The Introduction of Formal Insurance and its Effect on Redistribution[*]

DAN ANDERBERG[a,b,c]   and   KARLIJN MORSINK[d,e]

a) Royal Holloway University of London; b) Institute for Fiscal Studies;
c) CESifo; d) Utrecht University; e) University of Oxford

Abstract

Transfers motivated by altruism, guilt, and norms of giving play an important role in supporting individuals who suffer losses due to risk. We present empirical evidence from an artefactual field experiment in Ethiopia in which we introduce formal insurance in a setting where donors make redistributive transfers to recipients who experience losses. We find that donors tend to reduce their transfers to recipients who are offered insurance, whether or not they take it up. When insurance is rejected by a recipient, transfer reductions are larger for donors who firmly expect that the recipient would take up insurance. The results are consistent with a framework in which the introduction of insurance erodes norms of giving by revealing differences in the extent to which individuals value precautionary behaviour with respect to risk-taking. Welfare calculations show that when formal insurance is introduced, the welfare of those who fail to take it up may be reduced.

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I   Introduction

Private 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). While the literature has traditionally assumed that such private transfers are motivated by reciprocity and self-enforcing contracts (Kimball, 1988; Coate and Ravallion, 1993; Kocherlakota, 1996), recent empirical work finds that altruism, guilt, and norms of giving are important drivers (Aredo, 2010; Alger and Weibull, 2010; Jakiela and Ozier, 2015; Squires, 2018; Platteau, 2015; Barrett, Nourani, Patacchini, and Walker, 2019).[1]

Such private redistributive transfers, defined as *voluntary and non-reciprocal*, are however not unconditional but may depend on the value that donors place on decisions that have led to losses, such as decisions to take risk (such as precautionary behaviour) or expend effort (see for example Brock, Lange, and Ozbay (2013) and Cappelen, Hole, Sørensen, and Tungodden (2007); Cappelen, Konow, Sørensen, and Tungodden (2013)). When a new market is introduced, individual purchase decisions may reveal information to the donor about the extent to which the decision by the recipient is in line with the values of the donor. As a consequence, donors may become less altruistically minded or feel less guilty for not transferring, leading to the erosion of norms of giving. In contexts where individuals face heterogenous private constraints to adopting 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 a new market and its subsequent impact on redistributive transfers may lead some households to face more volatile consumption than before the market was introduced.

In this paper we investigate the effect of the introduction of formal insurance with incomplete take-up on private redistributive transfers to individuals suffering income losses.[2] To this end we present evidence from a survey and artefactual field experiment (Harrison and List, 2004) with farmers in rural Ethiopia.[3] We study the transfer decisions of participants playing the

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[1]Limited commitment (without altruism) and hidden income prevent transfers from being self-sustaining (Foster and Rosenzweig, 2001; Albarran and Attanasio, 2003; Kinnan, 2017)

[2]This is distinct from studies that have investigated crowding-out of reciprocal transfers that are the result of (self-enforced) contracts in informal or mutual risk-sharing arrangements (Arnott and Stiglitz, 1991; Albarran and Attanasio, 2003; Mobarak and Rosenzweig, 2012; Dercon et al., 2014; Berg et al., 2017).

[3]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).

role of donors, paired anonymously and randomly to recipients where, preceding the donors' transfer decisions, recipients may or may not be offered insurance, and if offered, may or may not take it up. A central component of our research design is that we elicit the individual donor's beliefs about the likelihood that the recipient takes up insurance if offered. Given that donors and recipients are randomly and anonymously paired, heterogeneity in beliefs is at odds with rational expectations. Nevertheless, we find wide heterogeneity in beliefs and that individually held beliefs play an important role in shaping transfers.

The paper makes three key contributions. First, we find that the mere availability of insurance to a recipient – whether or not it is taken up – can lead donors to reduce their transfers, a finding that is in line with Lenel and Steiner (2020). More specifically, we show that it is the combination of the recipients' action with the donor's beliefs about this action that shapes donor responses: transfer reductions to recipients who reject insurance are particularly large for donors who expect insurance to be taken up when offered. Hence, contrary to what is commonly assumed in the literature, we find that it is not the recipient's choice of action – failure to reduce risk when possible – *per se* that motivates donors to reduce transfers (see Cherry, Frykblom, and Shogren (2002); Cappelen, Hole, Sørensen, and Tungodden (2007); Cappelen, Konow, Sørensen, and Tungodden (2013); Brock, Lange, and Ozbay (2013)), but that there is heterogeneity in donor responses that reflects an underlying heterogeneity in their beliefs.

Second, we show that our findings are consistent with a framework where guilt/altruism are important drivers of transfers (Platteau, 2015; Jakiela and Ozier, 2015; Squires, 2018; Barrett et al., 2019) and where the introduction of insurance and subsequent uptake decisions may reveal underlying heterogeneity between a donor and a recipient. The donor may use these revealed differences as a motivation to reduce guilt and justify 'not-giving.' Our framework highlights how the introduction of formal insurance may reduce equilibrium private redistributive transfers. This finding complements the extensively studied crowding out effect of formal insurance on equilibrium reciprocity-based transfers (Arnott and Stiglitz, 1991; Attanasio and Ríos-Rull, 2000; Mobarak and Rosenzweig, 2012). We contribute to this literature by showing that, not just adoption of insurance, but its mere availability may crowd out socially determined non-reciprocity-based support. This is important because it implies that expected future informal transfers are more unreliable/unpredictable than what can be assumed based on transfers that are part of self-enforcing contracts, not only because people try to 'hide income' (Jakiela and Ozier, 2015; Kinnan, 2017) but also because they may use revealed differences as a reason not

to transfer.

Third, by interpreting the empirical findings through the lens of the framework we are able to draw some tentative welfare conclusions and find that, based on the transfer responses that we observe in our data, the introduction of insurance is likely to reduce the expected welfare for those individuals who fail to take it up. Generally, our analysis indicates that, in a context where redistributive transfers are an important mechanism for smoothing consumption, and where formal insurance when introduced has incomplete take-up, the insurance naturally facilitates consumption smoothing for those who take it up but the impact on the consumption volatility on those who fail to take it up is generally ambiguous.

Our presented framework is one of a local economy where individuals interact in pairs (drawn randomly and anonymously), face income risk, and make transfers to each other. There exists a **social norm of giving** – an expectation that an individual should share some of her income with a partner with a lower realized income. Due to the norm being internalized, an individual who deviates from the expected transfer will experience a disutility in the form of guilt or shame. There is also a **precautionary norm** that individuals should reduce risk when possible and there exists unobserved heterogeneity in the extent to which individuals value this norm, leading to incomplete take-up of insurance when introduced. As our experiment highlights significant and relevant heterogeneity in beliefs among donors about the insurance take-up decision by recipients, we model heterogeneity of beliefs by allowing for a simple belief bias whereby individuals misperceive the distribution of value-types and hence misperceive the average insurance take-up rate. Finally, those who place a high value on following the precautionary norm, feel less guilt towards partners who, by rejecting insurance, reveal themselves as placing a low value on precautionary behaviour. The framework thus captures the notion that the introduction of a new market, and subsequent purchase decisions, make salient underlying heterogeneity in values about precautionary behaviour and leads donors to modify their transfers in response.

In the experiment individuals are randomly assigned to pairs and subsequently 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 insurance condition each recipient is offered actuarially fair and complete insurance. She then has the choice, in private, of whether to accept or reject this offer. Through the strategy-method donors are asked *ex ante* if and how much they want to transfer to the recipient for each condition. With reference to the baseline condition

donors are asked *ex ante*, if and how much they want to transfer to the recipient in case the recipient experiences a loss. With reference to the insurance condition, donors are asked *ex ante*, 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 do not have an expectation of reciprocity.[4] All participant pairs play both the baseline and the insurance conditions, allowing transfers in the different arms to be compared while controlling for individual specific characteristics. This enables us to understand how decisions by recipients to reject an opportunity to reduce risk affect the transfers made by 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, preventing *ex ante* fairness concerns from explaining differences in transfers (Brock et al., 2013; Krawczyk and Le Lec, 2016). In real-life settings it is empirically challenging to distinguish to what extent transfers are motivated by guilt/altruism or reciprocity, and this will likely vary depending on how tight-knit and stable a local community is. Through this study we demonstrate that it is not only reciprocal transfers that are crowded out when a new market is introduced, but also altruism/guilt-based transfers.

The chosen population for the artefactual field experiment is Ethiopian farmers who are members of *Iddir*. 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, 1967). The relationships in these *Iddir* are generally perceived as strong: Dercon, Hoddinott, Krishnan, and Woldehanna (2008) show that when individuals in the Ethiopian Rural Household Survey (ERHS) are asked to report on the five most important people they can rely on in times of need for support, 57% of them include members of their *Iddir*. The objective of an *Iddir* is to provide mutual transfers and financial assistance in case of emergencies (Dercon et al., 2006; Pankhurst, 2008; Hoddinott et al., 2009; Aredo, 2010). These transfers either take the form of small fixed monthly contributions, which are stipulated in the Memorandum of Understanding (MoU) of the membership to the *Iddir*, as well as through larger transfers in the case of severe losses. This context is suitable for the current study because providing redistributive transfers

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[4]A lack of significant differences between transfers to recipients from the donor's own or another community suggests that donors do not perceive their transfers in the experiment as occurring within a broader local network, further supporting the interpretation that transfers are non-reciprocal.

to support peers who suffer income losses is the norm. In addition, the membership of *Iddir* has allowed us to team up half of our subjects to a partner from their own *Iddir* and half of the subjects to a partner from another *Iddir*, so that we can investigate if both baseline transfer behaviour as well as transfers in response to insurance offers differ depending on the identity of the partner.

We report four main findings from the experiments. First, we find that while insurance take-up is high, it is not complete. Second, we find that – despite the pairings of participants being anonymous – donors are heterogenous in their expectations about recipients' insurance decisions; this implies some form of belief bias. Third, we find that donors transfer less to recipients when the latter reject insurance compared to when they are not offered insurance, despite the fact that before-transfer income in both conditions is the same; this implies that donors react in their transfer decision to the insurance decisions of the recipients. Finally we find that the reduction of transfers to recipients who opt not to take up insurance is larger for donors who have a stronger belief that the recipient would take up insurance; this suggests that donors who receive information – via the recipients' take-up decisions – that reveals a difference in values, reduce their transfers relatively more.

Our work naturally connects to a literature on transfers in mutual or informal risk-sharing networks that allow individuals to smooth consumption in the face of risk (Cochrane, 1991; Mace, 1991; Coate and Ravallion, 1993; Foster and Rosenzweig, 2001; Townsend, 1994). In this literature, private transfers are modelled as reciprocal, either through enforceable contracts or via self-enforcing arrangements. These arrangements typically do not provide full insurance against losses because of limited commitment or information asymmetry (Coate and Ravallion, 1993; Attanasio and Pavoni, 2011) or aggregate shocks (Townsend, 1994). Offering formal indemnity insurance in this context may crowd out informal risk-sharing because the reciprocal transfers and the formal insurance both cover the same losses with formal insurance being preferred over transfers (Cutler and Gruber, 1996; Attanasio and Ríos-Rull, 2000; Albarran and Attanasio, 2003) (for example because the reciprocal transfers are faced with limited commitment (Albarran and Attanasio, 2003) or because there is hidden income (Jakiela and Ozier, 2015; Kinnan, 2017)). This literature also shows that if the process of crowding-out leads to lower risk coverage, for example because the formal insurance is incomplete, does not cover all risks, or excludes certain customers, this may lead to welfare reductions. A more recent literature demonstrates, however, that if the formal insurance covers aggregate shocks while the informal risk-sharing

covers idiosyncratic losses formal insurance and informal risk-sharing may be complementary and are welfare-enhancing (Mobarak and Rosenzweig, 2012; Dercon, Hill, Clarke, Outes-Leon, and Taffesse, 2014; McIntosh, Povel, and Sadoulet, 2019; Berg, Blake, and Morsink, 2017; Takahashi, Barrett, and Ikegami, 2019).

This paper also links to a literature on fairness and donor transfers to recipients who are responsible for their outcomes as a result of their effort and risk-taking decisions. In this literature, expending less effort and refraining from reducing risk-exposure leads, on average, to lower transfers from donors. This is typically explained by assuming that those who are expending low effort (Cherry et al., 2002; Cappelen et al., 2007) or those who do not protect against risk (Cappelen et al., 2013; Brock et al., 2013; Mollerstrom et al., 2015; Krawczyk and Le Lec, 2016; Lenel and Steiner, 2020) are "punished" for not taking responsibility for their outcomes. Our findings highlight a heterogeneity in donors' responses to recipient's decision not to reduce risk, and, importantly, that this heterogeneity is systematically related to the donor's expectations about the recipient's likely choice of action. Our findings provide support for a framework based on values-contingent motivations, rather than direct action-contingent motivations, which has the additional benefit of featuring well-defined and stable preferences making it a natural foundation for welfare analysis.

Our paper is closest to Lenel and Steiner (2020) who also use an artefactual field experiment to investigate donor transfers in response to insurance availability. Their experiments are conducted with a sample of low-income households in Cambodia where a subset already has access to health insurance. Like us they randomly vary if recipients get offered insurance and elicit donor transfers through the strategy method. They provide an additional condition where recipients are either informed or not about the likelihood of a transfer from the donor. Similar to us, Lenel and Steiner (2020) find that donors respond to the availability of insurance to the recipient – even if it is not taken up – by reducing their transfers, irrespective of the recipient's information. Relative to their study, we further highlight heterogeneity in beliefs among donors about the recipients likely take-up decisions, and show that the donors' responses to non-take-up are systematically related to their beliefs.

Our paper is also close to Strobl and Wunsch (2018) who use an artefactual field experiment with slum dwellers in Kenya to investigate if transfers by donors who are themselves exposed to risk, either randomly or by choice, make different transfers if the recipients experience losses that are the result of risky decisions rather than exogenous shocks. They do not observe any

differences in transfers. The findings are different from ours because Strobl and Wunsch (2018) experimentally vary the donor's risk exposure and risk choices whereas we focus directly on the beliefs held by donors, not varying the donor's risk exposure and choices.[5]

The paper is organized as follows. In Section 2 we present a simple theoretical framework that we use to interpret the findings from the experiment. In Section 3 we explain the experimental design. In Section 4 we discuss the descriptives, in Section 5 the results, and in Section 6 the welfare implications. Section 7 concludes.

II   A Framework

Consider an economy with a large population. Each individual i has a probability $p \in \{0, 1\}$ of having an income loss, making her realized income $y_i \in \{0, 1\}$. Insurance, when available, is assumed to be actuarially fair and complete. Hence an individual who takes up insurance has her uncertain income replaced with the certain income $1 - p$. Let $z_i \in \{0, 1\}$ denote individual i's insurance take-up decision. The individual's utility of consumption, denoted $u(c_i)$, is twice continuously differentiable, strictly increasing and strictly concave.

Insurance presents an opportunity for an individual to protect their income, and we assume that there exists a "precautionary" social norm that individuals should reduce risk when possible. We further assume that there is heterogeneity in the value, v_i, that individuals place on adhering to this social norm. In addition, we assume that all individuals face a common effort cost $c > 0$ of taking up insurance when available.

ASSUMPTION 1. *"**Heterogeneity in valuation of a precautionary norm.**" A proportion $\phi^H \in (0, 1)$ of individuals place a high value, v^H, on adhering to the precautionary social norm. The remaining proportion $\phi^L \in (0, 1)$ place only a low value, v^L, to adhering to the norm, where $v^L < v^H$. Additionally, all individuals face a common effort cost of $c > 0$ from taking up insurance.*

When insurance is available our focus will be on a separating equilibrium where only v^H-type individuals take up insurance – and are expected by others to take up insurance. Trivially, such

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[5]The sample Strobl and Wunsch (2018) use is also different from our sample. Theirs is a constructed sample resulting from the fact that only those donors with higher earnings than the recipient were asked to make transfers. These are, in the treatment effect they investigate to make claims about the role of recipient's choices, donors who chose a risky project over the safe project. Our sample consists of a random sample of farmers from *Iddir* in Ethiopia where the majority of the random sample of recipients chose the safe project (insurance) over the risky project when offered.

an equilibrium will exist if $v^H - c$ is sufficiently high while $v^L - c$ is sufficiently low.[6]

Each individual is randomly paired with a "partner," and partners may support each other through voluntary transfers. However, before insurance is introduced, individual i's attitude to the precautionary social norm, v_i, is private information, and hence not observable to the partner.

ASSUMPTION 2. *"Random pairing."* *Each individual i is randomly paired with another member of the population, denoted j (her "partner"). Income losses are uncorrelated across partners. Each individual's value type, $v_i \in \left\{ v^L, v^H \right\}$, is private information, but her insurance take-up decision z_i is observed by her partner.*

In our field experiment – where individuals are randomly and anonymously paired – we measure individual beliefs about the insurance take-up decision by the partner and find strong evidence of belief heterogeneity. Under fully rational expectations such heterogeneity could not occur as each indivdual would, in that case, correctly anticipate the equilibrium proportion of individuals taking up insurance, and as partners are randomly allocated, every individual would hold a belief about the partner's insurance choice that would correspond to the population average take-up rate.

This motivates us to allow for a belief bias. We find that, empirically, there is a positive correspondence between the observable characteristics of recipients who choose to take up insurance and the observable characteristics of donors with high expectations of take-up by their partners. As the roles were randomly allocated, this suggests a positive association between own take-up and expectations about take-up by others. To be consistent with this – within a separating equilibrium – we assume that v^H-type individuals perceive a higher frequency of v^H-type individuals than do v^L-type individuals. Specifically, let $\widetilde{\phi}_i^k$ denote individual i's perception of the proportion of individuals who are of value-type v^k, $k = L, H$. We then assume

ASSUMPTION 3. *"Belief bias."* $v_i = v^H$ *implies* $\widetilde{\phi}_i^H = \overline{\phi}$, *whilst* $v_i = v^L$ *implies* $\widetilde{\phi}_i^H = \underline{\phi}$, *where* $1 > \overline{\phi} > \underline{\phi} > 0$.

Note that we do <u>not</u> assume that each type <u>overestimates</u> the prevalence of the own type. For instance, both types may underestimate the prevalence of type v^H, but in that case type v^L do so more.

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[6]Note that since insurance has a direct consumption smoothing value, the existence of such an equilibrium does not require that $v^H > c$ but will typically require that $v^L < c$, that is that v^L place less value on following the precautionary norm than the direct effort cost of taking up insurance.

An individual may make a voluntary transfer to a partner with a lower realized income. Such redistributive transfers are guided by a "transfer" norm prescribing a socially-determined reference transfer level. Individual i may make a transfer, τ_i, that falls short of the socially prescribed level, but will then experience a feeling of guilt that is proportional to the size of her deviation, where a proportionality factor $1/\eta_i$ parameterizes guilt.

When insurance is available, i will infer v_j from z_j. This allows i to treat j more favourably or unfavourably depending on how she feels about the partner's type. We assume that i's feelings of guilt are lowered when she perceives that j does not share her own precautionary attitudes.[7] We thus assume that η_i has the following form,

$$\eta_i = \eta^b + \left(\underline{\eta} - \eta^b\right) I_{\{v_j = v_i\}} + \left(\overline{\eta} - \eta^b\right) I_{\{v_j \neq v_i\}} - \mu_i, \tag{1}$$

where η^b, $\overline{\eta}$ and $\underline{\eta}$ are constants, satisfying $\overline{\eta} > \eta^b$ and $\overline{\eta} > \underline{\eta}$.

In the absence of any insurance opportunities, individual i receives no signal of how her partner j values adherence to the precautionary norm and hence $\eta_i = \eta^b - \mu_i$, where $\eta^b > 0$ and where μ_i represents an individual attitude towards transfers. We assume that μ_i is i.i.d. across individuals, drawn from some distribution with zero mean, and that $Cov\left(\mu_i, v_i\right) = 0$, that is, an individual's attitudes to the two norms are unrelated. We will provide an empirical test of this below.

Given that chosen transfers reflect deviations from the socially-determined reference levels, the exact nature of the transfer norm is not essential for our purposes. Nevertheless, the most *natural* would be to assume a norm that prescribes *ex post* income equalization, whereby the partner with the higher realized income is expected to transfer half of the income difference. Note that under such a norm, transfers could be made not only to uninsured individuals with income losses, but also from an uninsured individual without an income loss to an insured partner as the latter will have paid the insurance premium p. However, the socially prescribed transfer in this case would be small (equal to $p/2$ under an *ex post* equalization norm), and given downward deviations, we would expect such transfers to be either zero or minor. In order to keep the exposition here as concise as possible we will focus on transfers to uninsured partners

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[7]The specification in (1) imposes a "symmetry" between types. In principle, there are four possible type-profiles that may be revealed by the introduction of insurance $\left\{\left(v^H, v^H\right), \left(v^L, v^H\right), \left(v^H, v^L\right), \left(v^L, v^L\right)\right\}$ and (1) could be generalized to have separate guilt in all four cases. However, given that transfers to insured partners are, and are predicted to be (see below), typically zero or small, observable transfers will provide little information about attitudes towards insured partners. Symmetry is thus assumed mainly for completeness and convenience.

who suffer income losses, with an assumed socially-prescribed transfer level denoted $\widetilde{\tau} > 0$.[8]

To summarize, we assume

ASSUMPTION 4. **"Transfer norm and guilt."** *There is a reference level $\widetilde{\tau} > 0$ for transfers to uninsured partners who suffer income losses. An individual who deviates from $\widetilde{\tau}$ by transferring τ_i experiences guilt at level $|\tau_i - \widetilde{\tau}| / \eta_i$. The factor η_i takes the form (1), where $\overline{\eta} > \eta^b$ and $\overline{\eta} > \underline{\eta}$, and where μ_i is distributed with zero mean and with $Cov(\mu_i, v_i) = 0$.*

Note $\underline{\eta}$ can be either higher or lower than η^b. Hence an individual may or may not become more sympathetic towards a partner whom she perceives to share her own attitudes to the precautionary norm. An individual – when called upon to make a transfer to an uninsured partner – chooses the transfer τ_i that solves $\max_{\tau_i} \{u(y_i - \tau_i) - |\tau_i - \widetilde{\tau}| / \eta_i\}$, thus balancing the own marginal utility of consumption with her feelings of guilt, that is, she sets $\tau_i = y_i - \zeta(1/\eta_i)$, where $\zeta(\cdot) = u'^{-1}(\cdot)$ is the inverse marginal utility.

Consider now the key empirical properties associated with a separating equilibrium. First, as only v^H-type individuals take up insurance, the take-up rate is less than unity, reflecting the proportion of this type in the population.

Prediction 1. *"Incomplete insurance take-up."* *When insurance is available, the equilibrium take-up rate is incomplete.*

In the equilibrium, all individuals will correctly predict that only v^H-type individuals will take up insurance. However, due to belief bias about the population type frequencies, there will exist heterogeneity in beliefs about the insurance take-up of others: v^H-type individuals will expect a higher take-up rate than will v^L-type individuals (though both types may underestimate it). As v^H-type individuals also take up insurance themselves, there will be a positive association between own take-up and beliefs.

Prediction 2. *"Belief heterogeneity with positive association to own take-up."* *When insurance is available, individuals will differ in their beliefs about the take-up behavior of others. Individuals who themselves take up insurance expect a relatively high rate of take-up by others.*

Consider now transfer behaviour. In the absence of insurance opportunities, any individual i who has herself not suffered a loss will transfer $\tau_i^b = 1 - \zeta\left[1/\left(\eta^b - \mu_i\right)\right]$ to a partner who has.

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[8]Under an *ex post* income equalization transfer norm, $\widetilde{\tau} = 1/2$.

In contrast, when insurance is available, the two different types will make different transfers. A v^H-type individual will, if called upon to make a transfer, infer that the partner must be of the opposite type v^L and will hence transfer $\underline{\tau}_i = 1 - p - \zeta\left[1/\left(\overline{\eta} - \mu_i\right)\right]$.[9] In contrast a v^L-type individual will infer that an uninsured partner shares her own precautionary attitudes and transfer $\overline{\tau}_i = 1 - \zeta\left[1/\left(\underline{\eta} - \mu_i\right)\right]$. If follows from Assumption 4 that $\underline{\tau}_i < \tau_i^b$ and also $\underline{\tau}_i < \overline{\tau}_i$ (whereas $\overline{\tau}_i - \tau_i^b$ is ambiguous). As v^H-type individuals reduce their transfers both in absolute and relative terms and also expect a high rate of insurance take-up, we have the following empirical implication.

Prediction 3. *"Transfer reductions and association with beliefs." A positive proportion of individuals respond to their partner rejecting insurance by reducing the transfer they would make compared to when no insurance is available. The remaining proportion of individuals will respond by either reducing their transfers less or possibly increase them. There is a positive association between an individual's beliefs about the insurance take-up by others and how much she reduces her transfer to a partner who rejects insurance.*

Transfers take a particularly simple form in the case of log-utility and satisfies $\tau_i = y_i - \eta_i$. In particular, in the absence of insurance, $\tau_i^b = 1 - \eta^b + \mu_i$ which shows that the model predicts heterogeneity in the baseline transfers. The other potential equilibrium transfers, $\underline{\tau}_i$ and $\overline{\tau}_i$, take similar forms and similarly include the individual fixed effect μ_i in the additive form.

III   EXPERIMENTAL DESIGN

For the field experiment, 378 farmers were selected from 16 *Iddir* from farming communities in rural Ethiopia. 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) (See Appendix A for full details of instructions and information provided to the subjects). 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 for a maximum period of three hours. In these sessions the farmers received the instructions for the experiment at the

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[9]The presence of p in this expression is due to the fact that the donor i has paid p as insurance premium, causing an income effect.

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 someone 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 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 experiment, and that they would be able to earn an additional amount between 0 and 100 ETB depending on the decisions they and others would make in the experiment. 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 experiment reflected a daily wage for unskilled labour, ranging between 50 and 150 ETB, during the timing of the experiment and were thus substantial.

THE PLAYERS' ROLES AND THE INCOME PROCESS

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."[10] 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 was adopted 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

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

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 the probability of an individual loss for recipient j was

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

<div align="center">Insurance offers</div>

A private lottery for the recipient determined whether or not she was offered an actuarially fair and complete insurance contract, $m_j \in \{0, 1\}$. Hence, this lottery determined if she played the baseline condition of the experiment or the insurance condition. In the baseline condition the recipient received no insurance offer, $m_j = 0$, and her income y_j would hence be either 28 or 100 with probability $p = 5/12$ and $1 - p = 7/12$ respectively as outlined above.

In the insurance condition, the recipient received an offer of insurance, $m_j = 1$, 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 condition, 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, in case of a loss, receiving a claim payment equal to the size of the loss (72). 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.
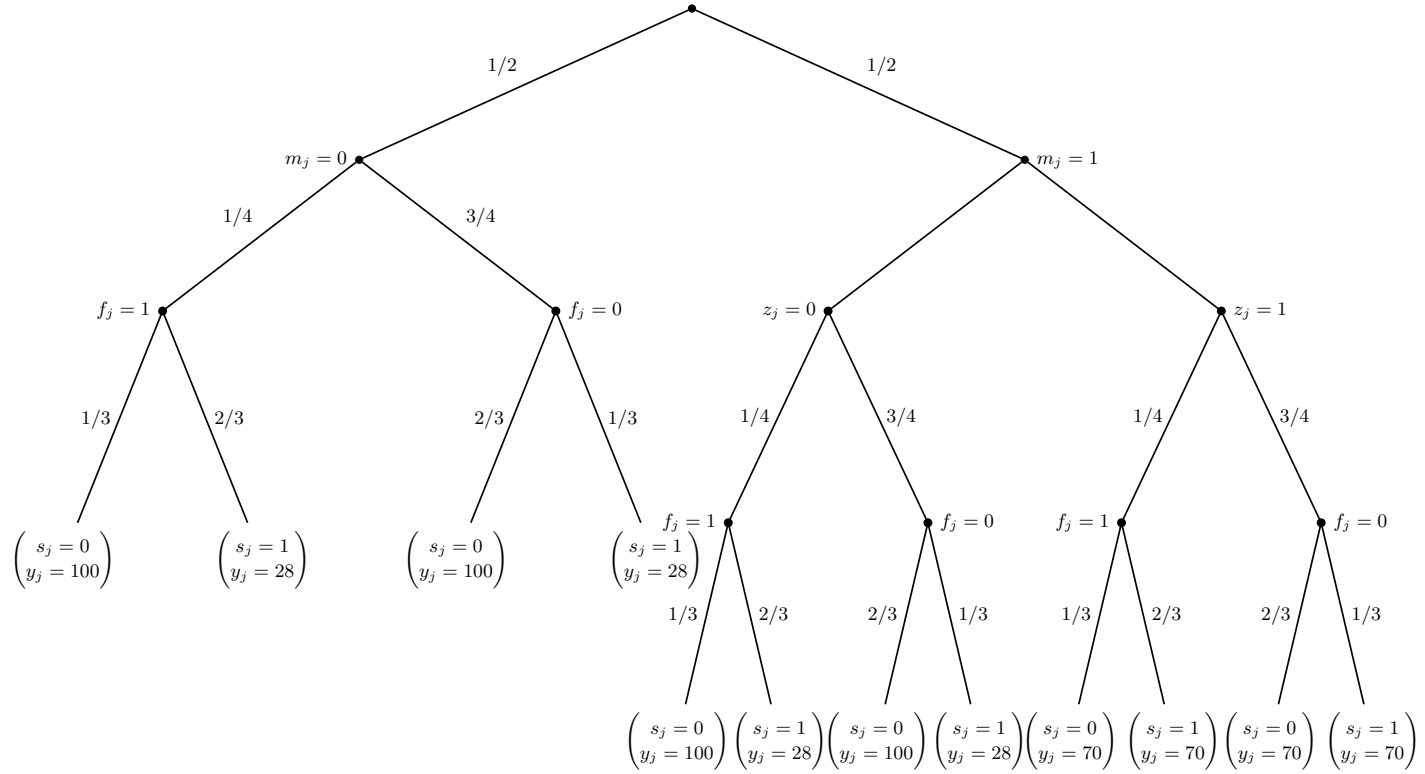
Figure 1: The income generating process for the recipient

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) and Brandts and Charness (2011)), τ_i^b, τ_i^0 and τ_i^1, each paid to j conditional on j experiencing an income loss $s_j = 1$, but differing with respect to the insurance offer and decision.[11,12] The first transfer, τ_i^b, would be made in the baseline case where j was not offered any insurance, $m_j = 0$. The second transfer τ_i^0 would be made in the event that j was offered insurance but opted not to take it up $z_j = 0$, and finally τ_i^1 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.

Donor beliefs about the recipients' insurance decision

After the donor specified her conditional transfers the donor's beliefs about transfers were elicited. To measure these beliefs 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.

Before starting, subjects received a central explanation and an individual explanation by their enumerator with a schematic representation of the experiment as shown in Figure A.1 in the Appendix A. Farmers answered three questions about the experiment to test their understanding: "*If the weather is bad and your crop is good, how much do you think your insurance claim*

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[11]The donor was not asked how much she wanted to transfer for the states where j did not experience a loss. Even though the donor might have wanted to 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.

[12]The order of the conditional transfers was not randomized as to minimize the cognitive load for the respondents. We acknowledge that the observed reduction in transfers between the "baseline" and "insurance reject" condition may be the result of order effects (e.g. "licensing"). It should be important to note though that a substantial fraction of our subjects, 79 out of 189, do not reduce transfers between these two conditions. Detailed information on pairwise comparisons of transfers and the full transfer profiles are provided in Table B.2 in Appendix B.

payment will be?," "*If the weather is bad and your crop is good, how much do you think your eventual payoff will be?*" and "*How much is the crop insurance premium?*" The expectations of real life weather and crop outputs of farmers were also elicited in the survey after the experiment to check for robustness to potential framing of the experiment in the context of agricultural risk. Robustness tests show that these expectations do not effect results.

SAMPLE CHARACTERISTICS

All subjects in the sample are a member of at least one *Iddir* and 98% report that they only have membership at one *Iddir*. The mean number of years that a respondent is a member of the *Iddir* is 7.33, with a standard deviation of 6.63. 99% of the sample makes fixed monthly contributions to the *Iddir* of, on average, 3.51ETB, which is part of the Memorandum of Understanding (MoU) of membership to the *Iddir*. In addition, 40% 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 74.00ETB and these are not part of the MoU. Subjects report that they themselves have received financial support from the *Iddir*, on average, 3.4 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. Financial support when losses occur is provided in case there is more than 50% crop loss.

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. 46% of the farmers were literate, and 55% had received no education, making it likely that a substantial fraction of the respondents is insufficiently financially literate to fully comprehend the details of an insurance product. Despite this, 90% of respondents answered all three understanding questions about probabilities and payoffs in the experiment correctly. All respondents were farmers and owned on average 3.8 units of livestock and 0.61 hectares of farm land. Only 24% had access to irrigation. 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?*"

Table 1: Descriptives and balancing test

	All	Recipient	Donor	t-test	N(All)
	(1)	(2)	(3)	(4)	(5)
Demographics					
Female	0.39	0.40	0.39	0.15	365
Age in years	43.25	42.17	44.32	-1.62	365
Married	0.81	0.82	0.80	0.64	365
Number of adults in household	2.23	1.75	2.70	-3.99***	365
Number of children in household	3.22	3.33	3.12	1.14	365
Literate	0.46	0.48	0.43	0.99	365
Education level	1.89	1.97	1.81	1.09	356
No education	0.55	0.53	0.57	-0.73	356
Primary complete	0.33	0.34	0.31	0.52	356
Secondary or more	0.12	0.13	0.12	0.36	356
High understanding	0.90	0.89	0.91	-0.70	372
Farm characteristics					
Farmer	1.00	0.99	1.00	-1.00	362
Tropical Livestock Units	4.10	4.09	4.10	-0.03	365
Land size in Tsemdi	2.48	2.49	2.48	0.09	376
Farm land irrigated	0.24	0.25	0.22	0.52	365
Probability of loss own farm $25-50\%$	0.21	0.23	0.20	1.96*	365

Note: All variables are binary unless otherwise indicated. "Education level" is a categorical variable from "0" to "8" with "0" being no education, and "8" being university. "High understanding" refers to respondents who answered all three understanding questions correctly. "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. Columns 2 and 3 give the means for the "recipients" and the "donors" respectively. Column 4 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 $p < 0.10^*$, $p < 0.05^{**}$, $p < 0.01^{***}$.
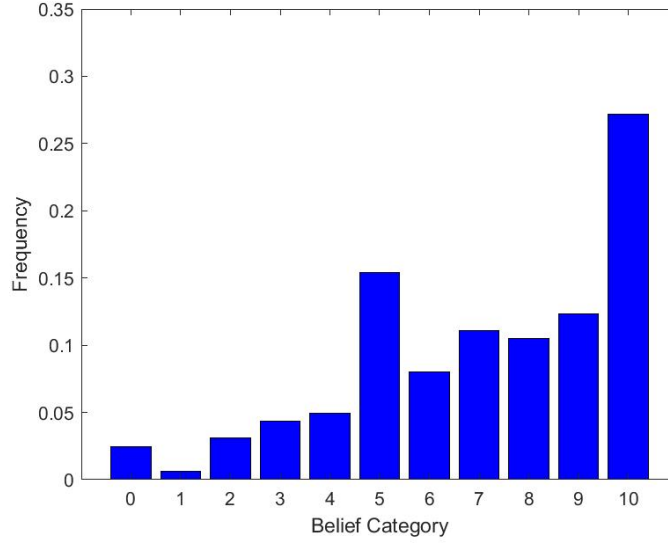
Figure 2: Distribution of donor's belief about the likelihood that the recipient took up insurance when offered

Note: Donors were asked for their belief about how likely it was that the 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. 162 donors have non-missing values on these beliefs.

ACTUAL AND EXPECTED INSURANCE TAKE-UP BEHAVIOUR

Out of all recipients who received an insurance offer, $m_j = 1$, 91% decided to take it up, $z_j = 1$.[13] Beliefs about take-up by partners among donors were also generally high, but exhibited substantial variation. 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 $b_j/10$ 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 $E_i[z_j|m_j = 1]$.

The framework presented in Section II makes three key predictions about the distribution of beliefs. First, our assumption of the existence of belief-bias implies that there should be heterogeneity in beliefs. Indeed, the empirical beliefs distribution in Figure 2, whilst clearly showing that most individuals do expect their partners to take up insurance, also exhibits a substantial

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[13]Demand for insurance is higher by 8.8 percentage points for recipients who are matched to a donor who is from a different *Iddir* as compared to a donor and recipient who are from the same *Iddir* but this difference is not statistically significant.

amount of heterogeneity. Such heterogeneity is *inconsistent* with rational expectations as, given random anonymous pairing, individuals should in that case hold the <u>same</u> expectation about the behaviour of their partner.[14]

Second, in the presented framework, both own take-up of insurance and beliefs about take-up by the partner reflect the individual's underlying unobserved value placed on precautionary behaviour. Hence beliefs should be positively associated with own insurance take-up. Note, however, that in the experiment we do not measure both own take-up and beliefs from the same individual, as doing so would prevent us from being able to attribute changes in transfers solely to the behaviour of the recipient. We can however test whether measured demographic characteristics associated with take-up (among recipients) are the same as those associated with beliefs about take-up (among donors). We present evidence that this is indeed the case in Table 2. Column 1 presents the coefficients from regressions of the binary insurance take-up decision by the recipient on each demographic and farm characteristic, while Column 2 presents the coefficients from regressions of the donor's belief about take-up on each characteristic. There is a strong overlap both in terms of the sign and the magnitude of the covariates that are significantly correlated with these outcome variables.[15] Since uptake is a binary indicator variable, while the belief variable falls in the unit interval, the coefficients are in principle comparable in size.[16] We provide a formal test of the null hypothesis that the coefficients in both the recipient's demand regressions and well as the donor's belief regressions are not different by estimating the simultaneous covariance of the models. The p-values of the χ^2 tests show that we can only reject this hypothesis in one out of 11 tests. This provides support for the assumption that there is

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[14]To check if the level of understanding of the respondent is responsible for the heterogeneity in beliefs, we present the distributions of beliefs for a subsample of donors with no formal education and a subsample of donors with formal education. These results are presented in Figure B.1 in Appendix B. We also conduct a two-sided Kolmogorov-Smirnov test and we fail to reject that the distributions of beliefs are the same for those with and without formal education (p-value=0.184).

[15]Control variables are literacy, eduction, the number of tropical livestock units, land size, and the probability of loss are positively and significantly correlated with the insurance take-up decision by the recipient. 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.

[16]We also ran 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 "Land size in Tsemdi," 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," "Education," "Number of adults in household," "Number of children in the household" "Farm land irrigated," "Land size in Tsemdi," and "Probability of loss own farm 25-50%" as significant predictors. This demonstrates substantial overlap.

some underlying latent process that determines own insurance take-up as well as beliefs about take-up of others.

Third and finally, we assume that the value the donor places on the precautionary norm, v_i, and the guilt the donor experiences when deviating from the transfer norm, μ_i, are independent. As the individual's beliefs reflect the value v_i whereas μ_i is reflected in her chosen transfers, the independence assumption implies that the beliefs of donor i should not be correlated with her baseline transfer τ_i^b. This is indeed borne out in the data (corr -0.12, p-value 0.13).

V   Results

Average transfer levels

The left hand of Figure 3 presents the cumulative distribution functions (CDFs) of transfers in each condition. The blue line shows the distribution of the "baseline" transfers, τ_i^b, chosen by the donors for the case where the recipient received no insurance offer. The green line show the distribution of the transfer τ_i^0 chosen by the donors for the case where the recipient rejected an offer of insurance. Finally, the red line show the distribution of τ_i^1 chosen by the donors for the case where the recipient accepted an offer of insurance.

A visual inspection of the CDFs shows that the "baseline" transfers first order stochastically dominate the "accepted-insurance" transfers, and the "rejected-insurance" transfers first order stochastically dominate the "accepted-insurance" transfers. With a single exception where the "insurance-rejected" transfer exceeds the "baseline" transfer for one respondent, the "baseline" transfers are always higher than the "insurance-rejected" transfers. We list the complete distributions of each transfer in Table B.1 in Appendix B.

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.

As argued above, it is not surprising that the donors provide only small transfers to recipients who accept insurance. Indeed, as will be shown below, the majority of donors chose to make zero transfers to the partner if the latter accepts insurance. This is consistent with the gap in realized income between a donor and an insured recipient being significantly smaller than the gap to an

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 $z_j \in \{0,1\}$ (1)	Donor belief $E_i(z_j\|m_j = 1)$ (2)	χ^2 test p-value (3)
Demographics			
Female	-0.041	-0.015	0.736
	(0.054)	(0.050)	
Age in years	-0.002	0.000	0.472
	(0.003)	(0.001)	
Married	0.111	-0.008	0.233
	(0.096)	(0.052)	
Number of adults in household	-0.022	-0.038***	0.515
	(0.028)	(0.013)	
Number of children in household	0.010	-0.005	0.503
	(0.017)	(0.013)	
Literate	0.063*	0.055*	0.885
	(0.036)	(0.031)	
Education level	0.023**	0.025**	0.944
	(0.010)	(0.010)	
Farm characteristics			
Tropical Livestock Units (TLU)	0.014*	0.001	0.104
	(0.007)	(0.001)	
Land size in Tsemdi	0.026*	-0.011	0.033
	(0.013)	(0.012)	
Farm land irrigated	0.053	0.095**	0.611
	(0.063)	(0.046)	
Probability of loss own farm $25 - 50\%$	0.020*	0.040***	0.313
	(0.012)	(0.014)	

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 $N = 93$ (those who were offered the insurance). 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 on the observables. 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, $E_i(z_j|m_j = 1)$. All variables are binary unless otherwise indicated. "Education level" 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. Column 3 presents the p-value of a χ^2 test of the hypothesis that there is no difference between the coefficient for the specific demographic in both models following an estimation of the simultaneous covariance of the models in Column 1 and Column 2. Significance levels $p < 0.10^*$, $p < 0.05^{**}$, $p < 0.01^{***}$

uninsured recipient suffering a loss. Hence any transfer from a donor to an insured recipient (motivated for instance by an income-equalizing transfer norm but with downward deviations) can naturally be expected to be negligible. More striking is the substantial shift in transfers towards zero in the insurance condition where the recipient rejects insurance, compared to the baseline "no insurance offer" condition. In all 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.
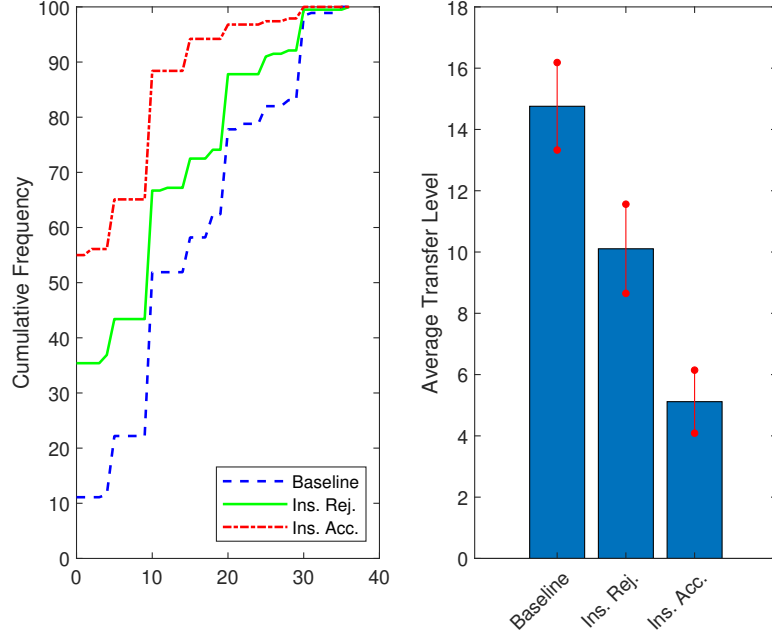

Figure 3: Distribution of transfers and average transfers by the donor

Note: The left panel gives the cumulative distribution functions of transfers by condition: the "baseline" transfer τ_i^b, the "rejected insurance" transfer τ_i^0 and the "accepted insurance" transfer τ_i^1. 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 τ_i^b and τ_i^0 (left panel) and of τ_i^b and τ_i^1 (right panel). The pairwise comparisons of all transfers and the full transfer profiles are provided in Table B.2 in Appendix B. The marker size in Figure 4 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 $\tau_i^b > 0$. Focusing first on the "rejected insurance" transfer (left panel), among the donors who chose a positive baseline transfer, $\tau_i^b > 0$, transfer τ_i^1 was on average close to 30 percent lower. The figure highlights that some donors

(79 donors) maintained the same transfer, $\tau_i^0 = \tau_i^b$, while some donors (84 donors) reduced their transfers, $\tau_i^0 < \tau_i^b$, often to zero; only a small number of donors (26 donors) increased their transfer.

Turning to the "accepted insurance" transfer, Figure 4 (right panel) shows that more than half of all the donors offered no transfer to a recipient who accepted insurance, $\tau_i^1 = 0$. The "accepted insurance" transfer was, on average, 65 percent lower than the baseline transfer (among donors for whom $\tau_i^b > 0$). Overall, 150 donors choose $\tau_i^1 < \tau_i^b$ while 15 donors kept the transfers equal, and 24 donors chose $\tau_i^1 > \tau_i^b$. As we observe all three transfers, τ_i^b, τ_i^0 and τ_i^1, 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. Figure 4 demonstrates that there is a strong correlation (corr 0.43, p-value < 0.001) between the baseline transfer τ_i^b and the rejected-insurance transfer τ_i^0. Hence e.g., if individual i makes a relatively large baseline transfer she will typically also make a relatively large transfer to the partner after she rejected insurance, consistent with the notion of an individual-fixed-effect transfer component that we develop in the model and estimate below.
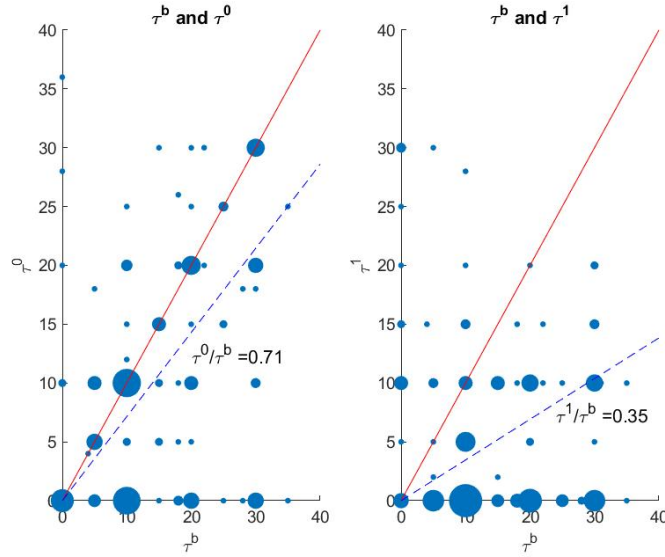

Figure 4: The empirical joint distributions of transfers

Note: The left panel plots the joint distribution of τ_i^b and τ_i^0. Marker size is proportional to the number of observations with that choice. The solid red line is the 45-degree line and the hatched blue line illustrate the average ratio of τ_i^0/τ_i^b (conditional on $\tau_i^b > 0$). The right panel plots the corresponding joint distribution of τ_i^b and τ_i^1. The correlation between baseline transfers τ_i^b and rejected-insurance transfers τ_i^0 is 0.43 (p-value < 0.001). The correlation between τ_i^b and the accepted-insurance transfer τ_i^1 is -0.08 (p-value 0.23).

In line with the framework, where we model an individual fixed effect transfer component, we estimate the following fixed effects regression,

$$\tau_i^k = \alpha + \beta_0 I_i^{k=0} + \beta_1 I_i^{k=1} + \mu_i + \epsilon_i^k, \quad k = b, 0, 1, \tag{3}$$

where τ_i^k is the observed transfer in ETB, I_i^k is a dummy indicator variable for the observed transfer being the "rejected insurance" transfer (τ_i^0) and the "accepted insurance" (τ_i^1) respectively, μ_i is the individual fixed effect, and ϵ_i^k is the decision-specific error term. The constant α thus captures the average baseline transfer τ_i^b, after removing the individual fixed effects and β_0 and β_1 measure the average deviations of the transfers given to recipients after rejecting/accepting insurance.

Column 1 of Table 3 presents the results from estimating (3) 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).[17] The 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. When the recipient is offered insurance and accepts it ($m_j = 1$ and $z_j = 1$) transfers are significantly reduced by 9.68 ETB. Columns 2 and 3 relate to heterogeneity in transfers, to which we turn next.

HETEROGENEITY IN TRANSFERS

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,

$$\tau_i^k = \alpha + \beta_0 I_i^{k=0} + \beta_1 I_i^{k=1} + \lambda_0 I_i^{k=0} E_i + \lambda_1 I_i^{k=1} E_i + \mu_i + \epsilon_i^k, \quad k = b, 0, 1, \tag{4}$$

where E_i is shorthand for our measure of donor beliefs, $E_i[z_j | m_j = 1] \in [0, 1]$.[18]

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's beliefs. β_0 and β_1 thus capture the transfer responses when the donor's belief is zero, while λ_0 and λ_1 capture the

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[17] The results are robust to clustering the standard errors at the session level or at the *Iddir* level.

[18] See Section IV for details of how this measure was constructed.

Table 3: Fixed effects regressions of baseline and insurance conditions on transfers

	(1)	(2)	(3)
Baseline (α)	14.84	15.31	14.84
	(0.49)	(0.49)	(0.49)
Ins. Rejected (β_0)	-4.71***	-0.34	-4.30***
	(0.77)	(2.71)	(1.03)
Ins. Accepted (β_1)	-9.68***	-10.63***	-10.32***
	(0.92)	(3.44)	(1.09)
Donor Belief $\times$ Ins. Rej. (λ_0)		-6.79**	
		(3.52)	
Donor Belief $\times$ Ins. Acc. (λ_1)		-0.28	
		(4.25)	
Own *Iddir* $\times$ Ins. Rej. (γ_0)			-0.66
			(1.54)
Own *Iddir* $\times$ Ins. Acc. (γ_1)			1.33
			(1.84)
Observations	567	486	558
Subjects	189	162	186

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. Lower sample sizes in Column 2 reflect missing values the belief question. Each regression includes individual donor fixed effects. "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 by 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". "Own *Iddir*" is a dummy indicating that the donor and the recipient are from the same *Iddir*. Standard errors are robust to individual level-heteroskedasticity. Significance levels $p < 0.10^*$, $p < 0.05^{**}$, $p < 0.01^{***}$.

additional effect of the insurance conditions on transfers when the donor's belief increases from zero to unity.

The results from estimating (4) are provided in Column 2 of Table 3. When the insurance 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 to be taken-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 offered insurance. It thus appears that donors who believe it to be likely that the recipient would take up insurance reduce their transfers more in response to non-uptake than do donors who believe it to be less likely that the recipient would take 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.

<center>ROBUSTNESS</center>

To check if our results on the heterogeneity by beliefs are driven by the respondent's understanding of the decision context we re-estimate (4) and include an interaction of the binary variable "No formal education" (versus "Formal education") with the insurance conditions. These results are presented in Column 3 in Table B.4 in Appendix B.[19] In Column 4 we add the interactions between all control variables and the insurance conditions.[20] This suggests that the effect of beliefs on transfers does not proxy for the effect of understanding or any of the other control variables.

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[19] For completeness, we also re-estimate (4) on the sub-samples of respondents with "No formal education" (Columns 2 and 5) and "Formal education" (Columns 3 and 6). Our results are also robust to these checks but the sample splits reduce the subsamples substantially, so we lose some power.

[20] These include female-dummy, age in years, married, number of adults in the household, number of children in the household, literate, education level, TLU, land size in Tsemdi, farm land irrigated, and probability of loss on the own farm 25%-50%

<center>26</center>

A potential alternative explanation of a reduction in transfers by the donor in response to the decision by the recipient to reject insurance might be that the donor wants to punish the recipient for not choosing precautionary behaviour, especially because a decision by the recipient not to take-up insurance may imply, in case the recipient experiences a loss, that the donor is expected to make a transfer. Theories of punishment in contexts similar to ours generally invoke expected future interactions as a rationale for punishing behavior while our setting is distinctly one-shot. There is, however, evidence that individuals in lab experiments and artefactual field experiments are also willing to punish the behaviour of others in contexts where the likelihood of repeated interactions is low, even if punishment is costly to the individual and the behaviour by the other does not negatively effect their income directly (Fehr and Fischbacher, 2004; Charness et al., 2008). The typical explanation for this behaviour is that it is guided by prescriptive norms in the population that are used to coordinate the actions of individuals in a manner that is in line with the population's objectives (Abrams et al., 2002; Henrich et al., 2006; Ohtsuki et al., 2009). Especially because of this it is logical that evidence shows that this punishment behaviour differs between individuals from the same group – who have a higher likelihood of repeated interactions – than individuals from a different group (Bernhard et al., 2006; Goette et al., 2006; Mendoza et al., 2014; McAuliffe and Dunham, 2016; Yudkin et al., 2016). If indeed punishment would explain the reduction in transfers, we would therefore expect transfer behavior to be different towards recipients from own versus other *Iddirs*.[21] Therefore we explore 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 (3) using interaction terms as follows,

$$\tau_i^k = \alpha + \beta_0 I_i^{k=0} + \beta_1 I_i^{k=1} + \gamma_0 I_i^{k=0} I_i^{Own} + \gamma_1 I_i^{k=1} I_i^{Own} + \mu_i + \epsilon_i^k, \quad k = b, 0, 1, \qquad (5)$$

β_0 and β_1 thus capture transfer responses when the donor knows that the recipient is not from the donor's *Iddir*, and γ_0 and γ_1 capture the additional response when the donor knows that the recipient is from the own *Iddir*. The results from estimating (5) are provided in column 3 of Table 3. The interaction terms are both economically small and not statistically significant. This suggests that the donor's transfer decision is not influenced by the identity of the recipient

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[21]There is no effect of the identity of the recipient on the transfers in the baseline, the insurance reject, or the insurance accept condition (τ^b: corr 0.22, p-value 0.88; τ^0: corr -0.43, p-value 0.77; τ^1: corr 1.55, p-value 0.14).

and thus any expectation of future interactions, making the alternative punishment hypothesis unlikely.

A further investigation of the analysis of variance in transfers at the *Iddir* level, presented in Table B.3 in Appendix B, shows that the standard deviation of the within *Iddir* effect is much larger than the standard deviation of the between *Iddir* effect for transfers in all conditions. The breakdown tests whether there is any evidence that members of different *Iddirs* behave systematically differently. The finding that the breakdown yields a low between variance is reassuring in that it indicates that there are no systematic differences between the *Iddirs* in terms of their transfer behavior, i.e. there is strong evidence of heterogeneity in behavior within *Iddirs*, but that heterogeneity is strongly replicated across the *Iddirs*. Together these results suggest that a social norm of transfers extends beyond the level of an *Iddir* and that the donor's response to a recipient's decision to reject an insurance offer is likely to be driven by individual-specific characteristics (such as values or social preferences (e.g., guilt)), even if these, indirectly, derive from a more general transfer or precautionary norm that applies across the population.

Finally, our framework builds on an assumption that beliefs about insurance take-up by the recipient are endogenous and causally determine transfer decisions. Our research design does not, however, exogenously vary beliefs to allow us to identify this presumed causal relationship. One might argue that donors make lower transfers for some other reasons than the revealed differences (e.g., as punishment, which we argue above is an implausible alternative) and ex-post rationalize these lower transfers by reporting low beliefs. We provide suggestive evidence against such alternative interpretations through the results we present in Table 2. There we show that the predictors of insurance take-up by the recipient are similar to the predictors of the donor's beliefs about the take-up decision by the recipient (only two out of the 11 coefficients are significantly different). This correspondence suggests that both are driven by some latent process that drives take-up and beliefs about take-up, which is something that an ex-post rationalization of transfers would struggle to produce.

VI   Discussion of Impacts on Welfare

In this discussion section we will draw some tentative welfare conclusions regarding the impact of the introduction of an insurance market in an economy with pre-existing redistributive transfers, by looking at possible impact on individuals' consumption. In doing so we will draw both on the framework presented in Section 2 and the findings from Section 5.

Our data is consistent with high uptake of insurance – when actuarially fair. Those taking up insurance will, in general, benefit from it. Specifically, within our setting, the primary effect on a v^H-type individual who takes up insurance will be consumption smoothing. Indeed, if they are matched with another v^H-type, they will have $E[y] = 1 - p$ as certain consumption. If they are matched with a v^L-type partner, who rejects insurance, they will still make some expected transfer to their partner which re-introduces some secondary variability to their consumption and a negative expected consumption effect.[22] But these secondary effects are dominated by the primary smoothing effect of insurance.

The larger concern is for the minority of individuals who fail to take up insurance when offered. For them the impact of the introduction of an insurance market is generally ambiguous. If a v^L-type individual i is matched with a v^H-type partner j who takes up insurance, then on the one hand they will no longer make any transfer (or only some minor transfer) as j is now insured. On the other hand, if they themselves suffer an income loss, they will receive a smaller transfer from j than they would have done in the absence of an insurance market, $\underline{\tau}_j$ rather than τ_j^b. A v^L-type individual who rejects insurance will thus generally experience a small gain in terms of expected consumption, but also an increase in consumption volatility. The latter effect may well dominate.

In order to analyze this possibility we can make a few further simplifications. First, suppose that p is small – small enough that the likelihood of two partners suffering a simultaneous income loss, that is p^2, is negligible, and also small enough that any potential income-equalizing transfers going towards insured partners can be ignored (as we did in Section 2). Furthermore, ignore for simplicity that there is heterogeneity μ_i in guilt/transfers so that all individuals make the same transfer, τ^b, in the absence of insurance (and similarly for the v-type-specific transfers made in the presence of an insurance market). Finally, assume, as suggested by the findings in Table 3, that a v^L-type individual – who has low beliefs about uptake by the partner and who does not themselves take up insurance – does not alter their transfer in response to non-take-up by the partner, that is, suppose that $\overline{\tau} = \tau^b$ for any v^L-type individual.

Under these conditions, a v^L-type individual i is equally well off if matched with another

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[22]In model terms, the consumption of a v^H-type individual i who is matched with another v^H-type is certain at $E[y] = 1-p$. In contrast, if matched with a v^L-type who does not take up insurance, the consumption of i, who has paid p as insurance premium, will, depending on the outcome of the partner, be $(1 - p)$ with probability $(1 - p)$ and $(1 - p - \underline{\tau}_i)$ with probability p. Hence, the matching with a v^L-type partner reintroduces some consumption risk via the transfer $\underline{\tau}_i$ and an expected consumption loss of $p\underline{\tau}_i$.

v^L-type partner j as she would be in the absence of an insurance market: trivially, as both i and j reject insurance and do not modify their transfers, the introduction of the insurance market is irrelevant to their outcomes. This also means that, in order to gauge the impact of the introduction of an insurance market on individual i, we only need to consider if i would be better or worse off if matched to a v^H-type individual j'.

Given that the double-loss probability p^2 is negligible, and given that i will consume $y_i = 1$ when neither i herself nor her partner j' suffers a loss, we only need to compare i's utilities for the cases where one of them suffers a loss and the other does not. Given that each of these two scenarios have probability $p(1-p)$, this reduces down to checking whether

$$p(1-p)[u(1) + u(\underline{\tau})] \geq p(1-p)\left[u\left(1 - \tau^b\right) + u\left(\tau^b\right)\right]. \tag{6}$$

If this inequality holds, then the v^L-type i is better off matching with a v^H-type partner who takes up insurance than she would be in the absence of any insurance market (or, equivalently, being matching with a v^L-type).[23] With log utility, this inequality simplifies to

$$\underline{\tau} \geq \left(1 - \tau^b\right)\tau^b. \tag{7}$$

The logic here is clear: i is better off matching with an insured partner j' if the transfer $\underline{\tau}$ that j' will make to i if i suffers a loss is not "too low," where "low" is in relation to the size of transfers that would mutually occur in the no-insurance regime. Note that the possible range for τ^b is $[0, 1/2]$ and that the right hand side is an increasing function of τ^b over this range, and thus maximized at $\tau^b = 1/2$, corresponding to *ex post* consumption equalization. Given that v^H-type individuals reduce their transfer to partners who reject insurance, we also have that $\underline{\tau} \leq \tau^b$.

Figure 5 showing, in green, all combinations of τ^b and $\underline{\tau}$ satisfying

$$\left\{\left(\tau^b, \underline{\tau}\right) | \underline{\tau} \geq \left(1 - \tau^b\right)\tau^b, \underline{\tau} \leq \tau^b\right\}, \tag{8}$$

that is, all combinations of τ^b and $\underline{\tau}$ under which a v^L-type is made better off by the introduction of insurance despite not taking it up herself. The figure illustrates that, unless the baseline

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[23]On the left hand side, 1 is the consumption enjoyed by i if she does not suffer a loss, but j' (who is insured) does, while $\underline{\tau}$ is the transfer she receives from j' if she suffers a loss. On the right hand side are the corresponding scenarios in the absence of insurace, where the partner with intact income transfers τ^b to the other.

redistributive transfer τ^b is quite close to *ex post* consumption equalization, even a fairly modest reduction in transfers to partners who fail to take up insurance make the latter worse off.
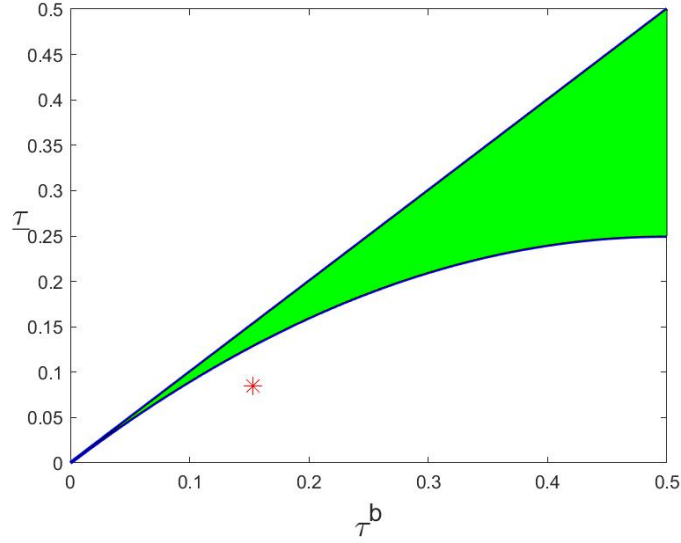

Figure 5: Combinations of τ^b and $\underline{\tau}$ under which a v^L-type is made better off by the introduction of insurance

Note: The figure shows the combination of τ^b and $\underline{\tau}$ under which a v^L-type is made better off by the introduction of insurance under the simplifying assumptions that p is small (so that the double-loss probability p^2 is a negligible), v^L types do not change their transfers in response to inferring that their parter is of the same type $\bar{\tau} = \tau^b$, log utility, and no individual transfer heterogeneity $\mu_i = 0$.

To illustrate, in our experiment, we observed baseline transfers in the order of 15.3 percent of the donors' income, well below the equalizing transfer of 50 percent. We also saw that donors with a high belief (approaching unity) about uptake by the partner would reduce their transfer by (up to) 6.8 percentage points, down to 8.5 percent. The point $\left(\tau^b, \underline{\tau}\right) = (0.153, 0.085)$ is illustrated in Figure 5 and falls in the range where a low type's welfare will be reduced as a consequence of the introduction of insurance. This suggests that a negative impact of the introduction of an insurance market on the expected welfare of those who fail to take it up, occuring via reduced redistributive transfers, is more than a remote possibility.

VII Conclusion

Transfers motivated by altruism, norms of giving, or guilt play an important role in supporting individuals who suffer income losses due to risk, especially in the absence of well-functioning in-

surance markets. But such redistributive transfers may depend on differences in values between donors and recipients of transfers. In this paper we present empirical evidence from an artefactual field experiment where donors make redistributive transfers to recipients and we elicit the individual donor's beliefs about the likelihood that the recipient takes up insurance, if offered. We show that the mere availability of insurance to a recipient – whether or not it is taken up – can lead donors to reduce their transfers and that this is explained by the combination of the recipients' action with the donor's beliefs about the likelihood of this action: reductions in transfers to recipients who reject insurance are particularly large for donors who expect insurance to be taken up when offered. Hence, we find that it is not the recipient's choice of action – failure to reduce risk when possible – per se that motivates donors to reduce transfers. We also show that our findings are consistent with an equilibrium framework where guilt/altruism are important drivers of transfers and the introduction of insurance and subsequent uptake decisions may reveal information about differences in values between a donor and a recipient, leading to a reduction in transfers.

Since emerging markets are becoming the main source of premium growth to the global insurance industry and individuals may face private constraints to adopting insurance, 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 the new market and its subsequent impact on redistributive transfers may lead some households to face more volatile consumption than before the market was introduced.

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Instructions to participants

The instructions in italic in curly brackets refer to actions by the instructor.

The experiments took place in March 2014. Groups of 20-24 farmers from lists of Iddir were invited to be seated in halls of the local farmer association. In each group half of the farmers were from one Iddir, and the other half from another Iddir. Before starting the actual experiment, the participants received this central explanation by an instructor using schematic representations of the experiment such as shown in Figure A.1.

Welcome. Today we want to better understand how you make decisions about risk and transfers to other people who are either from your own or from another *Iddir*. All of you will receive 50 ETB for you to keep as a compensation for your time and effort. You may also earn a maximum of an additional 100 ETB, depending on the decisions you and others make. The earnings you will take home will thus be between 50 and 150 ETB. The total participation time will not be more than three hours. You are free to leave at any time or refrain from answering any question. In case you decide to stop before the payment process at the end you will only receive the 50 ETB for the compensation of your time and effort, and no other amount earned with your decisions.

On your table there is a card with a number. We will use this number to identify you. To understand how you make decisions about risk and transfers we are going to give you some real money and ask you to make decisions about this money. Some of you will be exposed to a risk where you can earn higher or lower amounts of money. We will call these people j. Others are asked if they want to make transfers to people who lost money. We will call these people i. On your table there is another card, this is the "winnings card". We will record your endowment and the outcomes of decisions on this card so that we keep track of how much money you take home at the end.

We will determine randomly if you play the role of i or j by publicly drawing numbers from these two bags {*Hold up bags*}. We will do so in two steps. For the people from the first *Iddir* we will put the numbers 1-12 in the first bag, which correspond to the numbers on the cards on your table. The second bag contains 6 cards with an i written on it and 6 cards with a j written on it. We will first draw a number and next draw a card with an i or j to determine

who is assigned which role. This will be done publicly in front of the room. For the second *Iddir* we will put the numbers 13-24 in the first bag, which correspond to the numbers on the cards on your table. We will then repeat the process. The enumerators will record on your "winnings card" if you are assigned the role of i or j.

Next we are going to team you up with someone else in this room. You will not be told who this person is, but you will be told if this person is from your own or from another *Iddir*. We will do this by first putting all the numbers of farmers i from the first *Iddir* (6) in this bag {*Hold up first bag*} and half (3) of the numbers of farmers j from *Iddir* 1 and half (3) of the numbers of farmers j from *Iddir* 2 in this bag {*Hold up second bag*}. Privately, without announcing it in the room, we will draw one number from the first bag and one number from the second bag. These two individuals will form a pair. Next, we will put all the numbers of farmers i from the second *Iddir* in the first bag and half of the numbers of farmers j from *Iddir* 1 and half of the numbers of farmers j from *Iddir* 2 in the second bag. Again, privately, we will draw one number from the first bag and one number from the second bag. These individuals will again form a pair. You will not be told who you are teamed up with. You will only be told if the other person is from your own or from another *Iddir*. The enumerator will record on your "winnings card" if you are teamed up with someone from your own or from another *Iddir*.

At the start all of you will receive 100 ETB. Individuals who play the role of j may lose some of this money as a result of risk. Individuals who play the role of i may transfer some of their money to j in case j loses money as a result of the risk. We will first explain the risk to you. This risk is similar to weather risk and the risk of crop loss. The weather can either be good {*Point to the cloud and the sun on the sheet*} with some rain and some sun, or the weather can be bad {*Point to the sun on the sheet*}, with only sun but no rain. Good weather happens with a probability of 3 out of 4, while bad weather happens with a probability of 1 out of 4. We will simulate this by drawing tokens from an envelope. Blue tokens mean good weather and yellow tokens bad weather. We will put 3 blue tokens and 1 yellow token in the envelope {*Put 3 blue and 1 yellow token in the envelope*}. Now let's practice. {*Draw a token from the envelope and ask the farmers if the token indicates good weather or bad weather. Repeat this a second time*}.

As with weather risk and the risk of crop loss the quality of your crop will depend on the weather. Crops can either be good {*Point to the green crop on the sheet*} or bad {*Point to the yellow crop on the sheet*}. If it is good weather (blue token) there is a chance of 4 out of 6 that your crops will be good, and a chance of 2 out of 6 that your crops will be bad. However, if the

weather is bad (yellow) token, there is a chance of 4 out of 6 that your crops will be bad, and a chance of 2 out of 6 that your crops will be good. If the crops are good farmer j will keep 100 ETB. However, if the crops are bad farmer j will lose 72 ETB, and be left with 28 ETB. We will simulate this by making use of two differently coloured dice. If a blue token is drawn, which means the weather is good, we will use the red dice. The red dice has 2 yellow sides and 4 blue sides. If a yellow token is drawn, which means the weather is bad, we will use the white dice, which has 4 yellow sides and 2 blue sides. {*Ask the enumerators to distribute the dice*}. This means that in 5 out of the 12 possibilities there will be a bad crop and in 7 out of the 12 possibilities there will be a good crop. Now let's practice. {*First draw a token from the envelope and ask the farmers if the token indicates good weather or bad weather. Next ask the farmers which color dice we should use. Then ask the farmers to roll the dice to determine their crop loss. Then ask the farmers how much money they still have. Repeat this a second time*}.

After the risk has been determined farmer i will be asked if he/she wants to share some of her endowment (100 ETB) with farmer j in case farmer j had a bad crop. If the answer is yes farmer i will be asked how much he/she wants to share with farmer j.

In some cases, however, farmer j is asked, before the risk is determined, if he/she wants to protect himself/herself against risk. If so, he/she is asked to pay 30 ETB out of the 100 ETB endowment. In return for this payment before the risk, the farmer will be compensated in case they have a bad crop after the risk is determined. In this case he/she will receive a payout of 72 ETB. The 30 ETB as payment is exactly equal to the payout of 72 ETB multiplied by the probability that there is a bad crop, which is 5 out of 12.

If indeed the farmer j has decided to protect himself/herself against risk this means he/she will have an outcome of 70 ETB in case he/she has a good crop (100 ETB - 30 ETB) {*Point to the money on the sheet*} but he/she will also have an outcome of 70 ETB in case he/she has a bad crop (28 ETB - 30 ETB + 72 ETB) {*Point to the money on the sheet*}. To conclude: in case farmer j decides not to protect himself/herself he/she will either have 100 ETB with a chance of 7 out of 12, or 28 ETB with a chance of 5 out of 12. In case farmer j decides to protect himself/herself he/she will always have 70 ETB, irrespective of the quality of his/her crop (either good or bad).

Also in the case where farmer j has decided to protect himself/herself against risk, farmer i will be asked if he/she wants to share some of his/her endowment (100 ETB) with farmer j in case farmer j had a bad crop. If the answer is yes farmer i will be asked how much he/she

wants to share with farmer j.

A private lottery with a chance of 1 out of 2 for farmer j will determine if he/she is offered the opportunity to protect herself against risk. This means that farmer i will not be informed if farmer j received an offer or not before farmer i is asked to make transfers. In case farmer j will be offered the opportunity to protect himself/herself against risk he/she will also determine in private if he/she will accept the offer or reject the offer. The enumerator will record on the "winnings card" if farmer j received an offer and if farmer j decided to accept or reject this offer.

After the risk to farmer j's income has been determined, without knowing if j received an offer to protect himself/herself against risk, farmer i will then be asked three questions:

- In case farmer j did not receive an offer to protect himself/herself against risk and he/she experienced crop loss, would you like to transfer some of your 100 ETB endowment to farmer j? If yes, how much?

- In case farmer j received an offer to protect himself/herself against risk, decided to reject the offer, and he/she experienced crop loss, would you like to transfer some of your 100 ETB endowment to farmer j? If yes, how much?

- In case farmer j received an offer to protect himself/herself against risk, decided to accept the offer, and he/she experienced crop loss, would you like to transfer some of your 100 ETB endowment to farmer j? If yes, how much?

The enumerator will record the answers to these three questions on the "winnings card". At the end the actual offer, the actual decision by farmer j, the risk to $j's$ income, and the relevant decision by i will determine how much is transferred from i to j. So only one of these decisions will be used for actual payment.

After farmer i makes decisions about transfers he/she will be asked a question about their beliefs about the protection decision of farmer j: *How likely do you think it is that farmer j chose to protect himself/herself if offered?* To answer, farmer i is given ten tokens to indicate their belief. He/she is told he/she should give 10 tokens in case they think it is very likely that farmer j protected himself/herself in case the offer was made, and 0 tokens in case they think it is very unlikely that farmer j protected himself/herself in case the offer was made. Farmer i can choose any number of tokens to represent their belief.

What decisions you would like to make is a matter of personal choice and there are no correct or incorrect answers. You are requested to make your decisions on your own, without discussing with your neighbours. Please make your decisions in silence, and only communicate your final answer to the enumerator, who will then record your decisions on the "winnings card".

Please remember that the amount of money that you will actually take may depend on:

- the offer to farmer j

- the decision by farmer j to accept or reject the offer, if it was made

- the weather risk and risk of crop loss to the income of farmer j

- the transfer decision by farmer i

It is therefore important that you think carefully about each decision.

At the end everyone will be called, one-by-one, by the instructor for the payment process. Please bring your "winnings card" as this will inform the instructor about the final payment. As explained at the start, everyone will receive 50 ETB as a compensation for their time and effort. You may receive an additional maximum of 100 ETB based on the decisions you make. The money you will take home will thus be between 50 and 150 ETB.
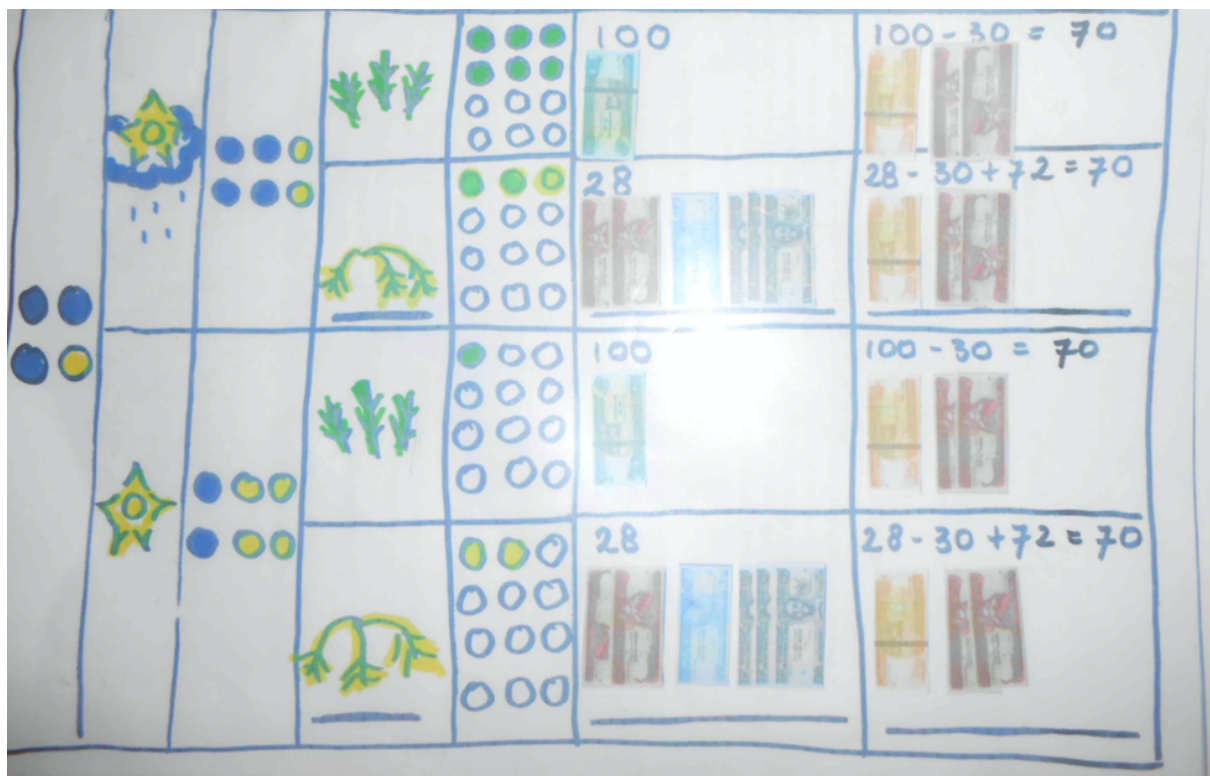
Figure A.1: Probabilities and payoffs with and without insurance

Note: The column on the left represents the four tokens with a 1/4 probability of drought. This determined if the second-stage dice (column 3 from left) either had a 1/3 probability of loss, or a 2/3 probability of loss. The 5th column presents the overall probabilities, the 6th column the payoff in ETB without insurance and transfers, and the 7th column the payoff in ETB with insurance (and without transfers).

Table B.1: The empirical distribution of each transfer

| Transfer	Baseline (τ_i^b)		Ins. Rejected (τ_i^0)		Ins. Accepted (τ_i^1)	
amount	Count	Cum.	Count	Cum.	Count	Cum.
0	21	11.1	67	35.4	104	55.0
1	0	11.1	0	35.4	0	55.0
2	0	11.1	0	35.4	2	56.1
3	0	11.1	0	35.4	0	56.1
4	1	11.6	1	36.9	0	56.1
5	20	22.2	14	43.4	17	65.1
6	0	22.2	0	43.4	0	65.1
7	0	22.2	0	43.4	0	65.1
8	0	22.2	0	43.4	0	65.1
9	0	22.2	0	43.4	0	65.1
10	56	51.9	44	66.7	44	88.4
11	0	51.9	0	66.7	0	88.4
12	0	51.9	1	67.2	0	88.4
13	0	51.9	0	67.2	0	88.4
14	0	51.9	0	67.2	0	88.4
15	12	58.2	10	72.5	11	94.2
16	0	58.2	0	72.5	0	94.2
17	0	58.2	0	72.5	0	94.2
18	8	62.4	3	74.1	0	94.2
19	0	62.4	0	74.1	0	94.2
20	29	77.8	26	87.8	5	96.8
21	0	77.8	0	87.8	0	96.8
22	2	78.8	0	87.8	0	96.8
23	0	78.8	0	87.8	0	96.8
24	0	78.8	0	87.8	0	96.8
25	6	82.0	6	91.0	1	97.4
26	0	82.0	1	91.5	0	97.4
27	0	82.0	0	91.5	0	97.4
28	2	83.1	1	92.1	1	97.9
29	0	83.1	0	92.1	0	97.9
30	29	98.4	14	99.5	4	100
31	1	98.9	0	99.5	0	100
32	0	98.9	0	99.5	0	100
33	0	98.9	0	99.5	0	100
34	0	98.9	0	99.5	0	100
35	2	100	0	99.5	0	100
36	0	100	1	100	0	100

Note: For each of the 189 donors, we observe three chosen transfer levels $\{\tau_i^b, \tau_i^0, \tau_i^1\}$. The table shows the complete empirical distribution of donor-choices of transfers for the baseline condition and the insurance conditions. The "baseline" transfer τ_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 $z_j = 1$. The Column "Count" presents the number of farmers out of 189 farmers who chose each transfer level. The Column "Cum" presents the empirical cumulative distribution. 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 τ in the empirical support, $\Pr\left(\tau_i^1 \leq \tau\right) > \Pr\left(\tau_i^0 \leq \tau\right) > \Pr\left(\tau_i^b \leq \tau\right)$

Table B.2: The distribution of transfer profiles

Pairwise Comparisons					
$\tau_1 < \tau_b$	150	$\tau_1 = \tau_b$	15	$\tau_1 > \tau_b$	24
$\tau_0 < \tau_b$	84	$\tau_0 = \tau_b$	79	$\tau_0 > \tau_b$	26
$\tau_1 < \tau_0$	108	$\tau_1 = \tau_0$	48	$\tau_1 > \tau_0$	33

Full Profiles					
$\tau_1 < \tau_b, \tau_0 < \tau_b, \tau_1 < \tau_0$	30	$\tau_1 = \tau_b, \tau_0 < \tau_b, \tau_1 < \tau_0$	n/a	$\tau_1 > \tau_b, \tau_0 < \tau_b, \tau_1 < \tau_0$	n/a
$\tau_1 < \tau_b, \tau_0 < \tau_b, \tau_1 > \tau_0$	7	$\tau_1 = \tau_b, \tau_0 < \tau_b, \tau_1 > \tau_0$	5	$\tau_1 > \tau_b, \tau_0 < \tau_b, \tau_1 > \tau_0$	3
$\tau_1 < \tau_b, \tau_0 < \tau_b, \tau_1 = \tau_0$	39	$\tau_1 = \tau_b, \tau_0 < \tau_b, \tau_1 = \tau_0$	n/a	$\tau_1 > \tau_b, \tau_0 < \tau_b, \tau_1 = \tau_0$	n/a
$\tau_1 < \tau_b, \tau_0 = \tau_b, \tau_1 < \tau_0$	55	$\tau_1 = \tau_b, \tau_0 = \tau_b, \tau_1 < \tau_0$	n/a	$\tau_1 > \tau_b, \tau_0 = \tau_b, \tau_1 < \tau_0$	n/a
$\tau_1 < \tau_b, \tau_0 = \tau_b, \tau_1 > \tau_0$	n/a	$\tau_1 = \tau_b, \tau_0 = \tau_b, \tau_1 > \tau_0$	n/a	$\tau_1 > \tau_b, \tau_0 = \tau_b, \tau_1 > \tau_0$	16
$\tau_1 < \tau_b, \tau_0 = \tau_b, \tau_1 = \tau_0$	n/a	$\tau_1 = \tau_b, \tau_0 = \tau_b, \tau_1 = \tau_0$	8	$\tau_1 > \tau_b, \tau_0 = \tau_b, \tau_1 = \tau_0$	n/a
$\tau_1 < \tau_b, \tau_0 > \tau_b, \tau_1 < \tau_0$	19	$\tau_1 = \tau_b, \tau_0 > \tau_b, \tau_1 < \tau_0$	2	$\tau_1 > \tau_b, \tau_0 > \tau_b, \tau_1 < \tau_0$	2
$\tau_1 < \tau_b, \tau_0 > \tau_b, \tau_1 > \tau_0$	n/a	$\tau_1 = \tau_b, \tau_0 > \tau_b, \tau_1 > \tau_0$	n/a	$\tau_1 > \tau_b, \tau_0 > \tau_b, \tau_1 > \tau_0$	2
$\tau_1 < \tau_b, \tau_0 > \tau_b, \tau_1 = \tau_0$	n/a	$\tau_1 = \tau_b, \tau_0 > \tau_b, \tau_1 = \tau_0$	n/a	$\tau_1 > \tau_b, \tau_0 > \tau_b, \tau_1 = \tau_0$	1

Note: The table shows the count distribution of transfer profiles. The top panel shows counts for pairwise comparisons while the lower panel shows the counts for each possible full profile. The "baseline" transfer τ_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 $z_j = 1$.
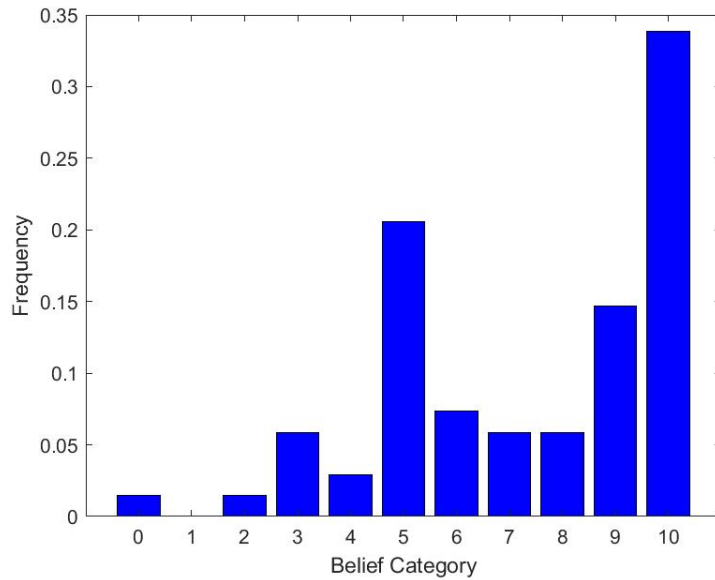
(a) Donors with formal education ($N = 68$)
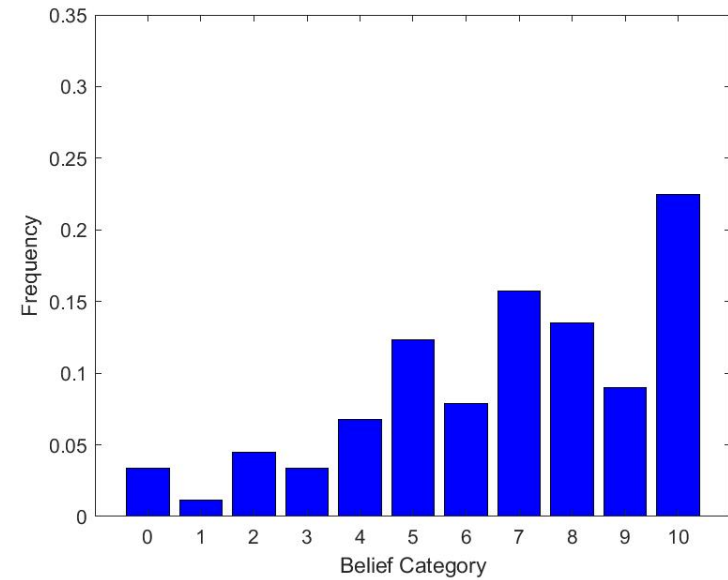
(b) Donors with no formal education ($N = 89$)

Figure B.1: Donor's beliefs about recipient's uptake by formal education

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". Panel (a) depicts the belief distribution for donors who did have any formal education and Panel (b) depicts the belief distribution for donors who did not have any formal eduction. A two-sided Kolmogorov-Smirnov test fails to reject that the distributions of beliefs are the same for those with and without formal education (p-value $= 0.184$)
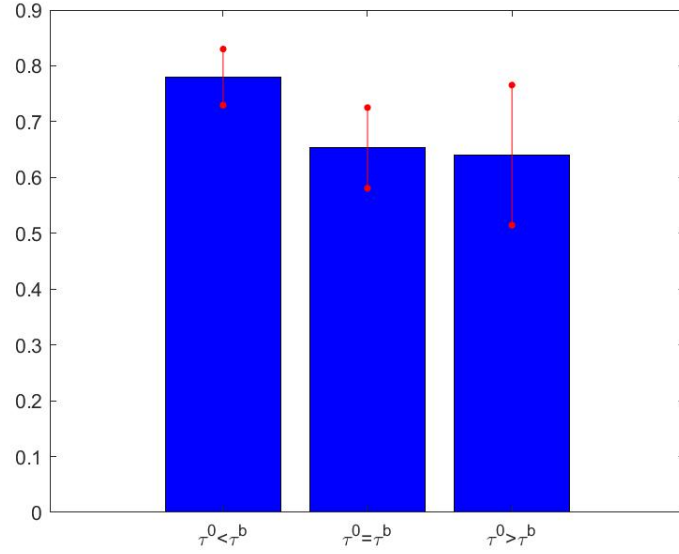
(a) Donor's beliefs by transfer profile
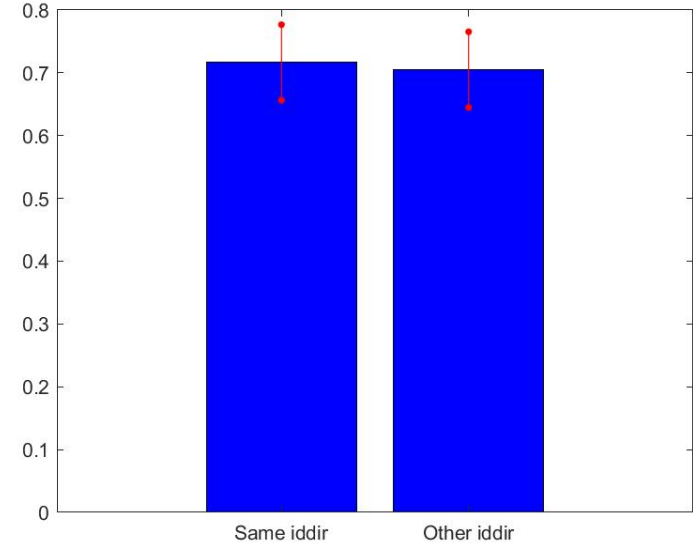
(b) Donor's beliefs by recipient identity

Figure B.2: Donor's beliefs about recipient's uptake by transfer profile and recipient identity

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". Panel (a) depicts the mean and 95% confidence interval of the distribution of beliefs by the transfer profile of the donor. Panel (b) depicts the mean and 95% confidence interval of the distribution of beliefs by the recipient's identity. A two-sided Kolmogorov-Smirnov test rejects the null-hypothesis of equality of belief distributions for those who reduce their transfers between the "baseline" and "insurance rejected" conditions and those who keep it the same in both conditions (p-value = 0.046). The two-sided Kolmogorov-Smirov test for those who increase transfers between the "baseline" and "insurance rejected" conditions relative to keeping transfers the same in both conditions has a p-value of 0.731, for those who decrease transfers relative to increase transfers the p-value is 0.194. The p-value for the test of for differences in beliefs depending on the identity of the recipient is 0.979.

Table B.3: Variation in transfers at the *Iddir* level

	Minimum transfers	Maximum transfers	F-statistic	p-value	Standard deviation between Iddir effect	Standard deviation within Iddir effect
Baseline (τ_i^b)	9.17 ETB	18.75 ETB	1.45	0.13	1.87	9.56
Insurance Rejected (τ_i^0)	5.00 ETB	16.25 ETB	1.41	0.15	1.81	9.74
Insurance Accepted (τ_i^1)	0.38 ETB	17.08 ETB	4.21	0.00	3.30	6.32

Note: Results of a one-way analysis of variance (ANOVA) model analyzing variance in transfers at the *Iddir* level. The F-statistic represents the ratio of variation between sample means across *Iddir* divided by the variation within *Iddir*. The ANOVA tests the null hypothesis that samples in all groups are drawn from populations with the same mean values. N=189 and there are 16 *Iddir*.

Table B.4: Robustness of regression results to inclusion of interactions between insurance conditions and "No Education", and all control variables

	(1)	(2)	(3)	(4)
Baseline (α)	14.84	15.31	14.97	14.94
	(0.49)	(0.49)	(0.49)	(0.49)
Ins. Rejected (β_0)	-4.71***	-0.34	1.53	17.46***
	(0.77)	(2.71)	(2.85)	(6.20)
Ins. Accepted (β_1)	-9.68***	-10.63***	-10.30***	-17.71**
	(0.92)	(3.44)	(3.56)	(7.74)
Donor Belief × Ins. Rej. (λ_0)		-6.79*	-7.05**	-6.92*
		(3.52)	(3.47)	(3.47)
Donor Belief × Ins. Acc. (λ_1)		-0.28	0.01	0.70
		(4.25)	(4.28)	(4.28)
Insurance conditions×No education interaction			v	
Insurance conditions×All control interactions				v
Observations	567	486	471	468
Subjects	189	162	157	156

Note: The dependent variable is the observed chosen transfer level. Each subject makes three transfer decisions. Each regression includes individual donor fixed effects. Column 1 and Column 2 restate Columns 1 and 3 from Table 3. "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 by 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". In Column 3 we add the interaction of the "No Education" variable with the "Insurance Rejected" condition and the "Insurance Accepted" condition. "No Education" is 1 if the subject attended no formal education and 0 otherwise. In Column 4 we add all the interactions between the control variables and the "Insurance Rejected" condition and the "Insurance Accepted" condition. The number of subjects reduces because of missing variables on controls. Significance levels $p < 0.10^*$, $p < 0.05^{**}$, $p < 0.01^{***}$.

Table B.5: Robustness of regression results to re-estimation on subsamples of those with and without formal education

	(1)	(2)	(3)	(4)	(5)	(6)
Baseline (α)	14.84	14.90	14.22	15.31	15.73	13.97
	(0.49)	(0.69)	(0.63)	(0.49)	(0.69)	(0.67
Ins. Rejected (β_0)	-4.71***	-5.29***	-3.51***	-0.34	-2.68	3.97
	(0.77)	(1.08)	(1.11)	(2.71)	(3.47)	(4.08)
Ins. Accepted (β_1)	-9.68***	-9.46***	-10.26***	-10.63***	-11.18**	-9.45**
	(0.92)	(1.27)	(1.11)	(3.44)	(4.75)	(4.87)
Donor Belief × Ins. Rej. (λ_0)				-6.79*	-4.74	-10.36*
				(3.52)	(4.55)	(5.24)
Donor Belief × Ins. Acc. (λ_1)				-0.28	0.82	-1.14
				(4.25)	(6.02)	(5.90)
Observations	567	306	231	486	267	204
Subjects	189	102	77	162	89	68

Note: Each subject makes three transfer decisions. Each regression includes individual donor fixed effects. Column 1 and Column 4 restate Columns 1 and 3 from Table 3. Columns 2 and 5 present the estimates from a re-estimation of the equations in Columns 1 and 4 respectively, on a restricted sample of those subjects who had attended no formal education. Colums 3 and 6 present the estimates from a re-estimation of the equations in Columns 1 and 4 respectively, on a restricted sample of those subjects who had attended formal education. "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 by 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". Significance levels $p < 0.10^*$, $p < 0.05^{**}$, $p < 0.01^{***}$.