Evaluating the Welfare of Index Insurance

by

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ABSTRACT.

Index insurance was conceived to be a product that would simplify the claim settlement process and make it more objective, reducing transaction costs and moral hazard. However, index insurance also exposes the insured to basis risk, which arises because there can be a mismatch between the index measurement and the actual losses of the insured. It is not easy to predict the direction in which basis risk is going to affect insurance demand, in contrast to the clear and strong predictions for standard indemnity insurance products. Index insurance can be theoretically conceptualized as a situation in which the individual faces compound risk, where one layer of risk corresponds to the potential individual's loss and the other layer of risk is created by the potential mismatch between the index measurement and the actual loss. Experimental evidence shows that people exhibit preferences for compound risks that are different from preferences exhibited for their actuarially-equivalent counterparts. We study the potential link between index insurance demand and attitudes towards compound risks. We test the hypothesis that the compound risk nature of index insurance induced by basis risk negatively affects both the demand for the product and the welfare of individuals making take-up decisions. We study the impact of basis risk on insurance take-up and on expected welfare in a laboratory experiment with an insurance frame. We measure the expected welfare of index insurance to individuals while accounting for their risk preferences, and structurally decompose the sources of the welfare effects of index insurance. Our results show that the compound risk in index insurance decreases the welfare of index insurance choices made by individuals. The behavioral inability to process compound risks decreases welfare when there is a compound risk of loss, whereas loss probability, basis risk and premium only impact the welfare of insurance choices when the risk of loss is expressed in its reduced, non-compound form. We also see, again, that take-up is not a reliable indicator of welfare. Furthermore, the drivers of increased welfare from index insurance are not be the same drivers of increased take-up, so take-up is not even a useful proxy for guiding policy to improve welfare.

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Index insurance is widely viewed as having great potential for addressing some of the risk management needs of billions of residents in developing countries, particularly in rural areas. The idea of an index contract is that the insured gets coverage for an idiosyncratic risk of loss that they face that is positively correlated with some easily observed and verifiable index.[1] Payment of a claim depends solely on outcomes with respect to the index, not with respect to outcomes that are specific to the insured. The advantages of index contracts are that claims can be instantly adjudicated without costly assessment procedures, there is no opportunity for moral hazard or adverse selection, and transparency concerns that are particularly severe in developing countries can be mitigated.[2]

The disadvantage of index insurance is equally simple to state: compared to a conventional indemnity product, it makes the worst possible outcome even worse, and makes the best possible outcome even better. The worst possible outcome is if the insured experiences a loss but the index is not triggered, and the best possible outcome is if the insured suffers no loss and the index is triggered so that a payment to the insured is made. One classical motive for purchasing indemnity insurance is to reduce variability of risky outcomes, so it is apparent that this feature of index contracts could rationally reduce demand for insurance by comparison, and even make the index

[1] The use of an index differentiates index insurance from "area-yield" insurance, which defines the loss to the insured by the average yield in some geographic area. Area-yield insurance was first written in Sweden in 1961, in Quebec in 1977, in the United States on a small scale in 1993 and then significantly in 1994 (Skees, Black and Barnett [1997; p. 431]). Halcrow [1949] originally proposed the idea, which was resurrected and developed by Miranda [1997] and Mahul [1999].

[2] Moral hazard is eliminated because there is nothing that the insured can do to affect the index outcome. Indeed, incentives to undertake self-protection and self-insurance remain intact. Adverse selection is eliminated because the contract does not differentiate between the correlation of the idiosyncratic risk and the index outcome. Adverse selection is an issue with *area-yield insurance* if contracts are *individual*, and specific to the correlation of the idiosyncratic risk and the area-yield risk, as proposed by Mahul [1999]: the insured can choose production activities to affect the correlation (Chambers and Quiggin [2002]), and the need to cover fixed costs requires an individual-specific indemnity schedule that is feasible only if the correlation is known to both the insured and the insurance company (Bourgeon and Chambers [2003]).

contract unattractive for a sufficiently risk-averse individual.[3]

Thus index insurance poses an important behavioral tradeoff. Usually when we talk about traditional indemnity insurance and actuarially-fair pricing, we are on firm ground recommending the purchase of the product for anyone that is risk averse, which is arguably everyone. But traditional products are hard to offer on a profitable basis in developing countries, hence making it attractive to modify the product in some way so as to make it less costly to offer (and settle claims on). But the simplest contractual modification, making the payout a function of some common index, could turn the firm ground of recommendation into a quicksand for those that would find the traditional product the most attractive (the most risk averse). What is the balance here, to allow us to say when a particular index insurance product is attractive or not? We spell out the answer to that challenging question in the simplest possible setting, guided by structural theory and empirical evidence of the risk attitudes of potential index insurance customers.

Demand for index insurance is also claimed to be notoriously low, particularly by academic researchers: see Giné et al. [2008], Giné and Yang [2009], Cole [2014] and Clarke [2016]. Many factors have been cited as possible explanations of such low take-up, such as lack of understanding, risk aversion, prior experience with insurance, basis risk, and premium. But worrying about "low take-up" surely presumes what we need to determine, whether there is an expected consumer surplus from purchasing the product in the first place. Our analysis tries to provide answers as to what "low" and "high" might mean for index insurance products, particularly when we study actual behavior.

We evaluate the expected welfare of index insurance contracts in a simple setting in which

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[3] Clarke [2016] provides a rich characterization of these possibilities, noting that they are an extension of familiar results from Doherty and Schlesinger [1990] on contractual non-performance by insurance companies.

we can control all potential confounds and yet still observe behavioral responses, a laboratory experiment. Given the importance of the issue for policies towards risk management in developing countries, the deep pessimism in recent academic literature about the real-world attractiveness of index insurance, the evidence that nonetheless "billions and billions are being served" with index contracts, and the unblinking enthusiasm of many policy-makers and non-governmental agencies for index insurance, we make no apology for starting this evaluation in a laboratory. The confounds of field evaluations of the effects of index insurance and the demand for the product make it impossible to make clean, simple evaluations of the welfare effects of the policy. Most evaluations, in fact, only talk about whether take-up is "too low" or "about right," with no coherent sense of what take-up is appropriate for the insured. Many evaluations actually dodge the issue of the welfare effect of the index contract *as insurance* by focusing on whether it is correlated with increased utilization of services or activities that are insured: that is not what insurance is designed to influence, and is at most a secondary benefit or cost of insurance as a risk management instrument. As usual, we view our laboratory experiment as a necessary predecessor to an informative and powerful field experiment.

A decided advantage of undertaking a controlled experimental evaluation, whether in the laboratory or the field, is that we can investigate the structural reasons for welfare losses from decisions about index insurance. We say "decisions" rather than take-up, since it is possible that losses arise from not taking up the product when the individual should do so. Conversely, admitting that behavior is not always consistent, take up of the product is not even a reliable indicator of a welfare gain. In the case of index insurance, the focus of theoretical attention has to be the compound risk that the contract generates: this is the *basis risk* that there is less than perfect, positive correlation between the aggregate index and idiosyncratic losses. In theoretical terms this draws attention to violations of the Reduction of Compound Lotteries (ROCL) axiom, which has been implicated in many experimental studies of Expected Utility Theory (EUT).

We lay out the basic theory of index insurance in section 1, identifying the role of ROCL, basis risk and risk preferences in welfare evaluation. By "risk preferences" we mean both the level of risk aversion that an individual exhibits in choice behavior as well as the type of psychological processes underlying that level of risk aversion. To keep matters simple, we focus on EUT and Rank-Dependent Utility (RDU) Theory, and further consider two variants of RDU in which the Compound Independence Axiom (CIA) or ROCL is relaxed. In section 2 we lay out the experimental design motivated by this theory, to allow us to identify welfare gains and losses at the individual level. A central subtlety of this design to undertake *normative* inferences is that we must have a measure of risk preferences of the individual that is separate from the index insurance choices, even if that might be viewed by some as *descriptively* restrictive. Section 3 presents our results, and section 4 draws conclusions.

Our results show that the compound risk in index insurance decreases the welfare of insurance choices made by individuals. Violation of the ROCL axiom by individuals decreases welfare when there is a compound risk of loss, whereas loss probability, basis risk and premium only impact the welfare of insurance choices when risk of loss is expressed in its reduced, non-compound form. Building on Harrison and Ng [2016], we again find that take-up is not a reliable indicator of welfare. Furthermore, the drivers of increased welfare from index insurance are not be the same drivers of increased take-up, so take-up is not even a useful proxy for guiding policy to improve welfare.

1. Theory

An index insurance product will only fully compensate for a loss based on a predetermined and objective index, and not whether the individual experiences a loss. For instance, assume that an individual has an initial endowment of \$20, and will lose \$15 if she experiences a loss event. The individual is given an opportunity to purchase index insurance, which would only pay out the \$15 indemnity if the index reflects that a loss event has occurred. This insurance would cost \$1.20, but the probability of the individual's outcome matching the index, the correlation, may vary. The possible monetary outcomes and their corresponding probabilities are summarized in Figure 1.

Notation necessarily becomes more complex with index insurance. There are 8 possible states, depending on the permutations of binary outcomes of if the individual chooses to purchase insurance $\{I_1, I_0\}$, if the index reflects a loss $\{L_1, L_0\}$, and if the individual's outcome matches the outcome of the index $\{P_1, P_0\}$.[4] For instance, if the individual chooses not to purchase insurance (I_0), the index reflects a loss outcome (L_1), and the individual's outcome matches the index (P_1), the individual would also experience a loss ($I_0L_1P_1$) and be left with \$5. If the individual's outcome does not match the index (P_0), she does not experience a loss ($I_0L_1P_0$) and would keep her \$20. By the same logic, $I_0L_0P_1$ = \$20 and $I_0L_0P_0$ = \$5.

If the individual chooses to purchase insurance (I_1) the outcomes are slightly more complex. If the index reflects a loss (L_1), and if the individual's outcome matches that of the index (P_1), the individual experiences a loss and receives a payout ($I_1L_1P_1$), hence she will keep her initial endowment less the premium (\$20 - \$1.20 = \$18.80). However if the individual's outcome does not match the index which shows a loss ($I_1L_1P_0$), the individual does not experience a loss but still

[4] Some states may have same final monetary outcome, but we consider them as separate states here to avoid making assumptions to combine probabilities.

receives a payout of \$15 on top of her initial endowment less premium (\$20 - \$1.20 +\$15 = \$33.80). This is the *upside basis risk*. Conversely if the individual's outcome does not match the index when the index does not show a loss ($I_1L_0P_0$), then the individual experiences a loss but receives no payout from insurance (\$20 - \$1.20 - \$15 = \$3.80). This is the *downside basis risk*.

A. Evaluating Welfare

Let W denote wealth, L denote the loss amount, π denote the insurance premium, p denote the probability of the index indicating a loss, ϱ denote the correlation[5] between the index and the outcome to the individual, and U(·) denote the utility function of the individual. Assuming the individual behaves consistently with EUT, the expected utility (EU) of the choice to *not purchase* insurance is

$$EU^0 = (p \times \varrho)\, U(W\text{-}L) + [p\times(1\text{-}\varrho)]\, U(W) + ((1\text{-}p)\times\varrho)\, U(W) + [(1\text{-}p)\times(1\text{-}\varrho)]\, U(W\text{-}L)$$

or, to link to the previous presentation,

$$EU^0 = (p \times \varrho)\, U(I_0L_1P_1) + [p\times(1\text{-}\varrho)]\, U(I_0L_1P_0) + ((1\text{-}p)\times\varrho)\, U(I_0L_0P_1) + [(1\text{-}p)\times(1\text{-}\varrho)]\, U(I_0L_0P_0).$$

The EU of the choice to *purchase* insurance is:

$$EU^1 = (p \times \varrho)\, U(W\text{-}\pi) + [p\times(1\text{-}\varrho)]\, U(W\text{-}\pi\text{-}L) + ((1\text{-}p)\times\varrho)\, U(W\text{-}\pi) + [(1\text{-}p)\times(1\text{-}\varrho)]\, U(W\text{-}\pi\text{-}L)$$

or

$$EU^1 = (p \times \varrho)\, U(I_1L_1P_1) + [p\times(1\text{-}\varrho)]\, U(I_1L_1P_0) + ((1\text{-}p)\times\varrho)\, U(I_1L_0P_1) + [(1\text{-}p)\times(1\text{-}\varrho)]\, U(I_1L_0P_0).$$

We can define the Certainty Equivalent (CE) as the wealth level that is equivalent to a lottery, so the CE of not purchasing insurance CE^0 is defined by $U(CE^0) = EU^0$, and the CE of purchasing insurance CE^1 is defined by $U(CE^1) = EU^1$. Expected welfare gain is measured by the consumer surplus (CS) from the option of purchasing insurance. This is the difference between the CE of purchasing insurance and the

[5] We assume that this correlation is non-negative, and lies in the closed nuit interval. This is a reasonable assumption for the practical settings in which index insurance is being proposed. In fact, our formal exposition treats ϱ as if it were a probability, which is only valid under this assumption.

CE of not purchasing insurance: $CS = CE^1 - CE^0$.

If we assume RDU as the decision-making model, the calculation of CS is similar once we calculate the corresponding CE values. The only complication is keeping track of how probabilities are transformed into decision weights: Appendix B explains this transformation in detail.[6] The RDU of not purchasing insurance then defined as RDU^{0}, and the RDU of purchasing insurance is RDU^1. The CE are then defined similarly, but using RDU instead of EU, so CE^0 is defined by $U(CE^0) = RDU^0$, and CE^1 is defined by $U(CE^1) = RDU^1$. The expected welfare gain is then calculated again as $CS = CE^1 - CE^0$. Since RDU^0 need not equal EU^1, and RDU^1 need not equal EU^1, and both will typically be quite different for a subject best characterized by RDU, the expected welfare gain of the option of purchasing insurance will depend on the characterization of risk preferences for the individual.

The same logic for evaluating the welfare gain extends to other variants on EUT, such as Dual Theory (DT) due to Yaari [1987] and Disappointment Aversion (DA) due to Gul [1991]. We do not consider Prospect Theory here, since all outcomes were in the gain domain in our experiments, but the logic extends immediately.

B. Welfare and Basis Risk Correlation

How does the CS from purchasing index insurance vary as the correlation varies? To provide concrete illustrations, assume utility follows the constant relative risk aversion (CRRA) model so that

$$U(x) = x^{(1-r)}/(1-r)$$

[6] The highest-ranked monetary outcome has a decision weight equal to the weighted probability, where the weighting function is to be defined. In our insurance choices there are only two monetary outcomes in each implied lottery, despite there being four outcomes in terms of states of nature. In this special case the decision weight on the smallest-ranked monetary outcome is 1 minus the decision weight on the highest-ranked monetary outcome. The probabilities of the top two monetary prizes are added prior to probability weighting, as are the probabilities of the bottom two monetary prizes. Thereafter the RDU is evaluated as if it only had two outcomes.

where x is the monetary outcome and r≠1 is a parameter to be estimated. For r=1 assume U(x)=ln(x) if needed. Thus r is the coefficient of CRRA under EUT: r=0 corresponds to risk neutrality, r<0 to risk loving, and r>0 to risk aversion. Values between 0.3 and 0.7 are typical for our subjects.

Figure 2 shows how the CS varies for this index insurance product across the risk parameter r, assuming the individual has EUT preferences. When there is 100% correlation and ϱ=1, so the outcome of the individual always matches the outcome of the index, the CS is larger if the individual is more risk averse. This follows from the fact that more risk averse individuals are willing to pay more for insurance. This is a special case of the index insurance contract where the compound lottery collapses into a simple indemnity contract.

As correlation decreases, so the probability of the outcome of the individual matching the index outcome decreases, the downside basis risk causes the CS to decrease at a greater rate for the more risk averse than the less risk averse individual. This causes the "twist" in Figure 2, which leads to the CS for the less risk averse individual being higher than the CS of the more risk averse individual. Regardless of level of risk aversion, the decrease in CS decreases as correlation decreases, because the positive impact of the upside basis risk is greater as correlation decreases to 0.4 < ½. Since we are only dealing with losses L from initial wealth W, a correlation less than ½ means there is a greater probability of the personal outcome not matching the index loss outcome, which would result in a payout being received even though the individual has not experienced a loss. As correlation decreases for this index insurance product, CS decreases to the point of becoming negative. This shows that the risk preferences of the individual and the correlation can affect whether the individual's decision to purchase insurance would result in an expected welfare gain or loss.

Figure 3 shows how CS varies as correlation decreases assuming an RDU decision-making model with a Power probability weighting function $\omega(p) = p^{\gamma}$. In this case $\gamma \neq 1$ is consistent with a deviation from the conventional EUT representation. The probability weighting parameter γ spans our expected range of 0.7 to 1.3, and the CRRA coefficient r is held constant at 0.6. Convexity of the probability weighting function, with $\gamma>1$, is said to reflect "pessimism" and generates, if one assumes for simplicity a linear utility function, a risk premium since $\omega(p) < p \ \forall p$ and hence the "RDU EV" weighted by $\omega(p)$ instead of p has to be less than the EV weighted by p. The converse is true for $\gamma<1$, and is said to reflect "optimism." When there is 100% correlation the presence of optimism causes the CS of purchasing insurance to be lower if γ is smaller, since the probability of no loss occurring is over-weighted. As the correlation decreases, this optimism increases the impact of underweighting of the downside basis risk and overweighting of the upside basis risk when purchasing insurance, which causes the expected welfare gain of purchasing insurance to increase as correlation decreases for optimistic individuals.

The converse is true for pessimistic individuals with a larger γ. Underweighting the probability that the individual will experience a loss though the index does not reflect a loss and overweighting the probability that the individual does not experience a loss and still receives a payout as the index is triggered causes the CS of purchasing index insurance to decrease more as correlation decreases. Once again, not only do the probability weighting parameters impact whether the expected welfare gain is positive or negative, and hence whether or not the "correct" decision estimated for the individual is to purchase or not to purchase index insurance, it also affects how much the insurance product will or will not benefit the individual.

Figure 4 shows how the CS is affected if we vary the parameter of an inverse-S probability weighting function $\omega(p) = p^\gamma / (p^\gamma + (1-p)^\gamma)^{1/\gamma}$ for an RDU decision making model while decreasing the correlation ϱ. This function exhibits inverse-S probability weighting (optimism for small p, and pessimism for large p) for $\gamma<1$, and S-shaped probability weighting (pessimism for small p, and optimism for large p) for $\gamma>1$. Once again the probability weighting parameter γ spans our expected typical range of 0.7 to 1.3, and the CRRA coefficient r is held constant at 0.6. A smaller $\gamma<1$ reflects an overweighting of the probabilities of extreme outcomes, while a larger $\gamma>1$ reflects an underweighting of the probabilities of extreme outcomes. When correlation is at 100%, the probability of the loss outcome is overweighted when $\gamma<1$ and underweighted when $\gamma>1$, which causes the CS of index insurance to be higher for smaller γ. As correlation decreases, there is a tradeoff between the impact of the probability of downside basis risk *versus* the impact of the probability of the upside basis risk. Increasing the probability of downside basis risk will cause the CS of insurance to decrease; however, increasing the probability of upside basis risk will cause the CS to increase. For $\gamma<1$, where the probabilities of extreme outcomes are overweighted, the impact of overweighting the downside basis risk initially dominates and causes the CS to decrease; however, for smaller correlations the impact of overweighting the upside basis risk increases. When $\gamma>1$, the extreme probabilities are underweighted, hence the impact of underweighting downside basis risk would initially cause the CS to decrease less; but the impact from underweighting the upside basis risk will increase for smaller correlations, causing a larger decrease in CS.

Using this methodology to calculate expected welfare gains implicitly assumes the Reduction Of Compound Lotteries (ROCL) axiom holds when we multiply the compound probabilities from the multiple steps to calculate EU or RDU. It would hence be inappropriate to use expected welfare calculated in this way to compare the effects of violating the ROCL axiom. We also make use of the two-step methodology explained in Segal [1990][1992] that does not assume ROCL, while still maintaining the independence axiom. We explain this methodology in detail later.

2. Experimental Design

Our experimental design has two essential tasks: one to elicit the risk preferences of the individual, and the other to elicit index insurance choices.

A. Risky Lottery Choices

Each subject was asked to make choices for each of 76 pairs of lotteries in the gain domain, designed to provide evidence of risk aversion as well as the tendency to make decisions consistently with EUT or RDU models. The battery is based on designs from Loomes and Sugden [1998] to test the Independence Axiom (IA), designs from Harrison, Martínez-Correa and Swarthout [2015] to test the ROCL axiom, and a series of lotteries that are actuarially-equivalent versions of some of our index insurance choices. Each subject faced a randomized sequence of choices from this 76. The analysis of risk attitudes given these choices follows Harrison and Rutström [2008]. The typical interface used is shown in Figure 5.

The key insight of the Loomes and Sugden [1998] design is to vary the "gradient" of the EUT-consistent indifference curves within a Marschak-Machina (MM) triangle.[7] The reason for this is to generate some choice patterns that are more powerful tests of EUT for any given risk attitude. Under EUT the slope of the indifference curve within a MM triangle is a measure of risk aversion. So there always exists some risk attitude such that the subject is indifferent, as stressed by Harrison [1984], and

[7] In the MM triangle there are always one, two or three prizes in each lottery that have positive probability of occurring. The vertical axis in each panel shows the probability attached to the high prize of that triple, and the horizontal axis shows the probability attached to the low prize of that triple. So when the probability of the highest and lowest prize is zero, 100% weight falls on the middle prize. Any lotteries strictly in the interior of the MM triangle have positive weight on all three prizes, and any lottery on the boundary of the MM triangle has zero weight on one or two prizes.

evidence of Common Ratio (CR) violations in that case has virtually zero power.[8]

The beauty of this design is that even if the risk attitude of the subject makes the tests of a CR violation from some sets of lottery pairs have low power, then the tests based on other sets of lottery pairs have to have higher power for this subject. By presenting subjects with several such sets, varying the slope of the EUT-consistent indifference curve, one can be sure of having some tests for CR violations that have decent power for each subject, without having to know *a priori* what their risk attitude is. Harrison, Johnson, McInnes and Rutström [2007] refer to this as a "complementary slack experimental design," since low-power tests of EUT in one set mean that there must be higher-power tests of EUT in another set.

A simple variant on these tests for a CR violation allow one to detect an empirically important pattern known as "boundary effects." These effects arise when one nudges the lottery pairs in CR and Common Consequence tests of EUT into the interior of the MM triangle, or moves them significantly into the interior. The striking finding is that EUT often performs better when one does this. Actually, the evidence is mixed in interesting ways. Camerer [1992] generated a remarkable series of experiments in which EUT did very well for interior lottery choices, but his data was unfortunately from hypothetical choices. These lotteries were well off the border. These lotteries can be contrasted with those in Camerer [1989] that were on the border, and where there were significant EUT violations. But Harless [1992] found that just nudging the lotteries off the boundary did not improve behavior under EUT for real stakes. So one natural question is whether the CR tests lead to EUT not being rejected when we are in the interior triangle, and to EUT being rejected when we are have choices on the boundary. Our battery replicates several of the sets of boundary CR tests originally proposed by Loomes and Sugden

[8] EUT does not, then, predict 50:50 choices, as some casually claim. It does say that the expected utility differences will not explain behavior, and that then allows all sorts of psychological factors to explain behavior. In effect, EUT has *no* prediction in this instance, and that is not the same as predicting an even split.

[1998], but with all lotteries moved into the interior of the MM triangle.

Our battery includes 15 lottery pairs based on Loomes and Sugden [2015] and a corresponding 15 lottery pairs that are interior variants of those 15 that are "on the border." Table C4 of Appendix C documents these 30 lottery pairs.

Harrison, Martínez-Correa and Swarthout [2015] designed a battery to test ROCL by posing lottery pairs that include an explicit compound lottery and a simple (non-compound) lottery. These lottery pairs have a corresponding set of pairs that replace the explicit compound lottery with it's actuarially equivalent simple lottery. Thus a ROCL-consistent subject would make the same choices in the first and second set. The compound lotteries are constructed by visually presenting two simple lotteries, but having some "double or nothing" option for one of them: Tables C1, C2 and C3 of Appendix C document these 30 lottery pairs.

Finally, we pose 16 lottery pairs that are actuarially-equivalent simple lotteries corresponding to 16 of the index insurance choices explained below. The objective is to present the "same" choices as the index insurance choices, but using the interface and abstract framing of a risky lottery choice, and assuming away the need to employ ROCL. The parameters for these lottery pairs are displayed in Table C5 in Appendix C, and Figure 5 shows the type of interface used.

B. Index Insurance Choices

We are primarily interested in observing how subjects' choices vary as the correlation factor varies across insurance choices, since a perfect correlation correspond to the traditional indemnity insurance product studied by Harrison and Ng [2016]. Subjects start with a $20 endowment and a 10% chance of losing $15. Each individual in Harrison and Ng [2016] is then offered 24 choices, where the premium of indemnity insurance with full coverage is varied from $0.20 to $4.80 in 20-cent increments, and for each premium decide if they want to purchase insurance or not. Each subject was classified as an EUT or RDU decision-maker, depending on which estimated model best explained the observed choices. Given the specific risk preferences estimated for each subject, the expected welfare gain from their battery of insurance choices was calculated.

We have extended the insurance choices of Harrison and Ng [2016] to include variation in correlation and loss probability, in addition to variation in premium amounts. We use a 4×4×2 framework for a total of 32 choices, displayed in Table 1. Correlation here is defined as the probability that the loss outcome of the individual matches the loss outcome of an independent index, and varies from +100% to +80%, +60% and +40%. Premium amounts vary around the actuarially fair premium of the initial insurance battery of $1.50, when the correlation is 100% and the loss probability set at 10%. Premia vary from much lower, slightly lower, slightly higher, and much higher than the actuarially fair premium: $0.50, $1.20, $1.80 and $3.50. The probability that the index reflects a loss is varied from 10% to 20%.

This insurance battery is applied across three treatments, designed to identify the structural source of welfare gains and losses:

- In the **Index Insurance (II)** treatment, the probability of the index experiencing a loss, and the probability of the personal outcome matching that of the index, are presented separately to the subjects. The monetary outcomes are also presented based on the outcomes of the index loss and personal event matching as separate events. Figure 6 displays a typical screenshot from this treatment.
- In the **Actuarially-Equivalent (AE)** treatment the probability of the index experiencing a loss, and the probability of the personal outcome matching that of the index, are still presented separately. However, the probabilities of the monetary outcomes are presented as final combined

lotteries as if ROCL applies. The screenshot in Figure 7 shows that the information presentation in this treatment matches the II treatment, apart from collapsing the compound lottery of the index insurance contract. The logic of the contract and underlying risk is still explained in the same manner in the instructions, so the natural context remains the same as the II treatment.

- In the **Naked Actuarially-Equivalent (Naked AE)** treatment the index loss probability and matching probability are not mentioned at all, and the AE lotteries corresponding to the index insurance contract are displayed using the abstract interface used for the risk lotteries task. As noted earlier, Figure 5 shows the interface used.
- In the **Index Insurance Contextual Cue (II-CC)** treatment we provided subjects with some text explaining the real-world context of the insurance choice problem defined by the Index Insurance (II) treatment. Apart from the text, shown in Box 1, the instructions were the same as the II treatment. In effect this treatment moves in the opposite direction than the AE and

With the exception of the Naked AE treatment, which was part of the risk aversion task, all of the insurance choices came after the risk aversion task, and were presented in the order shown in Table 1.

C. Welfare and Compound Risk Preferences

When we assume a CRRA utility function and EUT risk preferences to calculate the CS of purchasing insurance, a positive (negative) risk aversion parameter reflects risk aversion (loving) preferences, with a larger magnitude reflecting stronger preferences. We use the same insurance product that provides full indemnity against a 10% chance of losing $15 while starting with an initial endowment of $20 to demonstrate the impact of varying risk aversion on insurance demand in the presence and absence of basis risk. The cost of insurance is set at $1.80, which is slightly above actuarially fair insurance. We initially assume the ROCL axiom, which is the same as assuming compound risk neutrality when considering the impact of "simple" risk aversion on expected welfare gain.

When correlation is 1, or when there is no basis risk so that the individual's outcome matches the index outcome with certainty, an increase in (simple) risk aversion increases the CS of purchasing insurance. This corresponds to the conventional insurance theory stated in Clarke [2016], that an increase in risk aversion increases insurance demand in the absence of basis risk. This increase in risk aversion is shown in the red line in Figure 8, showing the effect on CS. The blue line in Figure 8 shows the impact of risk aversion on CS when basis risk is introduced: in this case we define basis risk as a 60% chance that the individual's outcome matches the index outcome. The blue line shows that this additional risk actually *decreases* the expected welfare gain of purchasing insurance as risk aversion increases.

When we compare the CS of purchasing insurance when there is no basis risk (red line) to the CS of purchasing insurance when there is basis risk (blue line), Figure 8 allows us to see that the expected welfare gain for the risk averse is reduced when basis risk is introduced. As risk aversion increases, this reduction in CS caused by the presence of basis risk increases. When the CRRA risk parameter is 0.7, or when there is moderate risk aversion, the CS is actually positive in the absence of basis risk: purchasing insurance for a moderately risk averse individual will lead to expected welfare gain. When basis risk is introduced, however, the CS of this insurance choice for the same moderately risk averse individual is negative: purchasing insurance in the presence of basis risk for this moderately risk averse individual will lead to expected welfare loss. In other words the presence of basis risk changes the "correct" insurance choice from "should purchase" to "should not purchase." This result of basis risk decreasing insurance demand for higher levels of risk aversion was first shown in Clarke [2016].

When we allow for violations of ROCL, while assuming a CRRA utility function, we use the CRRA risk parameter r for simple lotteries and the parameter $r + rc$ for compound lotteries, where rc

captures the additive effect of evaluating a compound lottery. This additional layer of risk compounds the impact of risk aversion on the expected welfare gain from insurance, and this impact of ROCL violations is shown by the dotted lines in Figure 9. When *rc* is positive (negative), as shown by the longer (shorter) dotted lines, there is compound risk aversion (loving) as *rc* increases (decreases) the CRRA risk parameter.

One oddity in using this methodology is that compound-neutral individuals and non-compound-neutral individuals will still have a different CS evaluated for the same insurance product *even in the absence of basis risk*. This is shown by the red lines in Figure 9, which show the CS when correlation is 1, so that the individual's outcome matches the index outcome with certainty, and there is no basis risk. The solid line in Figure 9 reflects the compound risk neutral CS, the short-dotted red line shows the compound risk loving CS, and the long-dotted red line shows the compound risk averse CS. We see that an increase in simple risk aversion increases CS in the absence of basis risk regardless of compound risk preferences. Using this methodology, however, shows that compound risk averse preferences increase CS and compound risk loving preferences decrease CS even though correlation is 1, which means there is no basis risk.

Compound risk aversion has a similar effect on the expected welfare gain of insurance as simple risk aversion. The blue lines show the CS of purchasing insurance when correlation is 0.6, so that is there is a 40% chance the individual's outcome does not match the index outcome. This introduces basis risk since there is a chance that the individual experiences a loss but the index does not reflect a loss and hence there is no insurance payout even though the individual experiences a loss. This is an example of downside basis risk. Upside basis risk refers to the case in which the individual does not experience a loss but the index reflects a loss so the individual receives a payout even though he has not experienced a loss.

The solid blue line in Figure 9 shows the expected welfare gain from purchasing insurance for compound risk neutral preferences, which is the same blue line in Figure 8 when we only considered simple risk preferences. The long-dotted blue line in Figure 9 shows the expected welfare gain for compound risk averse preferences and the short dotted blue line shows the expected welfare gain for compound risk loving preferences. The long-dotted blue lines in Figure 9 show that the effect on CS from an increase in compound risk aversion is similar to the effect on CS from an increase in simple risk aversion: compound risk aversion lowers the expected welfare gain from purchasing insurance. Conversely the short-dotted blue line shows that compound risk loving preferences increase CS relative to the solid blue line. Again the effect of compound risk loving preferences is similar to the effect of simple risk loving preferences.

As we have seen from Figure 8 when we only consider "simple" risk preferences, basis risk causes the expected welfare gain from purchasing insurance to decrease, and this decrease is larger as the level of risk aversion increases. This impact of basis risk on CS is more pronounced in Figure 9 when we also take compound risk preferences into account. When we assume moderate risk averse preferences ($r = 0.7$), Figure 9 shows that compound risk averse preferences increase CS when there is no basis risk (red), but compound risk averse preferences decrease CS when there is basis risk (blue). Without taking into account compound risk preferences, basis risk decreases CS of insurance for the moderately risk averse by \$1.26. When compound risk aversion is taken into account the size of this reduction in CS caused by basis risk increases to \$1.96. Compound risk aversion can further decrease insurance demand in the presence of basis risk, which could help explain why actual demand for index insurance has been lower than anticipated: we have yet to take into account the impact of compound risk preferences on index insurance welfare.

3. Experimental Evidence

A. Risk Preferences

Overall, the proportion of model classifications as EUT or RDU are similar to previously conducted experiments with this population, although there are slightly more subjects classified as EUT compared to previous samples. Figure 10 displays the classifications, based on tests of the null hypothesis that $\omega(p) = p$ and a 5% significance level. These estimates and hypothesis tests are undertaken *for each subject*. Exactly 60% of the subjects are classified as EUT, with the next most common model being the RDU specification with a Prelec [1998] probability-weighting function. This function is $\omega(p) = \exp\{-\eta(-\ln p)^{\varphi}\}$, and is defined for $0<p\leq 1$, $\eta>0$ and $\varphi>0$.[9] The distribution of model classifications of subjects conditional on insurance choice treatment is also similar, with slight differences. Just over 50% of subjects under the AE treatment were classified as EUT, and almost 40% were classified as RDU with the Prelec probability weighting function. This difference in distribution was offset by subjects under the II-CC treatment, where about ⅔ of subjects were classified as EUT, but only 9% were classified as RDU with the Prelec probability weighting function.

It is important that we assign the appropriate *model* of risk preferences to each subject, since the model classification influences the expected welfare calculated for each insurance choice. To illustrate this point, consider individual subject #2. The risk parameters were estimated based on his choices on lotteries in the risk task, and are displayed in Figure 11. If subject #2 was classified as EUT, he would be

[9] When $\varphi=1$ this function collapses to the Power function $\omega(p) = p^{\eta}$, and to EUT when $\eta = \varphi = 1$. Many apply the Prelec [1998; Proposition 1, part (B)] function with constraint $0 < \varphi < 1$, which requires that the probability weighting function exhibit subproportionality (so-called "inverse-S" weighting). Contrary to received wisdom, many individuals exhibit estimated probability weighting functions that violate subproportionality, so we use the more general specification from Prelec [1998; Proposition 1, part (C)], only requiring $\varphi > 0$, and let the evidence determine if the estimated φ lies in the unit interval. This seemingly minor point often makes a major difference empirically. In addition, one often finds applications of the one-parameter Prelec [1988] function, on the grounds that it is "flexible" and only uses one parameter. The additional flexibility over the Inverse-S probability weighting function is real, but minimal compared to the full two-parameter function.

moderately risk averse with a modestly concave utility function (r = 0.61). However, the preferred model is based on the log-likelihood *and* the hypothesis test that ω(p) = p, and for subject #2 that is the RDU model with the Inverse-S probability weighting function.[10]

Classifying subject #2 as RDU (Inverse-S) means the utility function is less concave, and the probability weighting function implies that the subject will overweigh extreme outcomes (γ = 0.7). Hence the subject would overestimate the probability of experiencing a loss, and would be willing to pay a higher premium to purchase the insurance. This overweighting of loss probability offsets the reduction in risk aversion under RDU, compared to when the risk premium is characterized entirely by curvature of the utility function.

Figures 12 and 13 illustrate the importance of this classification on the welfare calculations for subject #2. Each chart shows the CS calculated for each insurance choice made by subject #2. Blue bars indicate that subject had chosen to purchase insurance and red bars indicate that subject had chosen not to purchase insurance. The former chart shows the CS distribution if we had assumed subject #2 had EUT risk preferences, and the latter chart shows the CS distribution assuming subject #2 had RDU risk preferences with Inverse-S probability weighting function, the best-fit model based on the log-likelihood criteria. Different models of risk preference *type* can lead to *different* insurance decisions being recommended. For choices 7 and 13 under EUT, subject #2 choice to not purchase insurance resulted in a positive CS. Under RDU, however, these same choices resulted in a negative welfare gain. Using a different model of risk preference *type* can also impact the *size* of the expected welfare gain from an insurance choice, and not just the sign. Choice 17 becomes more beneficial when subject #2 is classified as RDU (Inverse-S) compared to EUT. Again, subject #2 made one set of choices over the risky

[10] Even though the Prelec probability weighting function is more flexible, it can generate slightly smaller log-likelihood values on occasions for numerical reasons. As it happens, it would not affect our conclusions, since the estimated functions are virtually the same (see the bottom two panels of Figure 11).

lotteries, so it is the classification of latent preferences given those choices that is driving these differences. Structural theory is essential to making the correct calculations about the sign and size of welfare.

B. Insurance Take-Up

The overall distribution of insurance choices is displayed in Figure 14. We define a "correct" choice is one in which the subject makes the choice to purchase or not purchase the insurance product on offer that is predicted by *correctly applying the risk preferences we estimate for that subject*. In other words, if the certainty-equivalent of the consumer surplus is positive when purchasing the insurance product, the "correct" decision is to purchase it; otherwise, the "correct" decision is not to purchase it. We use quotation marks for the word correct here, because our definition rests on theory and econometric inference about the risk preferences of individuals, and both of those might be wrong. But we firmly reject the view that one can determine what a correct insurance purchase decision is in the absence of some assumed theoretical and econometric structure.

Subjects make the "correct" choice more often when they are predicted to take up insurance based on their estimated risk preferences and the specific features of that insurance choice (the left panel, compared to the right panel). There appears to be no significant pattern when the estimated risk preferences predict that the subject should not purchase insurance (the right panel). A Fisher Exact test indicates that one can claim that these patterns of correct and incorrect decisions are significantly different across the two predictions.

Subjects making the correct choice more often than they should is driven by insurance choices in the AE treatment. Subjects in the AE treatment also choose to take up insurance more even when taking up insurance is predicted to result in negative welfare gain. This result is not observed in the II or

II-CC treatments. In those two treatments, when we predict that the subject should not take up insurance, the choice count of those who agree and do not take up insurance is higher than the choice count of those who do take up insurance. This is the first piece of evidence to suggest that compound risk might "scare away" potential buyers.

The distribution of choices for the II choices with a real world context (the II-CC treatment) is similar to the choices without the real world context (the II treatment). Detailed figures showing the breakdown of predicted count to actual choices by treatment can be found in Appendix E.

C. Comparing the II and AE Treatments

The breakdown by treatment of actual choices compared to predicted action to purchase insurance provides an initial insight into potential welfare losses. As noted, in Figure 14 the proportion of "correct" choices of take-up *for choices that are predicted to lead to take-up* are higher with the AE treatment than with the II treatment. However, the proportion of "correct" choices to not take-up *for choices that are predicted to lead to no take-up* are higher with the II treatment than with the AE treatment. Thus there is an interesting structural trade-off underlying the net welfare differences between the II and AE treatments. As it happens, the first effect is clearly much larger than the second effect, as a fraction of choices and as a number of choice. We would expect the same relative importance when these choice errors are translated into welfare loss.

In Figure 15 we compare the distribution of expected CS calculated from each insurance choice made in the II treatment to the expected CS calculated from each insurance choice made in the AE treatment. This comparison allows us to see if the decisions made in the AE treatment lead to greater welfare gains than the decisions made in the II treatment, and specifically provide a welfare metric to rigorously evaluate the trade-off in "correct" choices identified in Figure 14. The average CS in the AE treatment is indeed statistically significantly greater than the average CS in the II treatment, with a *t*-test showing a *p*-value < 0.01. This is yet another piece of evidence pointing towards ROCL and the presence of compound risk in the II product as the cause of potential buyers being discouraged from purchasing when they should.

Efficiency is defined as the sum of the actual CS each subject earns from all their insurance choices as a ratio of the total CS they could have earned if they had made every choice consistently with their risk preferences. The efficiency metric was developed by Plott and Smith [1978], and is defined at the level of the individual *subject*, whereas the expected welfare gain is defined at the level of each *choice* by each subject. In addition, efficiency provides a natural normalization of expected welfare gain on loss by comparing to the maximal expected welfare gain for that choice and subject. Both metrics are of interest, and are complementary. Figure 16 displays the efficiency comparisons, with the same conclusion as with the CS comparisons: the AE treatment leads to significantly greater efficiency.

D. Comparing the II and II-C Treatments

Comparing the distributions of expected CS calculated between the II treatments with and without real-life context in Figure 17 shows that there is no statistical difference between the expected welfare benefits from insurance choices in each case. The efficiency of subjects between the II treatment and the II-CC treatment, shown in Figure 18, provides a slightly different result, with the Kolmogorov-Smirnov test indicating that they do not have the same distribution ($p < 0.001$), despite the similarity of average efficiency. From our results we see that while take-up and welfare increase when compound lotteries are expressed in their reduced form, adding text to provide real-life context beyond the lab does not significantly change behavior, and does not discourage the validity of lab results for index insurance in the real world.

E. Allowing for ROCL Violations

One conceptual limitation of the current methodology for calculating the expected welfare benefits from insurance is that we assume the subject calculates CS by using ROCL. This is true whether the subject is classified as having EUT or RDU preferences, since both assume ROCL. We therefore consider variants of the EUT and RDU models that do not assume ROCL.

For EUT we follow Harrison, Martínez-Correa and Swarthout [2015] and consider a "source-dependent" model in which the individual has one risk attitude for simple lotteries and potentially another risk attitude for compound lotteries. In historical context, Smith [1964] proposed this specification as one that was consistent with the evidence from several of the thought experiments underlying (two-color) Ellsberg paradox. If we view these types of lotteries as defining different sources of risk, this specification deviates from ROCL to the extent that these risk attitudes differ.[11]

For RDU we apply the methodology from Segal [1990][1992] to relax the ROCL assumption, leading to what is often referred to as the Recursive RDU model. The basic idea is to assume the second-stage lotteries of any compound lottery are replaced by their certainty-equivalent, "throwing away" information about the second-stage probabilities before one examines the first-stage probabilities at all. Hence one cannot then *define* the actuarially-equivalent simple lottery, by construction, since the informational bridge to that calculation has been burnt. If this CE is generated by RDU, then one can apply RDU to evaluate the first-stage lottery using those CE as final outcomes. The Recursive RDU model assumes one set of RDU preference parameters, just applied recursively in this manner.[12]

[11] In a handful of cases the source-dependent EUT model does not solve for an individual, but the traditional EUT model does solve. In that case we assume the latter specification for this individual, at least as the best EUT characterization.

[12] It would be a simple matter to also consider a source-dependent Recursive RDU, or just a source-dependent RDU model. There is only one way for ROCL to be valid, but an infinite number of ways for it to be invalid.

Classification of Risk Preferences

Figure 19 shows that the overall distribution of risk preferences of subjects is similar whether or not we assume ROCL, and should be compared to Figure 10 where we assume ROCL. We find an even greater fraction of subjects classified as EUT, although here we stress that "EUT" is in fact the source-dependent EUT model and not EUT, which assumes ROCL.[13] The distribution conditional on treatment is also similar, with the exception of the II-CC treatment, where the distribution between RDU models is more balanced. Given the importance of the source-dependent EUT model, it is useful to identify how significant the deviations from ROCL are. Figure 20 shows the distribution of *p*-values, one per subject, testing the null hypothesis that the risk attitude for simple lotteries (r^{simple}) is the same as the risk attitude for compound lotteries ($r^{compound}$). We find that only 16% of the subjects are estimated to violate ROCL in this manner at the 5% significance level (i.e, where the null hypothesis is EUT and the alternative hypothesis is source-dependent EUT). Of course, from Figure 19 we see that over 20% of subjects are classified as Recursively RDU.

Comparison of Predicted Choices and Actual Choices

Relaxing ROCL in the calculation of welfare does not change our conclusions on the distribution of insurance choices (Figure 21). The movement of insurance choice count between buckets is small, and the largest shift is from choices to take-up insurance: the number of insurance choices that

[13] Nested hypothesis tests are not appropriate to use to determine if the source-dependent EUT (sdEUT) and recursive RDU (rRDU) models would be a better fit for each subject's choices, since the sdEUT model is not nested in the rRDU model. For the non-nested model comparisons we use the Vuong test and the Clarke test, described in Harrison and Rutström [2009]. The Vuong test compares the *observation-specific* likelihoods of each model, rather than using the *sum* of the likelihoods of each model as in nested hypothesis tests. The ratio of the sdEUT likelihood to the rRDU likelihood at the observation level is calculated, then the average log of that test statistic for each subject is tested for the null hypothesis that it is zero. If the test statistic is not asymptotically distributed standard normal, the non-parametric Clarke test is more suitable. Not only does each test tell us which model is a better fit, but it also provides some statistical confidence in the rejection of the null in the direction of the favored model.

matched the prediction to take-up insurance decreased by 74, from 2114 to 2040. Relaxing ROCL changes the "sign" of the expected welfare benefits. If the sign assuming ROCL is positive (negative) but changes to negative (positive) when relaxing ROCL, then the choice will switch from predicted to take-up (not take-up) to predicted to not take-up (take-up).

Comparison of Consumer Surplus and Efficiency

Relaxing ROCL still leads us to the same conclusion, that on average expected welfare gain is higher in the AE treatment than in the II treatment (Figures 22 and 23). Just as we found when we assume ROCL, a comparison of CS distributions shows expected welfare gain from insurance choices is not statistically significantly different between the II and II-CC treatments (Figure 24). When we relax the ROCL assumption however, efficiency in the II-CC treatment is statistically different and larger than efficiency in the II treatment (Figure 25). Thus, when we relax the ROCL assumption our results show that subjects are slightly more efficient when they are able to relate the experiment to its actual application in the field as index insurance.

Once again we look to an individual's welfare benefits from choices on insurance to illustrate the impact of relaxing the ROCL assumption. Figures 26 and 27 show the calculated CS for each insurance choice based on the risk model estimated for subject #116 with and without the ROCL assumption, respectively. The method for determining the preferred model is the same as described earlier. When ROCL is assumed, subject #116 is classified as RDU with a Prelec probability weighting function with a modestly concave utility function and a probability function that overweighs extreme outcomes. When we relax the ROCL assumption, however, subject #116 is classified as with the Source-Dependent EUT model with moderate risk aversion (r=0.56 for simple lotteries, and r=0.6 for compound lotteries). The CS distributions between the two models are similar, but there are still differences that impact how we evaluate subject #116's insurance take-up decisions. The decision to not take up insurance for choices 7 and 8 are incorrect when subject #116 is RDU (Prelec), since they result in negative CS. These same decisions to not take up insurance, however, become the correct choice under Source-Dependent EUT.

For choices 14, 15 and 16 and 30, 31 and 32, when we relax the ROCL assumption we still infer that the decision to not purchase insurance resulted in positive expected welfare benefits. However, those benefits are greater for these decisions when the ROCL assumption is relaxed. This is also seen in the efficiency calculated for subject #116, which is 0.56 if ROCL is assumed but 0.67 if it is not. Again, the persistent theme here is that latent, structural theory is needed to get the correct welfare evaluations.

F. The Reduction of Compound Lotteries Axiom

<u>Motivation</u>

It is apparent that the II contract differs formally from the standard indemnity contract by contractually transforming a simple risk into a compound risk, and in a way that necessarily increases the potential variability of final wealth levels for anyone purchasing the II contract. We say "necessarily" because we are studying naked II contracts that exist in a risk management vacuum: they are the only risk management tool available to our agents. In the field there exist a myriad of self-protection and self-insurance options, typically in the form of "informal insurance arrangements." After all, one function of households, villages and even ethnicity is to pool risks – whether they do it, or even do it well, is a separate issue. But if we consider the formal II contract in this broader setting, as one component of a potential individual or group risk management portfolio, it may be less exposed as a risk management instrument to the fact that it exacerbates the variability of risk. But that is not our setting, by design.

Our design deliberately isolates the II contract, and focuses a bright light on the role of ROCL in explaining why the compound risks of an II contract might generate welfare losses when real individuals make real choices, and why some of those losses might be significant in size. This is the point of our comparison of II and AE insurance contracts, and our use of individual-specific tests of the validity of ROCL in the abstract.

As a result, we must be very careful in making claims about welfare effects to not assume in the left hand what we are rejecting and evaluating in the right hand: the validity of the ROCL axiom. The EUT and RDU models considered to this stage as a way of characterizing risk preferences both assume the validity of ROCL. We now consider "variants" of EUT and RDU that do not assume ROCL, so that our welfare evaluation of II contracts can be undertaken on a theoretically consistent basis. We say "variants" in quotation marks since these are not EUT or RDU: we consider a Source-Dependent EUT (sdEUT) and Recursive RDU (rRDU) specification, respectively. The sdEUT model nests EUT, and the rRDU model nests RDU, but the rRDU model does not nest sdEUT in the same way that RDU nests EUT. Hence we cannot simply apply the same methodology as before to decide on the best characterization of risk preferences for an individual. To do that we would need to rely on non-nested hypothesis tests or mixture specifications of sdEUT and rRDU – the historical linkage between non-nested hypothesis tests and mixture models is documented in Harrison and Rutström [2009], and has been largely forgotten in modern econometric doctrine.

We intend to undertake non-nested hypothesis tests in order to determine the best characterization of the model of non-ROCL risk preferences for the individual.[14] But for now we adopt a simpler approach by assuming that the individual is *either* sdEUT *or* rRDU and evaluating the welfare costs of their decisions conditional on the implied risk preferences for that individual.

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[14] Harrison and Swarthout [2016] illustrate the approach we will use, in the context of evaluating the empirical strength of support for Cumulative Prospect Theory (CPT) compared to RDU and EUT, since RDU and EUT are not nested in CPT.

Statistical Analysis

A regression analysis is useful in understanding what is driving the typical differences in the welfare distribution between the II treatments and AE treatments. We are interested in the impact of parameters that vary across insurance choices, which are the correlation, the probability the index suffers a loss, and the premium. We are also interested in how characteristics of our subjects might influence their welfare choices.

One natural characteristic to also look at is how a subject's behavior with respect to the ROCL axiom influence the welfare from choices over compound lotteries.We measure violations of the ROCL axiom non-parametrically by making use of the 15 ROCL lottery pairs in our risk battery. Each subject was given 15 lottery choices between a simple lottery and a compound lottery (S-C lottery), as well as 15 corresponding lottery choices between the same simple lottery and a simple lottery that was actuarially-equivalent to that compound lottery (S-AE lottery). If the subject was making ROCL-consistent choices, the choices in each lottery pair would match: either choose the simple lottery in both choices or choose the compound and actuarially-equivalent lottery. We count the number of pairs out of the 15 that each subject does not make these ROCL-consistent choices as a measure of the degree to which each subject deviates from the ROCL axiom. This method of measuring compound risk preferences does not differentiate between compound-loving or compound-risk averse, and only measures if the lottery choice deviates from ROCL or not.

Another natural characteristic of interest is a subject's attitude towards risk. We include a variable for the level of risk aversion for each subject, which is the risk parameter r, estimated assuming all subjects have CRRA utility functions and behave according to EUT. In this respect we only use EUT descriptively, to provide a measure of the overall risk aversion of the subject, and not to claim that the subject is best characterized by EUT. We also include the square of the risk parameter, to test the result in Clarke [2016], that subjects might display a "hump-shaped" demand for index insurance which increases, then decreases, as risk aversion increases. We stress that these risk aversion characteristics are being considered heuristically here, since they are point estimates from a distribution and not data. For that reason we present the results of considering them separately.

We use CS calculated for each insurance choice, as well as the efficiency of each subject, to estimate expected welfare gain from insurance. We also look at efficiency at the choice level (Choice), which is simply a binary variable indicating whether or not the "correct" choice was made to purchase insurance if it is expected to have positive welfare compared to the status quo, or not to purchase insurance if it is expected to have negative welfare compared to the status quo. Finally we also compare the results for the three welfare metrics to the results on take-up. Since take-up and Choice are binary variables, a random effects probit model is used to measure the average marginal probability of insurance factors. Since CS is continuous, a random effects linear regression is used to measure the average marginal effect. A beta regression is applied to efficiency to measure the average marginal probability, since efficiency is a continuous variable between 0 and 1.[15]

We first look at the average marginal effects across treatments assuming all subjects are source-dependent EUT and that model is used to evaluate the CS for each subject. As we are considering the impact of ROCL violations, it is more appropriate to use a model that does not assume ROCL to calculate welfare. Welfare in the AE treatment is significantly impacted by the correlation, loss probability and premium (Table 2). CS is on average \$1.45 higher (p-value < 0.001) and subjects are 94.2% more likely to make the "correct" choice (p-value < 0.001) for a unit increase in correlation. Lower premiums and higher loss probabilities significantly increase both welfare and take-up.

[15] Because all but one of these regression models are non-linear in the estimated parameters, it is possible for the margin, which is the derivative of the prediction function, to be greater than 1.

Interestingly, correlation and premium do not significantly impact welfare when subjects are dealing with the compound lotteries in the II treatments (Table 3).

On the other hand, the ROCL violation count, our proxy for each subject's consistency with the ROCL axiom, significantly impacts welfare in the II treatments. For each decrease in the violation count, a subject is on average 4.0% more likely to make a "correct" choice (*p*-value = 0.003) that increases CS of that choice by $0.05 (*p*-value = 0.001) and increases the subject's efficiency by 5.0% (*p*-value = 0.008). The ROCL violation count does not significantly impact welfare in the simple lotteries in the AE treatment. Insurers promoting index insurance encourage take-up or increase the welfare benefits of II by tweaking the characteristics of the insurance product, such as reducing the basis risk between index and personal outcome, and lowering premiums to encourage take-up (e.g., Skees et al. [2001], Cole et al. [2013], Jensen et al. [2014]). Our results show that on average these strategies are effective in increasing the welfare of insurance products dealing with simple risk, but resources might be better focused on encouraging ROCL consistency in insurance with compound risks, possibly through education. Our results also show that this improvement in welfare through an increase in ROCL-consistency may not be reflected in a significant increase in take-up.

Our results show that there is a gender effect on welfare of insurance choices. On average females are 13.9% less likely to make a beneficial insurance choice (*p*-value = 0.015). As a result their expected welfare gain from insurance choices are on average $0.22 lower per choice (*p*-value = 0.007) and subjects are on average 23.0% less efficient (*p*-value = 0.002). This corresponds to the findings in Harrison and Ng [2016] with a simple indemnity product, where females were more likely to make the wrong decision to take up insurance when it was predicted that they should not. Our study finds that females might have benefitted more from the compound nature of index insurance, at least then the negative welfare impact of their insurance decisions were not significant. There were similar results for subjects who were college seniors and those who identified as Christian. On average in the AE treatment college seniors were making insurance choices that increased their welfare, while Christian students were making choices that decreased their welfare. This was consistent across all welfare metrics.

However, these demographics no longer have any significant impact in the II treatments. Once again these impacts can only be seen in calculated welfare, and not in take-up. Additionally, our results show that different demographics have different impacts between evaluating simple and compound insurance products. The sub-groups one might want to focus on when promoting simple insurance products may not be the same when considering compound insurance products. Black subjects were significantly making decisions that benefitted them less in the II treatments, but their decisions did not significantly impact welfare in the AE treatment.

To best approximate the assumptions of the theoretical model of "rational behavior" in Clarke [2016], we can restrict all evaluations to EUT and further to all observed decisions that generated a positive CS (i.e., that were the correct decision, given the implied EUT preferences for that subject). In this instance we do find a significant "hump-shaped" impact on take-up for the II treatment, looking at the joint impact for r and r^2. The same, predicted pattern arises even more strongly for impacts on CS under these assumptions: of course, under these assumptions the CS can be viewed as a richer measure of the strength of the "rational preference" implied by the theoretical model, whereas take-up is simply a binary indicator of the sign of the preference. There is also evidence for this predicted pattern on take-up when one considers relaxing the assumptions of the formal model of "rational behavior" underlying the predictions in Clarke [2016] by allowing some subjects to be characterized by RDU preferences. However, once we relax the assumption of ROCL, and use sdEUT or rRDU risk preferences to characterize individuals, the predicted pattern fails. This is not a surprise logically, but does show that these predictions from the perspective of "rational behavior" are not robust to the behavioral vagaries of real subjects making choices for real rewards. Similarly, when we relax the representation of the insurance task in terms of explicit compound lotteries and basis risk, in our AE treatment, there is no evidence for the predicted pattern with respect to take-up. These findings strengthen our argument that violations of the ROCL axiom should be considered as a first-order determinant when one studies the impacts of risk aversion on the welfare from index insurance products. Again, we stress that these estimated impacts from risk aversion are heuristic at best, since our risk aversion parameter is stochastic.

The average marginal effects by treatment for the standard methodology and for the methodology assuming all subjects are recursive RDU can be found in appendix F.[16] We also consider estimates in Appendix F that drop the stochastic variables, and show that we get essentially the same results as in Tables 2 and 3.

4. Conclusions

Index insurance poses an important policy puzzle. It promises to allow large-scale risk management instruments to be made available to poor, underserved populations. On the other hand, making the product attractive[17] is a behavioral challenge. Index insurance, by itself, exacerbates the risk faced by the insured if the sole measure of riskiness is the variability of potential outcomes: this is in sharp contrast to the effects of traditional indemnity products. Of course, the relevant issue is whether

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[16] Our conclusions from assuming that all subjects are recursive RDU are quite different from either the standard methodology or source-dependent EUT results, and seem more random and difficult to explain. ROCL consistency only significantly impacts the welfare in the AE treatment. The young make significantly less efficient choices for simple insurance but significantly more efficient decisions for compound insurance which is more complicated.

[17] By "making the product attractive" we do not just mean seeing the product purchased. One can (almost) always directly subsidize a product so that many people purchase it, but the critical step in designing a financially sustainable instrument is to make it attractive when there are some reasonable loadings. There are also many important policy settings in which index insurance thrives because it is required by government policy, in order for insurance companies to be allowed to sell other, more profitable products in their country. This is a cross-subsidy, for a public purpose.

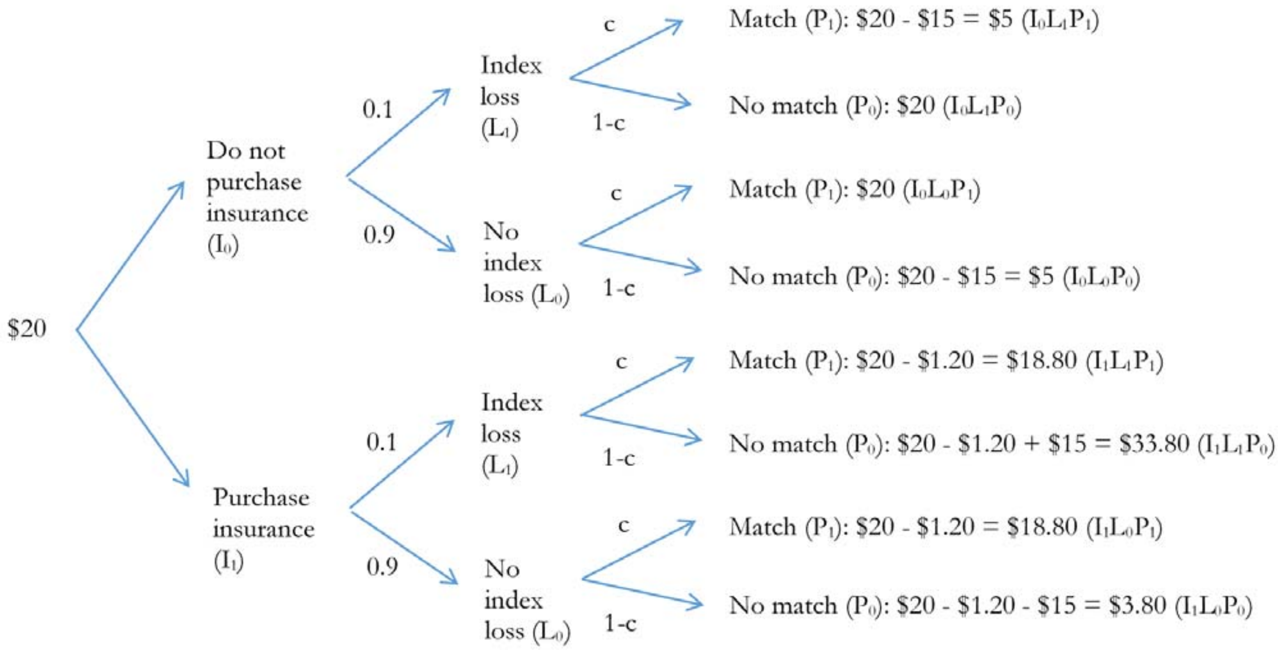
the expected benefit to the consumer of the change in the weighted distribution of outcomes exceeds the known premium. And that expected benefit depends on how the insured weights the probability of different outcomes, both the extreme outcomes and the typical outcomes.

Our results show that the compound risk in index insurance decreases the welfare of insurance choices made by individuals. Behavioral violation of the ROCL axiom decreases welfare when there is a compound risk of loss, whereas loss probability, basis risk and premium only impact the welfare of insurance choices when risk of loss is expressed in its reduced, non-compound form. We also see, again, that take-up is not a reliable indicator of welfare. Furthermore, the drivers of increased welfare from index insurance are not be the same drivers of increased take-up, so take-up is not even a useful proxy for guiding policy to improve welfare.

The upshot is that we need to know the specific risk preferences of the individual to determine if the expected benefit of the index insurance product exceeds the known premium. Risk preferences, in turn, mean more than just some "level of risk aversion," but includes the manner in which variability of outcomes are evaluated as well as the manner in which various probabilities are weighed. In the case of index insurance, we also have to be sensitive to the manner in which compound risks are assessed compared to simple risks, since index insurance explicitly relies on compound risks. Each of these dimensions of what we mean by risk preferences can be assessed, if we are careful to spell out specific structural theories of risk preferences and experimental designs that identify them.

Our results consistently point to the importance of evaluating how individuals process compound risks when evaluating the welfare effects of decisions to purchase index insurance products. Although this may come as no great surprise, the point to behavioral subtleties in the welfare evaluation of index insurance that demand greater attention. One obvious extension to our approach is to undertake a field evaluation. Another extension is to assess the role of formal index insurance products as one part of the wider portfolio of informal individual, household, village and state risk management instruments.

Figure 1: Decision Tree for Index Insurance Product



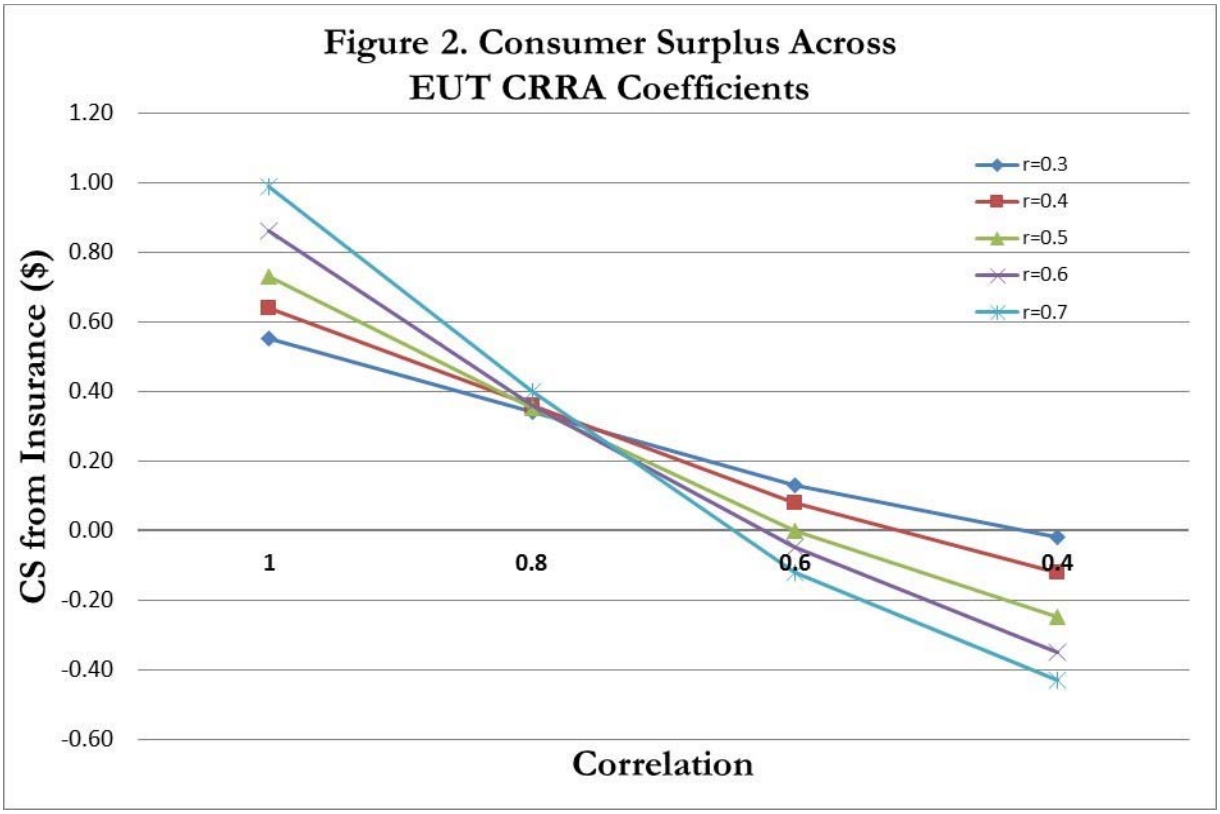


Figure 2. Consumer Surplus Across
EUT CRRA Coefficients
CS from Insurance ($)
1.20
1.00
0.80
0.60
0.40
0.20
0.00
-0.20
-0.40
-0.60
1
0.8
0.6
0.4
r=0.3
r=0.4
r=0.5
r=0.6
r=0.7
Correlation

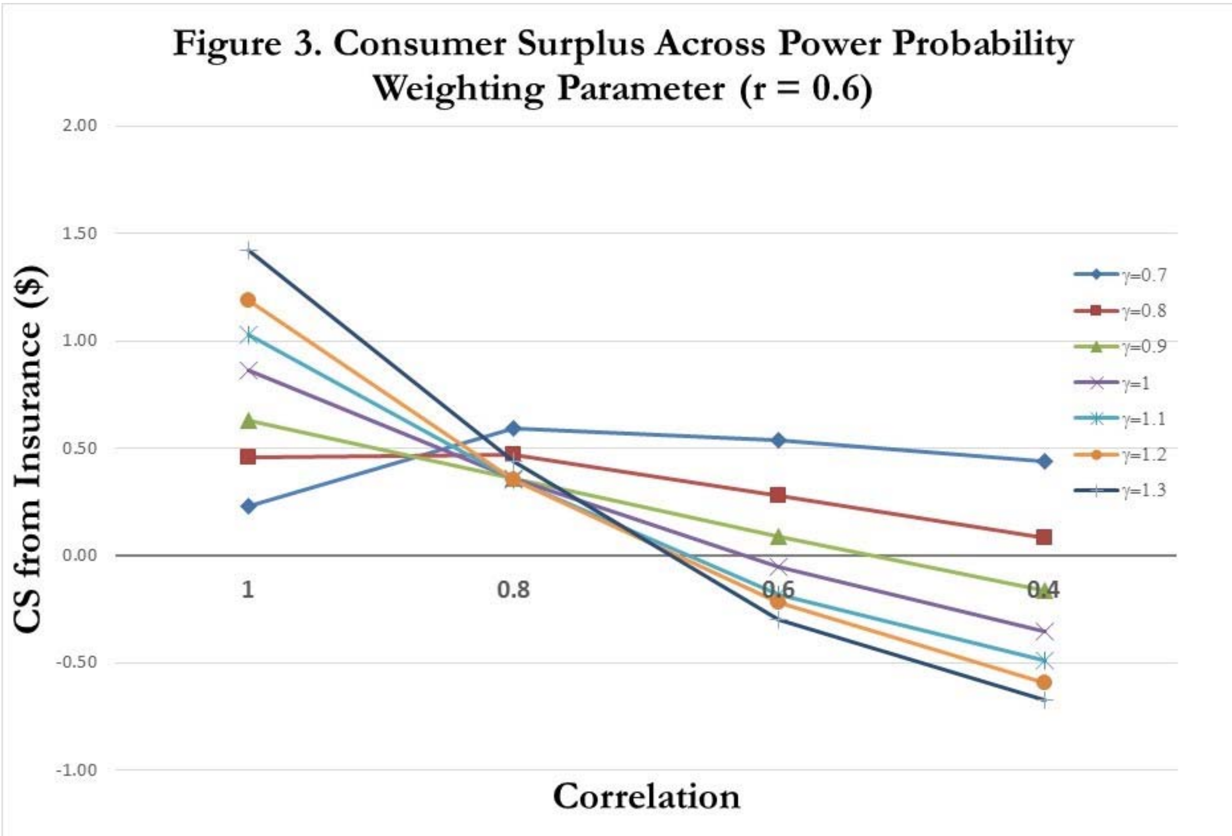


Figure 3. Consumer Surplus Across Power Probability Weighting Parameter (r = 0.6)
2.00
1.50
1.00
0.50
0.00
-0.50
-1.00
CS from Insurance ($)
1
0.8
0.6
0.4
Correlation
γ=0.7
γ=0.8
γ=0.9
γ=1
γ=1.1
γ=1.2
γ=1.3

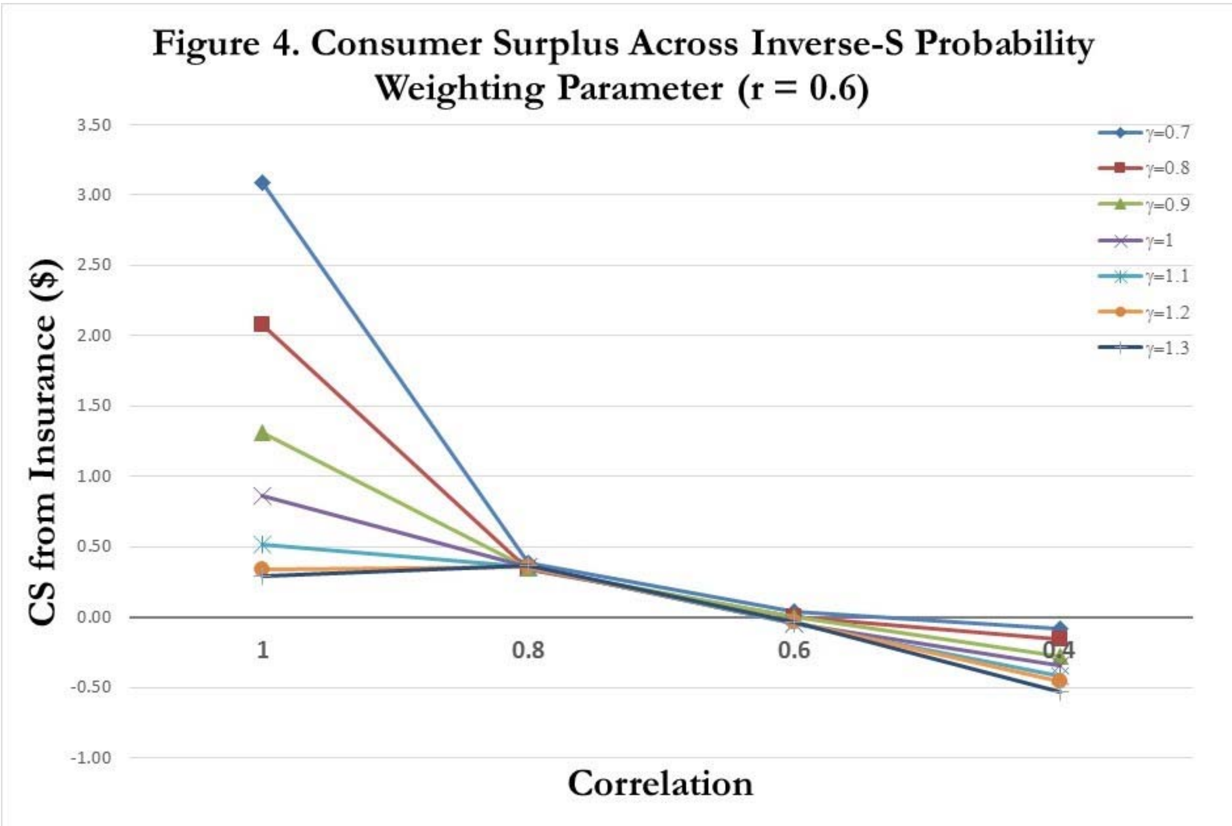


Figure 4. Consumer Surplus Across Inverse-S Probability Weighting Parameter (r = 0.6)
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
-0.50
-1.00
CS from Insurance ($)
1
0.8
0.6
0.4
Correlation
γ=0.7
γ=0.8
γ=0.9
γ=1
γ=1.1
γ=1.2
γ=1.3

Table 1: Index Insurance Contracts and Parameters in the Experiment

Choice	Correlation	Premium Amount ($)	Index Loss Probability	Initial Endowment ($)	Loss Amount ($)
1	1	0.5	0.1	20	15
2	0.8	0.5	0.1	20	15
3	0.6	0.5	0.1	20	15
4	0.4	0.5	0.1	20	15
5	1	1.2	0.1	20	15
6	0.8	1.2	0.1	20	15
7	0.6	1.2	0.1	20	15
8	0.4	1.2	0.1	20	15
9	1	1.8	0.1	20	15
10	0.8	1.8	0.1	20	15
11	0.6	1.8	0.1	20	15
12	0.4	1.8	0.1	20	15
13	1	3.5	0.1	20	15
14	0.8	3.5	0.1	20	15
15	0.6	3.5	0.1	20	15
16	0.4	3.5	0.1	20	15
17	1	0.5	0.2	20	15
18	0.8	0.5	0.2	20	15
19	0.6	0.5	0.2	20	15
20	0.4	0.5	0.2	20	15
21	1	1.2	0.2	20	15
22	0.8	1.2	0.2	20	15
23	0.6	1.2	0.2	20	15
24	0.4	1.2	0.2	20	15
25	1	1.8	0.2	20	15
26	0.8	1.8	0.2	20	15
27	0.6	1.8	0.2	20	15
28	0.4	1.8	0.2	20	15
29	1	3.5	0.2	20	15
30	0.8	3.5	0.2	20	15
31	0.6	3.5	0.2	20	15
32	0.4	3.5	0.2	20	15

Figure 5: Interface for Risk Aversion Lottery Choice

Figure 6: Interface for Insurance Choice in II Treatment

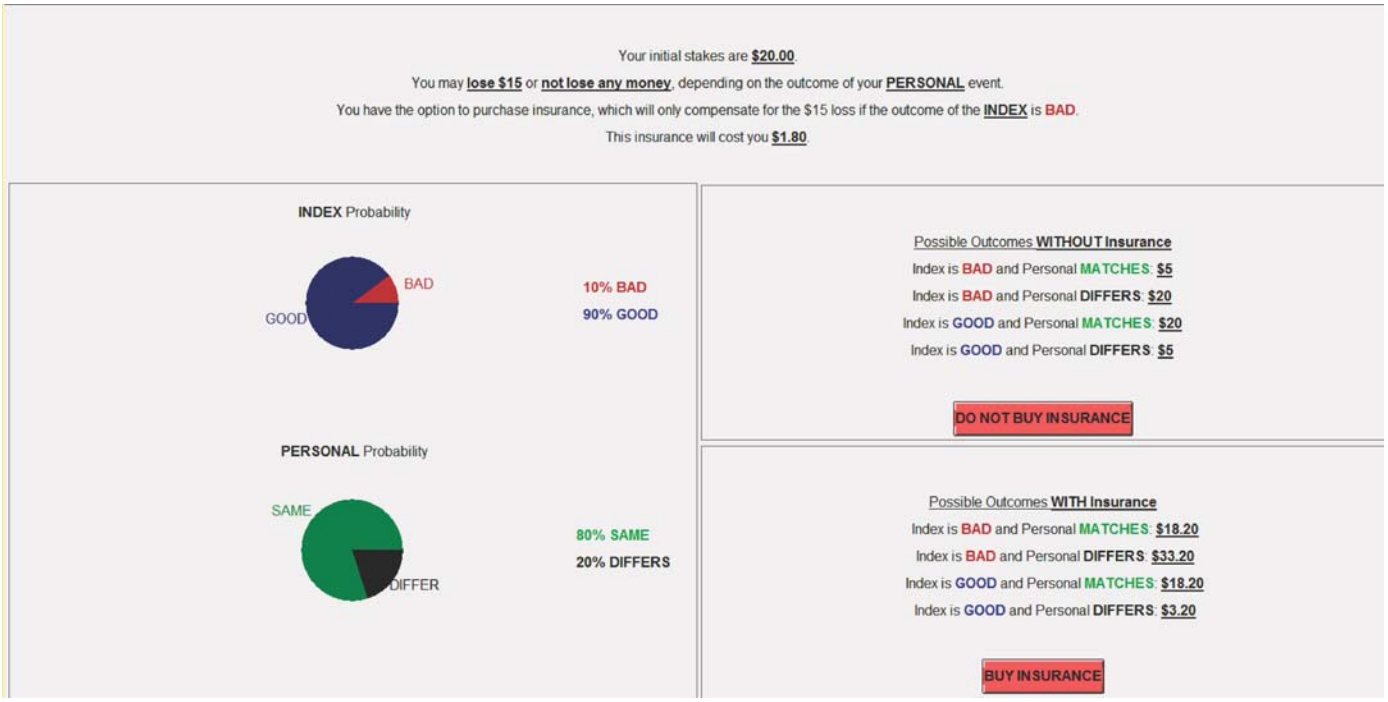
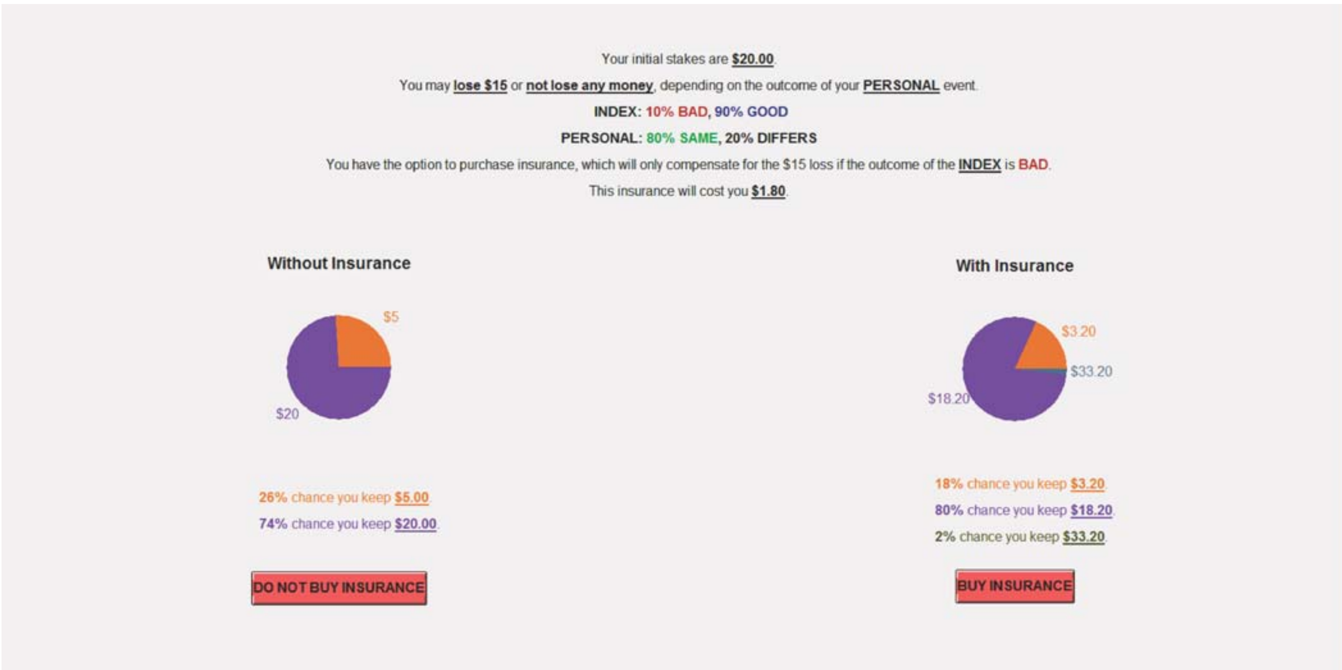


Figure 7: Interface for Insurance Choice in AE Treatment



Box 1: Additional Text Provided in Index Insurance Contextual Clue Treatment

Information on Real-World Counterpart

This task is based on a real-world insurance product known as index insurance, widely used for farmers who grow crops in poor countries.

Index insurance is insurance that is linked to an index such as rainfall, temperature, humidity or crop yields, rather than an actual loss. An example of index insurance is the use of an index of rainfall totals to insure against drought-related crop loss. Payouts occur when rainfall totals over some time period fall below some pre-agreed threshold that can be expected to result in crop loss in a geographic area.

One advantage of using the index is that, unlike traditional crop insurance, the insurance company does not need to visit farmers' fields to assess losses and determine payouts. That is expensive to do, and means that traditional premiums would have to be too high for most farmers to afford. Instead, index insurance uses data from rain gauges near the farmer's field. If these data show the rainfall amount is below the threshold, the insurance pays out; if the data show the rainfall amount exceeds the threshold, the insurance does not pay out. All the insurance company has to do, to figure out if it should pay out, is check the rain gauge. This reduces the cost of providing insurance to these farmers.

Figure 8: Effect of Simple Risk on Consumer Surplus

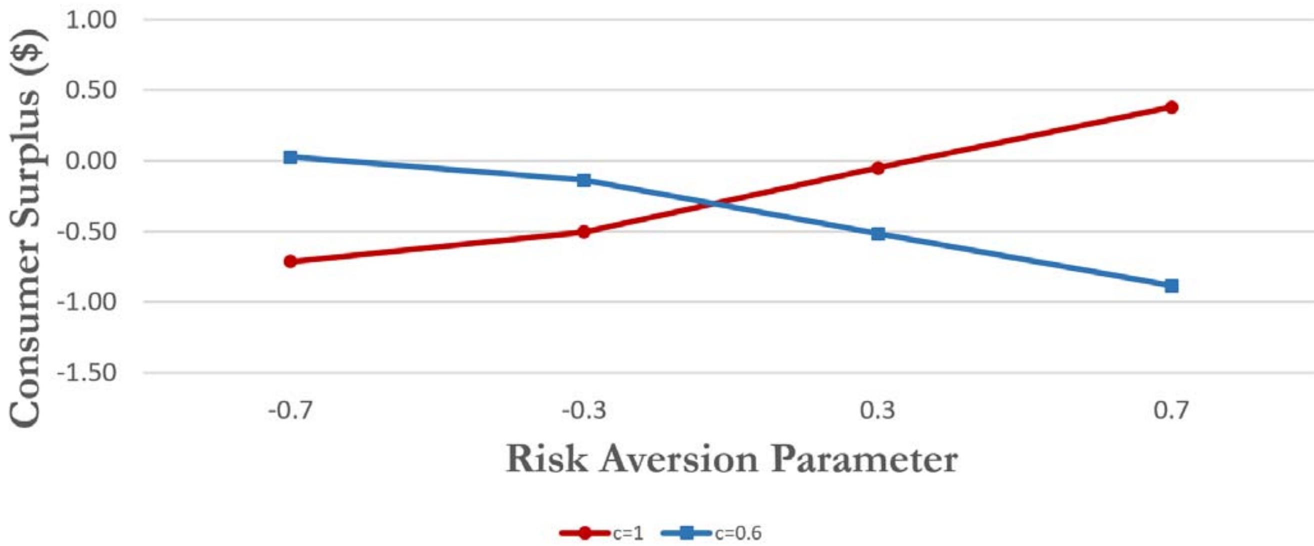


Figure 9: Effect of Compound Risk on Consumer Surplus

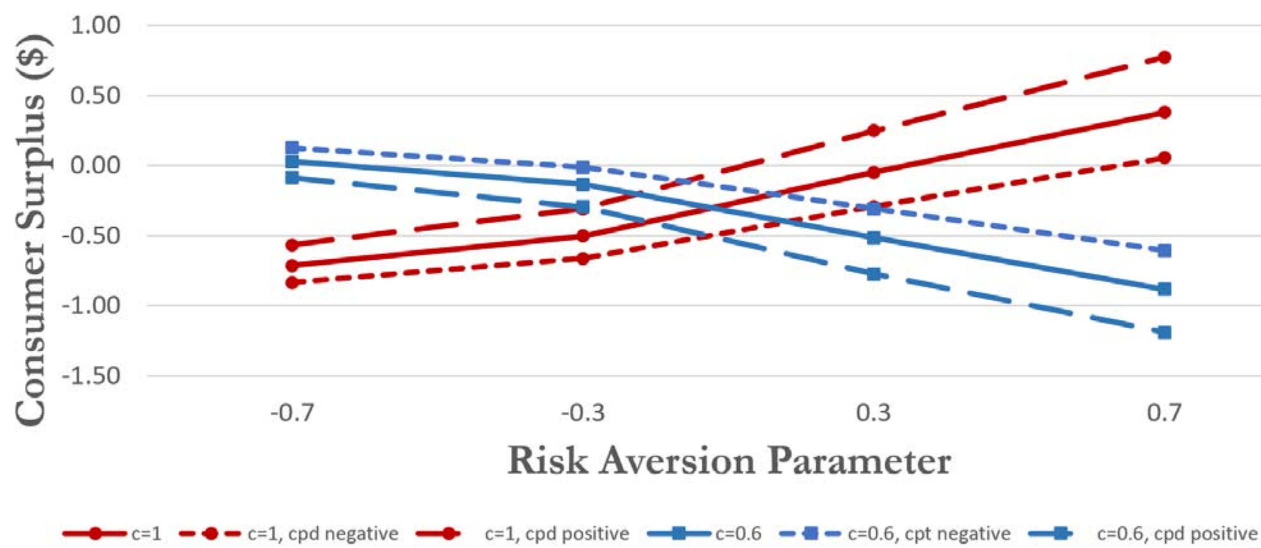


Figure 10: Classifying Subjects as EUT or RDU

N=145, one *p*-value per individual
Estimates for each individual of EUT and RDU specifications

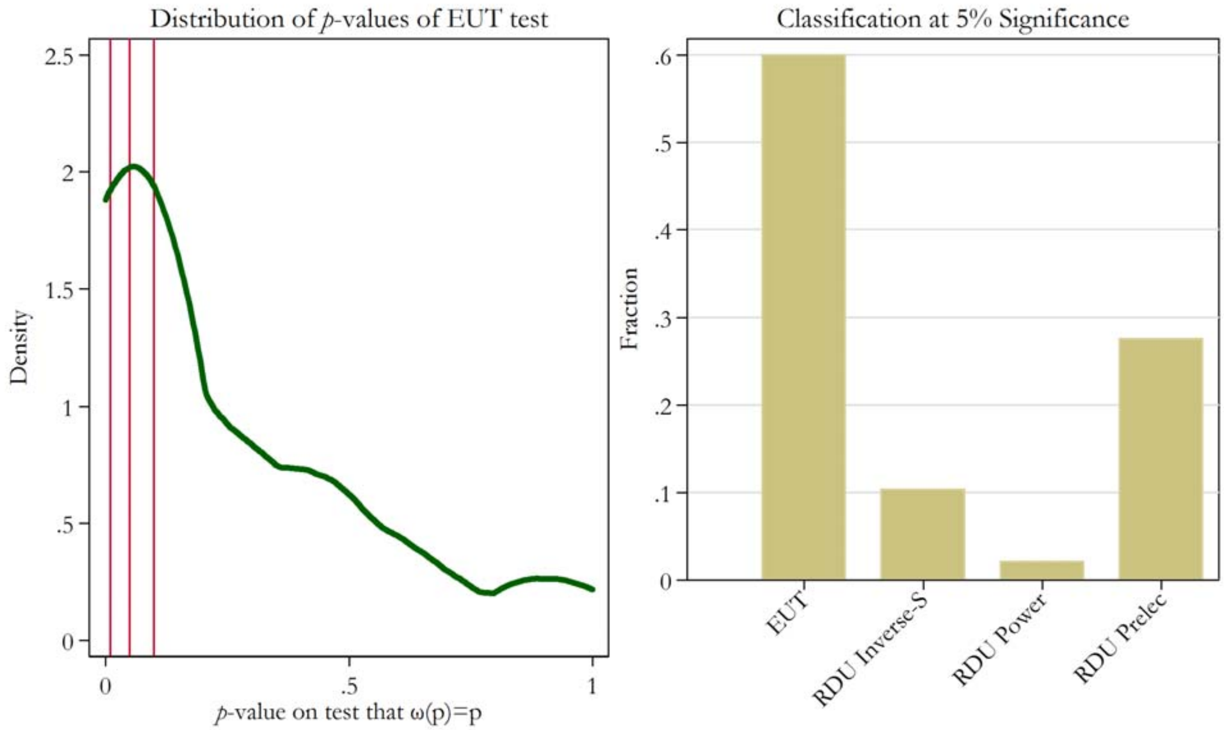


Figure 11: Estimated Risk Parameters for Subject #2

Subject #2 is classifed RDU with EUT *p*-value = 0.000 (< 0.05)

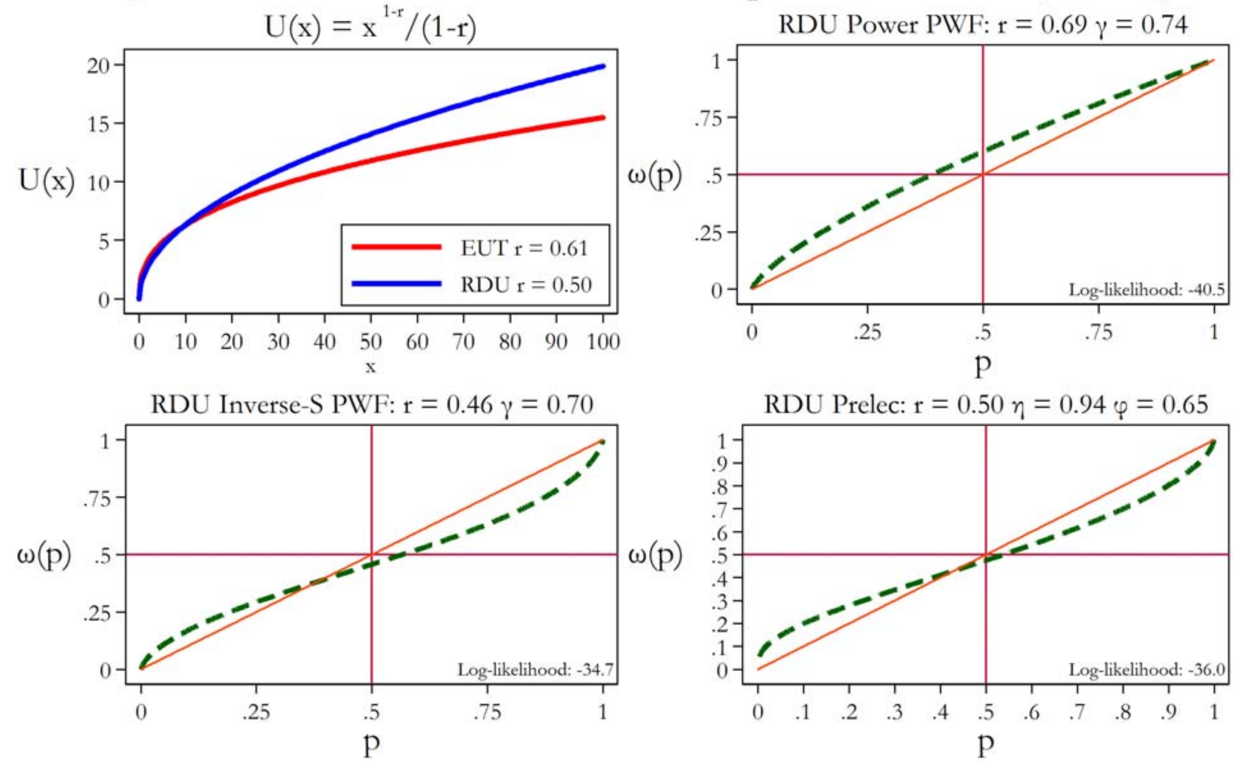


Figure 12: Consumer Surplus of Choices of Subject #2

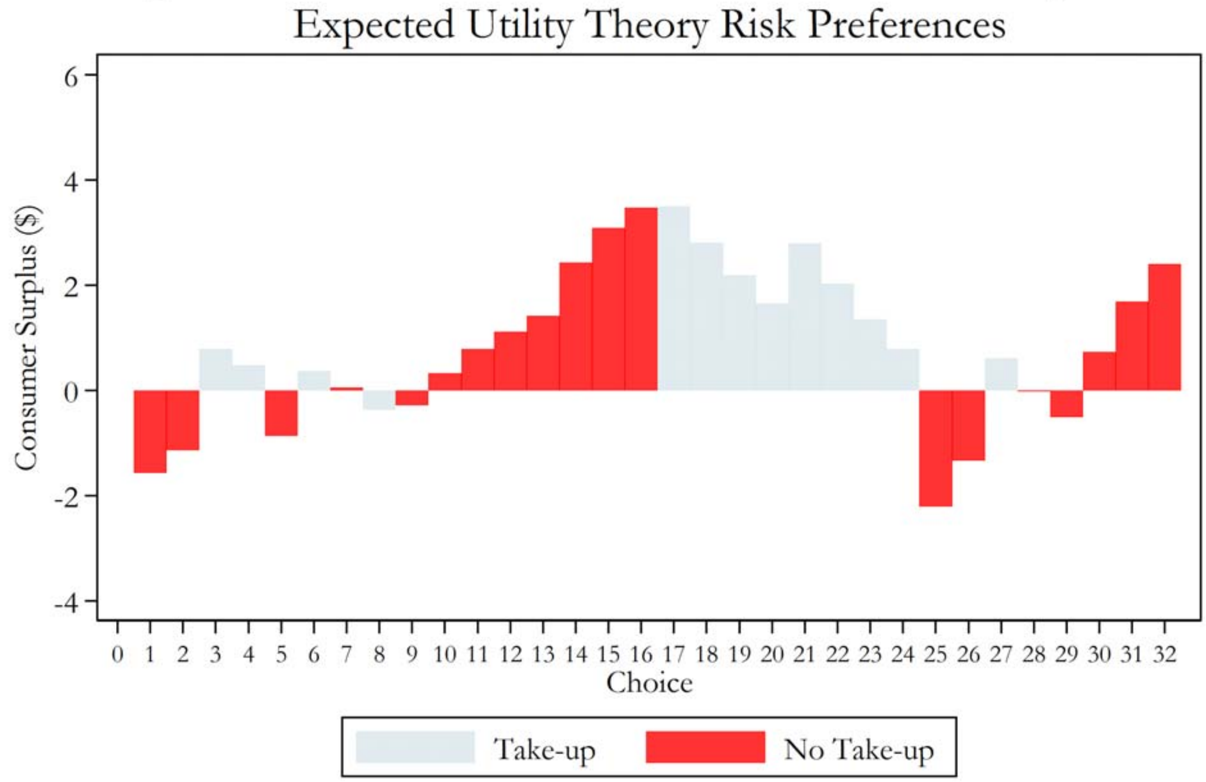


Figure 13: Consumer Surplus of Choices of Subject #2

Rank Dependent Utility (Inverse-S) Risk Preferences

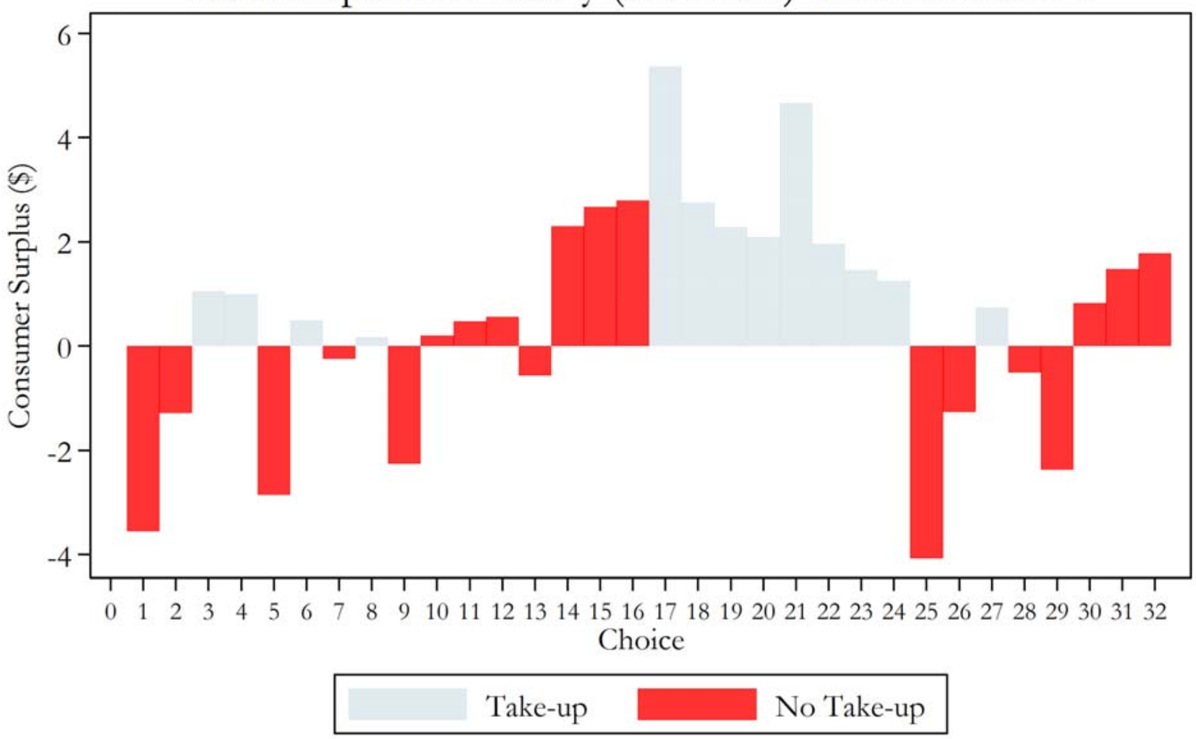


Figure 14: Proportion of Actual Take-Up to Predicted Choices

Fisher Exact Test 2-sided *p*-value < 0.001

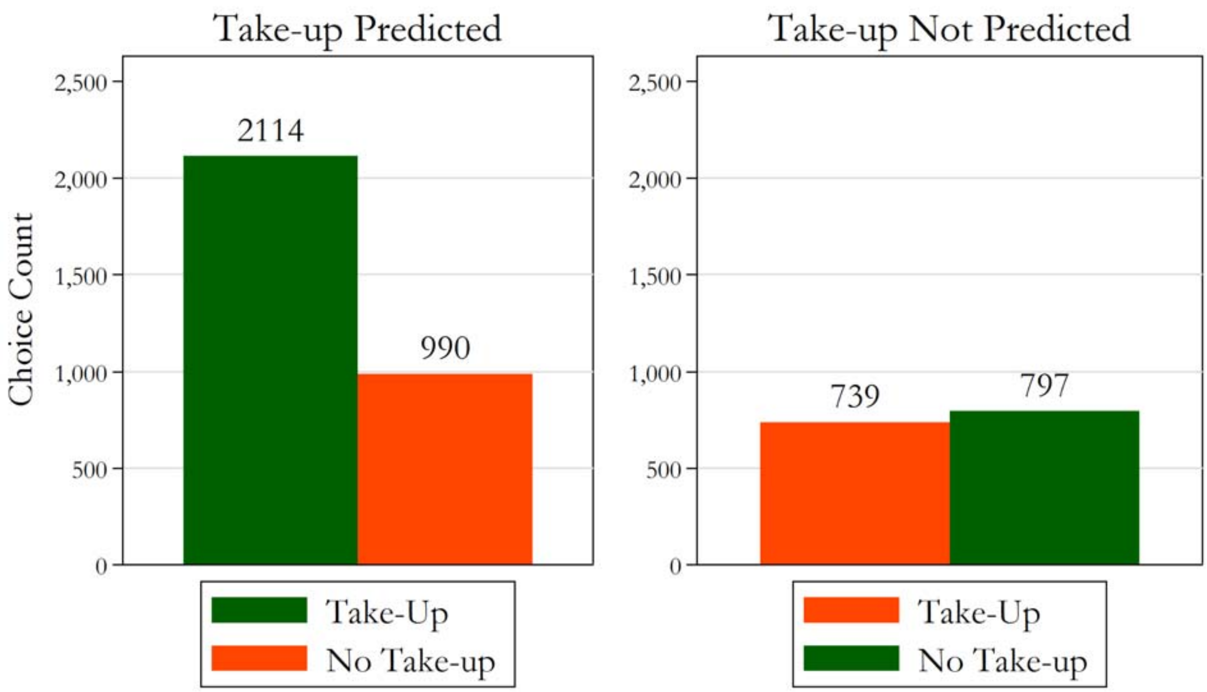


Figure 15: Comparison of Consumer Surplus Distribution for II and AE Treatments

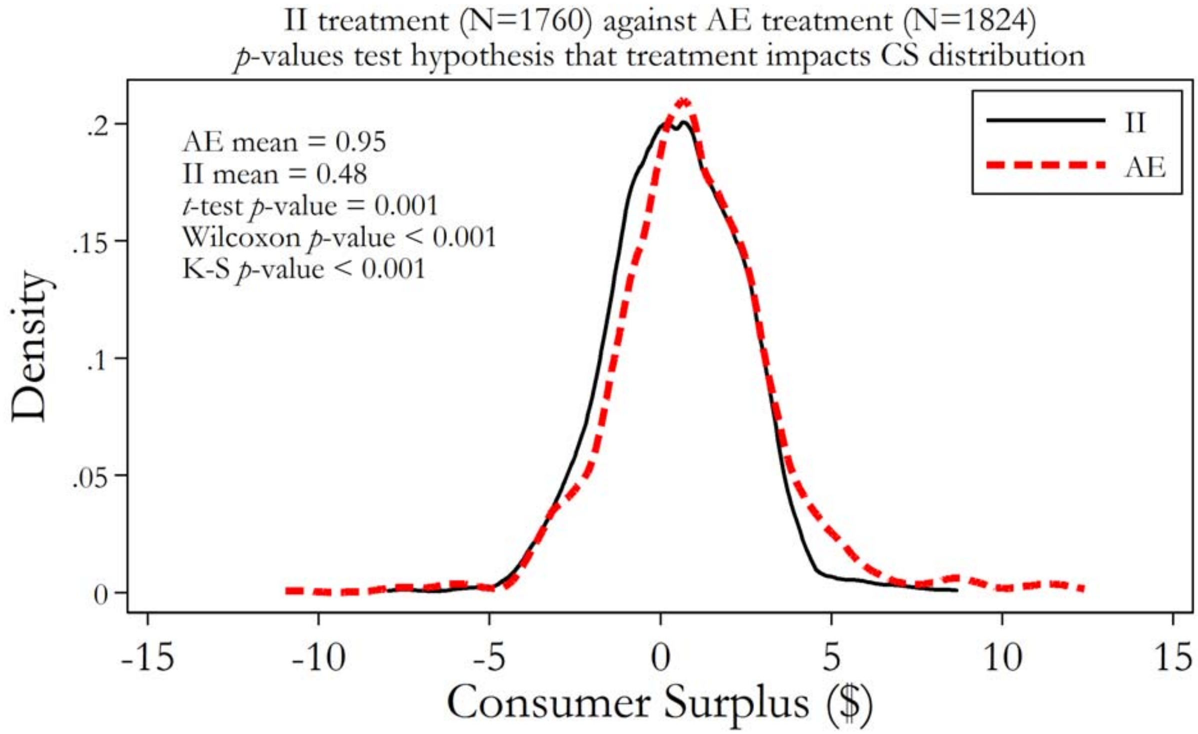


Figure 16: Comparison of Efficiency Distribution for II and AE Treatments

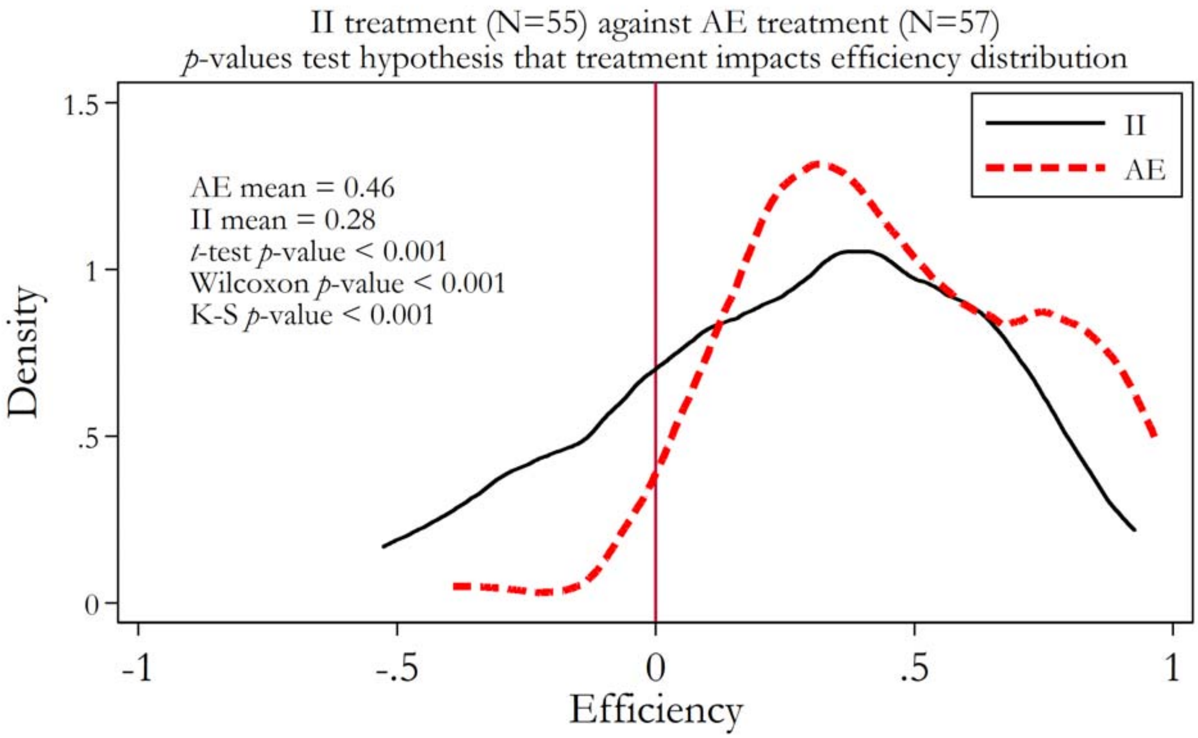


Figure 17: Comparison of Consumer Surplus Distribution for II and II-CC Treatments

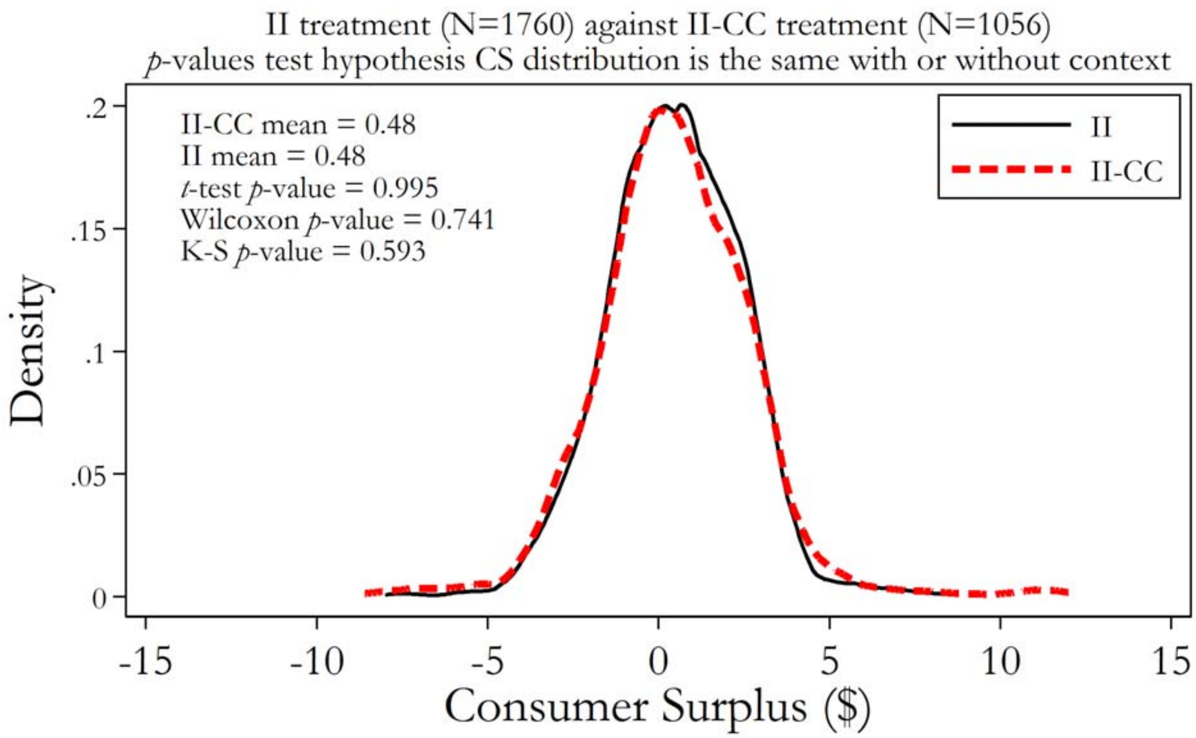


Figure 18: Comparison of Efficiency Distribution for II and II-CC Treatments

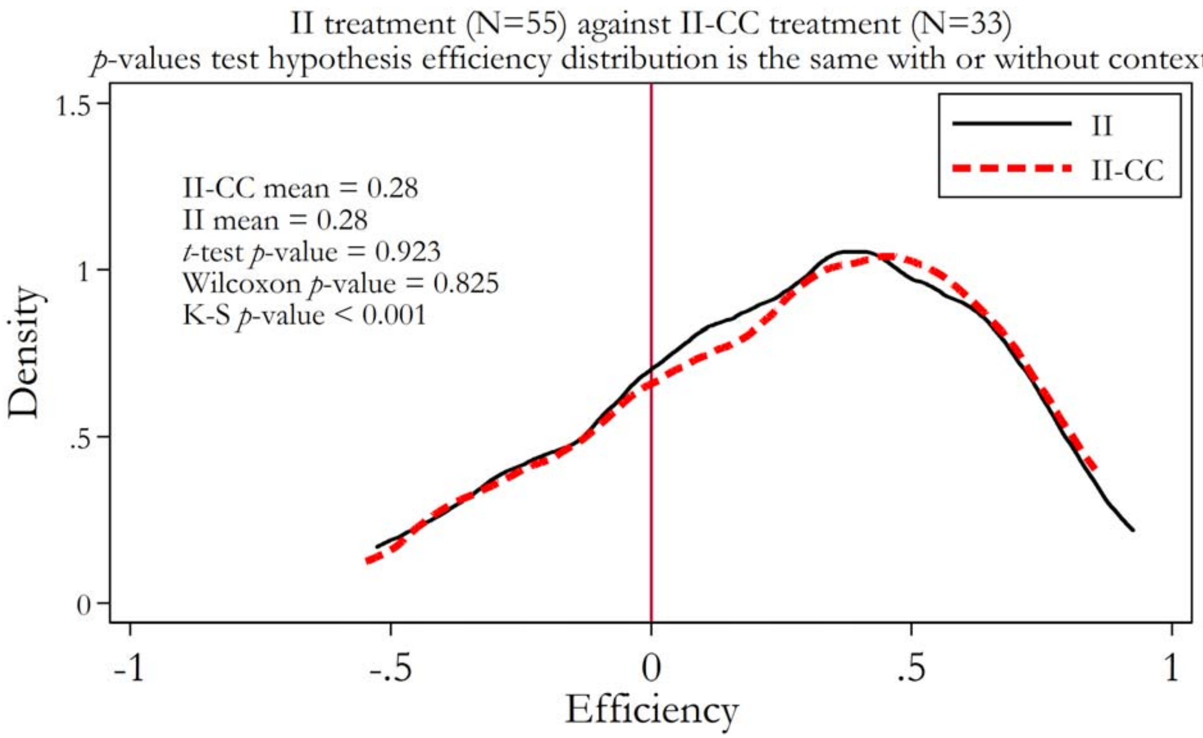


Figure 19: Classifying Subjects as Source-Dependent EUT or Recursive RDU Without Assuming ROCL

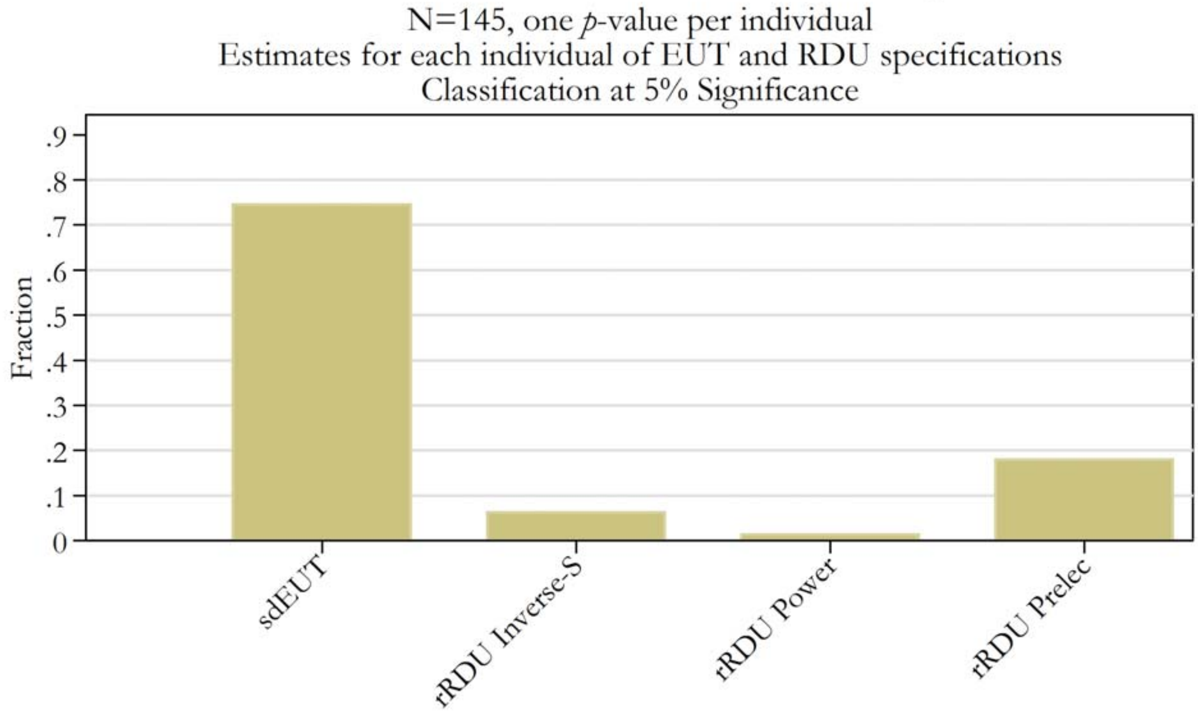


Figure 20: Tests of Source-Independence of EUT

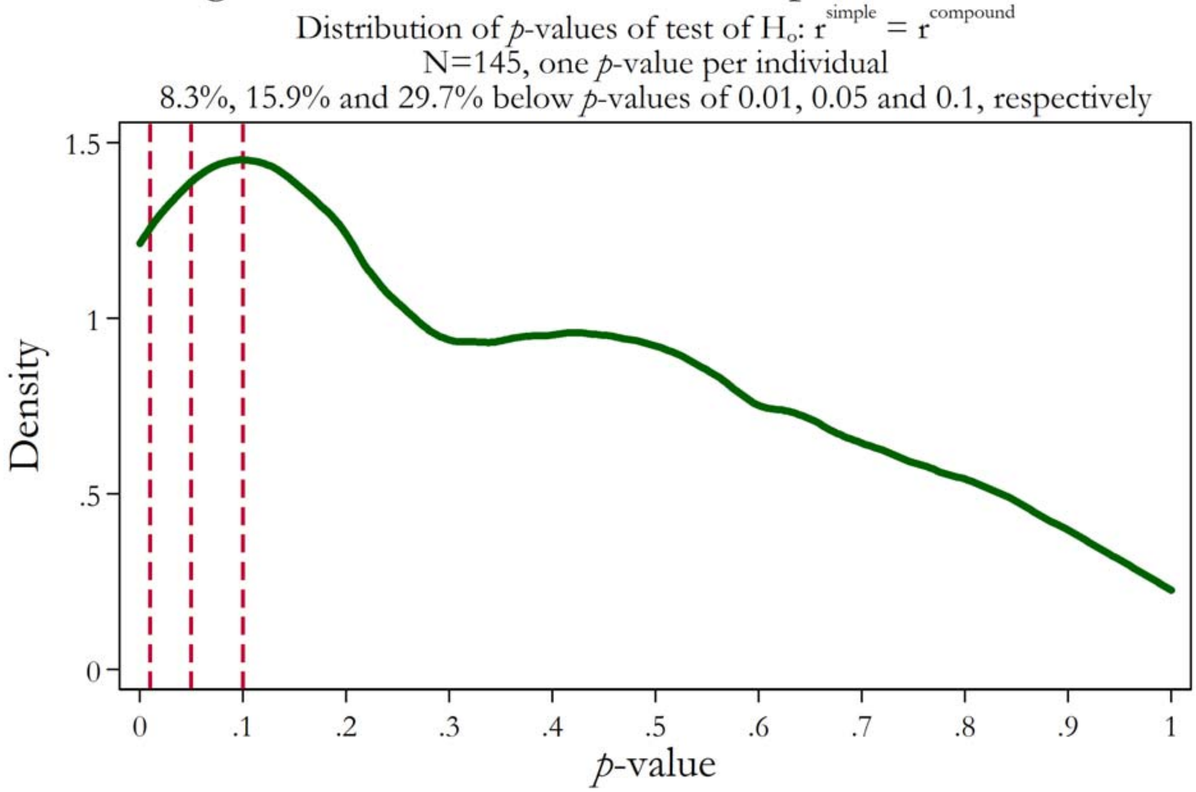


Figure 21: Proportion of Actual Take-Up to Predicted Choices Without Assuming ROCL

Fisher Exact Test 2-sided *p*-value < 0.001

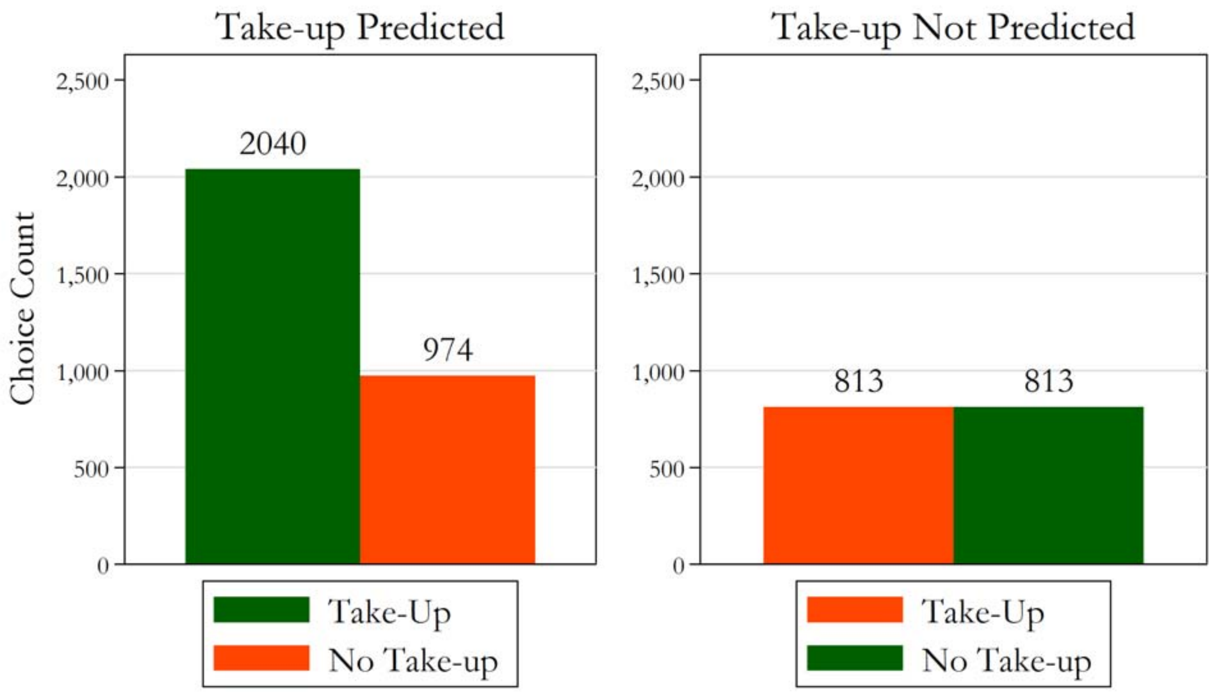


Figure 22: Comparison of Consumer Surplus Distribution for II and AE Treatments, Without Assuming ROCL

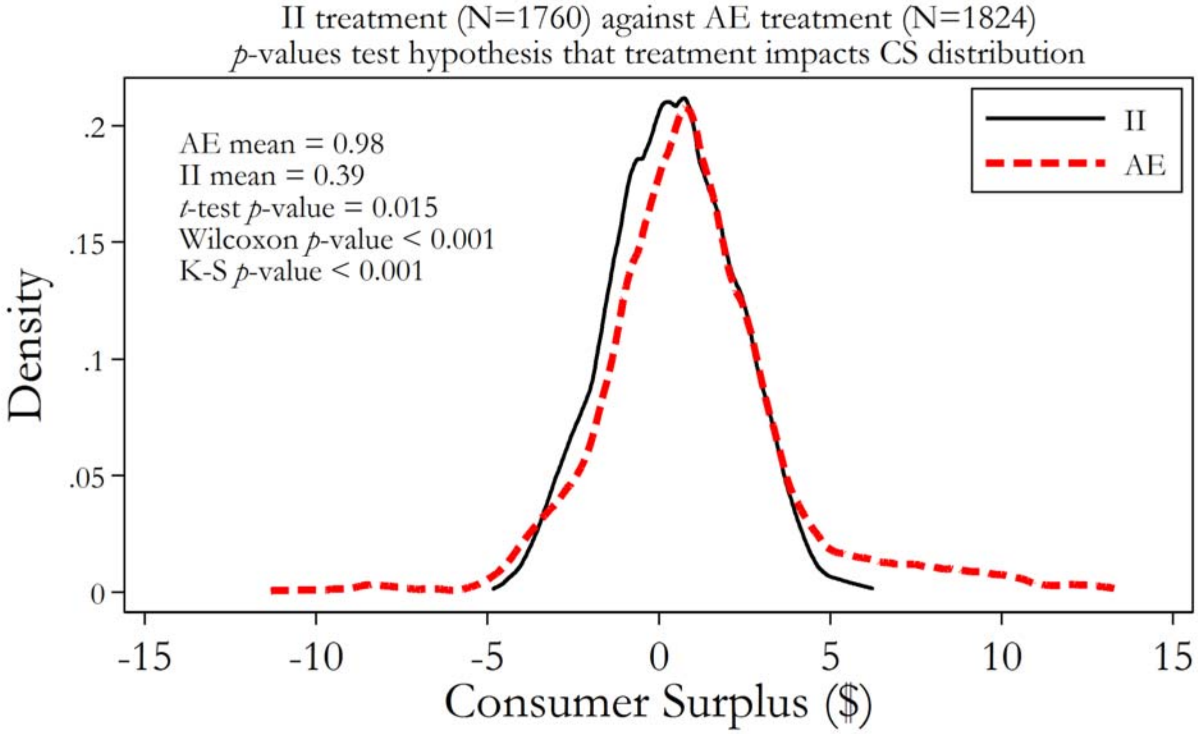


Figure 23: Comparison of Efficiency Distribution for II and AE Treatments, Without Assuming ROCL

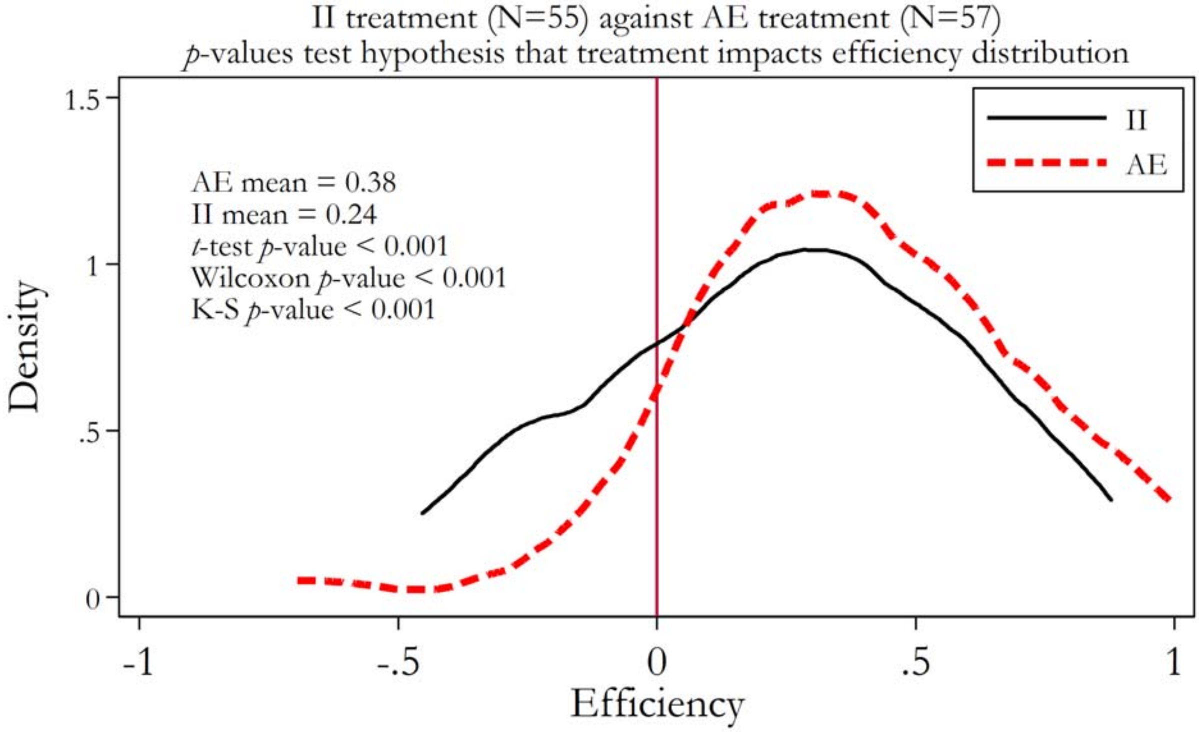


Figure 24: Comparison of Consumer Surplus Distribution for II and II-CC Treatments, Without Assuming ROCL

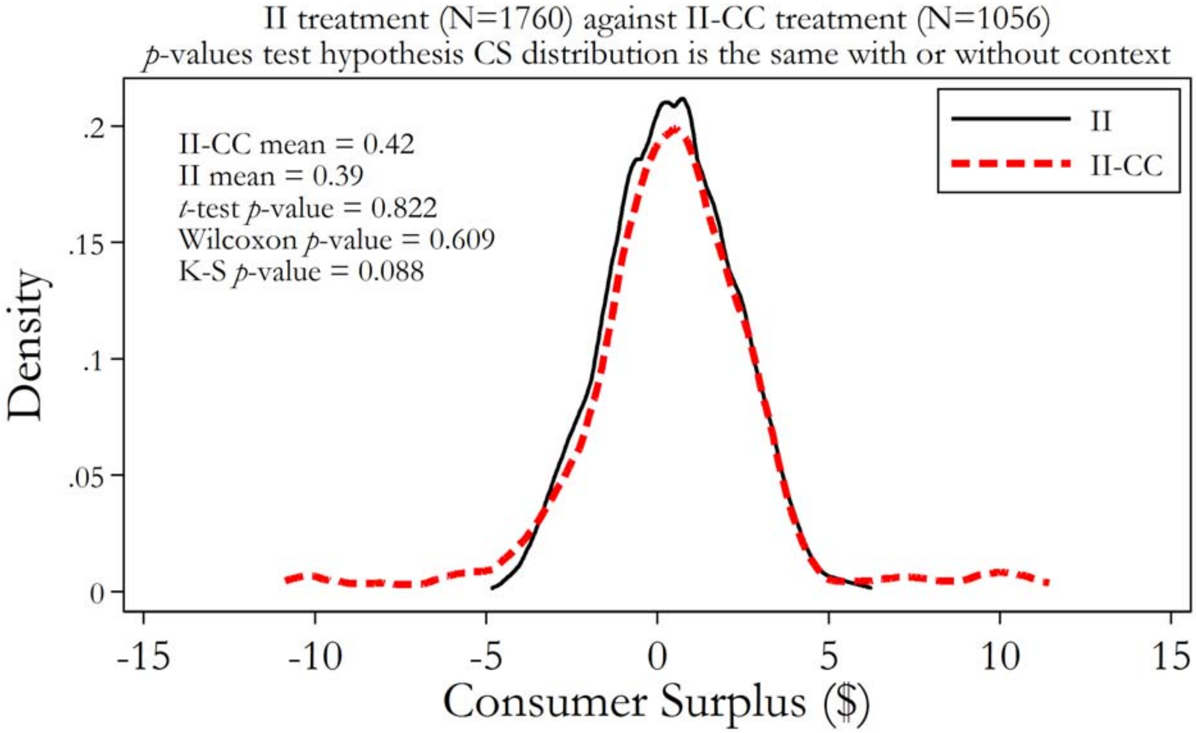


Figure 25: Comparison of Efficiency Distribution for II and II-CC Treatments, Without Assuming ROCL

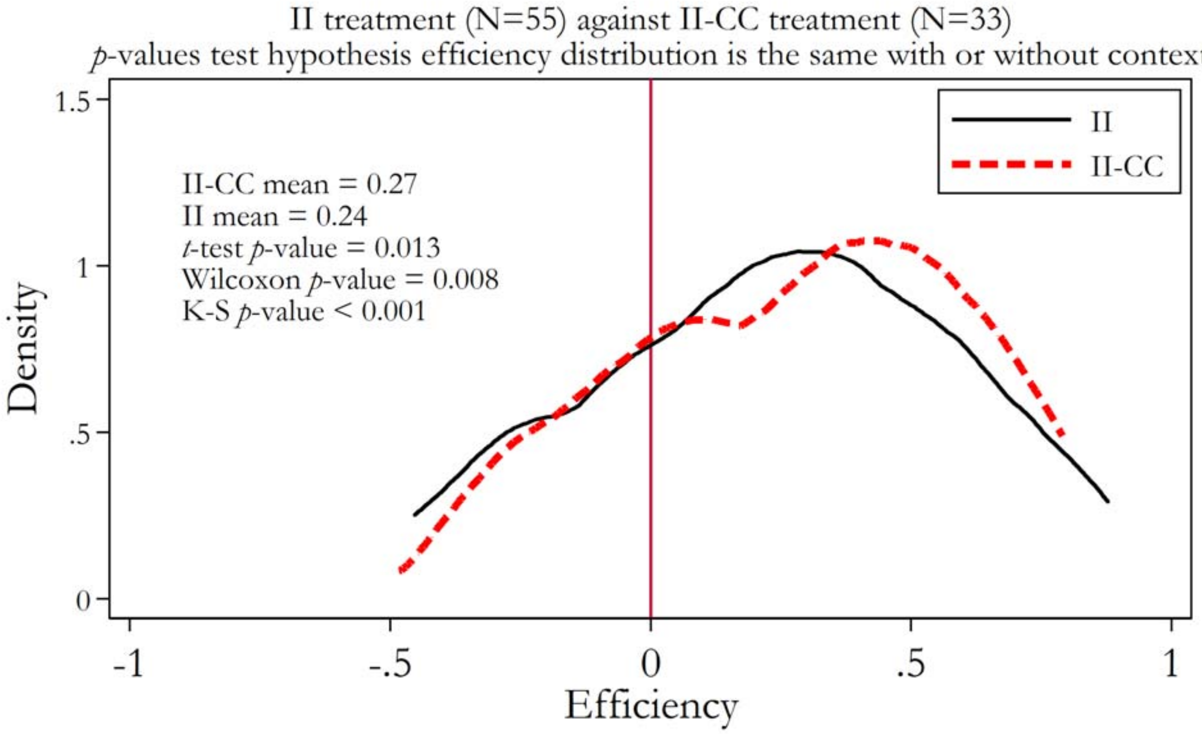


Figure 26: Consumer Surplus of Choices of Subject #116

Rank Dependent Utility (Prelec) Risk Preferences

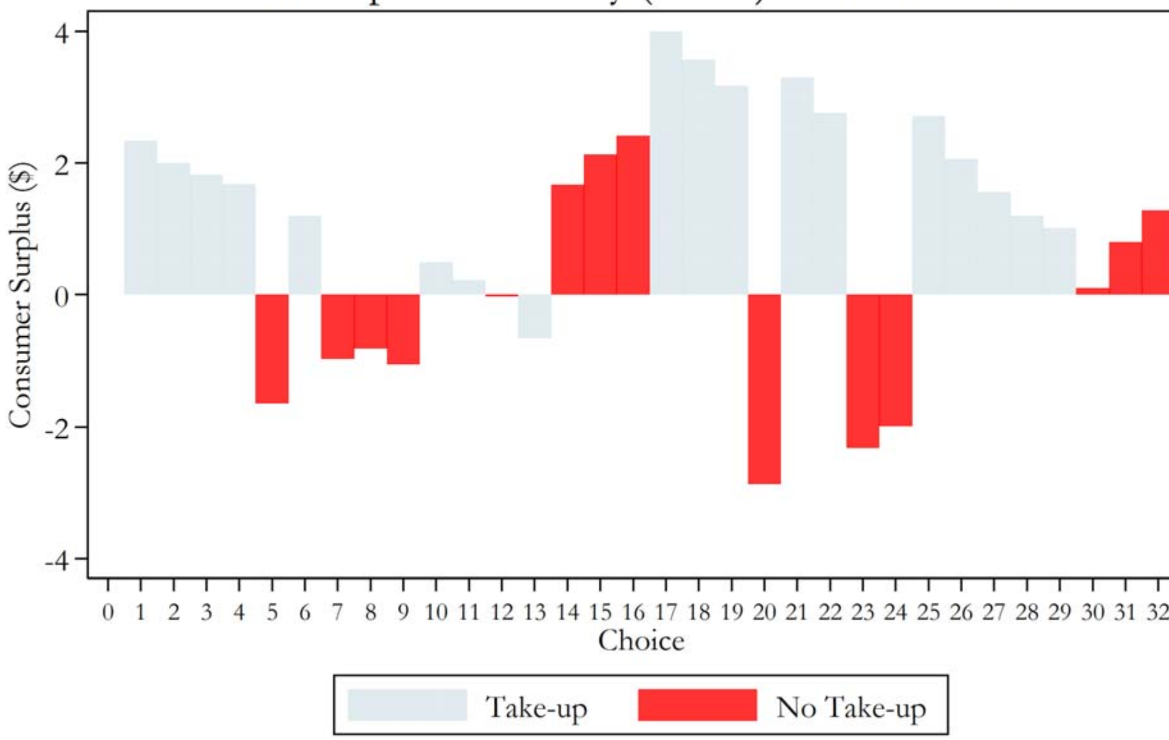


Figure 27: Consumer Surplus of Choices of Subject #116
Source-Dependent Expected Utility Theory Risk Preferences

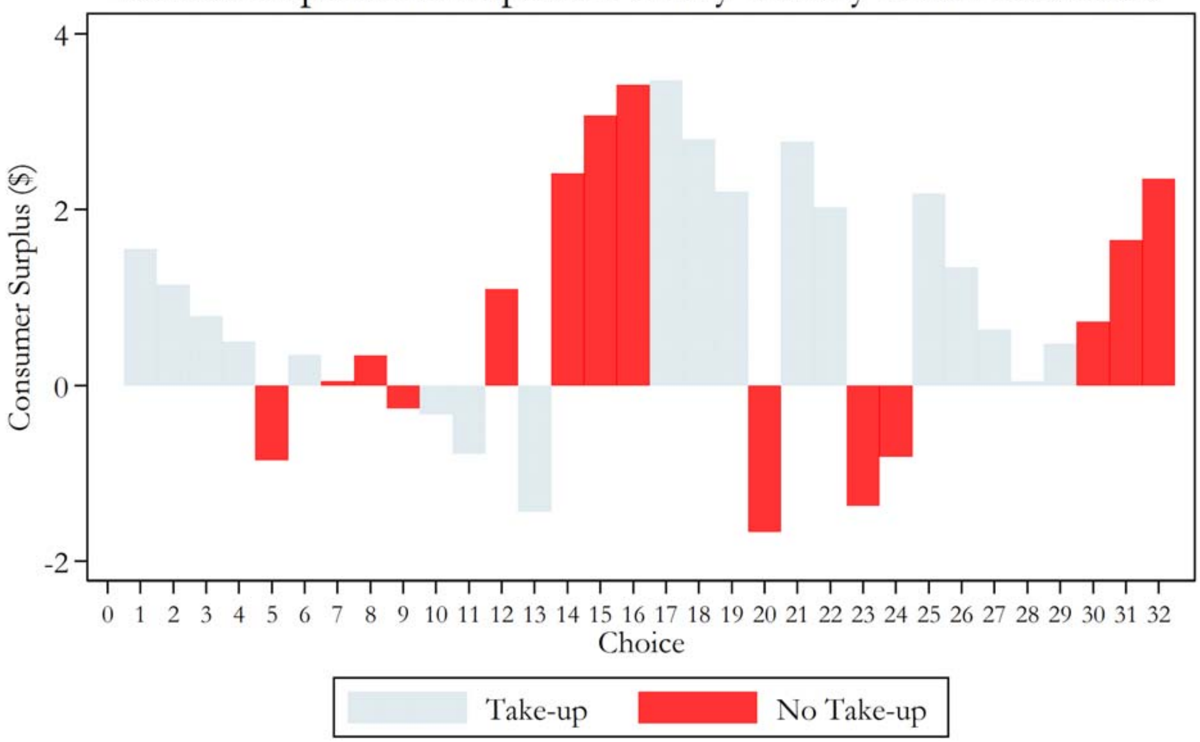


Table 2: Average Marginal Effects of Factors Affecting Welfare
Assuming Source-Dependent EUT in AE Treatment

Variables	Take-up	Choice	CS	Efficiency
Correlation	-0.0788	0.942***	1.453***	
	(0.745)	(<0.001)	(<0.001)	
Premium	-0.337***	-0.357***	-0.479***	
	(<0.001)	(<0.001)	(<0.001)	
Loss Probability	4.794***	4.978***	7.833***	
	(<0.001)	(<0.001)	(<0.001)	
ROCL Violation Count	0.00770	0.00628	0.00773	0.0232
	(0.900)	(0.717)	(0.633)	(0.305)
Young	-1.091*	-0.0645	0.105	0.0930
	(0.015)	(0.535)	(0.680)	(0.517)
Female	-0.125	-0.139*	-0.216**	-0.230**
	(0.635)	(0.015)	(0.007)	(0.002)
Black	-0.446	0.0882	0.0697	0.0511
	(0.275)	(0.259)	(0.499)	(0.648)
Asian	-0.482	0.130	0.0690	0.121
	(0.335)	(0.319)	(0.421)	(0.526)
Business Major	0.00939	-0.0663	-0.0645	-0.0822
	(0.971)	(0.264)	(0.195)	(0.297)
Freshman	-0.150	0.147	0.176	0.160
	(0.634)	(0.085)	(0.092)	(0.105)
Senior	0.190	0.253***	0.274**	0.298**
	(0.568)	(<0.001)	(0.001)	(0.002)
High GPA	-0.0974	-0.0210	0.0230	-0.0156
	(0.680)	(0.740)	(0.665)	(0.850)
Christian	-0.0290	-0.196*	-0.292**	-0.326**
	(0.944)	(0.033)	(0.006)	(0.009)
Insured	-0.156	-0.0976	-0.152*	-0.183*
	(0.532)	(0.116)	(0.043)	(0.043)

p-values in parentheses
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table 3: Average Marginal Effects of Factors Affecting Welfare Assuming Source-Dependent EUT in II Treatment

Variables	Take-up	Choice	CS	Efficiency
Correlation	0.172	-0.00286	0.0629	
	(0.430)	(0.984)	(0.836)	
Premium	-0.220***	-0.00114	-0.0119	
	(<0.001)	(0.976)	(0.883)	
Loss Probability	4.568***	2.372***	3.475*	
	(<0.001)	(<0.001)	(0.015)	
ROCL Violation Count	0.00537	-0.0396**	-0.0542***	-0.0499**
	(0.845)	(0.003)	(0.001)	(0.008)
Young	-0.722**	0.307*	0.480	0.486**
	(0.001)	(0.011)	(0.143)	(0.001)
Female	-0.0410	-0.00767	-0.0133	-0.00522
	(0.753)	(0.909)	(0.753)	(0.954)
Black	-0.301	-0.180*	-0.243**	-0.228*
	(0.152)	(0.027)	(0.008)	(0.037)
Asian	-0.453	-0.0956	-0.192	-0.137
	(0.060)	(0.377)	(0.079)	(0.336)
Business Major	-0.0474	-0.00131	0.0355	0.0294
	(0.722)	(0.985)	(0.604)	(0.761)
Freshman	-0.0829	-0.120	-0.0904	-0.104
	(0.602)	(0.166)	(0.198)	(0.390)
Senior	-0.237	-0.0801	-0.0392	-0.0478
	(0.168)	(0.331)	(0.673)	(0.672)
High GPA	-0.114	-0.0184	0.0278	0.0262
	(0.320)	(0.770)	(0.643)	(0.774)
Christian	-0.238	-0.117	-0.158*	-0.150
	(0.122)	(0.086)	(0.027)	(0.078)
Insured	0.355*	0.0536	0.109	0.0956
	(0.010)	(0.473)	(0.139)	(0.377)

p-values in parentheses

* $p<0.05$ ** $p<0.01$ *** $p<0.001$

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Appendix A: Experimental Instructions (NOT FOR PUBLICATION)

A.1 Lottery Choices

Choices Over Risky Prospects

This is a task where you will choose between prospects with varying prizes and chances of winning. You will be presented with a series of pairs of prospects where you will choose one of them. For each pair of prospects, you should choose the prospect you prefer to play. You will actually get the chance to play **one** of the prospects you choose, and you will be paid according to the outcome of that prospect, so you should think carefully about which prospect you prefer.

Here is an example of what the computer display of such a pair of prospects might look like.

The outcome of the prospects will be determined by the draw of a random number between 1 and 100. Each number between, and including, 1 and 100 is equally likely to occur. In fact, you will be able to draw the number yourself using two 10-sided dice.

Although not shown in this example, in the top left corner of your computer screen you can see how many choices you will be asked to make today.

In this example the left prospect pays five dollars ($5) if the number drawn is between 1 and 40, and pays fifteen dollars ($15) if the number is between 41 and 100. The blue color in the pie chart corresponds to 40% of the area and illustrates the chances that the number drawn will be between 1 and 40 and your prize will be $5. The orange area in the pie chart corresponds to 60% of the area and illustrates the chances that the number drawn will be between 41 and 100 and your prize will be $15.

Now look at the pie in the chart on the right. It pays five dollars ($5) if the number drawn is between 1 and 50, ten dollars ($10) if the number is between 51 and 90, and fifteen dollars ($15) if the number is between 91 and 100. As with the prospect on the left, the pie slices represent the fraction of the possible numbers which yield each payoff. For example, the size of the $15 pie slice is 10% of the total pie.

Each pair of prospects is shown on a separate screen on the computer. On each screen, you should indicate which prospect you prefer to play by clicking on one of the buttons beneath the prospects.

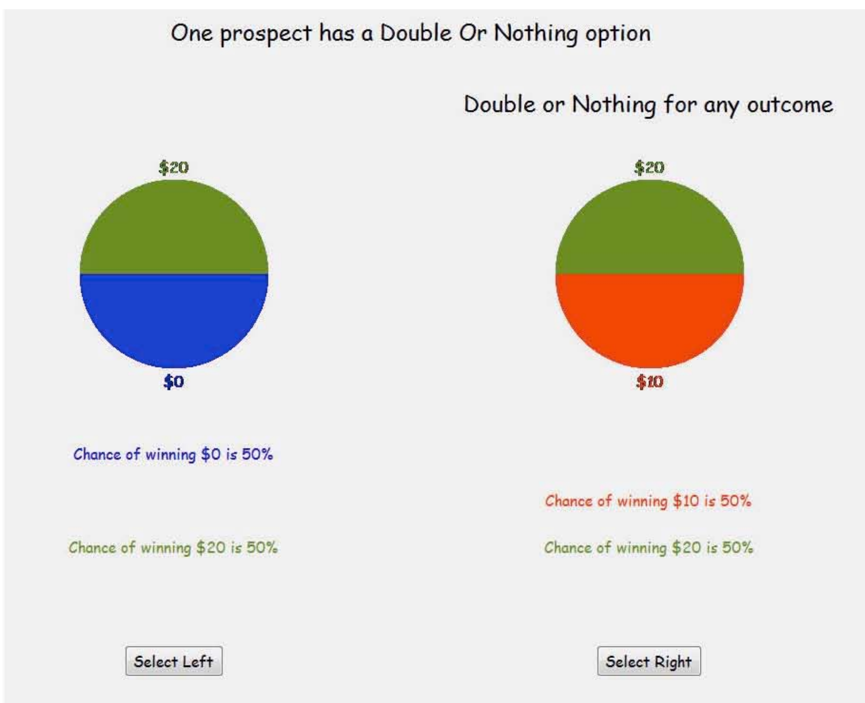
You could also get a pair of prospects in which one of the prospects will give you the chance to play "Double or Nothing." For instance, the right prospect in the next screen image pays "Double or Nothing" if the Green area is selected, which happens if the number drawn is between 51 and 100. The right pie chart indicates that if the number is between 1 and 50 you get $10. However, if the number is between 51 and 100 a coin will be tossed to determine if you get double the amount. If it comes up Heads you get $40, otherwise you get nothing. The prizes listed underneath each pie refer to the amounts before any "Double or Nothing" coin toss.

After you have worked through all of the pairs of prospects, raise your hand and an experimenter will come over. You will then roll two 10-sided dice until a number comes up to determine which pair of prospects will be played out. If there are 40 pairs we will roll the dice until a number between 1 and 40 comes up, if there are 80 pairs we will roll until a number between 1 and 80 comes up, and so on. Since there is a chance that any of your choices could be played out for real, you should approach each pair of prospects as if it is the one that you will play out. Finally, you will roll the two ten-sided dice to determine the outcome of the prospect you chose, and if necessary you will then toss a coin to determine if you get "Double or Nothing."

For instance, suppose you picked the prospect on the left in the last example. If the random number was 37, you would win $0; if it was 93, you would get $20.

If you picked the prospect on the right and drew the number 37, you would get $10; if it was 93, you would have to toss a coin to determine if you get "Double or Nothing." If the coin comes up Heads then you get $40. However, if it comes up Tails you get nothing from your chosen prospect.

It is also possible that you will be given a prospect in which there is a "Double or Nothing" option no matter what the outcome of the random number. This screen image illustrates this possibility.



Therefore, your payoff is determined by four things:

- by which prospect you selected, the left or the right, for each of these pairs;
- by which prospect pair is chosen to be played out in the series of pairs using the two 10-sided dice;
- by the outcome of that prospect when you roll the two 10-sided dice; and
- by the outcome of a coin toss if the chosen prospect outcome is of the "Double or Nothing" type.

Which prospects you prefer is a matter of personal taste. The people next to you may be presented with different prospects, and may have different preferences, so their responses should not matter to you. Please work silently, and make your choices by thinking carefully about each prospect.

All payoffs are in cash, and are in addition to the show-up fee that you receive just for being here.

A.2 Index Insurance (II) Treatment

II

Choices Over Insurance Prospects

In this task you will make choices about whether to insure against possible monetary loss. In each choice you will start out with an initial amount of money and, in the event of a loss, the loss amount will be taken from this initial stake. In each choice you will have the option to buy insurance to protect you against the possible loss, although you are not required to buy the insurance.

You will make 32 choices in this task. You will actually get the chance to play one of the choices you make, and you will be paid according to the outcome of that choice. So you should think carefully about how much each insurance choice is worth to you.

Each choice has two random events: the Index Event, and the Personal Event. Each event has two possible outcomes: *Good* and *Bad*. If the Personal Event outcome is *Bad*, then you will suffer a loss. You will decide whether to purchase insurance against this possible loss. However, insurance only covers the loss if the Index Event outcome is *Bad*.

If you do not purchase insurance, then only the outcome of the Personal Event will decide your earnings:

Personal Event	Your Earnings
Bad	Initial stake - Loss
Good	Initial stake

If you do purchase insurance, it is important for you to understand that insurance is not paid according to whether you actually suffer a loss. Instead, insurance is paid only according to the Index Event. Both events will decide your earnings:

Index Event	Personal Event	Your Earnings
Bad	*Bad*	Initial stake - Insurance cost - Loss + Insurance coverage
Bad	*Good*	Initial stake - Insurance cost + Insurance coverage
Good	*Bad*	Initial stake - Insurance cost - Loss
Good	*Good*	Initial stake - Insurance cost

So there are four possible outcomes if you purchase insurance. You might suffer a loss and receive insurance coverage. Or you might receive insurance coverage even when you do not suffer a loss. You might suffer a loss but not receive insurance coverage. Finally, you might not suffer a loss and also receive no insurance coverage.

Each event is determined by randomly drawing a colored chip from a bag. In general, each draw will involve two colors, and each decision you make will involve different amounts and mixtures of two colors. When making each decision, you will know the exact amounts and mixtures of colored chips associated with the decision. After you have decided whether or not to purchase insurance, the two events will be determined as follows.

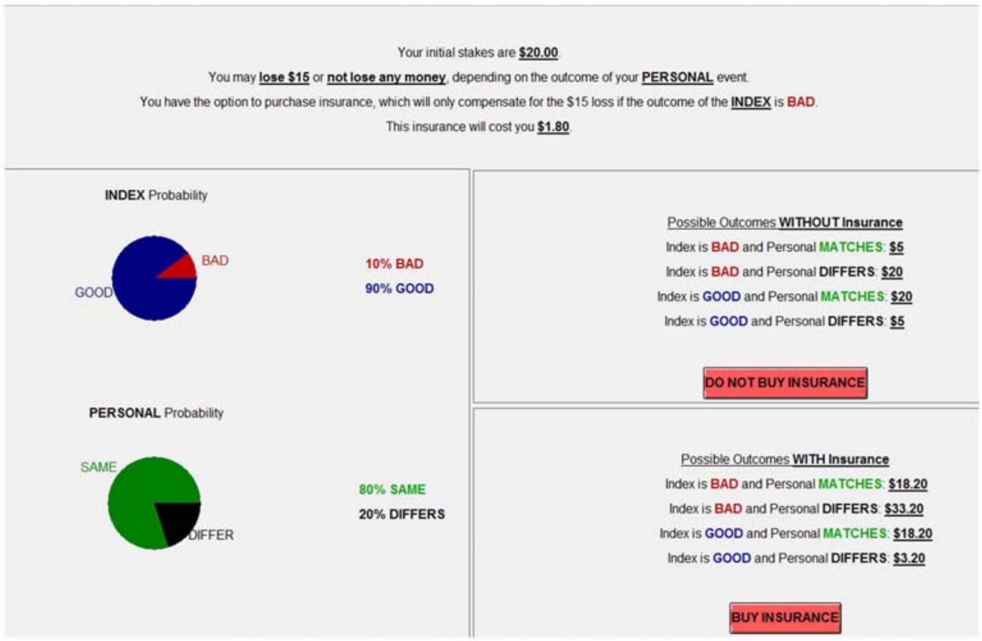
First, the Index Event will be determined with red and blue chips.

- If you draw a red chip, then the Index Event outcome is *Bad*.
- If you draw a blue chip, then the Index event outcome is *Good*.

Next, the Personal Event will be determined with black and green chips.

- If you draw a green chip, then the Personal Event outcome is the same as the Index Event outcome.
- If you draw a black chip, then the Personal Event outcome differs from the Index Event outcome.

Here is an example of what your decision would look like on the computer screen. The display on your screen will be bigger and easier to read.



In this example you start out with an initial stake of $20. If the outcome of the Personal Event is *Bad* you will lose $15, and if the outcome of the Personal Event is *Good* you will not lose any money. If you faced the choice in this example and chose to purchase insurance, you would pay $1.80 from your initial stake. You would pay this $1.80 before you drew any chips, so you would pay it regardless of the outcomes of your draws.

You will be drawing colored chips from bags to determine the outcomes of both events. First, you will draw a chip to determine the Index Event outcome. The pie chart shows that there is a 10% chance that the Index Event outcome is *Bad*, and a 90% chance that the Index Event outcome is *Good*. This means there will be 9 blue chips and 1 red chip in a bag, and the color of the chip you randomly draw from the bag represents the outcome of the Index Event. If a blue chip is drawn, the Index Event outcome is *Good*, and if a red chip is drawn the Index Event outcome is *Bad*.

Next, you will draw a chip to determine the Personal Event outcome. There is an 80% chance that the Personal Event outcome is the *Same* as the Index Event outcome and a 20% chance that the Personal Event outcome will *Differ* from the Index Event outcome. This means there will be 8 green chips and 2 black chips in a bag. If a green chip is drawn your Personal Event outcome is the *Same* as the Index Event outcome, and if a black chip is drawn your Personal Event outcome *Differs* from the Index Event outcome.

The possible outcomes if you **choose not to purchase insurance** are therefore as follows:

Index Draw	Personal Draw	Your Earnings
Red (*Bad*)	Green (*Same →Bad*)	$20 - $15 = $5
Red (*Bad*)	Black (*Different →Good*)	$20
Blue (*Good*)	Green (*Same →Good*)	$20
Blue (*Good*)	Black (*Different →Bad*)	$20 - $15 = $5

- If a red chip is drawn from the Index bag and a green chip is drawn from the Personal bag, your Personal Event outcome is *Bad*. You will lose $15 and be left with $5.
- If a red chip is drawn from the Index bag and a black chip is drawn from the Personal bag, your Personal Event outcome is *Good*. You will not lose any money and you keep your $20.
- If a blue chip is drawn from the Index bag and a green chip is drawn from the Personal bag, your Personal Event outcome is *Good*. You do not lose any money and you keep your $20.
- If a blue chip is drawn from the Index bag and a black chip is drawn from the Personal bag, your Personal Event outcome is *Bad*. You will lose $15 and be left with $5.

You can choose to purchase insurance, which will fully compensate the $15 loss only if the Index Event outcome is *Bad*. In this example the insurance will cost you $1.80, and if you chose to purchase insurance you would pay this $1.80 regardless of the outcomes of your draws.

The possible outcomes if you **choose to purchase insurance** are therefore as follows:

Index Draw	Personal Draw	Your Earnings
Red (*Bad, insurance will pay out $15)*	Green (*Same →Bad)*	$20 - $1.80 - $15 + $15 = 18.20
Red (*Bad, insurance will pay out $15)*	Black (*Different →Good)*	$20 - $1.80 + $15= $33.20
Blue (*Good*)	Green (*Same →Good*)	$20 - $1.80 = 18.20
Blue (*Good*)	Black (*Different →Bad*)	$20 - $1.80 - $15 = $3.20

- If a red chip is drawn from the Index bag and a green chip from the Personal bag, you will lose $15 but insurance will cover the loss. You will keep $18.20, net of the cost of insurance.
- If a red chip is drawn from the Index bag and a black chip from the Personal bag, you will not lose any money but you will still receive a payout from insurance. You will keep $33.20, net of the cost of insurance.
- If a blue chip is drawn from the Index bag and a green chip from the Personal bag, you will not lose any money. You will keep $18.20, net of the cost of insurance.
- If a blue chip is drawn from the Index bag and a black chip from the Personal bag, you will lose $15 and receive no payout from insurance. You will keep $3.20, net of the cost of insurance.

You should indicate your choice to purchase, or not purchase, the insurance by clicking on your preferred option on the computer screen.

There are 32 decisions like this one to be made, each shown on a separate screen on the computer. Each decision might have different chances for the Index Event outcomes, the Personal Event outcomes, or the cost of insurance, so pay attention to each screen. After everyone has worked through all of the insurance decisions, please wait in your seat and an experimenter will come to you. You will then roll two 10-sided die to determine which insurance decision will be played out. Since there are only 32 decisions, you will keep rolling the die until a number between 1 and 32 comes up. There is an equal chance that any of your 32 choices could be selected, so you should approach each decision as if it is the one that you will actually play out to determine your payoff. Once the decision to play out is selected, you will draw chips from the Index bag and the Personal bag to determine the outcome.

In summary:

- You will decide whether or not to purchase insurance in each of the 32 insurance decisions in this task.
- One of your decisions will be randomly selected to actually be played out using two 10-sided dice.
- You will suffer the specified monetary loss only if the Personal Event outcome is *Bad*.
- If you purchase insurance, it will pay out only if the Index Event outcome is *Bad*.

Whether or not you prefer to buy the insurance is a matter of personal taste. You may choose to buy insurance on some or all of your 32 choices, or none of the choices. The people next to you may be presented with different choices, insurance prices, and may have different preferences, so their responses should not matter to you. Please work silently, and make your choices by thinking carefully about each prospect.

All payoffs are in cash, and are in addition to the show-up fee that you receive just for being here, as well as any other earnings in other tasks. Are there any questions?

A.3 Actuarially-Equivalent (AE) Treatment

AE

Choices Over Insurance Prospects

In this task you will make choices about whether to insure against possible monetary loss. In each choice you will start out with an initial amount of money and, in the event of a loss, the loss amount will be taken from this initial stake. In each choice you will have the option to buy insurance to protect you against the possible loss, although you are not required to buy the insurance.

You will make 32 choices in this task. You will actually get the chance to play one of the choices you make, and you will be paid according to the outcome of that choice. So you should think carefully about how much each insurance choice is worth to you.

Each choice has two random events: the Index Event, and the Personal Event. Each event has two possible outcomes: *Good* and *Bad*. If the Personal Event outcome is *Bad*, then you will suffer a loss. You will decide whether to purchase insurance against this possible loss. However, insurance only covers the loss if the Index Event outcome is *Bad*.

If you do not purchase insurance, then only the outcome of the Personal Event will decide your earnings:

Personal Event	Your Earnings
Bad	Initial stake - Loss
Good	Initial stake

If you do purchase insurance, it is important for you to understand that insurance is not paid according to whether you actually suffer a loss. Instead, insurance is paid only according to the Index Event. Both events will decide your earnings:

Index Event	Personal Event	Your Earnings
Bad	*Bad*	Initial stake - Insurance cost - Loss + Insurance coverage
Bad	*Good*	Initial stake - Insurance cost + Insurance coverage
Good	*Bad*	Initial stake - Insurance cost - Loss
Good	*Good*	Initial stake - Insurance cost

So there are four possible outcomes if you purchase insurance. You might suffer a loss and receive insurance coverage. Or you might receive insurance coverage even when you do not suffer a loss. You might suffer a loss but not receive insurance coverage. Finally, you might not suffer a loss and also receive no insurance coverage.

Each event is determined by randomly drawing a colored chip from a bag. In general, each draw will involve two colors, and each decision you make will involve different amounts and mixtures of two colors. When making each decision, you will know the exact amounts and mixtures of colored chips associated with the decision. After you have decided whether or not to purchase insurance, the two events will be determined as follows.

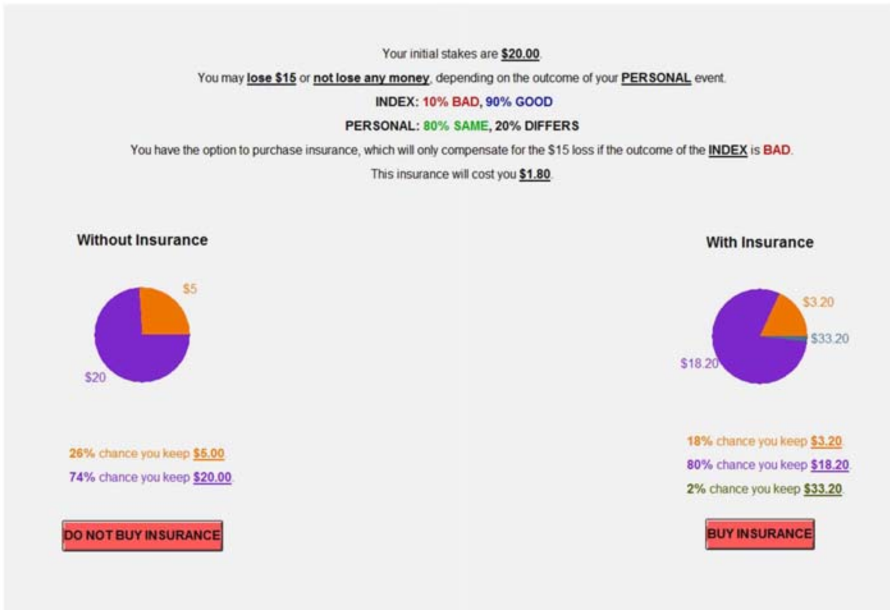
First, the Index Event will be determined with red and blue chips.

- If you draw a red chip, then the Index Event outcome is *Bad*.
- If you draw a blue chip, then the Index event outcome is *Good*.

Next, the Personal Event will be determined with black and green chips.

- If you draw a green chip, then the Personal Event outcome is the same as the Index Event outcome.
- If you draw a black chip, then the Personal Event outcome differs from the Index Event outcome.

Here is an example of what your decision would look like on the computer screen. The display on your screen will be bigger and easier to read.



In this example you start out with an initial stake of $20. If the outcome of the Personal Event is *Bad* you will lose $15, and if the outcome of the Personal Event is *Good* you will not lose any money. If you faced the choice in this example and chose to purchase insurance, you would pay $1.80 from your initial stake. You would pay this $1.80 before you drew any chips, so you would pay it regardless of the outcomes of your draws.

In this example there is a 10% chance that the outcome of the Index Event is *Bad*, and a 90% chance that the Index Event outcome is *Good*. However there is only an 80% chance that the Personal Event is the *Same* as the Index Event outcome and a 20% chance that the Personal Event outcome will *Differ* from the Index Event outcome. Based on these probabilities, the pie charts show the overall probabilities of the possible earnings and their respective amounts.

The pie chart on the left shows the possible earnings if you choose not to purchase insurance. Without insurance, the payouts depend only on the outcome of the Personal Event. Given that there is a 10% chance that the Index Event outcome is *Bad* and that there is an 80% chance that the Personal Event outcome is the *Same* as the Index Event outcome, the chance that the Personal Event outcome is *Bad* is 26% (= [10% × 80%] + [90% × 20%]), and the chance that the outcome of the Personal Event is *Good* is 74% (= 100% - 26%).

You will be drawing colored chips from bags to determine the outcomes of both events. First, you will draw a chip to determine the Index Event outcome. Since in this example there is a 10% chance of a *Bad* outcome for the Index event, the experimenter will place 1 red chip and 9 blue chips in the bag. The color of the chip you randomly draw from the bag represents the outcome of the Index Event. If a blue chip is drawn the Index Event outcome is *Good*, and if a red chip is drawn the Index Event outcome is *Bad*.

Next, you will draw a chip to determine the Personal Event outcome. Since there is an 80% chance that the Personal Event outcome is the *Same* as the Index Event outcome and a 20% chance that the Personal Event outcome will *Differ* from the Index Event outcome, there will be 8 green chips and 2 black chips in a bag. The color of the chip you randomly draw from the bag determines the outcome of the Personal Event. If a green chip is drawn your Personal Event outcome is the *Same* as that of the Index Event, and if a black chip is drawn your Personal Event outcome *Differs* from that of the Index Event.

The possible outcomes if you **choose not to purchase insurance** are therefore as follows:

Index Draw	Personal Draw	Your Earnings
Red (*Bad*)	Green (*Same* →*Bad*)	\$20 - \$15 = \$5
Red (*Bad*)	Black (*Different* →*Good*)	\$20
Blue (*Good*)	Green (*Same* →*Good*)	\$20
Blue (*Good*)	Black (*Different* →*Bad*)	\$20 - \$15 = \$5

- If a red chip is drawn from the Index bag and a green chip is drawn from the Personal bag, you will lose \$15 and be left with \$5.
- If a red chip is drawn from the Index bag and a black chip is drawn from the Personal bag, you will not lose any money and you keep your \$20.
- If a blue chip is drawn from the Index bag and a green chip is drawn from the Personal bag, you do not lose any money and you keep your \$20.
- If a blue chip is drawn from the Index bag and a black chip is drawn from the Personal bag, you will lose \$15 and be left with \$5.

You can choose to purchase insurance, which will fully compensate the \$15 loss only if the Index Event outcome is *Bad*. In this example the insurance will cost you \$1.80, and if you chose to purchase insurance you would pay this \$1.80 regardless of the outcomes of your draws.

The pie chart on the right shows the possible earnings if you choose to purchase insurance. Since the insurance is only paid out according to the outcome of the Index Event, outcomes from both the Index Event and the Personal Event will decide your earnings. There is an 80% chance that the Personal Event outcome is the *Same* as the Index Event outcome, hence there is an 80% chance you will either receive a payout when you suffer a loss <u>or</u> not receive a payout when you do not suffer a loss. If this happens your payout will be \$18.20: your initial stake of \$20 less the \$1.80 cost of insurance.

According to the pie chart the chance that the Index Event outcome is *Good*, but your Personal Event outcome *Differs*, is 18% (= 90% × 20%). This means that there is an 18% chance that your Personal Event outcome is *Bad* without insurance compensation. You will receive \$3.20: your initial stake of \$20 less the \$1.80 cost of insurance less the \$15 loss. The chance that the Index Event outcome is *Bad*, and your Personal Event outcome *Differs*, is 2% (= 10% × 20%). This means that there is a 2% chance that your Personal Event outcome is *Good* and you still receive insurance compensation. You receive \$33.20: your initial stake of \$20 less the \$1.80 cost of insurance plus the \$15 payout from the insurance.

If you choose to purchase insurance, the Index Event outcome and Personal Event outcome will be determined by drawing chips from bags, in the same way as if insurance was not purchased.

The possible outcomes if you **choose to purchase insurance** are therefore as follows:

Index Draw	Personal Draw	Your Earnings
Red (*Bad, insurance will pay out \$15*)	Green (*Same* →*Bad*)	\$20 - \$1.80 - \$15 + \$15 = 18.20
Red (*Bad, insurance will pay out \$15*)	Black (*Different* →*Good*)	\$20 - \$1.80 + \$15= \$33.20
Blue (*Good*)	Green (*Same* →*Good*)	\$20 - \$1.80 = 18.20
Blue (*Good*)	Black (*Different* →*Bad*)	\$20 - \$1.80 - \$15 = \$3.20

You should indicate your choice to purchase, or not purchase, the insurance by clicking on your preferred option on the computer screen.

There are 32 decisions like this one to be made, each shown on a separate screen on the computer. Each decision might have different chances for the Index Event outcomes, the Personal Event outcomes, or the cost of insurance, so pay attention to each screen. After everyone has worked through all of the insurance decisions, please wait in your seat and an experimenter will come to you. You will then roll two 10-sided die to determine which insurance decision will be played out. Since there are only 32 decisions, you will keep rolling the die until a number between 1 and 32 comes up. There is an equal chance that any of your 32 choices could be selected, so you should approach each decision as if it is the one that you will actually play out to determine your payoff. Once the decision to play out is selected, you will draw chips from the Index bag and the Personal bag to determine the outcome.

In summary:

- You will decide whether or not to purchase insurance in each of the 32 insurance decisions in this task.
- One of your decisions will be randomly selected to actually be played out using two 10-sided dice.
- You will suffer the specified monetary loss only if the Personal Event outcome is *Bad*.
- If you purchase insurance, it will pay out only if the Index Event outcome is *Bad*.

Whether or not you prefer to buy the insurance is a matter of personal taste. You may choose to buy insurance on some or all of your 32 choices, or none of the choices. The people next to you may be presented with different choices, insurance prices, and may have different preferences, so their responses should not matter to you. Please work silently, and make your choices by thinking carefully about each prospect.

All payoffs are in cash, and are in addition to the show-up fee that you receive just for being here, as well as any other earnings in other tasks. Are there any questions?

Appendix B: Numerical Examples of Decision Weights (NOT FOR PUBLICATION)

To understand the mechanics of evaluating lotteries using RDU it is useful to see worked numerical examples. Although this is purely a pedagogic exercise, in our experience many users of RDU are not familiar with these mechanics, and they are critical to the correct application of these models. Even the best pedagogic source available, Wakker [2010], leaves many worked examples as exercises, and many of the examples are correctly contrived to make a special pedagogic point.

We first review the general case, and then explain the application to index insurance.

B.1 General Rank-Dependent Decision Weights

Assume a simple power probability weighting function $\omega(p) = p^{\gamma}$ and let $\gamma = 1.25$. To see the pure effect of probability weighting, assume $U(x) = x$ for $x \geq 0$. Start with a two-prize lottery, then consider three-prizes and four-prizes to see the general logic. The lotteries in our risk aversion task contain up to 4 prizes and probabilities.

In the two-prize case, let y be the smaller prize and Y be the larger prize, so $Y > y \geq 0$. Again, to see the pure effect of probability weighting, assume objective probabilities $p(y) = p(Y) = ½$. The first step is to get the decision weight of the largest prize. This uses the answer to the question, "what is the probability of getting at *least* Y?"[18] This is obviously ½, so we then calculate the decision weight using the probability weighting function as $\omega(½) = (½)^{\gamma} = 0.42$. To keep notation for probability weights and decision weights similar but distinct, denote the *decision* weight for Y as w(Y). Then we have w(Y) = 0.42.

The second step for the two-prize case is to give the other, smaller prize y the residual weight. This uses the answer to the question, "what is the probability of getting at *least* y?" Since one always gets at least y, the answer is obviously 1. Since $\omega(1) = 1$ for any of the popular probability weighting functions,[19] we can

[18] This expression leads to what Wakker [2010; §7.6] usefully calls the "gain-rank." The "loss-rank" would be based on the answer to the question, "what is the probability of getting Y or *less*?" Loss-ranks were popular with some of the earlier studies in rank-dependent utility.

[19] The prominent exception is the probability weighting function suggested by Kahneman and Tversky [1979], which had interior discontinuities at p=0 and p=1.

attribute the decision weight ω(1) - ω(½) = 1 - 0.42 = 0.58 to the prize y. Another way to see the same thing is to directly calculate the decision weight for the smallest prize to ensure that the decision weights sum to 1, so that the decision weight w(y) is calculated as 1-w(Y) = 1 - 0.42 = 0.58. The two-prize case actually makes it harder to see the rank-dependent logic than when we examine the three-prize or four-prize case, but can be seen in retrospect as a special case.

With these two decision weights in place, the RDU evaluation of the lottery is 0.42 ×U(Y) + 0.58×U(y), or 0.42Y + 0.58y given our simplifying assumption of a linear utility function. Inspection of this RDU evaluation, and viewing the decision weights as if they were probabilities, shows why the RDU evaluation has to be less than the Expected Value (EV) of the lottery using the true probabilities, since that is 0.5Y + 0.5y. The RDU evaluation puts more weight on the worst prize, and greater weight on the better prize, so it has to have a CE that is less than the EV (this last step is helped by the fact that U(x) = x, of course). Hence probability weighting in this case generates a CE that is less than the EV, and hence a risk premium.

However, the two-prize case collapses the essential logic of the RDU model. Consider a three-prize case in which we use the same probability weighting functions and utility functions, but have three prizes, y, Y and **Y**, where **Y**>Y>y, and p(y) = p(Y) = p(**Y**) = ⅓.

The decision weight for **Y** is evaluated first, and uses the answer to the question, "what is the probability of getting at least **Y**?" The answer is ⅓, so the decision weight for **Y** is then directly evaluated as w(**Y**) = ω(⅓) = $(⅓)^{\gamma}$ = 0.25.

The decision weight for Y is evaluated next, and uses the answer to the more interesting question, "what is the probability of getting at *least* Y?" This is p(Y) + p(**Y**) = ⅓ + ⅓ = ⅔, so the probability weight is ω(⅔) = $(⅔)^{\gamma}$ = 0.60. But the only part of this probability weight that is to be attributed solely to Y is the part that is not already attributed to **Y**, hence the decision weight for Y is ω(⅔) - ω(⅓) = ω(Y) - ω(**Y**) = 0.60 - 0.25 = 0.35. This intermediate step shows the rank-dependent logic in the clearest fashion. One could equally talk about *cumulative* probability weights, rather than just probability weights, but the logic is simple enough when one thinks of the question being asked "psychologically" and the partial attribution to Y that flows from it. In the two-prize case this partial attribution is skipped over.

The decision weight for y is again evaluated residually, as in the two-prize case. We can either see this by evaluating $\omega(1) - \omega(2/3) = 1 - 0.60 = 0.40$, or by evaluating $1 - w(Y) - w(\mathbf{Y}) = 1 - 0.35 - 0.25 = 0.40$.

The general logic may now be stated in words as follows:

- Rank the prizes from best to worst.
- Use the probability weighting function to calculate the probability of getting at least the prize in question.
- Then assign the decision weight for the best prize directly as the weighted probability of that prize.
- For each of the intermediate prizes in declining order, assign the decision weight using the weighted cumulative probability for that prize less the decision weights for better prizes (or, equivalently, the weighted cumulative probability for the immediately better prize).
- For the worst prize the decision weight is the residual decision weight to ensure that the decision weights sum to 1.

The key is to view the decision weights as the *incremental* decision weight attributable to that prize.

Table B1 collects these steps for each of the examples, and adds a four prize example. From a programming perspective, these calculations are tedious but not difficult as long as one can assume that prizes are rank-ordered as they are evaluated. Our computer code in *Stata* allows for up to four prizes, which spans most applications in laboratory or field settings, and is of course applicable for lotteries with any number of prizes up to four. The logic can be easily extended to more prizes.

Figure B1 illustrates these calculations using the power probability weighting function. The dashed line in the left panel displays the probability weighting function $\omega(p) = p^{\gamma} = p^{1.25}$, with the vertical axis showing underweighting of the objective probabilities displayed on the bottom axis. The implications for decision weights are then shown in the right panel, for the two-prize, three-prize and four-prize cases. In the right panel the bottom axis shows prizes ranked from worst to best, so one immediately identifies the "probability pessimism" at work with this probability weighting function. Values of $\gamma < 1$ generate overweighting of the objective probabilities and "probability optimism," as one might expect.

Figure B2 shows the effects of using the "inverse-S" probability weighting function $\omega(p) = p^\gamma / (p^\gamma + (1-p)^\gamma)^{1/\gamma}$ for $\gamma = 0.65$. This function exhibits inverse-S probability weighting (optimism for small p, and pessimism for large p) for $\gamma<1$, and S-shaped probability weighting (pessimism for small p, and optimism for large p) for $\gamma>1$.

B.1 Rank-Dependent Decision Weights for Index Insurance Choices

Recall the notation for index insurance from the main text. There are 8 possible states, depending on the permutations of binary outcomes of if the individual chooses to purchase insurance $\{I_1, I_0\}$, if the index reflects a loss $\{L_1, L_0\}$, and if the individual's outcome matches the outcome of the index $\{P_1, P_0\}$.

For instance, if the individual chooses not to purchase insurance (I_0), the index reflects a loss outcome (L_1), and the individual's outcome matches the index (P_1), the individual would also experience a loss ($I_0L_1P_1$) and be left with $5. If the individual's outcome does not match the index (P_0), she does not experience a loss ($I_0L_1P_0$) and would keep her $20. By the same logic, $I_0L_0P_0$ = $20 and $I_0L_0P_0$ = $5.

The logic for the case in which the individual does purchase insurance (I_1) is the same, other than the fact that a premium is deducted for each outcome.

The essential point to take into account with this index insurance contract is that the top two prizes should be associated with the sum of the probabilities of each outcome, and then the bottom two prizes should be associated with the sum of the probabilities of each outcome. Then the analyses proceeds as if there were only two prizes. Table B2 illustrates. Panel A repeats the 4-prize example from Table B1, where all 4 prizes are distinct in value. Panel B changes the calculations in panel B assuming instead that the top 2 prizes are the same value, and the bottom 2 prizes are the same value. Panel C then shows an example from the text and Figure 1, assuming that $\varrho = 0.7$.

Table B1: Tabulations of RDU Examples

Prize	Probability	Cumulative Probability	Weighted Cumulative Probability	Decision Weight
		A. Two Prizes		
Y	0.5	0.5	$0.42 = 0.5^{1.25}$	0.42
y < Y	0.5	1	$1 = 1^{1.25}$	0.58 = 1 - 0.42
		B. Three Prizes		
Y	0.33	0.33	$0.25 = 0.33^{1.25}$	0.25
Y < **Y**	0.33	0.67	$0.60 = 0.67^{1.25}$	0.35 = 0.60 - 0.25
y < Y < **Y**	0.33	1	$1 = 1^{1.25}$	0.40 = 1 - 0.60 = 1 - 0.35 - 0.25
		C. Four Prizes		
Best	0.25	0.25	$0.18 = 0.25^{1.25}$	0.18
2nd Best	0.25	0.5	$0.42 = 0.50^{1.25}$	0.24 = 0.42 - 0.18
3rd Best	0.25	0.75	$0.70 = 0.75^{1.25}$	0.28 = 0.70 - 0.42 = 1 - 0.24 - 0.18
Worst	0.25	1	$1^{1.25}$	0.30 = 1 - 0.70 = 1 - 0.28 - 0.24 - 0.18

Figure B1: Power Probability Weighting and Implied Decision Weights for Gains

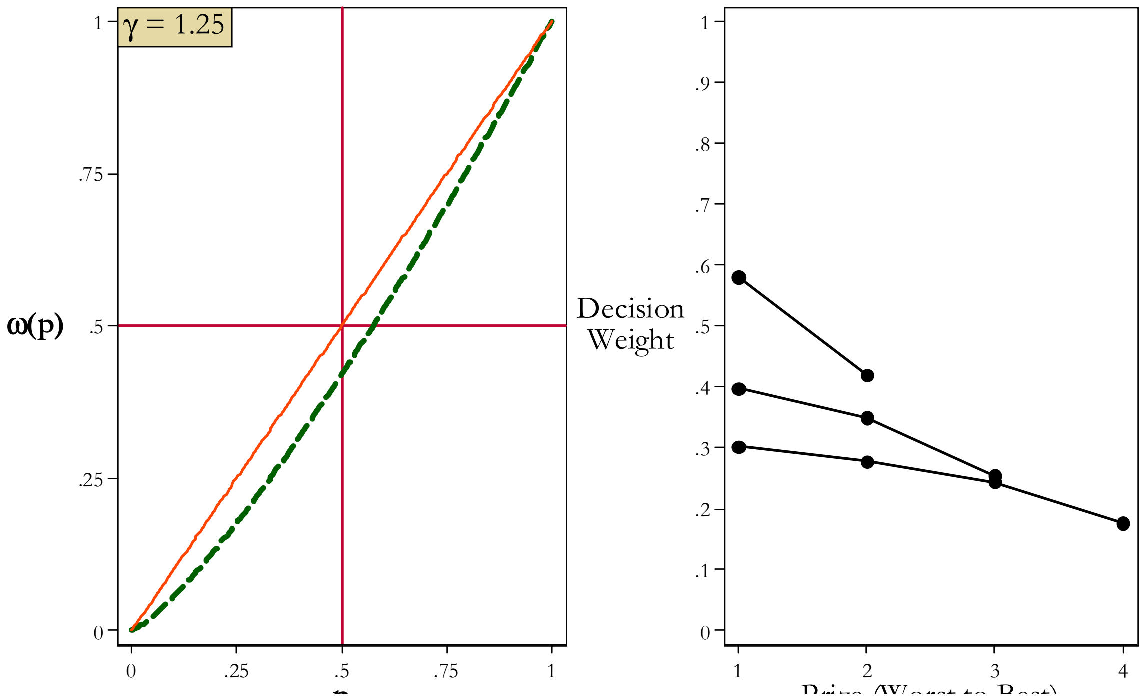


Figure B2: Inverse-S Probability Weighting and Implied Decision Weights for Gains

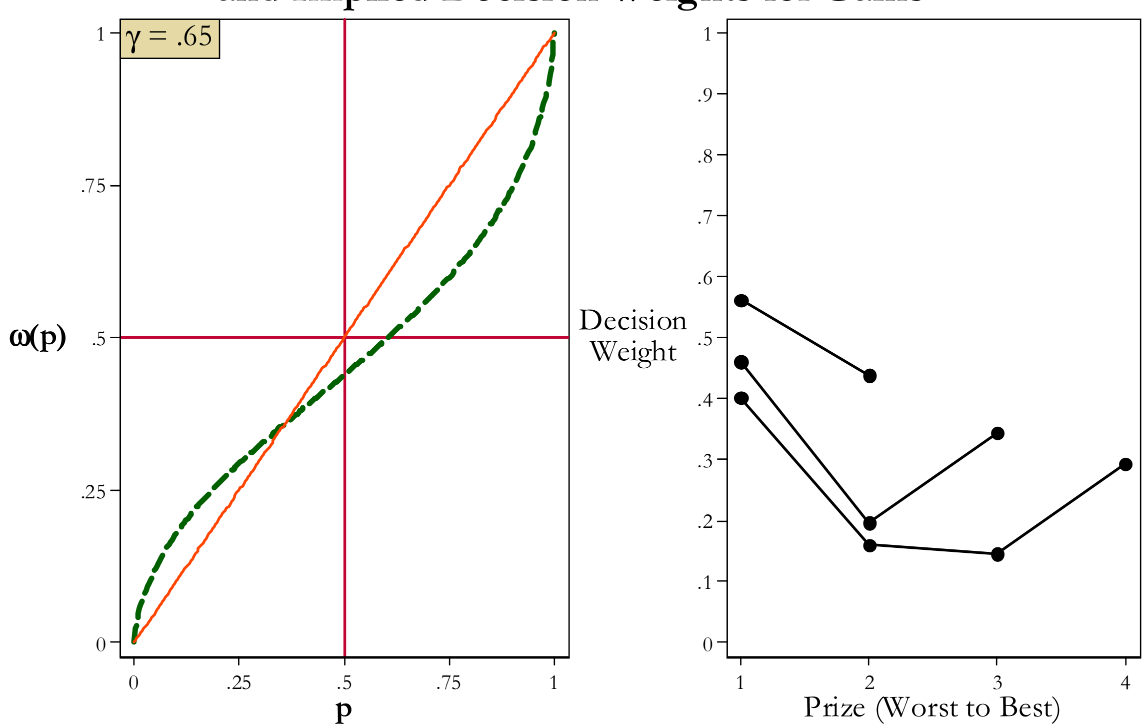


Table B2: Tabulations of RDU Examples Applied to Index Insurance

Prize	Probability	Cumulative Probability	Weighted Cumulative Probability	Decision Weight
		A. Four Distinct Prizes		
Best	0.25	0.25	$0.18 = 0.25^{1.25}$	0.18
2nd Best	0.25	0.5	$0.42 = 0.50^{1.25}$	0.24 = 0.42 - 0.18
3rd Best	0.25	0.75	$0.70 = 0.75^{1.25}$	0.28 = 0.70 - 0.42 = 1 - 0.24 - 0.18
Worst	0.25	1	$1^{1.25}$	0.30 = 1 - 0.70 = 1 - 0.28 - 0.24 - 0.18
		B. Four Prizes But Only Two Distinct Prize Levels		
Best 2nd Best	0.25 + 0.25	0.5	$0.42 = 0.50^{1.25}$	0.42
3rd Best Worst	0.25 + 0.25	1	$1^{1.25}$	0.58 = 1 - 0.42
		C. Index Insurance Not Purchased and $\varrho = 0.7$		
$I_0L_1P_0$ = \$20 $I_0L_0P_1$ = \$20	$0.1\ (1-\varrho) + 0.9\ \varrho = 0.025 + 0.675$	0.7	$0.640 = 0.7^{1.25}$	0.64
$I_0L_1P_1$ = \$5 $I_0L_0P_0$ = \$5	$0.1\ \varrho + 0.9\ (1-\varrho) = 0.075 + 0.225$	1	$1^{1.25}$	0.36 = 1 - 0.64

Appendix C: Risky Lottery Choices (NOT FOR PUBLICATION)

Table C1: Parameters for Double or Nothing Lotteries

Also see text for the Right Lottery in Table C2

	Left Lottery						Right Lottery					
Lottery ID	Prize 1	Probability 1	Prize 2	Probability 2	Prize 3	Probability 3	Prize 1	Probability 1	Prize 2	Probability 2	Prize 3	Probability 3
rdon1	$0	0.5	$10	0.5	$20	0	$0	0.5	$10	0.5	$20	0
rdon2	$0	0	$10	1	$20	0	$0	0.5	$10	0.5	$20	0
rdon3	$0	0	$10	1	$35	0	$0	0	$5	0.5	$18	0.5
rdon4	$0	0.25	$10	0.75	$70	0	$0	0	$35	1	$70	0
rdon5	$0	0	$10	1	$70	0	$0	0	$35	1	$70	0
rdon6	$0	0	$20	1	$35	0	$0	0	$10	0.5	$35	0.5
rdon7	$0	0	$20	0.5	$70	0.5	$0	0	$35	0.5	$70	0.5
rdon8	$0	0	$35	1	$70	0	$0	0	$35	0.5	$70	0.5
rdon9	$0	0	$20	0.5	$35	0.5	$0	0.5	$20	0	$70	0.5
rdon10	$0	0	$35	0.75	$70	0.25	$0	0	$35	1	$70	0
rdon11	$0	0	$20	1	$70	0	$0	0	$20	0.5	$35	0.5
rdon12	$0	0	$35	0.75	$70	0.25	$0	0	$35	0.5	$70	0.5
rdon13	$0	0.25	$10	0.75	$35	0	$0	0.5	$18	0.5	$35	0
rdon14	$0	0	$20	0.75	$35	0.25	$0	0	$18	0.5	$35	0.5
rdon15	$0	0	$20	0.75	$70	0.25	$0	0	$35	0.5	$70	0.5

Table C2: Text for Double or Nothing Lotteries

Also see parameters for the Right Lottery in Table C1

Lottery ID	Double or Nothing Text
rdon1	Double or Nothing if outcome 2 in right lottery
rdon2	Double or Nothing if outcome 2 in right lottery
rdon3	Double or Nothing for any outcome in right lottery
rdon4	Double or Nothing for any outcome in right lottery
rdon5	Double or Nothing for any outcome in right lottery
rdon6	Double or Nothing if outcome 2 in right lottery
rdon7	Double or Nothing if outcome 2 in right lottery
rdon8	Double or Nothing if outcome 2 in right lottery
rdon9	Double or Nothing if outcome 3 in left lottery
rdon10	Double or Nothing for any outcome in right lottery
rdon11	Double or Nothing if outcome 3 in right lottery
rdon12	Double or Nothing if outcome 2 in right lottery
rdon13	Double or Nothing if outcome 2 in right lottery
rdon14	Double or Nothing if outcome 2 in right lottery
rdon15	Double or Nothing if outcome 2 in right lottery

Table C3: Parameters for the Actuarially-Equivalent Lotteries

	Left Lottery						Right Lottery					
Lottery ID	Prize 1	Probability 1	Prize 2	Probability 2	Prize 3	Probability 3	Prize 1	Probability 1	Prize 2	Probability 2	Prize 3	Probability 3
rae1	$0	0.5	$10	0.5	$20	0	$0	0.75	$10	0	$20	0.25
rae2	$0	0	$10	1	$20	0	$0	0.75	$10	0	$20	0.25
rae3	$0	0	$10	1	$35	0	$0	0.5	$10	0.25	$35	0.25
rae4	$0	0.25	$10	0.75	$70	0	$0	0.5	$10	0	$70	0.5
rae5	$0	0	$10	1	$70	0	$0	0.5	$10	0	$70	0.5
rae6	$0	0	$20	1	$35	0	$0	0.25	$20	0.25	$35	0.5
rae7	$0	0	$20	0.5	$70	0.5	$0	0.25	$20	0	$70	0.75
rae8	$0	0	$35	1	$70	0	$0	0.25	$35	0	$70	0.75
rae9	$0	0.25	$20	0.5	$70	0.25	$0	0.5	$20	0	$70	0.5
rae10	$0	0	$35	0.75	$70	0.25	$0	0.5	$35	0	$70	0.5
rae11	$0	0	$20	1	$70	0	$0	0.25	$20	0.5	$70	0.25
rae12	$0	0	$35	0.75	$70	0.25	$0	0.25	$35	0	$70	0.75
rae13	$0	0.25	$10	0.75	$35	0	$0	0.75	$10	0	$35	0.25
rae14	$0	0	$20	0.75	$35	0.25	$0	0.25	$20	0	$35	0.75
rae15	$0	0	$20	0.75	$70	0.25	$0	0.25	$20	0	$70	0.75

Table C4: Parameters for the Lotteries Based on Loomes and Sugden [1998]

	Left Lottery						Right Lottery					
Lottery ID	Prize 1	Probability 1	Prize 2	Probability 2	Prize 3	Probability 3	Prize 1	Probability 1	Prize 2	Probability 2	Prize 3	Probability 3
ls2_lr	$10	0.3	$30	0	$50	0.7	$10	0.15	$30	0.25	$50	0.6
ls6_lr	$10	0.6	$30	0	$50	0.4	$10	0	$30	1	$50	0
ls7_lr	$10	0.6	$30	0	$50	0.4	$10	0.15	$30	0.75	$50	0.1
ls10_lr	$10	0.5	$30	0	$50	0.5	$10	0.1	$30	0.8	$50	0.1
ls13_rl	$10	0.5	$30	0.4	$50	0.1	$10	0.7	$30	0	$50	0.3
ls15_rl	$10	0.4	$30	0.6	$50	0	$10	0.5	$30	0.4	$50	0.1
ls17_lr	$10	0.1	$30	0	$50	0.9	$10	0	$30	0.25	$50	0.75
ls18_rl	$10	0.1	$30	0.75	$50	0.15	$10	0.4	$30	0	$50	0.6
ls21_lr	$10	0.7	$30	0	$50	0.3	$10	0.6	$30	0.25	$50	0.15
ls26_rl	$10	0.2	$30	0.6	$50	0.2	$10	0.4	$30	0	$50	0.6
ls29_rl	$10	0.5	$30	0.3	$50	0.2	$10	0.6	$30	0	$50	0.4
ls32_rl	$10	0.7	$30	0.3	$50	0	$10	0.8	$30	0	$50	0.2
ls34_rl	$10	0.1	$30	0.6	$50	0.3	$10	0.25	$30	0	$50	0.75
ls35_rl	$10	0	$30	1	$50	0	$10	0.25	$30	0	$50	0.75
ls39_rl	$10	0.5	$30	0.2	$50	0.3	$10	0.55	$30	0	$50	0.45
ls1i_lr	$10	0.12	$30	0.05	$50	0.83	$10	0.03	$30	0.2	$50	0.77
ls3i_lr	$10	0.27	$30	0.05	$50	0.68	$10	0.03	$30	0.45	$50	0.52
ls7i_lr	$10	0.54	$30	0.1	$50	0.36	$10	0.18	$30	0.7	$50	0.12
ls9i_lr	$10	0.08	$30	0.04	$50	0.88	$10	0.05	$30	0.1	$50	0.85
ls13i_lr	$10	0.65	$30	0.1	$50	0.25	$10	0.55	$30	0.3	$50	0.15
ls16i_lr	$10	0.88	$30	0.04	$50	0.08	$10	0.83	$30	0.14	$50	0.03
ls17i_rl	$10	0.04	$30	0.15	$50	0.81	$10	0.08	$30	0.05	$50	0.87
ls18i_rl	$10	0.14	$30	0.65	$50	0.21	$10	0.38	$30	0.05	$50	0.57
ls22i_lr	$10	0.66	$30	0.1	$50	0.24	$10	0.54	$30	0.4	$50	0.06
ls28i_rl	$10	0.12	$30	0.84	$50	0.04	$10	0.18	$30	0.66	$50	0.16
ls30i_rl	$10	0.45	$30	0.45	$50	0.1	$10	0.55	$30	0.15	$50	0.3
ls31i_lr	$10	0.48	$30	0.36	$50	0.16	$10	0.42	$30	0.54	$50	0.04
ls35i_lr	$10	0.2	$30	0.2	$50	0.6	$10	0.1	$30	0.6	$50	0.3
ls36i_rl	$10	0.02	$30	0.92	$50	0.06	$10	0.08	$30	0.68	$50	0.24
ls37i_lr	$10	0.48	$30	0.28	$50	0.24	$10	0.44	$30	0.44	$50	0.12

Table C5: Parameters for the Actuarially-Equivalent Index Insurance Lotteries

	Left Lottery						**Right Lottery**					
Lottery ID	Prize 1	Probability 1	Prize 2	Probability 2	Prize 3	Probability 3	Prize 1	Probability 1	Prize 2	Probability 2	Prize 3	Probability 3
iiae1	$4.5	0	$19.5	1	$34.5	0	$0	0	$5	0.1	$20	0.9
iiae2	$4.5	0.18	$19.5	0.8	$34.5	0.02	$0	0	$5	0.26	$20	0.74
iiae3	$4.5	0.36	$19.5	0.6	$34.5	0.04	$0	0	$5	0.42	$20	0.58
iiae4	$4.5	0.54	$19.5	0.4	$34.5	0.06	$0	0	$5	0.58	$20	0.42
iiae5	$3.8	0	$18.8	1	$33.8	0	$0	0	$5	0.1	$20	0.9
iiae6	$0	0	$5	0.26	$20	0.74	$3.8	0.18	$18.8	0.8	$33.8	0.02
iiae7	$3.8	0.36	$18.8	0.6	$33.8	0.04	$0	0	$5	0.42	$20	0.58
iiae8	$0	0	$5	0.58	$20	0.42	$3.8	0.54	$18.8	0.4	$33.8	0.06
iiae9	$3.2	0	$18.2	1	$33.2	0	$0	0	$5	0.1	$20	0.9
iiae10	$0	0	$5	0.26	$20	0.74	$3.2	0.18	$18.2	0.8	$33.2	0.02
iiae11	$0	0	$5	0.42	$20	0.58	$3.2	0.36	$18.2	0.6	$33.2	0.04
iiae12	$0	0	$5	0.58	$20	0.42	$3.2	0.54	$18.2	0.4	$33.2	0.06
iiae13	$1.5	0	$16.5	1	$31.5	0	$0	0	$5	0.1	$20	0.9
iiae14	$1.5	0.18	$16.5	0.8	$31.5	0.02	$0	0	$5	0.26	$20	0.74
iiae15	$0	0	$5	0.42	$20	0.58	$1.5	0.36	$16.5	0.6	$31.5	0.04
iiae16	$0	0	$5	0.58	$20	0.42	$1.5	0.54	$16.5	0.4	$31.5	0.06

Appendix D: Detailed Literature Review (NOT FOR PUBLICATION)

We look to the literature to see how previous studies have measured the impact of basis risk in index insurance. Table D1 collates the various welfare metrics used to evaluate insurance in the studies we are aware of.

Five studies are closer to our approach, so we provide more detail below on their approach. Clarke [2016] develops a theory for the rational demand of index insurance, explaining the impact of risk aversion, price and wealth on the demand for index insurance which has basis risk. Clarke and Kalani [2012] test the validity of the developed theory in an empirical study. Elabed and Carter [2015] take a different approach, instead applying a model of ambiguity aversion to explain the willingness to pay (WTP) for index insurance resulting from violations of the ROCL axiom. McIntosh, Povel and Sadoulet [2015] also estimate the WTP for insurance, but they use it to assess the demand for partial and probabilistic insurance. Finally, Swarthout [2012] is a progenitor of our study.

A. A Theory of the Rational Demand for Index Insurance

Clarke [2016] raises two empirical puzzles with regards to index insurance demand. The first is that the demand for weather index insurance, which is expected to offer protection against extreme adverse weather events, is lower than expected. The second is that demand seems to be particularly low from the most risk averse, when they are the ones who should benefit most from insurance. He makes use of a rational demand model to derive a theory to solve these puzzles, that is he assumes the consumer is a price-taking risk averse expected utility maximizer.

The critical feature of this model with basis risk is the nature of the joint probability structure of the index insurance product and the consumer's loss. Since the payout from insurance is imperfectly correlated with the individual's loss, purchasing index insurance both worsens the worse possible outcome and improves the best possible outcome. Although purchasing more index insurance could reduce the loss exposure of the individual when the individual outcome matches the outcome of the index, it will also increase exposure to a worse possible outcome when the individual experiences a loss but the index does not. Depending on which factor has a stronger impact, it is no longer obvious what the optimal amount of insurance a risk inverse individual should purchase.

The model is set up as follows. A decision maker holds strictly risk averse preferences over wealth, with a von Neumann-Morgenstern utility function U(W) satisfying $U'(W) > 0$ and $U''(W) < 0$.The decision maker is endowed with constant wealth w, is exposed to uninsurable zero mean background risk, and is exposed to the possibility of suffering a loss of L. There is also an index which is exposed to the binary possibility of experiencing a loss event or not. The index is not necessarily perfectly correlated with the loss and so there are four possible joint realizations of the index and individual loss. The table below shows the joint probabilities of all four possible outcomes, where p is the probability that the individual experiences a loss, and q is the probability that the index experiences a loss.

	$Index = 0$	$Index = I$	
$Loss = 0$	$1-q-r$	$q+r-p$	$1-p$
$Loss = L$	r	$p-r$	p
	$1-q$	q	

Clarke [2016] defines basis risk using the parameter r, which is defined as the joint probability that the individual experiences a loss but does not receive a payout, as the index does not experience the loss event. With this joint probability set-up, basis risk can vary while p and q remain constant. This definition of basis risk differs from the definition in our model, which is the probability the outcome for the individual's loss event is different from the outcome of the index loss event.

Solving for the optimal amount of coverage the individual should purchase to maximize expected utility, Clarke [2016] finds that for the classes of constant absolute and constant relative risk aversion, demand for actuarially unfair indexed cover is hump-shaped in the degree of risk aversion. First it increases is risk aversion increases, then it decreases at higher levels of risk aversion. Demand for actuarially-favourable indexed cover is either decreasing or decreasing-increasing-decreasing in risk aversion. Using similar methods, Clarke also finds that there is no monotonic relationship between demand and initial wealth, loss amount or premium loading.

B. Empirical Tests of a Theory of the Rational Demand for Index Insurance

Clarke and Kalani [2012] empirically test the results from Clarke [2016] by conducting a field experiment in villages in Ethiopia. They set up lottery choices in the gain frame which they call the benchmark, as well as insurance choices which they try to frame as losses, to test determinants for demand of index insurance, determinants of risk aversion, and effect of group insurance over individual insurance. They use the Ordered Lottery Selection design of Binswanger [1980], and applied it in their benchmark treatment, as well as in four insurance treatments. Subjects were given 65 Birr, and were told they could lose up to 50 Birr, then they were asked how much insurance they would prefer to purchase. We describe the two insurance treatments that our relevant to our study. The first is an individual indemnity treatment. Subjects are shown that there are 4 tokens in a bag, 3 blue and 1 yellow. If a yellow token is drawn, subjects will lose 50 Birr. Subjects can choose to purchase between 0 to 5 units of indemnity insurance to reduce the loss amount. One unit of indemnity insurance costs a premium of 8 Birr and with each unit of insurance purchased the loss when a yellow token is drawn is reduced by 10 Birr.

The second treatment is the individual index treatment. This insurance decision is based on a two-stage probability structure. In the first stage, a fair wheel is spun to select between a blue bag, and a yellow bag. The blue bag contains 3 blue tokens and 1 yellow token, and a yellow bag contains 1 blue token and 3 yellow tokens. A token is drawn from the bag selected in the first stage, and if a yellow token is drawn, the subject will lose 50 Birr. Once again subjects can choose to purchase between 0 to 5 units of insurance, but for this treatment the insurance will only pay out if the yellow bag is selected in the first stage. One unit of index insurance cost a premium of 3 Birr and led to a claim payment of 5 Birr in the event of the yellow bag being selected, and zero otherwise. There is basis risk, hence there is a chance that a subject who purchased insurance might incur a loss but not receive a payout.

Clarke and Kalani [2012] use structural maximum likelihood, like we do, to elicit risk preferences based on the choices made in the individual indemnity treatment. Like us, they assume a CRRA utility function, and that the population on average can have EUT or RDU risk preferences. They also use the mean-variance (MV) utility decision theory developed by Giné et al [2008] to see how well the risk choices fit that model. They also tested for how well the risk choices fit a mixture model between MV and RDU risk preferences. They find their data best fits the mixture model of MV and EUT.

As Clarke and Kalani [2012] used the Ordered Lottery Selection design, each subject only makes one insurance choice per treatment, hence they are only able to elicit average risk preferences for the sample population, and unlike our study they are unable to elicit risk preferences on the individual level. They also notice framing effects in their study. Although the benchmark and individual indemnity treatment are made up of numerically identical choices, they do not produce numerically consistent choices.

They run an ordered probit model on the choices from the individual index treatment to determine the how characteristics impact demand for index insurance. They find that subjects with intermediate levels of wealth have the highest take-up, with the poorest and richest subjects revealing a low demand for index insurance. This is consistent with the hump-shaped theoretical relationship between index insurance take-up and wealth derived by Clarke [2016] in an expected utility framework. However, unlike us, they do not use the risk preferences estimated from the benchmark or indemnity insurance to calculate willingness to pay (WTP) for insurance. In other words they do not compare how risk aversion should or could affect take-up. However, they do allude to this comparison in Clarke and Kalani [2012; p. 30]:

> This finding [of an "S-shaped" probability weighting function] is not surprising given the data; a large number of participants purchased more index insurance than is consistent with EUT or RDU with an inverse S-shape.

C. Compound Risk and the Welfare Evaluation of Index Insurance

In their field experiment, Elabed and Carter [2015] use WTP for a weather index insurance product to measure welfare benefit of the insurance for cotton farmers in Mali. As in our experiment, they take into account risk preferences when measuring welfare. However they assume that all the farmers evaluate risk aversion over insurance framed as a simple lottery ("simple risk aversion") using EUT. Their study looks into the impact of compound risk preferences from basis risk on WTP for weather index insurance. They make use of the Smooth Model of Ambiguity Aversion formalized by Kilbanoff, Marinacci and Mukerji [2005] (KMM) to separate preferences on simple risk and on compound risk. The premium for the compound lottery is approximated by the formula derived by Maccheroni et al. [2013], which breaks the premium down into a compound-risk premium and the classical Pratt risk premium, allowing the CE to be derived as the expected value of the lottery less the risk premium. WTP for the index insurance contract is then calculated as the difference between the CE of the index insurance contract and the CE of the simply lottery faced in the autarkic situation.

Their experiment is divided into two tasks, where one of the tasks is randomly selected to actually be played out for real money. The first task presents insurance contracts with no basis risk using a methodology similar to Binswanger [1980], where the menu of insurance options is presented to the subject, and they select their preferred choice. The options are presented to the subjects as blocks of insurance: six discrete yield levels are specified with a probability assigned to each level, and subjects were asked to select how much insurance coverage they wanted such that they would be guaranteed a minimum of that yield level. The probability, revenue and premium for each yield level were determined beforehand and shown to the subjects. Premia were set at 20% above the actuarially fair price. The actual yield outcome was then randomly selected based on the probabilities shown to the subjects. Assuming CRRA preferences, the subject's CRRA risk parameter was then inferred from the range consistent with the selected insurance contract. This experiment frames the risk parameter elicitation question in the context of insurance, unlike our experiment which used simple lotteries. Although the parameters of this experiment were set up to reflect real-life scenarios, with a 50% chance of a highest yield, this does not allow one to reliably identify non-EUT models. Furthermore, the range of CRRA risk parameter that can be captured only spans the intervals < 0.08 to > 0.55, with 56% of their subjects falling in these clopen intervals. The first interval corresponds to extremely slight risk aversion, risk neutrality, or even risk loving; the last interval corresponds to a significant fraction of risk aversion found worldwide using lottery tasks like these (see Harrison and Rutström [2008] for a review). Lastly, with this methodology only one data point is used to calibrate the risk preferences for each individual subject, hence there is no standard deviation on the value of simple risk aversion or compound risk aversion.

The second task presents the subjects with the index insurance contract, where there is a 20% chance the insurance will not pay out even though the subject has a low yield. Only downward basis risk is considered here. Given the price of the index insurance contract, a Switching Multiple Price List, following Andersen, Harrison, Lau and Rutström [2006], was used to elicit the minimum price of the "fail-safe" insurance where the index insurance would start being preferred over the "fail-safe" insurance contract. Such a set-up might frame the questions such that it leads subjects to select a certain price. Only compound risk aversion, and not risk loving, is considered. WTP to avoid basis risk is defined as the difference between the price the subject is willing to pay to avoid switching to index insurance and the market price of the "fail-safe" insurance, which was determined in the previous task as 120% of the actuarially fair premium. Using the CRRA risk parameter elicited from the first task and assuming constant compound risk aversion, the compound risk parameter was also estimated, and 57% of subjects were found to be compound risk averse to varying degrees. Using the estimated risk parameter and compound risk parameter to calculate the WTP of index insurance and assuming subjects will only choose to purchase insurance if their WTP lies above the market price of 120% of actuarially fair premium, considering compound risk aversion on top of the simple risk aversion could cut demand for index insurance by as much as half, relative to demand calculated from just considering simple risk aversion.

D. Welfare Evaluation of Partial and Probabilistic Insurance

McIntosh, Povel and Sadoulet [2015] define basis risk as risk that is not covered by the insurance product, and they test the impact of basis risk on insurance demand when it is expressed in two different ways. The first is when insurance is partial, in the sense that the insurance will pay out when there is a shock but it might not completely cover the loss. The second is when insurance is probabilistic, in the sense that the insurance may fail to pay out when there is a shock. They used a field experiment with coffee farmers in Guatemala to understand the demand for index-based rainfall insurance. Insurance demand is calculated using a flexible utility function at the individual level to evaluate WTP for insurance. The risk parameters of the utility function were estimated from actual insurance choices using a non-linear least squares estimator. They find that the average WTP for insurance increases as loss severity increases. This result holds even if the insurance payout remains constant, regardless of loss severity, which causes the insurance coverage to be even more partial as loss severity increases. Average WTP decreases, however, when payouts are more probabilistic: as the probability the insurance fails to pay for a shock increases, insurance demand decreases.

One way their methodology differs from ours is that they use the same insurance choices that they estimate risk parameters from to calculate the WTP of insurance. Applying the estimated risk parameters to the same data set that they were estimated from would result in the WTP for insurance to be biased, in the sense that these risk parameters are selected in order to maximize the likelihood that the observed insurance choice is the correct thing to do (by revealed preference). There is no allowance for mistaken choices, in the behavioral sense, and for the estimated WTP estimated to be negative (in statistical expectation). They also have less than 10 data points per subject to use to estimate risk parameters, which makes their results very noisy statistically. Also, their results only apply to villages that self-report in a survey that they are vulnerable to excess rainfall risk. Since the survey is hypothetical, this adds another layer of uncertainty to the validity of their results.

E. Prior Lab Experiments on Index Insurance at GSU

We based the design of our insurance battery on Swarthout [2012], who makes use of an exploratory laboratory experiment to investigate the behavioral foundations of index insurance purchase behavior. One attractive feature of his experiment is that in the laboratory he is able to define and control what the basis risk is and exactly how it appears to the subjects, which is more difficult to do in the field. On average, he finds that the subjects in his experiment increased insurance take-up as basis risk increased. This differs from our result, which shows that take-up is not significantly impacted by basis risk. The insurance battery he uses varies loss amount also, while we have kept our loss amount fixed, and that might have influenced the difference in results. He also estimates risk preferences using EUT and Cumulative Prospect Theory (CPT), and finds that both the probabilistic loss aversion and non-linear probability weighting in CPT, rather than the curvature of the utility function, are factors influencing insurance take-up. We have accounted for that aspect of risk preferences in our experiment by allowing for subjects to have non-EUT risk preferences consistent with RDU. We have also taken these estimates on risk preferences one step further to use them to evaluate welfare of the insurance choices, rather than just take-up.

Table D1: Literature Review of Welfare Metrics for Index Insurance

Study	Metric of Welfare	Measure	Data	Hypothetical or Real	Result
A. Welfare Measured by Take-up					
Giné et al. [2008]	Take-up of rainfall index insurance	Average	Household survey		Lack of understanding, but also credit constraints, limited familiarity, and risk aversion discourage insurance purchase. Being previously insured, connected to village networks and self-indentifying as 'progressive' encourage insurance purchase.
Hill and Robles [2011]	Take-up of varying weather securities	Average	Field experiment, actual insurance sold and survey	Choices on components of weather securities package (Real)	High take-up in Average and variance experimental game and pilot as weather securities are easily understood and fit heterogeneous farmers' needs. Crop and production choices, and soil characteristics have some explanatory power for security choices
Clarke and Kalani [2012]	Take up of index insurance, reduction of risk aversion	Average, variance, and Maximizing Expected Utilty (MEU)	Field experiment	Binswanger (Real)	Take-up is hump-shaped against wealth, where subjects with immediate levels of wealth have the highest take-up. There is no strong evidence of schooling, understanding of the decision problems or financial literacy significantly increasing take-up. Background risk however significantly affects take-up. Parametric assumptions matter when estimating determinants of risk aversion.
Hill, Hoddinott and Kumar [2013]	Reduced adverse consequence of shocks on income and consumption	Average	Survey	Double-bounded dichotomous choice contingent valuation method (Hypothetical); Binswanger (one Hypothetical, and one Real)	Those who faced higher rainfall risk, were less risk averse, more educated, more proactive, and richer, were more likely to purchase insurance. Offering insurance through a risk-sharing group increases demand for less educated females, but is constrained by lack of trust amongst neighbors.
Dercon et al. [2014]	Take-up of rainfall insurance	Average	Actual insurance sold and survey		Insurance demand increased when groups were exposed to training that encouraged sharing of insurance within groups. A suggested reason is that risk-sharing and index insurance can be shown to be complementary.
Vasilaky et al. [2014]	Take-up of index insurance	Average	Field experiment		Participation in educational game increases likelihood of purchasing insurance as well as amount purchased. The study focused on the context of scaling a large unsubsidized index insurance program.
Cole et al. [2014]	Take-up of rainfall index insurance	Average	Actual insurance sold and survey		Households in villages that have experienced insurance payouts are more likely to purchase in the following season, but this effect decreases over time. Households that have experienced payouts themselves are more likely to purchase two and three seasons later, than the first.

Jensen et al. [2014]	Demand for Index-based livestock insurance (IBLI)	Average	Actual insurance sold and survey		Basis risk and spatial adverse selection associated with division average basis risk dampen demand for IBLI. Households in divisions with greater average idiosyncratic risk are much less likely to purchase insurance. There is also strong evidence of intertemporal adverse selection as households purchase less coverage, conditional on purchasing, before seasons for which they expect good conditions.
Norton et al. [2014]	Optimal allocation of endowment between risk management options	Average	Field experiment and actual insurance sold	Allocation of endowment between risk management options (Real)	Participants exhibited clear preferences for insurance contracts with higher frequency payouts and for insurance over other risk management options, including high interest savings. The preference for higher frequency payouts is mirrored in commercial sales of the product, with commercial purchasers paying substantially higher premiums than the minimal, low frequency option available. Commercial insurance also has option for premiums to be payed through labor.
Hill et al. [2016]	Take-up of weather-based index insurance	Average	Field experiment	Binswanger (Hypothetical)	Weather insurance demand in India falls with price and basis risk, and is hump-shaped in risk aversion, with price sensitivity decreasing at higher levels of basis risk. Increased incentive to learn or learning by using are more effective than insurance training at increasing both understanding and demand. Over time, the impact of premium, new weather stations and increased training diminish, and receiving a payout encourages future uptake while previous purchase of insurance does not.
Jin et al. [2016]	Take-up of weather-based index insurance	Average	Household survey and field experiment	Multiple Price List (Real)	More than half of the farmers surveyed purchased the weather index insurance. Their main stated reasons were the support and subsidy from the government, and the belief that the probability of future crop losses due to weather events is high. The main reasons for not participating are farmer's low income, low trust in local insurers, and lack of understanding of the policy. The average farmer is moderately risk averse, and risk aversion has a positive effect on farmer's weather index insurance participation decisions.

B. Welfare Measured by Willingness to Pay

Chantarat et al. [2009]	Certainty equivalent (CE) of herd growth rate	CE	Simulation		Household initial herd size is the key determinant of the product's performance, more so than household risk preferences or basis risk exposure. The product works least well for the poorest. The product is most valuable for the vulnerable non-poor, for whom insurance can stem collapses in herd size following predictable shocks. Demand appears to be highly price elastic, and willingness to pay is, on average, much lower than commercially viable rates.

Elabed et al. [2013]	Willingness to Pay (WTP) for agricultural index insurance	CE	Field experiment	Binswanger and Multiple Price List (Real)	Index insurance demand decreases under both risk aversion and compound risk aversion as basis risk increases. Multi-scale contracts that depend on triggers at the district and village level may allow for lower triggers to reduce basis risk to the farmer, while avoiding moral hazard problem.
Bryan [2013]	MEU	MEU	Field experiment	Binswanger (Hypothetical)	Provides a theory that implies ambiguity may decrease the adoption of novel technologies and limit the value of insurance. The effect of ambiguity aversion decreases with experience, a policy of short-term subsidization, and long-term insurance may help to alleviate low demand.
Leblois et al. [2014]	MEU	CE	Field experiment and actual insurance sold	Multiple Price List (Real)	Length of cotton growing cycle is the best performing index considered. Gain from weather-index based insurance is lower than that of hedging against cotton price fluctuations provided by the national cotton company.
Elabed and Carter [2015]	Willingness-to-pay for agricultural index insurance	CE	Field experiment	Binswanger and sMPL (Real)	Allowing for compound risk aversion would significantly decrease the expected demand for insurance with a downside basis risk.
McIntosh et al. [2015]	WTP for probabilistic insurance	CE	Field experiment	Choices to purchase insurance (Real)	Average WTP for insurance increases as the loss severity increases, even if the payout is constant, which causes the insurance coverage to be more partial. Average WTP decreases, however, when payouts are more probabilistic, so that the probability the insurance fails to pay for an adverse event increases. Offering insurance on a group level does not increase demand for index insurance.
Clarke [2016]	MEU	MEU	Theory		A model for rational demand for index insurance products is presented which explains two puzzles regarding index insurance demand: why demand for index insurance is lower than expected and why demand is low for more risk averse individuals.

C. Welfare Measured by Risk Reduction Proxies

Skees et al. [2001]	Reduced revenue volatility of rainfall insurance	Coefficient of variation (CV) of expected revenue	Simulation on past data		A drought insurance program based on rainfall contracts would have reduced relative risk in Morocco.
Hess [2003]	Allowing risky farmers to maintain access to credit during drought and smooth income	Value-at-risk (VaR)	Simulation on past data		Integrated scheme can help banks reduce their lending volume while bringing down default rates and transaction costs. It can also help farmers stabilize their incomes and possible access to greater credit line from enhanced collateral

Vedenov and Barnett [2004]	Efficiency: Reducing exposure to yield risk	Mean root square of loss, VaR and CE of revenue	Simulation on past data		Weather derivatives may reduce risk, but complicated combinations of derivatives are needed to achieve reasonable fits (basis risk is not transparent). Results from in-sample do not translate to out-sample data.
Giné et al. [2007]	Reduced exposure to rainfall risk	Variance	Household survey		There are large diversification benefits from holding a portfolio of insurance contracts, even though all insurance payouts are driven by rainfall in the same Indian state.
Breustedt et al. [2008]	Risk reduction on farm level yields (vs regional level)	Mean-variance and second-degree stochastic dominance	Simulation on past data		Out of weather index, area yield index and farm yield insurance, none provide statistically significant risk reduction for every farm.
Giné and Yang [2009]	Take-up of loan to adopt new technology	Average	Actual insurance sold		Packaging rainfall insurance with loan to purchase high-yielding seed decreases take-up of loan for Maize and groundnut farmers in Malawi. This could be due to implicit insurance from limited liability in loan contract.
Hill and Viceisza [2012]	Take-up of fertilizer (input)	Average	Actual insurance sold		Presence of (mandated) insurance increases take-up of fertilizer. Take-up also depends on initial wealth and previous weather realizations that affect subjective beliefs of weather outcomes.
Carter and Janzen [2012]	Less costly risk management behavior	Average	Actual insurance sold and survey		Insured households anticipate making cash flow choices which will increase welfare over uninsured households anticipated cash flow choices. These decisions include maintaining consumption levels, and less reliance on assistance.
Cole et al. [2013]	Improved risk sharing of weather shocks - which should affect income variability	Average	Actual insurance sold and survey	Binswanger (Real)	Insurance demand is significantly price sensitive, with an elasticity of around unity. There is evidence that limited trust and understanding of the product, product salience and liquidity constraints also limit insurance take-up and demand.
Chantarat et al. [2013]	Reduction of livestock mortality risk	Average	Survey and household data		By addressing serious problems of covariate risk, asymmetric information, and high transactions costs that have precluded the emergence of commercial insurance in these areas to date, IBLI offers a novel opportunity to use financial risk transfer mechanisms to address a key driver of persistent poverty
Mobarak and Rosenzweig [2013]	Take-up of risky technologies and wage risk reduction for landless population	Average	Actual insurance sold and survey		As basis risk increases, index insurance take-up increases if there is also informal risk sharing. Although informal risk sharing in caste groups reduces the sensitivity of profit and output to rainfall, relative to index insurance, it also reduces average returns. Landless households are more likely to purchase index insurance if cultivators are also offered weather insurance.

McIntosh et al. [2013]	Take-up of fertilizer input	Average	Actual insurance sold and survey	Farmers in Ethiopia are subject to credit constraints that limit their fertilizer use, which is also sensitive to risk-related variables. Actual weather index insurance take-up is not correlated with hypothetically-stated WTP, and is sensitive to vouchers for insurance purchase.
Karlan et al. [2014]	Increase in investments in a risky input	Average	Actual insurance sold and survey	Uninsured risk is a binding constraint on farmer *ex ante* investment, but the liquidity constraints are not as binding as typically thought, so that credit markets alone are not sufficient to generate higher farm investments. Another finding is that there is sufficient demand for rainfall insurance, but factors such as basis risk, trust in the insurance company, and farmer's recent experience, affected their demand for insurance.
Jensen et al. [2016]	Reduction of basis risk of IBLI	Stochastic dominance, mean-variance, OLS, semi-variance	Actual insurance sold and survey	Covariate risk is spatially sensitive to the covariate region, resulting in spatial adverse selection. Basis risk, mainly idiosyncratic risk, is substantial, so insurance reduces risk but offers partial coverage.

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Figure E1: Proportion of Actual Take-Up to Predicted Choices (II)

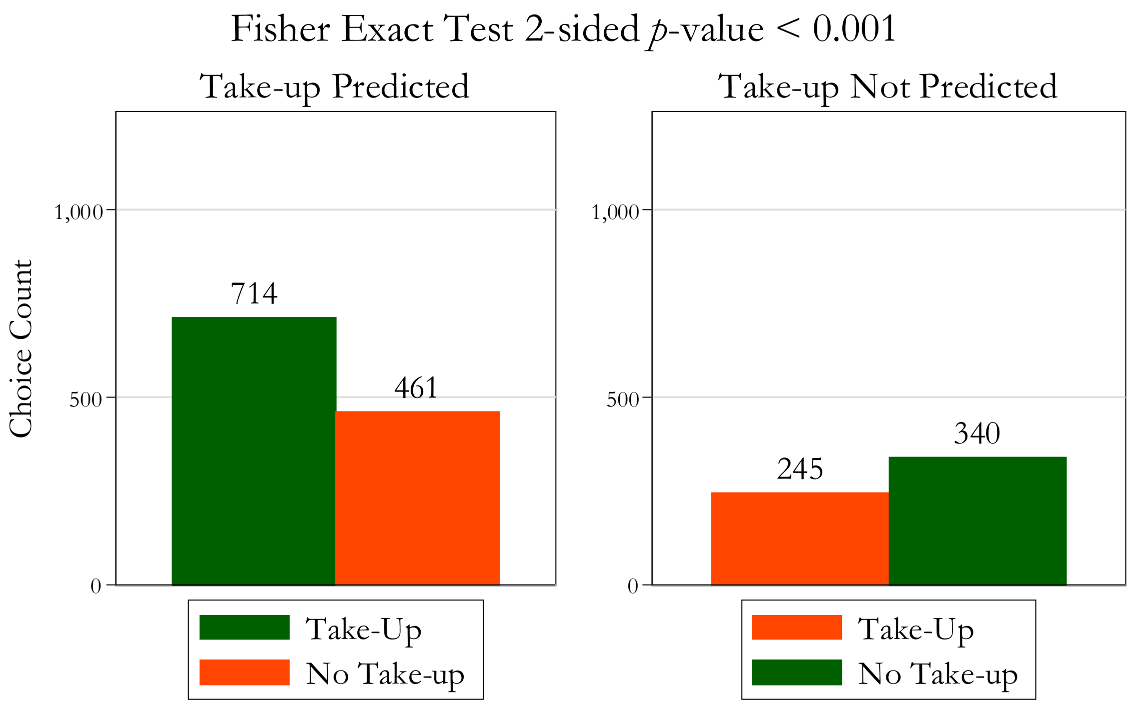


Figure E2: Proportion of Actual Take-Up to Predicted Choices (AE)

Fisher Exact Test 2-sided *p*-value < 0.001

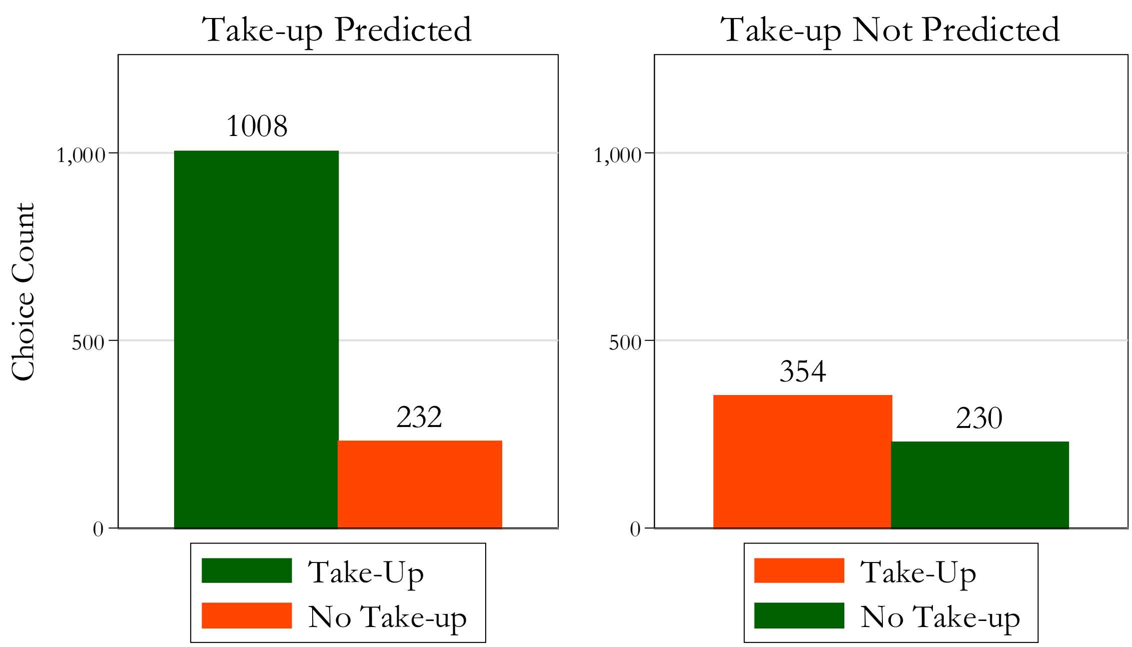
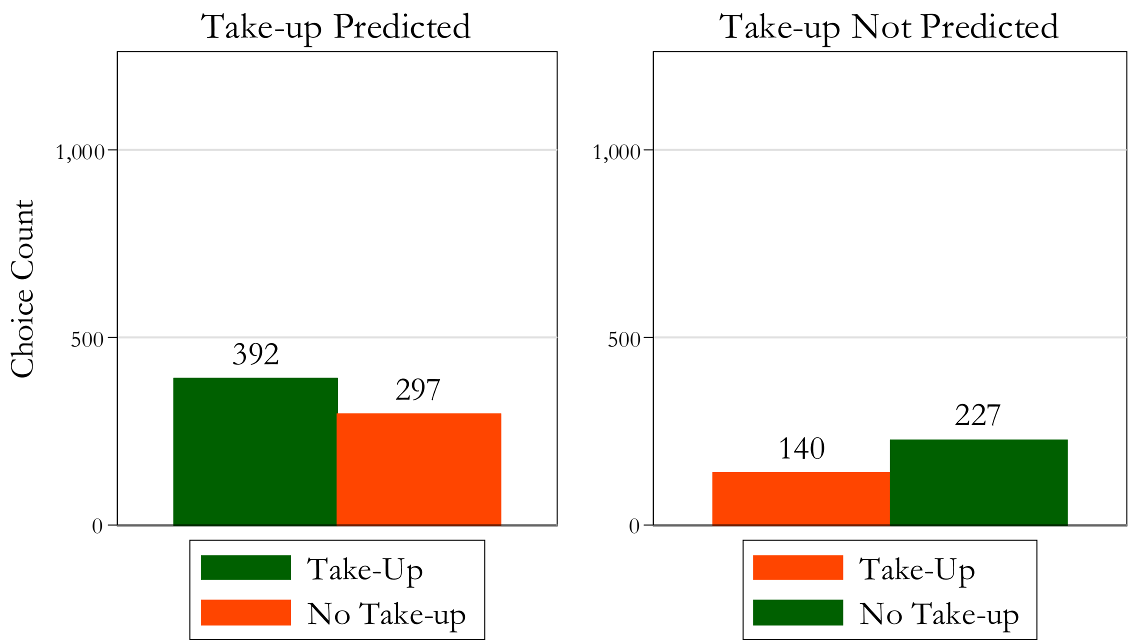


Figure E3: Proportion of Actual Take-Up to Predicted Choices (II-CC)

Fisher Exact Test 2-sided *p*-value < 0.001



Appendix F: Additional Tables (NOT FOR PUBLICATION)

Table F1: Average Marginal Effects of Factors Affecting Welfare Assuming Source-Dependent EUT in AE Treatment

	Take-up	Choice	CS	Efficiency
Risk Aversion	1.754	0.176	0.324	0.254
	(0.133)	(0.552)	(0.333)	(0.427)
(Risk Aversion)^2	-0.889	-0.591	-0.816*	-0.825*
	(0.399)	(0.081)	(0.016)	(0.027)
Correlation	-0.0761	0.944***	1.453***	
	(0.753)	(<0.001)	(<0.001)	
Premium	-0.337***	-0.359***	-0.479***	
	(<0.001)	(<0.001)	(<0.001)	
Loss Probability	4.790***	5.003***	7.833***	
	(<0.001)	(<0.001)	(<0.001)	
ROCL Violation Count	0.0476	-0.00401	-0.00353	0.0108
	(0.473)	(0.803)	(0.833)	(0.568)
Young	-0.992	-0.296*	-0.186	-0.216
	(0.062)	(0.011)	(0.458)	(0.202)
Female	-0.176	-0.0684	-0.130	-0.141
	(0.507)	(0.256)	(0.060)	(0.078)
Black	-0.997*	0.117	0.0755	0.0791
	(0.033)	(0.194)	(0.563)	(0.454)
Asian	-0.944	0.149	0.0691	0.134
	(0.055)	(0.210)	(0.579)	(0.414)
Business Major	0.0572	-0.0693	-0.0634	-0.0801
	(0.830)	(0.243)	(0.208)	(0.346)
Freshman	-0.339	0.190*	0.223	0.218*
	(0.306)	(0.014)	(0.062)	(0.011)
Senior	0.0884	0.288***	0.314***	0.354***
	(0.788)	(<0.001)	(<0.001)	(<0.001)
High GPA	-0.200	0.0196	0.0708	0.0343
	(0.425)	(0.740)	(0.243)	(0.676)
Christian	0.0620	-0.213*	-0.306**	-0.352**
	(0.886)	(0.019)	(0.008)	(0.004)
Insured	-0.205	-0.150*	-0.221*	-0.258**
	(0.418)	(0.018)	(0.015)	(0.006)

p-values in parentheses
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table F2: Average Marginal Effects of Factors Affecting Welfare Assuming Source-Dependent EUT in II Treatment

	Take-up	Choice	CS	Efficiency
Risk Aversion	0.00632	0.0482	0.162	0.136
	(0.984)	(0.688)	(0.231)	(0.426)
(Risk Aversion)^2	0.336	-0.0149	0.0273	-0.0730
	(0.504)	(0.932)	(0.896)	(0.754)
Correlation	0.173	-0.00287	0.0629	
	(0.429)	(0.984)	(0.836)	
Premium	-0.220***	-0.00116	-0.0119	
	(<0.001)	(0.976)	(0.883)	
Loss Probability	4.568***	2.372***	3.475*	
	(<0.001)	(<0.001)	(0.015)	
ROCL Violation Count	0.0123	-0.0388**	-0.0501**	-0.0483*
	(0.674)	(0.004)	(0.001)	(0.011)
Young	-0.719**	0.310*	0.491	0.495**
	(0.002)	(0.011)	(0.139)	(0.002)
Female	-0.0666	-0.0108	-0.0294	-0.0112
	(0.622)	(0.872)	(0.498)	(0.903)
Black	-0.276	-0.179*	-0.231**	-0.223*
	(0.170)	(0.029)	(0.009)	(0.039)
Asian	-0.417	-0.0898	-0.164	-0.121
	(0.085)	(0.412)	(0.125)	(0.401)
Business Major	-0.0481	-0.00190	0.0330	0.0273
	(0.716)	(0.979)	(0.628)	(0.776)
Freshman	-0.130	-0.128	-0.128	-0.123
	(0.416)	(0.130)	(0.085)	(0.299)
Senior	-0.276	-0.0869	-0.0705	-0.0638
	(0.093)	(0.316)	(0.428)	(0.588)
High GPA	-0.0989	-0.0204	0.0246	0.0183
	(0.390)	(0.753)	(0.675)	(0.845)
Christian	-0.242	-0.113	-0.147*	-0.141
	(0.128)	(0.099)	(0.037)	(0.102)
Insured	0.351**	0.0523	0.104	0.0918
	(0.010)	(0.481)	(0.158)	(0.393)

p-values in parentheses
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table F3: Average Marginal Effects of Factors Affecting Welfare Using Standard Methodology in AE Treatment

	Take-up	Choice	CS	Efficiency
Correlation	0.00877	0.932***	1.987***	
	(0.970)	(<0.001)	(<0.001)	
Premium	-0.324***	-0.303***	-0.570***	
	(<0.001)	(<0.001)	(<0.001)	
Loss Probability	4.897***	4.275***	9.212***	
	(<0.001)	(<0.001)	(<0.001)	
ROCL Violation Count	-0.0104	0.0243	-0.0394	0.0121
	(0.848)	(0.285)	(0.150)	(0.698)
Young	-1.085*	0.613***	-1.143	-0.126
	(0.015)	(<0.001)	(0.195)	(0.504)
Female	-0.111	-0.295**	-0.657***	-0.331**
	(0.662)	(0.007)	(<0.001)	(0.006)
Black	-0.325	-0.00417	-0.0355	0.0610
	(0.352)	(0.977)	(0.801)	(0.731)
Asian	-0.382	-0.165	-0.326*	-0.186
	(0.406)	(0.343)	(0.027)	(0.462)
Business Major	-0.0198	-0.130	-0.214*	-0.118
	(0.936)	(0.248)	(0.015)	(0.303)
Freshman	-0.117	0.0378	0.0496	0.0988
	(0.697)	(0.787)	(0.684)	(0.523)
Senior	0.160	0.127	-0.0853	0.0830
	(0.626)	(0.254)	(0.389)	(0.521)
High GPA	-0.0514	-0.103	-0.134*	-0.0477
	(0.817)	(0.351)	(0.039)	(0.695)
Christian	-0.00772	-0.181	-0.381***	-0.322
	(0.985)	(0.227)	(<0.001)	(0.092)
Insured	-0.138	-0.104	-0.267*	-0.191
	(0.552)	(0.249)	(0.020)	(0.084)

p-values in parentheses
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table F4: Average Marginal Effects of Factors Affecting Welfare Using Standard Methodology in AE Treatment

	Take-up	Choice	CS	Efficiency
RDU Classification	0.451	0.181	0.657***	0.253*
	(0.070)	(0.121)	(<0.001)	(0.028)
Risk Aversion	0.364	-0.154	-0.445**	-0.245
	(0.199)	(0.187)	(0.005)	(0.055)
(Risk Aversion)^2	0.0324	-0.0223	-0.0538***	-0.0323*
	(0.244)	(0.055)	(<0.001)	(0.014)
Correlation	0.00865	0.931***	1.987***	
	(0.970)	(<0.001)	(<0.001)	
Premium	-0.324***	-0.304***	-0.570***	
	(<0.001)	(<0.001)	(<0.001)	
Loss Probability	4.889***	4.271***	9.212***	
	(<0.001)	(<0.001)	(<0.001)	
ROCL Violation Count	0.0148	0.0436*	-0.00288	0.0316
	(0.805)	(0.022)	(0.917)	(0.173)
Young	-0.956*	0.614***	-0.894	-0.0370
	(0.040)	(<0.001)	(0.303)	(0.819)
Female	-0.0347	-0.265**	-0.621***	-0.329**
	(0.896)	(0.007)	(<0.001)	(0.001)
Black	-0.343	-0.0183	-0.0831	0.0733
	(0.279)	(0.889)	(0.558)	(0.607)
Asian	-0.290	-0.209	-0.396**	-0.222
	(0.544)	(0.158)	(0.003)	(0.262)
Business Major	0.00208	-0.155	-0.220**	-0.125
	(0.993)	(0.143)	(0.010)	(0.217)
Freshman	-0.172	0.128	0.244	0.233
	(0.556)	(0.291)	(0.085)	(0.073)
Senior	0.120	0.214*	0.169	0.227
	(0.714)	(0.048)	(0.068)	(0.056)
High GPA	0.0366	-0.0479	0.0256	0.0372
	(0.869)	(0.662)	(0.680)	(0.738)
Christian	0.0597	-0.132	-0.188	-0.237
	(0.884)	(0.299)	(0.089)	(0.091)
Insured	-0.196	-0.0985	-0.204	-0.152
	(0.385)	(0.249)	(0.068)	(0.109)

p-values in parentheses
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table F5: Average Marginal Effects of Factors Affecting Welfare Using Standard Methodology in II Treatment

	Take-up	Choice	CS	Efficiency
Correlation	0.117	-0.163	0.186	
	(0.584)	(0.221)	(0.530)	
Premium	-0.224***	-0.00145	-0.0450	
	(<0.001)	(0.966)	(0.560)	
Loss Probability	4.451***	2.528***	4.504**	
	(<0.001)	(<0.001)	(0.001)	
ROCL Violation Count	0.00282	-0.0262*	-0.0645***	-0.0457*
	(0.915)	(0.045)	(<0.001)	(0.028)
Young	-0.681**	-0.780***	-1.571***	-0.908***
	(0.001)	(<0.001)	(<0.001)	(<0.001)
Female	-0.0626	-0.0318	0.00705	-0.0299
	(0.602)	(0.632)	(0.894)	(0.751)
Black	-0.237	-0.192*	-0.180	-0.119
	(0.230)	(0.022)	(0.137)	(0.258)
Asian	-0.409	-0.198	-0.234	-0.161
	(0.073)	(0.068)	(0.134)	(0.276)
Business Major	-0.00980	0.0363	-0.0261	0.0240
	(0.936)	(0.598)	(0.738)	(0.812)
Freshman	-0.141	-0.104	-0.0974	-0.139
	(0.347)	(0.200)	(0.324)	(0.265)
Senior	-0.228	-0.0839	0.0117	-0.0529
	(0.159)	(0.307)	(0.926)	(0.660)
High GPA	-0.0970	-0.0140	-0.106	0.00689
	(0.379)	(0.821)	(0.120)	(0.940)
Christian	-0.247	-0.156*	-0.199*	-0.203*
	(0.102)	(0.028)	(0.019)	(0.029)
Insured	0.335*	0.102	0.0630	0.0931
	(0.013)	(0.159)	(0.453)	(0.387)

p-values in parentheses
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table F6: Average Marginal Effects of Factors Affecting Welfare Using Standard Methodology in II Treatment

	Take-up	Choice	CS	Efficiency
RDU Classification	0.160	0.0630	0.386***	0.143
	(0.164)	(0.356)	(0.001)	(0.136)
Risk Aversion	0.293	0.149*	0.310**	0.207
	(0.088)	(0.037)	(0.004)	(0.054)
(Risk Aversion)^2	-0.118	-0.239**	-0.437***	-0.356**
	(0.505)	(0.003)	(0.001)	(0.001)
Correlation	0.117	-0.164	0.186	
	(0.586)	(0.220)	(0.530)	
Premium	-0.224***	-0.00150	-0.0450	
	(<0.001)	(0.965)	(0.560)	
Loss Probability	4.448***	2.528***	4.504**	
	(<0.001)	(<0.001)	(0.001)	
ROCL Violation Count	0.00507	-0.0311*	-0.0606**	-0.0521**
	(0.853)	(0.017)	(0.002)	(0.009)
Young	-0.482	-0.782***	-1.353***	-0.893***
	(0.061)	(<0.001)	(<0.001)	(<0.001)
Female	-0.114	-0.0735	-0.0916	-0.100
	(0.346)	(0.250)	(0.161)	(0.264)
Black	-0.170	-0.159	-0.0130	-0.0532
	(0.382)	(0.069)	(0.910)	(0.648)
Asian	-0.344	-0.157	-0.103	-0.0972
	(0.129)	(0.172)	(0.491)	(0.548)
Business Major	-0.0485	0.0141	-0.0949	-0.0106
	(0.695)	(0.839)	(0.231)	(0.921)
Freshman	-0.211	-0.129	-0.204*	-0.185
	(0.148)	(0.120)	(0.041)	(0.146)
Senior	-0.246	-0.103	-0.0105	-0.0848
	(0.116)	(0.191)	(0.933)	(0.463)
High GPA	-0.114	-0.0366	-0.122	-0.0153
	(0.297)	(0.541)	(0.071)	(0.864)
Christian	-0.231	-0.131	-0.159	-0.175
	(0.123)	(0.085)	(0.052)	(0.098)
Insured	0.338*	0.0963	0.0687	0.0894
	(0.011)	(0.182)	(0.419)	(0.418)

p-values in parentheses
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table F7: Average Marginal Effects of Factors Affecting Welfare Assuming Recursive RDU in AE Treatment

	Take-up	Choice	CS	Efficiency
Correlation	-0.00773	0.485*	1.107*	
	(0.976)	(0.017)	(0.028)	
Premium	-0.339***	-0.215***	-0.945***	
	(<0.001)	(<0.001)	(<0.001)	
Loss Probability	4.761***	3.408***	14.18***	
	(<0.001)	(<0.001)	(<0.001)	
ROCL Violation Count	-0.0616	-0.0467	-0.584***	-0.0154
	(0.279)	(0.339)	(<0.001)	(0.730)
Young	-1.210**	-1.668***	-4.673***	-1.640***
	(0.004)	(<0.001)	(<0.001)	(<0.001)
Female	-0.00583	-0.0890	-0.351	-0.0406
	(0.983)	(0.689)	(0.130)	(0.826)
Black	-0.174	-0.00439	2.421***	-0.0222
	(0.607)	(0.987)	(<0.001)	(0.929)
Asian	-0.547	-0.154	1.198**	-0.0273
	(0.232)	(0.607)	(0.002)	(0.926)
Business Major	-0.0449	0.0753	0.830**	0.0803
	(0.861)	(0.748)	(0.003)	(0.693)
Freshman	0.0566	0.214	1.347***	0.276
	(0.860)	(0.407)	(<0.001)	(0.190)
Senior	0.120	-0.356	-0.937**	-0.230
	(0.704)	(0.330)	(0.003)	(0.442)
High GPA	-0.114	0.0653	0.819***	0.178
	(0.635)	(0.780)	(<0.001)	(0.358)
Christian	-0.454	-0.209	-0.676**	-0.273
	(0.248)	(0.471)	(0.007)	(0.300)
Insured	-0.147	-0.0726	-1.078***	-0.0828
	(0.584)	(0.735)	(<0.001)	(0.631)

p-values in parentheses
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table F8: Average Marginal Effects of Factors Affecting Welfare Assuming Recursive RDU in AE Treatment

	Take-up	Choice	CS	Efficiency
Risk Aversion	-0.280	-0.524*	-2.411***	-0.483*
	(0.248)	(0.022)	(<0.001)	(0.012)
(Risk Aversion)^2	-0.155	-0.224	-0.611	-0.240
	(0.433)	(0.265)	(0.076)	(0.147)
Correlation	-0.00816	0.484*	1.107*	
	(0.974)	(0.017)	(0.028)	
Premium	-0.339***	-0.215***	-0.945***	
	(<0.001)	(<0.001)	(<0.001)	
Loss Probability	4.769***	3.415***	14.18***	
	(<0.001)	(<0.001)	(<0.001)	
ROCL Violation Count	-0.0593	-0.0416	-0.550***	-0.0141
	(0.308)	(0.362)	(<0.001)	(0.743)
Young	-1.076*	-1.465**	-3.948***	-1.436***
	(0.025)	(0.002)	(<0.001)	(<0.001)
Female	0.0220	-0.0566	-0.414	-0.00278
	(0.933)	(0.793)	(0.131)	(0.988)
Black	-0.150	0.0259	2.543***	-0.000194
	(0.661)	(0.919)	(<0.001)	(0.999)
Asian	-0.448	0.0283	2.157***	0.143
	(0.342)	(0.923)	(<0.001)	(0.608)
Business Major	-0.0725	0.00735	0.432	0.0271
	(0.780)	(0.974)	(0.112)	(0.891)
Freshman	-0.0209	0.0786	0.766*	0.138
	(0.951)	(0.757)	(0.012)	(0.520)
Senior	0.0990	-0.411	-1.270***	-0.294
	(0.737)	(0.229)	(<0.001)	(0.308)
High GPA	-0.0887	0.134	1.259***	0.241
	(0.703)	(0.533)	(<0.001)	(0.191)
Christian	-0.449	-0.205	-0.515	-0.275
	(0.251)	(0.435)	(0.067)	(0.277)
Insured	-0.136	-0.0312	-0.705*	-0.0571
	(0.619)	(0.883)	(0.011)	(0.747)

p-values in parentheses
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table F9: Average Marginal Effects of Factors Affecting Welfare Assuming Recursive RDU in II Treatment

	Take-up	Choice	CS	Efficiency
Correlation	0.0953	0.301	1.463**	
	(0.682)	(0.086)	(0.004)	
Premium	-0.217***	-0.0106	-0.313**	
	(<0.001)	(0.757)	(0.008)	
Loss Probability	4.497***	1.392*	8.086***	
	(<0.001)	(0.023)	(0.001)	
ROCL Violation Count	0.00131	0.0180	0.0415	0.00808
	(0.959)	(0.397)	(0.313)	(0.730)
Young	-0.586*	-0.0126	0.595	0.499*
	(0.027)	(0.961)	(0.162)	(0.046)
Female	0.0121	-0.0882	-0.165	-0.117
	(0.919)	(0.333)	(0.461)	(0.255)
Black	-0.121	0.0417	-0.198	0.0538
	(0.451)	(0.719)	(0.663)	(0.674)
Asian	-0.243	-0.132	-1.413**	-0.0561
	(0.296)	(0.488)	(0.006)	(0.775)
Business Major	0.0386	-0.122	-0.0156	-0.136
	(0.749)	(0.240)	(0.923)	(0.228)
Freshman	-0.254	-0.215	-0.994**	-0.225
	(0.079)	(0.077)	(0.004)	(0.072)
Senior	-0.324*	0.0889	-0.179	0.0850
	(0.043)	(0.494)	(0.577)	(0.577)
High GPA	-0.0312	0.0153	0.180	0.0216
	(0.764)	(0.855)	(0.449)	(0.817)
Christian	-0.286	0.00129	-0.0704	-0.0339
	(0.057)	(0.991)	(0.688)	(0.779)
Insured	0.327**	0.0489	0.471*	0.0240
	(0.008)	(0.604)	(0.049)	(0.824)

p-values in parentheses
* $p<0.05$ ** $p<0.01$ *** $p<0.001$

Table F10: Average Marginal Effects of Factors Affecting Welfare Assuming Recursive RDU in II Treatment

	Take-up	Choice	CS	Efficiency
Risk Aversion	0.0831	-0.00152	-0.363	0.0323
	(0.375)	(0.987)	(0.280)	(0.730)
(Risk Aversion)^2	0.150	-0.0446	0.373	-0.0370
	(0.103)	(0.561)	(0.294)	(0.661)
Correlation	0.0957	0.301	1.463**	
	(0.681)	(0.086)	(0.004)	
Premium	-0.217***	-0.0106	-0.313**	
	(<0.001)	(0.758)	(0.008)	
Loss Probability	4.498***	1.391*	8.086***	
	(<0.001)	(0.024)	(0.001)	
ROCL Violation Count	0.00376	0.0166	0.0635	0.00593
	(0.885)	(0.417)	(0.096)	(0.795)
Young	-0.509	-0.0246	0.522	0.504
	(0.055)	(0.927)	(0.293)	(0.051)
Female	-0.00750	-0.0846	-0.160	-0.117
	(0.951)	(0.334)	(0.481)	(0.241)
Black	-0.163	0.0506	-0.214	0.0563
	(0.310)	(0.662)	(0.651)	(0.661)
Asian	-0.242	-0.138	-1.265**	-0.0697
	(0.292)	(0.468)	(0.009)	(0.723)
Business Major	0.0185	-0.117	-0.0431	-0.133
	(0.881)	(0.269)	(0.782)	(0.251)
Freshman	-0.281	-0.214	-0.868**	-0.237
	(0.054)	(0.083)	(0.005)	(0.061)
Senior	-0.352*	0.0907	-0.0929	0.0774
	(0.027)	(0.485)	(0.767)	(0.608)
High GPA	-0.0131	0.0152	0.0968	0.0290
	(0.904)	(0.865)	(0.664)	(0.768)
Christian	-0.280	0.000979	-0.0950	-0.0318
	(0.061)	(0.993)	(0.597)	(0.792)
Insured	0.300*	0.0574	0.393	0.0316
	(0.013)	(0.543)	(0.073)	(0.773)

p-values in parentheses
* $p<0.05$ ** $p<0.01$ *** $p<0.001$