# Insurance Demand and the Crowding Out of Redistribution

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**Abstract**

Altruistically motivated transfers play an important role in supporting individuals who suffer income losses due to risk, especially in the absence of well-functioning insurance markets. When formal insurance is introduced, recipients' insurance decisions may reveal information to donors that allows them to place recipients in a different light. Consequently, this may reduce support to insurance takers and non-takers, and hence lead to the crowding out of private redistributive transfers. We present empirical evidence on transfer decisions – with and without insurance – from a field experiment in Ethiopia. We find that donors, on average, reduce redistributive transfers to recipients who reject insurance, and that these effects are larger for donors whose belief that the recipient took-up insurance is stronger. We show that the findings are consistent with a model of altruistically motivated transfers with favouritism towards socially closer peers and where individuals perceive others to be closer to themselves than they actually are. The results point to the fact that the welfare implications of introducing insurance should take into account the impact on redistribution, especially in contexts where structural heterogeneity may prevent some from adopting insurance.

# I Introduction

A wealth of empirical evidence documents that private income transfers are often motivated by altruism, gift-giving, and guilt, without there being an expectation of reciprocity (Ben-Porath, 1980; Fafchamps and Lund, 2003; Kazianga, 2006; Alger and Weibull, 2010; Ligon and Schechter, 2012). Such private redistributive transfers play an important role in supporting individuals and households who suffer income losses due to various forms of risk, especially in the absence of well-functioning insurance markets (Townsend, 1994; Samphantharak and Townsend, 2018). Formal insurance is increasingly introduced into such emerging markets and these markets are becoming the main source of premium growth to the international insurance industry (Federal Insurance Office, U.S. Government, 2013; Swiss Re Institute, 2017). The introduction of formal insurance may, however, affect redistribution because insurance decisions reveal information about potential recipients to prospective donors, making them perceive the recipients in a different light compared to when insurance is not available. As a consequence donors may become less altruistically minded and reduce their support, resulting in the crowding out of private redistributive transfers. In contexts where individuals face private constraints to adopting financial products, for example because of a lack of liquidity or low levels of financial literacy (Casaburi and Willis, 2018; Ambuehl et al., 2018), the knock-on effect of the introduction of insurance and subsequent crowding-out of redistribution, may in turn lead some households to face more volatile consumption than before insurance was available.

This paper investigates the effect of the introduction of formal insurance with incomplete take-up on private redistributive transfers to individuals suffering income losses. To do so we first present empirical evidence on transfer decisions by donors to recipients – with and without insurance availability – from an artefactual field experiment implemented in rural Ethiopia. We find that the availability of insurance, on average, reduces redistributive transfers to recipients who reject insurance. Furthermore, these effects are larger for donors who are more likely to take-up insurance themselves, and whose belief that the recipient took-up insurance is stronger. We then develop a simple theory of insurance uptake and altruistically motivated transfers with favouritism towards socially closer peers, where individuals perceive others to be closer to themselves than they actually are. We show that, in equilibrium, the benefits of insurance availability can be very unevenly distributed, potentially making already vulnerable individuals worse off. These results point to the fact that the welfare implications of introducing insurance should take into account the impact on redistribution, especially in contexts where structural constraints may prevent insurance adoption. While it was known that the introduction of formal insurance can crowd out informal insurance (see below), the impact on voluntary and charitable redistributive transfers that do not have a reciprocal nature has not yet been investigated. The crowding out of redistribution – defined for our purposes as private non-reciprocal redistributive transfers – is particularly important in contexts where the development of an insurance market is part of policy to reduce poverty, as those individuals that face structural constraints to insurance adoption are also more likely to depend on redistribution and be most vulnerable to risk in the first place.

In the experiments, farmers from rural communities in Ethiopia are randomly and anonymously paired with either a member from their own community or a member from another community. The individuals in each pair are then randomly assigned to the role of donor or recipient. While the income of donors is certain, the income of recipients is subject to the risk of a loss. In the benchmark condition of the experiment recipients have no agency over the risk to their income. In the treatment condition each recipient is offered actuarially fair and complete insurance and she then has the choice, in private, of whether to accept or reject it. In the benchmark condition donors are asked if and how much they want to transfer to the recipient in case the recipient experiences a loss. In the treatment condition donors are asked, without knowing the actual insurance decision by the recipient, if and how much they want to transfer in the case where 'the recipient purchased insurance' and the case where 'the recipient did not purchase insurance'. The anonymous one-shot nature of the experiment delivers the focus on transfers that don't have an expectation of reciprocity. All pairs play both the benchmark and the treatment arm, so that transfers in the different arms can be compared while controlling for individual and pair-specific characteristics. This enables us to understand how a decision by the recipient to reject an opportunity to reduce risk to their income affects the transfers of donors with different characteristics. The experiment is also designed in such a way that the expected income to the recipient is the same across all arms. This facilitates the attribution of differences in transfers directly to the decision by the recipient.[1] Finally, the design allows us to investigate redistribution both between individuals who are part of the same community, as well as between individuals that are from different communities. This allows us to rule out

[1]Preventing ex-ante fairness concerns from explaining differences in transfers (Brock et al., 2013; Krawczyk and Le Lec, 2016)

that shared norms modify transfer behaviour (Bohnet and Frey, 1999). The chosen population — Ethiopian farmers – is suitable for the current study as they typically receive redistributive transfers after losses from risk from peers in their communities and have not yet been exposed to formal insurance that protects against risk.

In order to explain the findings of the experiment, we develop a model of a local economy where individuals face income risk and make altruistic transfers to each other. At the heart of the model is an assumption of unidimensional individual heterogeneity and stronger altruism towards peers of similar type, a form of favouritism based on "social distance" (Becker, 1957; Fershtman et al., 2005; Ahmed, 2007; Feld et al., 2016). With heterogeneity in types driving the individuals' insurance uptake decisions, the model captures the notion that the introduction of a new market makes salient the underlying social differences in the local economy and enables donors to modify their transfers in light of observable type-related take-up behaviour of the recipients. There are two main reasons for our choice of modelling social-distance-contingent altruism rather than a more direct action-contingent altruism (as could be motivated based on the social preferences literature noted below). First, our framework is one with well-defined and stable preferences. This has the benefit of facilitating an analysis of the welfare effects of the introduction of an insurance market. Second, we show that when combined with a"false consensus bias" assumption, according to which individuals believe the distribution of types to be closer to themselves than it actually is (Ross et al., 1977), the model replicates stylized facts from the experiment. Most importantly, the fact that differences in transfers between the treatment arms are heterogenous by proxies for the "social distance" between the donor and the recipient.

In particular the model assumes that each individual interacts with a random "partner" drawn from the local economy and predicts:

1. The equilibrium take-up of actuarially fair insurance is negatively related to type.
2. Lower types – who thus themselves take up insurance – have a higher expectation about the insurance take-up by their randomly allocated partners than higher types.
3. The transfer that an individual makes to her partner if the latter rejects available insurance is less than the transfer that she would provide to the same partner if insurance was not available, and the transfer-reduction is larger for donors with higher expectation of insurance take-up by the partner.

After characterising the equilibria with and without available insurance, we briefly consider welfare implications and conclude that – based on the model and the empirical evidence – the benefits generated by the introduction of a formal insurance market may be very unevenly distributed and may even be negative for some vulnerable groups.

Our work naturally connects to literature that uses models of social preferences to explain redistribution decisions by private donors. This work recognises that non-reciprocal voluntary transfers are influenced by the donor's evaluation of actions by the recipient that determine their outcomes, such as effort and risk-taking (Cherry et al., 2002; Konow, 2010; Cappelen et al., 2007; Cox et al., 2008, 2007; Cappelen et al., 2013; Brock et al., 2013). Across the board, donors seem to redistribute less to recipients who expend lower effort than they do themselves (Cherry et al., 2002; Cappelen et al., 2007). In the case of risky decisions the redistribution decisions seem to be a result of the recipient's actions, combined with the donor's preferences for ex-ante inequality in expected income, as well as ex-post inequality in realised income (Cappelen et al., 2013; Brock et al., 2013; Krawczyk and Le Lec, 2016). At the same time Mollerstrom et al. (2015) show that, conditional on their views about fairness, spectators who are asked to redistribute income across recipients that experience losses, transfer less to recipients whose losses are the result of a decision to not take-up insurance, rather than pure randomness. We contribute to this literature by demonstrating that donors, in the case of losses to the recipient, transfer less to the recipient when she was offered insurance and decided not to accept it. While it is an interesting finding that redistribution decisions are conditional on insurance decisions by a recipient, in itself it is problematic when one intends to conduct an analysis of the welfare effects of the introduction of an insurance market. Therefore we also provide a theoretical foundation for the donors' transfer behaviour as observed in the experiment, that is based on well-defined and stable preferences, and consistent with stylised facts emerging from the experiment.

To do so, in our model we specifically focus on the effect the "expected social distance" has on transfers. We define "expected social distance" as the difference between individuals based on the information that is available to identify their social group. Other studies have demonstrated that donors transfer less to recipients when they receive information that makes them perceive that the recipient is more socially distant to them (Charness and Gneezy, 2008; Rachlin and Jones, 2008; Goeree et al., 2010; Tajfel, 1970; Fowler and Kam, 2007). We argue that the introduction of an insurance market, and subsequent insurance decisions make available information to donors that they can use to establish social distance between them and the recipient. By introducing "type-based favouritism" we provide an explanation for the average reduction in transfers that we observe when recipients do not take-up insurance and experience losses. We provide further support for this explanation by demonstrating that this reduction is larger for those donors who perceive a larger social distance between them and the recipient.

This paper contributes to a literature on crowding-out of private transfers in the case of economic losses. For our purposes we define crowding-out as the process by which a third-party mechanism replaces private transfers that are used by individuals to smooth consumption after economic losses. As such we complement a literature that demonstrates that formal insurance can crowd-out transfers in (informal) risk-sharing arrangements (Arnott and Stiglitz, 1991; Attanasio and Ríos-Rull, 2000; Albarran and Attanasio, 2003; Mobarak and Rosenzweig, 2012; Dercon et al., 2014). In this literature private transfers are assumed to occur in a context of reciprocity where individuals can, at least partly, commit to an arrangement in which they agree to share future risk. This literature shows that if this process of crowding-out leads to lower risk coverage, for example because the insurance is incomplete, doesn't cover all risks, or excludes certain customers, this may lead to welfare reductions. An understanding of crowding out is thus crucial to designing and regulating welfare enhancing insurance markets. As mentioned, conceptually, this literature assumes private transfers are at least partly reciprocal. As mentioned above, evidence shows, however, that such transfers are often motivated by altruism, gift-giving, and guilt, without there being an expectation of reciprocity. The fact that such non-reciprocal private voluntary redistributive transfers can also be the object of crowding out has been investigated in a literature considering the consequences of government or donor transfers (Bergstrom et al., 1986; Andreoni, 1988; Bolton and Katok, 1998; Eckel et al., 2005). In this literature transfers are conceptually understood as resulting from warm-glow or altruistic preferences over a public good. It confirms that third-party contributions to the public good can lead to crowding-out of the non-reciprocal private transfers on a 'dollar-for-dollar' basis. We complement this literature by demonstrating experimentally, indeed, that formal insurance also has the potential to crowd-out non-reciprocal transfers. On top of this we show that introducing a formal financial mechanisms, can also change the degree of altruism, by revealing information about people's types. This is important because it may imply a process of crowding out of more than 'dollar-for-dollar', and that those who are particularly vulnerable to losses but are unable to take-up insurance are left worse off than before the introduction of insurance.

The paper is organized as follows. In Section 2 we explain the experimental design. In

Section 3 we discuss the descriptives, and in Section 4 the results. In Section 5 we present the model and investigate welfare implications. Section 6 concludes.

## II Experimental Design

To construct the sample, 378 farmers were selected from 16 *Iddir* from farming communities in rural Ethiopia. An *Iddir* can be described as an association made up by a group of individuals who are connected by ties of family, friendship, geographical area, jobs, or ethnic group (Mauri, 1987: 6-7). The objective of an *Iddir* is to provide mutual aid and financial assistance in case of emergencies. The 16 *Iddir* were selected from seven villages from three administrative regions in Tigray, one of the Northern provinces of Ethiopia. Each *Iddir* has a membership of between 100 and 200 farmers. Per *Iddir* three sessions were played with 24 Farmers (48 sessions in total) who were seated in private portable cubicles for a maximum period of three hours. Per session, farmers were anonymously and randomly teamed-up in two person groups leading to 189 groups. Half were teamed up with an anonymous other not from their own *Iddir* and half were teamed up with a farmer from their own *Iddir*. In the latter case they were informed that the other individual was from their own *Iddir* but they would otherwise remain anonymous. During the recruitment phase farmers were informed that they were eligible to participate in a survey and an experiment in which they would be teamed up with someone else and would be asked to make decisions about risk, insurance, and transfers. They were informed that they would receive a base-payment of 50 Ethiopian Birr (50 ETB; 2.5 USD) irrespective of the outcomes of their own or the decisions of the others in the experiments. They were also informed that they would be able to win an additional amount between 0 and 110 ETB depending on the decisions they and others would make in the experiments. Farmers were also informed that the total participation time, including the experiment, the survey and the payment would not be more than three hours. The incentives in the experiments reflected a daily wage for unskilled labour, ranging between 50 and 150 ETB, during the timing of the experiments and were thus substantial.

### The experiment

Subjects were informed that they would be randomly assigned to play a role of "i" or "j". The role of $i$ can be considered as "donor", the role of $j$ can be considered as "recipient".[2] Each

[2] In the explanation of the experiment to subjects, their roles were only referred to as $i$ and $j$, not "donor" and "recipient". This was done to prevent an effect of expectations about roles on behaviour.

player was provided with an initial endowment of 100ETB. This income was certain for the donor, $y_i = 100$. In contrast, the income for the recipient was uncertain as she faced a risk of a negative income shock, $s_j \in \{0, 1\}$. The negative income shock, $s_j = 1$, would occur with probability $p = 5/12$ and the recipient's income would then be reduced by 72ETB. The recipient's income would thus be $y_j \in \{28, 100\}$ with $E[y_j] = 70$ and $Var(y_j) = 1260$.

The income realization of the recipient was arrived at through a two-stage process designed to mimic the process whereby weather realisations determine the probability of crop losses. This structure was deliberately chosen as it best reflected the farmers' experience of losses to agricultural production and thus to enhance subjects' understanding.

In the first stage "weather", $f_j \in \{0, 1\}$, was simulated by a draw from an envelope that contained four tokens: three blue tokens representing "rainfall" ($f_j = 0$) and one yellow token representing "drought" ($f_j = 1$). In the second stage, the loss realization ("crop loss") $s_j$ was were simulated by two different coloured dice – a red and a white – with different probabilities of loss. If, in the first stage, a blue "rainfall" token was drawn ($f_j = 0$), in the second stage the red dice with a one-third probability of loss would be used. If, in the first stage, a yellow "drought" token was drawn ($f_j = 1$), in the second stage the white dice with a two-thirds probability of loss would be used.

Hence indeed

$$p \equiv \Pr(s_j = 1) = \sum_{f \in \{0,1\}} \Pr(f_j = f) \Pr(s_j = 1 | f_j = f) = \frac{3}{4} \times \frac{1}{3} + \frac{1}{4} \times \frac{2}{3} = \frac{5}{12}. \quad (1)$$

### The risky income of the recipient

A private lottery with probability of 1/2 for the recipient determined if she was offered an actuarially fair and complete insurance contract. Hence, this lottery determined if she played the benchmark condition of the experiment or the treatment condition. In the benchmark condition the recipient received no insurance offer and her income $y_j$ would hence be either 28 or 100 with probability $p = 5/12$ and $1 - p = 7/12$ respectively as outlined above.

In the treatment condition, the recipient received an offer of insurance and then had to decide whether to reject or accept, $z_j \in \{0, 1\}$. If she rejected the offer ($z_j = 0$) she would face the same risky income as in the benchmark treatment, whereas if she accepted the offer ($z_j = 1$) her uncertain income was replaced by the certain income of $E[y_j] = 70$. The certain income would be arrived at via the recipient paying a premium equal to the expected loss (30) and receive a claim payment equal to the size of the loss (72) in case of a loss. An endowment equivalent to the insurance premium (30 ETB) was given to $j$ before the experiment started so they had money to pay for the insurance premium. There was no direct cost of taking up insurance, so the rational decision for a risk averse individual (in the absence of any transfers) would be to take up the insurance.

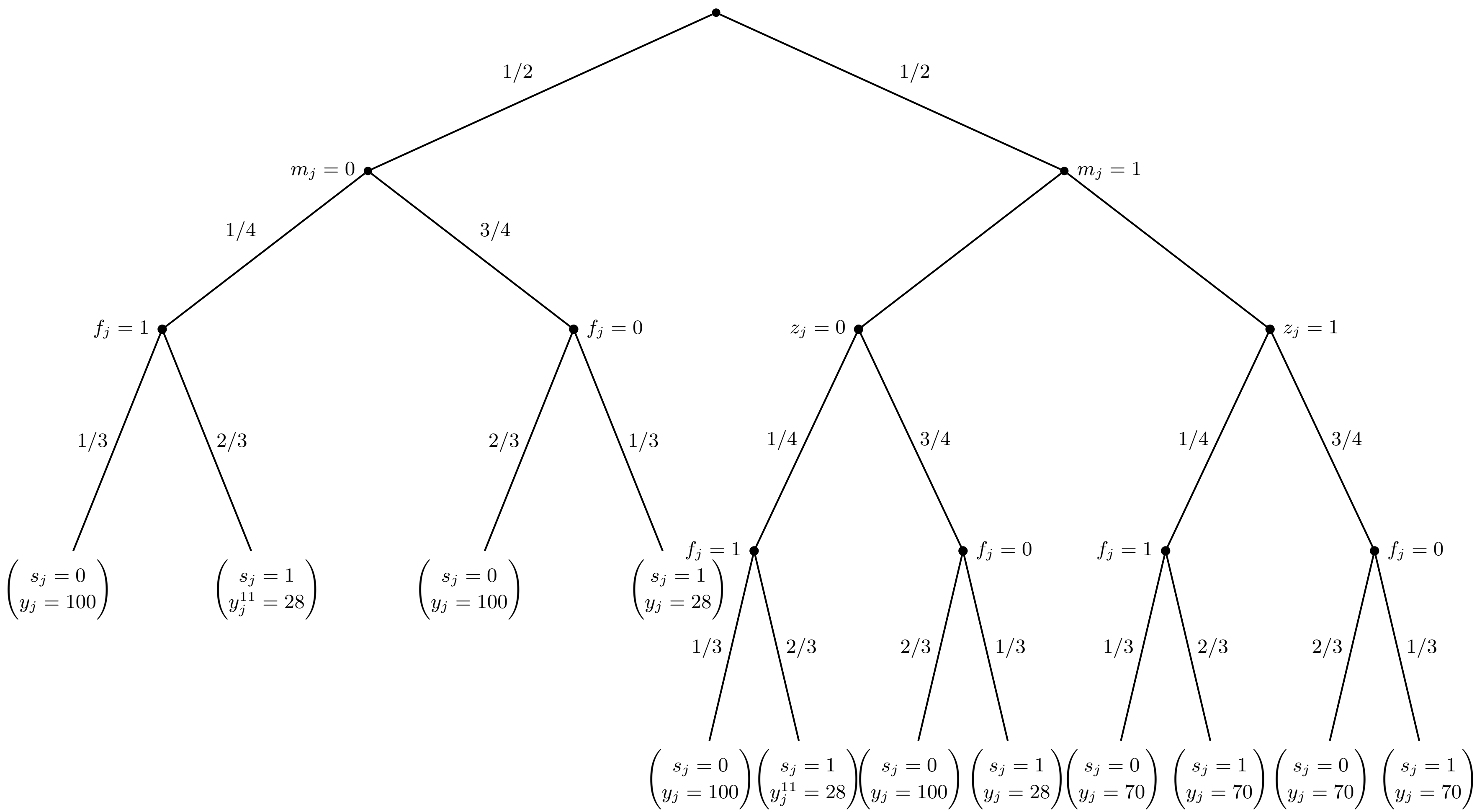


Figure 1: Income process of the recipient

Note: Probabilities are presented next to the branches of the tree. The states are presented at the nodes of the tree. Nature first decides, with a probability of 1/2, if the recipient receives an insurance offer ($m_j = 1$), or not ($m_j = 0$). In case there is no insurance offer there is a first-stage shock ($f_j$) and state-dependent second stage shock, ($s_j$). A first-stage shock, ($f_j = 1$), occurs with a probability of 1/4; the second-stage loss, $s_j = 1$, occurs with a state-dependent probability of $Pr(s_j = 1|f_j = 0) = 1/3$ or $Pr(s_j = 1|f_j = 0) = 2/3$. If nature decides that the recipient receives an insurance offer ($m_j = 1$), the recipient can choose not to take-up insurance, $z_j$=0, or to take-up insurance, $z_j$=1. For $z_j$=1 payoffs to $j$ are 70 ETB for all states. For $z_j$=0 payoffs to $j$ are the same as in the no insurance offer ($m_j = 0$).

### Transfers by the donor

Without knowing if $j$ received an insurance offer and, if she did, what her take-up decision was, $i$ was asked to specify three strategic conditional transfers (Selten, 1967; Brandts and Charness, 2011), $\tau_i^b$, $\tau_i^0$ and $\tau_i^1$, each paid to $j$ conditional on $j$ experiencing an income loss, but differing with respect to the insurance offer and the insurance decision.[3] The first transfer, $\tau_i^b$, would be made in the event that $j$ was not offered any insurance. The second transfer $\tau_i^0$ would be made in the event that $j$ was offered insurance but opted not to take it up, and finally $\tau_i^1$ would be made in the event that $j$ was offered insurance and took it up. The final payoffs to $i$ and $j$ were determined by nature's draw of the insurance offer, $j$'s take-up decision if offered, the realisation of $s_j$ and hence $y_j$, and the relevant transfer decision by $i$. Before starting the actual game, subjects received a central explanation and an individual explanation by their enumerator with a schematic representation of the game tree in extensive form, see Figure A.1 in Design Appendix A, which was used to show farmers the probabilities and payoffs in the game. Expectations of real life weather and crop outputs were elicited in the survey after the experiments to control for framing effects. Robustness tests show that they do not effect results. Before actual play farmers answered ten questions about the payoffs and probabilities in the game. The understanding was generally high, with more than 80% of subjects answering ten questions correctly.

## III Descriptives

Table 1 shows measures of key covariates and farm characteristics elicited for the full baseline sample. All baseline covariates, except for the number of adults in the household and the farmer's probability of experiencing $25-50\%$ crop loss[4] are balanced across donors and recipients. Out of all respondents 39% were female. All were farmers who owned on average 3.9 units of livestock and 0.61 hectares of farm land. Only 24% had access to irrigation, making their crops especially vulnerable to losses from weather variability. 46% of the farmers were literate, and 55% received no education, making it likely that a substantial fraction of the respondents is insufficiently financially literate to fully comprehend the details of an insurance product. All

[3]The donor was not asked how much she wanted to transfer for the states where $j$ did not experience a loss. Even though the donor might have wanted to transfer, it was decided to keep the number of decisions to a minimum to reduce cognitive load. We are most interested in the comparison of the states where $j$ experienced a loss as this is the typical state where redistributive transfers are made.

[4]The question asked was: *How many years out of the last ten years did you experience* $25-50\%$ *crop loss?*

subjects in the sample are a member of at least one *Iddir*[5] and 97% of the sample makes fixed monthly contributions to the *Iddir* of, on average, 6.49ETB, which is part of the Memorandum of Understanding (MoU) of membership to the *Iddir*. In addition, 35% of subjects make ex-post transfers to peers when they experience losses, irrespective of their monthly fixed contributions. These private ex-post transfers to peers in case of losses are 69.71ETB and subjects report that they themselves have received financial support from the *Iddir*, on average, three times. This shows that within the *Iddir* transfers to individuals who experience losses occur both on the basis of ex ante agreed contributions in the form of insurance, as well as on the basis of ex post transfers in cases of losses.

Table 1: Descriptives and balance

| | Mean | Recipient Mean | Donor Mean | t-test | Total N |
|---|---|---|---|---|---|
| **Demographics** | | | | | |
| Female | 0.39 | 0.40 | 0.39 | 0.15 | 365 |
| Age in years | 43.03 | 42.07 | 43.98 | -1.56 | 365 |
| Married | 0.81 | 0.82 | 0.80 | 0.64 | 365 |
| Number of adults in household | 2.11 | 1.71 | 2.51 | -4.84*** | 365 |
| Number of children in household | 3.17 | 3.28 | 3.07 | 1.25 | 365 |
| Literate | 0.46 | 0.48 | 0.43 | 0.99 | 365 |
| No education | 0.55 | 0.53 | 0.57 | -0.73 | 356 |
| Primary complete | 0.33 | 0.34 | 0.31 | 0.52 | 356 |
| **Farm characteristics** | | | | | |
| Farmer | 1.00 | 0.99 | 1.00 | -1.00 | 362 |
| Tropical Livestock Units | 3.90 | 4.02 | 3.79 | 0.56 | 365 |
| Land size in Tsemdi | 2.44 | 2.45 | 2.43 | 0.10 | 376 |
| Farm land irrigated | 0.24 | 0.25 | 0.22 | 0.52 | 365 |
| Probability of crop loss $25 - 50\%$ | 0.21 | 0.23 | 0.20 | 1.96* | 365 |
| **Riskaversion** | | | | | |
| Riskaversion | 3.00 | 3.20 | 2.83 | 1.50 | 224 |

Note: "Donor Mean" contains all individuals that were assigned the role of donor. Column 5 presents the test statistic for the null hypothesis that the mean in the donor group is equal to the mean in the recipient group. Lower sample sizes reflect that observations for that variable are missing. "Risk aversion" is a categorical variable from "0" to "5" with "0" being risk neutral and "5" being most risk averse. "Riskaversion" has a reduced number of observation because the ordered lottery selection to elicit risk preferences was not conducted for the first 7 out of 18 sessions. "No education" is a dummy for no education versus any level of education. "Primary complete" is a dummy for primary school versus any other level of education. "Tropical Livestock Units" is a count of the number of tropical livestock units. One "Tsemdi" is 0.25 hectares. "Probability of experiencing $25 - 50\%$ crop loss refers to the question *How many years out of the last ten years did you experience* $25 - 50\%$ *crop loss?* Significance levels $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

[5] Statistics on *Iddir* are not shown in Table 1

To assess subjects' risk preferences farmers played an incentivised ordered lottery selection experiment adopted from Binswanger (1981). In this experiment subjects were asked to make a choice between six lotteries in the gain domain, with a fixed probability of 1/2. The available choices, denoted $\{0, ..., 5\}$, correspond to increasing levels of risk aversion, starting at risk neutrality (0) and going to extreme risk aversion (5).[6] The six lottery choices in the ordered lottery selection experiment are presented in Table A.1 in Descriptives Appendix B. For simplicity we will refer to the ordered choice measure as "risk aversion". The final payoffs for the ordered lottery were determined by drawing coloured tokens from an envelope with the colours corresponding either to the low amount or the high amount in the lottery. The distribution of lottery choices made by the subjects is presented in Figure A.3 in Descriptives Appendix B. It shows that that the distribution of choices across the risky lotteries is uniformly distributed and that 28% of respondents chose option 0 – the lottery with the highest risk – representing risk neutrality. We also perform a regression analysis of "risk aversion" on individual covariates to check if risk aversion is a proxy for other covariates. Table A.2 in Descriptives Appendix B shows that there are no significantly strong correlates of risk aversion amongst the covariates.

Out of all 189 recipients 49% received an insurance offer (94 recipients) and out of those 91% decided to take up the insurance. Table 2 presents regressions of both the binary insurance take-up decision by the recipient, as well as the donor's belief about the likelihood that the recipient took insurance. To measure this belief we asked the donor: *How likely do you think it is that the recipient chose to take-up insurance when offered?*. The donor was given ten coins and asked to use the ten coins to indicate her belief. She was told that ten coins reflected a belief that it was very likely that the recipient took up insurance, and zero coins reflected a belief that it was very unlikely that the recipient took-up insurance. The distribution of the answers of the donors is presented in Figure 2.

[6]The risk aversion range is calculated based on Constant Relative Risk Aversion (CRRA) preferences and expected utility theory. As subjects were only required to make *one* choice among the different lotteries with a *fixed* probability, the Binswanger lottery is considered a simple procedure which is easily understood by subjects.

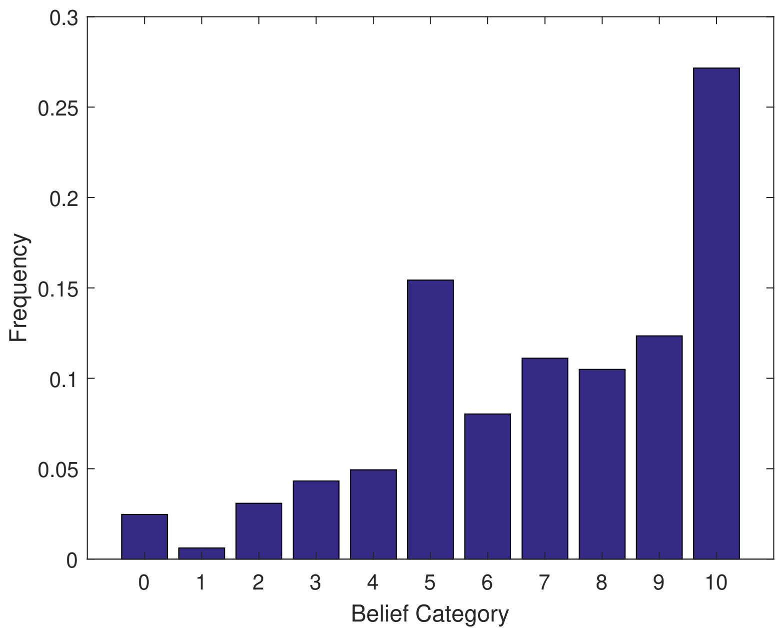


Figure 2: Donor's belief about the likelihood that the recipient took insurance when offered

Note: N=189. $E_i(z_j = 1|m_j = 1)$ consists of 10 categories, ranging from 0 to 10, with 0 being the donor's belief that it is very unlikely that the recipient accepted insurance; and 10 being the donor's belief that it is very likely that the recipient accepted insurance.

Column 1 in Table 2 presents the regressions of insurance take-up by the recipient on their own covariates. Literacy, eduction, the number of tropical livestock units, land size, and the probability of loss are positively and significantly correlated with the insurance take-up decision by the recipient. Column 2 in Table 2 shows results from regressions of the donor's beliefs about the likelihood that the recipient took insurance when offered, $E_i(z_j = 1|m_j = 1)$, and her own covariates. For ease of interpretation, the dependent variable has been rescaled from 0 to 1, so that the effect sizes are comparable to the parameter estimates in Column 1. Literacy, education, irrigation of farm land, and the probability of loss are positively and significantly correlated with the donor's belief while the number of adults in the households is negatively and significantly correlated with the donor's belief. Most importantly, as a stylized fact, there is a strong overlap both in terms of sign and magnitude of the covariates that are significantly correlated with both the recipient's take-up decision and the donor's belief about the take-up decision by their **randomly and anonymously** allocated recipient. This finding suggests that the same fundamental heterogeneity among individuals is associated not only with own take-up behaviour but also beliefs about the behaviour of others. We take this to be a stylized fact that a model will need to account for.

Table 2: Regressions of insurance take-up by the recipient and donors beliefs on covariates

| | **Recipient insurance take-up** ($z_j = 1$) | **Donor belief,** $E_i(z_j = 1 \vert m_j = 1)$ |
|---|---|---|
| | (1) | (2) |
| Age in years | -0.002 | < 0.001 |
| | (0.003) | (0.001) |
| Literate | 0.063 | 0.055 |
| | (0.036)* | (0.031)* |
| Education | 0.023 | 0.025 |
| | (0.010)** | (0.010)** |
| Female | -0.041 | -0.015 |
| | (0.054) | (0.050) |
| Married | 0.111 | -0.008 |
| | (0.096) | (0.052) |
| Number of adults in household | -0.022 | -0.038 |
| | (0.028) | (0.013)*** |
| Number of children in household | 0.010 | -0.005 |
| | (0.017) | (0.013) |
| Tropical Livestock Units | 0.014 | 0.001 |
| | (0.007)* | (0.001) |
| Land size in Tsemdi | 0.026 | -0.011 |
| | (0.013)* | (0.012) |
| Farm land irrigated | 0.053 | 0.095 |
| | (0.063) | (0.046)** |
| Probability of loss own farm $25-50\%$ | 0.020 | 0.040 |
| | (0.012)* | (0.014)*** |
| Riskaversion | -0.002 | 0.005 |
| | (0.008) | (0.011) |

Note: Column 1 presents the regressions of insurance take-up by the recipient on each single covariate, with clustering of standard errors at the session level. N=93, except for "Riskaversion" where there are 55 subjects because the ordered lottery selection to elicit risk preferences was not conducted for the first 7 sessions. Column 2 presents the regressions of the donor's belief about the insurance take-up decision by the recipient, with clustering of standard errors at the session level. The donor was asked how likely she thinks it is, on a scale from 0-10, that the recipient accepted insurance. For comparability to the estimates in Column 1 this variables was rescaled to run from 0-1. N=160, except for "Riskaversion" where there are 108 subjects. "Tropical Livestock Units" is a count of the number of tropical livestock units. One "Tsemdi" is 0.25 hectares. "Probability of experiencing $25-50\%$ crop loss refers to the question *How many years out of the last ten years did you experience* $25-50\%$ *crop loss?* "Riskaversion" is a categorical variable from "0" to "5" with "0" being risk neutral and "5" being most risk averse.Significance levels $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

In Table 2 it was established that the correlates of insurance take-up of an individual are similar to the correlates that determine the belief about the likelihood that someone else takes up insurance. Next, it will be demonstrated that individuals believe that they are more central in the distribution of types than they really are. Since insurance has not yet been introduced in these communities, it is not possible to use individuals' historic insurance take-up decisions.

Instead farmers' (beliefs about) own crop losses in the past ten years, and average crop losses in the Iddir in the past ten years are used. The own loss frequency was measured by asking farmers the question: *How many years out of the last ten years did you experience* $25-50\%$ *crop loss?*. Farmers were given ten coins and were told they each represented one year. They were then asked to indicate how many years out of the past ten years they experienced $25-50\%$ crop loss?. The perceived average loss frequency in the Iddir was measured based on the question: *On average, how many years out of the last ten years did farmers in your Iddir experience* $25-50\%$ *crop loss?*. Again they were asked to answer using coins. The actual average loss frequency in the Iddir was constructed based on averaging the own loss frequency of all farmers belonging to a particular Iddir. This is representative of the actual average loss frequency as these farmers were randomly selected from the list of farmers belonging to each Iddir and there was no refusal to participate. If farmers have rational beliefs, the ratio of the belief about the average loss frequency in the Iddir relative to the actual average loss frequency in the Iddir should be unity. The ratio in the sample is 1.16, implying that farmers, on average, overestimate the loss frequency in the Iddir. In Figure 3 this ratio for individual $i$ is plotted by $i$'s rank – measured in quartiles – within the actual loss frequency distribution in the Iddir. It is evident from Figure 3 that individuals with a relatively lower (higher) own loss frequency under- (over-) estimate the actual average losses amongst peers in the Iddir. Hence those low (high) in the local distribution perceive a lower (higher)-than-actual mean.

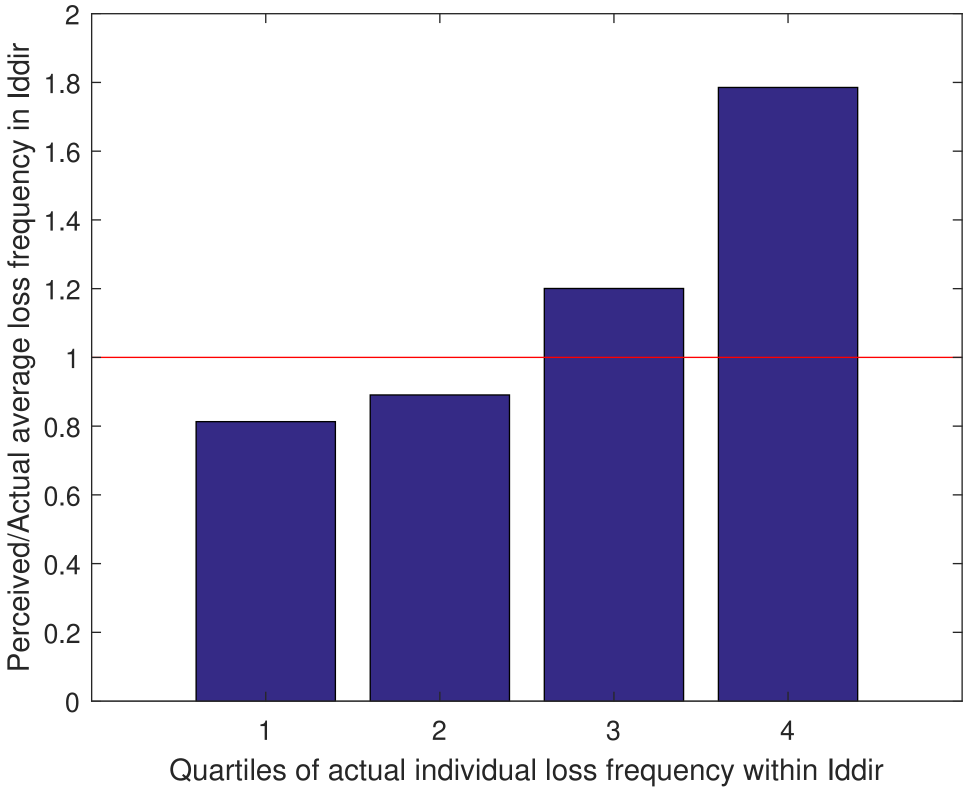


Figure 3: Difference between own loss frequency and actual and perceived average loss frequency

Note: N=189. The x-axis presents quartiles within the actual own loss frequency of farmers in the Iddir. The y-axis presents the ratio of perceived average loss frequency over actual average loss frequency within the Iddir. The own loss frequency was constructed based on the question: *How many years out of the last ten years did you experience* $25-50\%$ *crop loss?*. The perceived average loss frequency in the Iddir was constructed based on the question: *On average, how many years out of the last ten years did farmers in your Iddir experience* $25-50\%$ *crop loss?*. The actual average loss frequency in the Iddir was constructed based on averaging the own loss frequency of all farmers belonging to a particular Iddir. The red line represents the ratio where farmers' beliefs about the average loss frequency in the Iddir are correct.

## IV Results

Figure 4 shows histograms with 10 ETB bins of the transfers in each treatment condition.[7] Figures A.4, A.5, and A.6 in Results Appendix B present the binned and un-binned transfer data per treatment condition. The histograms in Figure 4 already demonstrates that there is a substantial shift in transfers towards zero in the treatment condition where the recipient rejects

[7]Table A.3 in Results Appendix B shows the regressions of transfers in the "no insurance offer" treatment condition on covariates.

insurance, compared to the 'no insurance offer' condition, despite the fact that the recipient has the same outcome before transfers. Figure A.2 in Results Appendix B shows the mean transfers per treatment condition with 95% confidence intervals. The mean transfers by the donor are 15ETB when the recipient received no insurance offer, $m_j$, and had an outcome before transfers of 28 ETB. When the recipient received an offer but did not take-up insurance, $z_j = 0|m_j = 1$ the donor transferred only 10 ETB, despite the fact that the outcome of the recipient before transfers was also 28 ETB. This is clear evidence that the recipient's insurance decision affected the donor's transfers. When the recipient did take insurance $z_j = 1|m_j = 1$, transfers were only 5 ETB, but in this case the recipient's outcome before transfers is 70 ETB. Figure A.4 in Results Appendix B shows that if we split transfers by the occurrence of the first-stage shock, $f_j$, there are no observable differences. When we interact treatment with the first-stage shock the interaction is not significant. This indicates that the first-stage shock does not affect the donor's transfers.

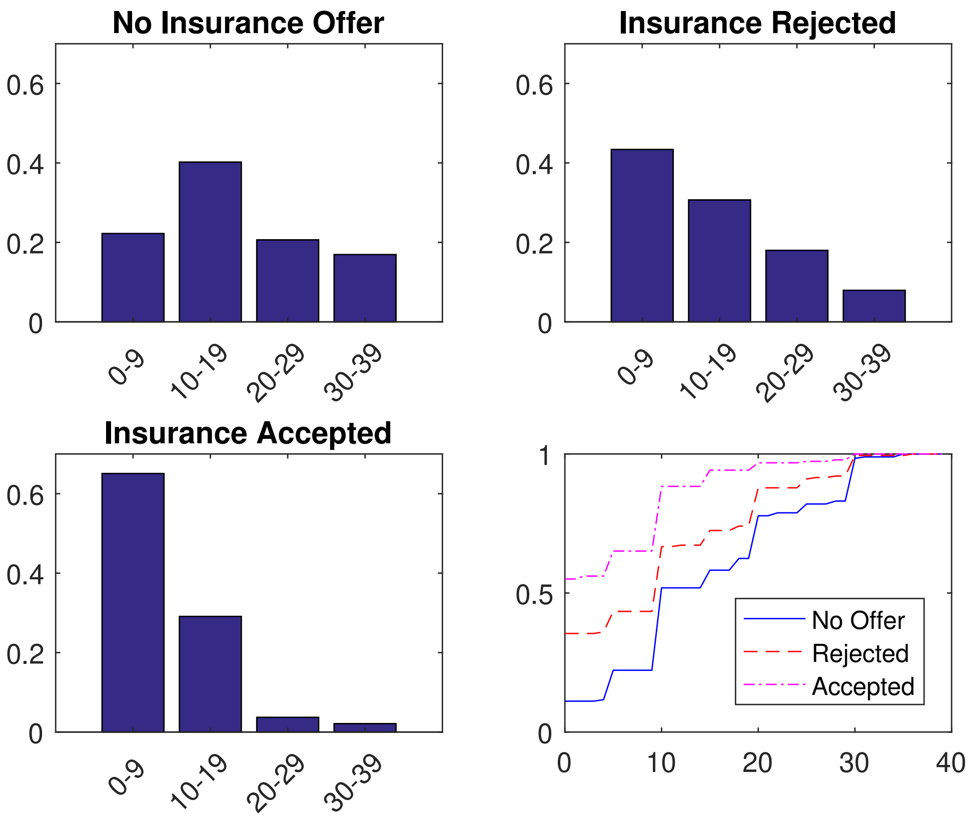


Figure 4: Histograms and densities of transfers per treatment arm

Note: N=189. Transfers are presented in 10 ETB bins. The upper left, upper right, and lower left panels show the histograms of the different treatment arms. The upper left panel presents transfers when the recipient received no insurance offer, $m_j = 0$, and has an outcome before transfers of 28 ETB. The upper right panel presents transfers for the condition where the recipient received an offer but did not take-up insurance, $z_j = 0|m_j = 1$. The recipient also had an outcome of 28 ETB before transfers. The lower left panel represents transfers by the donor for the case where the recipient did take insurance, $z_j = 1|m_j = 1$. The outcome of the recipient before transfers was 70 ETB in this case. The lower left panel presents the cumulative density plots for all treatment arms.

For the effect of the treatment condition on transfers the following fixed effects regression is estimated:

$$\tau_{it} = \alpha + \beta_1 T_{it}^{z_j=0} + \beta_2 T_{it}^{z_j=1} + \mu_i + \epsilon_{it} \tag{2}$$

where $\tau_{it}$ is the observed transfer in ETB; $T_{it}^{z_j=0}$ is a dummy indicating the treatment condition where j rejected insurance, with the 'no insurance offer' ($m_j = 0$) as the reference category. $T_{it}^{z_j=1}$ is a dummy indicating the treatment condition where j rejected insurance, with again the 'no insurance offer' ($m_j = 0$) as the reference category. The subscript $i$ refers to variation by donor, and the subscript $t$ to variation by treatment condition. $\mu_i$ is the donor specific error term and $\epsilon_{it}$ the error term per decision. $\beta_1$ and $\beta_2$ are the estimates of interest.

Table 3 presents the estimates from the regressions for the transfers made by the donors conditional on the treatment conditions. The estimation in Column (1) uses robust standard errors in line with the fact that the randomisation to donor or recipient occurred at the individual level Abadie et al. (2017). Nonetheless, Column (2) shows that the results are robust to clustering at the session level[8]. Transfers in the benchmark condition, when there is no insurance offer made to the recipient, $(m_j = 0)$, are on average 14.84 ETB. When $j$ is offered insurance and rejects the offer $(z_j = 0|m_j = 1)$ transfers are significantly reduced by 4.71 ETB (33%). When $j$ is offered insurance and accepts the offer $(z_j = 1|m_j = 1)$ transfers are significantly reduced by 9.68 ETB (67%). These treatment effects are significant at the 1% level and results are robust across the various specifications. In Column (3) in Table 3 the dependent variable is the relative transfer, whereby transfers in the treatment conditions "$z_j = 0|m_j = 1$" and "$z_j = 1|m_j = 1$" are a fraction of the transfers in the benchmark condition "$m_j = 0$". When the recipient rejects the insurance offer the donors reduce their benchmark transfers by 33% on average, while when the recipient accepts the insurance offer they reduce the benchmark transfers by 69%. Figure A.5 in Results Appendix B shows the histograms and 95% confidence intervals of the transfers per treatment condition, split by the recipients identity: either from the donor's own *Iddir* or another *Iddir*. The histograms seem qualitatively similar. Column (4) represents the estimation of the interaction of the recipients identity with the treatment conditions. The interaction terms are insignificant. This indicates that the donor's transfer decision is not influenced by the identity of the recipient and suggests that local norms, that may exist between donors and recipients from the same local network do not influence redistribution in the experiment.

[8] Results are also qualitatively similar when we cluster at the *Iddir* level

Table 3: Effect of the treatment conditions on transfers

| | Absolute transfers (1) | Absolute transfers (2) | Relative transfers (3) | Absolute transfers (4) |
|---|---|---|---|---|
| $m_j = 0$ (cons) | 14.84(0.49) | 14.84(0.56) | 1.00(0.02) | 14.84(0.49) |
| $z_j = 0 \mid m_j = 1$ ($\beta_1$) | -4.71(0.77)*** | -4.71(0.75)*** | -0.34(0.05)*** | -4.30(1.03)*** |
| $z_j = 1 \mid m_j = 1$ ($\beta_2$) | -9.68(0.92)*** | -9.68(1.29)*** | -0.62(0.06)*** | -10.32(1.09)*** |
| | | | | |
| $j\text{Own}Iddir \times z_j = 0 \mid m_j = 1$ | | | | -0.80(1.54) |
| $j\text{Own}Iddir \times z_j = 1 \mid m_j = 1$ | | | | 1.26 (1.82) |
| | | | | |
| Cluster robust | v | | v | v |
| Cluster session | | v | | |
| N | 567 | 567 | 567 | 567 |
| Subjects | 189 | 189 | 189 | 189 |
| Clusters | 189 | 18 | 189 | 189 |

Note: Fixed effects regressions. N refers to number of decisions made, 'Subjects' refers to number of subjects making decisions, 'Clusters' refers to the number of clusters. Dependent variable in (1), (2), and (4) is the absolute level of transfers. Dependent variable in (3) are the transfers as a share of the transfers in the reference condition ($m_j = 0$). "$m_j = 0$ (cons)" is the reference category and refers to the condition where the recipient received no insurance offer and has an outcome before transfers of 28 ETB. "$z_j = 0 | m_j = 1$" refers to the treatment condition where the recipient received an offer but did not take-up insurance. Here the recipient also had an outcome of 28 ETB before transfers. "$z_j = 1 | m_j = 1$" refers to the condition where the recipient did take insurance. The outcome of the recipient before transfers was 70 ETB in this case. Significance levels $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

### Heterogeneity by risk aversion and beliefs about the recipients' insurance decisions

Table 4 shows the interactions of the treatment conditions with the donor's beliefs about the likelihood that the recipient took insurance. One of the predictions of the model is that the transfer-reduction is larger for donors with a higher expectation of insurance take-up by the partner. In Column (1) the dependent variable is the amount of transfers in ETB.[9] In Columns (2) the dependent variable is the relative transfer as a proportion of the transfer in the benchmark condition, $m_j$.[10] When the treatment conditions are interacted with the donor's beliefs in Column (1) we can see that the direct significant negative effect of the condition where the recipient does not take-up insurance, $z_j = 0|m_j = 1$ disappears and is replaced by a significant negative interaction effect. An increase of one (out of 10) in the donor's belief about the likelihood that the recipient has taken insurance implies a further reduction of the transfers by 0.68ETB. There is no significant interaction of the donor's beliefs with the condition where the recipient does take-up insurance, $z_j = 1|m_j = 1$. The same effect occurs for the relative transfers, where the interaction of the treatment condition "$z_j = 0|m_j = 1$" with the donor's beliefs is negative and significant. On the other hand though, the direct negative and significant effect of the treatment condition where $j$ takes-up insurance, $z_j = 1|m_j = 1$ partly remains, but the interaction term is also negative and significant at the 10% level. What is interesting about these results is that when the recipient rejects insurance she has the same income before transfers in $m_j$ and $z_j = 0|m_j = 1$. The donor's choice to reduce transfers can thus only be driven by the decision of the recipient to reject insurance. It thus appears that donors who belief it is highly likely that the recipient takes-up insurance reduce transfers more than donors who beliefs it is highly unlikely that the recipient takes-up insurance. It is hypothesized that the donor's risk preferences can proxy for the donor's beliefs about the likelihood that the recipient takes up insurance. Therefore, to test for robustness, the same analysis is conducted for the donor's risk aversion. Table A.7 in Results Appendix B shows that the results are replicated.

[9] The specification of this regression is: $\tau_{it} = \alpha + \beta_1 T_{it}^{z_j=0} + \beta_2 T_{it}^{z_j=1} + \rho X_{it} + \gamma_1 X_{it} \times T_{it}^{z_j=0} + \gamma_2 X_{it} \times T_{it}^{z_j=1} + \mu_i + \epsilon_{it}$, where $X$ is "donor's belief about $z_j$" .

[10] The specification of this regression is $\frac{\tau_{it}^{z_j} - \tau_{it}^{b}}{\tau_{it}^{b}} = \alpha + \beta_1 T_{it}^{z_j=0} + \beta_2 T_{it}^{z_j=1} + \rho X_{it} + \gamma_1 X_{it} \times T_{it}^{z_j=0} + \gamma_2 X_{it} \times T_{it}^{z_j=1} + \mu_i + \epsilon_{it}$, where again $X$ is the "donor's belief about $z_j$".

Table 4: Effect of treatment on (relative) transfers interacted with donor's beliefs

| | (1) | (2) |
|---|---|---|
| $m_j = 0$ (cons) | 15.31(0.49) | 1.00(0.03) |
| $z_j = 0 \mid m_j = 1$ | -0.34(2.71) | 0.01(0.11) |
| $z_j = 1 \mid m_j = 1$ | -10.63(3.44)*** | -0.33(0.20)* |
| | | |
| $E_i(z_j = 1)\times\ z_j = 0 \mid m_j = 1$ | -0.68(0.35)** | -0.05(0.02)*** |
| $E_i(z_j = 1)\times\ z_j = 1 \mid m_j = 1$ | -0.03(0.42) | -0.04(0.02)* |
| n | 486 | 486 |
| Subjects | 162 | 162 |

Note: Fixed effects regressions. Standard errors are clustered at the individual level. $E_i(z_j = 1)$ consists of 10 categories, ranging from 0 to 10, with 0 being the donor's belief that it is very unlikely that the recipient accepted insurance; and 10 being the donor's belief that it is very likely that the recipient accepted insurance. 'Subjects' refers to number of subjects making decisions. Standard errors are clustered at the subject level. Significance levels $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

## V The Model

In this section we present a model of formal insurance and voluntary non-reciprocal redistributive transfers that is consistent with the results from the above experiment. A further ambition is that the model should have well-defined and stable preferences in order to investigate crowding-out and make welfare comparisons. The model presented below will predict that:

1. The take-up of actuarially fair insurance is incomplete due to privately observed constraints, that may have a relationship to demographic characteristics.

2. If there are demographic characteristics associated with own insurance take-up these should also be associated with higher expectation about the insurance take-up by a randomly allocated partner.

3. The transfer that an individual makes to her partner if the latter rejects available insurance is often less than the transfer that she would provide to the same partner if insurance was not available, and the transfer-reduction is larger for donors with a higher expectation of insurance take-up by the partner.

Before presenting the details of the model we start by outlining some of its key ingredients and how each is central to delivering the above predictions.

Our model is of a local economy where individuals are randomly matched with a partner. The first key ingredient is that individuals vary in "type" which is privately observed. When insurance is offered, the individuals face an insurance take-up costs that is monotonically increasing in their type. While type is an abstract concept in the model, it may have some relation to characteristics measured in the data.

The second key ingredient is an egocentric "false consensus bias" (Ross, Greene and House, 1977). As humans we find it difficult to project outside the bounds of our own consciousness, a cognitive shortcoming that often leads to systematic bias when comparing ourselves to others. In particular, the false consensus bias states that individuals tend to overestimate the number of people who possess the same attributes, hold the same beliefs, and make the same choices as they do.[11] It is thus a bias where individuals overestimate how typical they are and presume that a consensus exists on matters when there may be none.[12] In model terms, we will assume that all individuals perceive the distribution of types to be closer to their own type than it actually is and also presume that others share their believe. This generates an endogenous false consensus bias in terms of insurance take-up behaviour whereby lower types – who themselves are more likely to take up insurance – expect the aggregate take-up rate to be higher.

The third key ingredient is a type-based favouritism. A large literature started by Becker (1957) has focused on taste-based discrimination by a majority against a minority. More generally inter-group biases may arise either because individuals disfavor others or because they favor their own kind, with the two sources of discrimination being hard to disentangle (Goldberg, 1982). As a way forward, a recent literature has focused on the differential treatment of known- versus anonymous others, with favoritism (discrimination) identified as being more (less) generous towards someone known to be of your own (opposite) kind relative to an anonymous other. For instance, Feld, Salamanca and Hamermesh (2016) use a field experiment at a Dutch university where graders marked some exam papers without the student's name on it and some with it. In the latter case the name would convey the student's nationality (Dutch or German).

[11] In the behavioural economics literature particular attention has been paid to the closely related "projection bias", defined by Loewenstein, O'Donoghue and Rabin (2002) as the tendency of people to assume that their current tastes will remain unchanged and hence that their *future selves* will agree with their *current selves*.

[12] Mullen et al. (1985) report on 115 studies providing a wealth of evidence of false consensus effects. Criticizing the early literature, Dawes (1989) noted that it is perfectly rational to use information about own attributes/choices in the same way as information about any other randomly chosen individual. Dawes therefore argued for a stronger definition that states that a (truly) false consensus effect occurs when individuals consider information about themselves to be more informative than information about a randomly selected person from the same population. For evidence on this generalized version of the false consensus bias see e.g. Krueger and Clement (1994) and Engelmann and Strobel (2012).

Knowing the grader's nationality the authors find evidence of substantial favouritism, but no discrimination. Similar designs have previously been used in laboratory settings by Fershtman, Gneezy and Verboven (2005) and Ahmed (2007), finding evidence of both favoritism and discrimination.[13] In model terms, we assume that all individuals have caring preferences towards their partner, but that the strength of these preferences decreases with type-distance. When insurance becomes available, rejection of insurance by the partner is informative that her type is high, leading many potential donors to reduce their transfers, and even more so when the donor's own type is low.

### Setup

Consider an economy with a large population of individuals $i \in \{1, 2, ...\}$, heterogenous in type denoted $\theta_i \in \mathbb{R}$. Type has a distribution $\theta_i \sim N(\mu, 1)$ where $\mu$ is the mean/median of the distribution and where the variance has been normalized to unity.[14] $\theta_i$ is private information to individual $i$. For reasons that will become clear, it will be useful to define an individual's rank in the type distribution. Hence let $\Phi_i = \Phi(\theta_i; \mu)$ where $\Phi(\cdot; \mu)$ is the CDF for the normal distribution with mean $\mu$ (and unit variance).

Similar to (the recipients in) the experiment, the individuals face a risk of an income loss $s_i \in \{0, 1\}$. For simplicity, in the model we assume that, in the absence of an income loss, individual $i$ has an income of unity but that this is completely lost in case of an income loss. Hence $y_i \in \{0, 1\}$. The probability of a loss, denoted $p$, is the same for all individuals and income losses are independent across individuals. The utility of consumption is $u(c_i)$, where $u(\cdot)$ is defined on $\mathbb{R}_+$, is twice continuously differentiable, strictly increasing and strictly concave.

We next state some of the key model assumptions outlined above. First, each individual $i$ interacts with one other member of the economy denoted $j$ and referred to as $i$'s "partner" and pairings are random.

**Assumption 1. Random pairing**. Each individual $i$ is randomly paired with another member of the economy, denoted $j$, but each individual's type is private information.

[13]In the psychology literature it has been known since the 1970s that allocations of individuals into groups even based on trivial grounds can trigger a tendency to favor one's own group at the expense of others – the so-called "minimal group paradigm" (Tajfel et al. 1971). More recent refinements of this design have found that subjects are, if anything, more often motivated by own-group favoritism than discrimination (Gaertner and Insko, 2001).

[14]The assumption of normality is made for convenience only. The result would directly generalize to any symmetric unimodal distribution with support $[-\infty, \infty]$.

Second, while $\mu$ is the true location of the type distribution, any individual $i$ has a biased location belief, believing that others are more similar to her then they actually are.[15] We parameterize such belief-bias with a single parameter $\beta$.

**Assumption 2. Egocentric false consensus bias**. Let $\beta \in [0,1]$ and assume that individual $i$ believes that the location of the type distribution is $\mu_i \equiv (1-\beta)\,\mu + \beta\theta_i$ and also expects this to be the belief of all other individuals in the economy.

Third, individual $i$ cares about her partner, but more strongly so the more similar the partner is to herself. Hence we define $\delta_i \equiv |\theta_j - \theta_i|$ as the (Euclidean) type-distance between $i$ and her partner $j$.

**Assumption 3. Caring preferences declining in distance**. Individual $i$ has caring preferences towards her partner $j$ of strength $\alpha_i$ that decreases in the type-distance to the partner.

$$\alpha_i = a_0 - a_1\delta_i, \tag{3}$$

where $a_0 \in [0,1]$ and $a_1 \geq 0$.

*Remark* 1. In principle the linear formulation in (3) means that $i$ cares negatively about her partner if they are more than $\delta_i = a_0/\alpha_1$ distance units away from each other. The linear form is mainly for convenience as it makes the individual's expectation about $\alpha_i$ directly reflect her expectation about $\delta_i$.

Before proceeding it is worthwhile to consider the nature of the assumed belief-bias in some more detail. In particular any individual – except for someone who is exactly of median type – will be mistaken about her rank $\Phi_i$ in the distribution of types, and as a consequence she will also misperceive the expected distance between herself and her partner. We break this down in two steps.

First we define the true expected distance between $i$ and $j$ given $i$'s rank. In particular, let $\theta_i$ and $\theta_j$ be i.i.d. draws from the true type distribution, $N(\mu, 1)$, and define

$$\Delta(\Phi_i) \equiv E[\delta_i|\Phi_i] = E[|\theta_j - \theta_i|\,|\Phi(\theta_i;\mu) = \Phi_i]\,. \tag{4}$$

[15] Hence we assume that everyone has the same belief about the spread of the distribution. An underestimation of the spread would make a relatively central type underestimate her distance to other types, but will make a non-central type overestimate her distance.

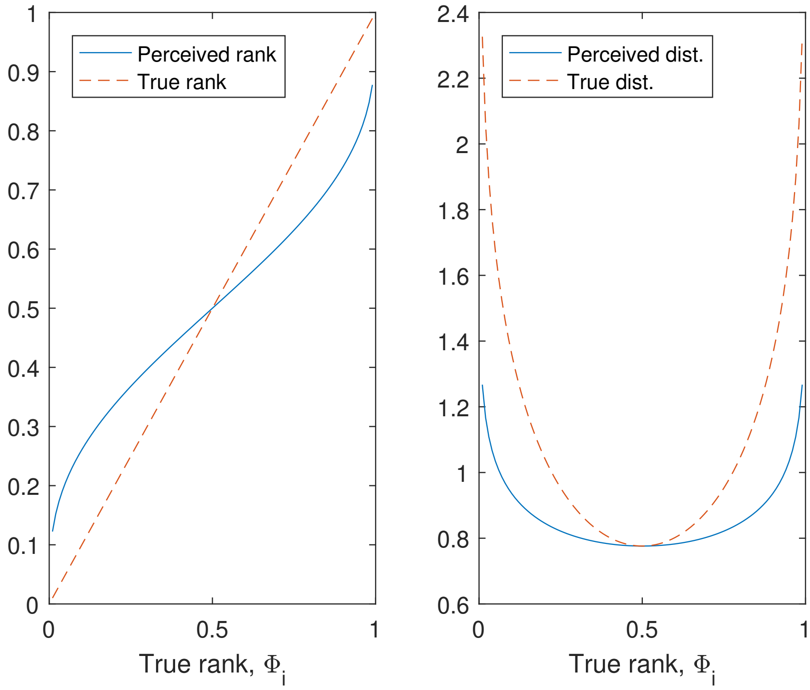


Figure 5: Perceived rank and perceived expected distance.

Note that, per construction, $\Delta(\Phi_i)$ does not depend on $\mu$.

Second, we define the own perceived rank of an individual of true rank $\Phi_i$ when the belief-bias is $\beta$. This is defined as,

$$\widetilde{\Phi}(\Phi_i;\beta) = \Phi(\theta_i, (1-\beta)\mu + \beta\theta_i) \text{ with } \theta_i = \Phi^{-1}(\Phi_i, \mu). \tag{5}$$

This function strictly depends on $\beta$ (but is still independent of $\mu$). The left panel of Figure 5 illustrates the individual's perceived rank as function of her true rank $\widetilde{\Phi}(\Phi_i;\beta)$ for the case of $\beta = 0.5$. The fact that the perceived rank is above (below) the red hatched 45 degree line at any true rank $\Phi_i < 0.5$ ($\Phi_i > 0.5$) highlights how, under biased beliefs, all types – except the true median – misperceive their rank, believing they are more central than they are.

The right panel illustrates $\Delta\left(\widetilde{\Phi}(\Phi_i;\beta)\right)$ – the expected distance to the partner perceived by the individual as a function of her true rank and given belief-bias $\beta = 0.5$. Due to bias any individual – except for the true median type – perceives an expected distance to the partner is lower than her true expected distance (shown by the red hatched line).

The following lemma formally notes that the expected distance to the partner perceived by any individual as a function of her true rank is indeed U-shaped and decreasing in the degree of bias.

**Lemma 1.** *The individual's perceived expected distance* $\Delta\left(\widetilde{\Phi}\left(\Phi_i;\beta\right)\right)$ *is U-shaped with respect to her true rank* $\Phi_i$ *with a minimum at* $\Phi_i = 1/2$ *and is decreasing in* $\beta$ *for all* $\Phi_i \in (0,1)$*, except for the true median* $\Phi_i = 1/2$*.*

**Proof.** See Theoretical Appendix.

### The No-Insurance Regime

We consider first the no-insurance environment. While types are private information the income realizations are mutually observable by partners. If $i$ does not suffer an income loss but her partner $j$ does, $i$ makes an ex post altruistically motivated transfer to $j$. $i's$ transfer is assumed to depend on her type, as different types perceive different distances to their randomly allocated partners.

In order to characterize the transfers made in this environment we can ignore bias for just a moment. Noting first that

$$E\left[\alpha_i|\Phi_i\right] = a_0 - a_1\Delta\left(\Phi_i\right), \tag{6}$$

it follows that, in the same way that $\Delta\left(\Phi_i\right)$ is U-shaped, $E\left[\alpha_i|\Phi_i\right]$ is inverted U-shaped (with a maximum at $\Phi_i = 1/2$). Consider then the transfer problem $\max_\tau \left\{u\left(1-\tau\right) + u\left(\tau\right)E\left[\alpha_i|\Phi_i\right]\right\}$. The solution to this problem, denoted $\tau^b\left(\Phi_i\right)$, is characterized by the associated first order condition,

$$\frac{u'\left(\tau^b\left(\Phi_i\right)\right)}{u'\left(1-\tau^b\left(\Phi_i\right)\right)} = \frac{1}{E\left[\alpha_i|\Phi_i\right]}. \tag{7}$$

$\tau^b\left(\Phi_i\right)$ is the transfer that would have been chosen by an individual of rank $\Phi_i$ in the absence of belief-bias. But of course, due to biased beliefs, the transfer chosen by an individual of true rank $\Phi_i$ reflects her perceived rank $\widetilde{\Phi}\left(\Phi_i;\beta\right)$ via her perceived expected distance $\Delta\left(\widetilde{\Phi}\left(\Phi_i;\beta\right)\right)$ rather than her true rank/expected distance. Hence the transfer chosen by an individual of true rank $\Phi_i$ and given the bias $\beta$ in the no-insurance regime is (slightly abusing the notation) given by

$$\tau^b\left(\Phi_i;\beta\right) = \tau^b\left(\widetilde{\Phi}\left(\Phi_i;\beta\right)\right). \tag{8}$$

The properties of the perceived expected distance (Lemma 1) thereby carry over to the transfer in the no-insurance regime: individuals who are further away from the true median, transfer less and more belief-bias implies that everyone (except a true median individual) transfers more. An example will be illustrated below.

### The Insurance Regime

Insurance, when available, is assumed to be actuarially fair and complete. Hence the premium associated with insurance is $p$ and an individual who takes up insurance has her uncertain income replaced with the certain income $1-p$. Let $z_i \in \{0,1\}$ indicate take-up by individual $i$. Taking up insurance is associated with a type-specific take-up cost.

**Assumption 4. Takeup cost**. Taking up insurance has a type-specific utility cost $\chi(\theta)$, where $\chi(\cdot)$ is defined on $\mathbb{R}$ and is continuous, strictly increasing and strictly convex in $\theta$, additionally satisfying $\lim_{\theta\to-\infty}\chi(\theta)=0$ and $\lim_{\theta\to+\infty}\chi(\theta)=\infty$.

We assume that partners observe each others' take-up decisions.

**Assumption 5. Observability of take-up decisions**. The take-up decisions $(z_i, z_j)$ of any set of partners $(i,j)$ are mutually observable within the pair.

*Remark* 2. Note that while individual $i$ observes $z_j$ and vice versa, neither observes the take-up decisions by non-partners in the economy. If individual $i$ could observe the aggregate take-up rate, her beliefs would be revealed to be wrong before making a potential transfer to $j$.

In this regime, transfers are made to uninsured individuals who suffer income losses.[16] Transfers may come either from individuals who took up insurance or from individuals who did not take up insurance but then did not suffer an income loss.

In order to characterize the equilibrium take-up decision of an individual of true type $\theta_i$ we need to characterize her beliefs about the take-up and transfer behaviour of others. Note that, since the individuals in the economy have biased beliefs about the location of the distribution of types, they will generally also have biased beliefs about the equilibrium behaviour of others. An individual of type $\theta_i$, who believes that the location of the type distribution is at $\mu_i$ (Assumption 2) – and expect that others share her belief – will thus anticipate an equilibrium consistent with this particular location of the type distribution.

[16]There will trivially not be any transfers between two insured partners as both have the same certain income. Given that $\alpha_i$ is stricly below unity and given that $p$ is small, an uninsured agent with her unit income intact will not make a transfer to an insured partner as their income gap of $p$ is small. Furthermore, there will be no transfers between two individuals who both choose to be uninsured and both suffer an income loss.

We thus proceed by characterizing the equilibrium that would obtain if a particular location $\mu_i$ was true and known to all, as this represents $i$'s beliefs about the behaviour of others. Such an anticipated equilibrium consists of an insurance take-up rate and description of the transfer that each individual in the particular type distribution would make. Given the arbitrary location of the distribution, it is more convenient to characterize the behaviour of individuals in terms of their rank.

As in the case of the no-insurance regime, the transfer made by an individual $i$ to a partner who has suffered an income loss will depend on her expected distance to the partner. However, whereas in the no-insurance regime the donor had no information about the identity of the partner, in the insurance regime the donor will have the information that the recipient chose not to take up insurance. All anticipated equilibria will have the standard property that there is a threshold type separting those who took insurance and those who rejected it. Hence if there is a take-up rate of $\widehat{\Phi}$ and $i$ observes that her partner declined insurance, she will infer that $\Phi_j > \widehat{\Phi}$. This will impact on her expected distance to $j$ and hence on her degree of caring.

We thus generalize the definition in (4) to the expected distance between a donor of type rank $\Phi_i$ and an uninsured partner when the insurance take-up rate is $\widehat{\Phi}$. Hence as before, let $\theta_i$ and $\theta_j$ be i.i.d. draws from $N(\mu', 1)$ where $\mu'$ is an arbitrary mean, and now define

$$\Delta\left(\Phi_i, \widehat{\Phi}\right) \equiv E\left[\delta_i | \Phi_i, \Phi_j \geq \widehat{\Phi}\right] = E\left[|\theta_j - \theta_i| \,|\Phi\left(\theta_i;\mu'\right) = \Phi_i, \Phi\left(\theta_j;\mu'\right) \geq \widehat{\Phi}\right]. \tag{9}$$

Note that $\Delta\left(\Phi_i, \widehat{\Phi}\right)$ does not depend on the arbitrary location $\mu'$.

Figure 6 illustrates the expected distance function $\Delta\left(\Phi_i, \widehat{\Phi}\right)$. The special case $\Delta(\Phi_i, 0)$ reduces to the distance function defined in (4) as the no-insurance case corresponds to the zero take-up case. Another special case is when both the donor's rank and the take-up rate goes to unity; in that case the expected distance approaches zero.

As in the case of no insurance, an expected distance maps into an expected level of caring by a donor of rank $\Phi_i$ for an uninsured partner when the take-up rate is $\widehat{\Phi}$, $E\left[\alpha_i | \Phi_i, \Phi_j \geq \widehat{\Phi}\right] = a_0 - a_1 \Delta\left(\Phi_i, \widehat{\Phi}\right)$.

Consider then the transfer from $i$ to $j$ when the take-up rate is $\widehat{\Phi}$, characterized through the

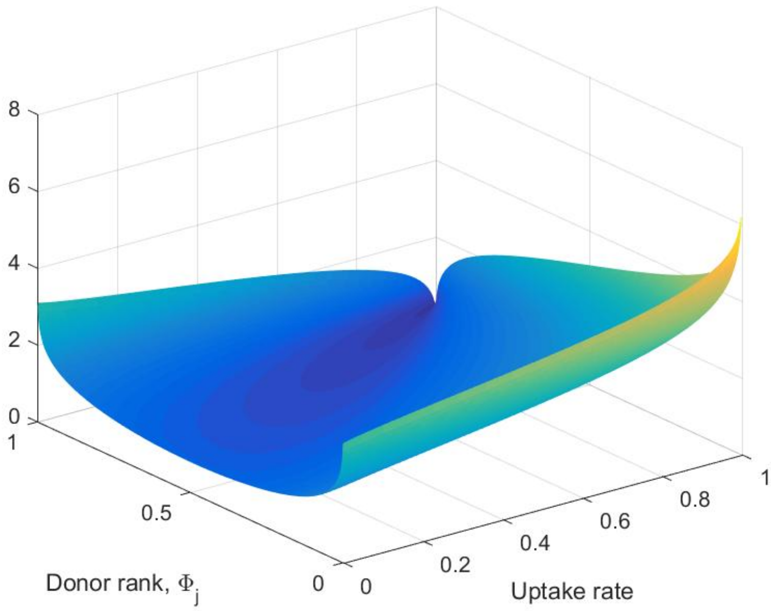


Figure 6: Expected distance by donor rank and uptake rate.

first order condition,

$$\frac{u'\left(\tau\left(\Phi_i,\widehat{\Phi}\right)\right)}{u'\left(1-pI_{\left\{\Phi_i\leq\widehat{\Phi}\right\}}-\tau\left(\Phi_i,\widehat{\Phi}\right)\right)}=\frac{1}{E\left[\alpha_i|\Phi_i,\Phi_j\geq\widehat{\Phi}\right]},\tag{10}$$

where $I_{\{\cdot\}}$ is the indicator function that is unity if the statement in brackets is true and zero otherwise. It is used here as the income of the donor is reduced from 1 to $1-p$ if she herself takes up insurance. The analytical convenience of $\tau\left(\Phi_i,\widehat{\Phi}\right)$ is that it does not depend on the location of the type-distribution. As such it characterizes the expectation of *any* individual in the economy of the transfer that would be made by *any* donor of rank $\Phi_i$ *if* the aggregate take-up rate was $\widehat{\Phi}$.

Using the fact that transfers depend on expected distance, we can further define $V^1\left(\Phi_i,\widehat{\Phi};\mu_i\right)$ as the expected utility – inclusive of caring for the partner but net of the own take-up cost – of an individual of rank $\Phi_i$ from accepting insurance when the aggregate take-up rate is $\widehat{\Phi}$ and the location of the type distribution is $\mu_i$. Similarly, we can define $V^0\left(\Phi_i,\widehat{\Phi};\mu_i\right)$ as the expected utility – again inclusive of caring – to an individual of rank $\Phi_i$ from rejecting insurance when the aggregate take-up rate is $\widehat{\Phi}$ and the location of the distribution is $\mu_i$. As the expressions for these functions involve a fairly large number of terms, their expressions have been relegated to Appendix ??. The dependence of both $V^1$ and $V^0$ on $\mu_i$ comes only from the caring for the expected take-up cost incurred by the partner. But this is independent of the own insurance choice; in particular, the expected net gain from acquiring insurance, defined as

$$V\left(\Phi_i, \widehat{\Phi}\right) \equiv V^1\left(\Phi_i, \widehat{\Phi}; \mu_i\right) - V^0\left(\Phi_i, \widehat{\Phi}; \mu_i\right), \tag{11}$$

is independent of the location $\mu_i$.

In the equilibrium anticipated by agent $i$ with location-belief $\mu_i$ there is an aggregate take-up rate $\widehat{\Phi}(\mu_i)$ with the property that an individual of rank $\widehat{\Phi}(\mu_i)$ has an expected net gain from acquiring insurance that exactly matches her take-up cost when the take-up rate is $\widehat{\Phi}(\mu_i)$. Hence it is the solution to the implicit equation,

$$V\left(\widehat{\Phi}, \widehat{\Phi}\right) - \chi\left(\Phi^{-1}\left(\widehat{\Phi}; \mu_i\right)\right) = 0. \tag{12}$$

**Definition 1.** An *anticipated equilibrium* given location-belief $\mu_i$ consists of (i) an insurance take up rate $\widehat{\Phi}(\mu_i) \in [0,1]$ that is the solution to (12) and (ii) a transfer function $\widehat{\tau}(\Phi, \mu_i) \equiv \tau\left(\Phi, \widehat{\Phi}(\mu_i)\right)$, where $\tau\left(\Phi, \widehat{\Phi}\right)$ is characterized by (10), describing the voluntary transfer made by an individual (either insured or uninsured without an income loss) of type rank $\Phi \in [0,1]$ to an uninsured partner with an income loss when the takeup rate is $\widehat{\Phi} \in [0,1]$.

For simplicity we assume that $V(0,0) > 0$.[17] The existence of an interior equilibrium $\widehat{\Phi}(\mu_i) \in (0,1)$ is then guaranteed by the fact take-up costs are very large for sufficiently high types (Assumption 4). While multiple equilibria are conceivable, this is not the focus here. Hence we assume the existence of a unique solution, which is then also locally stable.[18] As an upward shift in the location $\mu_i$ increases the $\theta$-value at every rank, it follows that an increase in $\mu_i$ is associated with a strict decrease in the anticipated take-up rate. As the perceived location $\mu_i$ is increasing in the true type $\theta_i$, the result immediately carries over to a monotonicity of the anticipated equilibrium with respect to individual type.

[17] This will always hold as long as caring is sufficiently limited: in that case the lowest type will not expect a sizeable transfer from a random partner if she remains uninsured and will hence opt to take up insurance even if no one else does so.

[18] Local stability means that $V\left(\widehat{\Phi}, \widehat{\Phi}\right) - \chi\left(\Phi^{-1}\left(\widehat{\Phi}; \mu_i\right)\right) = 0$ is strictly decreasing in $\widehat{\Phi}$ at $\widehat{\Phi}(\mu_i)$.

**Lemma 2.** *The anticipated insurance take-up rate, $\widehat{\Phi}(\mu_i)$ with $\mu_i \equiv (1-\beta)\mu + \beta\theta_i$, is, for any positive belief bias $\beta \in (0,1]$, decreasing in the individual's type $\theta_i$. In the absence of any belief bias, $\beta = 0$, all individuals anticipate the same insurance take-up rate.*

**Proof.** See Theoretical Appendix.

### The Full Equilibrium in the Insurance Regime

The anticipated equilibria vary across the individuals as they hold different beliefs about the location of the type-distribution and, as a consequence, also about the equilibrium behaviour of others. Full equilibrium in the insurance environment obtains when each individual behaves privately optimal given the behaviour that she anticipates of others.

**Definition 2. Full equilibrium in the insurance regime.** In the full equilibrium in the environment where insurance is available all individuals make insurance take-up and transfer decisions that are in accordance with their anticipated equilibria given their type-specific beliefs about the location of the type distribution.

Consider first the insurance take-up decision of an individuals of true rank $\Phi_i$. She beliefs that the location of the type distribution is $\mu_i = (1-\beta)\mu + \beta\Phi^{-1}(\Phi_i, \mu)$ and anticipates the take-up rate to be $\widehat{\Phi}(\mu_i)$. Moreover, she will take up insurance herself if and only if the rank that she perceives herself to be of, that is $\widetilde{\Phi}(\Phi_i;\beta)$, is no larger than $\widehat{\Phi}(\mu_i)$. Hence we can characterize the equilibrium insurance take-up as a function of true rank as follows,

$$z^*(\Phi_i;\beta) = \begin{cases} 1 & \text{if } \widetilde{\Phi}(\Phi_i;\beta) \leq \widehat{\Phi}\left((1-\beta)\mu + \beta\Phi^{-1}(\Phi_i,\mu)\right) \\ 0 & \text{if } \widetilde{\Phi}(\Phi_i;\beta) > \widehat{\Phi}\left((1-\beta)\mu + \beta\Phi^{-1}(\Phi_i,\mu)\right) \end{cases}. \tag{13}$$

Using that the individual's perceived rank is increasing in her true rank while her anticipated take-up rate is decreasing (Lemma 2) it follows that the full equilibrium also has a threshold property.

Proposition 1. *In the full equilibrium, given belief-bias $\beta \in [0,1]$, there will be a threshold type $\theta^*(\beta)$ such that $z^*(\Phi_i;\beta) = 1$ if $\Phi_i \leq \Phi(\theta^*(\beta);\mu)$ and $z^*(\Phi_i;\beta) = 0$ otherwise.*

**Proof.** See Theoretical Appendix.

We can further characterize the transfer made by each individual in the full equilibrium as a function of her true rank $\Phi_i$. Recall that $\tau\left(\Phi, \widehat{\Phi}\right)$, defined in (10), is the transfer that

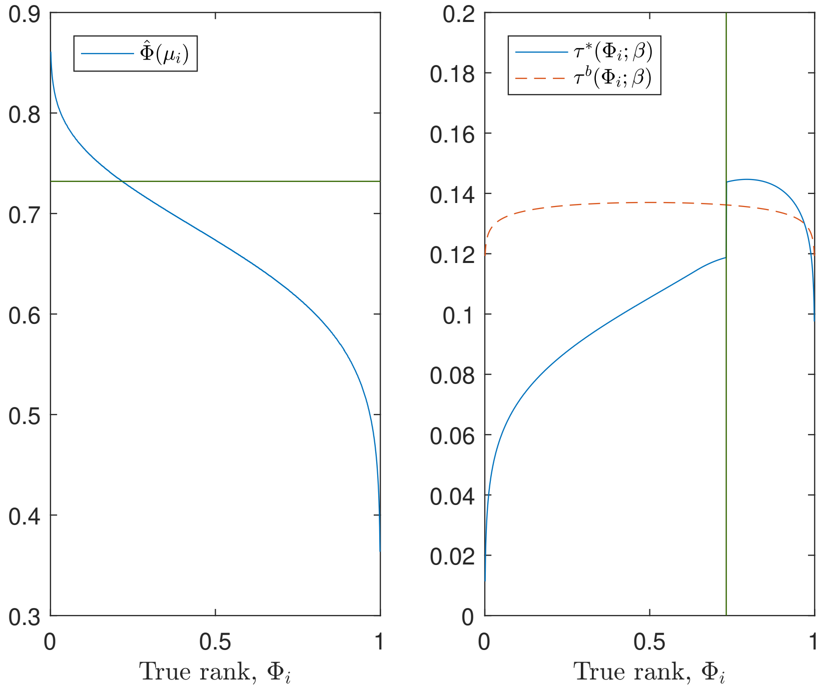


Figure 7: Anticipated take-up rates and equilibrium transfers

any individual $i$ anticipates to be made by a donor of rank $\Phi$ to an uninsured recipient when the take-up rate is $\widehat{\Phi}$. Hence $i$'s equilibrium transfer can be characterized as that expected of someone of her own perceived rank at her anticipated equilibrium takeup rate. That is,

$$\tau^* (\Phi_i; \beta) = \tau \left( \widetilde{\Phi} (\Phi_i; \beta), \widehat{\Phi} (\mu_i) \right) \text{ with } \mu_i = (1 - \beta) \mu + \beta \Phi^{-1} (\Phi_i, \mu) . \tag{14}$$

Comparison of (14) to (8) shows how the equilibrium transfers are a generalization of the transfers that would be made in the absence of insurance and hence zero take-up.

There is no general result on the relative size of the equilibrium transfer in the insurance regime $\tau^* (\Phi_i; \beta)$ and the baseline transfer $\tau^b (\Phi_i; \beta)$. This will generally vary with the individual's type. However, the model naturally predicts that low types will transfer less to partners who chose not to take up insurance than they would to the same partner had insurance not been available. This happens for two reasons. First, they transfer less due to a negative income effect as they have themselves obtained insurance and hence paid the premium $p$. But second, and more importantly, they transfer less as they have now received the information that the partner is of a relatively high type – of a rank above the donor's anticipated take-up rate – and hence the donor's caring is reduced.

To illustrate, consider the case of CARA utility, $u(c_i) = [1 - \exp(-\gamma c_i)]/\gamma$ and an exponential take-up cost function $\chi(\theta) = \nu \exp(\theta)$ where $\nu > 0$. The left panel of Figure **??** shows the anticipated take-up rate $\widehat{\Phi}(\mu_i)$ as a function of the individual's true rank when the bias parameter is $\beta = 0.5$, the true location is $\mu = -0.6$, the caring parameters are $a_0 = 0.25$ and $a_1 = 0.02$, the degree of risk aversion $\gamma = 2$, the loss risk is $p = 0.05$, and the take-up cost parameter is $\nu = 0.025$. The horizontal line indicates the full equilibrium insurance take-up rate.

The right panel illustrates the equilibrium transfers – with and without insurance available – by the donor's true rank (with the horizontal line now indicating the insurance take-up rate in the full equilibrium). The discontinuity in $\tau^*(\Phi_i; \beta)$ reflects the income effect obtaining from the fact that all individuals of true rank below the equilibrium take-up rate have obtained insurance and hence only have net income $1-p$. But the main difference is the sharp reduction of transfers made by low types due to their lower caring for their now revealed high type uninsured partners. Hence, in general, in an equilibrium with a high insurance uptake rate, the model naturally predicts that a majority of individuals will reduce their transfers to partners who rejects insurance, and the size of the transfer-reduction is larger for lower types who anticipate higher uptake rates.

### Welfare

While the model is consistent with the stylized facts from the experiment a further attractive feature is that it has well-defined and stable preferences, making it particularly suitable for welfare analysis. While a full welfare analysis goes beyond the scope of the current paper, we will here briefly discuss the likely effects of the introduction of an insurance market with a "high" equilibrium uptake rate.

The expected consumption of individuals who take up insurance can be expected to decrease – to below their expected income – as they bear the premium-cost of insuring their own income, but continue to make some positive expected transfers. However, the main effect on the insurance-takers is of course the positive effect of consumption smoothing through insurance. For the non-takers of insurance, the effects of the introduction of an insurance market is very much the opposite. Their expected income may well increase – to above their expected income – as they will rarely be making any transfers (as their partners are most commonly insured) but they still receive some transfers. However, as their mostly-insured partners reduce their transfers relative to the no-insurance setting, the increase in expected consumption may be modest and, most critically, their consumption will be less smoothed through transfers in the loss state.

As a result, while the majority of the individuals take up insurance and generally gain in terms of expected own utility of consumption, there will be a tail of the population who will fail to take up insurance and who will now face higher consumption volatility due to the general reduction of private redistributive transfers. While the impact on the welfare of this group – in terms of expected own utility of consumption – is generally ambiguous, if the reduction in private transfers is substantial, this group will be closer to autarky after the introduction of insurance and can then be expected to be worse off.[19]

## VI Conclusion

In this paper we demonstrate that the introduction of formal insurance can crowd-out redistribution because insurance decisions can reveal information to donors about potential recipients of private redistributive transfers that was not available before the introduction of insurance. To donors, this new information may allow them to place recipients in a different light, and reduce their support. In turn, this may lead to the crowding-out of private redistributive transfers. We show that, in equilibrium, the benefits of insurance availability can be very unevenly distributed, potentially making already vulnerable individuals worse off. This is important because altruistically motivated transfers play an important role in supporting individuals who suffer income losses due to risk, especially in the absence of well-functioning insurance markets that may not fully cover all relevant risks. Since emerging markets are becoming the main source of premium growth to the global insurance industry this is especially relevant to those who, due to structural heterogeneity, may face constraints to insurance adoption in these markets.

[19] Indeed, all of the above effects occur in the example above. For all types taking up insurance, expected consumption decreases, consumption variance decreases, and the expected own consumption utility increases. For all the non-takers, expected consumption increases, consumption variance increases, and the expected own consumption utility decreases.

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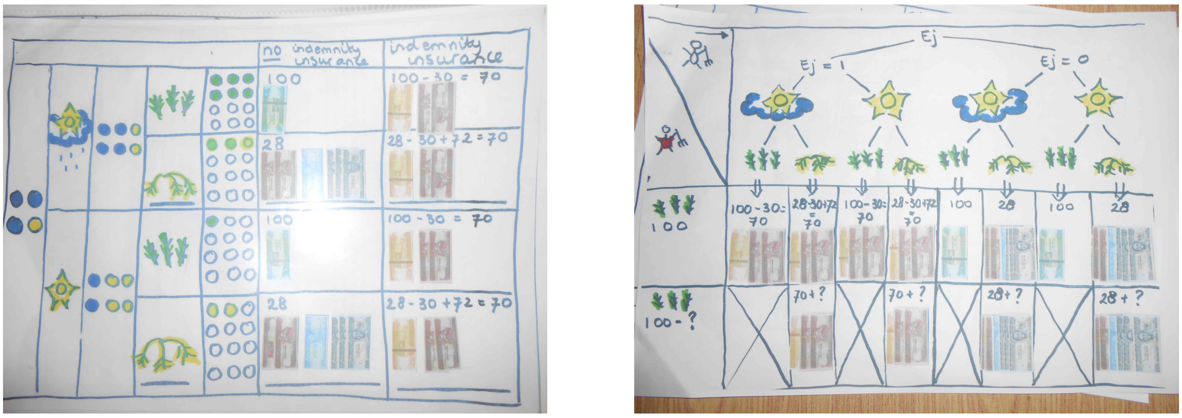


(a) (b)

Figure A.1: Game tree explained to farmers

Note: Payoffs are presented to farmers by using Ethiopian currency. (a) presents the states, probabilities, and payoffs for the insurance offer, $z_j = 0|m_j = 1$ and $z_j = 1|m_j = 1$. (b) presents the game tree as presented to farmers. Potential payoffs for the donor $i$ are presented in rows; potential payoffs for the recipient $j$ are presented in columns.

# A Appendices

## Design Appendices

## Theoretical Appendices

# B Proofs

**Proof of Lemma 1.** We note first that $\Delta(\Phi_i)$ defined in (4) is trivially U-shaped with a minimum at $\Phi_i = 1/2$ as types further away from the mean/median have a larger expected distance to a randomly allocated partner.

Next we demostrate a set of properties of the individual's perceived rank as a function of her true rank, $\widetilde{\Phi}(\Phi_i;\beta)$, defined in (5), starting with monotonicity in $\Phi_i$. To see this property, differentiate (5) with respect to $\Phi_i$ to obtain

$$\frac{\partial\widetilde{\Phi}(\Phi_i;\beta)}{\partial\Phi_i} = \left[\frac{\partial\Phi(\theta_i;\mu_i)}{\partial\theta_i} + \beta\frac{\partial\Phi(\theta_i;\mu_i)}{\partial\mu_i}\right]\frac{\partial\Phi^{-1}(\Phi_i;\mu)}{\partial\Phi_i}, \tag{A1}$$

with $\theta_i = \Phi^{-1}(\Phi_i;\mu)$ and $\mu_i = (1-\beta)\mu + \beta\Phi^{-1}(\Phi_i;\mu)$. But, naturally,

$$\frac{\partial\Phi(\theta_i;\mu_i)}{\partial\theta_i} = -\frac{\partial\Phi(\theta_i;\mu_i)}{\partial\mu_i} = \phi(\theta_i;\mu_i), \tag{A2}$$

where $\phi(\theta_i; \mu_i)$ is the normal probability density function given the mean $\mu_i$ (and unit standard deviation) evaluated at $\theta_i$. Hence, substituting, yields that

$$\frac{\partial \widetilde{\Phi}(\Phi_i; \beta)}{\partial \Phi_i} = (1-\beta)\,\phi\left(\Phi^{-1}(\Phi_i; \mu), (1-\beta)\mu + \beta\Phi^{-1}(\Phi_i; \mu)\right)\frac{\partial \Phi^{-1}(\Phi_i; \mu)}{\partial \Phi_i}. \tag{A3}$$

This shows that, for any $\beta \in (0,1)$, $\partial\widetilde{\Phi}(\Phi_i; \beta)/\partial\Phi_i > 0$ at any rank $\Phi_i$. In the limit where $\beta = 1$, $\partial\widetilde{\Phi}(\Phi_i; \beta)/\partial\Phi_i = 0$ as everyone perceives herself to be median. In the limit where $\beta = 0$, the individual's perceived mean $\mu_i$ coincides with the true mean and it follows that $\partial\widetilde{\Phi}(\Phi_i; \beta)/\partial\Phi_i = 1$ at any $\Phi_i$ as expected. We also note that the true median never misperceives her rank. This follows as evaluating (5) at $\Phi_i = 1/2$, immediately yields $\widetilde{\Phi}(1/2; \beta) = \Phi(\mu; \mu) = 1/2$ for any $\beta$ where we used that $\Phi^{-1}(1/2; \mu) = \mu$. These first two properties of the perceived rank implies that the U-shape of $\Delta(\Phi_i)$ carries over to $\Delta\left(\widetilde{\Phi}(\Phi_i; \beta)\right)$ for any $\beta \in (0,1)$.

Further, differentiating (5) with respect to $\beta$ yields that

$$\frac{\partial \widetilde{\Phi}(\Phi_i; \beta)}{\partial \beta} = -\phi(\theta_i; \mu_i)\left(\Phi^{-1}(\Phi_i; \mu) - \mu\right), \tag{A4}$$

where we used (A2) again. Since $\Phi^{-1}(\Phi_i; \mu)$ is smaller (larger) than $\mu$ when $\Phi_i < 1/2$ ($> 1/2$) it follows that $\partial\widetilde{\Phi}(\Phi_i; \beta)/\partial\beta > 0$ at any $\Phi_i < 1/2$ and $\partial\widetilde{\Phi}(\Phi_i; \beta)/\partial\beta < 0$ at any $\Phi_i > 1/2$. Hence the larger is $\beta$ the more central any type perceives herself to be and, as a consequence, she also perceives a smaller expected distance to her random partner. #

**The Expected Value Functions**

In order to characterize the expected values associated with taking up and rejecting insurance, we will need to slightly generalize the definition in (10) to allow for a specific income. Hence define $\tau\left(\Phi_i, \widehat{\Phi}; y_i\right)$ implicitly through

$$\frac{u'\left(\tau\left(\Phi_i, \widehat{\Phi}; y_i\right)\right)}{u'\left(y_i - \tau\left(\Phi_i, \widehat{\Phi}; y_i\right)\right)} = \frac{1}{E\left[\alpha_i | \Phi_i, \Phi_j \geq \widehat{\Phi}\right]}. \tag{A5}$$

This transfer can be interpreted as the voluntary transfer made by an donor of rank $\Phi_i$ and income $y_i$ to an uninsured partner $j$ when the expected take-up rate is $\widehat{\Phi}$.

We can now characterize the expected utility to an individual of rank $\Phi_i$ of accepting insurance – net of the own take up cost – when the expected take up rate is $\widehat{\Phi}$. Note that this expected utility, denoted $V^1\left(\Phi_i, \widehat{\Phi}, \mu_i\right)$, while net of the own take up cost, includes the caring for the partner,

$$
\begin{aligned}
V^1\left(\Phi_i, \widehat{\Phi}, \mu_i\right) \quad \equiv \quad & u(1-p)\left[\widehat{\Phi}+\left(1-\widehat{\Phi}\right)(1-p)\right] \\
& +u\left(1-p-\tau\left(\Phi_i, \widehat{\Phi}, 1-p\right)\right)\left(1-\widehat{\Phi}\right) p \\
& +\widehat{\Phi} u(1-p) E\left[\alpha_i | \Phi_i, \Phi_j \leq \widehat{\Phi}\right] \\
& +\left(1-\widehat{\Phi}\right)\left\{(1-p) u(1)+p u\left(\tau\left(\Phi_i, \widehat{\Phi}, 1-p\right)\right)\right\} E\left[\alpha_i | \Phi_i, \Phi_j>\widehat{\Phi}\right] \\
& -.\widehat{\Phi} E\left[\alpha_i \chi\left(\theta_j\right) | \Phi_i, \Phi_j \leq \widehat{\Phi}, \mu_i\right].
\end{aligned} \tag{A6}
$$

The first two terms capture the expected own utility from consumption. The following two terms, in contrast, captures the caring for the consumption utility of the partner. The former of the two terms is for the case where the partner $j$ takes up insurance. In this case, while $j$'s consumption is certain, $i$ does not know the exact identity of $j$ and hence holds an expectation over her own caring conditional on the fact that $j$ took up insurance. The fouth term captures the case where $j$ does not take up insurance, with two subcases: either $j$ does not have an income loss and thus enjoys the full unit income, or she does have an income loss, in which case $j$'s consumption is given by $i$'s transfer. Both these consumption levels are known to $i$, but again $i$ does not know $j$'s identity and thus holds an expectation over her own caring conditional on the fact that $j$ did not take up insurance. The final component captures $i$'s caring for the take-up cost incurred by $j$. Note that this final term is the only term where $\mu_i$ matters.

In a corresponding way, we can characterize the expected utility to an individual of rank $\Phi_i$ of rejecting insurance when the expected take-up rate is $\widehat{\Phi}$, denoted $V^0\left(\Phi_i, \widehat{\Phi}, \mu_i\right)$. The expression in this case is slightly more involved for two reasons. First, there is a larger set of possible outcomes to consider. Second, as $i$ may in this case receive a transfer from $j$ whose identity is not known to $i$, making the size of the transfer uncertain to $i$. Taking all possible outcomes into account, gives that

$$
\begin{aligned}
V^0\left(\Phi_i,\widehat{\Phi},\mu_i\right) \equiv\ & (1-p)\left[\widehat{\Phi}+\left(1-\widehat{\Phi}\right)(1-p)\right]u(1) \\
&+\left(1-\widehat{\Phi}\right)p^2u(0)+p\widehat{\Phi}E\left[u\left(\tau\left(\Phi_j,\widehat{\Phi},1-p\right)\right)|\Phi_j\leq\widehat{\Phi}\right] \\
&+\left(1-\widehat{\Phi}\right)p(1-p)\left\{E\left[u\left(\tau\left(\Phi_j,\widehat{\Phi},1\right)\right)|\Phi_j>\widehat{\Phi}\right]+u\left(1-\tau\left(\Phi_i,\widehat{\Phi},1\right)\right)\right\} \\
&+\widehat{\Phi}(1-p)u(1-p)E\left[\alpha_i|\Phi_i,\Phi_j\leq\widehat{\Phi}\right] \\
&+\left(1-\widehat{\Phi}\right)\left\{p^2u(0)+(1-p)^2u(1)\right\}E\left[\alpha_i|\Phi_i,\Phi_j>\widehat{\Phi}\right] \\
&+\widehat{\Phi}pE\left[\alpha_iu\left(1-p-\tau\left(\theta_j,\widehat{\Phi},1-p\right)\right)|\Phi_i,\Phi_j\leq\widehat{\Phi}\right] \qquad \text{(A7)} \\
&+\left(1-\widehat{\Phi}\right)p(1-p)\left\{\begin{array}{c} E\left[\alpha_iu\left(1-\tau\left(\Phi_j,\widehat{\Phi},1\right)\right)|\Phi_i,\Phi_j>\widehat{\Phi}\right] \\ +u\left(\tau\left(\Phi_i,\widehat{\Phi},1\right)\right)E\left[\alpha_i|\Phi_i,\Phi_j>\widehat{\Phi}\right]\end{array}\right\} \\
&-\widehat{\Phi}E\left[\alpha_i\chi(\theta_j)|\Phi_i,\Phi_j\leq\widehat{\Phi},\mu_i\right].
\end{aligned}
$$

The first three terms captures the expected own utility from consumption while the following four captures the caring for the partner's utility from consumption. The final term – which is identical to the final term in equation (A6) – again captures $i$'s caring for the partner's incurred take-up cost and is the only term where $\mu_i$ matters. #

**Proof of 2**. Immediate from comparative statics on (12) and using local stability. #

**Proof of Proposition 1**. The proof of Lemma 1 shows that $\widetilde{\Phi}(\Phi_i;\beta)$ is strictly increasing in $\Phi_i$ for any $\beta\in[0,1)$, and we also know that $\widetilde{\Phi}(\Phi_i;\beta)=1/2$ for all $\Phi_i$ at $\beta=1$ as, with complete bias, all individuals believe that they are median in the distribution. Hence $\widetilde{\Phi}(\Phi_i;\beta)$ is strictly decreasing in $\Phi_i$ for all $\beta\in[0,1)$ and independent of $\Phi_i$ if $\beta=1$. Lemma 2 shows that $\widehat{\Phi}(\mu_i)$ is strictly decreasing in $\mu_i$, and hence also in $\Phi_i$, for any $\beta\in(0,1]$ and independent of $\Phi_i$ if $\beta=0$. Hence it follows that $\widetilde{\Phi}(\Phi_i;\beta)-\widehat{\Phi}\left((1-\beta)\mu+\beta\Phi^{-1}(\Phi_i;\mu)\right)$ is strictly decreasing in $\Phi_i$ for any $\beta\in[0,1]$. #

Table A.1: Ordered Lottery Selection Design

| choice | prospect | expected payoff | risk aversion class | risk aversion range |
|---|---|---|---|---|
| 5 | (40, p=0.5; 40) | 40 | extreme | ($+\infty$; 7.51) |
| 4 | (75, p=0.5; 35) | 55 | severe | (7.51; 1.74) |
| 3 | (90, p=0.5; 30) | 60 | intermediate | (1.74; 0.81) |
| 2 | (120, p=0.5; 20) | 70 | moderate | (0.81; 0.32) |
| 1 | (150, p=0.5; 10) | 80 | slight-neutral | (0.32; 0.00) |
| 0 | (160, p=0.5; 0) | 80 | neutral-negative | (0.00; $-\infty$) |

Note: To assess subjects' risk preferences farmers played an incentivised ordered lottery selection experiment adopted from Binswanger (1981). In this experiment subjects were asked to make a choice between six lotteries in the gain domain, with a fixed probability of 1/2. The values are in Ethiopian Birr. The available choices, denoted $\{0, ..., 5\}$, correspond to increasing levels of risk aversion, starting at risk neutrality (0) and going to extreme risk aversion (5). The risk aversion range is calculated based on Constant Relative Risk Aversion (CRRA) preferences and expected utility theory.

Table A.2: Regression of risk aversion on covariates

| | **Coefficient** | **Robust standard error** |
|---|---|---|
| Age in years | 0.006 | 0.008 |
| Literate | 0.098 | 0.309 |
| Education | -0.042 | 0.132 |
| Female | 0.071 | 0.474 |
| Married | -0.674 | 0.498 |
| Number of adults in household | 0.038 | 0.101 |
| Number of children in household | -0.148 | 0.055 |
| Tropical Livestock Units | -0.016 | 0.024 |
| Land size in Tsemdi | -0.137 | 0.067 |
| Farm land irrigated | -0.638 | 0.423 |
| Probability of loss own farm $25-50\%$ | -0.045 | 0.191 |

Note: OLS regressions of Riskaversion on covariates with clustering of standard errors at the session level. N=222 (and not 378) because the ordered lottery selection to elicit risk preferences was not conducted for the first 7 sessions. Column 2 presents the coefficient for the effect of the covariate on risk aversion. Column 3 presents the robust standard error. Significance levels $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

Table A.3: Regression of transfers on covariates

| | **Coefficient** | **Robust standard error** |
|---|---|---|
| Age in years | 0.001 | 0.049 |
| Literate | -1.607 | 0.967 |
| Education | -0.449 | 0.417 |
| Female | 1.032 | 1.652 |
| Married | 0.261 | 1.115 |
| Number of adults in household | 0.188 | 0.443 |
| Number of children in household | 0.199 | 0.372 |
| Tropical Livestock Units | 0.099 | 0.203 |
| Land size in Tsemdi | 0.884 | 0.435* |
| Farm land irrigated | -1.656 | 1.477 |
| Probability of loss own farm $25 - 50\%$ | 0.099 | 0.697 |
| Risk aversion | -0.272 | 0.471 |

Note: OLS regressions of transfers in the condition where no insurance was offered ($m_j = 0$) on covariates with clustering of standard errors at the session level. N=189 except for risk aversion (N=117) because the ordered lottery selection to elicit risk preferences was not conducted for the first 7 sessions. Column 2 presents the coefficient for the regression of the covariate on risk aversion. Column 3 presents the robust standard error. Significance levels $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

Table A.4: Transfers when recipient does not receive an insurance offer.

| | no bin (1) | bins of 5 (2) | bins of 10 (3) |
|---|---|---|---|
| 0 | 21 (11.1) | 21 (11.1) | 21 (11.1) |
| 4 | 1 (11.6) | | |
| 5 | 20 (22.2) | 21 (22.2) | |
| 10 | 56 (51.9) | 56 (51.9) | 89 (58.2) |
| 15 | 12 (58.2) | 12 (58.2) | |
| 18 | 8 (62.4) | | |
| 20 | 29 (77.8) | 39 (78.8) | 45 (82.0) |
| 22 | 2 (78.8) | | |
| 25 | 6 (82.0) | 6 (82.0) | |
| 28 | 2 (83.1) | | |
| 30 | 29 (98.4) | 32 (98.9) | 34 (100.0) |
| 31 | 1 (98.9) | | |
| 35 | 2 (100) | 2 (100) | |

Note: N=189. Column (1) presents the raw data. Column (2) and Column (3) show the transfer data binned at intervals of 5 and 10 ETB.

Table A.5: Transfers when recipient rejects insurance

| | no bin (1) | bins of 5 (2) | bins of 10 (3) |
|---|---|---|---|
| 0 | 96 (25.0) | 96 (25.0) | 96 (25.0) |
| 1 | 2 (25.5) | | |
| 3 | 2 (26.0) | | |
| 4 | 1 (26.3) | | |
| 5 | 27 (33.3) | 32 (33.3) | |
| 10 | 80 (54.2) | 82 (54.7) | 135 (60.2)) |
| 12 | 2 (54.7) | | |
| 15 | 21 (60.2) | 21 (60.2) | |
| 18 | 6 (61.7) | | |
| 20 | 56 (76.3) | 62 (76.3) | 80 (81.0) |
| 25 | 18 (81.0) | 19 (81.3) | |
| 26 | 1 (81.3) | | |
| 28 | 5 (82.6) | | |
| 30 | 63 (99.0) | 70 (99.48) | 71 (99.5) |
| 31 | 1 (99.2) | | |
| 32 | 1 (99.5) | | |
| 35 | | 1 (99.7) | |
| 36 | 1 (99.7) | | |
| 38 | 1 (100) | | |
| 40 | | 1 (100) | 2 (100.0) |

Note: N=189. Column (1) presents the raw data. Column (2) and Column (3) show the transfer data binned at intervals of 5 and 10 ETB.

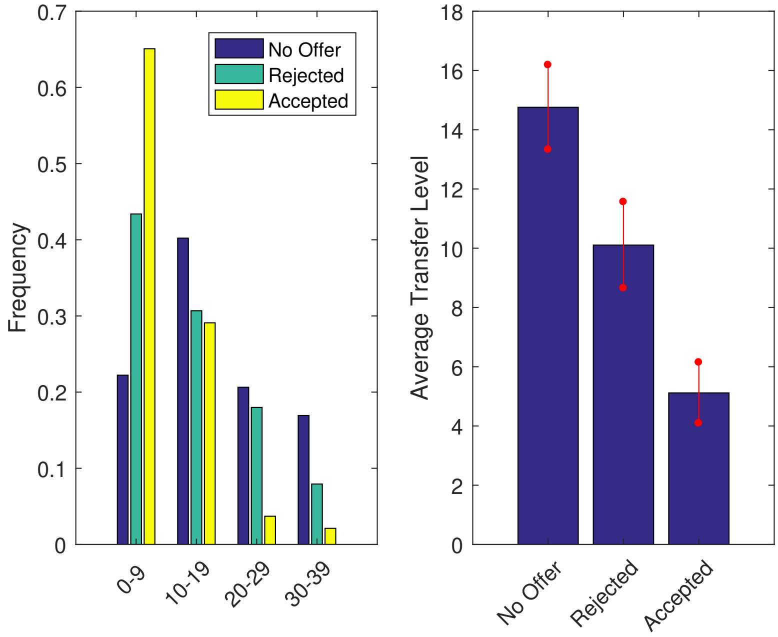


Figure A.2: Mean and confidence intervals of donor's transfers per treatment condition

Note: N=189. The left panel presents the frequency of transfers for the different treatment conditions at bins of 10ETB. The right panel shows the mean of transfers and the 95% confidence intervals. The left bar corresponds to the no insurance offer, $m_j$. The recipient has an outcome before transfers of 28 ETB. The middle bar corresponds to the condition where the recipient received an offer but did not take-up insurance, $z_j = 0|m_j = 1$. The recipient also had an outcome of 28 ETB before transfers. The bar on the right represents transfers by the donor for the case where the recipient did take insurance, $z_j = 1|m_j = 1$. The outcome of the recipient before transfers was 70 ETB in this case.

Table A.6: Transfers when recipient accepts insurance

| | no bin (1) | bins of 5 (2) | bins of 10 (3) |
|---|---|---|---|
| 0 | 194 (50.5) | 194 (50.52) | 194 (50.5) |
| 2 | 3 (51.3) | | |
| 3 | 1 (51.6) | | |
| 5 | 39 (61.8) | 44 (62.0) | |
| 7 | 1 (62.0) | | |
| 10 | 93 (86.2) | 93 (86.2) | 162 (92.7) |
| 15 | 25 (92.7) | 25 (92.7) | |
| 18 | 1 (92.97) | | |
| 20 | 11 (95.8) | 12 (95.8) | 15 (96.6) |
| 25 | 3 (96.6) | 3 (96.6) | |
| 28 | 2 (97.1) | | |
| 30 | 11 (100) | 13 (100.0) | 13 (100.0) |

Note: N=189. Column (1) presents the raw data. Column (2) and Column (3) show the transfer data binned at intervals of 5 and 10 ETB.

## Descriptives Appendices

## Results Appendices

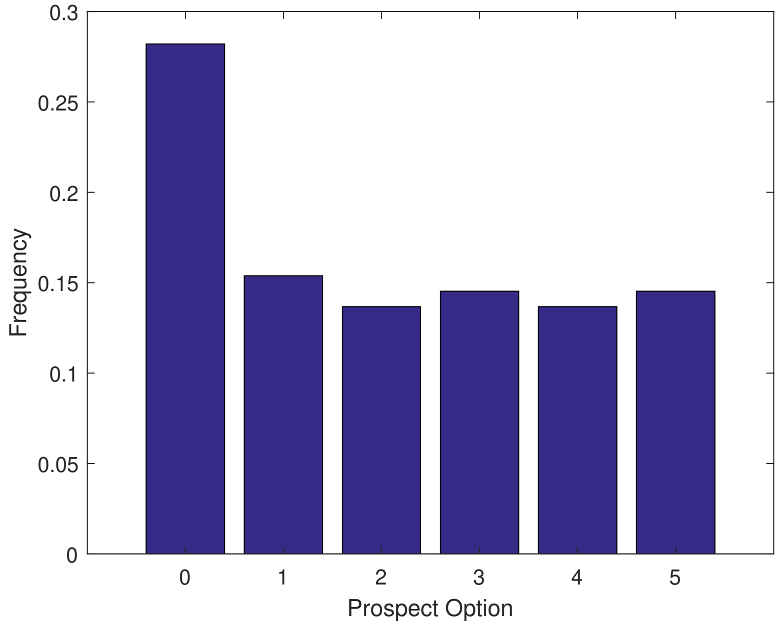


Figure A.3: Risk preferences: Ordered Lottery Selection

Note: Prospects in histogram correspond to prospects in Table 1 with 0 being risk neutral and 5 being most risk averse

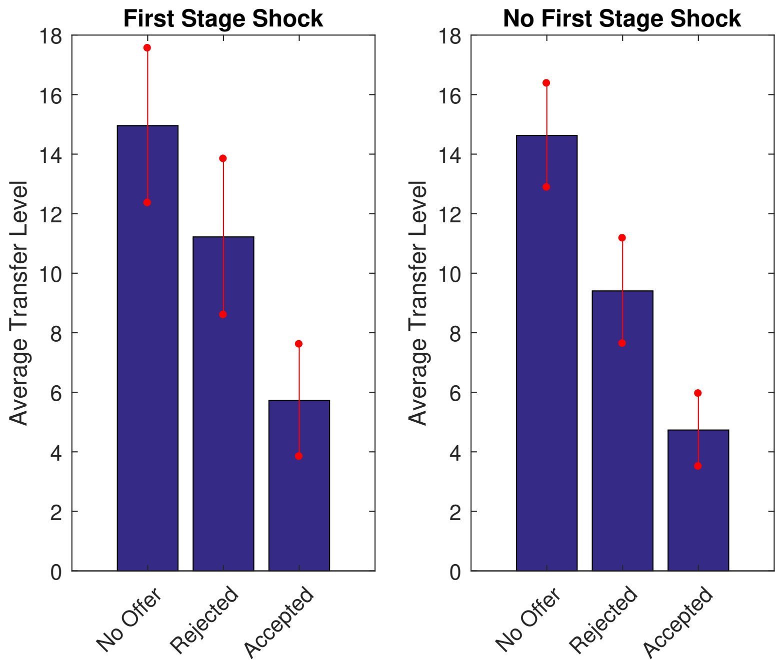


Figure A.4: Mean and confidence intervals of donor's transfers per condition by first-stage shock

Note: N=189. Transfers by donors in each treatment condition split by the occurence of the first stage shock, $f_j$. The left panel shows transfers for each treatment condition for the case when the first-stage shock did occur, the right panel for the case when the first-stage shock did not occur. For each panel, the left bar represents mean and confidence intervals of transfers when the recipient received no insurance offer, $m_j$, and has an outcome before transfers of 28 ETB. The middle bar represents transfers for the condition where the recipient received an offer but did not take-up insurance, $z_j = 0|m_j = 1$. The recipient also had an outcome of 28 ETB before transfers. The bar on the right represents transfers by the donor for the case where the recipient did take insurance, $z_j = 1|m_j = 1$. The outcome of the recipient before transfers was 70 ETB in this case.

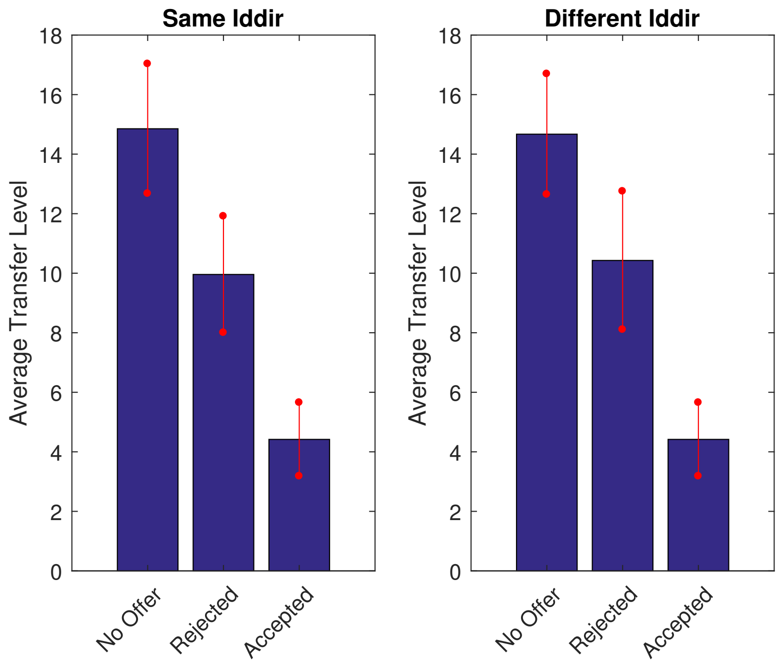


Figure A.5: Mean and confidence intervals of donor's transfers by identity of recipient

Note: N=189. Transfers by donors in each treatment condition split by the identity of the recipient. The left panel represents transfers for the case where the recipient is from the same Iddir as the donor; the right panel represents transfers for the case where the recipient is from a different Iddir. In each panel, the left bar represents mean and confidence intervals of transfers when the recipient received no insurance offer, $m_j$, and has an outcome before transfers of 28 ETB. The middle bar represents transfers for the condition where the recipient received an offer but did not take-up insurance, $z_j = 0|m_j = 1$. The recipient also had an outcome of 28 ETB before transfers. The bar on the right represents transfers by the donor for the case where the recipient did take insurance, $z_j = 1|m_j = 1$. The outcome of the recipient before transfers was 70 ETB in this case.

Table A.7: Effect of treatment on (relative) transfers interacted donor's risk aversion

| | (1) | (2) |
|---|---|---|
| $m_j = 0$ (cons) | 16.15(0.53) | 1.00(0.02) |
| $z_j = 0 \mid m_j = 1$ | -2.42(1.52) | -0.10(0.11) |
| $z_j = 1 \mid m_j = 1$ | -8.54(1.95)*** | -0.45(0.09)*** |
| | | |
| Risk aversion$\times$ $z_j = 0 \mid m_j = 1$ | -1.20(0.66)** | -0.08(0.03)*** |
| Risk aversion$\times$ $z_j = 1 \mid m_j = 1$ | -1.18(0.58)** | -0.09(0.02)*** |
| n | 351 | 351 |
| Subjects | 117 | 117 |

Note: N=189. Fixed effects regressions. Standard errors are clustered at the individual level. Risk aversion consists of 6 categories from 0-5 with zero being risk neutral and 5 being most risk averse, corresponding to the categories in Table A.1 in Appendix B. In Column (1) the dependent variable is the amount of transfers in ETB.[a] In Column (2) the dependent variable is the relative transfer as a proportion of the transfer in the benchmark condition, $m_j = 0$.[b] Significance levels $p < 0.10^{*}$, $p < 0.05^{**}$, $p < 0.01^{***}$.

[a]The specification of this regressions is: $\tau_{it} = \alpha + \beta_1 T_{it}^{z_j=0} + \beta_2 T_{it}^{z_j=1} + \rho X_{it} + \gamma_1 X_{it} \times T_{it}^{z_j=0} + \gamma_2 X_{it} \times T_{it}^{z_j=1} + \mu_i + \epsilon_{it}$, where $X$ is "riskaversion".

[b]The specification of this regression is $\frac{\tau_{it}^{z_j} - \tau_{it}^{b}}{\tau_{it}^{b}} = \alpha + \beta_1 T_{it}^{z_j=0} + \beta_2 T_{it}^{z_j=1} + \rho X_{it} + \gamma_1 X_{it} \times T_{it}^{z_j=0} + \gamma_2 X_{it} \times T_{it}^{z_j=1} + \mu_i + \epsilon_{it}$, where again $X$ is "riskaversion".