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.

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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, resulting in the crowding out of private redistributive transfers. In contexts where individuals face private constraints to adopting financial products, for example due to a lack of liquidity or low levels of financial literacy (Casaburi and Willis, 2018; Ambuehl et al., 2018), the introduction of insurance and subsequent crowding-out of redistribution, may 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 conduct an experiment involving farmers in rural Ethiopia and we develop a simple altruism-based theory. The empirical results and the theory show that the introduction of insurance can lead to the crowding-out of altruistically motivated transfers to recipients who fail to take-up insurance. This in turn implies that the benefits of insurance availability can be very unevenly distributed and some already vulnerable households are made 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 redistribution – defined for our purposes as private voluntary non-reciprocal redistributive transfers – has not yet been investigated. The crowding out of redistribution is particularly important in contexts where insurance is part of
policy to combat poverty or vulnerability (e.g. US social insurance programme Medicare), 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.

We conduct artefactual field experiments with farmers from rural communities in Ethiopia who are randomly and anonymously paired with another participant, drawn either from their own community or 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 baseline 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 this offer. In the baseline 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 experienced a loss’ and the case where ‘the recipient did not purchase insurance and experienced a loss’. 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 baseline and the treatment arm, allowing transfers in the different arms to be compared while controlling for individual and pair-specific characteristics. This enables us to understand how decisions by recipients 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. 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 that shared norms modify transfer behaviour (Bohnet and Frey, 1999). The chosen population — Ethiopian farmers — is suitable for the current study as redistributive transfers to support peers who suffer income losses are prevalent in their communities and these farmers have not yet been exposed to formal insurance that protects against risk. We find that donors transfer less to recipients when the latter reject insurance compared to when they are not offered any insurance. Second, we find

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1 Preventing ex-ante fairness concerns from explaining differences in transfers (Brock et al., 2013; Krawczyk and Le Lee, 2016)
that the donor’s transfer-reduction response to non-take-up by recipients is larger for donors who hold a stronger belief that the recipient would take up insurance if offered. Relatedly, we find that the predictors of insurance take-up by recipients and the predictors of the donor’s beliefs about take-up are similar. This suggests that donor types who themselves would have been more likely to take up insurance tend to reduce their transfers relatively more in response to non-take-up by recipients. Finally, there are no significant differences between transfers made to recipients from the donor’s own community and recipients from different communities.

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 also 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 population 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 well the stylized facts from the experiment. In particular, the core assumptions of the model are:

(i) That there is heterogeneity in the local population; an individual’s type is private information and high types have a high cost of taking up insurance.

(ii) Each individual engages with another anonymous member (“partner”) drawn randomly from the local population. All individuals are altruistic towards their anonymous partners, but more strongly so towards closer types.

(iii) A false consensus bias implies that all individuals believe the type distribution to be closer to themselves than it actually is.
When insurance is offered, each individual observes the partner’s take-up decision.

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 a 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, that is based on well-defined and stable preferences.

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 an individual perceives between herself and her partner based on the information available to her. 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 deduce social distance between them and the recipient.
This paper contributes to a literature on crowding-out of private transfers in the case of idiosyncratic economic losses. For our purposes we define crowding-out as the process by which a third-party mechanism diminishes 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 Rios-Rull, 2000; Albarran and Attanasio, 2003; Mobarak and Rosenzweig, 2012; Dercon et al., 2014). In this literature these private transfers are either part of enforceable contractual arrangements or occur as a result of self-enforceable contracts. The latter are sustained by the threat of exclusion from the informal arrangement whereby individuals remain in an autarkic equilibrium in which they will be unable to smooth their consumption in the future. Hence, these kind of informal risk sharing arrangements rely on reciprocal transfers. This literature shows that if the 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. 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

For the field experiment, 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.

In each farming community and per *Iddir* one or two sessions were played with between 20-24 farmers (18 sessions in total). The sessions were organised in buildings that would typically be used by local farmer associations to hold meetings, and were at walking distance for the farmers. Farmers were seated in private portable cubicles that were placed inside the buildings for a maximum period of three hours. In these sessions the farmers received the instructions for the experiment at the group level. Per session, farmers were anonymously and randomly teamed-up in two person groups leading to 189 pairs. 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.
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 donor i was provided with a certain income of \( y_i = 100 \) ETB. In contrast, the income for each recipient j was uncertain as they faced an individual risk of a negative income shock, \( s_j \in \{0, 1\} \). A negative income shock, \( s_j = 1 \), would occur with probability \( p = 5/12 \) and the recipient’s income would then be reduced by 72 ETB. 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 “crop loss” realization \( s_j \) was simulated using 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 the probability of an individual loss for recipient \( j \) was

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

**Insurance offers**

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 baseline condition of the experiment or the treatment condition. In the baseline condition the recipient received no insurance offer and her income \( y_j \) would hence be either 28 or 100 with

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2In 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.
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 baseline 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) 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: The income generating process for the recipient

Note: Where nature moves, 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 $j$ receives an insurance offer ($m_j = 1$) or not ($m_j = 0$). If offered insurance, the recipient then decides whether to accept ($z_j = 1$) or reject ($z_j = 0$) the offer. Nature then generates the recipient’s income loss/no-loss state in a two-stage process. In the first stage – representing weather – a “drought” ($f_j = 1$) occurs with probability 1/4 whereas “rainfall” ($f_j = 0$) occurs with probability 3/4. In the second stage, the actual crop realization is drawn with a weather-contingent probability. In the case of drought, the probability of a crop loss was $Pr(s_j = 1|f_j = 1) = 2/3$ whereas in the case of rainfall the probability of a crop loss was $Pr(s_j = 1|f_j = 0) = 1/3$. If the recipient was uninsured – either due to not having received an insurance offer ($m_j = 0$) or due to having rejected it ($m_j = 1$ but $z_j = 0$) – her payoff in the loss state ($s_j = 1$) is 28 whereas her payoff is 100 in the no-loss state ($s_j = 0$). If she is insured ($m_j = 1$ and $z_j = 0$) her payoff is 70 irrespective of the realized state.
Transfers by donors

Without knowing if $j$ received an insurance offer and, if she did, what her take-up decision was, the donor $i$ was asked to specify three strategic conditional transfers (strategy method: see: (Selten, 1967; Brandts and Charness, 2011)), $\tau^b_i$, $\tau^0_i$ and $\tau^1_i$, each paid to $j$ conditional on $j$ experiencing an income loss $s_j = 1$, but differing with respect to the insurance offer and decision. The first transfer, $\tau^b_i$, would be made in the baseline case where $j$ was not offered any insurance, $m_j = 0$. The second transfer $\tau^0_i$ would be made in the event that $j$ was offered insurance but opted not to take it up $z_j = 0$, and finally $\tau^1_i$ would be made in the event that $j$ was offered insurance and took it up $z_j = 1$. We will hence refer to the three conditions as the “baseline”, “rejected insurance” and “accepted insurance” condition respectively.

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 as show in Figure A.1 in Appendix A. 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. 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.

III Descriptives

Sample characteristics

Table 1 shows measures of key demographic and farm characteristics elicited for the baseline sample of donors and recipients. All individual and farm characteristics, except for the number of adults in the household and the farmer’s frequency of experiencing 25 − 50% crop loss are balanced across donors and recipients. Out of all respondents 39% were female. All were farmers who owned on average 3.8 units of livestock and 0.61 hectares of farm land. Only 24% had access to irrigation. 46% of the farmers were literate, and 55% received no education.

3The 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 make a 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.
making it likely that a substantial fraction of the respondents is insufficiently financially literate to fully comprehend the details of an insurance product. The 25-50% crop loss probability was on average 21%. This was elicited by asking *How many years out of the last ten years did you experience 25 – 50% crop loss?*.

To assess subjects’ risk preferences farmers played a simple incentivised ordered lottery selection experiment adopted from Binswanger (1981). Subjects were asked to make a choice between six lotteries, with a fixed probability of 1/2, in the gain domain. The available options, denoted \{0, ..., 5\}, correspond to increasing levels of risk aversion, starting at risk neutrality (0) and going to extreme risk aversion (5). For simplicity, we will use this measure in its original discrete ordered form and refer to simply as “risk aversion”. Further details are provided in Appendix A.

All subjects in the sample are a member of at least one *Iddir*. 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.

**Actual and expected insurance take-up behaviour**

Out of all 189 recipients 49% (94 recipients) received an insurance offer \( m_j = 1 \) and out of those 91% decided to take up the insurance, \( z_j = 1 \). Donors’ beliefs about insurance take-up by the paired recipient were also elicited. To measure this belief each donor was asked: *How likely do you think it is that the recipient chose to take-up insurance if 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 \( b_i \in \{0, 1, ..., 10\} \) is presented in Figure 2.

We will use that the scaled version of \( b_i \) – after dividing by 10 – falls in the unit interval and represents an increasing belief about uptake by the recipient. Hence we will refer to
Table 1: Descriptives and balancing test

<table>
<thead>
<tr>
<th>Demographics</th>
<th>All</th>
<th>Recipient</th>
<th>Dictator</th>
<th>t-test</th>
<th>N(All)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Female</strong></td>
<td>0.39</td>
<td>0.40</td>
<td>0.39</td>
<td>0.15</td>
<td>365</td>
</tr>
<tr>
<td><strong>Age in years</strong></td>
<td>43.08</td>
<td>42.11</td>
<td>44.04</td>
<td>-1.56</td>
<td>365</td>
</tr>
<tr>
<td><strong>Married</strong></td>
<td>0.81</td>
<td>0.82</td>
<td>0.80</td>
<td>0.64</td>
<td>365</td>
</tr>
<tr>
<td><strong>Number of adults in household</strong></td>
<td>2.11</td>
<td>1.71</td>
<td>2.51</td>
<td>-4.84***</td>
<td>365</td>
</tr>
<tr>
<td><strong>Number of children in household</strong></td>
<td>3.17</td>
<td>3.28</td>
<td>3.07</td>
<td>1.25</td>
<td>365</td>
</tr>
<tr>
<td><strong>Literate</strong></td>
<td>0.46</td>
<td>0.48</td>
<td>0.43</td>
<td>0.99</td>
<td>365</td>
</tr>
<tr>
<td><strong>Education</strong></td>
<td>1.89</td>
<td>1.97</td>
<td>1.81</td>
<td>1.09</td>
<td>356</td>
</tr>
<tr>
<td><strong>No education</strong></td>
<td>0.55</td>
<td>0.53</td>
<td>0.57</td>
<td>-0.73</td>
<td>356</td>
</tr>
<tr>
<td><strong>Primary complete</strong></td>
<td>0.33</td>
<td>0.34</td>
<td>0.31</td>
<td>0.52</td>
<td>356</td>
</tr>
<tr>
<td><strong>Secondary or more</strong></td>
<td>0.12</td>
<td>0.13</td>
<td>0.12</td>
<td>0.36</td>
<td>356</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Farm characteristics</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Farmer</strong></td>
<td>1.00</td>
<td>0.99</td>
<td>1.00</td>
<td>-1.00</td>
<td>362</td>
</tr>
<tr>
<td><strong>Tropical Livestock Units</strong></td>
<td>3.78</td>
<td>3.91</td>
<td>3.66</td>
<td>0.66</td>
<td>365</td>
</tr>
<tr>
<td><strong>Land size in Tsemdi</strong></td>
<td>2.44</td>
<td>2.45</td>
<td>2.43</td>
<td>0.10</td>
<td>376</td>
</tr>
<tr>
<td><strong>Farm land irrigated</strong></td>
<td>0.24</td>
<td>0.25</td>
<td>0.22</td>
<td>0.52</td>
<td>365</td>
</tr>
<tr>
<td><strong>Probability of loss own farm 25 – 50%</strong></td>
<td>0.21</td>
<td>0.23</td>
<td>0.20</td>
<td>1.96*</td>
<td>365</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Risk attitudes</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Riskaversion</strong></td>
<td>3.00</td>
<td>3.20</td>
<td>2.83</td>
<td>1.50</td>
<td>224</td>
</tr>
</tbody>
</table>

Note: “Education” is a categorical variable from “0” to “8” with “0” being no education, and “8” being university. “Tropical Livestock Units (TLU)” is a weighted count of the number of livestock. One “Tsemdi” is 0.25 hectares. “Probability of experiencing 25 – 50% crop loss” reports the answer to the question *How many years out of the last ten years did you experience 25 – 50% crop loss?*, divided by ten. “Risk aversion” is a categorical variable from “0” to “5” with “0” being risk neutral and “5” being the most risk averse (See Appendix A for further details). Lower sample sizes reflect that observations for that variable are missing. Risk aversion has a reduced number of observation because the ordered lottery selection experiment used to elicit risk preferences was not conducted for the first 7 out of 18 sessions. Columns 2 and 3 give the means for the “recipients” and the “donors” respectively. 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. Significance levels $p < 0.10^*$, $p < 0.05^{**}$, $p < 0.01^{***}$. 

12
Belief Category

0
0.05
0.1
0.15
0.2
0.25
0.3
Frequency

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

Note: Donors were asked for their belief about how likely it was that recipient with whom they were randomly and anonymously paired would take up insurance if offered. Responses were in 11 categories, \( b_i \in \{0, 1, 2, ..., 10\} \), with 0 representing “highly unlikely” to 10 representing “highly likely”. The figure depicts the distribution of reported beliefs among the 189 donors.
$b_j/10$ as measuring donor $i$’s belief about the insurance uptake decision $z_j$ of her randomly and anonymously allocated partner (if offered), and denote this $E_i[z_j|m_j = 1]$.

Table 2 presents regressions of both the binary insurance take-up decision by the recipient (column 1) as well as the donor’s belief about take-up (column 2) on individual demographic and farm characteristics. Literacy, education, 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. Literacy, education, probability of loss, and irrigation of farm land 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. Since uptake is a binary indicator variable, while the belief variable falls in the unit interval, the coefficients are in principle comparable in size.\(^4\) We also run a squareroot LASSO with all demographics and farm characteristics as potential predictors of the recipient’s take-up decision and donor’s belief about the take-up decision by the recipient respectively. For the recipient’s take-up decision the squareroot LASSO selects “Married”, “Number of adults in household”, “TLU”, “Farm land irrigated”, and “Probability of loss own farm 25-50%” as significant predictors. For the donor’s belief about the take-up decision by the recipient the square root LASSO selects “Literate”, “Number of adults in household”, “Farm land irrigated”, and “Probability of loss own farm 25-50%” as significant predictors.

The most striking finding from these results is that there is a strong overlap both in terms of sign and magnitude of the covariates that are significantly correlated with both the recipient’s actual take-up decision and the donor’s belief about the take-up decision by their randomly and anonymously allocated recipient partner. These findings are strongly suggestive of a fundamental heterogeneity in the population that drives not only individual insurance uptake behaviour but crucially also an individual’s expectation of uptake behaviour of others. The heterogeneity appears to relate to fundamental individual characteristics reflected in education/literacy and, possibly also, susceptibility to risk. In contrast, there is no discernible relationship between risk aversion on the one hand and either insurance take-up or beliefs about take-up on the other. This similarity suggests that with a lack of information about specific characteristics of the recipients they are teamed-up with, donors seem to believe that the characteristics that drive their own insurance decision are the same characteristics that drive the recipients’ insurance

\(^4\)We refrain, however, from testing formally for equality of coefficients. The outcome variables have a different nature, one is binary, and one is an interval variable so the error structure will, by definition, be different, making formal testing an inappropriate exercise.
decision. Hence, this suggests that donors believe that recipients are more similar to themselves than they really are.

To provide an additional test for this we use information about historical crop losses, and beliefs about crop losses of others and test if individuals who have a high likelihood of crop losses overestimate the likelihood of crop losses experienced by others. As noted above, as measure of own loss frequency the participants were asked the question: How many years out of the last ten years did you experience 25 – 50% crop loss? In addition, they were asked what they perceived to be the average loss frequency within their Iddir using the question: On average, how many years out of the last ten years did farmers in your Iddir experience 25 – 50% crop loss? If subjects believe that others are more similar to themselves than they really are this would imply that individuals who experienced frequent losses relative to their peers overestimate the loss frequency among their peers.

To do so we computed the empirical distribution of loss frequencies in each Iddir, and each individual farmer’s rank within that distribution. We then computed, for each farmer, the ratio of the empirical average loss frequency in the Iddir to the average loss frequency that she perceived. If farmers had a correct perception about the loss perception, this ratio would be unity. The results reported in Table 3 reveal a strong pattern: the more frequent an individual’s own losses are relative to her peers, the more likely she is to overestimate the frequency of losses among her peers. For instance, individuals who were is in the top quarter of the frequency of losses within their Iddir were found to overestimate the frequency of losses among their peers by close to 80 percent on average. Conversely, those who had below median loss frequencies systematically underestimated the average loss frequency among their peers.

IV Results

Average transfer levels

The left hand of Figure 3 presents a histogram with 10 ETB bins of the transfers in each treatment condition. The blue bars show the distribution of the “baseline” transfers, $\tau^b_i$, chosen by the donors for the case where the recipient received no insurance offer. The green bars show the distribution of the transfer $\tau^0_i$ chosen by the donors for the case where the recipient

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5 Ideally we would have used historical information on insurance take-up decisions, and beliefs about insurance take-up by others. However, insurance has not yet been introduced in these communities.

6 For both questions, the farmers were given 10 coins and told that each coin represented a year.
Table 2: Regressions of recipients’ insurance take-up decisions and donors’ beliefs about their paired recipient’s take-up decision on demographic and farm characteristics

|                        | Recipient take-up $z_j \in \{0, 1\}$ | Donor belief $E_i(z_j|m_j = 1)$ |
|------------------------|-------------------------------------|--------------------------------|
| Age in years           | -0.002                              | 0.000                          |
|                        | (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 (TLU) | 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)                        |
| Risk aversion          | -0.002                              | 0.005                          |
|                        | (0.008)                             | (0.011)                        |

Note: Note: Column 1 presents the regressions of insurance take-up of recipients $z_j \in \{0, 1\}$ on each individual covariate separately. The number of observations in each regression is $N = 93$, except for the case of “Risk aversion” where the number of observations is $N = 55$ as the lottery selection experiment was not run in the first 7 out of 18 sessions (see Appendix A for further details). Column 2 presents the regressions of the donor’s belief about the insurance take-up decision by the recipient. The number of observations in each regression is $N = 160$, due to some missing variables except for the case of risk aversion where $N = 108$ due the underlying lottery selection experiment not being run in the first 7 of the 18 sessions. The dependent variable in this case is derived from the categorical belief variable $b_i$ (the distribution of which was illustrated in Figure 2) through dividing by 10. As the resulting variable falls in the unit interval with 0 representing “highly unlikely” and 1 representing “highly likely”, we interpret the dependent variable as representing the donor’s expected value of the recipient’s take-up if offered, $E_i(z_j|m_j = 1)$. “Risk aversion” is a categorical variable from “0” to “5” with “0” being risk neutral and “5” being the most risk averse (See Appendix A for further details). “Education” is a categorical variable from “0” to “8” with “0” being no education, and “8” being university. Clustering of standard errors in all regressions at the session level (n=18). Significance levels $p < 0.10^*$, $p < 0.05^*$, $p < 0.01^{***}$
Table 3: Ratio of perceived to actual loss frequency among Iddir peers by rank of own loss frequency within the Iddir

<table>
<thead>
<tr>
<th>Own loss rank within Iddir</th>
<th>1st</th>
<th>2nd</th>
<th>3rd</th>
<th>4th</th>
</tr>
</thead>
<tbody>
<tr>
<td>Perceived/actual loss</td>
<td>0.81</td>
<td>0.89</td>
<td>1.20</td>
<td>1.79</td>
</tr>
<tr>
<td>frequency within Iddir</td>
<td>(0.07)</td>
<td>(0.06)</td>
<td>(0.09)</td>
<td>(0.07)</td>
</tr>
</tbody>
</table>

Note: A measure of “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? Respondents were further asked about the average loss frequency among their Iddir peers through the question: On average, how many years out of the last ten years did farmers in your Iddir experience 25 – 50% crop loss? For each Iddir we rank the respondents in terms of the count of own losses and place them into quartiles. For each respondent we take the ratio of her perceived loss frequency among peer to the average reported own loss frequency of the other respondents from the same Iddir. The table gives the average ratio by the within-Iddir quartile of own losses for all donors (N = 189).

rejected an offer of insurance. Finally, the yellow bars show the distribution of $\tau^1_i$ chosen by the donors for the case where the recipient accepted an offer of insurance. A simple visual inspection indicates that the empirical distribution of baseline transfers first order stochastically dominates both the distribution of “rejected-insurance” transfers, and the distribution of “accepted-insurance” transfers. On top of this the the distribution of “rejected-insurance” transfers first order stochastically dominates the distribution of “accepted-insurance” transfers. In Appendix A, the complete distributions are provided (Table A.1). Among the 567 observed chosen transfers by 189 donors there is only one violation of first order stochastic dominance.

The right panel of Figure 3 shows the mean and 95% confidence interval for each of the three transfers. The average transfer by donors to recipients in the case they are not offered insurance was close to 15 ETB. In contrast, the average transfer to recipients who reject insurance was only 10 ETB and the average transfer to recipients who accept insurance was further reduced to 5 ETB. The means are all statistically significantly different.

It is not surprising that the donors provide relatively smaller transfers to recipients who accept insurance: in this case both the donor and the recipient have certain incomes of 100 and 70 ETB respectively, so small transfers would be consistent with altruistically motivated income equalization. More striking is the substantial shift in transfers towards zero in the treatment condition where the recipient rejects insurance, compared to the baseline “no insurance offer” condition. In both treatment conditions the recipient has the same income prospect before transfers, so the donor’s decision to reduce transfers is clear evidence that the recipient’s insurance decision affected the donor’s transfers.
Figure 3: Mean and confidence intervals of donors’ transfers

Note: The left panel gives the empirical frequency of observed transfer, within bins of 10, by treatment arm: the “baseline” transfer $\tau_{bi}$, the “rejected insurance” transfer $\tau_{0i}$ and the “accepted insurance” transfer $\tau_{1i}$. The right panel shows the mean, with 95% confidence intervals, of each transfer. The number of observations for each transfer is $N = 189$.

Figure 4 provides further details by plotting the empirical joint distributions of $\tau_{bi}$ and $\tau_{0i}$ (left panel) and of $\tau_{bi}$ and $\tau_{1i}$ (right panel). The marker size is proportional to the number of observations making that choice-combination. The solid red line is the 45-degree line while the blue dashed line in each figure illustrates the average ratio of transfers among donors making a positive baseline transfer $\tau_{bi} > 0$. Focusing first on the “rejected insurance” transfer (left panel), among the donors who chose a positive baseline transfer, $\tau_{bi} > 0$, the transfer $\tau_{1i}$ was on average close to 30 percent lower. The figure highlights that some donors maintained the same transfer, $\tau_{0i} = \tau_{bi}$, while some donors substantially reduced their transfers, $\tau_{0i} < \tau_{bi}$, often to zero; only a small number of donors increased their transfer. Turning to the “accepted insurance” transfer (right panel), the figure shows that more than half of all the donors offered no transfer to a recipient who accepted insurance, $\tau_{1i} = 0$. The “accepted insurance” transfer was, on average, 65 percent lower than the baseline transfer (among donors for whom $\tau_{bi} > 0$), with only a few donors choosing $\tau_{1i} > \tau_{bi}$.

As we observe all three transfers, $\tau_{bi}$, $\tau_{0i}$ and $\tau_{1i}$, for each of the 189 donors, our design automatically controls for – observable or non-observable – individual factors that might affect
transfers chosen by a given donor. Therefore we estimate the following fixed effects regression,

\[ \tau^k_i = \alpha + \beta_0 I^{k=0}_i + \beta_1 I^{k=1}_i + \mu_i + \epsilon^k_i, \quad k = b, 0, 1, \]  

(2)

where \( \tau^k_i \) is the observed transfer in ETB, \( I^{k=0}_i \) is a dummy indicator variable for the observed transfer being the “rejected insurance” transfer (\( \tau^0_i \)) and the “accepted insurance” (\( \tau^1_i \)) respectively, \( \mu_i \) is a donor specific error term, and \( \epsilon^k_i \) is the decision-specific error term. The constant \( \alpha \) thus captures the average baseline transfer \( \tau^b_i \), after removing the individual fixed effects and \( \beta^0 \) and \( \beta^1 \) measure the average deviations of the transfers given to recipients after rejecting/accepting insurance.

Column 1 of Table 4 presents the results from estimating (2) pooling the 567 observed transfers made by the 189 donors. Robust standard errors are used reflecting the fact that the randomisation to donor or recipient occurred at the individual level Abadie et al. (2017). The results are robust to clustering the standard errors at the session level or at the Iddir level.

\(^7\) The results are robust to clustering the standard errors at the session level or at the Iddir level.
Table 4: Fixed effects regressions of transfers on treatment condition

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline ($\alpha$)</td>
<td>14.84</td>
<td>14.84</td>
<td>15.31</td>
</tr>
<tr>
<td></td>
<td>(0.49)</td>
<td>(0.49)</td>
<td>(0.49)</td>
</tr>
<tr>
<td>Ins. Rejected ($\beta_0$)</td>
<td>-4.71***</td>
<td>-4.30***</td>
<td>-0.34</td>
</tr>
<tr>
<td></td>
<td>(0.77)</td>
<td>(1.03)</td>
<td>(2.71)</td>
</tr>
<tr>
<td>Ins. Accepted ($\beta_1$)</td>
<td>-9.68***</td>
<td>-10.32***</td>
<td>-10.63***</td>
</tr>
<tr>
<td></td>
<td>(0.92)</td>
<td>(1.09)</td>
<td>(3.44)</td>
</tr>
<tr>
<td>Own Iddir $\times$ Ins. Rej.</td>
<td>-0.80</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.54)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Own Iddir $\times$ Ins. Acc.</td>
<td>1.26</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.82)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Donor Belief $\times$ Ins. Rej.</td>
<td></td>
<td>-6.79**</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(3.52)</td>
<td></td>
</tr>
<tr>
<td>Donor Belief $\times$ Ins. Acc.</td>
<td></td>
<td>-0.28</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(4.23)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>567</td>
<td>567</td>
<td>486</td>
</tr>
<tr>
<td>Subjects</td>
<td>189</td>
<td>189</td>
<td>162</td>
</tr>
</tbody>
</table>

Note: The dependent variable is the observed chosen transfer level. The number of observed transfers is $N = 567$ – three for each of the 189 donors. Each regression includes individual donor fixed effects. “Own Iddir” is a dummy indicating that the donor and the recipient are from the same Iddir. “Donor belief” is derived from the categorical belief measure $b_i \in \{0, 1, 2, ..., 10\}$ – the distribution of which was illustrated in Figure 2 – by dividing the 10. The belief measure used here, interpreted as $E_i(z_j|m_j = 1)$, thus falls in the unit interval with 0 representing “highly unlikely” and 1 representing “highly likely”. See notes to Table 2 for further details. Significance levels $p < 0.10^*$, $p < 0.05^{**}$, $p < 0.01^{***}$.

Baseline transfers, when there is no insurance offer made to the recipient, $m_j = 0$, are thus on average 14.84 ETB. When the recipient is offered insurance but rejects it ($m_j = 1$ but $z_j = 0$) transfers are significantly reduced by 4.71 ETB (or 32%). When the recipient is offered insurance and accepts it ($m_j = 1$ and $z_j = 1$) transfers are significantly reduced by 9.68 ETB (or 65%).

**Heterogeneity by beliefs about recipient behaviour and recipient identity**

We now consider whether the reaction of the donor to the recipient either rejecting or accepting insurance varies with her beliefs about uptake behaviour. To do so we use an extended fixed effect specification,

$$
\tau_i^k = \alpha + \beta_{0k}I_{i0} + \beta_{1k}I_{i1} + \lambda_{0k}E_i + \lambda_{1k}E_iE_i + \mu_i + \epsilon_i^k, \quad k = b, 0, 1, 
$$

(3)

where $E_i$ is shorthand for our measure of donor beliefs, $E_i(z_j|m_j = 1) \in [0, 1]$.

*See Section III for details of how this measure was constructed.
This extension thus allows the response of the donor to the recipient being offered insurance and either rejecting or accepting the offer to depend on the donor beliefs. $\beta_0$ and $\beta_1$ thus capture the transfer responses when the donor’s belief is zero, while $\gamma_0$ and $\gamma_1$ capture the additional effect of the treatment on transfers when the donor’s belief increases from zero to unity.

The results from estimating (3) are provided in column 3 of Table 4. When the treatment conditions are interacted with the donor’s beliefs the direct significant negative effect of the condition where the recipient rejects insurance ($m_j = 1$ but $z_j = 0$) disappears and is replaced by a significant negative interaction effect. This suggests that the reduction in transfer response by donors to the recipient rejecting insurance is driven by donors who firmly would expect insurance take-up by the recipient if offered: increasing the donor belief measure from zero to unity alters the transfer response from a non-response to a reduction of 6.8 ETB. What is interesting about these results is that when the recipient rejects insurance she has the same income prospect before transfers as when she is not offered insurance. 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 belief it is highly unlikely that the recipient takes-up insurance. In contrast, in the condition where the recipient accepts insurance ($m_j = 1$ and $z_j = 1$) the interaction with donor beliefs is both numerically small and not statistically significant. Hence in this case, where the recipient already has a certain income, the donor’s transfer reduction does not depend on her expectation about take-up.

A potential concern would be that the donor’s belief about the likelihood that the recipient takes up insurance proxies for her own risk aversion. We have however already seen in Table 2 that donor beliefs have a weak relation to our measure of risk aversion. In Column 5 in Table A.4 in Appendix A we present the results of adding the interaction between treatment conditions and risk aversion to the regression with the interactions between treatment and donors’ beliefs. We then find that the negative and significant interaction between transfers when recipients reject insurance and donor beliefs is robust, even though the interaction between risk aversion and the treatment is positive and significant. Crucially this means that the differential response of low and high risk averse donors is unrelated to the recipient behaviour as the probability of the recipient receiving an insurance offer is entirely exogenous. Our result is also robust to the inclusion of all interactions of the treatment with any of the control variables.

We next consider whether a donor’s transfer behaviour is different depending on whether
the recipient is from the own Iddir or from another Iddir. To do so, we extend the estimating equation (2) using interaction terms as follows,

\[ \tau_i^k = \alpha + \beta_0 I_i^{k=0} + \beta_1 I_i^{k=1} + \gamma_0 I_i^{k=0} I_{ Own} + \gamma_1 I_i^{k=1} I_{ Own} + \mu_i + \epsilon_i, \quad k = b, 0, 1, \quad (4) \]

This extension thus allows the response of the donor to the recipient being offered insurance and either rejecting or accepting the offer to depend on whether the recipient is known (or not) to be from the own Iddir. \( \beta_0 \) and \( \beta_1 \) thus capture transfer responses when the donor knows that the recipient is not from the donor’s Iddir, and \( \gamma_0 \) and \( \gamma_1 \) capture the the additional response when the donor knows that the recipient is from the own Iddir.

The results from estimating (4) are provided in column 2 of Table 4. The interaction terms are both economically small and not statistically significant. 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.

V A model

In this section we present a model of formal insurance and voluntary non-reciprocal redistributive transfers that is consistent with the experiment. A further ambition is that the model should have well-defined and stable preferences in order to investigate crowding-out of private voluntary redistributive transfers and make welfare comparisons. The experiments has produced the following results and stylized facts:

(i) The take-up of actuarially fair insurance by recipients is incomplete.

(ii) Demographic characteristics associated with own insurance take-up are also associated with higher expectations about the insurance take-up by a randomly allocated recipients.

(iii) Donor transfers to recipients who fail to take-up insurance when offered are significantly lower than transfers to the same recipients who received no insurance offer...

(iv) ...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. This is consistent with result (i).

To account for related variation in beliefs about insurance take-up by random anonymous others, the model will also assume that individuals exhibit an egocentric “false consensus bias” (Ross et al., 1977). Under such a bias individuals tend to misperceive the characteristics, choices and attitudes of others, believing that others are more similar to themselves than they actually are. 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.\(^9\) 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.\(^10\) 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) gener-

\(^9\)In the behavioural economics literature particular attention has been paid to the closely related “projection bias”, defined by Loewenstein et al. (2003) 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.

\(^10\)Mullen (1983) 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 (1989) 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 ?.
ous towards someone known to be of your own (opposite) kind relative to an anonymous other. For instance, Feld et al. (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). 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 et al. (2005) and Ahmed (2007), finding evidence of both favoritism and discrimination.\textsuperscript{11} 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). 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.

\textbf{Setup}

Consider an economy with a large population of individuals $i \in \{1, 2, \ldots\}$, 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.\textsuperscript{12} $\theta_i$ 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 $i$

\textsuperscript{11}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).

\textsuperscript{12}The assumption of normality is made for convenience only. The result would directly generalize to any symmetric unimodal distribution with support $[-\infty, \infty]$. 

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interacts with one other member of the economy denoted $j$ and is 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.

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 than they actually are. 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.

$$\alpha_i = a_0 - a_1 \delta_i,$$

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

**Remark 1.** In principle the linear formulation in (5) 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.

---

13Hence 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.
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

\[
\Delta (\Phi_i) \equiv E[\delta_i|\Phi_i] = E[|\theta_j - \theta_i| |\Phi(\theta_i; \mu) = \Phi_i].
\] (6)

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,

\[
\tilde{\Phi} (\Phi_i; \beta) = \Phi(\theta_i, (1 - \beta) \mu + \beta \theta_i) \text{ with } \theta_i = \Phi^{-1}(\Phi_i, \mu).
\] (7)

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 \( \tilde{\Phi} (\Phi_i; \beta) \) 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.

Figure 5: Perceived rank and perceived expected distance.

The right panel illustrates \( \Delta (\tilde{\Phi} (\Phi_i; \beta)) \) – 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 $\Delta \left( \tilde{\Phi} (\Phi_i; \beta) \right)$ 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 $E \left[ \alpha_i | \Phi_i \right] = a_0 - a_1 \Delta (\Phi_i)$,

$$E \left[ \alpha_i | \Phi_i \right] = a_0 - a_1 \Delta (\Phi_i), \quad (8)$$

it follows that, in the same way that $\Delta (\Phi_i)$ 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 $\max_\tau \{ u (1 - \tau) + u (\tau) E \left[ \alpha_i | \Phi_i \right] \}$. The solution to this problem, denoted $\tau^b (\Phi_i)$, is characterized by the associated first order condition,

$$\frac{u' (\tau^b (\Phi_i))}{u' (1 - \tau^b (\Phi_i))} = \frac{1}{E \left[ \alpha_i | \Phi_i \right]}, \quad (9)$$

$\tau^b (\Phi_i)$ 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 $\tilde{\Phi} (\Phi_i; \beta)$ via her perceived expected distance $\Delta \left( \tilde{\Phi} (\Phi_i; \beta) \right)$ 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
\[ \tau^b(\Phi_i; \beta) = \tau^b(\tilde{\Phi}(\Phi_i; \beta)) . \] (10)

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.\(^\text{14}\) 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

\(^{14}\)There will trivially not be any transfers between two insured partners as both have the same certain income. Given that \( \alpha_i \) is strictly 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.
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 expects that others share her belief – will thus anticipate an equilibrium consistent with this particular location of the type distribution.

**Anticipated equilibria**

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 separating those who took insurance and those who rejected it. Hence if there is a take-up rate of $\hat{\Phi}$ and $i$ observes that her partner declined insurance, she will infer that $\Phi_j > \hat{\Phi}$. This will impact on her expected distance to $j$ and hence on her degree of caring.

We thus generalize the definition in (6) to the expected distance between a donor of type rank $\Phi_i$ and an uninsured partner when the insurance take-up rate is $\hat{\Phi}$. Hence as before, let $\theta_i$ and $\theta_j$ be i.i.d. draws from $\mathcal{N}(\mu',1)$ where $\mu'$ is an arbitrary mean, and now define

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

(11)

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

Figure 6 illustrates the expected distance function $\Delta \left( \Phi_i, \hat{\Phi} \right)$. The special case $\Delta \left( \Phi_i, 0 \right)$ reduces to the distance function defined in (6) 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 \( \hat{\Phi} \),
\[
E \left[ \alpha_i | \Phi_i, \Phi_j \geq \hat{\Phi} \right] = a_0 - a_1 \Delta \left( \Phi_i, \hat{\Phi} \right).
\]

Consider then the transfer from \( i \) to \( j \) when the take-up rate is \( \hat{\Phi} \), characterized through the first order condition,
\[
\frac{u' \left( \tau \left( \Phi_i, \hat{\Phi} \right) \right)}{u' \left( 1 - p I_{\{\Phi_i \leq \hat{\Phi}\}} - \tau \left( \Phi_i, \hat{\Phi} \right) \right)} = \frac{1}{E \left[ \alpha_i | \Phi_i, \Phi_j \geq \hat{\Phi} \right]},
\]
where \( I_{\{\cdot\}} \) is the indicator function that is unity if the statement in brackets is true and zero otherwise. It is used here because the income of the donor is reduced from 1 to 1 \(- p \) if she herself takes up insurance. The analytical convenience of \( \tau \left( \Phi_i, \hat{\Phi} \right) \) 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 \( \hat{\Phi} \).

Using the fact that transfers depend on expected distance, we can further define \( V^1 \left( \Phi_i, \hat{\Phi}; \mu_i \right) \) 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 \( \hat{\Phi} \) and the
location of the type distribution is \( \mu_i \). Similarly, we can define \( V^0(\Phi_i, \hat{\Phi}; \mu_i) \) 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 \( \hat{\Phi} \) 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 B. 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

\[
V(\Phi_i, \Phi) \equiv V^1(\Phi_i, \hat{\Phi}; \mu_i) - V^0(\Phi_i, \hat{\Phi}; \mu_i),
\]

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 \( \hat{\Phi}(\mu_i) \) with the property that an individual of rank \( \hat{\Phi}(\mu_i) \) has an expected net gain from acquiring insurance that exactly matches her take-up cost when the take-up rate is \( \hat{\Phi}(\mu_i) \). Hence it is the solution to the implicit equation,

\[
V(\hat{\Phi}, \hat{\Phi}) - \chi\left(\Phi^{-1}(\hat{\Phi}; \mu_i)\right) = 0. \tag{14}
\]

**Definition 1.** An anticipated equilibrium given location-belief \( \mu_i \) consists of (i) an insurance take up rate \( \hat{\Phi}(\mu_i) \in [0, 1] \) that is the solution to (14) and (ii) a transfer function \( \hat{\tau}(\Phi, \mu_i) \equiv \tau(\Phi, \hat{\Phi}(\mu_i)) \), where \( \tau(\Phi, \hat{\Phi}) \) is characterized by (12), 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 take-up rate is \( \hat{\Phi} \in [0, 1] \).

For simplicity we assume that \( V(0, 0) > 0 \).\(^{15}\) The existence of an interior equilibrium \( \hat{\Phi}(\mu_i) \in (0, 1) \) is then guaranteed by the fact that 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.\(^{16}\) 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

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\(^{15}\)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.

\(^{16}\)Local stability means that \( V(\hat{\Phi}, \hat{\Phi}) - \chi(\Phi^{-1}(\hat{\Phi}; \mu_i)) = 0 \) is strictly decreasing in \( \hat{\Phi} \) at \( \hat{\Phi}(\mu_i) \).
$\mu_i$ 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.

**Lemma 2.** The anticipated insurance take-up rate, $\hat{\Phi}(\mu_i)$ 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 believes 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 $\hat{\Phi}(\mu_i)$. Moreover, she will take up insurance herself if and only if the rank that she perceives herself to be of, that is $\tilde{\Phi}(\Phi_i; \beta)$, is no larger than $\hat{\Phi}(\mu_i)$. Hence we can characterize the equilibrium insurance take-up as a function of true rank as follows,

$$
\begin{align*}
&z^*(\Phi_i; \beta) = \\
&\begin{cases}
1 & \text{if } \tilde{\Phi}(\Phi_i; \beta) \leq \hat{\Phi}\left((1 - \beta) \mu + \beta \Phi^{-1}(\Phi_i, \mu)\right) \\
0 & \text{if } \tilde{\Phi}(\Phi_i; \beta) > \hat{\Phi}\left((1 - \beta) \mu + \beta \Phi^{-1}(\Phi_i, \mu)\right)
\end{cases}
\end{align*}
$$

(15)

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 $\tau(\Phi, \hat{\Phi})$, defined in (12), is the transfer that any individual $i$ anticipates to be made by a donor of rank $\Phi$ to an uninsured recipient when the take-up rate is $\hat{\Phi}$. 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,

$$\tau^*(\Phi_i; \beta) = \tau(\hat{\Phi}(\Phi_i; \beta), \hat{\Phi}(\mu_i))$$

with $\mu_i = (1 - \beta) \mu + \beta \Phi^{-1}(\Phi_i, \mu)$.

Comparison of (16) to (10) 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 7 shows the anticipated take-up rate $\hat{\Phi}(\mu_i)$ 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

Figure 7: Anticipated take-up rates and equilibrium transfers
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.\textsuperscript{17}

\section{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.

\footnote{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.}


Appendix A: Further experiment description

Instructions to participants

Before starting the actual income and transfer game, the participants received a central explanation and an individual explanation by their enumerator using a schematic representation of the game tree in extensive form such as shown in Figure A.1.

The empirical distribution of transfers

For each of the 189 donors, we observe three chosen transfer levels \( \{\tau^b_i, \tau^0_i, \tau^1_i\} \). The lowest observed transfer is zero while the highest observed transfer is 36. Table A.1 shows the full empirical distribution of transfers by treatment arm across the 189 observed donors. As can be seen from the table, transfers are frequently chosen as multiples of five. In addition to showing the count distribution for each transfer, the table also provides the empirical cumulative distribution function (CDF). Inspection of the CDFs reveal that they - with only one exception at the top end of the support – exhibit first order stochastic dominance; for any given \( \tau \) in the empirical support, \( \Pr(\tau^1_i \leq \tau) > \Pr(\tau^0_i \leq \tau) > \Pr(\tau^b_i \leq \tau) \).

Risk preferences

To assess subjects’ risk preferences the participants played an incentivised ordered lottery selection experiment adopted from Binswanger (1981). In this experiment the subjects were asked to make a choice between six lotteries in the gain domain, each with a fixed probability of 1/2. The available choices, denoted \( r_i \in \{0, ..., 5\} \), correspond to increasing levels of risk aversion, starting at risk neutrality (0) and going to extreme risk aversion (5). The ordered lottery options are outlined in Table A.4. The final column gives a risk aversion range associated with each available choice option, 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. 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. For simplicity we will refer to the ordered choice measure as “risk aversion”, though it should be kept in mind that the scale \( \{0, 1, ..., 5\} \) has only an ordinal interpretation, not a direct cardinal one.
The final column of Table A.4 illustrates the distribution of choices in the ordered lottery selection experiment used to assess farmers’ risk attitudes. The most frequently observed choice was the most risky option with the highest expected value.

Table A.3 presents OLS regressions of the baseline transfer amount, $\tau^b_i$, and of risk aversion (ordered lottery choice) $r_i \in \{0, ..., 5\}$. The first regression also includes $r_i$ as a potential determinant of $\tau^b_i$. The table shows that the observed variation in the baseline transfer is not explained by any of the observed individual and farm characteristic. In particular, the regression finds no relation between the baseline transfer and our measure of risk aversion.

The second column of Table A.3 reports a regression of $r_i$ on the same demographic and farm characteristics, but finds no strong correlation. Recall also that the results presented in Table 2 found no strong association between individual risk aversion and insurance uptake (among recipients) and beliefs about uptake (among donors).

The findings thus suggest that risk attitude is a personal characteristic that is distinct from other sources of individual heterogeneity driving variation in uptake behaviour and in beliefs about uptake behaviour. This interpretation is further strengthened by the results presented in Table A.4. The first two columns of the table replicates columns 1 and 3 of Table 4. In the final column of Table A.4 the interactions between treatment condition and donor beliefs are replaced with corresponding interactions with donor risk aversion.

The regression shows that more risk averse donors reduce their transfers more in response to the recipient receiving an insurance offer, but the size of the reduction is not related to whether the offer was accepted or rejected. This is in stark contrast to the main finding of a sharp reduction in the transfer in response to the donor rejecting insurance by donors who firmly anticipate uptake.
Figure A.1: Schematic representation of the income generation process, transfers, and outcomes as presented individually to participants

Note: ??
Table A.1: The empirical distribution of transfers

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<th>Transfer</th>
<th>Baseline ($\tau_i^0$)</th>
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<th>Ins. Accepted ($\tau_i^1$)</th>
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<td>0</td>
<td>58.2</td>
<td>72.5</td>
</tr>
<tr>
<td>17</td>
<td>0</td>
<td>58.2</td>
<td>72.5</td>
</tr>
<tr>
<td>18</td>
<td>8</td>
<td>62.4</td>
<td>74.1</td>
</tr>
<tr>
<td>19</td>
<td>0</td>
<td>62.4</td>
<td>74.1</td>
</tr>
<tr>
<td>20</td>
<td>29</td>
<td>77.8</td>
<td>87.8</td>
</tr>
<tr>
<td>21</td>
<td>0</td>
<td>77.8</td>
<td>87.8</td>
</tr>
<tr>
<td>22</td>
<td>2</td>
<td>78.8</td>
<td>87.8</td>
</tr>
<tr>
<td>23</td>
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<td>78.8</td>
<td>87.8</td>
</tr>
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<td>0</td>
<td>78.8</td>
<td>87.8</td>
</tr>
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<td>25</td>
<td>6</td>
<td>82.0</td>
<td>91.0</td>
</tr>
<tr>
<td>26</td>
<td>0</td>
<td>82.0</td>
<td>91.5</td>
</tr>
<tr>
<td>27</td>
<td>0</td>
<td>82.0</td>
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</tr>
<tr>
<td>28</td>
<td>2</td>
<td>83.1</td>
<td>92.1</td>
</tr>
<tr>
<td>29</td>
<td>0</td>
<td>83.1</td>
<td>92.1</td>
</tr>
<tr>
<td>30</td>
<td>29</td>
<td>98.4</td>
<td>99.5</td>
</tr>
<tr>
<td>31</td>
<td>1</td>
<td>98.9</td>
<td>99.5</td>
</tr>
<tr>
<td>32</td>
<td>0</td>
<td>98.9</td>
<td>99.5</td>
</tr>
<tr>
<td>33</td>
<td>0</td>
<td>98.9</td>
<td>99.5</td>
</tr>
<tr>
<td>34</td>
<td>0</td>
<td>98.9</td>
<td>99.5</td>
</tr>
<tr>
<td>35</td>
<td>2</td>
<td>100</td>
<td>99.5</td>
</tr>
<tr>
<td>36</td>
<td>0</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

Note: The table shows the complete empirical distribution of donor-choices of transfers for each treatment condition. The “baseline” transfer $\tau_i^0$ would be provided to the recipient in the case the latter was not offered insurance, $m_j = 0$. The “insurance rejected” transfer would be provided to the recipient in the case the latter was offered insurance but rejected it, $m_j = 1$ but $z_j = 0$. The “insurance accepted” transfer would be provided to the recipient in the case the latter was offered insurance and accepted it, $m_j = 1$ and $z_j = 1$. 

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Note: To assess subjects’ risk preferences farmers played an incentivised ordered lottery selection experiment adopted from Binswanger (1981). In the 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. The final column provides the empirical distribution of choices.
Table A.3: Regression of the donor-chosen baseline transfer on individual and farm characteristics

<table>
<thead>
<tr>
<th></th>
<th>Baseline Transfer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age in years</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
</tr>
<tr>
<td>Literate</td>
<td>-1.607</td>
</tr>
<tr>
<td></td>
<td>(0.967)</td>
</tr>
<tr>
<td>Education</td>
<td>-0.449</td>
</tr>
<tr>
<td></td>
<td>(0.417)</td>
</tr>
<tr>
<td>Female</td>
<td>1.032</td>
</tr>
<tr>
<td></td>
<td>(1.652)</td>
</tr>
<tr>
<td>Married</td>
<td>0.261</td>
</tr>
<tr>
<td></td>
<td>(1.115)</td>
</tr>
<tr>
<td>Number of adults in household</td>
<td>0.188</td>
</tr>
<tr>
<td></td>
<td>(0.443)</td>
</tr>
<tr>
<td>Number of children in household</td>
<td>0.199</td>
</tr>
<tr>
<td></td>
<td>(0.372)</td>
</tr>
<tr>
<td>Tropical Livestock Units (TLU)</td>
<td>-0.016</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
</tr>
<tr>
<td>Land size in Tsemdi</td>
<td>0.884*</td>
</tr>
<tr>
<td></td>
<td>(0.435)</td>
</tr>
<tr>
<td>Farm land irrigated</td>
<td>-1.656</td>
</tr>
<tr>
<td></td>
<td>(1.477)</td>
</tr>
<tr>
<td>Probability of loss own farm 25 – 50%</td>
<td>0.099</td>
</tr>
<tr>
<td></td>
<td>(0.697)</td>
</tr>
<tr>
<td>Risk aversion</td>
<td>-0.272</td>
</tr>
<tr>
<td></td>
<td>(0.471)</td>
</tr>
</tbody>
</table>

Note: Column 1 presents the regressions of baseline transfers by the donor on each individual covariate separately. The number of observations in each regression is \( N = 160 \), due to some missing variables except for the case of risk aversion where \( N = 108 \) due the underlying lottery selection experiment not being run in the first 7 of the 18 sessions. (see Appendix A for further details). “Risk aversion” is a categorical variable from “0” to “5” with “0” being risk neutral and “5” being the most risk averse (See Appendix A for further details). “Education” is a categorical variable from “0” to “8” with “0” being no education, and “8” being university. “Tropical Livestock Units (TLU)” is a weighted count of the number of livestock. One “Tsemid” is 0.25 hectares. “Probability of experiencing 25 – 50% crop loss” reports the answer to the question How many years out of the last ten years did you experience 25 – 50% crop loss?, divided by ten. Clustering of standard errors in all regressions at the session level (n=18). Significance levels \( p < 0.10^* \), \( p < 0.05^{**} \), \( p < 0.01^{***} \)
Table A.4: Fixed effects regressions of transfers on treatment condition with interactions with risk aversion and control variables

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Baseline ($\alpha$)</strong></td>
<td>14.84</td>
<td>15.31</td>
<td>14.94</td>
<td>16.43</td>
<td>15.93</td>
</tr>
<tr>
<td></td>
<td>(0.49 )</td>
<td>(0.49 )</td>
<td>(0.49 )</td>
<td>(0.52 )</td>
<td>(0.51 )</td>
</tr>
<tr>
<td><strong>Ins. Rejected ($\beta_0$)</strong></td>
<td>-4.71***</td>
<td>-0.34</td>
<td>10.19*</td>
<td>-3.72</td>
<td>4.31</td>
</tr>
<tr>
<td></td>
<td>(0.77 )</td>
<td>(2.71 )</td>
<td>(5.79 )</td>
<td>(2.80 )</td>
<td>(7.19 )</td>
</tr>
<tr>
<td><strong>Ins. Accepted ($\beta_1$)</strong></td>
<td>-9.68***</td>
<td>-10.63***</td>
<td>-10.88</td>
<td>-13.68***</td>
<td>-17.38**</td>
</tr>
<tr>
<td></td>
<td>(0.92 )</td>
<td>(3.44 )</td>
<td>(8.19 )</td>
<td>(3.16 )</td>
<td>(8.10 )</td>
</tr>
<tr>
<td>Donor Belief $\times$ Ins. Rej.</td>
<td>1.29**</td>
<td>1.04**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.29**</td>
<td>1.04**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Risk Aversion $\times$ Ins. Acc.</td>
<td>0.91*</td>
<td>1.03</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.91*</td>
<td>1.03</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>All treatment*control interactions</strong></td>
<td>v</td>
<td>v</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>567</td>
<td>486</td>
<td>468</td>
<td>324</td>
<td>306</td>
</tr>
<tr>
<td>Subjects</td>
<td>189</td>
<td>162</td>
<td>156</td>
<td>108</td>
<td>102</td>
</tr>
</tbody>
</table>

Note: The dependent variable is the observed chosen transfer level. Each subject makes three transfer decisions. Each regression includes individual donor fixed effects. The first and second column restate Columns 1 and 3 from Table 4. In Column 3 all the interactions between the treatment and all control variables are added. The number of subjects reduces because of missing variables on controls. Column 4 presents the results for the interaction with risk aversion between – as measured by the ordered lottery option choice in the set \( \{0,\ldots,5\} \) described in Table 4. Here risk aversion is interacted with the dummy for the observed transfer being intended for the case where the recipient was offered insurance but rejected it (“Insurance Rejected”) and with the dummy for the observed transfer being intended for the case where the recipient was offered insurance and accepted it (“Insurance Accepted”). The number of observations is lower in this case as the lottery choice experiment was run only in 11 of the 18 sessions. In Column 5 we add the interaction with the donor’s belief about the insurance take-up decision by the recipient. In Column 6 we also add all interactions between the treatment and all control variables. The number of subjects reduces because of missing variables on controls. Significance levels \( p < 0.10^*, \ p < 0.05^{**}, \ p < 0.01^{***} \).
Appendix B: Proofs

Proof of Lemma 1. We note first that $\Delta(\Phi_i)$ defined in (6) 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 demonstrate a set of properties of the individual’s perceived rank as a function of her true rank, $\tilde{\Phi}(\Phi_i; \beta)$, defined in (7), starting with monotonicity in $\Phi_i$. To see this property, differentiate (7) with respect to $\Phi_i$ to obtain

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

(A.1)

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

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

(A.2)

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

$$\frac{\partial \tilde{\Phi}(\Phi_i; \beta)}{\partial \Phi_i} = (1 - \beta) \phi(\Phi^{-1}(\Phi_i; \mu), (1 - \beta) \mu + \beta \Phi^{-1}(\Phi_i; \mu)) \frac{\partial \Phi^{-1}(\Phi_i; \mu)}{\partial \Phi_i}. $$

(A.3)

This shows that, for any $\beta \in (0, 1)$, $\partial \tilde{\Phi}(\Phi_i; \beta) / \partial \Phi_i > 0$ at any rank $\Phi_i$. In the limit where $\beta = 1$, $\partial \tilde{\Phi}(\Phi_i; \beta) / \partial \Phi_i = 0$ 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 $\partial \tilde{\Phi}(\Phi_i; \beta) / \partial \Phi_i = 1$ at any $\Phi_i$ as expected. We also note that the true median never misperceives her rank. This follows as evaluating (7) at $\Phi_i = 1/2$, immediately yields $\tilde{\Phi}(1/2; \beta) = \Phi(\mu; \mu) = 1/2$ 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 $\Delta\left(\tilde{\Phi}(\Phi_i; \beta)\right)$ for any $\beta \in (0, 1)$.

Further, differentiating (7) with respect to $\beta$ yields that

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

(A.4)

where we used (A.2) again. Since $\Phi^{-1}(\Phi_i; \mu)$ is smaller (larger) than $\mu$ when $\Phi_i < 1/2 (> 1/2)$ it follows that $\partial \tilde{\Phi}(\Phi_i; \beta) / \partial \beta > 0$ at any $\Phi_i < 1/2$ and $\partial \tilde{\Phi}(\Phi_i; \beta) / \partial \beta < 0$ 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 (12) to allow for a specific income. Hence define $\tau(\Phi_i, \hat{\Phi}; y_i)$ implicitly through

$$u'(\tau(\Phi_i, \hat{\Phi}; y_i)) = \frac{1}{E[\alpha_i | \Phi_i, \Phi_j \geq \hat{\Phi}]}.$$  

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

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 $\hat{\Phi}$. Note that this expected utility, denoted $V^1(\Phi_i, \hat{\Phi}, \mu_i)$, while net of the own take-up cost, includes the caring for the partner,

$$V^1(\Phi_i, \hat{\Phi}, \mu_i) \equiv u(1 - p) \left[ \hat{\Phi} + \left( 1 - \hat{\Phi} \right) (1 - p) \right]$$

$$+ u \left( 1 - p - \tau(\Phi_i, \hat{\Phi}, 1 - p) \right) \left( 1 - \hat{\Phi} \right) p$$

$$+ \hat{\Phi} u (1 - p) E[\alpha_i | \Phi_i, \Phi_j \leq \hat{\Phi}]$$

$$+ \left( 1 - \hat{\Phi} \right) \left\{ (1 - p) u (1) + pu \left( \tau(\Phi_i, \hat{\Phi}, 1 - p) \right) \right\} E[\alpha_i | \Phi_i, \Phi_j > \hat{\Phi}]$$

$$- \hat{\Phi} E[\alpha_i \chi(\theta_j) | \Phi_i, \Phi_j \leq \hat{\Phi}, \mu_i].$$  

(A.6)

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 fourth 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 \( \Phi \), denoted \( V^0 (\Phi_i, \Phi, \mu_i) \). 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

\[
V^0 (\Phi_i, \Phi, \mu_i) \equiv (1 - p) \left[ \Phi + \left( 1 - \Phi \right) (1 - p) \right] u(1) + \left( 1 - \Phi \right) p^2 u(0) + p\Phi E \left[ u \left( \tau \left( \Phi_j, \Phi, 1 - p \right) \right) \right] | \Phi_j \leq \Phi
\]

\[
+ (1 - \Phi) p (1 - p) \left\{ E \left[ u \left( \tau \left( \Phi_j, \Phi, 1 \right) \right) \right] | \Phi_j > \Phi \right\} + u \left(1 - \tau \left( \Phi_i, \Phi, 1 \right) \right) \right\}
\]

\[
+ \Phi (1 - p) u (1 - p) E \left[ \alpha_i | \Phi_i, \Phi_j \leq \Phi \right]
\]

\[
+ (1 - \Phi) \left\{ p^2 u(0) + (1 - p)^2 u(1) \right\} E \left[ \alpha_i | \Phi_i, \Phi_j > \Phi \right]
\]

\[
+ \Phi p E \left[ \alpha_i u \left(1 - \tau \left( \theta_j, \Phi, 1 - p \right) \right) \right] | \Phi_i, \Phi_j \leq \Phi \right\] \tag{A.7}
\]

\[
+ (1 - \Phi) p (1 - p) \left\{ E \left[ \alpha_i u \left(1 - \tau \left( \Phi_j, \Phi, 1 \right) \right) \right] | \Phi_i, \Phi_j > \Phi \right\}
\]

\[
+ u \left(1 - \tau \left( \Phi_i, \Phi, 1 \right) \right) E \left[ \alpha_i | \Phi_i, \Phi_j > \Phi \right]
\]

\[
- \Phi E \left[ \alpha_i \chi \left( \theta_j \right) | \Phi_i, \Phi_j \leq \Phi, \mu_i \right].
\]

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 (A.6) – 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 (14) and using local stability. #

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