THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Risk sharing, networks and investment choices in rural India

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Abstract

Risk is central in the study of rural development. To cope with risk, smallholder farmers rely on a range of formal and informal insurance mechanisms: an extensive literature has explored their interactions. Yet, our understanding of the implications of these interactions for smallholder farmers' decision-making is incomplete. This thesis addresses this scholarly gap by shedding new light on the risk-related decisions of smallholder farmers and the mechanisms through which networks affect these decisions. To do so, it relies on a combination of experimental and non-experimental economic analyses. The first chapter draws on a framed field experiment in Gujarat, India to explore the effect of selling weather index insurance to groups (as opposed to individuals) on the investment decisions of the insured. The analysis reveals that group pressure reduces risk taking among individuals with group insurance in contexts with perfect information about peer investment decisions. Group insurance thus suffers from the same potential pitfall as group microcredit. The second chapter examines the extent to which informal transfers can explain take-up of individual weather index insurance. It aims to disentangle two channels through which informal transfers influence decisions to purchase insurance: (i) informal risk sharing and (ii) moral hazard. As in the first chapter, the study draws on a framed field experiment in Gujarat. The main finding of this experiment is that redistribution norms reduce take-up: moral hazard leads to lower levels of insurance coverage. The final chapter builds on these results with a non-experimental analysis of panel data from a rural household survey in India. It examines how cultural obligations to redistribute within networks affect investments in self-protection. The empirical evidence suggests that increases in individual income lead to higher investments, but increases in network income lead to lower investments due to moral hazard. Collectively, the three papers nuance our understanding of how redistribution norms affect the risk-related decisions of the rural poor. While not negating their consumption smoothing benefits, this thesis indicates that networks also affect decision-making via group pressure and moral hazard. Such externalities could be forestalled by targeting insurance in rural areas with weaker redistributive norms or modifying insurance policy designs. Further research on the welfare implications of such approaches is thus recommended.

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Introduction

Risk is a central concern for the rural poor. A key risk for rural households is agricultural yield volatility induced by shocks such as pests and rainfall variability. Climate change has brought the latter under the spotlight of policymakers and scholars: increasingly severe and varied weather conditions such as flood and drought leave the rural poor more and more vulnerable (IPCC, 2012). This puts a premium on risk mitigation as central to improving rural livelihoods in the developing world.

To cope with production risks such as rainfall variability, smallholder farmers rely on a range of risk mitigation tools. Within networks characterised by redistribution norms, one such tool is informal transfers. Often defined as gifts or loans, these informal monetary exchanges act as a form of informal insurance to smooth consumption during periods of financial hardship. Such transfers are widely recognised as frequent and central to financial security in developing countries (Fafchamps & Lund, 2003). Their important function as a safety net for the rural poor is clear. Yet, many scholarly works have failed to capture other potential externalities of such transfers for rural development. This thesis sheds light on several less well explored implications of informal transfers in a series of three essays. Essay 1 shows, via a framed field experiment, that selling insurance to groups – as opposed to individuals – reduces risk taking in other aspects of agricultural production due to group pressure; Essay 2 reveals in a second framed field experiment that networks reduce insurance coverage due to moral hazard via informal transfers; and Essay 3 draws on a non-experimental analysis to illustrate that moral hazard also limits adoption of self-protection tools.

All of the essays focus on rural India. Home to 33% of the world's poor, India is a central case in the study of rural development. Despite impressive growth rates in recent years, the benefits of this growth have not sufficiently trickled down to the rural poor: more than 47% of Indians work in the agriculture sector and 26% of rural Indians still live below the poverty line (World Bank, 2012).

Essay 1 first explores potential externalities of group dynamics in the case of weather index insurance - a microinsurance[1] product designed to mitigate the risk of rainfall variation. Purchasing a weather insurance policy entitles the owner to a payout if rainfall levels fall above or below a certain range at a nearby rainfall station during the monsoon season. Despite its consumption smoothing benefits during shocks, however, weather insurance take-up remains low (e.g. Cole et al., 2013; Gine, Townsend & Vickery, 2008).

Recognition of take-up and transaction cost challenges across a range of individual microinsurance products has led to a surge of interest in group microinsurance. Yet, few studies have considered the effect of the group structure on the investment decisions of the insured. In the case of weather insurance, this is an important omission. Essay 1 suggests that group insurance decreases risk taking in other aspects of agricultural production when groups internally manage insurance payout distribution and have perfect information about peer investment decisions. This reduction in risk taking arises because the group structure relaxes the clearly delineated ownership of insurance payouts that characterises individual policies. The group structure also formalises informal risk sharing by facilitating groups to award larger proportions of the group payout to peers with higher losses. For fear that risk-takers will demand higher proportions of the group payout in such an environment, groups pressure peers to take on less risk when investment decisions are public.

These findings are drawn from a framed field experiment in Gujarat, India. The experimental results indicate that group pressure leads to an 8% reduction in risk taking in contexts with perfect information and group insurance (relative to individual insurance). Group insurance thus suffers from the same potential pitfall as group microcredit (Fischer, 2013). As higher risk taking can lead to higher average

[1] Microinsurance is insurance for individuals without access to commercial and social insurance schemes (ILO, 2006). Similar to ordinary insurance, microinsurance products pool risk across individuals in order to reimburse individuals for a loss incurred due to an unpredictable event.

agricultural productivity – and thus, development (e.g. Duflo, Kremer & Robinson, 2008) – these findings of group pressure are a cause for concern. This research thus underscores the importance of greater attention to group selection, the information environment and the regulation of payout distribution in structuring insurance products.

Essay 2 explores a second potential interaction between informal transfers and weather insurance. In particular, this study aims to disentangle two channels through which informal transfers influence decisions to purchase individual weather insurance: (i) moral hazard and (ii) informal risk sharing. These channels are explored using the Becker-Degroot-Marschak (BDM) model to elicit willingness to pay (WTP) for weather insurance in a second framed field experiment in Gujarat. The core result from this experiment is that moral hazard reduces weather insurance take-up. When farmers know they are allowed to give and receive transfers after a shock has occurred, many decide not to purchase insurance. On the whole, I find movement on the extensive margin. Allowing informal transfers leads to a 14% increase in the number of people who are not willing to pay any price for insurance. Decreases in WTP are also pronounced among poorer individuals. Assuming expected utility preferences, these results are consistent with a model of moral hazard but not with a model of optimal risk sharing. The scholarly conclusion of these results is clear: while networks offer consumption smoothing benefits, they also lead to lower insurance coverage.

The first two essays both underscore the implications of networks for decision-making in the context of formal insurance. The final essay complements these insights in an examination of how cultural norms to redistribute within networks affect decisions to utilise self-protection tools (i.e. risk-reducing investments). A range of traditional, low-cost self-protection techniques such as levelling and bunding can reduce the risks associated with agricultural production. Yet, similar to weather insurance, take-up of these practices remains low among smallholder farmers. Determining optimal usage levels is, of course, thorny: there are multiple alternative tools available and farmer production functions and utility functions are unknown. Low take-up, however, does raise the question as to why many farmers do not adopt such practices and whether rural livelihoods could be improved through their greater usage. Akin to the second essay, the third essay seeks to resolve this conundrum by exploring the extent to which redistribution norms can explain investments in self-protection tools.

The main finding of this study is that moral hazard in the caste network reduces self-protection investments in rural India. These results emerge from a non-experimental analysis of panel data from the National Council of Applied Economic Research Rural Economic and Demographic Survey (NCAER REDS). This national rural household survey in 1982 and 1999 offers a unique opportunity to test the prediction that household and network income induce opposing effects on self-protection. Using a panel dataset, I am able to sidestep endogeneity concerns such as time-invariant unobservables by focusing on within-household changes in income and self-protection. I also implement an instrumental variable strategy by instrumenting for changes in income with inherited land in 1982 to address potential biases from time-variant unobservables and reverse causality. The empirical evidence supports the prediction that redistributive norms within the caste network induce a moral hazard problem. While increases in individual income lead to higher self-protection levels, increases in average caste income lead to lower self-protection levels.

Overall, this thesis challenges scholarly convictions about the role of networks for the rural poor. While not negating their consumption smoothing benefits, it contributes to a more comprehensive picture of networks by shedding light on additional channels through which they affect risk-related decisions. Depending on contextual factors such as the information environment, this research suggests that networks lead to lower risk taking due to group pressure, as well as lower insurance take-up and investments in self-protection due to moral hazard. Thus, the thesis provides a more well-rounded and nuanced picture of the role of networks in rural development.

This contribution is grounded in three empirical innovations in the study of networks, risk mitigation and investment decisions. First, this thesis lays new ground by directly comparing the effect of structuring weather insurance as a group - versus individual - product for the ex-post investment decisions of the insured. Second, it is the first study to uncover evidence of moral hazard in weather insurance take-up. And third, this thesis is the first to extend the study of moral hazard to investment in self-protection tools in India.

Beyond its theoretical and empirical innovations, several policy implications arise from this body of work. Most importantly, this thesis qualifies prior enthusiasm about group insurance. With group pressure to make low-risk investments, group structures are unlikely to be a panacea in their proposed form. Self-selection of groups is one potential direction identified for future research on reducing group pressure. A second policy implication of this research is that insurance take-up in rural markets will be more successful in geographic areas with weaker redistributive norms. In contexts with stronger norms, policy regulations such as mandating all-or-none group sales may help overcome moral hazard propensities (though this should be weighed against other implications of such a product structure). Increasing formal coverage through all-or-none policies or access to formal credit may also help to compensate for low adoption of self-protection tools.

Essay 1: Insurance structure, risk sharing and investment decisions: an empirical investigation of the implications of individual and group weather index insurance

1.1 Introduction

The welfare of most low-income agrarian households in developing countries is constrained by risk (Karlan, Osei, Osei-Akoto & Udry, 2014; Townsend, 1995).[2] While informal insurance mechanisms to cope with such risks are prevalent, they are insufficient in the face of aggregate-level shocks (Deaton, 1992; Townsend, 1994; Mazzocco & Saini, 2012). Yet, take-up of formal insurance is varied. Many suggest that selling formal insurance to groups could further strengthen the effectiveness of both informal and formal insurance mechanisms (e.g., Cole et al., 2013; Dercon, Vargas Hill, Clarke, Outes-Leon, & Taffesse, 2014; Clarke et al., 2012; Clarke, 2011). However, an important unknown is whether group dynamics may generate externalities in such a context. This study contributes to our understanding of one such externality in a framed field experiment. Consistent with a simple conceptual framework, this experiment shows that selling insurance to groups (vs. individuals) leads to changes in farmers' risk-related decisions depending on the information environment and the risk composition of the group.

To explore these interactions between insurance structure and farmer decision-making, this study focuses on the case of weather insurance. A number of recent studies suggest that weather insurance can help smallholder farmers to better cope with risk by smoothing consumption and increasing average agricultural productivity. This microinsurance product disburses payouts contingent upon high or low rainfall levels

[2] Some even assert the poor are stuck in risk-induced poverty traps: they can only afford to pursue low risk, low return opportunities (e.g., Rosenzweig & Binswanger, 1993; Dercon & Christiaensen, 2011, Fafchamps, 1992). For instance, farmers (i) curb input levels to limit losses in the event of a poor harvest; (ii) diversify their employment activities, stunting opportunities to specialise and foster comparative advantages; or (iii) plant weather-resistant crops with lower profit margins (in lieu of riskier crops with higher average returns) (Gine et al., 2008; Dercon & Christiaensen, 2011; Cole et al., 2010).

measured at local rainfall stations. When risk exposure is reduced through the purchase of such a product, smallholder farmers tend to take on greater risk through other investments, for example in their choice of crops, seeds and fertiliser (Hill & Viceisza, 2012; Mobarak & Rosenzweig, 2013; Galarza & Carter, 2008).[3] As riskier inputs are associated with higher average yields, weather insurance could thus offer an important contribution to rural development. However, the productivity-enhancing role of this financial product has been strongly curtailed by its low take-up levels (e.g., Cole et al., 2013; Gine, Menand, Townsend & Vickery, 2010).

Recent research has suggested that structuring weather insurance as a group product may be the panacea to take-up challenges (e.g., Cole et al., 2013; Dercon et al., 2014; Clarke et al., 2012; Clarke, 2011). Selling to groups has been shown to increase take-up of other microinsurance products through mechanisms such as social learning, lower training and marketing costs and lower transaction costs (de Nicola & Hill, 2011; Janssens & Kramer, 2013). Similar to microcredit, group insurance also addresses adverse selection issues and moral hazard problems. Moreover, in the case of weather insurance, it has been argued that the group structure would increase take-up by reducing basis risk, i.e. the imperfect correlation between insurance payouts (determined by aggregated data from local rainfall stations) and losses incurred on individual plots.[4] As index insurance with basis risk is enhanced by informal risk sharing to cover idiosyncratic shocks (Mobarak & Rosenzweig, 2013), it has been proposed that the complementarity of formal and informal risk sharing could be strengthened through internal control over group payouts (de Janvry, Dequiedt & Sadoulet, 2014).[5] Existing research fails to consider, however, that the group structure and internal payout distribution may affect farmers in other ways as well.

[3] Similar patterns are found with other forms of agricultural insurance as well (e.g. sow insurance in Cai, Chen, Fang & Zhou (2009) and crop price insurance in Karlan, Kutsoati, McMillan & Udry (2010).

[4] Basis risk is a significant impediment to take-up of formal weather insurance (Clarke, 2011).

[5] Proposals to launch group weather insurance in India and Ethiopia include this design feature.

Drawing on insights from the microcredit and insurance literatures, the aim of this study is to explore one such effect, namely the implications of group versus individual insurance for the investment decisions farmers make once insured, i.e. their *ex-post* investment decisions. To this effect, I develop a conceptual framework that deductively identifies two juxtaposed effects of the group structure on ex-post investment decisions: (i) higher risk taking due to *moral hazard* and (ii) lower risk taking due to *group pressure*. Similar to patterns in microcredit, which of these forces prevails first depends on the information environment.

My first prediction is that investment decisions are riskier under group insurance with imperfect information compared with individual insurance with perfect information (Table 1.1). This stems from the finding in microcredit that moral hazard increases in joint liability loans because group members can hide investment decisions from their peers under imperfect information (e.g., Stiglitz, 1990; Armendariz de Aghion & Morduch, 2005). As an individual insurance policy is formally sold to an individual, ownership of the insurance payout is clearly and formally delineated. In group insurance, on the other hand, allowing the group to internally distribute the payout blurs the ownership lines and increases the size of the pot earmarked for sharing. If individuals can legitimately claim ownership over different proportions of the group payout according to losses, the opportunity for moral hazard increases relative to under individual insurance.

Table 1.1 Risk taking relative to individual insurance with perfect information

	Individual Insurance	Group Insurance
Perfect Information		↓
Imperfect Information	-	↑

Under perfect information, on the other hand, my second prediction is that group pressure outweighs moral hazard: investment decisions thus become less risky under group insurance with perfect information compared to individual insurance with perfect information (Table 1.1). This reduction in risk taking due to group pressure is consistent with the microcredit literature (e.g., Fischer, 2013; Banerjee, Besley & Guinnane, 1994). Groups feel socially obligated to share the cost of crop failure (through higher insurance payouts), though they do not reap the benefits when risk taking farmers achieve successful yields. If groups distribute the insurance payout as a function of both individual income and investment decisions, they curb peer risk taking by penalizing risky investments through lower insurance payouts to the higher-risk taking members.

In addition to the information environment, this study highlights a second factor that contributes to these interactions between insurance structure and investment decisions: the risk composition of the group. Intuitively, if farmers have the same risk preferences, they should have comparable investment preferences and thus limited tension about peer decisions. With heterogeneous risk preferences, on the other hand, diverse investment preferences are more likely to arise. Heterogeneous preferences may thus lead to moral hazard and group pressure.

To quantify the effects of moral hazard and group pressure on investment decisions, I conducted a field experiment with a sample of 329 smallholder farmers in Gujarat, India. Reliance on an experimental approach was motivated by its ability to overcome two key challenges in empirical explorations of this topic: (i) few instances of group weather insurance currently exist in practice; and (ii) it is seldom possible to identify exogenous variation in insurance coverage. This experiment is structured as a series of Kharif[6] season simulations in which income is dependent on a fertiliser decision and a stochastic weather draw. Three different treatments with hypothetical insurance are randomly assigned across the sample: (i) individual insurance with perfect information about peer investment decisions (Individual Perfect); (ii) group insurance with perfect information about peer investment decisions (Group Perfect); and (iii) group insurance with imperfect information about peer investment decisions (Group Imperfect).

This benchmark experiment yields two overarching empirical results for the case of externally organised weather insurance groups.[7] First, in line with the conceptual framework's predictions, group pressure outweighs the effects of moral hazard and leads to an 8% reduction in risk taking in contexts with perfect information and group insurance (relative to individual insurance). Based on back of the envelope calculations, this sizeable reduction translates to an average 107 rupee (Rs) reduction in earnings per acre in this experiment. As the income range was limited due to constraints in the experimental design, this can be interpreted as a conservative estimate of the income effect in practice. In view of Duflo et al.'s (2008) finding that returns to fertiliser – a risky investment – range from 36 to 257%, an 8% reduction in risk taking could significantly constrain yields. This first finding is thus concerning from a development perspective. The second main result of this study is that these average effects interact with risk preferences. In particular, more risk averse individuals are found to take less risk in contexts with group insurance and imperfect information (relative to individual

[6] Kharif season is the summer planting period in South Asia (typically, June to October).
[7] in the context in which I operate, which aims to closely replicate reality.

insurance with perfect information). This could be due to concern about the quality of informal insurance in contexts with imperfect information.

This chapter contributes to the literature in two ways. First, this study is the first – to my knowledge – to empirically identify the relationship between insurance structure and ex-post investment decisions for the case of group weather insurance. Second, this research highlights the importance of – and points to the need for further research on – the information environment and group composition for disentangling the heterogeneous effects of this relationship. In order to better design and target insurance, further consideration should be given to these contextual factors.

In terms of policy implications, this study cautions against the uniform application of group insurance barring further research on the context under which group pressure arises. One potential avenue for mitigating group pressure may be variation in group formation mechanisms. This study has focused on the case of externally-organised weather insurance groups with diverse risk preferences. As individuals are more likely to risk share among peers with similar risk attitudes (Ghatak, 2000), one possible solution to group pressure may be to allow self-selection of groups. Extending this work to the study of self-selected groups or varying the combination of risk preferences within groups would thus be an interesting direction for further research.

The rest of this essay is organised as follows. First, I review the literature and detail the conceptual framework. Then, I discuss the experimental protocols and implementation strategy. Next, I present the empirical strategy and results. Finally, I conclude with a discussion of academic and policy implications.

1.2 Related literature and theoretical motivation

To motivate further study of the implications of the group structure for ex-post investment decisions, this section first reviews relevant insights from the literatures on: (i) microcredit and information sharing and (ii) insurance and information sharing. It then presents the structure of a simple conceptual framework in which farmers facing rainfall risk must each choose among investment products with varying levels of risk and return. By comparing expected payoffs and variations in risk, this framework outlines the intuition behind why the information environment differentially affects investment decisions across individual weather insurance and group weather insurance.

1.2.1 Related literature

Varying effects of group insurance first draw on the microcredit and information sharing literature. Many scholars have identified the problem of moral hazard - risk taking above first-best optimal levels - in group lending. When borrowers are jointly liable for a loan, the inability of one borrower to make loan payments means that the rest of the group must cover these payments to prevent a group default. The level of information sharing about peer investment decisions plays an important role here: imperfect information incentivises moral hazard by hiding risk taking above first best. Some studies even suggest that this phenomenon depends on risk preferences: in particular, less risk averse individuals choose significantly riskier investments when they can hide such decisions from peers in a joint liability loan (Fischer, 2013).

To solve the moral hazard problem, microcredit scholars have pointed to peer monitoring (e.g., Stiglitz, 1990; Armendariz de Aghion & Morduch, 2005; Conning, 2005; Chowdury, 2005). In contexts with perfect information, peer monitoring allows groups to hold individuals accountable for their investment decisions. The effect of peer monitoring, however, often goes beyond curbing moral hazard. A few studies suggest that peer monitoring reduces risk taking below socially optimal levels through group pressure (Fischer, 2013; Banerjee, Besley & Guinnane, 1994).[8] Perfect information about peer decisions and, in particular, project approval rights by peers, discourages risky investments. Fischer (2013) suggests this pressure helps to explain stunted growth in microbusinesses: groups cover the cost of peer failure but do not reap a share of the benefits when peer investments succeed. This disparity incentivises groups to discourage risk taking in peer businesses – a finding that is also consistent with the sociology literature on the role of social pressure in cooperation (e.g. Simmel, 1950; Coleman, 1988; Festinger, Schachter & Back, 1950).

The insurance literature also provides an important foundation for exploring interactions between insurance, the information environment and decision-making (e.g., Akerlof, 1970; Rothschild & Stiglitz, 1976; Cutler & Reber, 1998; Kinnan, 2014). A substantial literature has focused specifically on insurance in the agricultural sector: crop insurance, for instance, is widely recognised for its susceptibility to moral hazard (e.g., Smith & Goodwin, 1996).[9] Several recent papers have also studied group microinsurance (e.g., Janssens & Kramer, 2013; Clarke et al., 2012). This study fills an important gap in the literature on insurance and information, however, as the first to explore the implications of the group structure and the information environment for decision-making in the context of weather insurance.

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[8] As this study focuses on contexts with strong network effects and redistribution norms, approval rights and perfect monitoring are expected to be closely linked.

[9] Crop insurance provides a payout in the event of crop failure. Such a product incentivises moral hazard in contexts with imperfect information about farmer effort: an insurance agent visits each plot of land to determine payouts, but is not always present to monitor farmer effort.

1.2.2 Conceptual framework

Building on this literature, the following conceptual framework illustrates how changes in insurance structure and the information environment lead to differential effects on investment decisions. To clarify what this simple world looks like, consider a risky environment in which three randomly assigned[10] smallholder farmers grow cotton. In line with the experimental design described in the next section, this world has the following structure:

- At t=0, each farmer starts the period with the same endowment *e*.

- At t=1, each farmer is mandated[11] to purchase an individual weather insurance product. The payout *t* for this policy is triggered with probability *1-p*. Assuming the policy is actuarially fair, then $m = (1\text{-}p)t$ where *m* is the insurance premium. Importantly, this policy offers partial insurance, as payouts are determined at the rainfall station and are not perfectly correlated with losses suffered on individual plots of land. The three farmers live in close proximity and the probability of receiving a payout (*1-p*) or no payout (*p*) is identical across the three farms. Individual shocks and payouts are strongly correlated, but not perfectly correlated (i.e. there is limited basis risk). For tractability, the three farmers have the same expectation about basis risk.

- At t=2, each farmer aims to simultaneously optimise his investment decision among two fertilisers with cost *f*: (i) a low-risk fertiliser (*l*) and (ii) a high-risk

[10] That is, they do not self-select into a group. While this assumption limits the generalisability of this framework, it offers a relevant case as countries such as India strive towards universal coverage through national schemes. This research focus is also an important first step in understanding the implications of group insurance, and is a useful prerequisite to future studies on the implications of group insurance for specific sub-sets of the target population.

[11] While studying investment choices conditional on insurance is a narrower research question, the policy implications of this design are still important because India increasingly mandates insurance coverage by building it into agricultural loans. This theoretical focus is also taken to align with a feasible experimental design.

fertiliser (h). Fertiliser is used for illustrative purposes in this framework, though it can be applied to other key agricultural investment choices made by smallholder farmers that affect unobservable risks.[12]

The individual fertiliser choice is a function of the probability of drought on the individual plot and the individual's risk preferences r. The return on these two fertilisers depends on rainfall on the individual plot and a random component. Relative to fertiliser l, fertiliser h yields higher average returns ($y + a_i + b_i$) in periods with rainfall (p) and lower average returns (y-c_i) in periods with drought (1- p), where y is the base income, a_i is the income increase from rainfall, b_i is the return from high-risk fertiliser in rainfall and c_i is the loss in income from the high-risk fertiliser in drought. Subscripts denote heterogeneity across individuals due to idiosyncratic risk on individual plots of land.

Prior to choosing a fertiliser, the three farmers can informally discuss the two alternatives. Choices are then made simultaneously and privately.

- At t=3, these choices are revealed across the village, as there is perfect information about investment decisions.[13]

- At t=4, weather conditions are determined. As previously mentioned, each farmer's yields are affected by two factors: (i) exogenous rainfall at the individual plot and

[12] Different levels of risk can be undertaken through variation in either the (i) type or (ii) quantity of fertiliser used. In terms of type effects, risk may be increased by adopting a fertiliser that requires more precise rainfall to maximise yields or by experimenting with a new fertiliser that has a learning curve for determining optimal allocation. In terms of quantity effects, risk may be increased by augmenting fertiliser amounts: in seasons with insufficient rainfall, high fertiliser application leads to sunk expenditure costs and lower yields through soil scorching. This paper focuses on the former.

[13] As will be discussed in the experimental treatment design, choices are not revealed in the context of imperfect information.

(ii) an individual investment decision. When a shock occurs, it affects the entire group, but to varying degrees.[14]

- At t=5, each farmer receives income earned (and an insurance payout t if a shock occurs).

- At t=6, the three farmers can conduct informal transfers to mitigate idiosyncratic risk amongst themselves.

- Lastly, at t=7, the farmers return to t=0: this is a repeated game.

This framework can be used to illustrate how varying the type of insurance (from individual to group) and the information environment (from perfect information to imperfect information) may change investment decisions. For ease of comparison across different types of insurance, Table 1.2 presents payoffs in each state of the world (drought in Column 3 and optimal rainfall in Column 4), expected payoffs (Column 5) and the difference in payoffs across the two states (Column 6). Choosing the low-risk fertiliser l with no insurance corresponds to lottery A, which provides a payout of y in case of drought and $y + a_i$ in case of rainfall. Choosing the high-risk fertiliser h with no insurance corresponds to lottery B. Lotteries A' and B' correspond to choosing fertilisers l and h in contexts with individual insurance, respectively, etc.

[14] I assume that yields are imperfectly correlated across the three farmers to focus on the case in which risk sharing is possible.

Table 1.2 Fertiliser choice and expected payoffs[15]

(1) Lottery	(2) Risk-level	(3) Payoff in drought *(1-p)*	(4) Payoff in rainfall *(p)*	(5) Expected payoff (EP)	(6) = (4) - (3) Difference in payoff across *(1-p)* & *(p)*
NO INSURANCE					
A	Low-risk	y	$y + a_i$	$y + pa_i$	$\boldsymbol{a_i}$
B	High-risk	$y - c_i$	$y + a_i + b_i$	$y + pa_i - c_i(1\text{-}p) + pb_i$	$\boldsymbol{a_i + b_i + c_i}$
INDIVIDUAL WEATHER INSURANCE					
A^I	Low-risk	$y - m + t$	$y + a_i - m$	$y + pa_i$	$\boldsymbol{a_i - t}$
B^I	High-risk	$y - c_i - m + t$	$y + a_i + b_i - m$	$y + pa_i - c_i(1\text{-}p) + pb_i$	$\boldsymbol{a_i + b_i + c_i - t}$
GROUP WEATHER INSURANCE					
A^{II}	Low-risk	$y - m + t + d_i$	$y + a_i - m$	$y + pa_i + d_i(1\text{-}p)$	$\boldsymbol{a_i - t - d_i}$
B^{II}	High-risk	$y - c_i - m + t + d_i$	$y + a_i + b_i - m$	$y + pa_i - c_i(1\text{-}p) + pb_i + d_i(1\text{-}p)$	$\boldsymbol{a_i + b_i + c_i - t - d_i}$

y - base income | *c - income decrease from high-risk fertiliser in drought*
a - income increase from rainfall | *b - income increase from high-risk fertiliser in rainfall*
m - insurance premium | *p - probability of optimal rainfall at rainfall station*
t - insurance payout | *d - distribution of insurance payout (penalty/bonus)*

1.2.2.1 Individual insurance

To compare the differential payoffs and risk profiles of the six lotteries, let's start with individual insurance. Table 1.2 illustrates how individual insurance leads to greater risk taking than no insurance: expected payoffs are equal with and without insurance (Column 5), but individual insurance involves less risk because the difference in payoffs is lower (Column 6). I expect this risk reduction will lead some farmers with individual insurance to take on riskier ex-post investment decisions - and thus achieve higher average yields - than they would with no insurance.

Intuitively, the effect of perfect or imperfect information about investment decisions on risk taking is ambiguous. In scenarios with perfect information, peers can observe all rainfall levels in the village, investment decisions (h or l) and income realisations. If the information parameter is relaxed, peers can observe income realisations, but rainfall

[15] No Insurance and Individual Insurance are adapted from Hill and Viceisza (2012).

levels at the individual plot and investment decisions are private. In both cases, farmers do not have the financial power to withhold or seize the insurance payout t because payouts are distributed directly to each farmer. Imperfect information enables some moral hazard through informal transfer requests, but it also constrains the effectiveness of informal insurance. Thus, the effect of the information environment in the context of individual insurance is unclear.

1.2.2.2 Group insurance

As individual insurance faces challenges in practice – such as low take-up - now consider the effect of information on investments when the individual insurance policy at t=1 is changed to a group insurance policy with a payout of $3t$. While group insurance may address the aforementioned take-up problems, this rest of this section illustrates that - relative to the individual insurance benchmark - group insurance may exacerbate two other issues depending on the information environment: (i) high risk taking due to an increase in moral hazard in group insurance with imperfect information (Group Imperfect) and (ii) low risk taking due to group pressure in group insurance with perfect information (Group Perfect).

In contrast to individual insurance, group insurance awards the group physical control over the payout and the right to decide what proportion to distribute to each group member. A social planner exogenously imposes the following decision rule for this distribution process: [16] each individual's insurance payout is equal to $t + d_i$, where d_i is a distribution penalty or bonus determined as a function of two factors:

(i) individual i's fertiliser choice relative to the group average ($d_i > 0$ for individuals that take less risky investments and $d_i < 0$ for individuals that take more risky investments) and

[16] As this study will describe, such a decision rule is consistent with farmer behaviour in the experiment.

(ii) individual i's income realisation relative to the group average ($d_i > 0$ for individuals with income below the group average and $d_i < 0$ for individuals with income above the group average).

As the group payout $3t$ is fixed, $d_1 + d_2 + d_3 = 0$. Drawing on the microfinance literature (Fischer, 2013), such a decision rule is consistent with the logic that groups support losses, but discourage risk taking because they have to share the cost of crop failure (by awarding a larger proportion of $3t$ to group members with greater losses) and do not necessarily reap the benefits when a group member has a successful crop.

With this structure in mind, let's first explore the case of "Group Imperfect". As a benchmark, a farmer with "Individual Imperfect" can hide his choices and ask for informal transfers, but peers do not have a formal obligation to fully insure his losses. Under "Group Imperfect", however, one would intuitively expect moral hazard to be even higher because the insurance payout is controlled by the group and partitioned according to the abovementioned distribution rule. As fertiliser choices are private, the farmer now has an added incentive to choose fertiliser h because he can hide this choice from the group and then claim a higher d_i.

Relative to individual insurance, group insurance introduces an additional source of moral hazard by increasing the size of the pot that is earmarked for sharing. Contrary to the clearly delineated ownership of an insurance payout from an individual policy, ownership of a group payout depends on losses suffered. As the farmer's dominant strategy is to lie under imperfect information, the redistribution rule is based on the only publicly available information: income realisations. However, such an adjustment still leaves room for moral hazard. If the group awards higher payouts to individuals with lower income ($d_i > 0$ for individuals with income below the group average and $d_i < 0$ for individuals with income above the group average), a farmer is more likely to choose fertiliser h under "Group Imperfect" than under "Individual Imperfect" because it generates higher expected payoffs. Such an effect is then magnified if farmers suspect their peers will choose fertiliser *h*; as the cost of insuring these investments is too high, the choices of others may be distorted and they may engage in risky practices as well (Fischer, 2013).

Let's now consider the case of group insurance and perfect information about peer investment choices ("Group Perfect"). In line with the decision rule, "Group Perfect" is expected to lead to lower risk taking relative to "Individual Perfect". Under "Group Perfect", the group redistributes $3t$ as a function of both individual income and fertiliser choice (*l* or *h*). To reduce the likelihood of doling out larger payout proportions to support high losses by risk-takers, groups pressure members to take less risk. This is achieved by increasing the penalty ($d < 0$) in order to reduce the expected payoff of Lottery B'' (as you may recall, Lottery B'' corresponds to selecting fertiliser *h* under group insurance). If $d_i(1\text{-}p)$ is large and negative for risk-takers, a farmer with "Group Perfect" is more likely to choose fertiliser *l* than under "Individual Perfect" because the difference in expected payoffs across fertiliser *l* and *h* is reduced. Thus, group pressure is expected to outweigh moral hazard in "Group Perfect" (relative to "Individual Perfect").

For these predictions about investment decisions to hold, a second factor – in addition to the information environment - should be kept in mind. Importantly, the risk preference composition of the group is expected to affect the relationship between insurance structure and investment decisions. In particular, one would not expect significant levels of group pressure to occur amongst groups with homogeneous risk preferences – which is likely to arise if group members self-select (Ghatak, 2000; Attanasio, Barr, Cardenas, Genicot & Meghir, 2012). With heterogeneous preferences, on the other hand, group members are likely to have different investment choices. As this study focuses on the case of groups that are randomly assigned - i.e. they do not self-select – heterogeneous preferences are the main case of interest.

In contexts with imperfect information, it should also be kept in mind that certain risk preferences may also lead to heterogeneous effects. In particular, less risk averse individuals may be more likely to free ride (Fischer, 2013; Janssens & Kramer, 2013). On the other hand, more risk averse individuals may be more likely to reduce risk taking due to greater reliance on informal risk sharing and concern that it is a less effective form of insurance under imperfect information.

The literature on group risk aversion also points to several possible implications of risk preferences in a group setting. In contexts with perfect information, group pressure may lead to a convergence of investment decisions to the average: less risk averse farmers are pressured to make less risky choices while more risk averse farmers are pressured to take riskier investments that match the group norm.[17] Some studies would even suggest that groups conform to below average individual risk levels.[18]

In sum, the dominant effect of moral hazard and group pressure on ex-post investments may differ according to the type of insurance, the information environment and risk preferences within the group. In this regard, this framework leads to three testable predictions: (i) investment decisions will be less risky in “Group Perfect” than in “Individual Perfect” due to relatively higher levels of group pressure in “Group Perfect”; (ii) investment decisions will be riskier in “Group Imperfect” than “Individual Perfect” due to relatively higher opportunities for moral hazard in “Group Imperfect”; and, a clear comparative static following from the first two predictions, (iii) investment decisions will be less risky in “Group Perfect” than in “Group Imperfect” due to stronger group pressure and moral hazard effects, respectively. Importantly, heterogeneous risk preferences within groups are likely to exacerbate these predictions.[19]

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[17] Alternatively, more risk averse individuals may feel they having nothing to lose from taking on higher risk because the less risk averse majority would dictate the distribution rule in their favour.

[18] Groups are found to be more risk averse when faced with low probabilities of winning (e.g., Baker, Laury & Williams, 2008; Shupp & Williams, 2008; He, Martinsson & Sutter, 2011).

[19] One can envision several secondary effects of group versus individual insurance and perfect versus perfect information that fall outside the primary focus of this study. For instance,

1.3 Experimental design

To determine how big the effect of different insurance structures are and how these effects depend on the information environment, I conducted a framed field experiment with smallholder farmers in Gujarat, India. While the external validity of a lab experiment is more limited than a field experiment, a lab setting offers valuable first insights into the research topic at hand. First and foremost, a lab experiment facilitates a cleaner analysis. For instance, narrowing the risk factors to rainfall levels and input choice through a lab environment enables a more robust analysis of the interactions between these two risks and insurance - in a field experiment, there are multiple other drivers of crop failure that cannot be disentangled. As proposed by Levitt and List (2007), this cleaner approach should still be externally valid as I simulate real world decisions with similar ethical considerations, peer scrutiny and high financial stakes.

A second motivation for employing a lab design is that it is a cost efficient method for taking a first look at the implications of group insurance. As group insurance could affect farmers' investment decisions, it is preferable to investigate these predictions in a lab setting before launching real products that could have welfare-reducing effects. This experiment thus acts as a proof of concept to provide a preliminary exploration of the issue at hand.

Finally, a lab experiment is more effective at capturing the effect of insurance on investment decisions, as it is difficult to measure variation in investment decisions by offering real high-yield seeds or fertiliser in a field experiment. Participants may already have trusted distribution channels for purchasing these products, and thus skew the results by making random choices in the games because they have no intention of purchasing products offered by the experiment.

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imperfect information could decrease risk taking across all scenarios because it constrains informal risk sharing. On the other hand, group weather insurance could increase risk taking by facilitating enhanced risk sharing (though this is unlikely to be the dominant effect given that informal risk sharing is common practice among the rural poor).

With these rationales in mind, this experiment was conducted with a sample of 329 smallholder farmers from the Ahmedabad district in Gujarat, India. Gujarat offers an ideal case for exploring this topic as one of the main hubs for weather insurance sales in India. More broadly, India offers an important country case as its microinsurance industries and insurance regulations are among the most advanced in the developing world (ILO, 2006), and the Indian government is committed to the spread of microinsurance in the coming years (Gine, Menand et al., 2010).

Participants were recruited for this experiment through assistance from *Taluka* Development Officers and *Sarpanch* (block and village level government representatives, respectively). All participants (i) grow cotton, (ii) own between 1 and 10 acres of land, (iii) are at least 18 years old and (iv) live within 10 km of a rainfall station. The experiment was conducted in a temporary experimental laboratory in Ahmedabad in March and April 2013, a time of year in which cotton farmers have fewer fieldwork responsibilities.

Upon arrival, participants were organised into groups of three to simulate local communities in the experiment.[20] To reduce the risk of informal transfers among group members after the lab, participants were matched in groups with farmers from other blocks.[21] While these random group assignments limit (a conservative view of) the external validity of these findings to externally-organised - as opposed to self-selected - weather insurance groups, this is an important first question and paves the way for subsequent research on self-selected groups.

Each farmer was paired with an interviewer, who was responsible for individually explaining the games, testing participant comprehension and collecting participant data

[20] Twenty-four participants (eight farmers from three villages) were interviewed per day, organised into eight sessions with three farmers each. Two sessions were run at a time in adjoining rooms.

[21] Blocks are district sub-divisions comprising groups of villages.

on a personal laptop. The interview lasted approximately two hours and had four components: a Binswanger lottery game to measure risk preferences;[22] the experiment on investment decisions I examine in this study; a second experiment on informal insurance and weather insurance take-up explored in Essay 2, and a series of follow-up questions to collect data on the participant's characteristics and decision-making processes in the lab. The order of the two experiments (on investment decisions and take-up) were randomised across the sample to control for the risk that playing one game first might affect choices in the second.

Participants were paid privately at the end of the session for their earnings in one randomly selected round of either this experiment, the take-up experiment or the Binswanger lottery to measure risk aversion.[23] Total earnings per participant ranged from Rs 150 to Rs 570. Average earnings were Rs 267 (approximately \$5),[24] equivalent to approximately three days' wages from farm labour.

1.3.1 Experiment overview

The central component of this experiment is a series of Kharif season simulation rounds that follow the same timing of events laid out in the conceptual framework:[25]

[22] In the Binswanger lottery, participants are offered a choice between eight lotteries, each of which is determined by drawing a black or white ball from a bag. Each outcome has probability 0.5. The amounts for each of these lotteries are demonstrated with an image of the corresponding rupee notes (Binswanger, 1980; Fischer, 2013; see Appendix II). The actual ball draw takes place at the end of the interview, so as not to influence participant choices throughout the other games and follow-up questions.

[23] Participants are only paid for one round so that individuals do not partially self-insure across rounds (Fischer, 2013).

[24] Participants also received free travel to and from Ahmedabad and lunch on-site. Travel time to the laboratory ranged from 1.5 to 2.5 hours.

[25] See Appendix I – Phase 5 for experiment script example.

t=0	t=1	t=2	t=3	t=4	t=5	t=6	t=7
Give endow-ment	Mandate insurance	Choose investment	Announce investment choice (GP + IP)	Introduce weather	Reveal earnings & insurance payout t (IP) or 3t (GP + GI)	Allow transfers	End. Go to t=0

To obtain an unbiased estimate of the effect of insurance structures and information access on investment decisions, small variations in this timing are introduced by randomly assigning participants to one of the following three treatments: [26]

- Individual Perfect (IP) - <u>individual</u> insurance with *perfect* information about peer investments
- Group Perfect (GP) - <u>group</u> insurance with *perfect* information about peer investments
- Group Imperfect (GI) - <u>group</u> insurance with *imperfect* information about peer investments

In the treatment with <u>individual</u> insurance, payouts are awarded directly to each participant when a drought occurs. In treatments with <u>group</u> insurance, insurance payouts are awarded to the group as a whole when a drought occurs and the group decides internally what proportion of the payout goes to each member.

In treatments with *perfect* information, investment decisions are made public to the entire group before the weather conditions are revealed for that round. According to anecdotal evidence, perfect information is closer to existing practices of sharing information about agriculture-related choices with peers (in many rural societies

[26] While it would be interesting to include a fourth treatment group with individual insurance and imperfect information, sample size restrictions limited how many treatments could be included.

including Gujarat). [27] [28] In the treatment with *imperfect* information, investment decisions are kept private. It should be noted that individuals have an opportunity to informally discuss what they think about the investment options in all treatments before purchasing; thus, the only difference between *perfect* information and *imperfect* information is whether or not final choices are announced to group members.

Taking this treatment design into account, the rest of this section reviews the timing of events in more depth:[29]

t=0 Give endowments

Each farmer is given one acre of land and a cash endowment of 18,600 Game Rupees (Rs).[30] In each round, participants start with a zero balance and are then given a new endowment of Rs 18,600.[31] Immediately after receiving the endowment, each participant has to pay Rs 10,000 for agricultural inputs (excluding fertiliser). The remainder of the endowment is for purchasing insurance and fertiliser.

t=1 Mandate purchase of an insurance product

Each farmer is presented with a mandatory insurance policy. The face value of this actuarially fair policy is m=Rs 3,600 per person. This policy is sold at a discounted random price of between Rs 0 and 3,600.[32] Following a similar approach to Hill and

[27] This is also consistent with the literature on social learning, for which information sharing is a prerequisite (e.g. Foster & Rosenzweig, 1995; Cai, de Janvry & Sadoulet, 2013).

[28] However, as it is not definitive which world (perfect or imperfect information) is closest to reality, a conservative interpretation of the results in this study is that comparing "Group Perfect" and "Group Imperfect" serves to bound the effect.

[29] Prior to commencing the game, the following timing of events is explained in great depth to each participant individually. Questions to test comprehension are posed periodically throughout the instructions.

[30] For this experiment, 100 game rupees are equal to 1 real rupee.

[31] This design feature was included to control for potential income effects. As results in later rounds may still be affected, I run several regressions to test for round effects.

[32] This discount is introduced to be consistent with the take-up experiment (see Chapter 2). While not in the conceptual framework, a discounted price should not have any significant implications for the interpretation of the results in this study as it is employed across all treatments.

Viceisza (2012), insurance is mandated to ensure sufficient take-up levels to measure the impact of different insurance scenarios.[33]

In the "Individual Perfect" treatment, this is an individual policy with a payout t = Rs 10,800 when a drought occurs in the village (with probability $1-p$). In the "Group Perfect" and "Group Imperfect" treatments, this is a group policy with a payout $3t$ = Rs 32,400 for the entire group.

As this is an index policy, shocks are measured at a central rainfall station and t is set independently of individual-level losses, thus introducing a limited level of basis risk. Importantly, this experimental design assumes a more limited degree of basis risk than has historically characterised many weather insurance products by focusing only on scenarios in which the farmer suffers a loss and receives an insufficient payout.[34] While this component of basis risk includes a slightly different distribution of payoffs from the (somewhat contested) conventional understanding of the term,[35] I expect this structure may map more closely with the distribution of lotteries of new and future weather insurance structures that reduce basis risk through the installation of more rainfall stations, use of satellite data and development of hybrid products with area yield insurance.[36] Importantly, as the component of basis risk depicted in this experiment is constant across the three treatment groups and insurance is mandated, this design choice should not influence the treatment effect. Moreover, whether the experimental

[33] As aforementioned, this design feature is included to reduce sample size requirements. It is nonetheless in line with national decisions in countries such as India to mandate insurance coverage by building it into agricultural loans.

[34] Basis risk can be so severe that a farmer receives a payout in years with good yields (upside basis risk), or does not receive a payout in years with low yields (downside basis risk). In this experiment, I exclude these two extreme scenarios and focus on limited levels of basis risk in which losses are incurred and insufficient payouts are disbursed. The narrow range of basis risk assumed in this game should be kept in mind when evaluating the external validity of these results.

[35] Basis risk has been modelled and defined in a number of ways (e.g., Clarke, 2011; Karlan et al., 2014).

[36] This design feature also aimed to simplify the experiment in order to maximise participant comprehension.

design incorporates full basis risk or a component of basis risk is a secondary concern; for the experimental design, one merely needs an unobservable factor that allows for moral hazard.

t=2 Make investment decision

Each participant is offered three fertiliser products that span a range of risk and return levels (Table 1.3).[37][38] All products cost Rs 5,000. As in the conceptual framework, on average, participants that choose risky investments have higher income in rounds with optimal rainfall (*p*) and lower income in rounds with drought (*1-p*). Expected income for the three fertilisers increases with the level of risk. Payoffs are set such that individuals with different levels of risk aversion will have different expected utilities, and thus, distinct preferences for one of the three products.[39]

For each fertiliser, income follows a random beta distribution dependent on two factors: (i) the investment decision at t=2 and (ii) a random weather condition at t=4.[40] The random weather draw (*p* or *(1-p)*) affects the entire group, but individual earnings may vary within these draws, as rainfall varies from plot to plot and investment decisions have different payoffs. As earnings can fall anywhere in the ranges in Table 1.3 for any fertiliser, however, it is impossible to know with complete certainty which fertiliser an individual has chosen based on their income.

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[37] To simplify the experiment, I focus on one important investment choice that smallholder farmers commonly face. Fertiliser is a key determinant of agricultural income; proper usage of fertiliser is associated with higher average productivity (Duflo et al., 2008).

[38] Offering three products diverges from the two options that were presented in the simplified conceptual framework. However, this difference in the experimental design should not have any implications for the interpretation of the empirical results.

[39] These risk and return levels are constant across all treatments; as basis risk does not vary across the treatments, this experiment does not test the effect of basis risk.

[40] The beta distribution is used because it can have finite support for precise ranges (Rs 500-7,500 in drought, and Rs 25,000-35,000 in optimal rainfall). Moreover, the shape and mean of the beta distribution can be manipulated to align with average earnings for each fertiliser and weather condition.

Table 1.3 Fertiliser options (in Rs)[41]

	Average income if drought ($1-p=1/3$)	Average income if optimal rainfall ($p=2/3$)	Expected Income
Low-risk fertiliser	6,000	27,000	20,000
Average-risk fertiliser	3,500	30,000	21,167
High-risk fertiliser	2,000	31,000	21,333
	Income range if drought	Income range if optimal rainfall	
	Rs 500-7,500	Rs 25,000-35,000	

After learning about these three fertilisers, participant comprehension is tested by asking each participant to privately explain the difference between them. Participants are then instructed to gather with their group members to discuss the three alternatives informally. This discussion takes place in all three treatments, thus reducing the risk that social learning or herding drives the treatment effect in "Group Perfect". Fertiliser choices are made simultaneously and privately after this discussion.

t=3 Publicly announce investment decision (in GP and IP only)

After decisions have been made, participants in "Group Perfect" and "Individual Perfect" must publicly announce their choice to the group.

t=4 Randomly introduce shock (probability $1 - p = .33$) or no shock (probability $p = .67$)

When a shock occurs ($1\text{-}p = .33$), it affects the entire group, but to varying degrees.

t=5 Reveal income earned and insurance payout if relevant (*t* in IP; *3t* in GP and GI)

Income earned varies across the group. Broadly in line with average earnings for growing cotton on one acre of land in Gujarat, individual income ranges from Rs 500 to 7,500 $(y - c_i)$ when there is a shock, and Rs 25,000 to 35,000 $(y + a_i + b_i)$ when there is

[41] These averages are parameters of a beta distribution

no shock.[42] Participants must announce their true earnings to the group in all treatments. As this experiment tests for *ex-ante* moral hazard, the only hidden information is the investment decision.

In the “Individual Perfect” treatment, an insurance payout t=Rs 10,800 is distributed directly to each participant when a shock occurs. In the “Group Perfect” and “Group Imperfect” treatments, the group receives Rs 32,400 and is given free rein over how to disburse the payout within the group.

t=6 Allow informal transfers

After income and payouts have been distributed, participants can informally redistribute amongst themselves if they reach such an agreement with any of their group members. Such a transfer can be used by participants with individual insurance that try to mitigate idiosyncratic risk informally or by participants with group insurance that are not satisfied with the group distribution rule and decide to reallocate earnings bilaterally.

t=7 Start the game again at t=0 if a white ball is drawn

The minimum number of rounds in this game is one and the maximum number of rounds is eight. Participants are not aware that the game is limited to eight rounds. At the end of each round, the group continues to the next round with a probability of 67%: if a white ball is drawn from a bag containing two white balls and one violet ball (Fischer, 2013).

The possibility of playing multiple rounds aims to mirror dynamic interactions that farmers have with peers in real life. While participants start each round with the same endowment,[43] repeated interactions facilitate information sharing about peer preferences. In the case of “Group Imperfect”, the only information shared is through

[42] If the farmer chooses the low-risk fertiliser, $b_i = c_i = 0$

[43] To control for wealth effects.

informal discussions about the fertiliser products and the announcement of income realisations: information thus increases incrementally with each subsequent round, but remains imperfect.

To summarise, there are only two differences in the timing of events across the treatment groups: (i) whether or not fertiliser choices are publicly announced at t=3 and (ii) how insurance payouts are disbursed at t=5 (Table 1.4). In all treatments, farmers have an opportunity to discuss the fertiliser options, must publicly announce income earned and can informally make transfers after income and insurance payouts have been distributed.

Table 1.4 Summary of treatments

	Fertiliser discussion t=2	Public announcement of fertiliser choice t=3	Public announcement of income realisation t=5	Group payouts t=5	Informal risk sharing t=6
Group Perfect (GP)	x	x	x	x	x
Group Imperfect (GI)	x		x	x	x
Individual Perfect (IP)	x	x	x		x

This treatment design facilitates exploration of three key predictions relating to the implications of insurance structure and the information environment for ex-post investment decisions.[44]

Prediction 1:

On average, each individual is predicted to weakly decrease the amount of risk that they take from “Individual Perfect” to “Group Perfect”.

Prediction 2:

On average, each individual is predicted to weakly increase the amount of risk that they take from “Individual Perfect” to “Group Imperfect”.

Prediction 3:

On average, each individual is predicted to weakly increase the amount of risk that they take from “Group Perfect” to “Group Imperfect”.

1.4 Experimental results

This section reviews the empirical strategy undertaken to analyse the implications of the group structure and the information environment for ex-post investment decisions. First, I discuss the descriptive statistics for my sample. Then, I present my analysis of the treatment effect on investment choice. This is followed by a discussion of mechanisms through which these effects transpire. Finally, I conduct several robustness checks of my analysis.

[44] Assuming heterogeneous risk preferences across farmers.

1.4.1 Descriptive statistics

The results presented in this study are based on 667 rounds of the investment game, played by 319 farmers.[45] Summary statistics overall and disaggregated by treatment group for several key farmer and household characteristics are presented in Table 1.5 at the individual level. The average age of participants was 41 and the majority of participants had completed fewer than 7 years of schooling.

Table 1.6 shows differences in means across treatment groups. The number of differences that are statistically significant is consistent with what one would expect from a random allocation across treatments. In an F-test of joint significance of all covariates, I do not reject the hypothesis that the covariates are jointly uncorrelated with treatment assignment (p=0.81). No covariates are significant at the 10% level or lower when regressing treatment assignment on all covariates and clustering at the group level. This provides confidence in the integrity of the randomisation and suggests this sample has balance on unobservables.

For nearly all of the variables, the difference in means is not statistically different from zero. The main unbalanced observables relate to small subgroups within the sample (i.e. farmers that have completed 11^{th} to 12^{th} grade and the distribution of six female participants across the sample). To address any differences, controls for variables with statistically significant differences are included in the regression analysis.

[45] Of the 329 individuals surveyed after the pilot stage, 10 were excluded from this analysis (7 with incomplete control variable data, 1 that would not play the Binswanger lottery, and 2 that had a missing group member and thus only played the games in a group of 2). Inclusion of these observations does not change the results significantly.

Table 1.5 Summary statistics

	All Farmers	Individual Perfect (IP)	Group Perfect (GP)	Group Imperfect (GI)
Socioeconomic Characteristics				
Gender (1= Male)	0.98	0.99	1.00	0.97
	(0.12)	(0.10)	(0.00)	(0.18)
Age (years) mean	40.70	41.44	41.43	39.41
	(13.11)	(12.89)	(13.05)	(13.36)
median	40.00	40.00	40.00	40.00
Education				
Illiterate	0.22	0.23	0.23	0.20
	(0.41)	(0.42)	(0.42)	(0.40)
Class 1 to 7	0.42	0.41	0.43	0.42
	(0.49)	(0.49)	(0.50)	(0.50)
Class 8 to10	0.25	0.24	0.25	0.26
	(0.43)	(0.43)	(0.44)	(0.44)
Class 11 to 12	0.09	0.10	0.05	0.11
	(0.28)	(0.31)	(0.21)	(0.32)
Graduate	0.02	0.02	0.04	0.01
	(0.15)	(0.14)	(0.19)	(0.09)
Plot size (acres) mean	5.17	5.22	5.06	5.22
	(2.60)	(2.59)	(2.55)	(2.69)
median	4.57	5.14	4.57	4.85
Landowner	0.92	0.93	0.91	0.94
	(0.26)	(0.26)	(0.29)	(0.24)
Village distance from Ahmedabad (Km)	91.18	89.43	92.58	91.36
	(25.77)	(24.60)	(26.38)	(26.29)
Caste				
Scheduled Castes (SC)	0.16	0.13	0.13	0.15
	(0.37)	(0.34)	(0.33)	(0.35)
Scheduled Tribes (ST)	0.01	0.00	0.01	0.01
	(0.10)	(0.07)	(0.07)	(0.09)
Other Backward Classes (OBC)	0.62	0.66	0.66	0.54
	(0.49)	(0.48)	(0.47)	(0.50)
Other	0.21	0.20	0.20	0.24
	(0.41)	(0.40)	(0.40)	(0.43)
Risk aversion parameter				
Est. Coefficient of Partial Risk Aversion	1.21	1.34	1.11	1.20
	(1.93)	(2.09)	(1.75)	(1.96)
Experience of weather risk / Rainfall risk exposure				
Experienced drought in last 3 years	0.44	0.44	0.44	0.44
	(0.50)	(0.50)	(0.50)	(0.50)
Number of observations	319	97	106	116

Note: standard deviations in ( ).

Table 1.6 Difference in means across treatment groups

	GP vs. IP	GI vs. IP	GI vs. GP
Socioeconomic Characteristics			
Gender (1= Male)	-0.02	0.01	0.03*
	(0.02)	(0.01)	(0.02)
Age (years)	-2.03	-0.01	2.02
	(1.81)	(1.82)	(1.78)
Education			
Illiterate	-0.03	0.00	0.03
	(0.06)	(0.06)	(0.06)
Class 1 to 7	0.01	0.02	0.01
	(0.07)	(0.07)	(0.07)
Class 8 to10	0.02	0.02	0.00
	(0.06)	(0.07)	(0.06)
Class 11 to 12	0.01	-0.06	-0.06*
	(0.04)	(0.04)	(0.04)
Graduate	-0.01	0.02	0.03
	(0.02)	(0.02)	(0.02)
Plot size (acres)	0.00	-0.16	-0.15
	(0.36)	(0.36)	(0.35)
Landowner	0.01	-0.02	-0.03
	(0.03)	(0.04)	(0.04)
Village distance from Ahmedabad (Km)	1.93	3.15	1.22
	(3.51)	(3.59)	(3.54)
Caste			
Scheduled Castes (SC)	0.00	0.07	-0.07
	(0.05)	(0.05)	(0.05)
Scheduled Tribes (ST)	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)
Other Backward Classes (OBC)	0.00	-0.12*	0.12*
	(0.07)	(0.07)	(0.07)
Other	0.00	0.05	-0.04
	(0.06)	(0.06)	(0.06)
Risk aversion parameter			
Est. Coefficient of Partial Risk Aversion	-0.14	-0.23	-0.09
	(0.28)	(0.27)	(0.25)
Experience of weather risk / Rainfall risk exposure			
Experienced drought in last 3 years	0.00	0.00	0.00
	(0.07)	(0.07)	(0.07)

Note 1: standard errors of the differences in ( ).
Note 2: *** p<0.01, ** p<0.05, * p<0.1
Note 3: P-value from F-test of joint significance of all covariates above is 0.51. No covariates are significant at the 10% level or higher when regressing treatment on all covariates and clustering at the group level. Results available upon request.

1.4.2 Main analysis

This section presents regression analyses of the implications of the group structure and the information environment for the level of risk taking in ex-post investment decisions. To do so, the following ordinal logit analysis is first employed:

$$Y_{ij} = \beta_o + \beta_1 GP_j + \beta_2 GI_j + \beta_3 GP_j R_i + \beta_4 GI_j R_i + \beta_5 R_i + \beta_6 X_i + \varepsilon_{ij} \qquad (1.1)$$

where Y_{ij} equals the fertiliser choice of the farmer (one for low-risk, two for average-risk, three for high-risk) for individual i in group j.[46] GP_j is equal to one for farmers in the "Group Perfect" treatment and zero otherwise, GI_j is equal to one for farmers in the "Group Imperfect" treatment and zero otherwise, R_i is an individual measure of risk aversion, GP_jR_i is the interaction effect between the "Group Perfect" treatment and risk aversion, GI_jR_i is the interaction effect between the "Group Imperfect" treatment and risk aversion, X_i represents a vector of individual-level baseline control variables and ε_{ij} is the error term. The base category is Individual Perfect (IP).

The above-mentioned interaction terms with an individual measure of risk preferences (the coefficient of partial risk aversion[47]) are included in some specifications to explore whether treatments have varying effects among individuals that are more risk averse or less risk averse. As discussed in the conceptual framework, I expect less risk averse individuals may be coerced to make less risky[48] choices in a group setting, while more

[46] Several basic statistics on the dependent variable are presented in Table A1.1. The distribution of investment decisions by treatment group confirms that there was variation in the dependent variable, fertiliser choice. Nearly 50% of participants preferred the high-risk fertiliser. Preferences in the remainder of the sample were more or less split across the low-risk and average-risk fertilisers.

[47] Risk aversion parameters are presented in Table A1.2. The sample is relatively well distributed across the risk spectrum, though slightly more risk loving than in previous studies. Approximately 9% of the farmers in this study selected the riskiest lottery, Gamble H, which is high in comparison to the less than 2% that selected this gamble in Binswanger (1980) and low levels in similar games by Holt and Laury (2002). Participant comprehension of the Binswanger lottery was tested carefully in this study, so it is unlikely that lack of understanding is driving this trend.

[48] In this context, risky denotes increasing risk as well as increasing expected return.

risk averse individuals may be swayed to conform to the group norm. Moreover, less risk averse individuals may be more prone to moral hazard, while more risk averse individuals may make less risky decisions due to greater reliance on informal insurance (which weakens under imperfect information).

Control variables include education, caste, age, gender, assets, landowner status, exposure to a shock in the last three years, playing the investment or take-up game first, round number, preference for high returns, influence by group members, receiving news from TV, receiving news from the newspaper, a dichotomous variable equal to one if all group members are of the same caste and an inefficient risk aversion choice.[49] Errors are clustered at the group level.

B_1 and B_2 capture the main treatments effects relative to the base category, "Individual Perfect." In line with the conceptual framework, I expect B_1 to be negative if group pressure leads to lower risk taking in the "Group Perfect" treatment. I expect B_2 to be positive if moral hazard induces more risk taking in the "Group Imperfect" treatment. B_3 will be positive if group pressure declines as risk aversion increases. B_4 will be negative if the incentive for moral hazard declines as risk aversion increases.

[49] Lotteries D and F in the Binswanger lottery are inefficient as they introduce added risk without increasing the expected payoff.

Table 1.7 Impact of group insurance and information access on investment decision: ordinal logit

Treatment effects relative to base category: Individual Perfect (IP)

Dependent variable: Investment Choic	Full Sample				Excluding Risk Aversion Categories D and F			
	(1) Ord Logit	2) Ord Logit	(2a) Odds Ratio	3) Ord Logit	(4) Ord Logit	(5) Ord Logit	(5a) Odds Ratio	(6) Ord Logit
Group Perfect (GP)	-0.34	-0.63**	0.53	-0.55*	-0.45	-0.85***	0.44	-0.87**
	(0.31)	(0.29)	(0.15)	(0.32)	(0.31)	(0.30)	(0.13)	(0.35)
Group Imperfect (GI)	0.08	-0.20	0.82	0.20	-0.04	-0.33	0.72	0.11
	(0.30)	(0.25)	(0.21)	(0.30)	(0.31)	(0.27)	(0.19)	(0.33)
GP*Risk Aversion				-0.08				-0.01
				(0.10)				(0.11)
GI*Risk Aversion				-0.33***				-0.31***
				(0.10)				(0.11)
Risk Aversion		0.00	1.00	0.15**		0.01	1.01	0.12
		(0.04)	(0.04)	(0.07)		(0.05)	(0.05)	(0.08)
Cut-point	-1.09***	0.84	0.84	-0.04	-1.19***	1.02	1.02	-0.01
	(0.23)	(2.58)	(2.58)	(2.65)	(0.22)	(2.58)	(2.58)	(2.55)
Cut-point	-0.11	2.11	2.11	1.25	-0.17	2.38	2.38	1.37
	(0.24)	(2.59)	(2.59)	(2.66)	(0.23)	(2.60)	(2.60)	(2.55)
Observations	667	667	667	667	517	517	517	517
Controls	NO	YES	YES	YES	NO	YES	YES	YES
Wald	2.4	205.9	205.9	201.1	2.4	173.9	173.9	174.3
Pseudo R-squared	0.004	0.145	0.145	0.152	0.005	0.160	0.160	0.170
P-value of test GP = GI*	0.135	0.123	0.123	0.085	0.211	0.103	0.103	0.043

Note 1: Dependent variable = 1 if the farmer adopts low-risk fertiliser, 2 if the farmer adopts average-risk fertiliser and 3 if the farmer adopts high-risk fertiliser. Other controls are education, caste, age, gender, assets, landowner status, exposure to a shock in the last three years, playing the investment or take-up game first, round number, preference for high returns, influence from group members, receiving news from TV, receiving news from the newspaper, same caste and choosing an inefficient risk aversion lottery (omitted from table).

Note 2: Robust standard errors clustered at the group level in ( ).

Note 3: *** p<0.01, ** p<0.05, * p<0.1

Note 4: Interaction terms are included in the relevant specifications.

This section presents the main results from several specifications in the ordinal logit analysis. All specifications present treatment effects relative to the base category, "Individual Perfect". The left panel presents regressions using the full dataset. Column 1 of Table 1.7 first presents the main regression without controls. In line with the conceptual framework's first prediction, the coefficient of "Group Perfect" is negative. However, it is not significant. My preferred estimate in Column 2 includes controls to gain precision. "Group Perfect" (-0.63) is negative and significant at the 5% level. For ease of interpretation, Column 2a presents the same regression in Column 2 as odds ratios: the odds ratio for "Group Perfect" (0.53) suggests that the odds of investing in high-risk fertiliser versus the combined average and low-risk fertilisers are 1.9 times greater for farmers with "Individual Perfect" than farmers with "Group Perfect", holding all other factors constant.[50]

This reduction in risk taking is in line with the first prediction that group pressure to take less risk outweighs moral hazard more under "Group Perfect" than under "Individual Perfect". By introducing financial control over group payouts in contexts with perfect information about peer choices, groups appear to significantly pressure peers to take less risky investments. While group insurance could also theoretically encourage risk taking by mitigating idiosyncratic risk through facilitated risk sharing, any such effect appears to be overshadowed by group pressure to curb risk taking. Indeed, this is consistent with findings from follow-up questions, which affirm that some participants felt group pressure to select a certain fertiliser product.

In practical terms, this significant difference also aligns with calculations based on average investment decision data and suggests that the group pressure mechanism leads to an 8% reduction in risk taking from "Individual Perfect" to "Group Perfect."[51] Based

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[50] The same odds ratio of 1.9 times applies to the odds of investing in low-risk fertiliser versus the combined categories of average- and high-risk fertiliser.

[51] Of course, the external validity of these results depends on the information environment in reality. In contexts with less than perfect information, the coefficients of "Group Perfect and

on conservative back-of-the-envelope calculations, this sizeable reduction translates to an average Rs 107 decline in earnings per acre in this experimental context. However, this estimate should be viewed as a conservative estimate of the income effect, as the income range of this experiment was limited by constraints in the experimental design. Indeed, in view of Duflo et al.'s (2008) finding that returns to fertiliser – a risky investment - range from 36 to 257%, an 8% reduction in risk taking could significantly constrain yields.

My second prediction - that risk taking will be higher in “Group Imperfect” due to heightened moral hazard relative to the base category “Individual Perfect” – has limited support in the data. The coefficient for “Group Imperfect” in my preferred specification (Column 2) is negative and insignificant. One possible explanation for this result is that participants may believe informal insurance is less effective in contexts with imperfect information and they thus need to reduce overall risk exposure through less risky investments. Alternatively, participants in “Group Imperfect” may be concerned that choices are not completely private: while never conclusive, groups may pressure group members to make less risky choices by speculating which fertilisers peers choose based on their income levels.[52]

Column 3 provides a first look at heterogeneity within these results according to risk preferences. With the inclusion of interaction terms, the coefficient of “Group Perfect” is still significant, but the magnitude of the coefficient has decreased slightly. The interaction term between “Group Perfect” and risk aversion is not significant. The interaction between “Group Imperfect” and risk aversion, on the other hand, is negative and significant at the 1% level, indicating some variation according to risk preferences.

“Group Imperfect” bound the effect of the group insurance structure and suggest that moral hazard is a secondary effect to group pressure.

[52] A final possible explanation is that high risk taking in “Individual Perfect” is driven by competitiveness to ‘look good’ when fertiliser choices must be announced. Due to sample size restrictions, it was not possible to include a fourth treatment with individual insurance and imperfect information to test this. However, as there is less risk taking in “Group Perfect”, this would suggest that risk taking does not have a positive image.

Marginal effects presented later in this section provide further evidence on mechanisms and heterogeneity across risk aversion levels.

Finally, to explore Prediction 3 – that risk taking is lower in "Group Perfect than in "Group Imperfect" - the bottom of Table 1.7 conducts a t-test to compare differences across the two treatments for each specification.[53] Consistent with my earlier findings, this comparative static shows that risk taking is statistically significantly lower in "Group Perfect" under certain risk preferences (Col. 3). In particular, "Group Imperfect" is associated with higher risk taking than "Group Perfect" among risk-loving individuals. However, as risk aversion increases, this difference declines.

The main specifications also indicate that investment decisions are affected by several statistically significant control variables. A preference for high returns and higher wealth are associated with higher risk taking. Playing this game first in the interview and influence from group members are associated with less risk taking. The directions of these relationships are in line with expectations and therefore contribute to confidence in how lab participants played the investment game.

The right panel in Table 1.7 now runs the same regressions, but excludes observations from individuals that selected Gamble D and Gamble F in the Binswanger lottery. As these gambles are inefficient, participants that select these choices are sometimes dropped with an expectation that such players may also not take games seriously (e.g., Stein & Tobacman, 2011).[54] Excluding these observations marginally increases the size of the coefficients of interest and increases the level of significance. For instance, the main coefficient of interest "Group Perfect" in Column 2 is now -0.85 and significant at the 1% level.

In Table 1.8, average marginal effects by level of risk aversion provide a more detailed look at the heterogeneity in these results. The first section of the table compares

[53] Controlling for interaction terms in the relevant specifications.

[54] As previously mentioned, extensive comprehension testing was utilised to ensure participants understood the games.

average marginal effects across “Group Perfect” and “Individual Perfect,” providing further support for the group pressure story. Average marginal effects suggest that most farmers are 11 to 17 percentage points less likely to adopt the high-risk fertiliser in “Group Perfect” than in “Individual Perfect”. As these differences are significant across most risk aversion levels, this is consistent with the literature suggesting that groups reduce risk taking below average individual risk levels (e.g., Baker et al., 2008; Shupp & Williams, 2008; He et al., 2011). Even risk averse individuals reduce risk taking in “Group Perfect”, suggesting everyone may fear punishment through reduced insurance payouts.

Comparing average marginal effects across “Group Imperfect” and “Individual Perfect” does not reveal a statistically significant difference at most risk aversion levels. The one exception is that farmers with severe to extreme levels of risk aversion are more likely to choose low risk fertiliser in “Group Imperfect” than in “Individual Perfect”. This difference supports the idea that more risk averse individuals are concerned informal insurance is less effective with imperfect information, and thus decide to reduce risk exposure through less risky investment decisions. Given the small sample size in these categories, however, this finding should be taken with caution. Overall, the statistically insignificant differences across “Group Imperfect” and “Individual Perfect” suggests that heightened opportunities for moral hazard in “Group Imperfect” are overcome by the reduction in risk taking due to reduced informal risk sharing under imperfect information.

The final section of Table 1.8 compares “Group Perfect” and “Group Imperfect”. Among farmers with slight to negative risk aversion levels, the probability of adopting the low-risk fertiliser is approximately 11 percentage points higher with perfect information. These farmers are also 14 to 15 percentage points less likely to adopt the high-risk fertiliser with perfect information. These average marginal effects are consistent with the overarching theories that group pressure is more dominant and reduces risk taking in the “Group Perfect” treatment.

As risk aversion levels increase, however, these trends weaken and ultimately reverse. While the sample of farmers with extreme or severe risk aversion is too small to carry much weight, the average marginal effects tentatively suggest that more risk averse farmers are less likely to adopt the low-risk fertiliser in “Group Perfect” than in “Group Imperfect”. As previously mentioned, this suggests that more risk averse individuals are concerned about the quality of informal insurance in contexts with imperfect information.[55]

[55] Unfortunately, my sample is too small to delve further into the precise combinations of risk preferences that may exacerbate treatment effects.

Table 1.8 Average marginal effects by level of risk aversion

	Fertiliser choice	Risk aversion level: Extreme	Severe	Intermediate	Inefficient	Moderate	Inefficient	Slight to neutral	Neutral to Negative
IP - GP:	Low-risk	0.1340	0.1200**	0.0966**	0.0935**	0.0903*	0.0885*	0.0866*	0.0851*
		(0.09)	(0.06)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
	Average-risk	0.0748*	0.0539**	0.0320**	0.0298**	0.0275**	0.0263*	0.0251*	0.0241*
		(0.04)	(0.03)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
	High-risk	-0.2088	-0.1739**	-0.1286**	-0.1233**	-0.1179**	-0.1148*	-0.1116*	-0.1092*
		(0.13)	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
IP - GI:	Low-risk	0.3477***	0.1860***	0.0302	0.0140	-0.0021	-0.0112	-0.0203	-0.0274
		(0.09)	(0.05)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
	Average-risk	0.1029***	0.0685***	0.0125	0.0058	-0.0009	-0.0047	-0.0085	-0.0115
		(0.04)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
	High-risk	-0.4506***	-0.2545***	-0.0427	-0.0199	0.0029	0.0159	0.0289	0.0389
		(0.10)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
GP -GI:	Low-risk	0.2443**	0.0840	-0.0624	-0.0770*	-0.0915*	-0.0997**	-0.1078**	-0.1140**
		(0.12)	(0.07)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
	Average-risk	0.0390	0.0201	-0.0187	-0.0235*	-0.0284*	-0.0312**	-0.0340**	-0.0362**
		(0.04)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
	High-risk	-0.2833**	-0.1041	0.0811	0.1006*	0.1199*	0.1308**	0.1417**	0.1502**
		(0.14)	(0.09)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)
Sample size		36	47	78	73	188	77	108	60

Note 1: Standard errors in ( ).

Note 2: *** p<0.01, ** p<0.05, * p<0.1

1.4.3 Suggestive evidence on mechanisms

This section contributes additional evidence on the mechanisms through which the insurance structure affects investment decisions by exploring differences in the dispersion of investment decisions within groups. Intuitively, if group pressure is a dominant force in "Group Perfect," this would lead to a convergence in investment decisions as members choose less risky investments. Alternatively, the group structure could increase dispersion by facilitating coordination among members to mitigate risk through diversified investment choices and shared earnings (Gine, Jakiela, Karlan & Morduch, 2010). To disentangle which of these conflicting forces prevails, it is worth empirically exploring the effect of the group structure on the dispersion of investment decisions.

At the group level, several trends in the data provide suggestive support for the group pressure story. While choices converge slightly from Round 1 to Round 2 across all treatments, on average, all group members select the same investment most frequently in "Group Perfect" (Table A1.3). Correspondingly, the average standard deviation of investment decisions within the group is lowest in "Group Perfect" (Table A1.4).[56]

In contrast to the dispersion story in which farmers diversify investments and share earnings informally, the data reveals only low levels of risk sharing. Excluding negative transfers, the average level of risk sharing through formal and informal transfers hovers around 7% across the sample.[57][58] The average standard deviation of final earnings is

[56] This dispersion may provide a lower bound on the difference across treatments because "Group Perfect" also has the highest average standard deviation of risk preferences within the group (which would normally contribute to higher dispersion in investment decisions).

[57] In 442 of 667 observations (66%), no risk sharing took place at all. Among the remaining third that did engage in risk sharing, many made reciprocal transfers that were returned in subsequent rounds. Some also made large transfers to group members for expenses such as purchasing a tractor, which technically fell outside the scope of the experiment but were not prohibited. Such transfers actually increased disparities in income across the group and can partly explain the low level of risk sharing overall.

[58] While this result is lower than in some other studies (e.g., compared to 14% in Fischer, 2013), it is not surprising given that players did not know each other and that the structure of the

highest in “Group Perfect”, though the average transfer given (including formal transfers through group insurance distribution and informal transfers) was also highest in “Group Perfect” (approximately Rs 1,500 in “Group Perfect” versus approximately Rs 900 in “Group Imperfect” and “Individual Perfect”) (Table A1.5). Transfers are noticeably lower in “Group Imperfect”, providing further support for the idea that imperfect information reduces risk taking by inhibiting informal risk sharing.

To assess whether these group-level differences are statistically significant in support for the group pressure story, an OLS regression is employed to measure the effect of the insurance structure and information access on variance in investment decisions within groups:

$$V_j = \beta_o + \beta_1 GP_j + \beta_2 GI_j + \beta_3 GP_j S_i + \beta_4 GI_j S_i + \beta_5 S_i + \beta_6 X_j + \varepsilon_j \tag{1.2}$$

where V_j equals the level of variance in investment decision for group j. GP_j is equal to one for farmers in the “Group Perfect” treatment and zero otherwise, GI_j is equal to one for farmers in the “Group Imperfect” treatment and zero otherwise, S_i is standard deviation of risk aversion at the group level, GP_jS_i is the interaction effect between the “Group Perfect” treatment and standard deviation of risk aversion, GI_jS_i is the interaction effect between the “Group Imperfect” treatment and standard deviation of risk aversion, X_j represents a vector of individual-level baseline control variables averaged at the group level and ε_j is the error term. The base category is Individual Perfect (IP).

The set of interaction terms with standard deviation of risk aversion are included as groups with more homogenous risk preferences are expected to have more homogenous investment choices and thus less motivation for group pressure in “Group Perfect.”

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game interrupted informal arrangements to make reciprocal transfers (because the game ended with a 33% probability in each round).

Table 1.9 reveals differential treatment effects on variance in investment decisions within the group. The coefficient for “Group Perfect” is negative across all specifications. This is consistent with the prediction that group pressure reduces the dispersion of investment decisions. In spite of a limited sample size for analyses at the group level, these results are significant with the inclusion of controls in Columns 2 and 3. The significance level and size of the coefficient increase with the inclusion of interaction terms in Column 3, but the interaction terms are not significant.

Table 1.9 OLS regressions: variance in investment decisions

Treatment effects relative to base category: Individual Perfect (IP)

Dependent variable: Variance in investment choice within the group			
	(1) OLS	(2) OLS	(3) OLS
Group Perfect (GP)	-0.21	-0.22*	-0.29**
	(0.13)	(0.12)	(0.14)
Group Imperfect (GI)	0.03	0.01	0.04
	(0.12)	(0.10)	(0.13)
GP*Standard Deviation Risk Aversion			0.05
			(0.07)
GI*Standard Deviation Risk Aversion			-0.03
			(0.07)
Standard Deviation Risk Aversion		-0.01	-0.01
		(0.03)	(0.06)
Constant	0.63***	3.43***	3.48***
	(0.11)	(1.08)	(1.09)
Observations	228	228	228
Controls	NO	YES	YES
R-squared	0.036	0.192	0.197
P-value of test GP = GI[4]	0.011	0.024	0.015

Note 1: Other controls are education, caste, age, gender, assets, landowner status, exposure to a shock in the last three years, round number, preference for high returns, receiving news from tv, receiving news from the newspaper and same caste (omitted from the table).
Note 2: Robust standard errors clustered at the group level in ( ).
Note 3: *** p<0.01, ** p<0.05, * p<0.1
Note 4: Interaction terms are included in the relevant specifications.

1.4.4 Robustness checks

This section reviews several robustness checks for the empirical analysis. A first potential concern is that events in earlier rounds (such as weather or earnings levels) affect participant behaviour in later rounds. In the first panel of Table 1.10, I explore this possibility by running the ordinal logit regressions from Table 1.7 and restricting the sample to the cleanest data: observations from the first round.[59] While these

[59] The first round is also the round in which information about group members is completely private; in subsequent rounds, past earnings provide limited information about group members' risk preferences.

regressions are limited by the small sample size, the coefficient of "Group Perfect" is negative as in earlier specifications. Interestingly, the coefficient of "Group Imperfect" (0.69) is now significant at the 10% level in Column 3, suggesting that there may have been some moral hazard in the first round.

A second possible concern is that participants did not give quality responses in the first round because they did not fully understand how the game works. While this scenario is unlikely because participants received in-depth instructions and comprehension was tested prior to commencing the game, I explore this concern in the second panel of Table 1.10 by excluding the first round of data. These are the same regressions as with Round 1, plus one additional control: the average occurrence of drought is included as a proxy for subjective beliefs about drought risk in the current season. As past weather experiences have been shown to affect participants' perception of future weather conditions (e.g., Hill & Viceisza, 2012), it is important to consider whether such beliefs affect my results. For instance, participants that believe in the law of small numbers will expect that early draws decrease the likelihood of similar draws in the long run (Rapoport & Budescu, 1997; Rabin, 2002); i.e. that early draws of optimal rainfall increase the probability of suffering from a drought in subsequent rounds. Alternatively, good weather in many rounds may lead participants to become optimistic about their luck with future weather draws.

The regressions excluding Round 1 are in line with predictions and results from the full sample. "Group Perfect" is negative and significant at the 10% level in my preferred specification (Column 5). This effect appears to have strengthened from the first round, suggesting there may have been some learning over time. However, the coefficient of "Group Imperfect" is now negative. Though insignificant, this is in

Table 1.10 Ordinal logit by round

Treatment effects relative to base category: Individual Perfect (IP)

Dependent variable: Investment Choic	Round 1 Only				Round 2 Onwards			
	(1) Ord Logit	(2) Ord Logit	2a) Odds Ratio	(3) Ord Logit	(4) Ord Logit	(5) Ord Logit	5a) Odds Ratio	(6) Ord Logit
Group Perfect (GP)	-0.13	-0.44	0.64	-0.35	-0.34	-0.92*	0.40	-0.86
	(0.32)	(0.33)	(0.21)	(0.40)	(0.31)	(0.48)	(0.19)	(0.54)
Group Imperfect (GI)	0.28	0.05	1.05	0.69*	0.08	-0.60*	0.55	-0.39
	(0.28)	(0.32)	(0.33)	(0.39)	(0.30)	(0.34)	(0.18)	(0.40)
GP*Risk Aversion				-0.07				-0.05
				(0.13)				(0.14)
GI*Risk Aversion				-0.50***				-0.19
				(0.13)				(0.15)
Risk Aversion		0.01	1.01	0.23***		-0.04	0.96	0.04
		(0.07)	(0.07)	(0.08)		(0.06)	(0.05)	(0.11)
Cut-point	-0.79***	1.37	1.37	0.52	-1.09***	3.78	3.78	2.93
	(0.23)	(3.18)	(3.18)	(3.08)	(0.23)	(2.49)	(2.49)	(3.05)
Cut-point	0.04	2.51	2.51	1.71	-0.11	5.24**	5.24**	4.39
	(0.22)	(3.20)	(3.20)	(3.09)	(0.24)	(2.66)	(2.66)	(3.12)
Observations	319	319	319	319	348	348	348	348
Controls	NO	YES	YES	YES	NO	YES	YES	YES
Wald	2.3	155.2	155.2	158.9	2.4	.	.	.
Pseudo R-squared	0.004	0.178	0.178	0.196	0.004	0.149	0.149	0.151
P-value of test GP = GI*	0.156	0.137	0.137	0.080	0.135	0.509	0.509	0.497

Note 1: Dependent variable = 1 if the farmer adopts low-risk fertiliser, 2 if the farmer adopts average-risk fertiliser and 3 if the farmer adopts high-risk fertiliser. Other controls are education, caste, age, gender, assets, landowner status, exposure to a shock in the last three years, playing the investment or take-up game first, round number, preference for high returns, influence from group members, receiving news from TV, receiving news from the newspaper, same caste and choosing an inefficient risk aversion lottery (omitted from the table). Round 2 onwards also includes a proxy for perception

Note 2: Robust standard errors clustered at the group level in ( ).

Note 3: *** p<0.01, ** p<0.05, * p<0.1

Note 4: Interaction terms are included in the relevant specifications.

contrast to my original predictions and the positive coefficient in the first round data. One possible explanation for this is that it took one round for participants in "Group Imperfect" to realise that informal insurance was less effective with imperfect information or that groups would still speculate about investment decisions based on income levels.

Finally, to complement my ordered logit analysis, I also present logit and linear probability regressions in Table A1.6. As approximately half of the sample selected the riskiest fertiliser, I run logit regressions by combining the low-risk and average-risk fertiliser into one category. In general, the logit and linear results are in line with my ordinal logit results: "Group Perfect" is associated with lower levels of risk taking than "Individual Perfect". The coefficient for "Group Perfect" is significant at the 10% level in Columns 1 and 3. Consistent with earlier findings, the coefficient for "Group Imperfect" is insignificant and hovers around zero.

1.5 Conclusion

This study offers several important findings about group insurance with relevant lessons for both scholars and practitioners. The first finding is that, in the context of perfect information about investment decisions, farmers covered by group insurance pursue less risky investments than when covered by individual insurance. By introducing financial control over group payouts in contexts with perfect information, groups pressure peers to reduce risk taking by 8% on average. Even some risk averse individuals reduce risk taking under group insurance and perfect information, suggesting that everyone may fear punishment through reduced insurance payouts. Based on Duflo et al.'s (2008) finding of high returns to fertiliser, group pressure in the context of group insurance could significantly constrain yields.

As suggested by similar risk taking among farmers with group insurance and imperfect information versus farmers with individual insurance and perfect information, a second finding is that moral hazard is not a significant concern in the group context. Interestingly, this study reveals small variations in this effect: more risk averse individuals take even less risk under group insurance and imperfect information than under individual insurance and perfect information. Moral hazard incentives appear to be overpowered either by the reduction in informal insurance under imperfect information or concern that information is not completely hidden.

Collectively, these findings – that interactions between insurance structure, the information environment and risk preferences matter for investment decisions – contribute to the academic literature on group pressure and provide further support for the work of Fischer (2013) and Banerjee et al. (1994) through extensions to the microinsurance context. This research also acts as a subtle but important qualifier to recent research that has promoted the group structure of insurance as a means to increasing take-up (e.g., de Janvry et al., 2014; Cole et al., 2013; Dercon et al., 2014; Clarke et al., 2012). While the benefits for take-up are not disputed, reductions in risk taking in the group context and thus potential constraints on agricultural productivity are brought to light, suggesting the group structure is not the panacea some claim.

In addition to the academic contribution of this work to our understanding of group behaviour, this research is particularly pertinent to development practitioners and policymakers as proposals to launch group weather insurance products gather momentum. Several developing countries are currently launching large-scale microinsurance schemes – including weather insurance – which puts a premium on designing weather insurance products that maximise welfare benefits for the rural poor. The main findings of this study caution against the uniform application of group insurance without further research. While allowing groups to distribute payouts may increase take-up, whether or not the group structure enhances agricultural productivity will depend on its interaction with contextual variables. This study has begun to shed light on the interaction with two such variables: the information environment and risk preferences. To ensure group insurance structures are designed to maximise overall benefits – rather than only take-up – further research is needed on methods to reduce the problem of group pressure arising from such contextual variables.

One potential avenue for mitigating group pressure may be variation in group formation mechanisms. This study has focused on the case of externally-organised weather insurance groups with diverse risk preferences. As Ghatak (2000) asserts that individuals are more likely to risk share among peers with similar risk attitudes, one possible solution to group pressure may be to allow self-selection of groups. Indeed, several studies have highlighted the efficiency gains of self-selection in risk sharing arrangements – and thus provide complementary empirical support for this recommendation (Chandrasekhar, Kinnan & Larreguy, 2013; Breza et al., 2013; Gine, Jakiela et al., 2010). While groups may also self-select according to other criteria, extending this work to the study of self-selected groups and varying the combination of risk preferences within groups would be an interesting area for further research.

In sum, this study qualifies prior enthusiasm about group insurance structures. Whether or not group structures benefit the insured will depend on interactions with contextual factors, including the information environment and risk preference composition. This puts a premium on future group insurance designs that take into account the potential broader implications of group insurance structures – and future research that sheds light on such design options.

Essay 2: Informal insurance and moral hazard: determinants of weather insurance take-up

2.1 Introduction

As discussed in Essay 1, weather insurance was developed to help smallholder farmers smooth consumption in the face of aggregate-level rainfall shocks (Gine et al, 2008). However, despite numerous marketing and product improvements in recent years, take-up has been limited (e.g., Cole et al., 2013; Gine, Menand et al., 2010).[60] This is puzzling given the high subsidies that have accompanied these products. It is also not consistent with the prediction of economic theory that purchasing actuarially fair insurance is the utility-maximising choice for rational, risk-averse individuals. As smallholder farmers appear to be, at least for high payoff levels, risk averse on average (Binswanger, 1980), this prediction should hold for weather insurance take-up.[61] To resolve this puzzle, recent studies have examined the effect of a range of constraints including low wealth levels of farmers, lack of liquidity, low levels of financial literacy, lack of trust in insurance companies and basis risk (Gine & Yang, 2009; Cole et al., 2010; Gine et al., 2008; Cole et al., 2013). Yet, in these studies, a large fraction of low take-up remains unexplained.

This essay contributes to our understanding of barriers to insurance coverage with empirical evidence of an additional determinant: informal transfers. Informal transfers are key tools for mitigating financial shocks among the rural poor (Townsend, 1994; Udry, 1994). In view of the overlapping objectives of informal transfers and formal insurance, it follows intuitively that their usage may be intertwined. While some studies have shown formal and informal insurance to be complements in contexts with basis

[60] As low as 5% to 25%, even with significant subsidies (e.g. Gine et al., 2008; Cole et al., 2013).

[61] As a caveat to this, it should be noted that Clarke (2011) proposes – under certain assumptions - that the relationship between insurance and risk preferences is ambiguous in contexts with basis risk. In line with proposals for future weather insurance and hybrid products, this study focuses on the case of insurance with limited basis risk, which has also suffered from low take-up.

risk (e.g., Dercon et al., 2014; Mobarak & Rosenzweig, 2013), an important unknown is how they interact in contexts with more limited (or without) basis risk. As basis risk is increasingly reduced by pairing weather insurance with other products and technologies such as area yield insurance and satellite data, this case is increasingly important.

In addition to empirically testing the effect of informal transfers on take-up, the aim of this study is to unpack two alternative channels through which this effect may transpire. Moral hazard – the first channel – arises via transfers organised *after* a shock occurs. Due to strong redistribution norms, transfers to reallocate income are frequent and central to financial security in developing countries (Fafchamps & Lund, 2003). In an environment with a moral obligation to support peers in times of need, some individuals may reduce their willingness to pay for insurance if they know that they can ask their insured peers for transfers in the event of a shock. Such behaviour can then have ripple effects: individuals who normally purchase insurance may also reduce their willingness to pay because they feel a cultural obligation to share insurance payouts informally with their network when these payouts are public knowledge. Lower investment due to moral hazard has been identified in other domains (e.g., Bandiera & Rasul, 2006; Di Falco & Bulte, 2011; 2012), further motivating a closer look at the applications of this trend for weather insurance take-up. The implications of this phenomenon for weather insurance have been explored in the theoretical literature (de Janvry et al., 2014), but have yet to be tested empirically.

Informal risk sharing – the second channel – refers to an explicit agreement to share a policy amongst peers by purchasing together and exchanging informal transfers. Access to informal transfers may affect take-up through such a channel if farmers are not expected utility maximisers. Moreover, such an arrangement may arise among farmers that are not familiar with insurance or that do not fully trust the insurance provider. Importantly, arrangements to informally share risk by buying a policy together are not motivated by moral hazard because they are explicitly organised *before* income realisations are known. In the case of weather insurance, such arrangements can increase or decrease take-up depending on how likely farmers are to purchase full policies independently.

Bringing together insights from the literatures on informal risk sharing and redistribution norms, I disentangle these two channels through which informal transfers can affect formal insurance via a framed field experiment with 290 smallholder farmers in Gujarat, India. This experiment is structured as a series of Kharif season simulations in which willingness to pay (WTP) is elicited for a simple weather insurance product. An empirical test of the relative importance of moral hazard and informal risk sharing lends itself well to disentanglement in a laboratory setting such as this in which informal transfers can be limited.

An additional virtue of this experimental design is that I abstract away from the issue of risk sharing to mitigate basis risk[62] by eliciting WTP for a weather insurance product with a limited degree of basis risk and can then focus on alternative channels through which transfers affect weather insurance take-up. The experiment is designed such that farmers want to purchase insurance assuming expected utility preferences. If farmers are expected utility maximisers, then a decrease in WTP could only be explained by moral hazard. However, if farmers are not expected utility maximisers, they may want to share a policy.

Two treatment arms are randomly assigned across the sample to unpack the effect of transfers on insurance take-up: (i) insurance *without* the right to give and receive transfers (No Transfer) and (ii) insurance *with* the right to give and receive transfers (Transfer). The difference across these two treatment effects captures the overall effect of access to informal transfers. Cross-referenced follow-up questions are then used to disentangle the mechanisms through which this effect occurs.

[62] This has been explored by Mobarak and Rosenzweig (2012).

The core result from this experiment is that moral hazard reduces weather insurance take-up. On the whole, I find movement on the extensive margin. Allowing informal transfers leads to a 14% jump in the number of people unwilling to pay any price for insurance. Assuming expected utility preferences, this is consistent with a model of moral hazard but not consistent with a model of informal risk sharing to try out a policy. When farmers are allowed to give and receive transfers after a shock has occurred, many decide not to purchase insurance. The experiment also reveals a more pronounced decline in WTP among poorer individuals. Lastly, there is some evidence that informal risk sharing to try out a policy affects take-up, but it is limited. The scholarly implication is clear: while networks offer consumption smoothing benefits, they also reduce weather index insurance coverage due to moral hazard.

Beyond its scholarly relevance, these findings have important policy repercussions. Informal transfers are likely to increase with the growing momentum of group weather insurance policies: group structures facilitate information sharing and strengthen networks through repeated interactions. Against this backdrop, increasing weather insurance take-up requires amendments in the product design and targeting to account for the downward pressure of moral hazard – for instance, through sales in geographical areas with weaker redistribution norms or through all or none sales of group weather insurance.

To derive these generalisations, this essay is organised as follows. First, I discuss the related literature and theory about the interactions between informal transfers and formal insurance. Then, I review the experimental protocols and implementation strategy. Next, I present the empirical strategy and discuss the results. Finally, I conclude with a discussion of potential academic and policy implications.

2.2 Related literature and theoretical motivation

A range of scholarly works has examined the interaction between informal transfers and insurance (e.g., Dercon et al., 2014; Mobarak & Rosenzweig, 2012). Yet, the literature fails to distinguish between the implications of transfers motivated by (i) moral hazard and (ii) risk sharing to try out a policy. To theoretically disentangle these effects on formal insurance, I bring together insights from two, hitherto largely separate, literatures on: (i) redistribution norms and decision-making and (ii) formal and informal insurance interactions. Drawing on these literatures and deductive reasoning, I explore the effects of the moral hazard channel and the informal risk sharing channel on take-up in the following basic conceptual framework.

In line with the experimental design described in the next section, consider a simplified world in which three farmers in a village face the risk of crop yield loss due to drought or flood.

- At t=0, each farmer has an endowment of one acre of land on which he grows cotton. As cotton yields are highly sensitive to rainfall levels, income y fluctuates according to local rainfall conditions.

- At t=1, each farmer learns about a weather index insurance policy and discusses the policy with the other farmers in the village. This policy is actuarially fair, i.e. $m = (1\text{-}p)t$ where m is the insurance premium, $1\text{-}p$ is the probability of a shock occurring in the village and t is the insurance payout.

  The farmers are risk averse and follow a von Neumann-Morgenstern utility function. The natural prediction of this model is that the farmers will decide to purchase the insurance policy because expected utility is higher with insurance than without insurance.

- At t=2, each farmer decides whether or not to purchase the insurance policy. This decision is public and simultaneous across the village.

- At t=3, a random weather condition is revealed at the village level. A shock occurs with probability *1-p* and optimal rainfall occurs with probability *p.*

- At t=4, income earned and insurance payouts (when relevant) are revealed. Income varies across the group, ranging from y_{sl} to y_{sh} when there is a shock and y_{nl} to y_{nh} when there is no shock. However, insurance payouts (t) are constant across all farmers, reflecting a limited level of basis risk.[63] While index insurance policies are historically subject to high basis risk, this framework focuses on formal-informal interactions in the context of limited basis risk – a case of particular importance in view of rising efforts to reduce basis risk through hybrid products and the use of satellite data.[64]

- At t=5, the three farmers have an opportunity to engage in informal transfers.

- Lastly, at t=6, the farmers return to t=0: this is a repeated game.

The aim of this study is to unpack two channels through which the right to exchange transfers at t=5 may affect insurance take-up at t=2. The first channel is moral hazard. Assuming expected utility preferences, farmers demand full insurance coverage.

[63] As discussed in Essay 1, basis risk refers to the imperfect correlation between insurance payouts (which are determined by aggregated data from local rainfall stations) and shocks experienced at the household level (Clarke, 2011). While not central to this framework, the three farmers have the same expectation about the limited degree of basis risk in this context.

[64] While outside the scope of this study, it is important to note that the formal-informal insurance relationship is altered in contexts with high basis risk. According to Dercon et al. (2014), demand for index insurance is expected to be higher among peers that can share risk informally: the complementarity of formal weather insurance and informal risk sharing is strengthened if farmers can mitigate basis risk by purchasing insurance and agreeing ex-ante to equalise income by reallocating payouts through informal transfers according to individual losses. Consistent with this intuition, Mobarak and Rosenzweig (2012) find that informal risk sharing is a complement to formal weather insurance in contexts with high basis risk.

However, introducing access to informal transfers may reduce take-up of formal insurance by encouraging moral hazard (Arnott & Stiglitz, 1991). Farmers have an incentive to support their peers when suffering from a shock if they wish to have support themselves in future years (Sahlins, 1972; Dzingirai, 2004). In other words, gift-giving is a "culturally constructed livelihood strategy" (Hospes & Lont, 2004, p. 15). If redistribution norms implicate a moral obligation for the financially solvent to support free riders (Scott, 1976), moral hazard may decrease take-up as farmers know they can ask for a transfer and thus are less dependent on formal insurance.

Such a phenomenon is in line with empirical studies linking redistributive norms to moral hazard – and moral hazard to changes in risk mitigation. Di Falco and Bulte (2012), for instance, find that redistribution norms foster a free riding culture and lower adoption of soil conservation measures. Jannsens and Kramer (2014) also find evidence of free riding among less risk averse individuals in the context of health insurance in Tanzania. In a related literature, Bandiera and Rasul (2006) find that many farmers strategically wait to adopt new crops with the intention of benefiting from peer knowledge once a number of other farmers in the network have tested the crop.

In turn, the literature suggests that these instances of moral hazard generate ripple effects due to a fear of free riding. For instance, Di Falco and Bulte (2011) propose that redistribution norms may stunt income growth as individuals increase non-sharable durable accumulation to avoid supporting free riders. Grimm, Hartwig and Lay (2013) find that redistributive pressures from family and kin reduce incentives to invest in enterprise capital in Burkina Faso. Finally, Baland, Guirkinger & Mali (2011) find evidence of inefficient borrowing and saving in Cameroon in an effort to avoid pressure to redistribute by 'appearing poor'.

Similar to these trends in other domains, moral hazard may reduce take-up of weather insurance. In particular, I expect some farmers to reduce their willingness to pay for insurance if they can ask their insured peers for transfers in the event of a shock. As a result, farmers who would otherwise purchase insurance may also reduce their willingness to pay because of a cultural obligation to share insurance payouts informally with their network when these payouts are public knowledge. This downward pressure arises as the insured recognise that they cover the full financial costs of weather insurance while reaping only part of its benefits. A similar argument is developed theoretically by de Janvry et al. (2014). They propose that formal insurance against common shocks is crowded out by informal risk sharing because a farmer will not purchase insurance if he anticipates that his peers will avoid insurance and attempt to free ride. In their model, the decision to purchase insurance by one farmer provides a positive externality for his peers. As households may only purchase full coverage for one household, sharing payouts with others limits coverage of the insured household.

The second channel through which informal transfers may affect weather insurance take-up is informal risk sharing. This could arise if we relax the assumption that farmers are expected utility maximisers. In doing so, farmers may decide to share a weather insurance policy by exchanging informal transfers to cover the premium and share the payout because they don't want full insurance. Moreover, the uncertainty surrounding this new financial product means that some farmers may want to test it out without making a full financial investment. Farmers may prefer informal risk sharing arrangements with peers that they trust over large insurance companies. By making an ex-ante arrangement for one farmer to purchase insurance and other(s) to contribute to the premium through informal transfers, farmers can purchase partial coverage under what would otherwise be an indivisible product. Depending on how likely these individuals are to purchase a full policy independently, this mechanism will lead to an increase or decrease in take-up.

Importantly, the relevance of the moral hazard and informal risk sharing channels may also vary according to heterogeneous personal characteristics. In particular, risk preferences may lead to differential levels of moral hazard. Drawing on Fischer (2013) and Janssens and Kramer (2014), less risk averse individuals are more likely to reduce insurance coverage when informal support through redistribution requests is available. A second factor that may affect transfers through both the moral hazard and risk sharing channels is wealth. Wealthier farmers may be more vulnerable to redistribution requests. However, they are also less likely to rely on informal transfers for financial stability (Munshi & Rosenzweig, 2014; Ligon, Thomas & Worrall, 2000). They may thus abstain from participating in the informal network and be less likely to reduce WTP due to a fear of free riding. By the same logic, and given their higher expendable income, wealthier farmers may also be less likely to share a policy with peers. Less wealthy farmers, on the other hand, may commit to greater moral hazard due to financial vulnerability.

To summarise, informal transfers are expected to affect weather insurance take-up through different channels. Depending on utility equations and farmer characteristics, two stylised expectations are proposed:

1. Informal transfers motivated by moral hazard are expected to decrease weather insurance take-up. A farmer is less likely to purchase insurance when he can request redistribution transfers from his peers. Farmers that are concerned about redistribution pressure from free riding peers are also less likely to purchase insurance.

2. Informal transfers motivated by informal risk sharing to try out a new policy will lead to an increase or decrease in weather insurance take-up, contingent upon the amount of insurance that would have been purchased without access to informal transfers.[65]

The next section presents an experimental design to empirically examine these theoretical expectations in a laboratory setting.

[65] While outside the scope of this study and likely to be a secondary effect, informal transfers motivated by informal risk sharing to mitigate low levels of basis risk will increase weather insurance take-up.

2.3 Experimental design

To measure the extent to which informal transfers affect weather insurance take-up, I conducted a second framed field experiment with smallholder farmers in Gujarat. This experiment elicited farmers' willingness to pay (WTP) for hypothetical insurance products while varying rights to make transfers. Though the external validity of a lab experiment is more limited than a field experiment, a lab setting offers valuable insights into the research topic at hand by facilitating a cleaner analysis. It would not be feasible to prohibit informal transfers in a real-world setting and, concomitantly, examine the interactions of formal insurance with distinct types of informal transfers.[66]

With these advantages in mind, this lab experiment was conducted with a sample of 290 smallholder farmers from the Ahmedabad district in Gujarat.[67] Participants for the experiment were recruited through assistance from Taluka Development Officers and Sarpanch (block and village level government representatives). All participants (i) grow cotton, (ii) own between 1 and 10 acres of land, (iii) are at least 18 years old and (iv) live within 10 km of a rainfall station.

To ensure a clean treatment effect, networks were artificially simulated in the experiment by grouping together farmers with similar socio-economic backgrounds. To reduce the risk of shared winnings via informal transfers among participants after the lab, participants were matched into groups of three with farmers from other blocks that they had never met. The external validity of the findings thus plausibly extend, at a minimum, to networks with low social capital (which have shared norms, values and attitudes but limited social trust) in developing countries with collective societal norms to support peers.

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[66] As discussed in Essay 1, such an experiment should also offer important lessons by simulating real world decisions with similar ethical considerations, peer scrutiny and high financial stakes (Levitt & List, 2007).
[67] As discussed in Essay 1, Gujarat offers an ideal case for exploring this topic as one of the main hubs for weather insurance sales in India.

I expect that common socio-economic characteristics within the sample (such as wealth levels and cultural backgrounds) also strengthen network effects in this experiment through a more generalised form of trust. While several studies suggest that network effects are strongest when trust is nurtured through repeated interpersonal interactions (e.g., Fafchamps, 2004), Platteau (1994) emphasises that a more generalised form of trust can be fostered through general knowledge about the population's background. Consistent with this, Munshi (2004) finds that information linkages are weaker in heterogeneous populations. Moreover, a number of studies highlight the importance of common characteristics in strong network effects. For instance, Foster and Rosenzweig (1995) find that farmers respond more to information from peers with similar wealth levels, common clan membership, age and gender. Conley and Udry (2010) suggest that common growing conditions and credit arrangements also matter.

As discussed in Essay 1, this experiment was held in a temporary experimental laboratory in Ahmedabad, India in March and April 2013.[68] Each individual interview lasted approximately two hours and had four components: a Binswanger lottery game to measure risk preferences, this experiment on weather insurance take-up, a second experiment on ex-post investment decisions[69] and a series of follow-up questions to collect data on participants' characteristics and decision-making processes in the lab. The order of the two experiments (on take-up and investment decisions) was randomised across the sample to control for the risk that playing one game first might affect decisions in the second.[70]

[68] A time of year in which cotton farmers have fewer fieldwork responsibilities.

[69] See Essay 1.

[70] Refer to Essay 1 for further information on lab setting, the Binswanger lottery and participant earnings.

2.3.1 Experiment overview

The central component of this experiment is a series of Kharif season simulation rounds in which farmers are asked to make decisions about purchasing insurance. As laid out in the conceptual framework, the timing of each round is as follows:[71][72]

t=0	t=1	t=2	t=3	t=4	t=5	t=6
Give endowment	Present insurance	Elicit WTP	Introduce weather	Reveal earnings & insurance payout	Allow transfers (in "Transfer")	End. Go to t=0

To determine an unbiased estimate of the effect of informal transfers on willingness to pay for formal insurance, small variations in this timing are introduced by randomly assigning participants to one of the following two treatments: (i) "No Transfer" (NT) and (ii) "Transfer" (T). In the "No Transfer" treatment, no informal transfers are allowed amongst group members. In the "Transfer" treatment, participants have an opportunity to engage in informal transfers with other group members in each round. These transfers can be used to share the cost of an insurance premium, an insurance payout and/or farm earnings. The rest of this section details the timing of events and differences in this timing across the two treatments.

[71] See Appendix I – Phase 4 for experiment script example.

[72] Prior to commencing the game, these instructions are explained in great depth to each participant individually. Questions to test comprehension are posed periodically throughout the instructions.

t=0 Give endowments

Each farmer is allotted one acre of land and an endowment of 18,600 Game Rupees (Rs). In each round, participants start with a zero balance and are given a new endowment of Rs 18,600. Immediately after receiving the endowment each participant has to pay Rs 15,000 for agricultural inputs. The remainder of the endowment can be used to purchase insurance and/or added to the final earnings for the round.

t=1 Present the insurance

Participants are presented with an actuarially fair insurance policy with a face value of Rs 3,600 and a set payout of Rs 10,800. Participants are told that this policy will be offered for a discounted random price between Rs 0 and Rs 3,600.[73]

Participants are then given an opportunity to discuss the insurance product with the other two interviewees. In "Transfer", this discussion is also an opportunity to make an informal risk sharing arrangement (i.e. to agree to share earnings or one or more insurance products through informal transfers at the end of the round).

t=2 Elicit WTP for insurance

Next, participants' valuation of the insurance product is measured using the Becker-DeGroot-Marschak (BDM) mechanism (Becker, DeGroot & Marschak, 1964). The BDM game, as it is more commonly called, helps to elicit each participant's true valuation of the insurance product. To play the game, the participant first formulates a bid for the insurance policy. If the bid is greater than a random price generated by the computer, the participant has to purchase the policy. If the bid is lower than the random price, the participant cannot buy the policy. The BDM game is played privately, but participants have to announce their bid and whether or not they purchased insurance after all group members have played.

[73] As weather insurance products are still relatively new in India, they are normally subsidised and sold under face value to increase take-up rates.

t=3 Randomly introduce shock (probability 1-p = .33) or no shock (probability p = .67)

When a shock occurs (1-p = .33), it affects the entire group, but to varying degrees.[74]

t=4 Reveal income earned and insurance payout (if relevant)

Income earned varies across the group - ranging from Rs 500 to 7,500 when there is a shock and Rs 25,000 to 35,000 when there is no shock.

Insurance payouts are a set value of Rs 10,800, independent of losses suffered. As shocks are measured at a central rainfall station, insurance payouts are not perfectly correlated with individual level losses.[75] This experimental design focuses on scenarios in which the farmer suffers a loss and receives an insufficient payout, thus assuming a more limited form of basis risk than has historically characterised many weather insurance products. Importantly, as the component of basis risk depicted in this experiment is constant across the two treatment groups, it should not influence the treatment effect.

Once income and insurance payouts have been distributed, participants must announce their true earnings to the group.

t=5 Allow transfers (in "Transfer" only)

Participants in "Transfer" can informally reallocate earnings and insurance payouts amongst themselves if they so wish. Transfers can be arranged at this time or have been organised at t=1 through an ex-ante arrangement to informally share an insurance policy.[76] Participants in "No Transfer" proceed directly to t=6.

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[74] The three farmers have the same expectation about basis risk. They don't know whether others are closer or further from the rainfall station.

[75] A detailed explanation of this limited component of basis risk is given in an informational session about the weather insurance product before the game begins.

[76] For instance, one farmer may purchase the policy with an informal agreement that his peers will make transfers for part of the premium cost or will receive part of the payout less the premium in the event of a shock.

t=6 Individuals with income above Rs 9,000 start again at t=0 if a white ball is selected

The minimum number of rounds in this game is one and the maximum number of rounds is eight. Participants are not aware that the game is limited to eight rounds. At the end of each round, the group continues to the next round with a probability of 67%: if a white ball is drawn from a bag containing two white balls and one violet ball (Fischer, 2013).

If the game continues, players with less than Rs 9,000 are not allowed to participate in the subsequent round. This rule incentivises participants in "Transfer" to give transfers at the end of each round as a means to mobilise financial support for future rounds. Peers that did not engage in informal transfers in previous rounds may be punished by being excluded from transfers when they fall beneath the Rs 9,000 threshold themselves.[77]

In summary, the only difference in the timing of events across the two treatment groups is whether or not informal transfers are allowed at t=5 (Table 2.1). Farmers have an opportunity to discuss the insurance product in both treatments, but those in "Transfer" can also utilise this informal discussion period to make informal risk sharing arrangements.

[77] While one may argue a shortage of social trust in the lab environment because participants do not know each other prior to arrival, ex-ante arrangements made during discussions at t=1 are overseen by the interviewers. Moreover, as previously mentioned, participants have an incentive to build a relationship with group members from whom they may need assistance in subsequent rounds.

Table 2.1 Summary of treatments

	Insurance discussion with peers t=1	Public elicitation of WTP t=2	Public announcement of income realisation t=4	Informal transfers t=5
No Transfer (NT)	x	x	x	
Transfer (T)	x	x	x	x

This experimental design facilitates exploration of key predictions relating to the implications of informal transfers for weather insurance take-up. Comparing the two treatments is expected to capture the effect of transfers through both the moral hazard and informal risk sharing channels. The experiment is designed such that purchasing insurance is the welfare maximising choice for farmers with expected utility preferences. It is not possible to overinsure. Thus, the only incentive to reduce the level of formal coverage when given the opportunity to exchange informal transfers in "Transfer" would be moral hazard. If moral hazard dominates, I expect WTP to be lower in "Transfer" than in "No Transfer". This will arise if some individuals give lower insurance bids with the intention of asking peers for transfers if a shock occurs. In turn, those who are afraid of pressure to give transfers to free riders may also give lower bids.[78]

If farmers do not have expected utility preferences, I expect informal risk sharing to try out a policy will dominate the overall effect. Access to transfers will then lead to an increase or decrease in WTP. Similarly, if participants are unsure about weather insurance and want to test it out, the difference across treatments will capture diverse bids by individuals that made agreements with group members to purchase a policy

[78] Unfortunately, it is not possible to disentangle the effect of moral hazard from the effect of fear of free riding or wealth effects on risk aversion in this experimental design. This would offer an interesting area for further research.

together. Whether this increases or decreases WTP depends on how likely individuals are to purchase insurance independently without transfer rights.[79]

To disentangle the effect of the moral hazard and informal risk sharing channels, I record all informal transfers between group members and ask follow up questions at the individual level about what motivated each transfer and when it was arranged. Transfers that were arranged before playing the WTP game are categorised as informal risk sharing arrangements. Transfers that were arranged after a shock occurred are categorised as redistribution arrangements and may be due to moral hazard. This data is cross-referenced across each pair for accuracy.

2.4 Experimental results

This section presents the empirical strategy undertaken to analyse the implications of informal transfers for weather insurance take-up. First, I discuss the descriptive statistics for my sample. Then, I present my analysis of the treatment effect on willingness to pay for insurance. This is followed by a discussion of mechanisms through which transfers may affect take-up and several robustness checks.

2.4.1 Descriptive statistics

The results presented in this study are based on 564 rounds of the take-up game, played by 290 farmers.[80] Summary statistics overall and disaggregated by treatment group for several key farmer and household characteristics are presented in Table 2.2 at the individual level. The average age of participants was 43 and the majority of participants had completed less than 7 years of schooling. The average plot size is five acres. Most farmers had not heard of weather insurance prior to the experiment.

[79] Some participants may also be willing to pay marginally more because they can share payouts to mitigate basis risk. However, this is not anticipated to be a primary effect, as the level of basis risk in the experimental design is quite limited.

[80] Of the 294 individuals surveyed after the pilot stage, 4 were excluded from this analysis (2 with incomplete control variable data and 2 that would not play the Binswanger lottery). Inclusion of these observations does not change the results significantly.

Table 2.2 also shows differences in means across treatment groups. For nearly all of the farmer and household characteristics, the difference in means across treatment groups is not statistically different from zero. The only unbalanced observable is gender, though it is not noteworthy in percentage terms: 100% of "No Transfer" are men and 96% of "Transfer" are men.[81]

The number of statistically significant differences is consistent with what we would expect from a random allocation across treatments. In an F-test of joint significance of all covariates, I do not reject the hypothesis that the covariates are jointly uncorrelated with treatment assignment (p=0.42). No covariates are significant at the 10% level or lower when regressing treatment assignment on all covariates and clustering at the group level. This provides confidence in the integrity of the randomisation and suggests this sample has balance on unobservables.

[81] Controls are included in the regression analysis to address this difference.

Table 2.2 Summary statistics

	All Farmers	No Transfer (NT)[1]	Transfer (T)[1]	NT vs. T[2]
Socioeconomic Characteristics				
Gender (1= Male)	0.98	1.00	0.96	0.04**
	(0.14)	(0.00)	(0.20)	(0.02)
Age (years) mean	42.57	42.42	42.72	-0.30
	(13.05)	(12.99)	(13.15)	(1.54)
median	42.00	42.00	43.00	
Education				
Illiterate	0.19	0.16	0.22	-0.06
	(0.39)	(0.36)	(0.41)	(0.05)
Class 1 to 7	0.42	0.47	0.37	0.09
	(0.49)	(0.50)	(0.49)	(0.06)
Class 8 to10	0.29	0.26	0.31	-0.05
	(0.45)	(0.44)	(0.46)	(0.05)
Class 11 to 12	0.07	0.08	0.06	0.02
	(0.26)	(0.27)	(0.24)	(0.03)
Graduate	0.03	0.03	0.03	0.01
	(0.17)	(0.18)	(0.17)	(0.02)
Weather insurance familiarity				
Participant understands the product perfectly.	0.02	0.02	0.02	0.00
	(0.14)	(0.14)	(0.14)	(0.02)
Participant understands the product somewhat.	0.02	0.03	0.01	0.02
	(0.13)	(0.16)	(0.08)	(0.02)
Participant has heard of the product, but does not understand what it is for or how it works.	0.03	0.03	0.03	0.00
	(0.16)	(0.16)	(0.17)	(0.02)
Participant has not heard of weather insurance.	0.93	0.92	0.94	-0.02
	(0.25)	(0.27)	(0.23)	(0.03)
Plot size (acres) mean	5.10	5.04	5.16	-0.11
	(2.44)	(2.49)	(2.40)	(0.29)
median	5.14	4.57	5.14	
Landowner	0.90	0.89	0.91	-0.03
	(0.30)	(0.32)	(0.28)	(0.04)
Village distance from Ahmedabad (Km)	88.76	90.03	87.45	2.58
	(24.58)	(25.46)	(23.66)	(2.94)
Caste				
Scheduled Castes (SC)	0.15	0.16	0.14	0.02
	(0.35)	(0.36)	(0.34)	(0.03)
Scheduled Tribes (ST)	0.01	0.01	0.02	-0.01
	(0.12)	(0.10)	(0.14)	(0.01)
Other Backward Classes (OBC)	0.59	0.59	0.60	-0.02
	(0.49)	(0.49)	(0.49)	(0.04)
Other	0.25	0.25	0.24	0.01
	(0.43)	(0.43)	(0.43)	(0.04)
Decision Parameter				
Estimate of Coefficient of Partial Risk Aversion	1.20	1.14	1.26	-0.12
	(1.98)	(1.90)	(2.06)	(0.23)
Experience of weather risk / Rainfall risk exposure				
Experienced drought in last 3 years	0.43	0.42	0.45	-0.03
	(0.50)	(0.50)	(0.50)	(0.06)
Have bought at least one other form of agricultural insurance	0.39	0.39	0.39	0.00
	(0.49)	(0.49)	(0.49)	(0.06)
Know someone that has received a payout from any insurance (weather, crop, life, health, etc.)	0.54	0.55	0.54	0.01
	(0.50)	(0.50)	(0.50)	(0.06)
Number of observations	290	148	142	

Note 1: standard deviations in ( ); 2: standard errors of differences in ( ); 3: *** p<0.01, ** p<0.05, * p<0.1

A first look at the dependent variable, willingness to pay (WTP), is presented in Table A2.1. In both treatments, WTP increased as rounds progressed. Interestingly, mean WTP was higher in “No Transfer”, but median WTP was higher in “Transfer”. Figures 1 and 2 help to unpack this contrast: 14% more “Transfer” participants were not willing to pay anything for insurance than “No Transfer” participants (Figure 2.1). Of the 258 observations in “Transfer”, 41 made zero bids. In “No Transfer”, on the other hand, only 6 out of 306 observations made zero bids. The density plot in Figure 2.2 also reveals that more participants in “No Transfer” have higher WTP.

Figure 2.1 Distribution of WTP across treatments

“No Transfer” “Transfer”

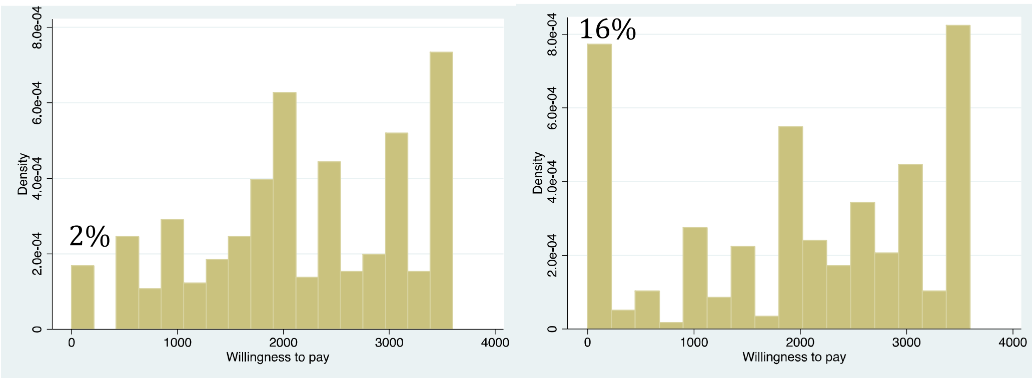
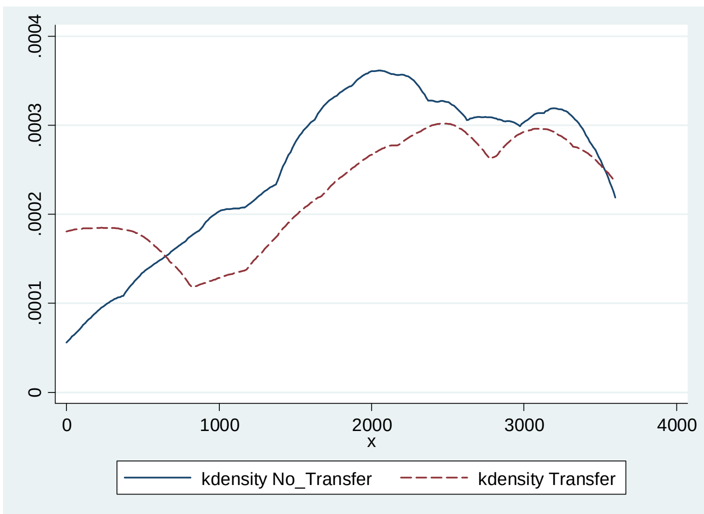


Figure 2.2 Kernel density by treatment



2.4.2 Main analysis

This section presents regression analyses to explore whether these differences across treatments in Figures 2.1 and 2.2 are statistically significant and through which channel(s) these effects may transpire. The following ordinary least squares regression is first employed to test the effect of informal transfers on willingness to pay for insurance using linear and non-linear specifications.

$$Y_{ij} = \beta_o + \beta_1 T_j + \beta_2 T_j R_i + \beta_3 T_j P_i + \beta_4 R_i + \beta_5 P_i + \beta_6 X_i + \varepsilon_{ij} \qquad (2.1)$$

Y_{ij} equals the willingness to pay for insurance for individual i in group j. T_j is equal to one for individuals in "Transfer" and zero otherwise, R_i is an individual measure of risk aversion, P_i is an individual measure of plot size, T_jR_i is the interaction effect between "Transfer" and risk aversion, T_jP_i is the interaction effect between "Transfer" and plot size, X_{ij} represents a vector of individual-level baseline control variables and ε_{ij} is the error term.

The interaction with risk aversion is included to explore whether treatments have varying effects according to individual risk preferences. In particular, less risk averse individuals may be more likely to free ride through redistribution requests (Janssens & Kramer, 2014; Fischer, 2013). Participant plot size is used as a measure of wealth and is interacted with the treatments as less wealthy individuals are more likely to rely on wealthy peers for financial support and thus may be more affected by access to informal transfers (Munshi & Rosenzweig, 2014). Moreover, wealthy individuals may have a greater fear of free riding or may exit the informal network.

The other controls are gender; a dichotomous variable equal to one if all group members are of the same caste; round number; education level; religion; and playing the investment game/take-up game first. Errors are clustered at the group level.

In this regression, B_1 captures the main treatment effect and is positive or negative depending on which mechanism dominates. If B_1 is positive, this indicates that the dominant channel through which informal transfers affect WTP is informal risk sharing to try out a policy. If B_1 is negative, this could be driven by moral hazard or informal risk sharing to try out a policy. As previously mentioned, follow up questions at the end of the experiment are used to disentangle these channels further. I expect B_2 will be positive if moral hazard is higher among less risk averse individuals. As more risk averse individuals are less likely to free ride on their peers, the difference across treatments (as captured by B_1) is expected to decrease as risk aversion increases. Lastly, B_3 will be positive if individuals become less reliant on informal transfers as wealth increases or negative if wealthier individuals fear free riding from their peers.

Table 2.3 presents the first set of OLS regressions. The left panel focuses on the dependent variable WTP. The negative coefficient across all specifications suggests that either moral hazard or risk sharing to try out a policy are the dominant channel. Columns 1 and 2 present the effect of "Transfer" on WTP without and with controls, respectively (relative to the base category, "No Transfer"). In Column 3, interaction terms with risk aversion and plot size are included. The "Transfer" coefficient increases in size from Column 2 to 3 and is now significant at the 5% level. In line with expectations, this suggests that, holding all other factors constant, access to informal transfers is associated with a Rs 497 decrease in WTP among farmers with a one acre plot. As plot size increases, this difference declines, suggesting that moral hazard is higher among the financially vulnerable.

Table 2.3 OLS regressions: impact of transfer rights on WTP

Treatment effects relative to base category: No Transfer (NT)

Dependent variable:	WTP			Dichotomous variable = 1 if WTP>0		
	(1)	(2)	(3)	(4)	(5)	(6)
Transfer (T)	-162.33	-154.26	-564.42**	-0.14***	-0.14***	-0.23***
	(175.88)	(155.57)	(248.71)	(0.04)	(0.04)	(0.07)
T*Risk Aversion			51.30			0.01
			(46.41)			(0.01)
T*Plot size			67.16*			0.01
			(40.44)			(0.01)
Risk Aversion		27.83	2.12		0.01**	0.00
		(20.88)	(31.34)		(0.00)	(0.00)
Plot size		30.42	-0.73		0.01	0.00
		(19.69)	(22.97)		(0.00)	(0.00)
Constant	2,171.24***	2,947.04***	3,104.25***	0.98***	1.05***	1.08***
	(111.49)	(587.17)	(591.30)	(0.01)	(0.19)	(0.19)
Observations	564	564	564	564	564	564
Controls	NO	YES	YES	NO	YES	YES
R-squared	0.01	0.08	0.09	0.06	0.09	0.10

Note 1: The other controls are gender, same caste, round number, education, religion, and playing the investment game/take-up game first (omitted from the table).
Note 2: Robust standard errors clustered at the group level in ( ).
Note 3: *** p<0.01, ** p<0.05, * p<0.1

As access to informal transfers may only affect a subset of individuals or may not have a linear relationship with WTP, the right panel of Table 2.3 explores the effect of transfer rights on definitive decisions not to purchase insurance. Using a linear probability model, the dependent variable is collapsed into a dichotomous variable equal to one if WTP>0 and zero otherwise. In these regressions, "Transfer" is negative and significant at the 1% level across all specifications. Column 5 presents my preferred specification with the inclusion of controls to increase precision: the "Transfer" coefficient suggests that the predicted probability of bidding more than Rs 0 is 14% lower in "Transfer" than in "No Transfer". In other words, transfers lead to a reduction in willingness to bid for insurance. The risk aversion control variable is also now significant, indicating that an increase in risk aversion is associated with an increase in

WTP>0. Including interaction terms with risk aversion[82] and plot size in Column 6 increases the size of the "Transfer" coefficient to -0.23, but the interaction terms are not significant.

Lastly, the regressions in Table 2.3 also indicate that WTP is affected by several statistically significant control variables. In line with expectations, higher WTP is associated with higher education levels, higher round numbers, higher risk aversion levels and all group members having the same caste level (in at least one specification). The control for religion is also negative and significant in several specifications, indicating that Hindus are willing to pay less than Muslims or Jains. However, given the small number of non-Hindus in this sample, this finding should not be weighted heavily.

As noted in Essay 1, it is also useful to focus the analysis on participants that made efficient choices in the Binswanger risk preference game as they may be more likely to take the take-up game more seriously. The regressions in Table 2.3 are presented in Table A2.3 excluding participants that selected Binswanger Gambles D and F. While the sample size decreases, the "Transfer" coefficient remains significant at the 5% level or lower in Columns 3 and 6 and increases marginally in size across all specifications.

As the dependent variables WTP and WTP>0 are not continuous, it is also appropriate to use alternative specifications to the standard OLS approach. The left panel of Table 2.4 employs an ordinal logit specification to take into account that the dependent variable WTP is measured in increments of 100 between 0 and 3,600. For ease of interpretation, I present the ordinal logit regression in Column 3a as odds ratios.

[82] The distribution of risk preferences is presented in Table A2.2. The sample is relatively well distributed across the risk spectrum, though slightly more risk loving than in previous studies. Approximately 8% of the farmers in this study selected the riskiest lottery, Gamble H, which is high in comparison to the less than 2% that selected this gamble in Binswanger (1980) and low levels in similar games by Holt and Laury (2002). Participant comprehension of the Binswanger lottery was tested carefully in this study, so it is unlikely that lack of understanding is driving this trend.

Consistent with the OLS regressions in Table 2.3, the treatment effect is negative and only significant with the introduction of interaction terms in Column 3, which indicates that transfers reduce WTP among individuals with small plot sizes.

Table 2.4 Ordinal logit and logit: impact of transfer rights on WTP

Treatment effects relative to base category: No Transfer (NT)

Dependent variable:	WTP				Dichotomous variable = 1 if WTP>0			
	Ord Logit	Ord Logit	Ord Logit	Odds Ratio	Logit	Logit	Logit	Odds Ratio
	(1)	(2)	(3)	(3a)	(4)	(5)	(6)	(6a)
Transfer (T)	-0.12	-0.16	-0.95**	0.39	-2.25***	-2.26***	-2.86**	0.06
	(0.29)	(0.27)	(0.46)	(0.18)	(0.55)	(0.57)	(1.33)	(0.08)
T*Risk Aversion			0.08	1.07			-0.15	0.86
			(0.08)	(0.09)			(0.24)	(0.21)
T*Plot size			0.13*	1.14			0.15	1.16
			(0.08)	(0.09)			(0.21)	(0.25)
Risk Aversion		0.03	-0.01	0.99		0.19*	0.33	1.39
		(0.04)	(0.05)	(0.05)		(0.10)	(0.21)	(0.29)
Plot size		0.06	0.00	1.00		0.08	-0.04	0.96
		(0.04)	(0.03)	(0.03)		(0.07)	(0.20)	(0.19)
Constant	-2.45***	-3.77***	-4.20***	-4.20***	3.91***	2.95*	3.45*	31.43
	(0.24)	(1.10)	(1.15)	(1.15)	(0.47)	(1.59)	(1.99)	(62.44)
Observations	564	564	564	564	564	564	564	564
Controls	NO	YES	YES	YES	NO	YES	YES	YES
Wald	0.19	.	.	.	16.65	33.97	41.21	41.21
Pseudo R-squared	0.00	0.01	0.01	0.01	0.12	0.15	0.15	0.15

Note 1: Other controls are gender, same caste, round number, education, religion, and playing the investment game/take-up game first (omitted from the table). Education is excluded from the logit regressions because it perfectly predicts several observations. Exclusion of this variable does not significantly change the coefficients of interest.
Note 2: Robust standard errors clustered at the group level in ( ).
Note 3: *** p<0.01, ** p<0.05, * p<0.1

In the right panel of Table 2.4, I run the same regressions using a logit model and the dependent variable equal to one if WTP>0 and zero otherwise. All specifications in this panel are significant at the 1% level. Odds ratios in Column 6a suggest that, holding all other factors constant, the odds of being willing to pay more than Rs 0 are 16.7 times higher for farmers in “No Transfer” than farmers in “Transfer”.

Collectively, the results in Tables 2.3 and 2.4 indicate that informal transfers crowd out demand for formal insurance for some individuals. Farmers are less likely to buy insurance when it is possible to give and receive transfers. However, this effect is most pronounced at lower levels of willingness to pay and among individuals with smaller plot sizes. Indeed, this heterogeneity is consistent with the earlier discussion about the distribution of WTP in Figure 2.1. These findings thus qualify the conclusions of Dercon et al. (2014) and Mobarak & Rosenzweig (2012), highlighting the importance of contextual factors and indicating that informal transfers reduce take-up in the context of limited idiosyncratic risk.

2.4.2.1 Group-level trends

Further insights into the relationship between informal transfers and formal insurance can be seen in trends at the group level. A preliminary exploration of descriptive statistics first reveals that the average standard deviation of WTP within the group is higher in "Transfer" than in "No Transfer" (Table A2.4). The average standard deviation of final earnings within the group is also higher in "Transfer", indicating that informal risk sharing is incomplete. The average transfer given in "Transfer" was quite low: Rs 1,250. In 197 of 258 (76%) "Transfer" observations, no transfers took place at all. Among the remaining 24% that did engage in informal transfers, some made reciprocal transfers that were returned in subsequent rounds.[83]

To explore these group level trends further, the following OLS regression tests the effect of transfers on the dispersion of WTP within the group:

$$V_j = \beta_o + \beta_1 T_j + \beta_2 T_j W_j + \beta_3 W_j + \beta_4 X_j + \varepsilon_j \tag{2.2}$$

[83] A handful also made large transfers to group members for expenses such as purchasing a tractor, which actually increased disparities in income across the group and can partly explain the low level of risk sharing overall. The low level of transfers may also in part be attributed to informal arrangements to make reciprocal transfers that were interrupted because the game ended with a 33% probability in each round.

where V_j equals the level of variance in WTP for group j. T_j is equal to one for groups within "Transfer" and zero otherwise, W_j is the average WTP of the group, T_jW_j is the interaction effect between "Transfer" and average WTP of the group,[84] X_j represents a vector of average baseline control variables and ε_j is the error term.

Controls include gender; a dichotomous variable equal to one if all group members are of the same caste; plot size; risk aversion; round number; education level; and insurance associations.

Employing this regression in Table 2.5, Column 1 first reveals that "Transfer" is associated with higher variance in WTP and is significant at the 5% level without interaction terms. Including interactions in Column 2 increases the magnitude of the coefficient, though the significance level falls to 10%. In Columns 3 and 4, variance in the number of people that are willing to bid WTP>0 is also greater in "Transfer" and significant at the 1% level. Whether these trends are due to moral hazard or informal risk sharing remains an open question to be explored in the next section.

[84] This variable is divided by 1,000 to enable interpretation in the table.

Table 2.5 Variance in WTP within the group

Treatment effects relative to base category: No Transfer (NT)

Dependent variable	(1) Variance in WTP	(2) Variance in WTP	(3) Variance in WTP>0	(4) Variance in WTP>0
Transfer (T)	532,191.16**	936,214.10*	0.08***	0.24***
	(235,241.77)	(473,486.50)	(0.02)	(0.05)
T * Average WTP		-196,940.60		-0.08***
		(187,722.81)		(0.02)
Average WTP	-96,903.12	7,758.38	-0.05***	-0.01
	(101,413.64)	(109,843.75)	(0.01)	(0.01)
Constant	5,819,051.33***	5,564,781.95***	0.41**	0.30*
	(1,671,030.52)	(1,664,288.56)	(0.17)	(0.17)
Observations	192	192	192	192
R-squared	0.26	0.27	0.37	0.43

Note 1: The other controls are gender, same caste, plot size, risk aversion, round number, education, and insurance associations (omitted from the table).
Note 2: Robust standard errors clustered at the group level in ( ).
Note 3: Average WTP is divided by 1,000
Note 4: *** p<0.01, ** p<0.05, * p<0.1

2.4.3 Suggestive evidence on mechanisms

To isolate the channel through which transfer rights reduce willingness to pay, participants were asked at the end of each interview *when* each transfer had been arranged – before playing the WTP game (ex-ante) or after the weather condition was revealed (ex-post). This information was matched across participants to confirm that the same answers were given for each transfer. According to participants, only 7-14% (5-10 out of 70) of transfers were arranged ex-ante while 86-93% (60-65 out of 70) of transfers were arranged ex-post.[85] This evidence indicates that the moral hazard channel is the dominant driver behind the higher number of zero bids in "Transfer" than in "No Transfer", i.e. that moral hazard significantly reduces take-up on the extensive margin. Among the 10 transfers that were arranged ex-ante, 7 of these groups arranged for one individual to purchase a policy while their peers gave Rs 0 bids (and informally

[85] Five observations could not be matched, perhaps due to an ambiguous risk sharing arrangement.

transferred a contribution toward the premium cost thereafter). This suggests that some groups were also sharing a single policy through informal risk sharing. However, they are in the minority.

Breaking the data down by round also helps to provide further evidence on the channels through which transfers affect take-up. Table 2.6 thus runs the regressions separately with observations from Round 1 in the left panel and Round 2 onwards in the right panel. As in Chapter 1, I also include one additional control in regressions for Round 2 onwards: the average occurrence of drought is used as a proxy for subjective beliefs about drought risk in the current season.[86]

If participants want to try out the policy to learn about it, I expect the "Transfer" coefficient in Table 2.6 to go toward zero over time as participants develop trust in the providers and better understand the product. However, the statistically significant negative effect on WTP only appears from Round 2 onwards. Moreover for WTP>0, the coefficient only declines from 0.23 to 0.22 from Round 1 to Round 2 onwards. These trends help to rule out the informal risk sharing channel and provide further support for the conclusion that moral hazard reduces weather insurance take-up.

[86] The occurrence of drought in the experiment was fairly uniform across treatments and across rounds. Overall, "No Transfer" participants experienced relatively fewer droughts (Table A2.5).

Table 2.6 OLS regressions by round

Treatment effects relative to base category: No Transfer (NT)

	Round 1		Round 2 onwards	
Dependent variable:	(1) WTP	(2) WTP > 0	(3) WTP	(4) WTP > 0
Transfer (T)	-382.60	-0.23**	-707.38**	-0.22**
	(318.76)	(0.09)	(269.46)	(0.08)
T*Risk Aversion	45.47	0.02*	51.27	0.00
	(48.46)	(0.01)	(78.25)	(0.01)
T*Plot size	21.13	0.01	81.78	0.01
	(47.05)	(0.01)	(50.25)	(0.01)
Risk Aversion	47.10	0.01	-39.55	0.00
	(32.82)	(0.00)	(45.79)	(0.01)
Plot size	-0.58	0.00	17.02	0.00
	(27.96)	(0.01)	(34.01)	(0.01)
Constant	2,730.05***	0.94***	2,851.57***	1.32***
	(786.87)	(0.24)	(1,054.11)	(0.18)
Observations	290	290	274	274
Controls	YES	YES	YES	YES
R-squared	0.09	0.11	0.13	0.13

Note 1: Other controls are gender, same caste, round number, education, religion, playing the investment game/take-up game first, and a weather perception proxy (in Columns 3 and 4) (omitted from the table).
Note 2: Robust standard errors clustered at the group level in ( ).
Note 3: *** p<0.01, ** p<0.05, * p<0.1

Table 2.6 also offers useful robustness checks for the empirical analysis. A first concern in this analysis is that events in earlier rounds (such as weather or earnings levels) might affect participant behaviour in later rounds. The left panel of Table 2.6 explores this possibility by limiting the analysis to the cleanest data: observations from the first round. In Column 1, the regression for the dependent variable WTP has a consistent sign with earlier results, but it is not significant (which could be attributed to the small sample size in these regressions). Using WTP>0 as a dependent variable in Column 2 also reveals consistent findings with earlier regressions, namely a negative coefficient and statistically significant difference between "No Transfer" and "Transfer".

A second possible concern is that data from the first round may be subject to higher measurement error if participants did not fully understand how the game works. Though such a concern is unlikely due to in-depth instructions and comprehension testing, the right panel of Table 2.6 explores this concern by excluding observations from the first round.

The results from Round 2 onwards are also consistent with my main findings. The "Transfer" coefficient in Column 3 is negative and significant at the 5% level. Interestingly, the size of the coefficient is higher and only significant from Round 2 onwards, suggesting that learning may indeed matter in understanding the game. This difference across rounds may also be driven by growing fear of free riding as participants get to know their peers over the course of the game.

2.5 Conclusion

Drawing together the literatures on formal-informal insurance interactions and on redistribution norms, this framed field experiment yields key findings for our understanding of low weather insurance take-up. First, in contrast to the findings of Dercon et al. (2014) and Mobarak & Rosenzweig (2012) for high basis risk, this study indicates that informal transfers reduce take-up in the context of limited idiosyncratic risk. Consistent with expected utility preferences, the main finding of this study is that the primary channel through which this substitutive relationship transpires is moral hazard. When farmers have the ability to give and receive transfers, they are less likely to purchase at any price. Moreover, a decrease in willingness to pay is pronounced among individuals with smaller plot sizes. In terms of scholarly implications, this research thus highlights an important distinction between transfers for risk sharing to try out a policy versus transfers due to redistribution pressures that has previously been less well defined in the economics literature.

This research also provides important policy lessons on how weather insurance should be marketed and structured in order to maximise the potential productivity-enhancing benefits of insurance coverage. One possible tool to address the dampening effect of moral hazard on take-up is to focus the expansion of weather insurance in areas where redistribution norms are less pronounced. Alternatively, one could mandate all or none purchases when weather insurance is sold to groups. Group weather insurance is still in pilot stages and some have suggested that group policies should be sold to microfinance groups, because it would be easier to sell within existing structures. In such contexts, the effect of moral hazard may be exacerbated without appropriate regulation as group members know each other well and can exert redistributive pressure on insured peers. Moral hazard could be reduced by introducing a requirement that everyone in the group has to purchase a policy. However, as shown in Essay 1, group insurance may raise other potential challenges. Moreover, an all-or-none requirement might reduce overall take-up depending on whether a majority of members are interested in purchasing. Exploring these cut-off points and interactions would thus be a noteworthy area for further research.

Essay 3: Networks, self-protection and moral hazard

3.1 Introduction

Self-protection technologies play an important role in rural development by helping to reduce risk exposure. Yet, in spite of such benefits, adoption levels are varied. An open question is whether networks can help us to understand this variation. A number of papers have studied the role of networks in facilitating knowledge sharing and diffusion of other forms of technology (e.g., Foster & Rosenzweig, 1995; Bandiera & Rasul, 2006). What is less well understood, however, is whether networks may also affect take-up of self-protection technologies through their provision of informal insurance. Individuals rely on peers for informal transfers in the face of financial shocks - particularly in areas with limited access to formal financial tools (Fafchamps & Lund, 2003). Akin to the pattern of moral hazard identified in formal insurance markets (e.g., Arnott & Stiglitz, 1991; Essay 2), access to this financial support from peers may distort incentives to invest in self-protection due to moral hazard. This study provides empirical support for such a proposition and suggests that such informal transfers crowd out investment in self-protection tools.

To explore the extent to which moral hazard reduces self-protection investments, this study focuses on the case of soil conservation. Soil conservation is a fundamental self-protection strategy against short- and long-term production risk such as weather variability. Yet, in many developing countries, only a small share of smallholder farmers invest in low cost soil conservation methods such as bunding and levelling. In the case of India, bunding and levelling were utilised by only 9% and 16% of the rural population respectively in 1999 (NCAER, 1999). As there are multiple alternative risk mitigation tools available and farmer production functions and utility functions are unknown, it is difficult to discern whether these usage levels are optimal. According to Di Falco and Bulte (2012), members of kin constrain investment in soil conservation in

Ethiopia. However, the linkages between other types of networks and self-protection investments remain less well defined.

Complementing Essay 2's experimental findings on formal insurance, this study takes a non-experimental approach to unpack the interaction between redistribution norms in caste networks[87] and investment levels in traditional forms of self-protection in rural India. Normally, this would be a difficult issue to study. However, a basic conceptual framework and intuition point to clear and testable contrasting effects on self-protection. In particular, conditional on household income, this framework predicts that increases in average network income lead to decreases in self-protection investments due to moral hazard. In contrast, conditional on average network income, increases in household income are expected to increase investments in self-protection due to a relaxed credit constraint.

The National Council of Applied Economic Research Rural Economic and Demographic Survey (NCAER REDS) data – a national rural household survey – in 1982 and 1999 offers a unique setup to test this prediction that household and network income have opposing effects. Using a panel dataset, I am able to sidestep endogeneity concerns such as time-invariant unobservables by focusing on within-household changes in income and self-protection. To address the risk of time-variant unobservables and simultaneity bias, I also implement an instrumental variable strategy by instrumenting for changes in income with inherited land in 1982.

The main analysis of this study supports the idea that self-protection is reduced by moral hazard in the context of redistribution norms. While increases in household income are associated with small average increases in self-protection, increases in average network income are associated with notable decreases in self-protection. In particular, a 1% increase in average caste income is associated with a 0.01 p.p. decrease

[87] A primary source of informal transfers in India (Munshi & Rosenzweig, 2009; 2014).

in the probability of both levelling and bunding. This decline is consistent with the prediction that informal transfers crowd out investment in self-protection.

While recognizing it is not possible to test for all possible endogeneity concerns, this analysis provides a first look and does not rule out the theory that caste networks reduce investment in self-protection due to moral hazard. In particular, these findings provide several contributions. First, they offer useful preliminary insights for our understanding of moral hazard for self protection and suggest that network effects extend beyond the kinship unit. They also expand our understanding of network externalities for risk-related technology adoption. Lastly, this study starts to shed light on the long-term effects of networks on self-protection decisions by utilising a long-term panel and focusing on changes in permanent income.

The primary policy recommendation arising from this work is the need for further exploration of aggregate effects and heterogeneity within the relationship between informal transfers and self-protection as alternative data sources become available. In particular, measuring moral hazard in datasets with shorter time horizons, for alternative self-protection tools and with detailed data on risk preferences and wealth levels would help to bolster these findings. Exploring the extent to which access to credit reduces these effects would also be an interesting direction for future research.

The rest of this essay is organised as follows. First, I review the literature in the context of a simple conceptual framework on networks, self-protection and moral hazard. I then present the empirical strategy and discuss the results before concluding with academic and policy implications.

3.2 Related literature and theoretical motivation

Many scholarly works have studied the interactions between networks and decision-making of the poor. Some studies have highlighted the benefits of network effects for social learning and the diffusion of new technologies (e.g. Foster & Rosenzweig, 1995). Others have pointed to potential variations in such effects. For instance, Bandiera and Rasul (2006) suggest some farmers strategically wait to adopt new crops in order to benefit from peer experience once a large number of other farmers in the network have tested the technology.

A number of papers have also explored the implications of redistributive norms for risk-mitigating efforts. Most focus on decisions to purchase formal insurance products, the findings of which appear context-specific. Several studies suggest that the opportunity to exchange informal transfers can reduce formal insurance take-up due to moral hazard (e.g., Arnott & Stiglitz, 1991). Indeed, Jannsens and Kramer (2014) find evidence of free riding among less risk averse individuals who purchase less health insurance in a lab experiment in Tanzania and Essay 2 finds similar trends in the case of weather insurance. Other studies have shown, however, that networks increase the purchase of formal weather insurance when there are high levels of basis risk (Dercon et al., 2014; Mobarak & Rosenzweig, 2012).

Drawing on these mixed findings, an important question is whether moral hazard also affects the adoption of self-protection tools. Ligon (1998) finds evidence of moral hazard within some village networks in South India. Di Falco and Bulte (2012) also suggest that redistribution norms foster a free riding culture and lead to lower adoption of soil conservation efforts among members of kin in Ethiopia. However, quantifying the degree of moral hazard in self-protection for other types of networks that extend beyond village borders is more limited.

To that effect, this study focuses on the caste network, a prominent risk-sharing group in rural India. While a number of studies have concentrated on the village as the informal risk sharing group of interest, the caste network is better placed to insure against aggregate level shocks and is increasingly viewed as a more relevant unit for informal insurance in practice. For instance, Mazzocco and Saini (2012) find evidence of higher levels of risk sharing at the caste level than the village level in rural India.[88] Indeed, informal loans from caste members are quite sizeable – making up 14% of the total value of loans received by households in rural India – and are disproportionately used to cover consumption and emergency expenses. 25% of households participated in informal transfers with caste members in 1982 and 20% in 1999 (Munshi & Rosenzweig, 2009). As shocks do not necessarily occur in all years, these percentages are noteworthy. In view of the prominence of caste networks as a source for informal transfers, this study focuses on caste as the primary network unit.[89]

To further motivate an exploration of the interactions between caste networks and self-protection, the following basic conceptual framework lays out potential implications of increases in household and network income for such investments.

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[88] Fafchamps and Lund (2003) also assert that informal risk sharing is more prominent in the network of friends and relatives than the village network in the Philippines.

[89] To reduce measurement error, I also exclude observations in castes with fewer than 15 households or with household heads less than 18 years old (Munshi & Rosenzweig, 2009).

3.2.1 Conceptual framework

Consider a simplified world with the following timing of events:

t=0	t=1	t=2	t=3	t=4	t=5	t=6
Begin season with endowment e	Discuss investment	Make investment decision	Introduce weather	Reveal earnings	Exchange informal transfers	End. Go to t=0

- At t=0, farmer i in network j has a land endowment e on which he grows wheat. The farmer's income y is subject to high variability due to fluctuations in local rainfall conditions.
- At t=1, farmer i is presented with a self-protection tool with cost c and given the opportunity to discuss the product with other farmers in the network. Farmer i is risk averse and follows a standard von Neumann-Morgenstern utility function. The natural prediction is that he will decide to invest in self-protection because his expected utility is higher with actuarially fair self-insurance.
- At t=2, each farmer in the network decides whether or not to purchase the self-protection tool. This decision is public and simultaneous across the network.
- At t=3, a random weather condition is then introduced.
- At t=4, income earned is introduced. Income varies across the network, ranging from y_{sl} to y_{sh} when there is a shock and y_{nl} to y_{nh} when there is no shock.
- At t=5, the farmers have an opportunity to engage in informal transfers within the network. [90]
- Lastly, at t=6, the farmers return to t=0: this is a repeated game.

Building on a theoretical model by Alger and Weibull (2010), such an environment may lead farmer i to reduce investments in self-protection by fostering moral hazard. One way to illustrate this is to consider the implications of an exogenous positive shock to

[90] The farmers do not have access to formal insurance.

the average income of the network. This shock increases the network's capacity to provide farmer i with a transfer in the event of a negative income shock. The opportunity for moral hazard through lower investments in self-protection is thus increased. If he experiences a negative shock to income, he can ask wealthier members of his network for a transfer at t=5.

This framework thus offers a first testable prediction: conditional on farmer *i*'s income, an increase in average network income leads to a decrease in investment in self-protection due to moral hazard.

An increase in farmer *i*'s income, on the other hand, is expected to offer a contrasting effect on self-protection efforts. Economic theory suggests that a direct effect of an increase in farmer income is that it relaxes the farmer's credit constraint and thus facilitates higher investment in self-protection. In line with theory, several empirical studies have shown that investments in formal insurance, for instance, increase as wealth increases (e.g. Gine et al., 2008; Gine & Yang, 2008).

However, one could envision this effect to be limited by two factors. First, an increase in income may also lead to a declining sensitivity to risk. Assuming Decreasing Absolute Risk Aversion (DARA) preferences, the farmer may become less risk averse as wealth increases. Such an effect would thus dampen the positive effect of household income on investment in self-protection tools.

A second potential limitation on this increase in investment is a fear of free riding (Di Falco & Bulte, 2011; Baland et al., 2009; Grimm et al., 2013; Alger & Weibull, 2010). A farmer who would otherwise engage in self-protection may also reduce his efforts for fear of free-riding peers in the network. This is because of a cultural obligation to share income informally with the network when financial success is public knowledge. Recognition that one may cover the full financial costs of self-protection while reaping only part of the benefits is expected to put a downward pressure on investments.

Indeed, this is consistent with the theoretical model of de Janvry et al. (2014) for formal weather insurance: a farmer will not purchase insurance if he anticipates that his peers will not purchase insurance and attempt to free ride on his policy. Such predictions may thus also hold for investments in self-protection.

In spite of these potential downward pressures,[91] the overarching effect of an increase in household income leads to the following second prediction: conditional on average network income, an increase in household income will increase investments in self-protection by relaxing the credit constraint. This prediction thus stands in direct contrast to the negative effect of network income on self-protection.

3.3 Empirical analysis

This section discusses the main empirical analysis to test the abovementioned predictions, beginning with the identification strategy and main specification, followed by descriptive statistics, then the main estimates and, finally, robustness checks.

3.3.1 Identification strategy and specification

To explore the implications of networks for self-protection efforts, I use the National Council of Applied Economic Research Rural Economic and Demographic Survey (NCAER REDS) in 1982 and 1999. As informal risk sharing is a prominent practice in India (Townsend, 1994), this rural panel household survey offers an important case for exploring the issue at hand. Data was sampled in 16 major states: 250 villages are included, with 4979 households in 1982 and 7474 households in 1999. The increase across rounds is due to the inclusion of surveys from split-off households that partitioned after the 1982 round as well as some new households.

To construct a balanced panel from the NCAER REDS, data from split-off households in 1999 are averaged and matched with the 1982 observations. Due to data limitations,

[91] Disentangling these channels falls outside the scope of this paper.

it is not possible to track self-protection practices on individual plots of land over time. Average values are thus used for 1999 split-offs to avoid overweighting households that may exhibit similar behaviour in risk-related decisions.

This REDS dataset includes information on income, self-protection investments and a number of household and farm characteristics such as education levels and plot information. For the independent variable, I focus on agricultural income[92] in the previous survey year as a primary measure of income – both at the household level and averaged at the network level. While a more comprehensive measure would also be useful, inconsistencies in the survey design across rounds preclude use of such a variable without introducing significant measurement error.

For the dependent variable, one could choose from a wide range of self-protection tools available to smallholder farmers in rural India. This study focuses specifically on two common, low-cost investments that can help to reduce production risk. First, *levelling* is an agricultural technique used to standardise the level of topsoil, either manually by dragging a beam across the plot or with a laser land levelling technology.[93] Levelling can be implemented for large areas of land or can be used to even out contours on a slope. It is typically – though not exclusively - employed for crops that benefit from level basin irrigation (for instance, wheat or rice). Levelling reduces production risk by ensuring a more uniform application of water, thus decreasing the farmer's dependency on irrigation between 10% and 30%. Levelling can also reduce long-run production risk by preventing salt concentrations and land degradation (Lybbert, Magnan, Spielman, Bhargava & Gulati, 2013; Abdullaev, Ul Hassan & Jumaboev, 2007).[94]

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[92] Pro-rated by household size.

[93] Laser levelling is increasingly popular in India and is commonly subsidised (Lybbert et al. 2013).

[94] While most studies highlight the soil conservation benefits of this technique, some suggest it can also lead to soil erosion in certain cases by changing surface soil characteristics (Martinez-Casasnovas & Ramos, 2009).

The second self-protection technique, *bunding,* involves placing stones around the contours of a slope. Bunding reduces production risk by increasing soil moisture and protecting against soil erosion. Soil erosion is a particularly important risk to production levels on hilly plots as it weakens soil nutrients and increases water runoff. In sum, levelling and bunding are low-cost tools for mitigating production risk by reducing dependency on water availability through more efficient irrigation and by promoting soil conservation.[95] To test the effect of increases in income on self-protection, dichotomous variables equal to one if household i invested in the prior year and zero otherwise are generated separately for levelling and bunding.

As the analysis relies on a panel dataset, I eliminate the effect of any unobserved time-invariant factors that may affect the dependent variable. Without a panel, the coefficients of interest may be biased. For instance, the gradient of a farmer's plot may affect decisions to invest in bunding. Moreover, risk preferences – which are correlated over time – are also an important determinant of self-protection investments and could bias cross-sectional results. By focusing on *changes* within households from 1982 to 1999 in a fixed effects model, I can remove such time invariant unobservables.

[95] When used according to plot characteristics and crops grown.

To explore the implications of networks for investment in self-protection, I thus employ the following regression equation:[96]

$$\Delta R_{it} = \beta_1 \Delta X_{it} + \beta_2 \Delta \bar{X}_{it} + \Delta \varepsilon_{it} \tag{3.1}$$

where ΔR is the change in self-protection from 1982 to 1999; ΔX is the change in household income; $\Delta \bar{X}$ is the corresponding change in average income of the rest of the caste and $\Delta \varepsilon$ is the change in unobserved determinants of self-protection for household i at time t.

I expect that conditional on household income, an increase in average caste income should decrease household investment in self-protection (due to crowding out by informal transfers) ($B_2 < 0$). Conditional on average caste income, however, an increase in household income is expected to increase household investment in self-protection due to an improved financial capacity ($B_1 > 0$).[97] Thus, comparing the difference in signs across network and household effects is expected to capture any effects of moral hazard on investment choices.

However, a remaining concern with this strategy is that unobserved time-variant factors could still affect the dependent variable and thus bias the estimated effects of changes in household income and caste income. For instance, improvements in local access to credit between 1982 and 1999 could lead to increases in income and could also facilitate higher investments in self-protection due to strengthened financial capacity. There is also a risk of simultaneity bias, as increases in self-protection may lead to increases in average income.

[96] Adapted in part from Munshi and Rosenzweig (2009; 2014).

[97] Though this effect may be limited due to a fear of free riding or DARA effects.

An instrumental variable (IV) approach is best applied to address these remaining endogeneity concerns.[98] Following Munshi and Rosenzweig (2009; 2014), I employ inherited land at the household level and average inherited land at the network level as IVs. As inherited land introduces a permanent change in wealth, this IV can be interpreted as the causal impact of permanent anticipated changes in income on changes in self-protection. In terms of the compliers, I expect changes in average network income to affect everyone in the sample that has inherited land and engages in informal transfers within the network. Moral hazard may be particularly pronounced among poorer households that have lower financial capacity and thus a more constrained ability to invest in self-protection. It may be less pronounced among wealthier households who are more likely to have exited the informal insurance arrangement.

Inherited land by the head of household offers a plausible valid instrument for changes in income. As an exogenous positive shock, it is a strong predictor of changes in income from 1982 to 1999. Importantly, as a historical instrument, it should overcome the risk of reverse causality. Moreover, as land is rarely sold in rural India,[99] inherited land is expected to be uncorrelated with the dependent variables (changes in levelling and bunding) other than through its correlation with change in income.

To test the strength of this IV and any remaining concern of omitted variable bias, I run robustness checks at the end of this section. A primary concern is that the exclusion restriction may be violated if there are other channels through which inherited land affects self-protection. For instance, households with more inherited land may also have higher levels of education and thus are better able to understand and invest in more self-protection. As my main regression focuses on the effect of *changes* in income on *changes* in self-protection, education *levels* are unlikely to be a concern. Moreover, such a concern is not likely to bias the household and network coefficients in the

[98] As well as the concern of measurement error in the income data.

[99] Less than 3% of all households sold land between 2000 and 2005 (according to the India Human Development Survey (IHDS), Munshi & Rosenzweig, 2009).

opposing directions that I predict. However, I include education levels of the household head – as well as other additional regressors – to check the robustness of these results. While acknowledging that some risk of omitted variable bias may still remain, this analysis offers a useful first look by giving the hypothesis (that networks crowd out self-protection due to moral hazard) a chance to fail.

3.3.2 Descriptive statistics

Table 3.1 presents descriptive statistics for the sample in 1982 and 1999. As illustrated, investments in levelling and bunding were 3% and 8% respectively in 1982 but increased substantially to 9% and 16% in 1999. Average income grew from Rs 834 to Rs 3,559 over the same period (per household individual).[100] Average inherited land was 693 acres in 1982.

Table 3.1 Descriptive statistics

	1982	1999
Risk mitigation measures		
Levelling	0.03	0.09
	(0.17)	(0.29)
Bunding	0.08	0.16
	(0.27)	(0.36)
Income measures		
Household income	833.62	3,558.96
	(1,291.73)	(11,223.55)
Grow non-basin irrigation crops	0.69	0.29
	(0.46)	(0.44)
Other descriptive statistics		
Plot size (acres)	719.30	616.84
	(1,043.68)	(951.16)
Inherited land (acres)	692.93	
	(1,033.60)	

Note 1: standard deviations in ( ).
Note 2: Statistics computed for castes with >15 households and with household heads >18 years old in 1982

[100] Within castes, income inequality also increased 42% over this time period (Munshi & Rosenzweig, 2014).

3.3.3 Main estimates

To explore the implications of changes in income on investments in self-protection, OLS regressions are first presented in Table 3.2. In line with expectations, an increase in household income is associated with a statistically significant increase in bunding and levelling. However, the effect of an increase in caste income is more mixed: it is associated with a statistically significant decrease in bunding, but it has no effect on levelling. As time variant unobservables – such as changes in access to credit – may bias these coefficients, the rest of this section focuses on the instrumental variable estimates.

Table 3.2 OLS regressions

Dependent variable:	(1) Change in levelling	(2) Change in bunding
Change in log household income	0.12***	0.10***
	(0.04)	(0.04)
Change in log caste income	0.07	-0.15***
	(0.04)	(0.05)
Constant	0.04***	0.10***
	(0.01)	(0.01)
Observations	2,964	2,964
R-squared	0.017	0.007

Note 1: Robust standard errors in ( ).
Note 2: *** p<0.01, ** p<0.05, * p<0.1

Table 3.3 presents reduced form regressions. The coefficient of household inherited land[101] is positive and significant at the 5% level for changes in levelling in Column 1. This suggests that household inherited land is positively correlated with increases in levelling between 1982 and 1999. However, household inherited land is insignificant in Column 2 for changes in bunding.

[101] Inherited land is measured in acres divided by 10,000 in Tables 3.2 and 3.3 for ease of presentation.

The main coefficient of interest, average caste inherited land, is negative and significant at the 1% level for both bunding and levelling. In line with expectations, these results support the idea that households in castes with more inherited land engaged in less self-protection.

Table 3.3 Reduced form regressions

Dependent variable:	(1) Change in levelling	(2) Change in bunding
Household inherited land	0.17**	-0.06
	(0.08)	(0.12)
Average caste inherited land	-0.64***	-1.37***
	(0.15)	(0.23)
Constant	0.08***	0.15***
	(0.01)	(0.01)
Observations	2,961	2,961
R-squared	0.006	0.015

Note 1: Robust standard errors in ( ).
Note 2: *** p<0.01, ** p<0.05, * p<0.1

First stage parameters are estimated in Table 3.4 for the two main independent variables: change in log household income and change in log caste income in Columns 1 and 2, respectively. In line with expectations, the coefficients of household inherited land and average caste inherited land are positive across both specifications. Apart from household inherited land in Column 2, all coefficients are significant at the 1% level. In Column 1, the coefficient of household inherited land indicates that a 100 acre increase in inherited land is associated with a 0.6% increase in household income. A 100 acre increase in average caste inherited land is associated with a 1% increase in caste income (Column 2). The large F-statistics and low p-values in both columns suggest these instruments have sufficient power.

Table 3.4 First stage regressions

Dependent variable:	(1) Change in log household income	(2) Change in log caste income
Household inherited land	0.57***	0.02
	(0.12)	(0.03)
Average caste inherited land	0.70***	1.03***
	(0.18)	(0.08)
Constant	0.02**	0.14***
	(0.01)	(0.00)
F-stat 1	54.0	115.5
	(0.00)	(0.00)
Observations	2,961	2,961
R-squared	0.046	0.073

Note 1: Robust standard errors in ( ).

Note 2: *** p<0.01, ** p<0.05, * p<0.1

Note 3: Household income is prorated by household size.

Building on these first stage results, instrumental variable estimates are presented in Table 3.5. These estimates support my main prediction that an increase in network income is significantly correlated with a reduced probability of investing in levelling and bunding. The coefficient of change in log caste income is negative and significant at the 1% level in both specifications. This means that – holding other factors constant – a 1% increase in average caste income is associated with a 0.008 and 0.013 p.p. decrease in the probability of levelling and bunding, respectively. As previously mentioned, these IV estimates can be interpreted as the causal impact of permanent anticipated changes in income on investments in levelling and bunding. Given that self-protection rates were already quite low in 1982 (3% and 8% in levelling and bunding, respectively), this downward pressure on adoption is noteworthy.

Table 3.5 Second stage regressions

Dependent variable:	(1) Change in levelling	(2) Change in bunding
Change in log household income	0.32*	-0.07
	(0.17)	(0.21)
Change in log caste income	-0.83***	-1.28***
	(0.24)	(0.32)
Constant	0.19***	0.32***
	(0.03)	(0.05)
Observations	2,964	2,964

Note 1: Robust standard errors in ( ).
Note 2: *** p<0.01, ** p<0.05, * p<0.1
Note 3: Household income is prorated by household size.

In line with expectations, change in log household income is also significant at the 10% level and positive in Column 1. This suggests that increases in household income are associated with increased investments in levelling. In contrast, change in log household income is not significant in Column 2. This is consistent with the reduced form results, and suggests that the instrument household inherited land is not well correlated with changes in bunding investments.

Overall, the positive and negative coefficients for household and caste income respectively are consistent with the predictions that informal transfers crowd out self-protection. Several alternative theories can be proposed, but they do not align with these diverging signs. For instance, if we assume networks engage in full risk sharing, one would expect an increase in network income to also increase household investments in bunding and levelling. However, this story is not consistent with the empirics. Such a theory is also negated by Munshi and Rosenzweig's (2009) rejection of the model of full risk sharing using the NCAER panel. Alternatively, one may expect that farmers have DARA preferences and become less risk averse as wealth increases; this would result in a negative coefficient for changes in log household income, which is also not borne out in the data.

A third alternative theory could be that an increase in the network's average inherited land also increases the network's capacity to provide informal credit for households to invest in their farms. However, in such a scenario, one would not expect change in log caste income to have a positive coefficient. This would also conflict with Munshi and Rosenzweig (2014)'s finding that the caste network provides support primarily for consumption and cash flow emergencies such as illness rather than for loans to further investment.

Lastly, one may be concerned that wealthier farmers have better land quality and thus require lower investments in bunding, for instance. However, as land is rarely sold in India (Munshi & Rosenzweig, 2009), this is also unlikely to be captured in a fixed effects regression that focuses on the effect of changes in income.

3.3.4 Robustness checks

In this section, I conduct robustness checks to explore several outstanding uncertainties and rival explanations in this analysis. A first concern may be that the observed effects are driven by differences in education levels. As wealthier households are more educated on average, they may be more likely to start investing in self-protection and to share this knowledge amongst themselves. While such an effect is less likely to be captured in a measure of change in investments from 1982 to 1999, it is still possible that this effect would introduce an upward bias on my coefficients and lead me to underestimate the downward pressure of caste income on investments in self-protection.

A second potential bias that could arise is that split-off households may have younger household heads that are either more ambitious or less risk averse in technology adoption. This could also lead to an upward bias on the coefficient of change in log household income or change in log caste income.

Lastly, it is important to consider that certain self-protection methods may be more or less effective depending on the type of crops grown. In particular, levelling is more commonly used in large areas to improve the effectiveness of basin irrigation for crops such as rice and wheat. An increase in the growth of crops that require furrowing such as cotton, maize or sugarcane, on the other hand, is less likely to require investments in levelling. With the spread of high-yield varieties of cotton in India and the corresponding increases in income that this has generated, it is thus important to consider the effect of changes in crop choice on investments in self-protection.

To address these potential concerns, I include the education of the household head, a dummy demarcating split-off households and a dummy demarcating change in production of non-basin irrigation crops (cotton, maize and sugarcane)[102] as additional regressors in the IV estimates in Table 3.6. Inclusion of these controls increases the size of the main coefficient of interest in both columns: change in log caste income is negative and significant at the 1% level. The coefficient of change in log household income, on the other hand, is no longer significant in Column 1. While this raises some concern, it could be explained by the notable drop in sample size with the inclusion of controls. Overall, the instrumental variable approach is not perfect, but it is difficult to explain these results through alternative reasoning and this analysis does not rule out the idea that informal transfers crowd out investments in self-protection.

[102] As highlighted in Table 3.1, planting of non-basin irrigation crops appears to have dramatically decreased from 1982 to 1999. This is likely due to measurement error because the response options changed across the two surveys. While the resulting signs in Table 3.6 are in line with expectations (negative and significant for levelling, insignificant for bunding), these should not be relied on too heavily.

Table 3.6 Second stage regressions with controls

Dependent variable:	(1) Change in levelling	(2) Change in bunding
Change in log household income	0.20	-0.38
	(0.23)	(0.28)
Change in log caste income	-0.97***	-1.83***
	(0.28)	(0.43)
Change in non-basin irrigation crops	-0.04**	0.04
	(0.02)	(0.03)
Splitoff household dummy	0.04*	0.01
	(0.02)	(0.03)
Education	0.02**	0.05***
	(0.01)	(0.01)
Constant	0.17***	0.41***
	(0.04)	(0.07)
Observations	1,993	1,993

Note 1: Robust standard errors in ( ).
Note 2: *** p<0.01, ** p<0.05, * p<0.1
Note 3: Household income is prorated by household size.

3.4 Conclusion

To conclude, this study used a unique panel survey dataset to test the extent to which informal transfers crowd out investment in self-protection tools. The main finding of this analysis is that increases in network income lead to decreases in self-protection. This supports the idea that self-protection is reduced by moral hazard in the context of redistribution norms. While it should be acknowledged that endogeneity issues may still remain, these results are not consistent with alternative explanations. This study thus offers a useful first look given available data and provides an important extension of the informal insurance literature to the case of caste networks and self-protection.

In view of the long-term benefits of soil conservation and other self-protection tools for rural development, it is worth considering potential policy implications of informal transfers crowding out self-protection. As several studies have found that insurance and credit are substitutes (e.g. Karlan & Zinman, 2011), one potential policy strategy to increase investments in self-protection is to further the availability of formal credit. This would thus provide an interesting avenue for future work.

It should also be kept in mind that the effectiveness of such interventions may vary and targeting initiatives could prove beneficial. In particular, poorer members of a caste may be more responsive, as they may place greater reliance on informal insurance arrangements. To bolster this study's findings on aggregate effects and to explore potential sources of heterogeneity that may benefit from targeting, further research is needed. In particular, future panel datasets covering shorter time horizons, alternative self-protection tools and detailed data on risk preferences and wealth levels would offer a fruitful direction for further exploration.

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Appendix I – Experiment Script[103]

Phase 1: Participant consent

Give hard copy of consent form to the participant

"Risk sharing mechanisms, access to information and investment choices"
Laura Munro, London School of Economics and the Centre for Micro Finance
Contact details for this study: --------- -----------

The purpose of this study is to understand rural farmers' circumstances and financial choices especially relating to insurance and investment choices. This study is a key element of the principal researcher's doctoral research at the London School of Economics. It will also help in the design of future weather insurance products for farmers such as you. In the study, you will play a series of games in which you have the opportunity to earn real money. These games will simulate a series of Kharif[104] seasons; each season you will be asked to either value an insurance product or choose an investment product. These choices and random variations in rainfall levels will determine your earnings for the game and your participation today. Your participation in this study will take about two hours. If you have any questions about the study, they will be answered for you.

For your participation in the study, you will receive a minimum of Rs 150. You can earn up to a maximum of Rs 400 depending on how you perform in the games that we play. Lunch will be provided and your transportation costs to/from Ahmedabad will also be covered.

Your participation in this study is purely voluntary, and you may withdraw your participation or your data at any time without any penalty to you. You may decline to answer any question.

Your data will be kept completely confidential by storing it in a password-protected file in a physically secure location. You will not be asked for any personally identifiable information. When the research is completed, all data files will be kept protected in a secure location by the principal researcher at the London School of Economics.

I have read the description of this study, my questions have been answered, and I give my consent to participate. Yes No

Village of participant: ____________________

[103] This protocol has drawn on Stein and Tobacman (2011) and Fischer (2013) for several questions and instruction texts.

Today you will play three games, some of which have several rounds. We will play (1) one round of the black and white game and (2) then several rounds of a game called the blue game and (3) several rounds of a game called the red game.

Phase 2: Binswanger lottery (the black and white game)

OK, let's start with the Black and White game. In this game, the amount of money you win is based on picking a coloured stone. We will put two stones in this pouch. One stone is white. The other is black. You will then choose one stone from the pouch without looking.

If you pick the white stone you will win the amount shown in white. If you pick the black stone you will win the amount shown in black.
Distribute project choice sheets and tokens.
We will give you choices about which game you want to play. Look at the sheet in front of you. It describes eight games. The colour on the page tells you how much you win for each colour stone. If you play Game A, how much do you win if you pick the white stone? ________
You said 50 Rupees. That's correct!
How much do you win if you pick the black stone in Game A? ________
You said 50 Rupees. That's correct!
The choice is yours. There are no right or wrong answers. Note that this game will be played FOR REAL MONEY, so think carefully! If you choose 'I don't know', you won't play the game and will not have the opportunity to win any extra money.

Which of the following gambles would you prefer?
a. Rs 50 for white, Rs 50 for black
b. Rs 45 for white, Rs 95 for black
c. Rs 40 for white, Rs 120 for black
d. Rs 35 for white, Rs 125 for black
e. Rs 30 for white, Rs 150 for black
f. Rs 20 for white, Rs 160 for black
g. Rs10 for white, Rs 190 for black
h. Rs 0 for white, Rs 200 for black
i. I don't know=9

At the end of your session here today, you will be paid privately in rupees for your earnings in one of the rounds that you played today, either in the black and white game, the blue game or the red game. Suppose you play one round of the black and white game, three rounds in the blue game and five rounds in the red game. We will put one orange token for the black and white game labelled BW; three blue tokens labelled 1, 2, and 3; and five red tokens labelled 1, 2, 3, 4 and 5 in the pouch and you will pick a token from the pouch without looking.

Let's say that you select a blue token labelled with the number 3 ***(show token)***. This means that you will be paid your earnings for the third round of the take-up game. Do you have any questions about this?

At the end of the day, you will be paid individually and privately. No one will see exactly how much you earn.

Phase 3: Introduction to weather insurance

Have you heard of weather insurance? Can you explain to me what it is? ***Rate comprehension.***

a. ***Participant understands the product perfectly.***
b. ***Participant understands the product somewhat.***
c. ***Participant has heard of the product, but does not understand what it is for or how it works.***
d. ***Participant has not heard of the product.***

Weather Insurance is an index based insurance product for the Kharif monsoon. This provides cover for financial losses arising due to deficient rainfall. The cover is operative during the monsoon months i.e. June to September. The sum insured under one policy is Rs 10,800.

Here is a short video to introduce you to how weather insurance helps to protect a farmer against the risk of low income from drought.

Show Video

In this video we have seen:

- Sukhiram explain how a farmer can reduce risk of income loss from drought
- How weather insurance works.
- How one can get a payout from weather insurance if suffering from deficit rainfall.

Do you have any questions about what you just saw?

Note down participant questions _____________

Now we will give you a bit more detail about the specifics of the policy.

In each district where weather insurance is sold, a primary rainfall station is chosen as the reference station. These stations are chosen on the basis of presence of consistent historical rainfall data, and are managed by the Indian Meteorological Department (IMD).

There are 16 rainfall stations in the Ahmedabad district. You receive a payout if a drought is recorded at your local rainfall station. Everyone within a 10 kilometre radius of the rainfall station that purchases weather insurance will receive the same payout of Rs 10,800 if there is a drought recorded at their local station. Using one location to determine payouts makes the product more affordable and ensures that you receive your payout faster. However, be aware that rainfall levels at this station are only an approximation of rainfall on your plot of land. So you may earn only Rs 500 from crop sales while another farmer earns Rs 7,500. While you suffered different losses, both of you will receive a payout of Rs 10,800 if you are insured.

Do you understand? Yes No
Do you have any other questions before we start the first game? _________________

Phase 4: Take-up game (the blue game)[105]

This game is called the blue game. In the first part of each round, we want to see how much you value a weather insurance policy. In contrast to the other game you play today, the purchase of insurance is NOT mandatory in this game. The game works like this. First you have to state what is the maximum amount of money you would pay to have the weather insurance policy we just described. Then we will make a randomly drawn offer to sell it to you. If this offer is lower than the amount you said you would be willing to pay, then you pay the amount of our offer and take the insurance policy. If the amount we offer is higher than what you said you would be willing to pay, then you do not purchase the insurance policy and are uninsured this round.

You will be best off if you state the real maximum amount you would be willing to pay to get the insurance policy.

We will start by looking at a sample situation. Let's say Sutha is playing the game for a weather insurance policy. He states that the maximum amount he would pay for the policy is Rs 2,500. He is then randomly offered the policy for Rs 2,600. What happens?

1. Sutha does not buy the weather insurance policy.
2. Sutha pays Rs 2,500 for the weather insurance policy
3. Sutha pays Rs 2,600 for the weather insurance policy.

You answered Sutha does not buy the insurance policy. You're right! Since the bid of Rs 2,600 was higher than the Rs 2,500 that Sutha said he would be willing to pay, he does not buy the policy and is uninsured this round.

Next let's look at another situation. Again, assume that Sutha says the maximum amount he would pay for the policy is Rs 2,500. However, this time he is randomly offered Rs 2,000 for the policy. What happens now?

[105] The following script is for the "Transfer" treatment. Scripts for other treatment can be provided on request.

1. Sutha does not buy the weather insurance policy.
2. Sutha pays Rs 2,500 for the weather insurance policy
3. Sutha pays Rs 2,000 for the weather insurance policy.

You answered Sutha pays Rs 2,000 for the insurance policy. You're right! Since the bid of Rs 2,000 was lower than the Rs 2,500 that Sutha said he would be willing to pay, he gives Rs 2,000 and takes the policy.

In each round you will be offered a weather insurance policy like Sutha. You will then be asked the maximum amount of money you would be willing to pay for this product.

After giving your bid, you will be randomly offered a price at which you can purchase this product. The offer price will be somewhere in between Rs 0 and Rs 3,600. If this offer price is lower than the maximum price you said you were willing to pay for the product, you will pay the offer price and purchase the policy. If the offer price is more than your maximum, you will keep the product.

It is in your best interest to think about each question thoroughly and give the actual maximum price you would be willing to pay!

Please verify that you understand – Yes or No

Let's do a practice run. The results from this question will not affect your final payment. We are offering a weather insurance with a market price of Rs 3,600. The payout from this policy is Rs 10,800 in the event of a drought at your local rainfall station during the Kharif season. What is the maximum amount you would pay to have this insurance coverage? Our offer price will be between Rs 0 and Rs 3,600. Give your bid by placing this token on the corresponding amount.

Give bid sheet and token to the participant.

You said the maximum amount you're willing to pay for this policy was: Rs ______

Your computer will now randomly select an offer price between 0 and 3,600 for this policy. The offer price is Rs ______.

You get to buy the policy. You said the maximum amount you would be willing to pay was Rs _____. Our random offer of Rs ______ was smaller than the maximum amount you said you were willing to pay, so you get to buy the policy.

Do you have any questions? Yes   No

Valuing the weather insurance product is only one part of this game. Now let's explain the timing of the rest of game. In this game, each participant owns one acre of land. The game will be comprised of several rounds – each round represents one Kharif season. At the beginning of each round, you will be given Rs 18,600. One hundred game rupees are equal to one real rupee.

Immediately after receiving the endowment of Rs 18,600 each participant will have to pay Rs 15,000 for agricultural inputs. The remainder of the endowment can be used to purchase insurance or can be allocated to your final earnings for the round. The face value of the insurance policy is Rs 3,600. This policy is actuarially fair and provides a payout of Rs 10,800 in the event of a drought. We may offer a random discount on this price – you can expect that our offer price will be between Rs 0 and 3,600.

Before you decide how much you are willing to pay for this policy, you will be given an opportunity to talk with the other participants in your group. After this break, you will be asked for your willingness to pay for the insurance product. This valuation will be given publicly. All group members will know how much you are willing to pay for insurance and whether or not you are insured this round.

Next, you will be told whether or not a drought occurs in this round. The probability of a drought occurring is 1 in 3 (33%). When a drought occurs, it affects the entire group, but to varying degrees.

Then you will be told how much income you earned. Income ranges from Rs 500-7,500 when there is a drought, and Rs 25,000-35,000 when there is optimal rainfall (no drought). In this game, average earnings in a drought are Rs 4,000. Average earnings in rainfall are Rs 30,000.

You will have to tell your group members how much you earn.

Insurance payouts are a standard value of Rs 10,800 for all members of the group that purchase an insurance policy. Payouts are determined at a rainfall station up to 10 kilometres away; rainfall levels at this station are used to approximate rainfall on all of your plots of land, but it is not a perfect approximation. If there is a drought in this round, you may receive only Rs 500 in earnings while another group member earns up to Rs 7,500 from selling part of his crop. Though you suffered different losses, you will receive the same payout of Rs 10,800 if you are each insured in addition to your crop sales earnings.

Do you understand? Yes No

After you receive your earnings and/or insurance payout, you will be allowed to make transfers with members of your group. You may want to give part of your earnings to another group member or to ask for a transfer yourself. You are only eligible to play in subsequent rounds if you have at least Rs 9,000 at the end of the round. If you have less than Rs 9,000 you will have to rent out your land at the end of this round in order to survive – the penalty for doing this is that you cannot play in the next round. Keep in mind that if you suffer from a drought and do not have insurance or receive a transfer from your peers, there is a 70% chance that you cannot play in the next round.

At the end of each round, your total earnings will be recorded. A ball will then be drawn from this bag ***(show bag)*** to determine whether or not there is a next round for all eligible players. This bag contains 10 white balls and 5 violet balls. If a white ball is drawn, the game continues and players with a balance of Rs 9,000 in the previous round are allowed to participate. These participants will start with a zero balance and then be given a new endowment of Rs 18,600. If a violet ball is drawn, the game ends for all players.

We may play several rounds of this game and the next game. If one of the rounds from these games is selected for your final payment, we will pay you one real rupee for every 100 game rupees that you scored in that round.

If you earned Rs 30,000 in this round, how many real rupees would you be paid for this game? _________

You said Rs 300. That's correct!

Remember, every round counts but you will only be paid in real rupees for one of the rounds from these two games or the Black and White game. If the round chosen is one in which your group members played but you did not because you did not have sufficient points in the previous round, you will not receive any payment for this game

Now let's run the first round.

Here is your endowment of Rs 18,600 for this round. ***Give participant game rupees.***

To prepare for planting this season, you must first pay Rs 15,000 for agricultural inputs. Everyone in the group purchases the same inputs.

Exchange Rs 15,000 for input vouchers.

The remainder of your endowment can be used to purchase insurance or can be saved for the end of the round. The probability of a drought occurring is one in three (33%). When a drought occurs, it affects the entire group, but to varying degrees.

We are offering a weather insurance product with a market value of Rs 3,600. This policy pays out Rs 10,800 in the event of bad rainfall. What is the maximum amount you would pay to have this insurance coverage for the next Kharif round? Our offer price will be between Rs 0 and Rs 3,600. Take a moment now to think about how much you are willing to pay for this product.

Before you make your decision, we will have a brief break. You can discuss with your group members if you wish. Remember that you are allowed to ask what your peers think about weather insurance or to ask how much they plan to bid for the insurance product.

At this time, you are also allowed to discuss with one or more of your group members whether you are interested in sharing your payouts through transfers at the end of the round.

You don't need to share any information or make any arrangements – this is entirely up to you. You can only play in the next round if you have Rs 9,000 at the end of this round. Keep in mind that if you suffer from a drought and do not have insurance or receive a transfer from your peers, there is a 70% chance that you cannot play in the next round.

Your final bid will be collected publicly after this break. All group members will know how much you are willing to pay for insurance. They will also know whether or not you are insured and how much income you earn in each round.

Give three minute break. Record discussion.

OK the break is now over. Please return to your respective seats.

Our offer price for this policy will be between Rs 0 and Rs 3,600. What is the maximum amount you would pay to have this insurance coverage for the next Kharif round? Give your bid by placing this token on the corresponding amount.

Give bid sheet and token to the participant.

You said the maximum amount you would be willing to pay for this policy was: Rs ________

Your computer will now randomly select an offer price between Rs 0 and 3,600 for this policy. The offer price is Rs ______.
You get to buy the policy. You said the maximum amount you would be willing to pay was Rs _____. Our random offer of Rs ______ was smaller than the maximum amount you said you were willing to pay, so you get to buy the policy.

Give insurance policy.

Now please announce to your group members how much you were willing to pay for insurance and whether or not you got insurance.

Now, one member from your group will randomly select the weather conditions for this round. This bag contains three tokens: one for drought and two for optimal rainfall.

This means there is a one in three chance that your region will suffer from a drought. Player ___, can you please choose a token from this bag?

The weather for this period is: _______ Drought or Rainfall

Show token to all participants

Your earnings this period are: _______

Give corresponding game rupees.

You purchased a weather insurance policy so you will also receive an insurance payout of Rs 10,800.

Give corresponding game rupees. Announce earnings and insurance payout to other group members.

Now you may have a break to discuss the season with your group members. If you wish to give any of your rupees to other participants, now is your opportunity to do so. Remember that you are only eligible to play in the next round if you have Rs 9,000 or more at the end of this round.

Give three-minute break. Record discussion.

What transfers did you give and/or take?

1) Transfers given ______ to Player ____

2) Transfers given ______ to Player ____

3) Transfers taken _______ from Player ______

4) Transfers taken _______ from Player ______

Please count your final rupees for this round. You should have _______. Is this correct?

1) Yes
2) No
    a) Please rectify any discrepancies _________

Collect cash and tell farmer to write down their earnings.

As you earned more than Rs 9,000 in this round, you are eligible to play again if there is another round.

Whether or not there is a next round depends on which ball is drawn from this bag containing 10 white balls and 5 red balls. If a white ball is drawn, the game continues. If a red ball is drawn, the game ends.

Player ___ please choose a ball from the bag without looking.

Player ___ selected a white ball so the game will continue for another round.

Phase 5: Investment game (the red game)[106]

In this game, each participant owns one acre of land. The game will be comprised of several rounds – each round represents one Kharif season. At the beginning of each round, each participant will be given an endowment of Rs 18,600. Immediately after receiving the endowment, each participant will have to pay Rs 10,000 for agricultural inputs (excluding fertiliser).

The remainder of the endowment (Rs 8,600) is for purchasing insurance and fertiliser. In contrast to the other game you play today (the blue game), the purchase of insurance is <u>mandatory</u> in this game. This insurance policy has a face value of Rs 3,600 <u>per person</u> and provides a payout of Rs 32,400 <u>to the group</u> in the event of a drought. We may offer a random discount on this price for the whole group, so the actual price that you have to pay will vary across rounds.

After you have purchased your insurance coverage, you will be offered a choice between three different fertiliser products, with varying levels of risk and return. All investment products cost Rs 5,000:

1) ***Low-risk, low-return fertiliser***: average income is Rs 27,000 if optimal rainfall, average income is Rs 6,000 if drought
2) ***Average-risk, average-return fertiliser:*** average income is Rs 30,000 if optimal rainfall, average income is Rs 3,500 if drought
3) ***High-risk, high-return fertiliser:*** average income is Rs 31,000 if optimal rainfall, average income is Rs 2,000 if drought

Each product has higher returns, and higher risk, than the last. Products with higher returns are particularly sensitive during drought years. Keep in mind that the probability of a drought occurring is one in three (33%). When a drought occurs, it affects the entire group, but to varying degrees. <u>On average</u>, individuals using high-risk fertiliser will have lower payouts in drought years than individuals using low-risk fertiliser. However, individuals using high-risk fertiliser are likely to have higher payouts

[106] The following script is for the "Group Perfect" treatment. Scripts for other treatments can be provided on request.

in optimal rainfall years than individuals using low-risk fertiliser. This is because the high-risk, high return fertiliser has more rigid rainfall needs.

Before finalizing your fertiliser choice in each round, you will publicly announce your choice to your group members and have a few minutes to discuss this choice. At the end of this break, you will reveal your final choice publicly in front of your peers.

Do you have any questions about the difference between these three products?

a. Yes ________________________

b. No

Ask the farmer to explain the difference between these three products in their own words and rate their comprehension.

After you have made your investment selection and paid for your insurance, you will be told whether or not a drought occurs in this round. Then, you will be told how much income you earned and whether you received an insurance payout. You will have to announce your income to the rest of the group at this time. Insurance payouts are a standard value of Rs 32,400 for the group as a whole. Upon receiving a payout, the group has a few minutes to decide how to distribute this internally among the group members. Payouts are determined at a rainfall station up to 10 kilometres away; rainfall levels at this station are used to approximate rainfall on all of your plots of land, but it is not a perfect approximation. If there is a drought, you may receive only Rs 500 in earnings this round while another group member earns up to Rs 7,500 from selling part of his crop.

Do you understand? Yes No

Ask if it is possible to have 500 rupee earnings in drought when own low-risk fertiliser.

After you have received your payout, you will be allowed to make transfers with members of your peer group. You may want to give part of your earnings to another group member or to ask for a transfer yourself.

At the end of each round, your earnings will be recorded. A ball will then be drawn from this bag ***(show bag)*** to determine whether or not there is a next round. This bag contains 10 white balls and 5 red balls. If a white ball is drawn, the game continues. If a red ball is drawn, the game ends for all players.

Now let's run the first round.

Here is your endowment of Rs 18,600 for this round. ***Give participant game rupees.***

To prepare for planting this season, you must first pay Rs 10,000 for agricultural inputs (excluding fertiliser). Everyone in the group purchases the same inputs.

Exchange Rs 10,000 for input vouchers.

The remainder of your endowment is for purchasing insurance and fertiliser. Purchase of the insurance policy is mandatory. The probability of a drought occurring is one in three (33%). When a drought occurs, it affects the entire group, but to varying degrees. By purchasing insurance, your group is guaranteed a payout of Rs 32,400. You will have to decide amongst yourselves how to split up this amount when a drought is recorded at the local rainfall station. The face value of this policy is Rs 3,600 per participant. We may offer a random discount on this price, so you can expect that our offer price will be between Rs 0-3,600.

Before you learn the price you will have to pay for insurance, you need to decide what kind of fertiliser you would like to apply on your land. We are offering a choice between three different fertiliser products, with varying levels of risk and return. All fertiliser products cost Rs 5,000.

1) *Low-risk, low-return fertiliser:* average income is Rs 27,000 if optimal rainfall, average income is Rs 6,000 if drought
2) *Average-risk, average-return fertiliser:* average income is Rs 30,000 if optimal rainfall, average income is Rs 4,000 R if drought
3) *High-risk, high-return fertiliser:* average income is Rs 33,000 if optimal rainfall, average income is Rs 2,000 if drought

Each product has higher returns, and higher risk, than the last. Products with higher returns are particularly sensitive during drought years. Keep in mind that the probability of a drought occurring is one in three (33%). When a drought occurs, it affects the entire group, but to varying degrees. On average, individuals using high-risk fertiliser will have lower payouts in drought years than individuals using low-risk fertiliser. However, individuals using high-risk fertiliser are likely to have higher payouts in optimal rainfall years than individuals using low-risk fertiliser. This is because the high-risk, high return fertiliser has more rigid rainfall needs. That said, your earnings are determined not only by your fertiliser choice but also by how much rain you received on your individual plot of land. As each player may receive different amounts of rain, it is impossible to know with complete certainty which fertiliser someone in your group chose simply by looking at their earnings.

Before you choose your investment for this round, we will have a brief break. You can discuss with your group members if you wish.

Give three-minute break. Record discussion.

OK the break is now over. Please return to your respective seats.

Which fertiliser would you like to choose? Please announce this choice publicly to the entire group.

You selected the _________ product, which will help you earn ______ on average if there is optimal rainfall and ______ on average if there is a drought.

Take 5,000 game rupees and give corresponding fertiliser voucher.

Now, your computer will randomly select an offer price between 0 and 3,600 per person for your insurance policy. The offer price is Rs ______ per person. Please pay this amount now.

Take corresponding game rupees from participant and give insurance policy.

Now, one member from your group will randomly select the weather conditions for this round. This bag contains three tokens: one for drought and two for optimal rainfall. This means there is a one in three chance that your region will suffer from a drought. Player _____, can you please choose a token from this bag?

The weather for this period is: _______ Drought Rainfall

Show token to all participants

Your earnings this period are: _______. Please announce your earnings to the group.

Give corresponding game rupees

Your group will receive your insurance payout of Rs 32,400. You may now discuss amongst yourselves how to distribute this payout.

Give corresponding game rupees and three minutes to distribute. Record discussion. _____________

Now you may have a break to discuss the season with your group members. If you wish to give any of your rupees to other participants, now is your opportunity to do so.

Give three-minute break. Record discussion.

a. Transfers given ______ to Player _____

b. Transfers given ______ to Player _____

c. Transfers taken _______ from Player ______

d. Transfers taken _______ from Player ______

Please return to your respective seats and count your final tokens for this round. You should have _______.

Is this correct? Yes No Please describe and rectify any discrepancies _________

Collect cash and tell farmer to write down their earnings.

Whether or not there is a next round depends on which ball is drawn from this bag containing 10 white balls and 5 violet balls. If a white ball is drawn, the game continues. If a violet ball is drawn, the game ends.

Player ___ please choose a ball from the bag without looking.

Player ___ selected a white ball so the game will continue for another round.

Phase 6: Follow up questions

You will now be asked some basic questions about your experience, your life, your savings practices, needs, your experience with risk and insurance in this interview.

The first few questions relate to the blue game (the take-up game) in which you were asked to value an insurance product.

1. In Round _ of the blue game, you gave a transfer to Player ___. When was this transfer arranged_?
    - i. Before purchasing insurance
    - ii. After the rainfall levels were revealed
  - b. What motivated this transfer? _________

2. In Round _ of the blue game, you took a transfer from Player ___. When was this transfer arranged_?
    - i. Before purchasing insurance
    - ii. After the rainfall levels were revealed
  - b. What motivated this transfer? _________

3. Were you ever concerned that group members would not purchase insurance and then ask you for a transfer?
  - a. Yes
    - i. If yes, would you have been willing to pay more for weather insurance if uninsured peers could not ask for transfer requests? Yes / No / I don't know
  - b. No

The next few questions relate to the red game (the investment game) in which you were asked to make investment choices.

4. Do you think the method your group used to distribute payouts was fair?
  - a. Yes
  - b. No
    - i. If no, how would you have done things differently?

5. In Round _ of the red game, you gave a transfer to Player ___. When was this transfer arranged_?
    - i. Before purchasing insurance
    - ii. After the rainfall levels were revealed
  - b. What motivated this transfer? _________

6. In Round __ of the red game, you took a transfer from Player ___. When was this transfer arranged_?

   i. Before purchasing insurance
   ii. After the rainfall levels were revealed

   b. What motivated this transfer? _________

7. The most common fertiliser you chose in this game was _________. Why did you prefer this product? ______________

   a. I was attracted by the average high returns
   b. I knew I could ask for transfers if I earned low income
   c. I followed the fertiliser choices of Player 1,2,3 None _____
   d. My group pressured me to choose this product

8. In Round 1, you selected the ______ fertiliser. Why? ___________________

9. In Round __, you changed your investment from ______ to _________. What prompted this change? ________________

10. Did your group ever pressure you to choose a particular fertiliser?

   a. Yes
      i. If yes, how? ____________
   b. No

11. The next question relates to the two games in general: If you were to take financial advice from someone in your group, which person would it be?

   a. Player 1
   b. Player 2
   c. Player 3
   d. I don't know

12. Did this player's choices in the games affect your own choices:

   a. In the blue game
      i. Yes
         1. If yes, how? _________
      ii. No
   b. In the red game
      i. Yes
         1. If yes, how? _________
      ii. No

Now we have some general questions for you.

13. What is your sex?
    a. Male
    b. Female

14. What is the main tenancy agreement?
    a. I own my land and cultivate it myself
    b. 50/50 sharecropping – I am the owner
    c. 50/50 sharecropping – I am the tiller
    d. 75% owner/25% tiller – I am the owner
    e. 75% owner/25% tiller – I am the tiller
    f. 75% tiller/ 25% owner – I am the owner
    g. 75% tiller/ 25% owner – I am the tiller
    h. I work for a salary
    i. I don't know
    j. Others=996

15. What crops did you grow in the Kharif season 2012?
    a. CROP 1 ______
    b. CROP 2 ______
    c. CROP 3 ______

16. What is your household plot size (in *bigha*)? ________________

17. Have you adopted any new technologies in the last three years? Select all that apply.
    a. Irrigation
    b. Fertiliser
    c. Different seeds
    d. Other ________________
    e. None

18. Did you use irrigation for any of your Kharif season crops in 2012?
    a. Yes
    b. No

19. Did you use fertiliser for any of the crops grown in the Kharif season 2012?
    a. Yes
    b. No

20. What is your religion?
    a. Hindu
    b. Muslim
    c. Jain
    d. Christian
    e. Other ________________

21. What is your caste/community group?
    a. SC
    b. ST
    c. OBC
    d. Other

22. What is your age? ________________

23. How many people are currently in your household? ________________

24. Were you born in this village?
    a. Yes
    b. No
        i. If no, from where did you migrate? Village, Taluka: ________________

25. What level of education have you completed?
    a. Illiterate
    b. Class 1 to 7
    c. Class 8 to 10
    d. Class 11 to 12
    e. Graduate
    f. Post graduate
    g. Other ________________

26. How do you get news updates? Select all that apply:
    a. Family
    b. TV Channel
    c. Radio
    d. Friends
    e. Neighbours
    f. News Paper/ Magazines
    g. Internet
    h. PRI Officers
    i. Mass updates via mobile text message
    j. Other ________________

27. Roughly how much income could you gain from drawing on savings and selling assets during an emergency that costs Rs 15,000 (e.g., health, accident, etc.)?

a. Rs 200-Rs 500
b. Rs 500-Rs 1,000
c. Rs 1,000-Rs 2,000
d. Rs 2,000-Rs 5,000
e. Rs 5,000-Rs 10,000
f. More than Rs 10,000
g. I don't know

28. Roughly how much money could you borrow (e.g., from banks, friends and/or informal moneylenders) if there was an emergency that costs Rs 15,000 (e.g., health, accident, etc.)?

a. Rs 200-Rs 500
b. Rs 500-Rs 1,000
c. Rs 1,000-Rs 2,000
d. Rs 2,000-Rs 5,000
e. Rs 5,000-Rs 10,000
f. More than Rs 10,000
g. I don't know

29. What are the biggest risks to your income? Please identify the top two:

a. Too much rain
b. Not enough rain
c. Timely availability of Inputs (Seed, Fertiliser, Pesticide)
d. Variation in quality of Inputs (Seed, Fertiliser, Pesticide)
e. Change in market prices from one year to another
f. Crop disease
g. Animal hazard
h. Change in seed, fertiliser or pesticide prices from one year to another
i. Other

30. Do you know anyone who has ever received a payout from any form of insurance (weather, crop, life, health, accident, etc.)?

a. Yes
b. No

31. Which of the following products do you most closely associate insurance with?

a. A savings product
b. An investment product
    i. If you selected investment product, do you think it is a good investment? ________

c. None of the above
d. I don’t know

32. What do you think of insurance providers in general? Select all that apply.

a. They provide a useful service
b. They are not trustworthy
c. Purchasing their products implies a fear and lack of faith in God
d. Their products are not useful to me – I am self-reliant and protect my family against risk in other ways
    i. If yes, please specify ________________ (e.g., family support)
e. I don’t know

33. In the past three years, have you faced a sudden shock to your consumption (e.g., crop failure, family illness)?

a. Yes
    i. What was it? __________________
    ii. When was it?
    iii. 1 month ago
    iv. 3 months ago
    v. 6 months ago
    vi. 1 year ago
    vii. 2 years ago
    viii. 3 year ago
    ix. What did you do to get by?
    x. Sold assets (e.g., gold, jewellery, animals)
    xi. Took a child out of school
    xii. Relied on savings
    xiii. Received help from relatives/neighbours
    xiv. Worked more
    xv. Took out large loans
    xvi. Received help from the government
    xvii. Other (specify) ________________
b. No

34. What is your experience with the following insurance products?

Product	Heard of	Offered	Bought	If not bought, why not?
Weather insurance in a loan Weather insurance a stand-alone product				
Crop insurance from government Crop insurance from private sector				

Phase 7: Payment

We are now going to play the black and white stone game. You chose the following gamble: ______

Give participant pouch with black and white stone.

You selected the ________ stone. This means you will be paid ___________ if the selected round for payment is the black and white stone game.

We are now going to randomly choose one of the rounds that you played in either the black and white game, the blue game or the red game to determine your payout. In this bag are tokens labelled for each round of each game. Please select a token to determine your payout.

You selected round ______ You will be paid ______ for your participation today.

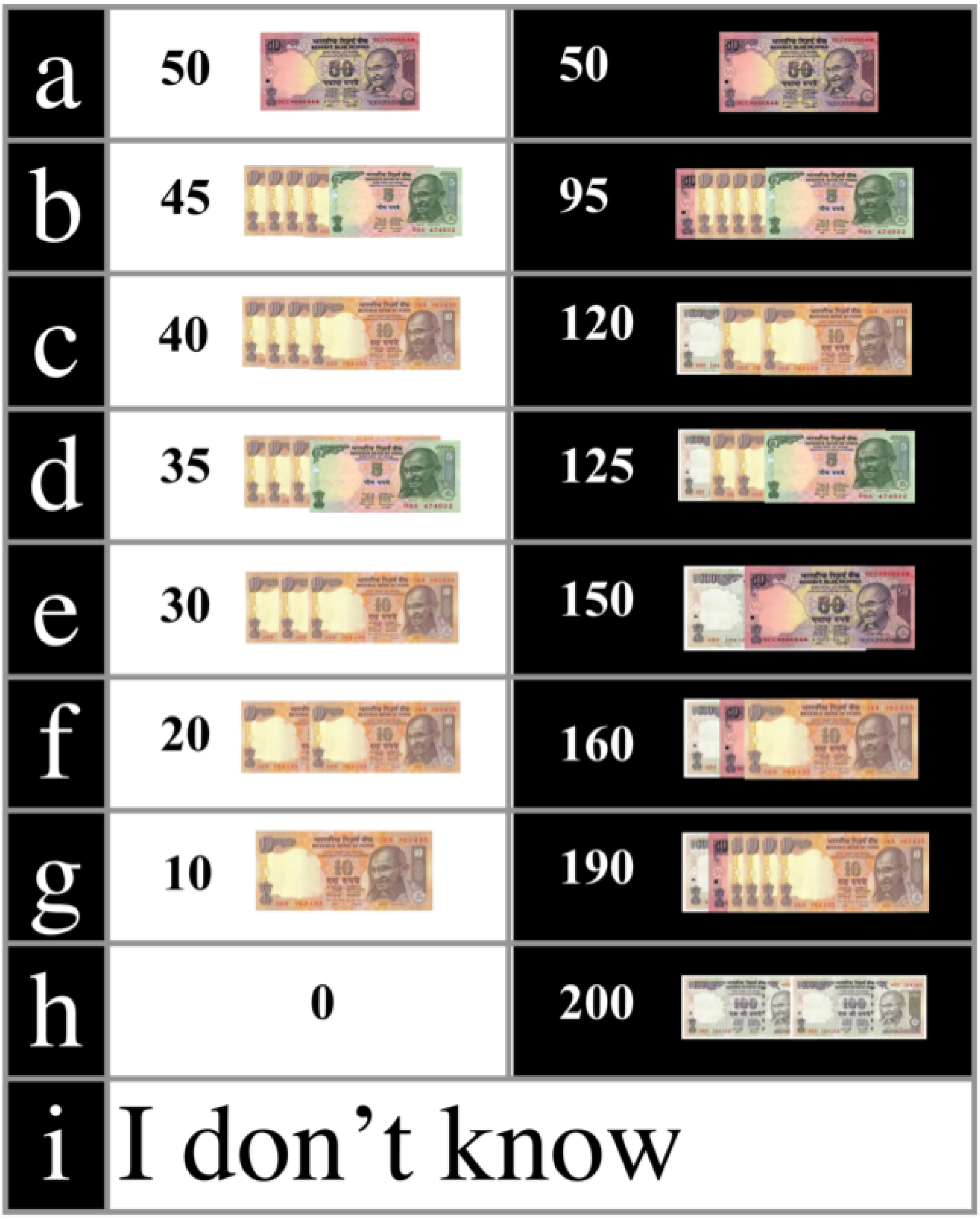
This is the end of the survey. Thanks for participating!

Question for the interviewer: What was the general level of understanding of the participant?

a. Participant understood everything perfectly
b. Participant mostly understood
c. Participant had some minor struggles
d. Participant had major struggles and did not really understand

Question for the interviewer: Any additional comments _______________

Appendix II- Binswanger lottery



Appendix III- Additional tables

Table A1.1 Fertiliser preferences (in %)

	(1) Low-risk fertiliser	(2) Average-risk fertiliser	(3) High-risk fertiliser	Mean investment choice
Individual Perfect (IP)	24.68	22.94	52.38	2.28
Group Perfect (GP)	30.96	25.89	43.15	2.12
Group Imperfect (GI)	25.52	18.83	55.65	2.30
All Farmers	26.84	22.34	50.82	2.24

Table A1.2 Risk aversion parameters

Approximate Coefficient of Partial Risk Aversion (CPRA)							
	Payoffs						
Gamble	White (high)	Black (low)	Risk level	Upper bound	Lower bound	Coefficient used for regressions	% of respondents
a	50	50	Extreme	∞	7.51	8	5.31
b	45	95	Severe	7.51	1.74	4.625	6.25
c	40	120	Intermediate	1.74	0.812	1.276	14.69
d	35	125	Inefficient			0.920	11.25
e	30	150	Moderate	0.812	0.316	0.564	23.75
f	20	160	Inefficient			0.361	11.88
g	10	190	Slight to neutral	0.316	0	0.158	17.19
h	0	200	Neutral to Negative	0 to -∞		0	9.38
I don't know	0	0				Observation dropped	0.31

Note: Draws on Binswanger (1980) and Stein & Tobacman (2011)

Table A1.3 Percentage of groups that all select the same investment

	Round 1	Round 2	All Rounds
Individual Perfect (IP)	30.93	45.76	37.66
Group Perfect (GP)	30.19	51.79	39.59
Group Imperfect (GI)	18.10	25.00	23.85
Total	26.02	39.57	33.28

Table A1.4 Dispersion within the group

	Individual Perfect (IP)	Group Perfect (GP)	Group Imperfect (GI)	Total
Average std. dev. of investment choices within group	0.61	0.47	0.67	0.59
	(0.51)	(0.44)	(0.44)	(0.47)
Average std. dev. of risk preferences within group	1.36	1.15	1.31	1.27
	(1.46)	(1.39)	(1.56)	(1.48)
Average std. dev. of earnings within group	3,596.98	4,543.26	3,924.11	3,994.24
	(3,131.55)	(4,781.22)	(4,460.78)	(4,172.00)

Table A1.5 Transfers given

	Average transfer (in Rs)	% insured
Individual Perfect (IP)	900.4	7.5%
	(2,453.07)	(4.79)
Group Perfect (GP)	1,523.4	8.0%
	(3,498.20)	(0.22)
Group Imperfect (GI)	913.3	4.7%
	(3,359.48)	(0.16)
Total	1,088.4	6.6%
	(3,132.26)	(0.19)

Table A1.6 Impact of group insurance and information access on investment choice: logit and LPM

Treatment effects relative to base category: Individual Perfect (IP)

Dependent variable:	Investment Dummy (0-1)[5]		Investment Choice (1-2-3)[6]	
	(1) Logit	(2) Logit	(3) OLS	(4) OLS
Group Perfect (GP)	-0.65*	-0.49	-0.22**	-0.18
	(0.33)	(0.32)	(0.11)	(0.11)
Group Imperfect (GI)	-0.04	0.36	-0.07	0.07
	(0.31)	(0.36)	(0.09)	(0.10)
GP*Risk Aversion		-0.15		-0.03
		(0.15)		(0.03)
GI*Risk Aversion		-0.37**		-0.12***
		(0.15)		(0.03)
Risk Aversion	0.01	0.20*	0.00	0.06***
	(0.05)	(0.12)	(0.02)	(0.02)
Constant	2.43	1.38	1.50*	1.78**
	(3.25)	(3.15)	(0.76)	(0.75)
Observations	667	667	667	667
R-squared			0.279	0.291
Wald	147.5	170.4	.	.
Pseudo R-squared	0.243	0.252	.	.
P-value of test GP = GI[4]	0.048	0.037	0.166	0.128

Note 1: Other controls are education, caste, age, gender, assets, landowner status, exposure to a shock in the last three years, playing the investment or take-up game first, round number, preference for high returns, influence from group members, receiving news from TV, receiving news from the newspaper, same caste and choosing an inefficient risk aversion lottery (omitted from table).
Note 2: Robust standard errors clustered at the group level in ( ).
Note 3: *** p<0.01, ** p<0.05, * p<0.1
Note 4: Interaction terms are included in relevant specifications
Note 5: Dependent variable = 0 if the farmer adopts low-risk or average-risk fertiliser and 1 if the farmer adopts high-risk fertiliser.
Note 6: Dependent variable = 1 if the farmer adopts low-risk fertiliser, 2 if the farmer adopts average-risk fertiliser and 3 if the farmer adopts high-risk fertiliser.

Table A2.1 Dependent variable: WTP (in Rs)

	Mean									Median
Round	1	2	3	4	5	6	7	8	All Rounds	All Rounds
No Transfer (NT)	2,057	2,290	2,198	2,124	2,764	2,400	2,000	3,133	2,181	2,100
Transfer (T)	1,798	2,233	2,072	2,500	2,950	3,450	no obs.	no obs.	2,008	2,200
All Farmers	1,930	2,265	2,142	2,254	2,829	2,820	2,000	3,133	2,102	2,200

Table A2.2 Risk aversion parameters

Approximate Coefficient of Partial Risk Aversion (CPRA)							
	Payoffs					Coefficient	
Gamble	White (high)	Black (low)	Risk level	Upper bound	Lower bound	used for regressions	% of respondents
a	50	50	Extreme	∞	7.51	8	5.82
b	45	95	Severe	7.51	1.74	4.625	5.48
c	40	120	Intermediate	1.74	0.812	1.276	12.33
d	35	125	Inefficient			0.920	11.30
e	30	150	Moderate	0.812	0.316	0.564	22.60
f	20	160	Inefficient			0.361	13.01
g	10	190	Slight to neutral	0.316	0	0.158	20.55
h	0	200	Neutral to Negative	0 to -∞		0	8.22
I don't know	0	0			Observations dropped		0.68

Note: Draws on Binswanger (1980) and Stein & Tobacman (2011)

Table A2.3 OLS regressions excluding risk aversion categories D & F

Dependent variable:	WTP			Dichotomous variable = 1 if WTP>0		
	(1)	(2)	(3)	(4)	(5)	(6)
Transfer (T)	-140.64	-144.49	-722.32**	-0.15***	-0.16***	-0.27***
	(189.39)	(162.75)	(289.95)	(0.04)	(0.04)	(0.08)
T*Risk Aversion			55.15			0.02*
			(46.52)			(0.01)
T*Plot size			96.08**			0.02*
			(47.53)			(0.01)
Risk Aversion		38.73*	10.37		0.01**	0.00
		(21.52)	(31.52)		(0.00)	(0.00)
Plot size		2.03	-43.49		0.00	0.00
		(24.72)	(27.25)		(0.01)	(0.01)
Constant	2,158.40***	2,943.90***	3,204.43***	0.99***	1.09***	1.13***
	(117.76)	(598.01)	(614.50)	(0.01)	(0.19)	(0.20)
Observations	435	435	435	435	435	435
Controls	NO	YES	YES	NO	YES	YES
R-squared	0.00	0.09	0.11	0.08	0.11	0.13

Note 1: The other controls are gender, same caste, round number, education, religion, and playing the investment game/take-up game first (omitted from the table).
Note 2: Robust standard errors clustered at the group level in ( ).
Note 3: *** p<0.01, ** p<0.05, * p<0.1

Table A2.4 Dispersion within the group

	No Transfer (NT)	Transfer (T)	All Farmers
Average standard deviation of WTP within group	544.46	796.06	658.95
	(469.11)	(604.43)	(548.97)
Average standard deviation of WTP>0 within group	0.03	0.16	0.09
	(0.12)	(0.26)	(0.21)
Average standard deviation of risk preferences within group	1.24	1.43	1.33
	(1.53)	(1.60)	(1.56)
Average standard deviation of earnings within group	2,751.68	5,284.79	3,904.31
	(1,344.60)	(5,101.17)	(3,793.87)

Table A2.5 Occurrence of drought by round (in %)

Round	1	2	3	4	5	6	7	8	All Rounds
No Transfer (NT)	18.2	18.1	19.5	29.4	45.5	0.0	0.0	0.0	19.4
Transfer (T)	26.8	29.9	9.4	11.1	50.0	0.0	no obs.	no obs.	25.2
All Farmers	22.4	23.3	15.1	23.1	47.1	0.0	0.0	0.0	22.1