Basis Risk, Social Comparison, Perceptions of Fairness and Demand for Insurance: A Field Experiment in Ethiopia

Berber Kramer
International Food and Policy Research Institute

Maria Porter
University of Arizona

Solomon Bizuayehu Wassie
Bahirdar University

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Abstract: Index insurance is considered an important strategy to reduce agricultural risk and increase smallholder farmers' investments. However, insured farmers may develop mistrust of insurance if they experience crop losses and do not receive a payout, for instance because index insurance covers only a subset of covariate risks. At the same time, insurance for idiosyncratic risks would introduce differences in payouts within social networks, which might be considered unfair, introduce jealousy, and further depress demand for insurance. We conduct lab-in-the-field experiments with farmers in Ethiopia to examine the effects of a novel insurance approach that ensures insurance payouts for farmers with crop losses due to idiosyncratic events. We also examine the effects of informing farmers about their neighbors' experiences alongside their own. We find that such social comparison increases perceived fairness of weather index insurance. In addition, providing complete insurance coverage for crop losses increases farmers' perceived fairness of outcomes and willingness to pay, without introducing jealousy over neighbors receiving different payouts. Finally, we find that the increase in willingness to pay for complete insurance is concentrated among men and risk averse respondents.

Keywords: index insurance, basis risk, social comparison, lab experiment, Ethiopia
JEL codes: Q12, D14, D91, O12

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1. Introduction

Climate change is increasingly exposing smallholder farmers to production risk due to natural hazards such as drought, heat, excess rainfall, hail, and pests and diseases (Porter et al., 2014), resulting in an increasingly unmet need for insurance against agricultural losses due to such shocks. Yet, the supply of reliable indemnity insurance coverage against such weather events remains limited. One reason for this is the high transaction cost of supplying small insurance policies to individual farmers in remote villages and indemnifying losses through in-person audits of affected fields (Kramer et al., 2022). In addition, asymmetric information between farmers and insurance providers can give rise to adverse selection and moral hazard (Hazell et al., 1986). As a result, smallholder farmers' livelihoods remain vulnerable to extreme weather shocks, discouraging investments in profitable agricultural activities among risk averse farmers, while also reducing access to credit for such investments (Dercon and Hoddinott, 2004; Barrett and McPeak, 2006; Cai et al., 2009; Mobarak and Rosenzweig, 2012; Cai, 2013; Karlan et al., 2014; Cole et al., 2017; Ahmed et al., 2020).

Weather index insurance (WII) was designed to overcome these challenges by using an index that can be measured at low cost, cannot be influenced by farmers, and is a good proxy for losses, such as remotely sensed rainfall measures. However, WII schemes in developing countries relying on such indices face a major challenge due to basis risk (Mobarak and Rosenzweig, 2012; Cole et al., 2013; Matul et al. 2013; Hill et al., 2016), which means that the index and associated payouts do not correlate adequately with actual crop losses. As a result, farmers may end up paying the insurance premium without receiving a payout when experiencing crop damage ('downside' basis risk). Alternatively, they may receive payouts during good years when they did not suffer actual losses ('upside' basis risk).

Basis risk can arise from design error, for instance due to poorly matched zonal data to design the insurance policy (Stigler and Lobell, 2023). Basis risk can also arise from temporal variation in crop phenology or growth stages, creating differences in when a crop is vulnerable to extreme weather, and thus optimal insurance coverage windows (Afshar et al, 2021). In addition, by covering covariate production risks only, idiosyncratic production risks - for instance due to limited spatial correlation in an index (such as rainfall), or perils that are not reflected in the index (such as pest or disease) - introduce an additional layer of basis risk (Clement et al, 2018, Stigler and Lobell, 2023).

Although insurance is most useful for low-probability high-loss occurrences with rare payouts, insurance providers face the dilemma that a low payout frequency would suppress demand for the product. Prior research has found that to raise demand for insurance, basis risk must be reduced (Doherty and Richter, 2002; Elabed et al., 2013; Clarke, 2016; Jensen et al., 2018; Clement et al, 2018; Ceballos and Kramer, 2019; Vosper and Checchi, 2022). Downside basis risk can lead farmers to believe that insurance will not trigger a payout when needed, and even upside basis risk has been associated with reduced demand (Vosper and Cecchi, 2022). Innovations to address basis risk can improve understanding and trust in an insurance product (see Carter, 2011, Kramer et al., 2023).

In this article, we examine the role of downside basis risk due to idiosyncratic production risks in depressing demand for index insurance, focusing on perceptions of fairness of products with and without such risk, as well as on the potential challenges that may arise due to neighbors receiving different insurance payouts. By means of a lab-in-the-field experiment in the Amhara region of Ethiopia, we address two main research questions. First, how does eliminating downside idiosyncratic basis risk in insurance affect perceptions of fairness in insurance outcomes and willingness to pay for insurance? To address this first question, we introduce a WII product with no downside basis risk to a random subset of our study respondents in the context of games framed in terms of real-world types of situations in which potential crop losses are insured through WII. Second, to what extent does willingness to pay for index insurance depend on whether respondents can compare insurance-related outcomes directly with one's neighbors? To address this second question, we cross-randomize our two insurance products with whether farmers are informed of seasonal outcomes and related insurance payouts only for themselves and then separately for their neighbors, or as a direct comparison between their own and neighbors' outcomes.

Social comparisons with one's neighbors or peers can lead to several impacts on decisions regarding take-up of insurance. Farmers are more likely to take up insurance when they are introduced to it via a trusted intermediary, and when it is framed as beneficial to groups with whom they identify (Cole et al., 2013). Some farmers may only purchase WII when it is offered to a trusted group (Hill et al., 2013). Demand for WII often depends on farmers' own prior experience with the product, as well as that of their social network (Cole et al., 2014; Karlan et al., 2014; Stein, 2018). Such peer effects could be explained by recency bias, which could be addressed by explicitly making social comparisons in insurance outcomes, as we do in this paper.

Providing insurance for idiosyncratic or localized risks could influence the way in which social comparison affects insurance demand. Insurance for idiosyncratic events may lower demand because it introduces differences in payouts within social networks, which may be considered unfair. At the same time, social reference points decrease the attractiveness of insurance for correlated risks (such as WII). Willingness to pay for disaster insurance is higher for idiosyncratic risk than for covariate risk (Friedl et al., 2014), suggesting a larger positive effect of social comparison on demand when basis risk is reduced.

We demonstrate that when farmers make direct comparisons with their neighbors, who also experience downside basis risk events, they perceive the insurance product to be fairer than when they cannot make such direct comparisons between themselves and neighbors. We also show that exogenously induced variation in perceived fairness is associated with improved willingness to pay, suggesting that improved demand is at least partially explained by outcomes being fairer. Finally, as predicted by economic theory (Clarke, 2016), we show that willingness to pay for index insurance is particularly sensitive to basis risk among risk averse farmers. We also find higher sensitivity to basis risk among men, whereas one's understanding of index insurance is not a major driver of willingness to pay.

Our study is related to several other studies that have used experimental economics to improve farmers' understanding of insurance (Carter et al., 2008; Cai and Song, 2017). Earlier experiments found that farmers can identify levels of basis risk and prefer products with less basis risk (Janzen et al., 2021). Yet, this same research found that farmers would increase their coverage levels either if they have greater understanding of index insurance, or if the insurance product has lower basis risk; a puzzling finding was that improving in both dimensions does not raise demand for insurance.

Our study also contributes to the literature on gender differences in demand for weather index insurance by documenting how reducing basis risk and social comparison affect demand differently for men and women. While such peer effects are particularly salient for women making financial decisions (Field et al., 2016), there has been limited research on gender differences in take-up of insurance, and the evidence that is available generally finds that women are either less likely to take up insurance than men; or if insuring at equal rates, women obtain less coverage than men (Timu and Kramer, 2023). In a study in the Sahel, in comparison to men, women purchased agricultural insurance less often, instead opting to save for other forms of idiosyncratic risk (Delavallade et al., 2015), and in Ethiopia, women were purchasing lower-value coverage (Bageant and Barrett, 2017). In Bangladesh, though men and women purchased agricultural insurance at similar rates, men purchased more units of insurance than women (Clarke and Kumar, 2017). In another study in Bangladesh involving a hypothetical choice experiment to evaluate valuations of different attributes of weather index insurance, Akter et al. (2016) found that compared to men, women have less trust in insurance institutions and therefore lower take-up rates.

This article makes several valuable contributions to the literature on index insurance design. First, we take seriously the potential challenges of introducing idiosyncratic payouts amongst neighbors. Our study provides the first step towards understanding how social comparison across neighboring farmers might relate to demand for an insurance product that addresses downside basis risk but also introduces variation in payments across neighbors. Existing experiments on index insurance and basis risk typically have farmers perform individual decision tasks, and do not consider the social comparisons that might occur within villages, for instance when there is idiosyncratic risk and farmers compare their outcomes and insurance payouts with those of neighboring farmers. Second, our study is designed to identify the role of perceived fairness and understanding of insurance products in determining willingness to pay for a product. Existing research finds that lowering basis risk improves demand, but do not identify the channels through which this occurs. Third, analysis across subgroups of farmers informs us about meaningful differences in the degree to which downside basis risk affects demand for insurance across subsets of the target population.

The remainder of this article proceeds as follows: Section 2 explains the background institutional context for our field experiments; Section 3 outlines our lab in the field experiments and econometric methods; Section 4 presents the empirical results; and Section 5 concludes.

2. Background

Our experiment was implemented in 2021 in partnership with the Rural Resilience Initiative (R4) program in Ethiopia. In 2011, the World Food Programme (WFP) and Oxfam America launched the R4 program, which is active in Ethiopia, Kenya, Malawi, Senegal, Zambia, and Zimbabwe (R4 Rural Resilience Initiative, 2018). The R4 program is aimed at enabling vulnerable rural families to increase their food and income security by managing climate-related risks. A primary aim of R4 has been to provide affordable weather index insurance by estimating losses using rainfall measured through satellite remote sensing. But basis risk is particularly problematic in countries such as Ethiopia, where the topography of target areas limits spatial correlation in local rainfall.

In an effort to reduce downside basis risk, the R4 program began introducing farmers in Ethiopia to a novel insurance approach that aims to improve crop monitoring and add a layer of fail-safe insurance using smartphone pictures. Under this picture-based insurance (PBI) approach, R4 field staff equipped with smartphones send in geo-referenced smartphone pictures of insured crops on a regular basis through a dedicated smartphone application called AzmeraCam. Field staff send in images not only post-damage, but also pre-damage, to monitor crop management and prevent moral hazard. The resulting time-lapse provides ‘eyes on the ground,’ reducing information asymmetries and costs of loss verification, two previously insurmountable challenges for traditional indemnity insurance. The images are reviewed by a team of agronomists from the Ethiopian Institute for Agriculture Research (EIAR) to assess images for the cause and extent of crop damage and to determine whether the farmer should receive an *ex gratia* payout, in case there are no (or low) insurance payouts triggered by the weather insurance index.

While R4 provides insurance for different crops, our experiment focuses on teff, which is one of Ethiopia’s most important crops (Bachewe et al., 2015; Taffesse et al., 2018). Teff covers 22.5% of the total area allocated for grain production (CSA, 2021). Teff is grown across a wide share of areas, and at many different altitudes. It is a highly valuable commodity compared to wheat or maize. In some parts of Ethiopia, teff is grown as a commercial crop. Teff is a late maturing crop, so that it can often serve as an important safeguard for resilience and for ensuring food security; when other staple crops such as maize or wheat experience poor harvests, farmers can respond by cultivating larger areas with teff. In our sample of respondents, 91% had cultivated teff in the 12 months preceding the survey. After teff, the most popular crops are maize (60% of respondents) and beans (48% of respondents).[1]

3. Experimental Design and Econometric Methods

In June 2021, we conducted lab-in-the-field experiments with 480 farmers in the Amhara region of Ethiopia. We chose two zones of Amhara where R4 had ongoing activities: South Gondar and East Gojjam. We selected two districts (*woredas*) from each zone, and within each *woreda*, we

[1] Wheat is generally more common in the Amhara region. However, crops can be highly varied across different topographies.

selected three villages (*kebeles*). For each of the 12 *kebeles*, we then randomly sampled 20 households from a list of beneficiaries targeted by R4. For each household, we surveyed the household head, as well as another household member of the opposite gender. This resulted in a total sample of 480 respondents (243 women and 237 men), of whom 373 respondents (77 percent) reported participating in the R4 program.

Incentivized games within the lab-in-the-field experiment were framed in terms of a real-world type of decision to take up insurance coverage for potential crop losses, with insurance for covariate risks exhibiting basis risk due to the presence of idiosyncratic production risk. Depending on treatment, crop losses could be insured either through only satellite-based monitoring of rainfall (to cover covariate production risks), or also through picture-based crop monitoring (to cover both covariate and idiosyncratic production risks, and thereby eliminating downside basis risk altogether).

Participants completed two tasks for the insurance product that was offered in their experimental treatment arm: first we asked for their perceptions of fairness of outcomes in various hypothetical insurance-related scenarios (which also served as insurance education), followed by an incentivized elicitation of their willingness to pay for this insurance product.

3.1. Hypothetical Insurance-Related Scenarios: With and Without Social Comparison

We presented respondents with eight hypothetical insurance scenarios to elicit fairness perceptions. In addition to randomizing whether farmers could take up insurance only for covariate risks or for both covariate and idiosyncratic risks, we cross-randomized whether farmers were nudged to make a social comparison. In one treatment, they were informed of seasonal outcomes only for themselves and then separately for their neighbors (no social comparison). In the other treatment, scenarios were presented as a comparison between their own and neighbors' outcomes (social comparison). As an example, see the following scenario with an idiosyncratic downside basis risk event:

"*Imagine the following scenario: You have had a good season and no crop damage. The satellite data also indicates that there is no crop damage. However, your neighbor has had a bad season with significant crop damage. The satellite data does not pick up on this.*"

In the treatment without social comparison, respondents were first presented with scenarios about themselves (for example, "*Imagine the following scenario: You have had a good season and no crop damage. The satellite data also indicates that there is no crop damage.")*, and then upon answering all questions related to those scenarios, they were presented with scenarios about their neighbors (for example, *"Imagine the following scenario: Your neighbor has had a bad season with significant crop damage. The satellite data does not pick up on this."*).

Following each scenario, we asked the respondent whether they thought the insurance product would make them a payout in this year (which, for the example above, was the case for neither of the two products); and whether it would make a payout to their neighbor in this year (which, for the example above, was the case only for the product covering both covariate and idiosyncratic risks). We did this to confirm that they had understood the explanation. When they answered correctly, we reiterated that this was indeed how the insurance product worked, and when respondents answered incorrectly, we provided additional explanation to ensure that they understood why they themselves or their neighbors were (not) eligible to receive a payout. Once it was clear that respondents understood the insurance payment mechanism, we asked them if they perceived the insurance result in this scenario to be fair.[2]

3.2. Willingness to Pay Experiment

Following the hypothetical scenarios, we presented respondents with an incentivized game designed to elicit willingness to pay (WTP) for a specific agricultural index insurance product.[3] To that end, we used a standard Becker–DeGroot–Marschak (BDM) approach to incentivize respondents' choices (Becker et al., 1964). We provided respondents with an experimental show-up fee and gave them the option to use a portion of this endowment to purchase insurance in the game. They were asked to indicate their maximum WTP for insurance, knowing that afterwards, the insurance premium would be randomly selected from a range of potential premiums. If their WTP was higher than or equal to the randomly selected premium, they would end up receiving insurance coverage against that crop failure in the experimental games, and they would pay the randomly selected premium out of their show-up fee, regardless of the outcome of the crop output. This setup encouraged respondents to indicate their maximum WTP for the insurance product, because if the randomly selected premium was to be lower (higher) than their maximum WTP, then the respondent would (not) be insured against crop failure in this game and (not) end up paying the insurance premium.

[2] Before presenting these scenarios, we also provided a brief tutorial on how insurance works. This tutorial differed for WII and NDBR treatments, to ensure respondents were receiving consistent information about the same product for which they would be asked their willingness to pay. A brief knowledge questionnaire before and after the tutorial indicates it was effective in improving subjects' understanding of insurance (see Appendix Table 2).

[3] To ensure that respondents were presented with the game setup and instructions in the same way, we recorded a video explaining the game and instructions. Enumerators showed all respondents this video.

Respondents were randomized to receive either WII only in the game, or WII with no downside basis risk (from now on referred to as WII for WII only, or NDBR for WII with no downside basis risk).

The experiment was designed so that the average expected payout to each participant, that is, the size of the stakes in the experiment, was equal to the average premium of R4's satellite weather index insurance product. Given that the average R4 premium is about 10 percent of the sum insured, the sum insured in the experiment was a much smaller amount than the amount generally covered by R4's insurance program. The average sum insured amongst farmers in our sample who were insured by R4 was 2,917 Birr; whereas the sum insured in the experiment was only 290 Birr.

Figure 1 outlines the series of choices faced by respondents, along with respective payouts in a decision tree. We presented respondents with the following scenario: "*Suppose you have planted your crop. If your crop has no damage, we will pay you 390 Birr. But if your crop is damaged, we will pay you 100 Birr*." There was a one in four probability that crop damage would occur; that is, respondents had a 75% chance of not experiencing crop failure, in which case they would earn 390 Birr, and with a 25% chance, respondents would experience crop failure and earn only 100 Birr. Uninsured respondents therefore would have expected earnings of 317.5 Birr.

{Figure 1 here}

Under the NBDR treatment, insured respondents paid the insurance premium *X*, and if experiencing crop failure (with a probability of 0.25), they would receive an insurance payout of 290 Birr (the sum insured), yielding total earnings of 390 Birr minus the premium paid. If not experiencing crop failure (with a probability of 0.75), there was a 90% probability that the farmer earned 390 Birr minus the insurance premium, without receiving an insurance payout. There was also a 10% probability of an upside basis risk event – scenarios in which despite the farmer having a good year (and earning 390 Birr), the satellite index-based portion of the insurance product detected poor weather outcomes, triggering a 290 Birr payout, increasing total earnings to 670 Birr minus the insurance premium. Thus, expected earnings in the NDBR treatment equaled 411.75 Birr minus the premium (see Figure 1), with an actuarially fair insurance premium of 290 Birr x (0.25 + 0.75*0.10) = 94.25 Birr; that is, if charged this premium, a farmer would expect to earn 317.5 Birr.

In contrast, in the WII treatment, we introduced downside basis risk. If an insured respondent experienced crop failure (which happened 25% of the time), there would be a 3 in 5 probability of the product triggering a payout, yielding total earnings of 390 Birr minus the premium paid; but there was also a 2 in 5 probability that no insurance payout was triggered, yielding earnings of only 100 Birr minus the premium paid. In the event of no crop failure (happening 75% of the time), payments to farmers were determined exactly in the same way as they were determined under the NDBR treatment: they would receive 390 Birr minus the premium paid with a 90% chance, and 670 Birr minus the insurance premium with a 10% chance. Thus, expected earnings for those in the WII treatment were 382.75 Birr net of the insurance premium (see Figure 1), with an actuarially fair premium of 290 Birr x (0.25*0.60 + 0.75*0.10) = 65.25 Birr. Farmers charged with this premium expected earnings of 317.5 Birr, as in the NBDR treatment.

3.3. Summary of Experimental Design

We summarize the experimental design in Table 1. Of the 480 respondents, 29 respondents chose not to purchase the insurance product in the incentivized game. Since our focus is on estimating the relative impact of basis risk and social comparison on WTP for insurance, we exclude these 29 respondents from our analysis.[4] Of the remaining 451 respondents, 221 respondents were offered WII in the BDM game and saw scenarios related only to WII, whereas the remaining 230 respondents were offered WII with no downside basis risk (the NDBR treatment) and saw scenarios related only to this type of insurance product. Among respondents in the WII treatment, 109 respondents saw hypothetical scenarios without social comparison and 112 respondents saw scenarios with social comparison. Similarly, among respondents in the NDBR treatment, 120 respondents saw scenarios without social comparison and 110 respondents saw scenarios with social comparison.

{TABLE 1 here}

3.4. Risk and Time Preferences Elicitation

As the decision to purchase insurance is related to one's tolerance for risk, we elicited individual risk preferences. We followed the staircase method proposed by Falk et al. (2018), which has relatively high stakes and responsive sequences of questions to ensure choices are rationally consistent (see Appendix Figure 1). In this approach, we asked respondents if they would prefer either a sure payment, or a draw with a 50% chance of receiving 18,100 Birr and the same 50% chance of receiving nothing. The sure payment varied for each question, and each respondent saw only five questions in total. In the first question, the sure payment was 9,650 Birr, which was slightly higher than the risk neutral sure payment of 9,050 Birr. Whenever the respondent chose the sure payment, the next question showed a lower sure payment; whenever

[4] These 29 respondents are fairly evenly distributed across treatments, and balancing tests for the entire sample are similar to that of the main sample used in the analysis (see Appendix Table 1).

the respondent chose the lottery, the next question showed a higher sure payment than previously.

The final highest possible sure payment respondents could see was 18,750 Birr. If respondents selected the lottery when this sure payment was higher than the 18,100 Birr they could win in the lottery, we interpret this as an indication that they were either not paying attention or did not understand the question. Out of the 29 respondents who saw this question, only 7 respondents selected the lottery in this case. For these 7 respondents, variables related to risk preference are treated as missing in our analysis.

We used a similar approach to elicit time preferences (See Appendix Figure 2). Following the staircase method in Falk et al. (2018), respondents saw a series of hypothetical questions in which they chose between either 6450 Birr at the time of the survey or a higher amount of Birr to be received in 12 months.

3.5. Sample Characteristics and Balancing Tests

We summarize sample characteristics in this section. Table 2 provides means and standard errors across the four treatments for all variables included in the analysis.

{TABLE 2 here}

We successfully recruited farmers who have had experience with R4's WII product. Of the 451 farmers in our study, 77% of households were R4 beneficiaries; and around 70% of respondents held an R4 policy in the previous growing season. On average, respondents planted 0.6 hectares of teff in the season prior to being surveyed. On average, 53% of respondents reported significant damage to this crop in that same season. However, only 28% of respondents indicated that they had input into coping strategies for addressing such teff losses. On average, there were 5.4 total members in the household, with 3.3 adult members on average. About 40% of households fell below the national poverty line. About 75% of households owned a mobile phone.

In terms of respondent characteristics, 50% of respondents were household heads, and 50% were women. The average age of a respondent was 38 years of age. Over half of respondents were illiterate. In terms of access to financial instruments, 49% of respondents could borrow from informal sources, and 64% of respondents had a savings account.

Using the hypothetical risk preference elicitation approach outlined above, 73% of respondents were risk averse, with respondents choosing the risky option about the 30% of the time on average. In terms of time preferences, respondents selected the lower present-biased amount 76% of the time. Regarding their understanding of insurance, on average, respondents correctly answered four out of six questions related to their knowledge and understanding of insurance (see Appendix Table 2 for details).

All household and individual level characteristics are balanced across the four treatments, with *p*-values from an F-test for differences in means across treatments exceeding 0.05 for all variables. There is only one variable where we find an imbalance that is significant at the 10 percent level: in the WII treatment without social comparison, 39% of respondents could obtain an informal loan, while this was around 50% or slightly higher in each of the other three treatment groups. All other *p*-values are well above the 10% critical level.

3.6. Descriptive Results

In comparison to WII, eliminating downside basis risk significantly increased farmers' perceived fairness of the conditions under which insurance payments were determined (see

Figure 2). Whereas outcomes are perceived as fair in just under 75% of WII scenarios, in the NBDR treatment, over 85% of scenarios are perceived as fair (on average across respondents). When we focus only on scenarios involving potential downside basis risk events, these differences become even more pronounced. In the WII treatment, 45% of scenarios with downside basis risk events are perceived as fair. Corresponding scenarios in the NBDR treatment, where the downside basis risk is eliminated by providing insurance for idiosyncratic risks, are perceived to be fair 80% of the time. In both cases, the difference in perceived fairness between treatments is statistically significant ($p < 0.01$).

{FIGURE 2 here}

Respondents' maximum willingness to pay as a percentage of the sum insured was also considerably higher under NDBR than WII (see Figure 3). Whereas maximum willingness to pay for WII averaged around 35% of the sum insured, for respondents in the NDBR treatment, it was over 40% of the sum insured. This difference is statistically significant ($p <0.01$). We observe relatively small differences in the maximum willingness to pay across treatments with and without social comparison.

{FIGURE 3 here}

The incentivized BDM field experiment enables us to construct demand schedules across treatments. Since WTP does not differ considerably by social comparison treatment, we combine treatments with and without social comparison into one WII and one NBDR treatment. In Figure 4, we plot the insurance premium on the y-axis and on the x-axis the percentage of respondents whose maximum WTP is equal to or higher than that insurance premium (in other words, the percentage of respondents taking up insurance at a given premium). The demand schedule for

WII generally falls below that of NDBR. Since NDBR payouts occur more frequently than WII payouts, the NDBR actuarially fair premium of 94.25 Birr is higher than that of WII (65.25 Birr). No matter the insurance product offered, most respondents are willing to pay at least the actuarially fair premium: nearly 90% of respondents in the WII treatment and around 67% of respondents in the NBDR treatment.

{FIGURE 4 here}

4. Estimation Methods and Results

4.1. Estimation Methods

We affirm the above findings while controlling for related factors by estimating the following multivariate regression for respondent *i* in household *h* in village *v*:

$$Y_{ihv} = \beta_0 + \beta_1 NDBR_{hv} + \beta_2 Social_{hv} + \beta_3 NDBR_{hv} * Social_{hv} + X_{ihv} + \varepsilon_{ihv} \qquad (1)$$

We focus on two outcomes Y_{ihv}, one for each part of the experiment: (i) an indicator for the respondent perceiving a high proportion (80% or more) of outcomes in hypothetical scenarios to be fair; and (ii) the natural logarithm of the respondent's maximum willingness to pay for the insurance premium. For the first outcome variable, capturing perceptions of fairness, we estimate a regression using two variations: one variation that considers all eight scenarios; and another variation that considers only the scenarios with potential downside basis risk events. We estimate equation (1) using OLS (results are consistent with logit estimation for the two dichotomous outcome variables).

For each outcome variable, β_1 estimates the marginal effect of being offered NDBR rather than WII in treatments without social comparison; β_2 estimates the marginal effect of the social comparison treatment for respondents being offered WII only; and β_3 estimates the additional effect of the social comparison treatment for respondents in the NDBR treatment.

We estimate four models for each outcome variable. Model 1 does not include any further covariates. Model 2 controls for the following covariates: whether the respondent is the household head; the gender and age of the respondent; an indicator for whether respondent is illiterate; number of adults in the household; household size; household poverty index determined by asset ownership and housing characteristics; an indicator for whether any household member owns a mobile phone; whether the household is participating in the R4 program at the time of the survey; whether the household had ever purchased WII from R4; and risk and time preferences measured by the share of risky and impatient decisions made in hypothetical games (see Falk et al. 2018). Model 3 includes these controls as well as several additional covariates: number of hectares the respondent planted teff in the most recent main (Meher) season; an indicator for whether the respondent experienced significant teff-related damage in that season; whether the respondent has input into decisions on how to cope with teff related losses; and whether the respondent has a savings account.[5] Model 4 includes the initial set of controls included in Model 2 and village fixed effects. Since we have two respondents per household, and randomization was done at the household level, all standard errors are clustered by household. Finally, we also estimate randomization inference-based p-values (using the STATA command randcmd, see Young, 2019).[6]

In addition to estimating these treatment effects, we also estimate the effect of fairness perceptions on WTP for insurance. We do so by regressing WTP on the indicator for a

[5] To maintain a consistent sample across models, we replaced missing observations with the mean of the variable for all continuous variables, and with a zero value for all indicator variables; we also included indicators for missing values for each variable with missing values.
[6] These p-values are consistent with all results reported here (available upon request from the authors).

respondent perceiving outcomes to be fair in a high proportion (at least 80%) of scenarios with potential basis risk events.

$$WTP_{ihv} = \beta_0 + \beta_1(High\ Fairness\ Perception)_i + X_{ihv} + \varepsilon_{ihv} \quad (2)$$

This relationship between fairness perceptions and WTP may be explained by a couple of factors. First, since the NDBR product involved no downside basis risk, in comparison to the WII product, respondents are likely to perceive the NDBR product as fairer and would on average be willing to pay more for it. But in addition, respondents who may perhaps be more trusting or more inclined to indicate a situation is fair, might also be more prone to indicate a higher WTP. Such unobservable characteristics might bias our estimates.

Taking these potential issues into consideration, we estimate this regression using both OLS and 2SLS. In 2SLS, we instrument the indicator for high fairness perceptions of scenarios with potential basis risk events by our treatment variables: indicators for the NDBR treatment, social comparison treatment, and their interaction term. Thus, equation (1) above serves as the first stage, when the outcome variable is the indicator for high fairness perceptions in scenarios with potential basis risk events.

It is worth noting that while our instrumental variables were exogenously allocated through our experimental design, the 2SLS approach likely violates the exclusion restriction. That is, it is highly plausible that the treatments directly impacted WTP and did not impact WTP only to the extent to which our treatments shifted fairness perceptions. Thus, 2SLS estimates provide an upper bound (likely over-estimate) on the impact of one's perception of fairness of the insurance product on one's willingness to pay for it.[7]

[7] Estimated treatment effects in OLS regressions (equation 1) are robust to controlling for fairness (results available upon request).

4.2. Estimation Results

In Table 3, we summarize estimated treatment effects on respondents' perceptions of fairness across the different hypothetical insurance scenarios. In the first four columns, we include all hypothetical insurance scenarios; in the second set of columns, we focus only on the scenarios with downside basis risk events.

In terms of the overall set of insurance scenarios, respondents are about 20% more likely to have a high level of perceived fairness for NDBR compared to WII ($p < 0.01$ for all four models). However, the social comparison treatment does not affect this outcome, with relatively low coefficient estimates.

When we restrict the scenarios only to those with potential basis risk events, coefficient estimates on NDBR are five times higher than in the previous models that include all insurance scenarios. When faced with scenarios with potential basis risk events, respondents are 50% more likely to have a high perception of fairness of NDBR relative to WII ($p < 0.01$).

In addition, in scenarios with potential basis risk events, respondents with WII are 25% to 28% more likely to consider outcomes to be fair in the social comparison treatment ($p < 0.01$). That is, when respondents see that their neighbors experiencing the same basis risk (which is harder to see when scenarios for oneself and one's neighbors are presented separately), perceptions of fairness increase. In the case of NDBR, the social comparison treatment becomes less important, with negative coefficient estimates on the interaction term ($p < 0.01$ for Model 5, and $p < 0.05$ for Models 6, 7, and 8). This interaction term is, in absolute size, a bit smaller than the effect of social comparison alone, meaning that in NDBR scenarios where farmers with WII would have suffered downside basis risk events, the social comparison treatment slightly increases perceived fairness.

{TABLE 3 here}

In Table 4, we summarize results of regressions on one's maximum willingness to pay for the insurance premium in the BDM field experiment (in natural logs). We summarize results from three sets of regressions: in Panel A, we present estimates from reduced form regressions on treatment indicators; in Panel B, we present OLS estimates on the indicator variable for high fairness perceptions of scenarios with potential basis risk events; and in Panel C, we present 2SLS estimates on this variable, which has been instrumented by our treatment indicators. Across the three panels, in Columns (2)-(4), we include various control variables as outlined above. For each panel, results are consistent across the four specifications.

Reduced form estimates indicate that on average, respondents are willing to pay 21% to 24% more for PBI compared to WII, 22% with the full set of covariates or 21% with village fixed effects. All estimates are statistically significant ($p < 0.01$).

{TABLE 4 here}

The social comparison treatment has negative coefficient estimates in the WII treatment, while the interaction between this treatment and NDBR is positive, reducing the effect of social comparisons to be closer to zero. These coefficient estimates are not statistically significant.

As we might expect, respondents who perceive a high proportion of insurance outcomes to be fair have a higher WTP for the insurance product than others. In Panel B, OLS estimates indicate that those with a high degree of perceived fairness, particularly in scenarios involving potential basis risk events, have a 12% to 14% higher willingness to pay for the related insurance product. These estimates are statistically significant ($p < 0.01$) across all specifications. The 2SLS estimates in Panel C are considerably higher than OLS estimates, which may be due to a violation of the exclusion restriction if the treatments influence WTP through mechanisms other than a respondent's perceived fairness. Considering 2SLS estimates as an upper bound, respondents who perceived most scenarios with potential basis risk events as fair - because of our treatments - were willing to pay 43% to 46% more for the insurance product as a result.

4.3. Subgroup Analysis of Treatment Effects

To identify differences in treatment effects across different subgroups of respondents, we estimate treatment effects for six subgroups determined by differences in gender, whether the respondent understands insurance (answering correctly 5 or more of the 6 insurance knowledge questions asked at the end of the insurance modules), and whether the respondent is risk averse (i.e., in a series of hypothetical decisions between a lottery and a sure payment, the respondent chose a sure payment amount below the risk neutral sure payment of 9050 Birr; see Appendix Figure 1).

In comparing men and women, the positive effect of eliminating downside basis risk on WTP is primarily concentrated among men (see Table 5). Men in the NBDR treatment are willing to pay about 30% more for insurance compared to men who are offered WII ($p < 0.01$), and coefficient estimates on the social comparison treatment and the interaction term are very small in absolute size, and not statistically significant. In contrast, for women, coefficient estimates on NBDR are low in magnitude and not statistically significant when we control for additional covariates beyond demographics, or for village fixed effects (with a coefficient estimate on NDBR that is significant at the 10 percent level only in the first model, where we only control for demographics). For women, the interaction term between NDBR and the social comparison treatment varies between 0.14 ($p < 0.01$) and 0.155 ($p < 0.1$), depending on the included covariates. Summing the coefficients on NDBR and the interaction terms, women have a 14% to 17% higher WTP for insurance with NDBR compared to WII when they are in the social comparison treatment.

{TABLE 5 here}

While there are no statistically significant treatment effects on women's WTP for insurance, women with a high perception of fairness of the insurance scenarios presented to them have a 12% to 13% higher WTP for insurance compared to women who do not have such fairness perceptions. These estimates are statistically significant when controlling only for demographics ($p < 0.01$), and when we include further covariates and village fixed effects ($p < 0.05$). Estimates are similar for men, although estimates are statistically significant so long as the full set of covariates is excluded ($p < 0.10$).

As we might expect, these OLS estimates are considerably lower than 2SLS estimates. Since men are more greatly impacted by the NDBR treatment, when we use this variable as an instrument for fairness perceptions, we get much higher estimates on WTP, with men who perceive the majority of scenarios to be fair willing to pay about 60% more for the insurance premium ($p < 0.01$). Since women are not significantly impacted by treatments, their instrumented fairness perceptions shifted WTP by about 24% to 28% ($p < 0.05$).

One's understanding of insurance can also be an important factor in WTP for insurance premiums. We split our respondents into two groups: those with high insurance knowledge who answer at least five of the six insurance related questions correctly by the end of the insurance module; and those who answer less than five questions correctly are categorized as having low insurance knowledge (Table 6).[8] Respondents in both categories have higher WTP for insurance with NDBR than WII. Coefficient estimates are nearly double in the group with low insurance

[8] 43% of respondents answered 5 or more questions correctly.

knowledge (27% vs. 15%), but these estimates are not statistically significantly different across the two sets of respondents. Perhaps not surprisingly, those with high knowledge of insurance are willing to pay about 14% to 17% less for WII in the social comparison treatment compared to the treatment without such direct comparisons ($p < 0.1$). For both groups, the interaction term is not statistically significant.

{TABLE 6 here}

Interestingly, perceptions of fairness in insurance scenarios similarly impact the two sets of respondents. While OLS estimates indicate that those with high fairness perceptions of insurance scenarios are willing to pay 11% to 15% more for insurance than others, 2SLS estimates indicate that fairness perceptions shift WTP by 40% to 48%.

Where we do see consistent estimates in differences among respondents is when we compare WTP across risk averse and risk loving respondents (Table 7).[9] While WTP is similar for insurance with NDBR as for WII among risk loving respondents, risk averse respondents are willing to pay 24% to 26% more for insurance with NDBR than WII ($p < 0.01$). The social comparison treatment has no impact on WTP for risk averse respondents. However, among risk loving respondents, WTP is 26% to 29% lower for WII in the social comparison treatment; and the interaction term is in the opposite direction and even higher in magnitude (30% to 39%), suggesting WTP is either somewhat higher or similar for NDBR than WII when in the social comparison treatment. However, only some of these estimates are statistically significant, and only at 10 percent significance levels. Estimates may be imprecise due to both relatively small

[9] Note that these two samples are distinct from the gender distinction. That is, we have similar shares of risk averse men (75%) and women (72%).

impacts among risk loving respondents, and a relatively smaller sample of risk loving respondents.

{TABLE 7 here}

While fairness perceptions do not shift WTP for risk loving respondents, there is considerable impact of fairness perceptions on WTP among risk averse respondents. OLS estimates indicate that risk averse respondents who perceive most insurance scenarios they see as fair are willing to pay 14% to 16% more for insurance compared to those who do not have such high fairness perceptions. Since the NDBR treatment also impacts risk averse respondents' WTP, 2SLS estimates are even higher. Risk averse respondents with high perceptions of fairness of the insurance scenarios are willing to pay 42% to 50% more for insurance compared to other risk averse respondents. All estimates on risk averse respondents are statistically significant ($p < 0.05$). As in the case of the overall sample, the 2SLS estimates are likely an upper bound on the relationship between fairness perceptions and WTP.

5. Conclusion

Smallholder farmers in developing countries are exposed to a range of risks, which often remain uninsured, having large negative welfare consequences, both ex post and ex ante. Index-based insurance aims to improve welfare, but many more localized idiosyncratic risks (e.g., due to topography, introducing spatial variation in rainfall, or from perils that have a more idiosyncratic nature than weather events, such as pests and disease) are difficult to insure, creating "basis risk," mistrust, and lowering demand.

We have found that eliminating downside basis risk by providing insurance for idiosyncratic risks increases farmers' perceived fairness of outcomes as well as their willingness to pay for insurance, without introducing jealousy over neighbors receiving payouts for idiosyncratic events. In WII treatments with social comparison, farmers perceive outcomes as fairer than in treatments without social comparison, likely because they realize that they are not the only ones affected by basis risk, and that this is how the product works. This is an important insight that could be used to strengthen insurance education in index-based insurance programs.

Perceived fairness and absolute willingness to pay for insurance are higher when there is no downside basis risk, and social comparison does not reduce perceived fairness when all potential downside basis risk events are insured. In other words, while an insurance product without downside basis risk will introduce differences in insurance payouts across neighbors, this will not deter farmers from taking up the product, even if in a context of social comparison, this product could have introduced jealousy.

Our subgroup analyses by gender, insurance knowledge, and risk aversion find interesting areas of heterogeneity. Effects of introducing a product with no downside basis risk on WTP for insurance are mainly concentrated in the sample of male participants. This suggests that providing an insurance product without downside basis risk may have larger effects on insurance demand among men. One reason for these differences between men and women may be due to the fact that women face additional risks related to fertility and childcare that are not experienced by men (Delavallade et al., 2015). Given our framing of how basis risk would be addressed via smartphone images of crop growth, we did not address these risks specific to women. Our finds contrast with a study in Kenya, where reducing basis risk increased demand for insurance mainly among women farmers (Kramer et al., 2023).

Eliminating downside basis risk increases WTP for insurance regardless of insurance knowledge, although coefficients are in absolute terms larger among farmers who do not understand insurance as well. This is consistent with the idea of an insurance product with little downside basis risk being more tangible and easier to understand in populations where insurance illiteracy is a concern.

Finally, consistent with theory, eliminating downside basis risk has a large effect on demand – especially among risk averse farmers. By contrast, risk loving participants reduce their demand for WII in response to social comparison, but not the NDBR treatment. Further research is needed to understand these different responses across different preferences for risk.

There is strong donor interest in methods for reducing basis risk, through innovations such as remote sensing to predict crop yields, using gridded weather data, crop modeling or radar data to predict crop losses, or relying on picture-based crop monitoring to provide picture-based insurance (PBI) payouts to farmers who have visibly suffered crop losses. Our experiment was conducted as formative research for an impact evaluation of this latter PBI approach. By being participatory and tangible, and by delivering plot-level assessments of damage, picture-based fail-safe triggers may reduce basis risk and improve trust and understanding among smallholder farmers, which are key challenges for index-based insurance (Ceballos et al., 2019). Picture-based monitoring offers a promising option to observe crops at a finer scale than satellite imagery (Hufkens et al., 2019). Prior research in India found PBI to be more cost-effective than area yield index-based insurance products that use crop cutting experiments to measure yields (Ceballos et al., 2019). One could also consider audits that use crop cutting experiments to implement fail-safe triggers (Berhane et al., 2015; Flatnes and Carter, 2015). As such, PBI is designed to combine key advantages of both index-based insurance—timely compensation and low costs —and indemnity insurance—minimum basis risk and a tangible product.

Such technological innovations can be paired with other approaches to raising demand for index insurance. We have shown that peer comparisons can improve farmers' perceptions of fairness of insurance outcomes. Improvements can be made in index design quality (Rigo et al., 2022; Stigler and Lobell, 2023). Demand can also be spurred by delayed premium payments (Casaburi and Willis 2018, Belissa et al. 2019, Liu et al., 2020), and subsidized premiums; smart subsidies can temporarily raise demand and create learning (McIntosh et al., 2013; Ahmed et al., 2020; Stoeffler and Opuz, 2022).

While index insurance does not crowd out informal risk sharing (Takahashi et al., 2018), farmers may informally insure one another against idiosyncratic basis risk, which can encourage insurance take-up (Dercon et al., 2014). Thus, eliminating basis risk may simply erode such informal risk sharing, instead of increasing insurance take-up.

This paper did not explore the perceived fairness of differences in outcomes due to technology adoption, and this remains an area for future research. Should PBI or other insurance products with low downside basis risk prove successful in becoming widely adopted by smallholder farmers, with affordable insurance premiums for farmers, and reducing downside basis risk, farmers may be willing to adopt new technologies. As smallholder farmers tend to be risk averse, they are often reluctant to adopt new agricultural production technologies. In comparison to conventional seeds and practices of farmers, improved technologies such as new seed varieties or agricultural management practices inevitably entail incurring additional costs for inputs (e.g. seeds of improved varieties, fertilizers, pesticides, implements, etc.) and management (labor and follow-up). Limited research on the dynamics between technology adoption decisions and insured risk has indicated that existing insurance products do not influence farmers' investment decisions (Ayalew et al., 2022). With improved insurance products and lower downside basis risk on offer, farmers may become more willing to take on new and costly investments. In doing so, they may see improved yields, particularly in the face of droughts, and increased incomes and profits. Increased incomes can lead to savings and further investments in agricultural production, helping smallholder farmers out of a poverty trap. With improved livelihoods of farmers, they may see greater access to credit, which can further improve livelihoods.

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Figure 1. Decision Tree for Experiment Eliciting WTP for Insurance

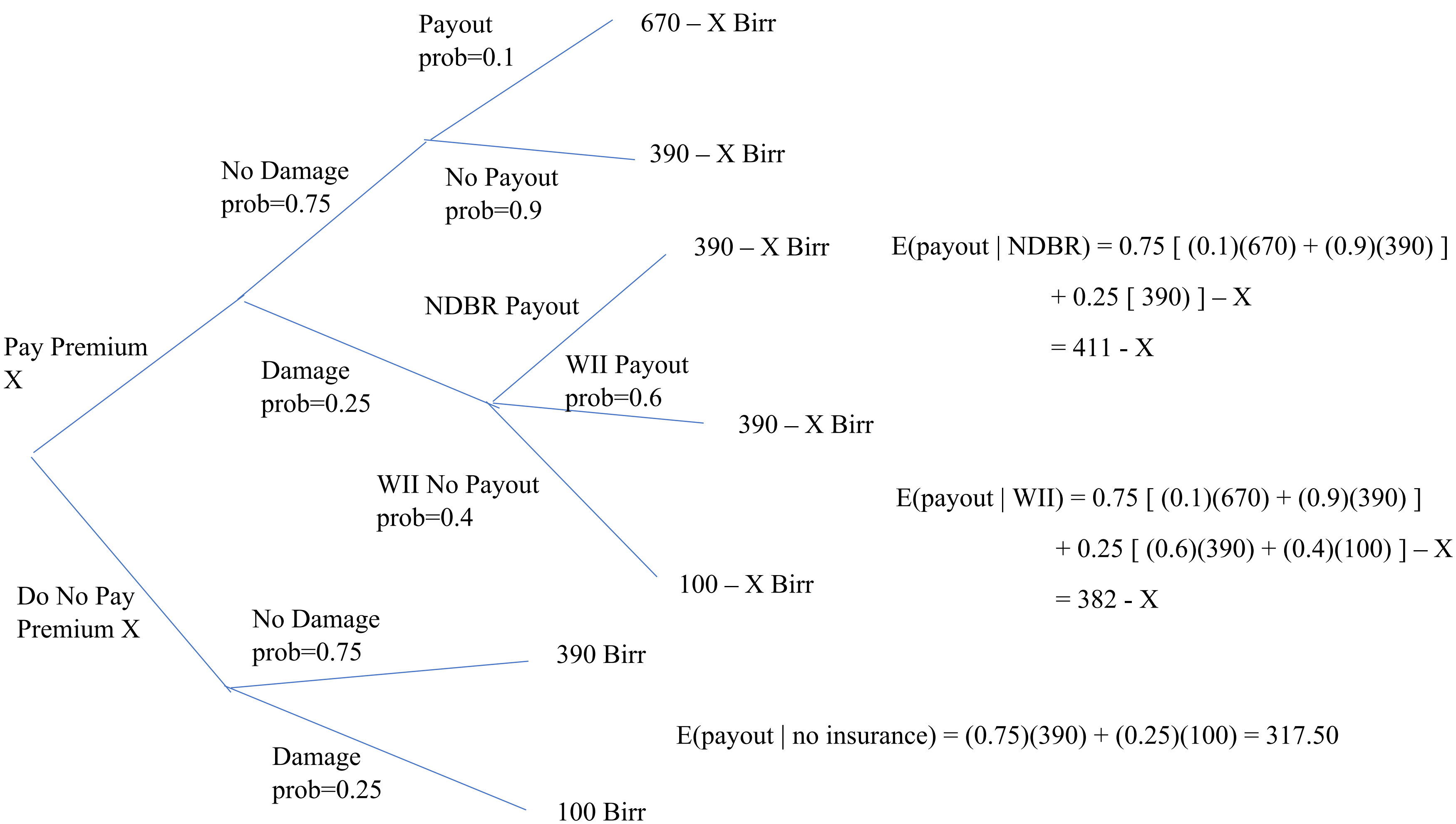
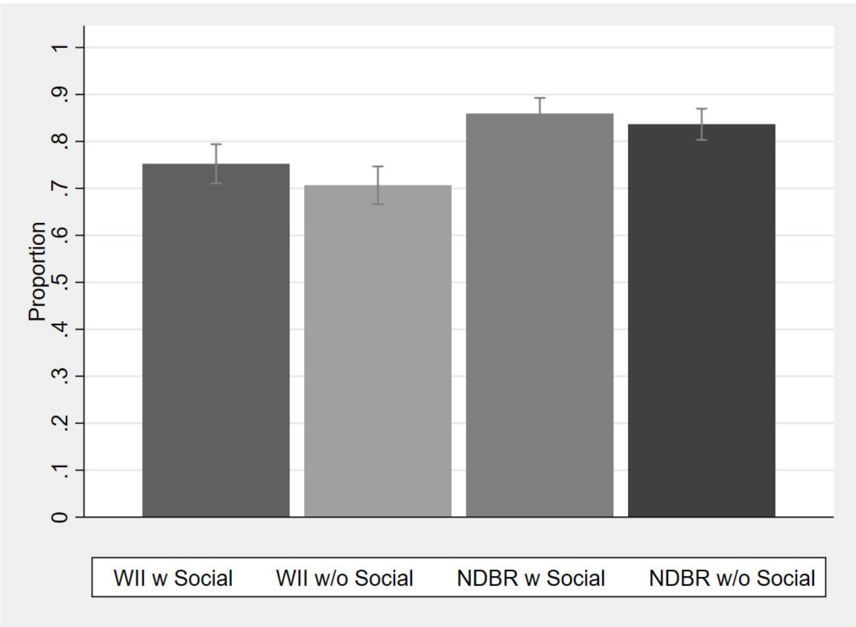


Figure 2. Perceived fairness for WII and NDBR, by treatment group

Panel A

Average proportion of hypothetical insurance scenarios considered to be fair outcomes (averaged across respondents)



Panel B

Average proportion of hypothetical insurance scenarios with potential downside basis risk events considered to be fair outcomes (averaged across respondents)

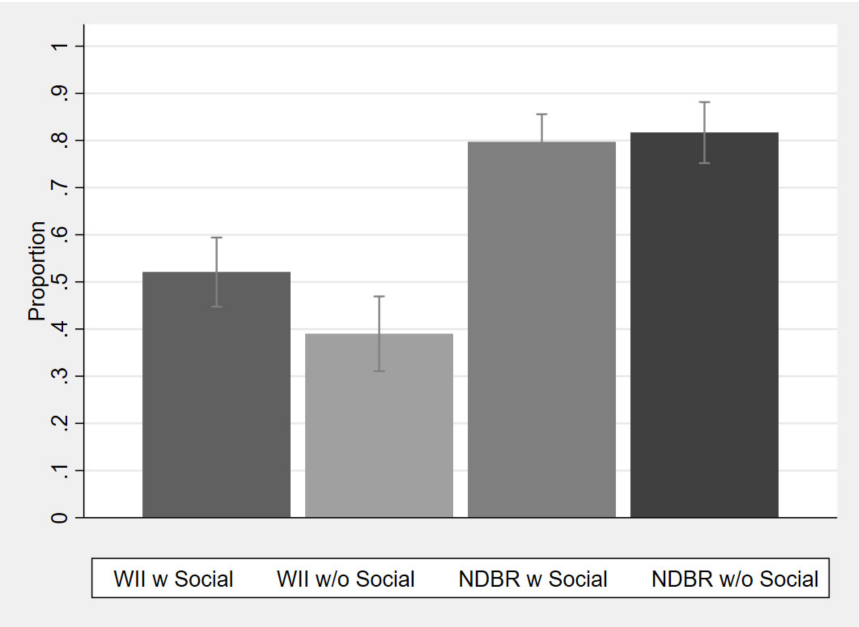


Figure 3. Maximum willingness to pay as percentage of sum insured

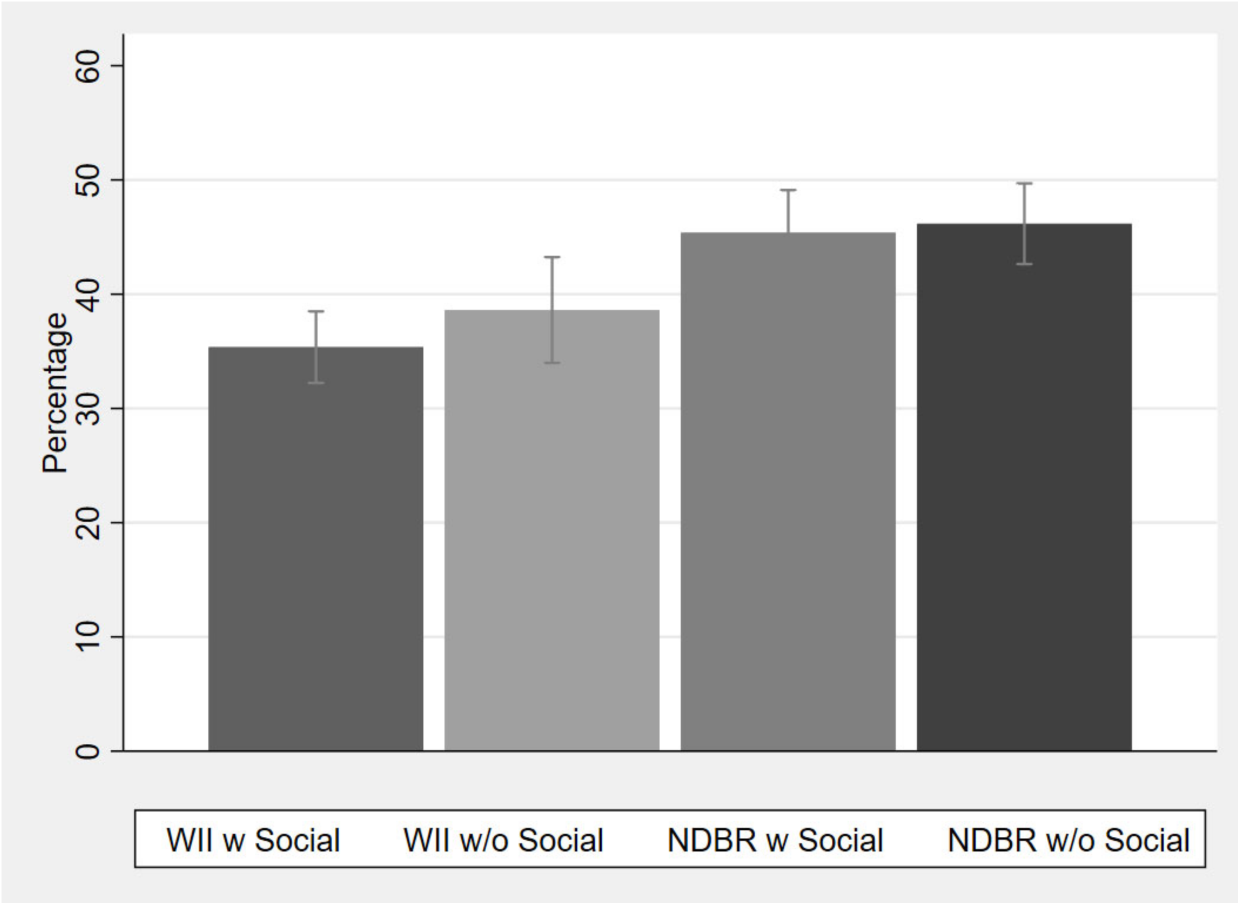


Figure 4. Demand for Weather Index Insurance, with and without Downside Basis Risk

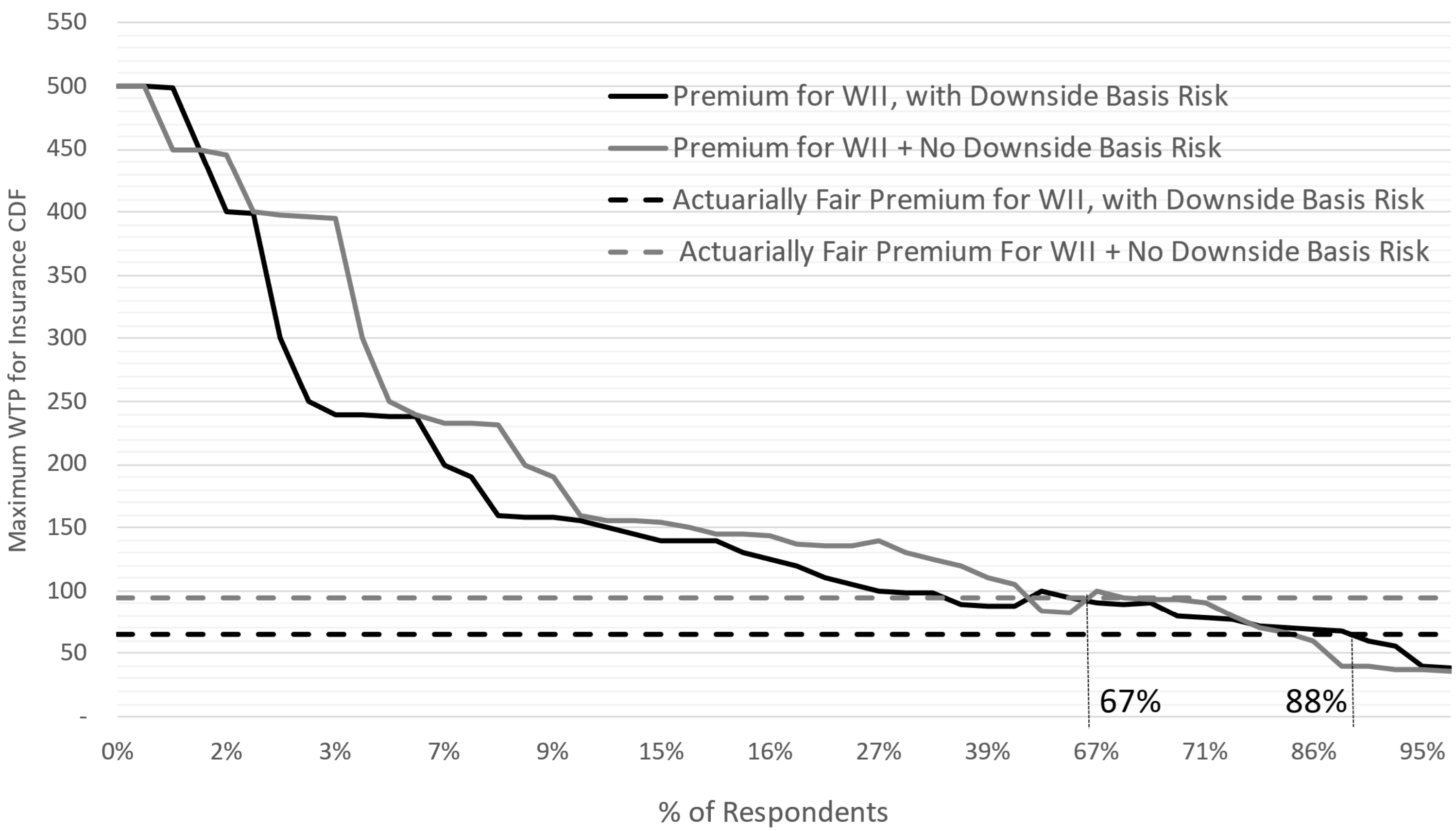


Table 1. Lab in the Field Experimental Design

	Type of insurance: WII or WII + NDBR	
No comparison vs priming of a comparison between own and neighbors' payouts	WII, no social comparison (109 respondents)	WII + NDBR, no social comparison (120 respondents)
	WII, social comparison (112 respondents)	WII + NDBR, social comparison (110 respondents)

Table 2. Descriptive Statistics and Balancing Tests Across Treatments

	WII W Social	WII W/O Social	NDBR W Social	NDBR W/O Social	F-test for balance p-value
HH is R4 client	0.768	0.807	0.791	0.717	0.683
	(0.057)	(0.053)	(0.055)	(0.058)	
Respondent had R4 Insurance	0.723	0.752	0.709	0.608	0.271
	(0.057)	(0.054)	(0.055)	(0.055)	
Hectares planted with teff in most recent season	0.768	0.559	0.552	0.531	0.715
	(0.219)	(0.040)	(0.036)	(0.034)	
Had significant damage to teff in most season	0.518	0.514	0.564	0.533	0.910
	(0.052)	(0.053)	(0.054)	(0.049)	
Respondent has input into coping with teff-related losses	0.304	0.312	0.227	0.267	0.488
	(0.044)	(0.045)	(0.042)	(0.041)	
HH size	5.286	5.541	5.445	5.333	0.853
	(0.220)	(0.233)	(0.218)	(0.209)	
Number adults in HH	3.196	3.495	3.345	3.267	0.614
	(0.168)	(0.162)	(0.170)	(0.183)	
HH poverty index	28.513	27.261	26.018	27.137	0.571
	(1.304)	(1.065)	(1.194)	(1.125)	
HH member owns phone	0.804	0.743	0.727	0.717	0.621
	(0.049)	(0.052)	(0.057)	(0.054)	
Respondent is HH head	0.464	0.495	0.500	0.525	0.170
	(0.020)	(0.015)	(0.014)	(0.019)	
Respondent is a woman	0.518	0.495	0.500	0.492	0.614
	(0.015)	(0.012)	(0.014)	(0.015)	
Respondent's age	37.955	39.890	39.436	36.208	0.152
	(1.395)	(1.334)	(1.287)	(1.198)	
Respondent is illiterate	0.545	0.550	0.509	0.542	0.929
	(0.045)	(0.043)	(0.050)	(0.048)	
Respondent can get informal loan	0.500	0.394	0.564	0.492	0.079
	(0.042)	(0.044)	(0.051)	(0.046)	
Respondent has savings account	0.652	0.661	0.655	0.600	0.793
	(0.051)	(0.048)	(0.048)	(0.048)	
Share of risky decisions made in hypothetical risk game	0.325	0.239	0.319	0.309	0.136
	(0.029)	(0.029)	(0.031)	(0.029)	
Share of present biased decisions in hypothetical time preference game	0.746	0.794	0.774	0.732	0.525
	(0.033)	(0.032)	(0.033)	(0.032)	
Number of insurance questions answered correctly (by end of module)	4.223	4.229	3.991	3.967	0.187
	(0.094)	(0.123)	(0.122)	(0.117)	
Number of observations	112	109	110	120	
Number of clusters	60	58	60	66	

Table 3. Treatment Effects on High Perception of Fairness

	All Scenarios				Scenarios with Downside Basis Risk Events			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NDBR = 1	0.185***	0.201***	0.205***	0.174***	0.509***	0.524***	0.512***	0.478***
	(0.054)	(0.055)	(0.057)	(0.056)	(0.061)	(0.063)	(0.064)	(0.065)
Social Comparison = 1	0.070	0.075	0.073	0.076	0.279***	0.273***	0.272***	0.253***
	(0.062)	(0.064)	(0.066)	(0.064)	(0.067)	(0.068)	(0.070)	(0.068)
NDBR * Social Comp. = 1	-0.044	-0.058	-0.051	-0.033	-0.226***	-0.233**	-0.231**	-0.179**
	(0.073)	(0.076)	(0.078)	(0.074)	(0.086)	(0.090)	(0.090)	(0.090)
Demographics included	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Additional covariates	No	No	Yes	No	No	No	Yes	No
Village Fixed Effects	No	No	No	Yes	No	No	No	Yes
Mean % Respondents with High Fairness Perceptions for WII Without Social Comparison:								
	70.6%				26.6%			
Observations	451				451			

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Treatment Effects on Willingness to Pay for Insurance Premium

	(1)	(2)	(3)	(4)
Panel A. Reduced Form				
NDBR = 1	0.238***	0.229***	0.218***	0.209***
	(0.051)	(0.050)	(0.051)	(0.055)
Social Comparison = 1	-0.057	-0.064	-0.074	-0.052
	(0.058)	(0.056)	(0.057)	(0.053)
NDBR * Social Comp. = 1	0.022	0.036	0.051	0.046
	(0.073)	(0.072)	(0.073)	(0.072)
Panel B. OLS				
High Fairness Perception	0.125***	0.138***	0.131***	0.119***
(Basis risk event scenarios)	(0.042)	(0.041)	(0.041)	(0.042)
Panel C. IV-2SLS				
High Fairness Perception	0.463***	0.450***	0.443***	0.431***
(Basis risk event scenarios)	(0.095)	(0.091)	(0.095)	(0.099)
Demographics included	No	Yes	Yes	Yes
Additional covariates	No	No	Yes	No
Village Fixed Effects	No	No	No	Yes
Observations				451
Mean WTP for WII Premium Without Social Comparison:				106 Birr
Mean WTP for insurance premium (low fairness perception)				105 Birr

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Gender Differences in Treatment Effects on WTP for Insurance Premium

	Men			Women		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Reduced Form						
NDBR = 1	0.314***	0.310***	0.308***	0.119*	0.105	0.095
	(0.087)	(0.088)	(0.098)	(0.063)	(0.064)	(0.066)
Social Comparison = 1	-0.055	-0.061	-0.035	-0.086	-0.102	-0.078
	(0.095)	(0.098)	(0.096)	(0.070)	(0.072)	(0.068)
NDBR * Social Comp. = 1	-0.033	-0.042	-0.036	0.121	0.140	0.155*
	(0.121)	(0.125)	(0.127)	(0.090)	(0.092)	(0.091)
Panel B. OLS						
High Fairness Perception	0.128*	0.095	0.123*	0.132***	0.126**	0.116**
(Basis risk event scenarios)	(0.066)	(0.067)	(0.067)	(0.047)	(0.051)	(0.050)
Panel C. IV-2SLS						
High Fairness Perception	0.592***	0.614***	0.566***	0.269**	0.244**	0.282**
(Basis risk event scenarios)	(0.174)	(0.190)	(0.182)	(0.108)	(0.116)	(0.121)
Demographics included	Yes	Yes	Yes	Yes	Yes	Yes
Additional covariates	No	Yes	No	No	Yes	No
Village Fixed Effects	No	No	Yes	No	No	Yes
Observations		225			226	
Mean WTP WII, No Social Comp.		111	Birr		102	Birr
Mean WTP for insurance premium (low fairness perception)		97	Birr		113	Birr

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, *p<0.1

Table 6. Differences in Treatment Effects on WTP for Insurance Premium: High vs. Low Insurance Knowledge

	High Insurance Knowledge			Low Insurance Knowledge		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Reduced Form						
NDBR = 1	0.158**	0.166**	0.153*	0.277***	0.263***	0.261***
	(0.076)	(0.082)	(0.078)	(0.067)	(0.068)	(0.076)
Social Comparison = 1	-0.168*	-0.166*	-0.139*	0.009	-0.011	0.024
	(0.089)	(0.099)	(0.080)	(0.076)	(0.080)	(0.078)
NDBR * Social Comp. = 1	0.131	0.130	0.119	-0.012	0.016	0.004
	(0.118)	(0.124)	(0.115)	(0.101)	(0.103)	(0.105)
Panel B. OLS						
High Fairness Perception	0.124**	0.119*	0.137**	0.148***	0.138***	0.109*
(Basis risk event scenarios)	(0.059)	(0.060)	(0.055)	(0.051)	(0.052)	(0.058)
Panel C. IV-2SLS						
High Fairness Perception	0.426***	0.392**	0.457***	0.475***	0.483***	0.467***
(Basis risk event scenarios)	(0.159)	(0.163)	(0.164)	(0.106)	(0.119)	(0.125)
Demographics included	Yes	Yes	Yes	Yes	Yes	Yes
Additional covariates	No	Yes	No	No	Yes	No
Village Fixed Effects	No	No	Yes	No	No	Yes
Observations		190			261	
Mean WTP WII, No Social Comp.		109	Birr		103	Birr
Mean WTP for insurance premium (low fairness perception)		97	Birr		110	Birr

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7. Differences in Treatment Effects on WTP for Insurance Premium: Risk Loving vs. Risk Averse

	Risk Loving			Risk Averse		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Reduced Form						
NDBR = 1	0.025	0.039	-0.077	0.261***	0.235***	0.265***
	(0.154)	(0.158)	(0.192)	(0.055)	(0.057)	(0.056)
Social Comparison = 1	-0.287*	-0.261	-0.287*	-0.040	-0.056	-0.025
	(0.170)	(0.176)	(0.171)	(0.062)	(0.063)	(0.058)
NDBR * Social Comp. = 1	0.361*	0.302	0.392*	-0.004	0.007	-0.013
	(0.189)	(0.193)	(0.203)	(0.088)	(0.088)	(0.085)
Panel B. OLS						
High Fairness Perception	0.047	0.031	0.016	0.159***	0.137***	0.153***
(Basis risk event scenarios)	(0.090)	(0.102)	(0.099)	(0.044)	(0.043)	(0.046)
Panel C. IV-2SLS						
High Fairness Perception	0.209	0.137	0.020	0.487***	0.418***	0.495***
(Basis risk event scenarios)	(0.266)	(0.261)	(0.416)	(0.100)	(0.101)	(0.097)
Demographics included	Yes	Yes	Yes	Yes	Yes	Yes
Additional covariates	No	Yes	No	No	Yes	No
Village Fixed Effects	No	No	Yes	No	No	Yes
Observations		116			313	
Mean WTP WII, No Social Comp.		130	Birr		101	Birr
Mean WTP for insurance premium (low fairness perception)		120	Birr		100	Birr

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

SUPPLEMENTARY ONLINE APPENDIX

TO

"Basis Risk, Social Comparison, Perceptions of Fairness and Demand for Insurance:

A Field Experiment in Ethiopia"

Appendix Table 1. Descriptive Statistics and Balancing Tests (all surveyed households)

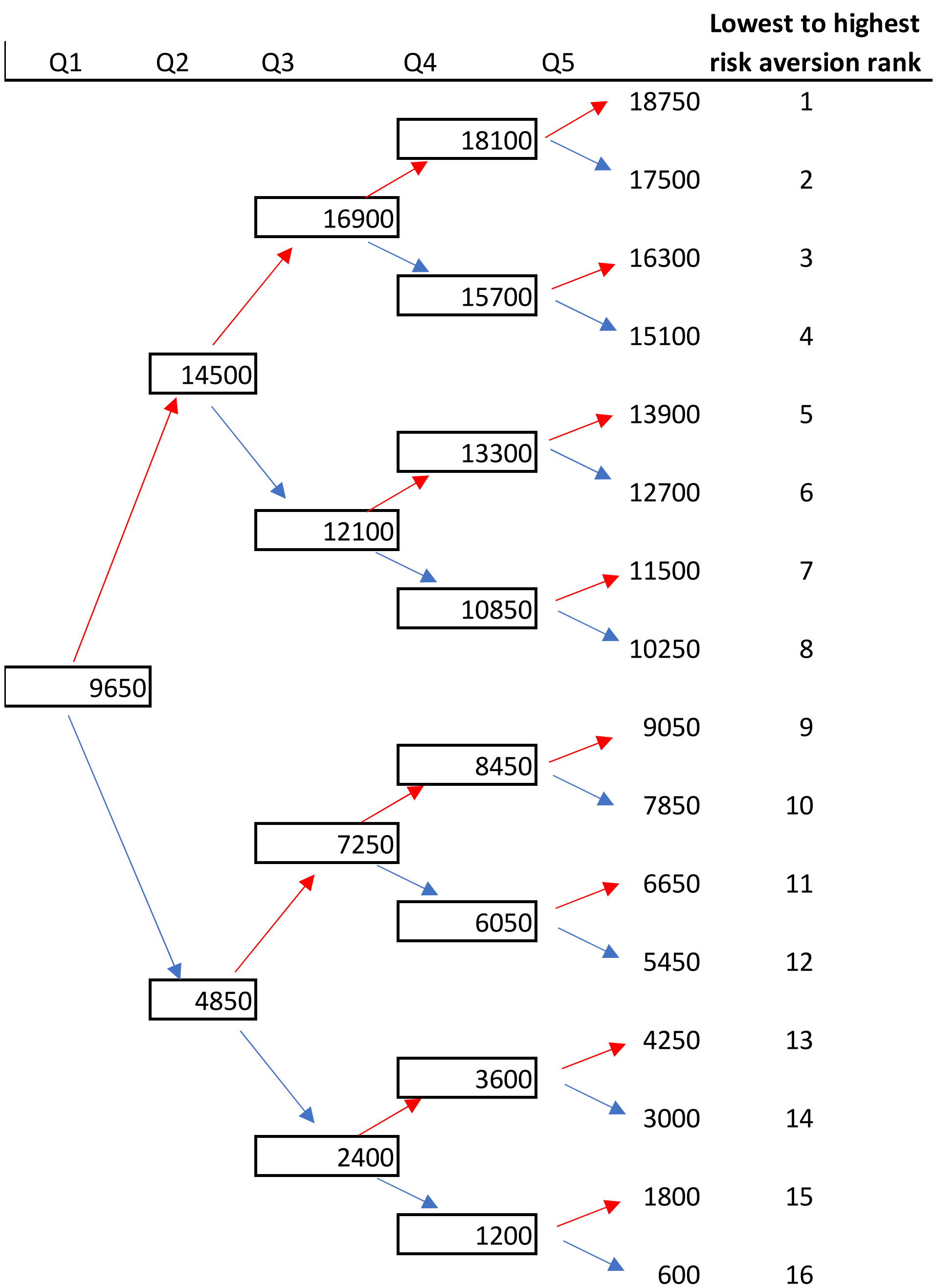
	WBI W Social	WBI W/O Social	PBI W Social	PBI W/O Social	balance p-value
WTP data is missing	0.043	0.052	0.091	0.055	0.540
	(0.018)	(0.021)	(0.028)	(0.020)	
HH is R4 client	0.778	0.809	0.802	0.724	0.687
	(0.055)	(0.051)	(0.052)	(0.056)	
Respondent had R4 Insurance	0.726	0.748	0.719	0.622	0.348
	(0.055)	(0.052)	(0.052)	(0.054)	
Hectares planted with teff in most recent season	0.770	0.547	0.529	0.530	0.753
	(0.227)	(0.042)	(0.039)	(0.036)	
Had significant damage to teff in most recent season	0.574	0.590	0.648	0.576	0.702
	(0.052)	(0.053)	(0.050)	(0.052)	
HH Size	5.256	5.496	5.471	5.339	0.854
	(0.227)	(0.223)	(0.211)	(0.210)	
Number adults in HH	3.179	3.522	3.331	3.260	0.483
	(0.167)	(0.157)	(0.163)	(0.187)	
HH poverty index	28.550	26.991	26.223	27.032	0.614
	(1.332)	(1.056)	(1.135)	(1.109)	
HH member owns phone	0.812	0.713	0.736	0.717	0.447
	(0.047)	(0.054)	(0.055)	(0.053)	
Respondent is HH head	0.479	0.504	0.496	0.520	0.246
	(0.016)	(0.013)	(0.004)	(0.014)	
Respondent is a woman	0.521	0.504	0.504	0.496	0.367
	(0.011)	(0.010)	(0.004)	(0.009)	
Respondent's age	38.291	40.261	39.810	36.094	0.077
	(1.334)	(1.340)	(1.296)	(1.185)	
Respondent is illiterate	0.556	0.565	0.521	0.543	0.903
	(0.044)	(0.042)	(0.046)	(0.046)	
Respondent can get informal loan	0.509	0.396	0.559	0.516	0.073
	(0.042)	(0.044)	(0.050)	(0.046)	
Respondent has savings account	0.661	0.658	0.645	0.595	0.754
	(0.050)	(0.049)	(0.046)	(0.048)	
Share of risky decisions made in hypothetical risk game	0.314	0.241	0.313	0.311	0.226
	(0.030)	(0.029)	(0.032)	(0.031)	
Share of present biased decisions in hypothetical time preference game	0.756	0.796	0.771	0.721	0.378
	(0.032)	(0.031)	(0.031)	(0.031)	
Number of insurance questions answered correctly (by end module)	4.222	4.209	4.000	3.976	0.228
	(0.095)	(0.119)	(0.114)	(0.117)	
Number of observations	117	115	121	127	480
Number of clusters	60	60	61	66	247

Appendix Table 2. Percent of respondents who answered insurance knowledge question correctly

	1st instance question is seen					
	Not corrected for wrong answer 2nd time		Corrected for wrong answer 2nd time		Final instance question is seen	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
TRUE or FALSE? Index insurance accurately measures yield loss that occurs in a farm.	0.22	0.41	0.13	0.34	0.39	0.49
TRUE or FALSE? If I pay my insurance premium this year, I will know for sure that I will receive a payout at the end of 8 months.	0.36	0.48	0.33	0.47	0.60	0.49
TRUE or FALSE? Just because we cannot see a satellite, we should not use the rainfall data provided by it.	0.52	0.50	0.43	0.50	0.61	0.49
TRUE or FALSE? If I pay my insurance premium this year, I will be insured for a period of 2 years.	0.44	0.50	0.42	0.49	0.69	0.46
TRUE or FALSE? The premium amount paid to an insurer depends on how much the sum insured is.	0.83	0.38	0.75	0.43	0.85	0.36
Which of the following is insured from loss of yield for a farmer? Lack of rain water, poor soil quality, poor farming practices	0.95	0.22	0.93	0.26	0.96	0.20

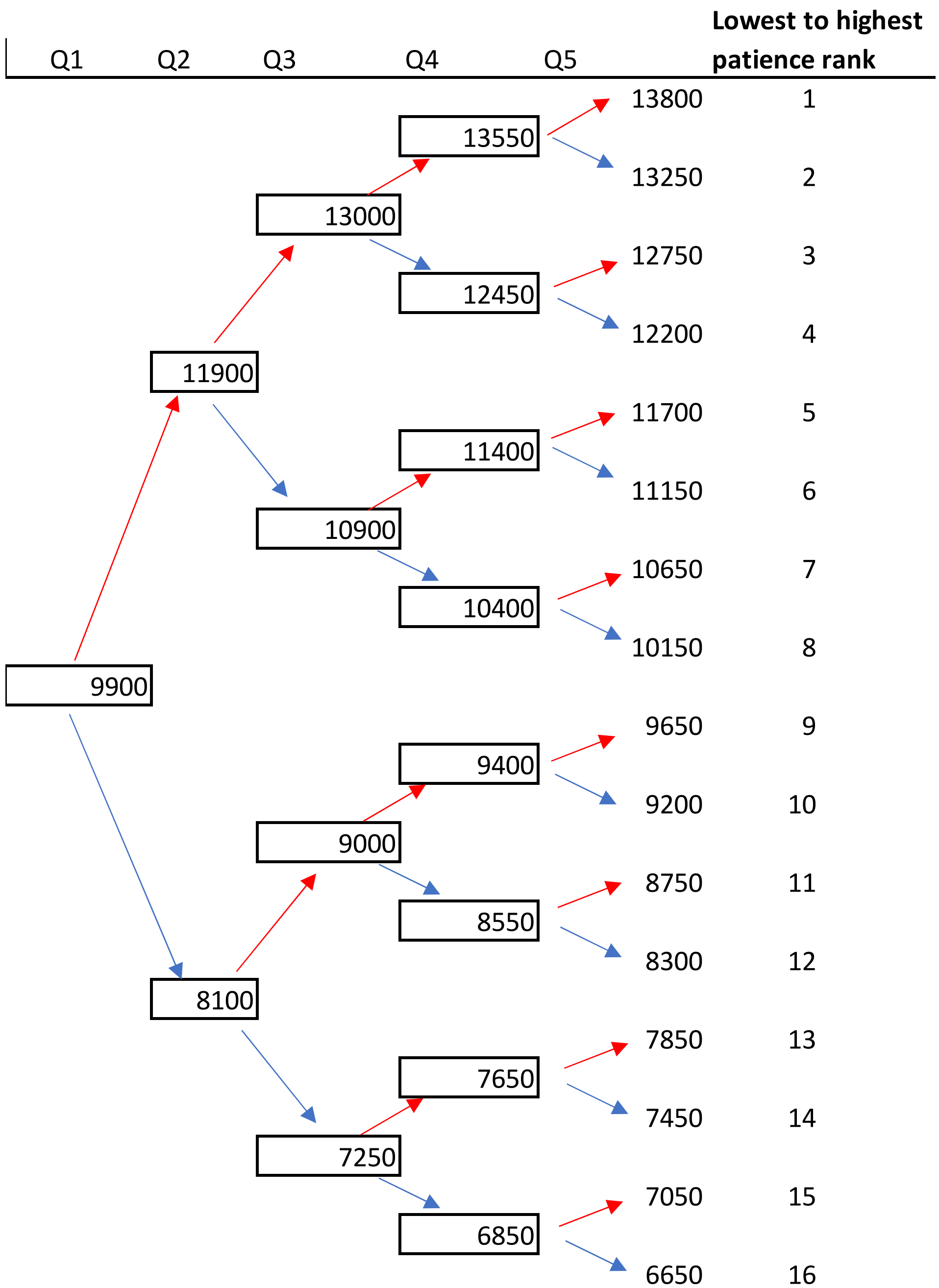
Notes; We asked respondents these six questions to elicit their knowledge of insurance, both before and after a brief tutorial on insurance. The questions are ordered by lowest to highest proportion answered correctly after the insurance tutorial. There were a few cases where respondents gave the correct answer when they saw a question for the first time, but then later on after the explanation of insurance, they answered the same question incorrectly. In the first two columns, we do not correct for such possible errors and guesses. In the middle two columns, we assume they did not understand the question if they answered correctly in only the first instance of seeing the question.

Appendix Figure 1. Staircase method for measuring risk preferences



Notes: (1) All the arrows pointing upwards are for those whose choice is the 50/50 chance of getting 18,100 Birr
(2) All the arrows pointing downwards are for those whose choice is the sure payment for specified Birr

Appendix Figure 2. Staircase method for measuring time preferences



Notes: (1) All the arrows pointing upwards are for those whose choice is receiving 6,450 BIRR today

(2) All the arrows pointing downwards are for those whose choice receiving the specified Birr in 12 months