

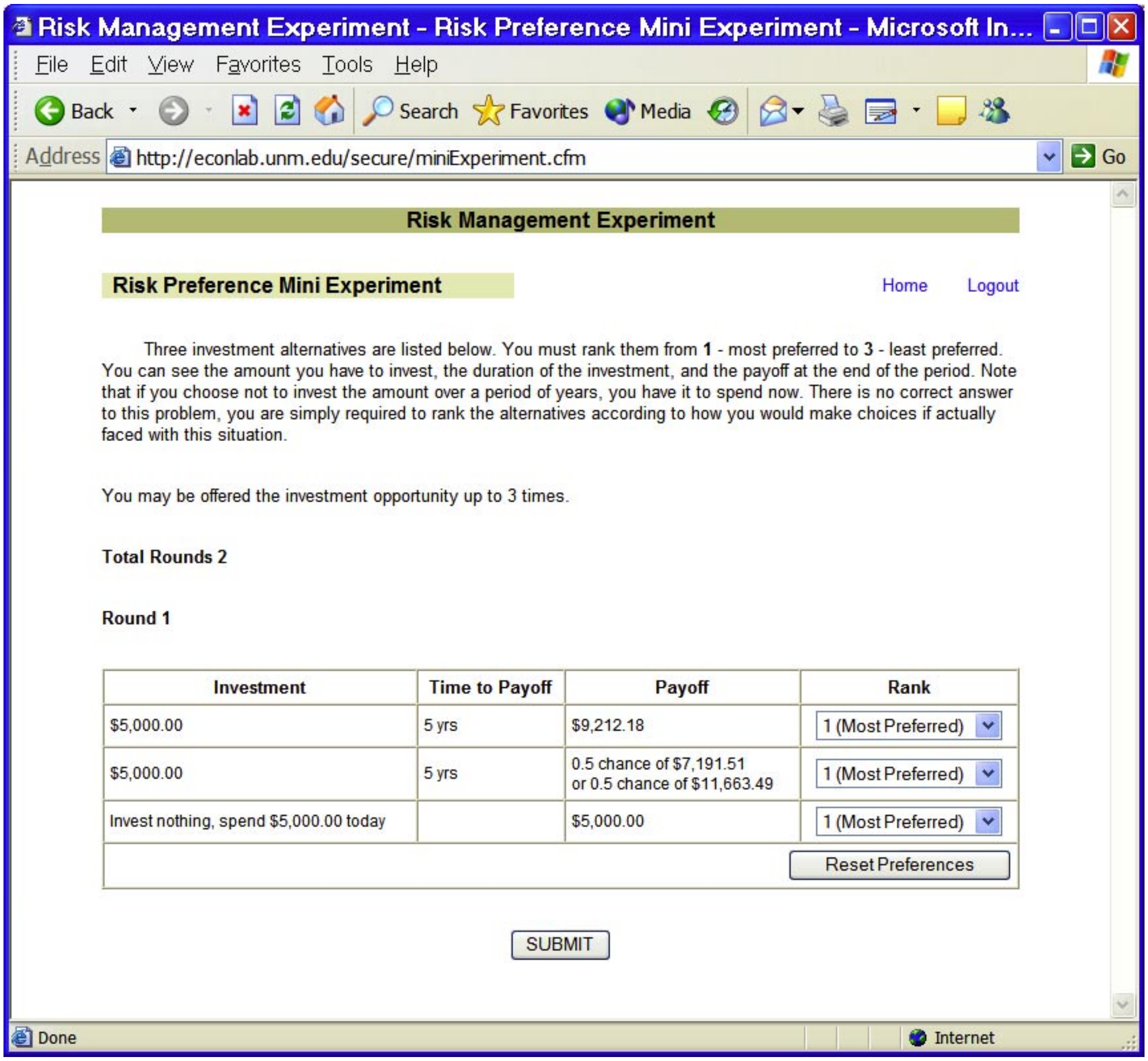
Post Registration, Personal Welcome and Introduction Page Screen Capture



Appendix D. Screen Captures—Continued
Survey Screen Capture

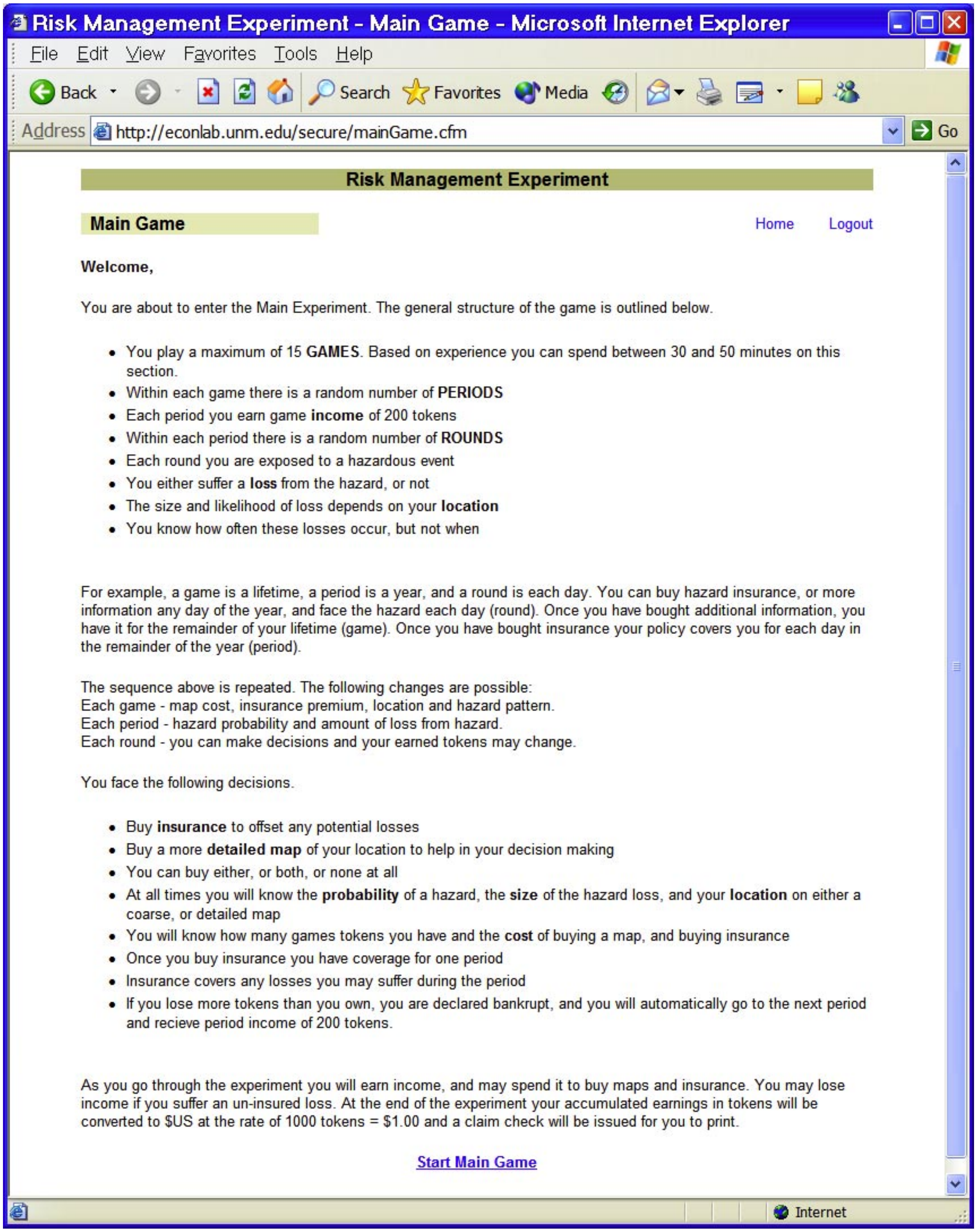


Appendix D. Screen Captures—Continued
Risk Preference Mini Experiment Screen Capture

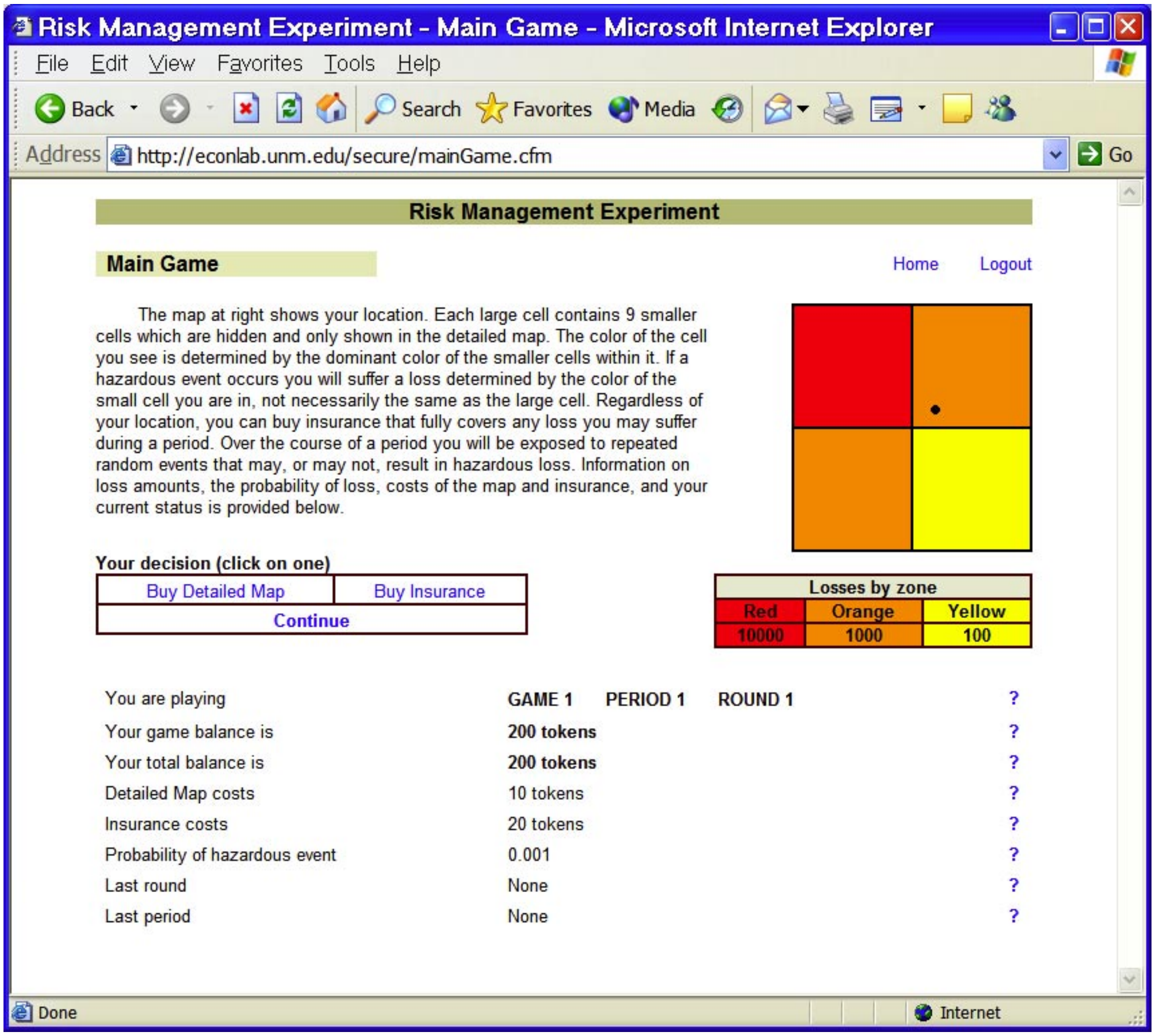


Appendix D. Screen Captures—Continued

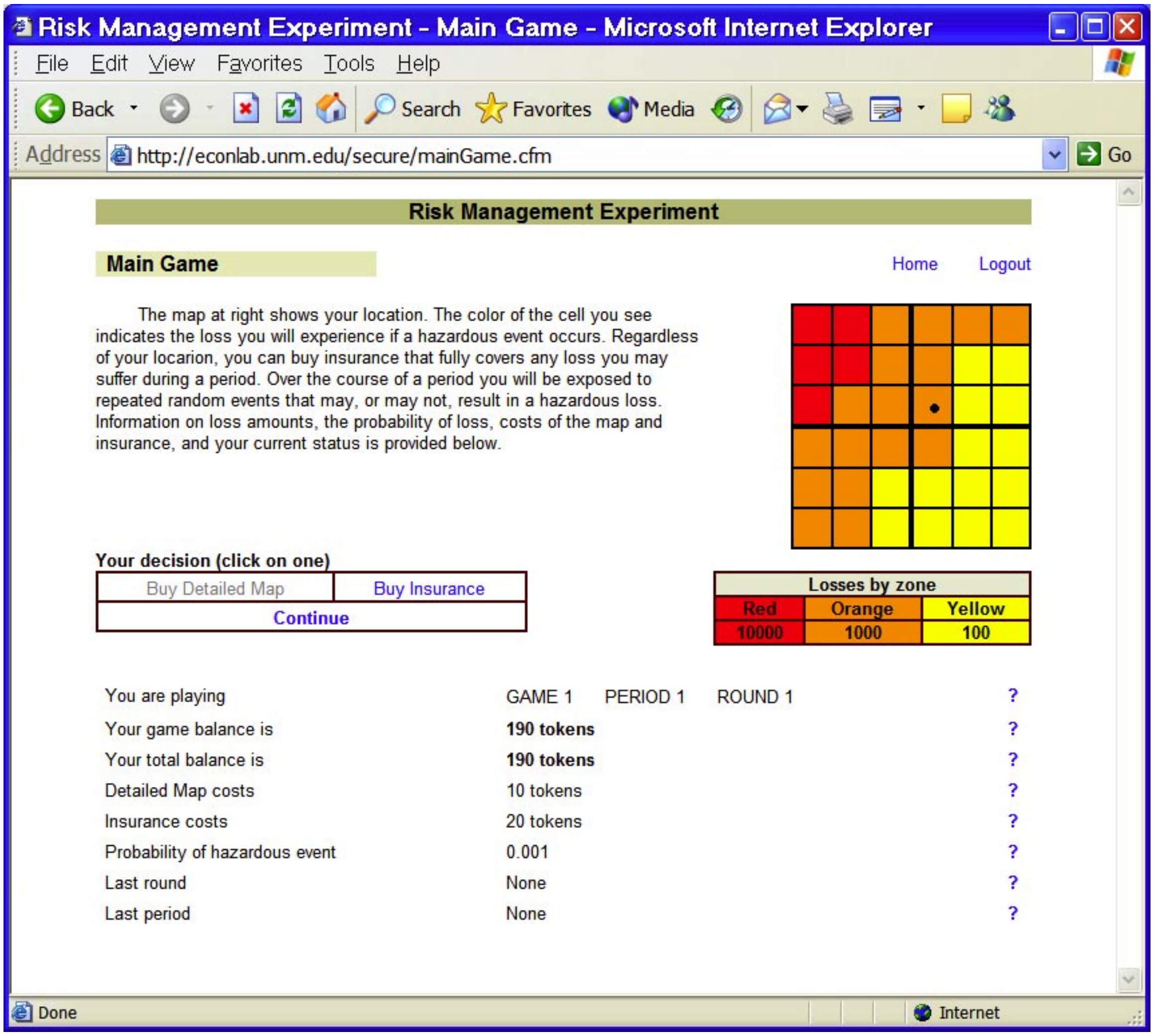
Main Experiment Welcome Screen Capture



Appendix D. Screen Captures—Continued
Main Decision Page Screen Capture



Appendix D. Screen Captures—Continued
Main Decision Page With Detailed Map Screen Capture



Appendix E. Continuation Screen Captures— Result of Event Draw Page, Subject Must Acknowledge to Continue