Credit, weather shocks, and migration: evidence from a field experiment in India

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Abstract In developing countries, most poor households experience strongly volatile income streams because of a large exposure to climatic, economic and policy shocks, combined with a lack of appropriate insurance devices. Using a field experiment, I investigate whether Self-Help Groups (SHG) can help households to cope with rainfall shocks in villages of East India over a seven year period. I show that SHGs withstand remarkably large rainfall shocks, and that credit flows are far more stable in treated villages. In line with a simple model of occupational choice with costly migration, I find that households in treated villages increase seasonal migration in response to a drought, especially when owning little land. As a result, they experience a higher food security over the year. These results imply that informal financial institutions like SHGs help finance temporary risk management strategies, in order to cope with important covariate income shocks such as droughts.

Keywords: Microfinance, weather shocks, income smoothing, migration, food security.

JEL Classification Numbers: O13, O15, G21, Q54

1 Introduction

It is well-documented that poor households living in rural areas of developing countries often experience extremely volatile income due to their large exposure to economic and climatic shocks, combined with a lack of appropriate insurance devices. For instance, the 2017 Global Findex found that about half of households that rely on agriculture as their main source of income reported experiencing a bad harvest or significant loss of livestock in the previous five years. The majority of these households bore the entirety of the loss on their own, with only a minority receiving any kind of compensation (Demirgüç-Kunt et al., 2018).

While risk and volatility exist everywhere, they are especially problematic for poor populations in developing countries because of a variety of factors. First, risk is costlier for households close to subsistence, because a small negative shock can tip them into malnutrition and underdevelopment traps.[1] Second, poor households are disproportionately likely to lack the necessary human, physical, and financial capital to recover from shocks. In particular, they often have no or little access to formal financial services (credit, savings, insurance) that could be relied on to cope with shocks ex-post or develop mitigating strategies ex-ante. Third, developing countries and rain-fed agriculture are disproportionately vulnerable to global climate change (Yohe et al., 2006; World Bank, 2010; IPCC, 2014; FAO, 2016). Moreover, weather-related income shocks, because of their covariate nature, are

[1]For instance, even short episodes of child under-nutrition can cause long-lasting damages in health and human capital, not affording school expenses for a prolonged period can lead to school drop-out, and delaying the treatment of illnesses can increase the morbidity and future health costs. Several studies have showed that uninsured income shocks can lead to adverse human development outcomes such as health and education (Jacoby and Skoufias, 1997; Jensen, 2000; Alderman et al., 2006; Maccini and Yang, 2009; Groppo and Kraehnert, 2016) and long-run poverty (Dercon, 2004; Dercon et al., 2005; Premand and Vakis, 2010).

difficult to deal with through informal insurance arrangements among local communities. As a result, the World Bank estimates that 26 million people are falling into poverty each year because of natural disasters (Hallegatte et al., 2017). Moreover, an even larger number of small-holder farmers are caught in poverty traps, as they seek to minimize potential losses by engaging in low-yield, low-variability agriculture practices, with little investment in farm inputs.

The rapid development of microfinance in many parts of the world could thus be expected to have helped otherwise-constrained poor users to manage weather-related income shocks. Despite the importance of the question, we know surprisingly little about such 'insurance aspect' of microcredit, partly because it has usually been conceived mostly as a means to start a business or to afford big lump-sum expenses. In fact, it is often argued that income risk is a major factor of default on microloans, which has triggered the rapid development of microinsurance products in recent years. However, evidence about demand and impact of such products has been disappointing (see Cole et al., 2013; Karlan et al., 2014; Platteau et al., 2017), and the 'microinsurance promise' has been losing impetus even among policy circles.[2]

This paper studies whether local savings and credit associations, in the form of Self-Help Groups (SHGs), can help households to cope with large covariate income shocks such as droughts in villages of East India. SHGs are informal groups of villagers (often women) with homogeneous background, who voluntarily come together to save small amounts on a regular basis and take loans for which they are

[2]For instance, the Global Index Insurance Facility, a major multi-donor trust fund launched in 2009 to support index-insurance schemes implemented by IFC and the World Bank, has been constantly reducing the number of projects being financed over time, from 7 in 2011 to 4 in 2013 and 2014, 1 in 2015, 2 in 2016, and 0 in 2017.

jointly liable. They represent the dominant microfinance model in India, and one of the world's largest and most sustainable (more details about SHGs are given in section 2).[3] By offering relatively cheap and flexible credit, and combining internal accumulating savings with group credit from commercial banks, SHGs present interesting characteristics to help members to absorb adverse income shocks, even when those are largely covariate. Indian agriculture employs a very large, though declining, fraction of the country's active population (from 60% in 2000 to 43% in 2017 according to ILO statistics). It is also extremely dependent on erratic monsoon rainfall, especially given the low irrigation coverage and the effects of climate change (Gadgil and Gadgil, 2006; World Bank, 2006; Asada and Matsumoto, 2009; Prasanna, 2014). As a consequence, rainfall shocks have been documented to significantly affect agricultural profits, wages and ultimately the welfare of rural households in India (e.g. Rosenzweig and Binswanger, 1993; Cruz et al., 2007; Cole et al., 2013).

I exploit a field experiment that randomized access to SHGs in villages spread over the entire state of Jharkhand and surveyed a sample of households three times between 2004 and 2009 to evaluate changes in living standards. There are three main findings. First, I show that SHGs remain a strong source of credit in presence of rain shocks. While credit access virtually dries up in control villages one year after a bad monsoon, during the crucial bridge period preceding the new harvest, households in treated villages enjoy a steady access to credit, and are even able to borrow counter-cyclically. This is made possible thanks to the large

[3]Today, there are about 8.7 million bank-linked SHGs in India (NABARD, 2018). This represents a remarkable achievement, especially given the general acknowledgment that standard microfinance products remain more suited to urban and periurban areas than the to the rural world.

pool of savings of SHGs, which collect weekly savings from their members, and to their linkage with formal banks from which they can jointly borrow. Such credit is not useful to stabilize agricultural production, and treated and control villages are equally vulnerable to rainfall shocks. I find that average rice yields decrease by about 30 percentage points following a monsoon that is one standard deviation below the historical average rainfall level in the district. By contrast, I find that this better access to credit enables member households to use seasonal migration to avoid or mitigate future income shocks. Consistent with a simple theoretical model of occupational choice between agriculture and costly migration, I show that the effect is driven by the reaction of the poorest farmers, who are about 7 percentage points more likely to migrate when the monsoon is one standard deviation below average. Finally, I show that SHG households enjoy a greater food security over the year than other households. On average, they go hungry about 11% less often during the year following a one standard-deviation monsoon shock.

To my knowledge, this is the first paper to provide direct causal evidence about how microcredit enables households to react to large, precisely-measured, and exogenous climatic shocks. In particular, it shows that even small-scale, local and poor-oriented credit institutions such as SHGs can contribute to the mitigation of covariate shocks, despite the fact that they are not a priori designed as an insurance scheme. Moreover, this is one of the few papers investigating the impact of microfinance on seasonal migration.

There are, however, many related papers. First, there is a vast literature on risk coping and management in developing countries. Informal risk-sharing arrangements with neighbors, friends, or family have often been shown to be largely imperfect in smoothing income shocks, especially when coming from weather events

(Dercon and Krishnan, 2000; Fafchamps and Lund, 2003; Kazianga and Udry, 2006; Maccini and Yang, 2009; Groppo and Kraehnert, 2016; Tiwari et al., 2017). Second, some papers studying the impact of microcredit provide indirect evidence about the reaction to income shocks. In their randomized evaluation of a high-rate, high-risk consumption loan market in three urban areas of South Africa, Karlan and Zinman (2010) find that treated households were significantly less likely to experience hunger and more likely to retain their job during a very short period (6-12 months) after the intervention. Beaman et al. (2014) report on another field experiment on savings and credit groups in Mali that are not too different in their basic functioning from Indian SHGs, with the two big exceptions that groups are never linked to commercial banks and that the pool of money is shared out completely at the end of each yearly cycle, which considerably limits the scope for insurance. They find that households in intervention villages better smooth food consumption over the year, coming mostly from an increase in their livestock holdings. Beegle et al. (2006) use observational panel data from Tanzania and show that households respond to transitory income shocks - a dummy for positive self-reported crop loss due to animals and other calamities - by increasing child labor as a buffer, but that this effect is lower when households are richer and have access to credit. Through an instrumental variable approach, Kaboski and Townsend (2005) show that microfinance institutions providing increasing savings services and emergency consumption loans in Thailand significantly reduce the likelihood that a household declares to have reduced consumption in what it says was a low-income year. Using a household-level panel dataset from Bangladesh, Islam and Maitra (2012) find that self-declared health shocks are fairly well insured and do not have any significant effect on household consumption, mostly because households use livestock as buffer.[4] Yet, households having access to microcredit are less likely to sell productive assets in response to health shocks. Third, a few recent papers have studied the link between microfinance and seasonal migration. In a field experiment in rural Bangladesh, Bryan et al. (2014) find that a one-time cash or credit subsidy to cover the cost of migration for work during the lean agricultural season increases seasonal migration among rural households, leading to improvements in household consumption and food security. By contrast, Khandker et al. (2010), using cross-sectional survey data, show that the probability of seasonal migration and microfinance membership are negatively correlated.

The remaining of the paper is as follows. I start with some background information in section 2. Sections 3 and 4 describe the data the empirical strategy. I then present the results, starting with agriculture in section 5, followed by credit in section 6, and then migration and consumption in section 7.

2 The SHG program and the context

2.1 The context

In 2002, an NGO called PRADAN launched a large microfinance program in several states of East India, based on the creation of women-only SHGs. This evaluation focuses on the state of Jharkhand, which is one of the poorest Indian states. Rural poverty rate was estimated to be as high as 41% in 2012 by the Planning Commission, and the female literacy rate as low as 55%, ten percentage points below the national average, according to the 2011 Indian census. The state

[4] It is worth noting that health shocks being idiosyncratic, they tend to be relatively better insured through informal means (Townsend, 1994; Kochar, 1995).

is mostly rural (76% of its 33 millions inhabitants) and its population consists of about 26% tribals and 12% scheduled castes, which are known to be the most vulnerable groups of the Indian society. Villages are very isolated on average, and their inhabitants live mostly out of subsistence agriculture and seasonal labor work. Rain-fed paddy is by far the predominant crop in the state, followed by pulses, maize, wheat and oilseeds. Average paddy yields are around 1,800 kg per hectare, 75% of the national average (2016 data from the Directorate of Economics and Statistics). The agriculture in the state suffers from erratic rainfall, coupled with low irrigation coverage (5.3% of agricultural area in 2014). Those characteristics imply that the food security needs of households can be met through own cultivation for at most six months of the year (Kabeer and Noponen, 2005). As a result, migration to urban centers and to nearby states in search of seasonal employment is widespread. Other sources of supplementary income are livestock and non-timber forest produce, especially in forest areas. In its 2008 India State Hunger Index, the International Food Policy Research Institute estimated that Jharkhand was suffering from the second highest level of hunger and malnutrition prevalence in India (Menon et al., 2008).

PRADAN established a list of potential intervention villages (based on their high poverty incidence), located in four geographic clusters covering the entire state of Jharkhand.[5] Among that list, 24 villages were randomly selected to launch PRADAN's SHG program between April and June 2002, and 12 other villages from the same districts were kept as the control group. In treated villages, the

[5]Within geographical clusters around the local offices, PRADAN chooses to work with relatively disadvantaged communities and poor villages, where no other NGO has worked before. A study by CGAP (2007) found that PRADAN had deeper-than-average outreach: almost all SHG members are tribal people or members of scheduled castes, 85% have no homestead land or only marginal nonagricultural land and almost 90% live in thatched huts or are squatters.

program was explained in public village meetings, and groups of between 10 and 20 interested women were formed (one important rule imposed by PRADAN is that there may be only one member per household).

2.2 How do SHGs work and what role can they play in presence of weather shocks?

After some initial training and capacity building from the NGO, each group chooses a name and distributes the roles of president, secretary, cashier, and accountant.[6] It then sets rules such as weekly meeting times, minimum contributions per member at each meeting (usually 5 or 10 INR, i.e. 0.5-1 USD per month), the interest rate charged on loans that are given to group members[7], and fines for non-attendance or late payment.

After several months of smooth functioning, a savings account is opened at a commercial bank near the village to deposit group savings, and, usually after about two years, groups showing mature financial behavior are enabled to access bank loans (the group is then said to be *linked*). At that point, groups are autonomous and the intervention of the NGO is only required to solve occasional problems (though PRADAN keeps track of the financial records of all SHGs through regular reports by accountants). Bank loans are always made to the group as a whole, without collateral and at subsidized interest rates (fluctuating around 12% per annum).

[6] The roles of president, secretary, cashier usually rotate, the role of accountant can be external.

[7] In practice, I observe virtually no deviation from the interest rate of 2% monthly, which is suggested by the NGO. However, interest rates might be higher for very large amounts because they require extra group borrowing from the bank.

At a typical meeting, each member deposits the agreed minimum weekly savings or more, pays the interest on the loan she has taken (if any) and possibly pays back part of the principal. Interests earned on internal loans remain within the group and become part of its pool of funds. Members who do not have a loan yet can require one to the group. Loans are individual but they have to be agreed on by the group and repayment is public. There is a strong peer pressure ensuring due repayment, in order to preserve the group's resources. Yet, there is generally a lot of flexibility and understanding within the group when a member is not able to pay the weekly installment and asks, for example, to pay double next time or when her cash flows become more favorable.[8] The savings and interest revenues of the group help to cushion irregular cash flows and adjust to urgent and unexpected situations, while keeping with the repayment of bank loans. If a member fails to repay or to come to meetings for a prolonged period, group representatives will visit her house in order to get her back paying. In (rare) cases of actual default, the group first withdraws on the defaulting member's group savings and, if this is not enough, eventually pays for her out of the group's pool of funds.

In short, the bank-linked SHG model can provide access to savings and credit services in remote rural areas (as well as other potential benefits from the group structure, such as peer support and other social services), in a relatively cheap and sustainable way.[9]

[8] A study by CGAP (2007) found that the average Portfolio at Risk > 90 days of PRADAN SHGs was over 20%. They explain that, "although this level of loan delinquency would be disastrous for most microcredit providers, SHGs are surviving despite this. This has to do with the fact that a significant part of the SHG loans are used for crop cultivation and livestock rearing, neither of which offer a monthly cash flow. Yet, loan installments remain fixed at monthly [or even weekly] intervals, [...] sometimes out of a desire to keep a discipline of 'repaying something in each meeting'. Thus the high level of late repayments in SHGs does not always translate into defaults." As a matter of fact, we observe extremely few outright defaults in our data.

[9] CGAP (2007) estimated that the average cost of promoting and supporting SHGs in India is

In particular, SHGs can allow members to borrow in response to negative income shocks, in order to absorb (part of) the losses and maintain their production and consumption in the following period (or at least recover more quickly). Several features of SHGs are important in this respect. First, SHGs are meeting weekly (or even more often if needed) and there is no fixed order in loan taking (unlike ROSCAs for instance). That is, members can ask any amount at any time - with the important restrictions that (i) the group needs to agree and (ii) the money needs to be available. Second, as already explained, repayment is somewhat flexible. Third, SHGs lend out of a pool of accumulated savings and external bank loans. As a consequence, several members can take loans together and SHGs are potentially able to insure at least partially against all sorts of income shocks, including covariate weather shocks.[10] Another possibility is that SHGs allow better ex-ante risk management, such as seasonal migration in anticipation of negative shocks, because they help finance the (direct or indirect) costs of such strategies. Finally, SHGs certainly go beyond mere credit and savings activities. They constitute strong groups of peers meeting regularly, which gives individuals good information on what others are doing as well as a strong reason to stay together. As a consequence, SHGs can potentially support informal risk sharing among members.

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around 18 USD per group member (20 USD for PRADAN groups), and that the average return on assets (ROA) after adjusting for loan loss provisions is around 9% (16% for PRADAN groups). Deducting the costs supported by the promoting NGO, SHGs break even on average. The study concludes that "The Indian SHG model can work sustainably in well-managed programs. Compared to other microfinance approaches, the SHG model seems to be producing more rapid outreach and lower cost." A similar conclusion is reached by Dave and Seibel (2002), who compute ROAs ranging from 1.4 to 7.5% for a sample of SHGs in Andra Pradesh and Karnataka. Several studies confirm the longevity of SHGs, such as Gaiha and Nandhi (2008) and Baland et al. (2018).

[10]Note that even large rainfall shocks are certainly not fully covariate, since there exists important heterogeneity among members regarding land ownership (from no land to relatively big plots), main occupation, assets, family structure, etc.

3 Data

3.1 Households' living standards

The data come from a field experiment aiming at measuring the impact of PRADAN's intervention. In each SHG village, we randomly selected 18 SHG member households from PRADAN's members listing, as well as 18 nonmembers. In the control villages, we randomly selected 18 households.[11] The full sample therefore consists in 1080 households, which were interviewed three times, in 2004, 2006, and 2009.

The questionnaire records detailed information about household demographics, recurrent and durable expenditures, consumption, asset ownership, credit and savings, labor market participation and self-employment, migration, food vulnerability, land ownership and agriculture, health, education, benefits from governmental programs, some measures of female empowerment and participation in village activities. All surveys were carried during the same period of the year, namely January-March, which corresponds to the pre-harvest period of the winter season. Appendix A provides the full list of villages that were surveyed, as well as basic descriptive statistics at the district and village levels. We observe no statistically-significant difference between treated and control villages (and very similar point estimates), which validates the randomization of villages. Because of member self-selection, differences between SHG and other households are more pronounced (see Table 17). On average, SHG members come more often from scheduled castes, are less likely to be landless, and are younger households with more young children, compared to other households in the same village. Yet, when pooled together,

[11] Nonmember and control households were selected using a using a random-walk procedure.

member and nonmember households in treated villages are not very different from control households (except for landlessness). All regressions will systematically control for those household characteristics and correct for sampling probabilities.

The overall attrition rate across rounds is relatively small, at 6.7%.[12] The vast majority (77.2%) of the households have been interviewed in all survey rounds and 11.9% have been interviewed in two rounds. More important are the changes in membership status that occurred between the surveys. These changes occur essentially due to the creation of new groups or the disappearance of some groups. Table **??** reports the percentage of members exiting and entering SHGs over time. New entries essentially arise from the creation of new groups after 2004.[13] Overall, the average rate of change in member status across rounds is 13%.

[Table **??** *here.]*

3.2 Rainfall

Statistically, the state of Jharkhand, with an average annual rainfall above 1,000 mm, is not considered as suffering from chronic drought. Nevertheless, it is characterized by high concentration and volatility of rainfall: more than 80% of the rainfall comes during the Southwest monsoon between June and September, and some years can be extremely wet while others can be extremely dry. Global

[12]One of the reasons for this attrition is the Naxalite rebellion in the region, which prohibited us from visiting a member village for security reasons in round 3 (Kera). We replaced this village by another randomly chosen SHG village from the same district. Excluding Kera, the average attrition rate is only 5%. We will use the entire sample in our econometric estimate, but the results are fully robust to the exclusion of this particular village.

[13]Entering an existing group is relatively hard due to the size limit of the groups and the requirement that newcomers must contribute to the group an amount equal to the accumulated savings per member at that time.

warming, in particular, is making monsoon rains increasingly erratic (Singh et al., 2014; Loo et al., 2015).

I use rainfall data from the Global Precipitation Archive (Matsuura and Willmott, 2012), which provides monthly precipitation at 0.5 degree spatial resolution ($\sim$ 50 km, corresponding roughly to the average district size). I retrieve data from 1980 to 2008 for the nine districts of the sample. I construct a measure of standardized precipitation deficit for each district-year, by taking the annual rainfall deviation from the long-term district average and dividing by the long-term district standard deviation:

$$RD_{dy} = \frac{Rain\_avg_d - Rain_{dy}}{\sigma(Rain)_d} \tag{1}$$

where d and y stand for district and year, respectively. Because this paper focuses on income *shocks*, I replace RD=0 if RD<0 (higher-than-average rainfall). This measure has the advantage of being continuous and easy to interpret: a positive value means a worse monsoon than the norm in each district. Moreover, the slope estimates correspond to a one standard deviation change in rainfall.[14] Mean district rainfall and standard deviation are calculated over a rolling window of the ten years immediately preceding the current year, i.e. 1998-2007 for the year 2008, 1997-2006 for the year 2007 and so on, which represent the relevant rainfall history.

Figure 1 shows substantial variation in the sample, both across districts and over time. Roughly speaking, 2000 and especially 2005 were bad monsoon years (the latter being ex-post officially recognized as a drought year for the whole

[14] One standard deviation of the sample distribution of monsoon rainfall corresponds to about 25 cm on average (one fourth the average monsoon rainfall). The maximum standardized rainfall deviations observed over the sample period are -3.2 on the negative side and 2.6 on the positive side, see figure 1.

state), while 2006 and especially 2007 received very generous rainfall. During the other years of the survey period, average precipitations were closer to average, though with important inter-district variation. Indeed, thanks to the stratification strategy, the sample includes villages in all agro-climatic zones composing the state of Jharkhand.[15]

Figure 1: District-level standardized deficit of monsoon rainfall during survey period

[15]The South Eastern Plateau receives relatively more rain and has the highest cropping intensity, the Central and North Eastern Plateau is the biggest zone and presents a lower intensity, and the Western Plateau is the hilliest region, with an average agricultural profile roughly comparable the the previous region. Rice (predominantly) and maize are cultivated in all three regions, pulses especially in the Central and North Eastern Plateau as well as the Western Plateau, and wheat especially in the Central and North Eastern Plateau.

4 Empirical strategy

Although average rainfall is predictably different from place to place, the deviation of each year's rainfall from its local mean is serially uncorrelated and largely unpredictable at the start of the season.[16] Thus, rainfall shocks are exogenous and unanticipated, spread over space, and their incidence is balanced between SHG members and comparison households thanks to the design of the survey. I can therefore examine the treatment effect of microcredit on shock responses, which is conditional on a shock having occurred. In order to control for self-selection into membership, I include household fixed effects in all estimations.

Our approach is to estimate the effect of SHGs on the village population, irrespective of households' membership (intention-to-treat estimates, or ITT), following a simple difference-in-difference strategy. We do this by comparing the average evolution of the households living in SHG villages to that in the control villages in which no SHGs were created in 2002. Using data from the three survey rounds (2004, 2006 and 2009), we adopt the following baseline specification:

The coefficient β is the main coefficients of interest and measures the difference between households in treated and control villages in times of rainfall deficit (controlling for normal times differences). This coefficient therefore measures the average effect of having access to SHGs at the village level, taking into account that part of the population does not directly participate in the intervention (70%

[16] As Morduch (1995) points out, if an income shock can be predicted beforehand, then households might side-step the problem by engaging in costly ex ante smoothing strategies (e.g. diversifying crops, plots and activities). The data in such a situation would (incorrectly) reveal that income shocks do not matter. However, rainfall in Jharkhand is relatively important on average but is erratic. Hence it is the delay in the onset of the monsoon and the distribution of rainfall that mainly matter. Moreover, rainfall does not appear to be serially correlated (using a Q test, I was unable to reject the hypothesis that rainfall follows a white-noise process over the period 1980-2010 for all districts).

on average). This ITT approach has the advantage of avoiding any selection bias, and to factor in potential spillovers from member to nonmember households within villages.[17]

My baseline specification takes the form of the following difference-in-difference equation:

$$Y_{idy} = \alpha + \rho RD_{dy} + \beta(RD_{dy} \text{ x } SHG_i) + \gamma H_{iy} + \lambda_y + \eta_i + \epsilon_{idy}, \tag{2}$$

where Y_{idy} is the outcome of interest (farm productivity, credit, consumption etc.) of household i in district d and year y. RD_{dy} is a measure of rainfall deficit in district d and year y (see previous section for its precise definition). I focus on the rain between June and September, which corresponds to the monsoon period and concentrates more than 80% of yearly rainfall on average. It is also the period that is crucial for agriculture, residual rains being scattered over the rest of the year. Although the standardization implies that the range of the previous shock variable is limited, I also check for nonlinearities in the effect of rainfall by including its squared value in the regression equations. Indeed, for some outcomes, only extreme shocks could matter. SHG_i is a dummy variable taking value one if household i is member of an SHG at the start of the program (given that this measure is time-invariant, the base level is absorbed by the household fixed effect). Finally, H_{iy} is the household size in equivalent adults[18], λ_y are year fixed

[17]Because of self-selection into SHGs, member and nonmember households will tend to represent different sub-samples of the village population, thus confounding the estimated effect of the treatment on the treated. Moreover, I do not compute the LATE estimator for direct participation given the likely crowding-in or -out effects on the non-participants in treated villages.

[18]I use the equivalence scale proposed by Townsend (1994), who computes male-adult equivalent consumption according to the following age-sex weights (estimated from a dietary survey in rural Andhra Pradesh and Maharastra): for adult males, 1.0; for adult females, 0.9; for males and females aged 13-18, 0.94 and 0.83, respectively; for children aged 7-12, 0.67 regardless of

effects that account for economy-wide shocks and η_i are household fixed effects that accounts for households' fixed characteristics and average behavior (thus controlling for the self-selection into SHGs as well as fixed village and district features). Throughout, standard errors are clustered at the household level (i.e. the treatment level) in order to account for the correlation of standard errors and potential heteroskedasticity.

With the variable SHG referring to the original membership, the β coefficient delivers a conservative lower bound for the ATT given imperfect compliance with the assignment to treatment (see section 3.1). Obviously, it is only if a household participates to an SHG at the date of the shock that it can potentially derive any direct shock-mitigating effect from membership. Yet, using the contemporaneous definition would be problematic because, in presence of household fixed effects, all the identification of the coefficient attached to the SHG variable would come from households who changed membership over time. Though actual movements into and out of SHGs are limited (such that (non)members in 2004 are still much more likely to be (non)members in 2009 than other households, see section 3.1), those could be endogenous and lead to a biased estimation of both the base and the interaction effects. The original membership definition allows to wipe out all unobserved characteristics that affected the initial selection into SHGs, and focus on the interaction term. The only remaining potential source of endogeneity would have to come from characteristics that affect behavior only in periods of shocks and that would therefore not be fully accounted for by controlling for households' average behavior through fixed effects. For instance, SHG members could be

gender; for children 4-6, 0.52; for toddlers 1-3, 0.32; and for infants 0.05. Hence this measure reacts very slowly to fertility decisions, but could change quickly over time through migration.

systematically more risk-averse, which could lead them to protect more against shocks. This is unlikely to be a strong concern for at least three reasons. First, risk-aversion is very likely to affect mean outcomes (e.g. if households adopt ex-ante risk mitigation mechanisms), which means that fixed effects should account at least partly for it. Second, there is no evidence that SHG members are more risk-averse at baseline based on the 2002 pre-treatment data. For instance, controlling for wealth, they are as likely to be entrepreneurs as other households and do not take significantly smaller loans from moneylenders controlling for total credit. Third, the SHG program was launched after two years of relatively generous rainfall (1999 and 2000), which limits the likelihood that the SHG members' original decision to participate in the program was linked to the experience of bad rain shocks. All the more so that they have exactly the same probability of being farmers (34%) than other households from the same village before joining SHGs. Nevertheless, in appendix, I check the robustness of the main results through an instrumental-variable strategy.

5 Agriculture

Most of the households surveyed are small landholders (owing about 2 acres on average), who by and large practice a subsistence agriculture with limited marketable surplus. Rice, in particular, often represents the main source of food and income. In our sample, it represents 80% of households' total agricultural production on average (50% of agricultural income) and is cultivated by virtually all (95%) agricultural households (76% of all households). By contrast, the second crop most frequently cultivated, potato, concerns only 32% of the sample. In the region, only kharif rice is cultivated, which is planted during the monsoon and is harvested in November-December, i.e. just before the survey.[19]

I first provide descriptive statistics about rice production following a good or a bad monsoon. It appears clearly that rice production and income depends heavily on the relative monsoon abundance. Average yields and sales drop by respectively one third and more than half in bad years. There does not appear to have much risk-mitigation adaptation at the intensive margin (e.g. in sown area). Rice production is overwhelmingly aimed at home consumption in all years (though even more so after a negative shock).

Table 1: Rice production descriptive statistics

	good monsoon	bad monsoon	p-value†
Average yields (kg/acre)	851.8	582.0	0.00
Total production (kg)	817.3	527.2	0.00
Probability of producing a positive quantity	0.82	0.74	0.00
Probability of a complete crop failure	0.01	0.05	0.00
Total sown area (acres)	1.29	1.16	0.03
Total sown area if >0 (acres)	1.57	1.53	0.56
Probability of selling on the market if prod. >0	0.15	0.07	0.00
Total quantity sold if prod. >0 (kg)	76.2	31.4	0.00
Production for home consumption (%)	96.3	98.3	0.00
Observations	1197	1996	

Notes: Good and bad monsoons refer to June-September rainfall episodes respectively above and below the historical district average. † 2-sided t-test for differences in means.

Table 2 confirms that rice production in the area of study is very sensitive to monsoon quality. Column 1 shows that a sizable fraction of households react to the observed rainfall at the extensive margin, as the probability of producing a positive quantity decreases by about 6 percentage points (p.p.) for a one-standard deviation

[19] By contrast, rabi crops are harvested in Spring and do not rely directly on monsoon rains. In Jharkhand, rabi crops cultivation is relatively limited and is unequally distributed geographically, mainly because of underinvestment in irrigation facilities. For instance, wheat, the main rabi crop, is only cultivated by 23% of the sample. As a result, rabi production has only very limited capacity to mitigate shocks to the main kharif production. It also implies a longer recall in the survey and a more complicated shock identification, as rabi crops rely on residual soil moisture from the monsoon season and are partly irrigated.

deficit with respect to the average rainfall in the district. This is especially true for landless households, who have to enter rental or sharecropping agreements if they decide to produce. Looking at the interaction term, I find that SHG members do not react differently. In column 3, I estimate a 28% semi-elasticity of rice yields (kg per acre). Moreover, the significance of the squared term in column 4 indicates that the relation is quadratic (see the joint-significance test at the bottom of the table). That is, extreme events generate even larger drops, which points to the existence of fixed factors limiting the production capacity such as land and household sizes or liquidity to buy inputs. For instance, a rain deficit of two standard deviations is associated with a 70% yields drop (see the graph of the estimated relationship in appendix). Recalling that home-grown rice represents the basis of food consumption, this yield shock implies a dramatic income loss. Again, SHG members are as affected as other households. Finally, bad rainfall also affects negatively market participation (from an already very low level in average times), implying lower cash earnings.[20]

Though rice is undoubtedly the single most crucial crop for households' consumption and income - and also the most dependent on monsoon rainfall - table 3 shows that the conclusion is similar if one looks at other crops. Potatoes are the second most common crop and also cultivated during the kharif season. We see that potato yields are also strongly affected by the monsoon, which might translate into an even larger income shock given that potatoes have a higher commercial

[20]Hence consumption needs clearly dominate any potential strategic market participation that could be induced by price effects. In the data, I indeed estimate an elasticity of -1.4 (significant at the 1% level) between the price obtained on rice sales and the quantity of monsoon rainfall (after controlling for year and village fixed effects, and clustering standard errors at the village level). This finding thus reflects the low integration of food markets in the study area, as well as the fact that most of the small farmers in our sample lack both the surplus and the technical capacity to store rice from one year to the next.

Table 2: Agricultural production: rice

	(1)	(2)	(3)	(4)	(5)	(6)
	producing probability		log yields		selling probability	
Rain deficit (D)	-0.0552***	-0.0416**	-0.278***	-0.226***	-0.0303*	-0.0452**
	(0.0163)	(0.0170)	(0.0504)	(0.0559)	(0.0155)	(0.0194)
D_squared		-0.00646		-0.0558**		0.0108
		(0.00694)		(0.0231)		(0.00732)
D x SHG	0.0130	0.0147	0.0182	0.00930	0.0107	0.0104
	(0.00938)	(0.00940)	(0.0299)	(0.0300)	(0.0101)	(0.0111)
D_sq. x SHG		-0.00400		0.0400		-0.000234
		(0.00844)		(0.0275)		(0.00823)
Observations	3088	3088	2360	2360	2360	2360
p-value: joint sig. _D		0.0145		0.000		0.0664
p-value: joint sig. _DxSHG		0.290		0.307		0.517

OLS FE estimation. Clustered standard errors in parentheses (*p<0.10, **p<0.05, ***p<0.01).
All equations include a constant, time and household fixed effects, and control for household size.

value. Pooling all crops together, we find a similar concave relationship as above, reflecting the fact that rice is the overwhelmingly dominant component of the crop mix. Columns 5 and 6 confirm that rain shocks also imply lower cash income, as total proceeds from agricultural sales on the market are 18 percentage points lower following a one standard-deviation monsoon deficit.

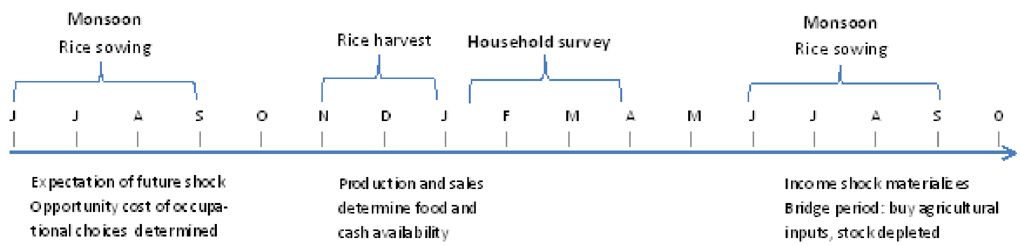
Table 3: Agricultural production: other crops

	(1)	(2)	(3)	(4)	(5)	(6)
	log potato yields		log all-crop yields		log total proceeds (+1)	
Rain deficit (D)	-0.298**	-0.0122	-0.253***	-0.186***	-0.184*	-0.354**
	(0.130)	(0.207)	(0.0494)	(0.0557)	(0.0974)	(0.173)
D_squared		-0.177**		-0.0689***		0.0743
		(0.0820)		(0.0225)		(0.0692)
D x SHG	-0.0988	-0.156*	-0.00468	-0.0176	0.0396	-0.00838
	(0.0760)	(0.0864)	(0.0283)	(0.0276)	(0.0670)	(0.0997)
D_sq. x SHG		0.0891		0.0500*		0.0231
		(0.0736)		(0.0258)		(0.0719)
Observations	605	605	2491	2491	3088	2360
p-value: joint sig. _D		0.0056		0.000		0.122
p-value: joint sig. _DxSHG		0.185		0.133		0.945

OLS FE estimation. Clustered standard errors in parentheses (*p<0.10, **p<0.05, ***p<0.01).
All equations include a constant, time and household fixed effects, and control for household size.

To sum up, we find that our monsoon deficit measure identifies strong income shocks, and that SHG members do not withstand rain shocks better. This is quite intuitive, as there is not much one can do against bad rain when cultivating rain-fed rice (except, of course, ex-ante risk-mitigating investments such as irrigation, which are arguably too complex and costly given the size and scope of SHGs). In the next sections, I look et how a series of non-agricultural outcomes are affected by that shock, and whether SHG members are better able to smooth the associated income volatility. Figure 2 sketches the timing of events as well as their potential consequences on the non-agricultural outcomes that are the object of the next sections. The strongest income shock is expected one year after a bad monsoon, when stocks are depleted and farmers still have to wait several months before the new harvest.

Figure 2: Timing of the shocks and survey over the year



6 Credit

This section focuses on credit, which is likely to be the main channel through which the insurance effect of SHGs materializes. I thus want to test the hypothesis that SHGs bring easier access to credit, even in periods of bad rain. The survey collected data about loans taken during the two years prior to the survey, so that we can expect rain in both t and t-1 to matter, though t-1 should probably have a higher impact because the income loss due to a bad harvest would then be fully realized. Thanks to the exact date at which loans have been taken, I can verify which is the relevant rain episode for each loan. In table 4 below, I enumerate the relevant combinations of the timing of loans and rainfall that I will explore in the analysis.[21] First, I check for 'immediate' effects that might happen contemporaneously to rain shocks, for instance in order to finance agricultural expenditures to take advantage of a good monsoon or, to the contrary, in order to finance risk-mitigation strategies in anticipation of a bad harvest (e.g. seasonal migration). Second, I study borrowing one year after the monsoon, which is the crucial moment at which the corresponding income shock is mostly going to materialize. Indeed, it corresponds to the hungry season in rural Jharkhand and households are expected to seek credit in order to make the two ends meet before the new harvest, especially following a negative rain shock. At the same time, it might be a period of acute shortage of credit if traditional lenders suffered bad harvests themselves. Moreover, given that traditional lenders often require to start repaying immediately, it might be harder to take credit after a bad shock. Finally, regressing credit outcomes in January-May on the rain shock that will be coming in the following months allows to check the validity of my estimation strategy: if shocks are indeed unexpected, future rain should not have any significant effect. Another validity check will consist in a placebo analysis using pre-treatment (2002) credit data. If SHG members react differently to shocks (expectations) because of SHG membership and not because of unobserved characteristics, they should not

[21]Note that I do not use the loans in t-1 because (i) they do not identify additional combinations and (ii) they might suffer from recall bias (which could be different for member and nonmember households).

behave differently than other households at baseline.

Table 4: Matching dates of loans and relevant rainfall episodes

Loans ╲ Rain	June-September t	June-September $t-1$
June-December t	immediate response (expectation of future shock)	income shock
January-May t	falsification test	-

Table 5 provides some descriptive statistics about the borrowing behavior of SHG members and other households. On average, SHG members are more than twice as likely to borrow any amount over the first half of the year, and 50% more likely to do so in the second half. The probability to borrow is higher in June-December than in January-May, especially for nonmembers for whom the probability more than doubles. This reflects the fact that, as we have seen, the second half of the year corresponds to main agricultural season. On the one hand, this period requires the purchase of agricultural inputs and, on the other hand, it requires more food purchases because the previous year's stock of grain is depleted. Total credit follows the same pattern, though the difference between member and nonmember households is less stark, reflecting the fact that nonmembers take on average bigger loans but less often. Moreover, the is an important dispersion in the amounts borrowed, with nonmembers' credit during the critical June-December period presenting by far the highest standard deviation observed in the data. Finally, the last columns allows to note how important is credit for the farmers in the sample. Over the year, total credit amounts on average to about 22% and 14% of members' and nonmembers' income respectively.

Table 6 regresses a dummy variable indicating whether an individual borrowed during the time window indicated in the header row. I find that nonmembers do not react immediately to a monsoon deficit, while members are 6 p.p. more

Table 5: Borrowing: household-level descriptive statistics (2004-2009)

	Probability (%)		Total credit (INR)		*For comparison:*
	Jan-May	Jun-Dec	Jan-May	Jun-Dec	Income[1] (INR)
Member households	39.5	57.6	957 (3,475)	1,343 (3,390)	20,535 (21,376)
Other households	18.3	38.8	675 (3,285)	1,158 (4,308)	19,493 (19,200)

Std deviation in parentheses.

[1] Sum of all remunerations received and the net value of agricultural production over the year.

likely to borrow after a one standard-deviation deficit - e.g. to finance alternative activities in expectation of a low future agricultural income. Using the quadratic specification, I do find a significant convex relationship for nonmembers, who tend to borrow more often when the monsoon is generous, and an opposite, concave relationship for member households. Effects are especially large during the 'income shock' period. Roughly one year after a negative rain shock, during the period of highest relative scarcity, nonmembers experience a sharp drop in their probability to borrow. The relationship is about flat up to a deficit of -1 and decreasing more and more rapidly as the deficit increases. I estimate that a one standard deficit of rain is associated with a 25 p.p. drop in the access to credit. By contrast, the borrowing probability is very stable for SHG members.

given that the traditional sources of credit are relatives and bigger farmers from the same community

In appendix, I graph the estimated quadratic relationships for the two periods, illustrating the strong procyclicality in the access to credit of nonmembers and the stability / countercyclicality for members. The last four columns present the results of the two validation tests. I first regress the probability to borrow between January and May over the rain that has yet to come (in June-September), and find no significant effect. Then, I check if there was any pre-treatment difference in the borrowing behavior of SHG members and other households. I use the 2002 baseline restricted survey, which collected credit data for a subsample of (future) SHG members and other households in treated villages. Despite the lower number of observations, I find that the access to credit depends positively on the quantity of rainfall for all households. That is, SHG members, before gaining access to SHG credit, are not different than other households in treated villages. Hence the previous findings are unlikely to be driven by a selection effect.

The analysis of loan amounts (table 7) delivers very similar results to the previous ones, indicating that most of the action takes place at the extensive margin and that loan sizes are not reduced in shock times.[22] Indeed, conditional on having access to credit, rain shocks have no significant impact on total credit. Therefore, the effect of SHG membership is mostly about giving easier access to credit to more people in periods of hard times, without increasing debt levels. Note that the previous effect is not due to ever-greening, which could happen if SHG members simply rolled over their loans during difficult periods. Indeed, regressing repayments provides a mirror image, implying that repayment rates keep up with borrowing rates. This is natural given that repayment has to be regular within the SHG framework.

Given that the need for credit is theoretically inversely related to last year's rainfall, the observed relation suggests credit rationing from informal lenders. As a matter of fact, more than half of the loans to nonmembers come from neighbors and relatives (see table 8), who are likely to be affected by the same rain shock. In fact, even their most important source of credit, moneylenders, are often larger farmers living in the same village or its neighborhood and are therefore not insulated

[22]Because the distribution of credit is right skewed and presents an important mass at zero, I regress the log of amounts plus one. Using a Poisson regression on levels gives very similar results.

Table 6: Borrowing probability

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
period:	immediate		income shock		falsification		income shock baseline	
Rain deficit (D)	-0.0243	-0.0386	-0.0529*	-0.204***	0.0223	0.0523	-0.133***	0.113
	(0.0238)	(0.0273)	(0.0275)	(0.0533)	(0.0275)	(0.0484)	(0.0466)	(0.213)
D_squared		0.0314***		-0.0499***		-0.0215*		-0.0972
		(0.0106)		(0.0152)		(0.0121)		(0.0843)
D x SHG	0.0603***	0.0830***	0.111***	0.185***	-0.00937	-0.0302	-0.0333	0.184
	(0.0145)	(0.0152)	(0.0183)	(0.0641)	(0.0172)	(0.0342)	(0.0586)	(0.277)
D_sq. x SHG		-0.0555***		0.0261		0.0189		-0.0922
		(0.0120)		(0.0217)		(0.0248)		(0.116)
Observations	3085	3085	3085	3085	3085	3085	550	550
p-value: joint sig. _D		0.0126		0.0007		0.217		0.0137
p-value: joint sig. _DxSHG		0.000		0.000		0.678		0.634

Dependent variable: dummy variable taking value 1 if any loan was taken during specified period and 0 otherwise.
OLS FE estimation. Clustered standard errors in parentheses (*p<0.10, **p<0.05, ***p<0.01).
All equations include a constant, time and household fixed effects, and control for household size.

Table 7: Total credit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
period:	immediate		income shock		falsification		income shock baseline	
Rain deficit (D)	-0.205	-0.352*	-0.374*	-1.462***	0.0397	0.114	-1.203***	-0.664
	(0.177)	(0.201)	(0.202)	(0.377)	(0.207)	(0.360)	(0.351)	(1.634)
D_squared		0.233***		-0.358***		-0.147		-0.210
		(0.0772)		(0.109)		(0.0947)		(0.636)
D x SHG	0.408***	0.552***	0.715***	1.170***	0.0155	-0.218	-0.349	0.501
	(0.109)	(0.114)	(0.133)	(0.445)	(0.126)	(0.256)	(0.432)	(2.001)
D_sq. x SHG		-0.355***		0.162		0.177		-0.361
		(0.0876)		(0.154)		(0.203)		(0.825)
Observations	3085	3085	3085	3085	3085	3085	547	547
p-value: joint sig. _D		0.00937		0.00057		0.233		0.0033
p-value: joint sig. _DxSHG		0.000		0.000		0.669		0.648

Dependent variable: ln (total credit taken during specified period +1).
OLS FE estimation. Clustered standard errors in parentheses (*p<0.10, **p<0.05, ***p<0.01).
All equations include a constant, time and household fixed effects, and control for household size.

against local rain shocks in most cases. Moreover, those lenders might anticipate lower repayment rates and be more reluctant to lend after a shock. By contrast, member households take the overwhelming majority of their loans from SHGs, and their credit access is virtually unaffected by rain shocks. This is remarkable, given that the basic concept underlying SHGs is the pooling of local resources, which could have been expected to dry up in case of adverse rainfall shocks.

Table 8: Average conditions of different loan options (2004-2009)

	SHG	Moneylender	Neighbor	Relative	Bank
interest rate (% monthly)	2.4	8.1	3.3	2.2	2.9
amount (INR)	1,271	3,238	3,052	3,673	11,182
duration (months)	7.0	8.7	7.0	9.0	20.3
frequency current SHG members (%)	87.4	3.1	2.9	3.3	2.9
frequency other households (%)	9.6	30.5	26.9	24.8	4.6
number of loans	3,156	473	422	413	73

There are different reasons that can explain why SHGs are able to keep lending in case of important and largely covariate shocks. As mentioned in section **??**, the first and foremost reason is that SHG members do not lend to each other out of their *current* money, but out of a pool of accumulated savings that has been growing over time. Moreover, that pool is being complemented by external loans from commercial banks. That is, while the scope for risk pooling is certainly not infinite due to the limited scale of operation, SHGs work as micro financial intermediaries, which can usually meet individual credit needs thanks to the collection of regular deposits and borrowing from commercial banks.

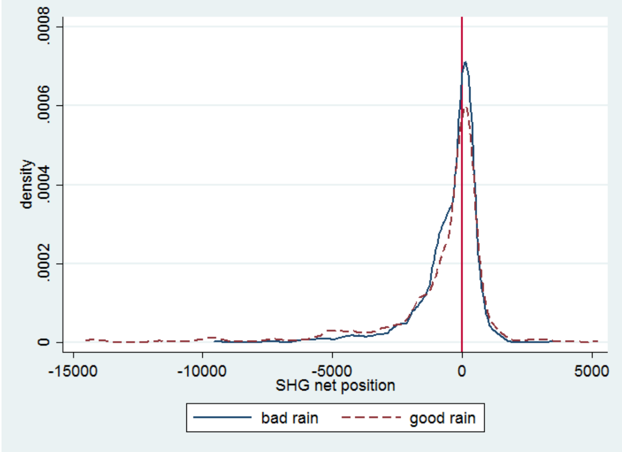
I first check the availability of savings as a function of the monsoon quality in t-1 (unfortunately, having no data about bank loans, I cannot check the availability of this subcomponent of SHG funds - though it is expected to be stable as those are large commercial financial institutions external to the village). Graph 3 displays the the distribution of the net annual position of SHG members - i.e. the sum of the regularly deposits over the year (excluding loan repayment) minus the sum of loans, one year after a monsoon below or above median.[23] Strikingly, the distributions appear very similar in good and bad years.[24] Moreover, both distributions are centered around zero, s.t. the most frequent pattern is to fully collaterize SHG loans over the year. Indeed, more than half of SHG members display a net position comprised between -500 and +500 Rupees. This can be explained by the policy of requiring small deposits at every meeting, which is usually fairly strictly followed. With weekly deposits of 10 Rupees, it leads in any case to yearly savings of about 400 Rupees minimum. Yet, this is of course not true for all members: there is an important mass of net contributors to the group and another larger mass of net borrowers. In any case, it is clear that the system does not break up after a bad monsoon: members keep saving regularly and the modal behavior remains taking out roughly the same amount of credit than one's own savings.

Another aspect of SHG resilience is the evolution of repayment performances (though the previous discussion implies that groups break even only with savings, at least for the modal member). Table 9 displays some statistics about repayment performance. Outright defaults are extremely rare in our data. By contrast, delays in repayment are frequent. I observe that a bad monsoon affects negatively the promptitude of repayment of SHG loans but not of other loans. In fact, other loans tend to display better repayment performances in case of bad rain, which is likely to come from a stricter selection of borrowers and harsher loan recovery

[23]SHGs keep two separate accounts fro each member, one for the regular deposits and one for the loans taken and repaid. It is only if there is a problem of repayment that the savings account is used to absorb the debt.

[24]A fixed-effect regression of SHG net position on rain deficit of the form of equation (2) gives positive and insignificant estimates.

Figure 3: Net SHG position and monsoon intensity in t-1: Kernel density estimate



practices in period of fund scarcity. This is in line with the fact that contractual duration decreases sharply in bad years for those loans. As a consequence, despite the extension of the repayment period, the availability of savings implies that bad rainfall shocks have no major consequence on SHGs' sustainability.

Table 9: Borrowing: average loan repayment performance

	Bad rain in t-1		Good rain in t-1	
	SHG loans	Other loans	SHG loans	Other loans
Default (%)	1.32	0.62	0.67	1.01
Late repayment‡(%)	40.9	27.8	28.9	38.4
Median contractual duration (months)	3	2	5	6
Nb. of loans	1349	630	1752	871

† Late repayment is equal to one in case (time to repay > contractual duration) if the loan is repaid or (time elapsed from the date of borrowing > contractual duration) if the loan is not repaid (and is equal to zero otherwise).

The availability of credit in periods of covariate income shocks is all the more important that private transfers also dry up in those periods. In table 10, I show that, during the year starting 6 months and ending 18 months after a bad monsoon, all households in the sample receive significantly less transfers (semi-elasticity of 50%).[25] This is indicative evidence that informal insurance mechanisms fail to cope

[25] In the interest of space, I report only the linear specification, as the quadratic term is never significant.

with such shocks in the villages of the sample, since most households are affected.[26] Moreover, the fact that SHG households are as affected as other households suggests that there is neither crowding out nor crowding in of informal insurance in this context. Interestingly, households appear to give out as much, resulting in much lower net positions: one standard-deviation monsoon deficit generating a loss between 2,000 and 3,000 INR in net transfers (corresponding to a semi-elasticity close to 100%). The last three columns confirm that such effects do not take place immediately at the time of the drought but rather when the income shock materializes at harvest time the following year.

Table 10: Private transfers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Monsoon t-1				Monsoon t	
	In	Out	Net	Net	In	Net	Net
Rain deficit (D)	-0.506**	0.115	-2778.2***	-2178.2***	0.0078	-11.64	209.8
	(0.222)	(0.312)	(950.4)	(661.7)	(0.186)	(736.7)	(516.9)
D X SHG	0.134	-0.200	857.8	316.8	0.029	418.8	248.4
	(0.161)	(0.203)	(652.9)	(503.3)	(0.101)	(517.6)	(354.4)
Observations	1974	1974	1974	1935	1974	1974	1935

OLS FE estimation. Dep. var.: ln (transfers in last 12 months +1) in col. 1, 2, 5; (transfers in - transfers out) in col. 3, 4, 6 and 7. Col. 4 and 7 drop observations below the 1^{st} and above and 99^{th} percentiles.
Std errors clustered at the household level in parentheses (*p<0.10, **p<0.05, ***p<0.01).
All equations include a constant, time and household fixed effects, and control for household size.

7 Migration and food security

This section focuses on the two main outcomes of interest: seasonal migration as a strategy to mitigate expected agricultural income shocks, and food security as a key measure of medium-term vulnerability.

In oder to guide the econometric analysis, I start by sketching a simple one-

[26] An ITT framework, with a treatment dummy defined at the village level gives similar results: a strong decrease in received and net transfers and no difference in SHG villages.

period model of seasonal migration, which captures the fact that land is both a productive asset that has to be abandoned in case of migration, and a wealth indicator that can help bearing the costs and risk of migration. Suppose a village populated of agricultural households who differ only in the size of their land (L). When the rainy season comes, households will choose either to stay in the village and work in agriculture or to migrate in order to look for alternative income. Their decision will depend on rainfall as well as on the opportunity and direct costs of migration. The timing of the period (year) events is as follows. First, households receive a fixed endowment of liquid wealth, which depends positively on land (e.g. last year's savings): w(L), with $w' > 0$. Landless households receive a basic wage $w(0) = \underline{w}$. Second, Nature determines the level of rainfall (R). Third, households decide between agriculture and migration occupations. Agricultural output is an increasing function of land (L) and rainfall (R): $Y_A = F(L, R)$, with $f'_L > 0$ and $f'_R > 0$. Rainfall is a stochastic process, which is assumed for simplicity to take two potential values, high or low. For the ease of notation, I denote Y_A^+ and Y_A^- the agricultural output associated with respectively high and low rain levels, with $Y_A^+(L) > Y_A^-(L)$, $\forall L$. Instead, if they decide to migrate, they pay a sunk cost (e.g. travel and settling costs) $\gamma > \underline{w}$ and receive a risky income $\tilde{Y_M} = \pi Y_M^+ + (1-\pi)Y_M^- > \gamma$, where π is the probability to get a high income from migration. If they do not have enough savings, they can borrow at the interest rate r>0 in order to finance migration costs. Fourth, at the end of the period, they enjoy utility from total income: $U(Y_A + Y_M)$, with $u' > 0$ and $u'' = 0$.[27] Given

[27] Assuming risk aversion would not modify the basic argument developed here. In fact, decreasing marginal utility of consumption would reinforce the pro-poor effect of the reduction of migration costs offered by SHGs. Moreover, in a two-period model, SHGs could then be shown to bring the additional advantage of reducing the variance of migration income if members can borrow in case they get the low income from migration. Yet, this should not impact differently

that I observe positive migration rates in the data, I focus on the relevant case in which migration is profitable in case of bad rain: $U(\tilde{Y_M} - \gamma) > U(Y_A^-)$.

Poor households might migrate or not depending on the credit market conditions. Households' utility from migration is

$$\tilde{U_M} = \mathbf{1}_{w(L)<\gamma} \left\{ U(\tilde{Y_M} - (1+r)(\gamma - w(L)) \right\} + \mathbf{1}_{w(L)\geq\gamma} \left\{ U(\tilde{Y_M} + w(L) - \gamma) \right\} \quad (3)$$

and they prefer to migrate if this quantity is larger than the home income

$$U_H = U(Y_A(L,R) + w(L)). \quad (4)$$

In figure 4, I plot the two curves with respect to land. Both curves slopes upwards and, beyond the point $w(L) = \gamma$, the slope of the $\tilde{U_M}$ curve $(u'w')$ is necessarily flatter than the slope of the U_H curve $(u'(f_L' + w'))$. Whether the first part of the $\tilde{U_M}$ curve has a steeper slope, $u'(1+r)w' \lesseqgtr u'(f_L'+w')$, depends on how large is the informal interest rate, i.e. the marginal productivity of capital plus local lenders' transaction costs and mark-up, relative to the marginal productivity of capital. If $\tilde{U_M}$ is flatter than $\tilde{U_H}$ over its entire domain, everyone with $w(L) \leq \gamma$ migrates for sure, and SHGs should have no impact on migration decisions. Instead, in the other case, migration costs represent a binding constraint and the poorest households cannot afford to migrate. Figure 4 represents this second case, which corresponds to what I find in the data and to what is typically observed in reality (e.g. Winters et al., 2001; Skeldon, 2002; Bryan et al., 2014; Angelucci, 2015).[28] In

poor and less poor households, unless risk aversion and poverty are correlated and/or subsistence thresholds are introduced. In the data, migration costs seem to be the most binding constraint, which mostly affects the poorest households.

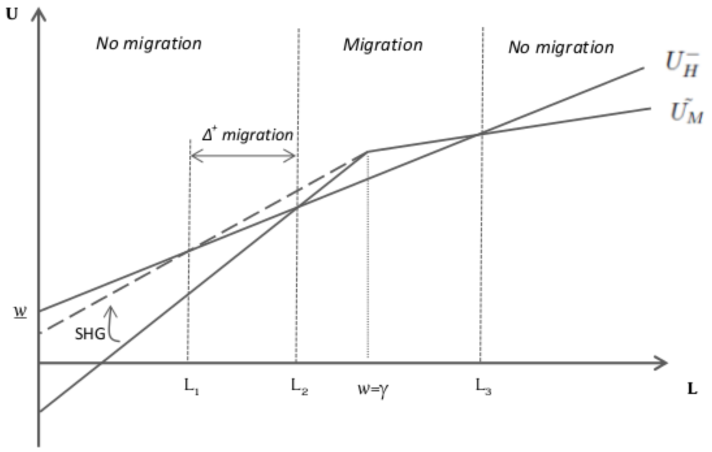
[28]An alternative model, which would match the stylized fact that the poorest households

such a situation and if rain is bad, households do not migrate if they are too poor and would have to support too high borrowing costs, do migrate when they are rich enough to self-finance migration costs, and give up migrating when they are 'too rich' and would have to give up a higher income at home. This identifies three zones, with migration occurring in the middle one, where migration costs are not prohibitive and the opportunity cost is not too large. When rain increases, the U_H curve shifts upwards, yielding an unambiguous reduction in the probability of migration. In such a setting, SHGs, by dramatically decreasing the cost of borrowing, affect the cost of migration for its members whose land is such that $w(L) < \gamma$ (and do not modify the choice of relatively richer households). In that zone, the slope of the $\tilde{U_M}$ curve decreases and the intercept, $U(\tilde{Y_M} - (1+r)(\gamma - \underline{w})$, moves upwards. This yields an unambiguous increase in migration (see dashed line).

Hence, this simple model delivers several testable predictions regarding the impact of SHGs on migration, depending on the level of households' land. If all nonmember households migrate in case of bad rain, cheaper credit should not affect choices - at least at the extensive margin. The other extreme, nonmember households never migrating, can happen if all households belong to the zone beyond L_3 - where the cost constraint is not binding anymore and 'rich' households face a too high opportunity cost of migration - or if all households are poorer than L_2. In the first case, SHGs should not bring any change, while, in the second case,

typically fail to migrate, would have lenders require collateral and lend maximum kL $(0 < k < 1)$. In such a model, the poorest households (for whom $kL < \gamma$) would be quantity-constrained instead of price-constrained. SHGs, by removing the physical collateral requirement (replaced by social collateral), would similarly increase the migration of poor households. Yet, in the data, the most important aspect of SHGs is to decrease the cost of credit for its members, who are not excluded from the credit market before the opening of SHGs.

Figure 4: Household utility function at home and with migration in case of bad rain



they will weakly increase the migration of the richest households in the sample (those between L_1 and L_2). The intermediate scenario is when only a fraction of nonmembers migrate. Depending on whether migrants are relatively poorer or richer than the average household, such a mixed situation can happen in the zones respectively to the left of L_3 or to the right of L_2. In the first case, migration costs represent a barrier to migration for the poorest households in the sample, and SHGs should increase the probility of migration for relatively 'poorer' member households (those between L_1 and L_2).[29] In the second case, SHGs should have, once again, no effect. To sum up, SHGs are only expected to affect migration rates in two cases: (i) when nonmembers do not migrate because they are too poor, and (ii) when the relatively richer nonmembers migrate and the relatively poorer do not. In the first case, SHGs will affect the richest households in the sample, while they will help the poorest (though not necessarily the poorest of the poor) in the

[29]Whether the poorest of the poor are migrating depends on how low is pushed L_1. If the SHG interest rate is low enough, we can have a situation in which $L_1 = 0$ and all poor households migrate.

other case.

I now turn to the data. Seasonal migrants are defined as household members who have been out of the household in order to work for less than six months during the year preceding the survey. Table 11 presents some basic statistics about seasonal migration in the sample. On average, migration episodes last 3.4 months. By far the most frequent destination is West Bengal, the neighbor state that is a major agricultural producer and home of some big manufacturing industries especially in the Calcutta region. Other frequent destinations include New Delhi, Maharasthra, and elsewhere in Jharkhand. Seasonal migration appears to be profitable: migrants get an average daily wage above 70 roupies, which compares favorably with the average daily wage of 59 roupies that laborers get at home. Yet, it is also riskier: the standard deviation of migrants' wage is 31.4 roupies, against 23 roupies for home laborers. At the end of the migration spell, each migrant brings back home remittances of about 3,200 roupies on average (in addition to what might have been potentially transfered while away). Member and other households look very similar while abroad but differ in their probability of migrating. In terms of the model, it is clear that some nonmembers do migrate. Moreover, those tend to be richer than average, as nonmember households who own less than the median land size are more than 7 percentage points more likely to migrate following a bad monsoon than other households (19.0% against 11.8%). I therefore expect an SHG impact especially on the poorest households.

The results of the econometric analysis are shown in table 12. I use the usual specification and regress different outcomes measuring the migration reaction immediately after observing a monsoon deficit. I find that nonmember households tend to react to rainfall shocks by increasing somewhat their seasonal migration,

Table 11: Migration: descriptive statistics (2004-2009)

	Members households	Other households
A. Migrant level		
Duration (months)	3.3 (1.5)	3.5 (1.6)
Wage (INR)	71.2 (30.5)	69.0 (32.3)
Remittances brought home (INR)	3,110 (3,738)	3,227 (3,003)
B. Household level		
Probability to migrate (%)	18.3	14.4
Number of seasonal migrants	0.22 (0.54)	0.19 (0.56)
Total income (INR)	1,301 (3,567)	1,109 (3,479)
Total remittances (INR)	559 (1,873)	528 (2,006)

Standard deviation between parentheses

though the effect disappears using the quadratic rain deficit. By contrast, I find a robust and stronger reaction of SHG members, especially for large monsoon deficits (see the graphical representation in appendix). This is true for the probability of migrating, the income earned outside of the household, and the remittances brought back in the household. For a one-standard deviation deficit, the three outcomes increase respectively by 5 p.p., 46% and 20% because of SHG participation. In line with the above model, I distinguish between households with different land holdings. In practice, in order to avoid complex triple interactions, I re-run the estimation separately in the two subsamples below and above the sample median land holding (1 acre). I find that richer nonmembers migrate more, which indicates that migration costs represent a binding constraint. Consistent with the theoretical predictions for that zone, the SHG effect is driven by the poorest members. Indeed, those are the most likely to lack the savings needed to (co-)finance migration costs during the bridge period preceding the new harvest.

Hence, the SHG credit taken during the 'immediate' period defined above seems to facilitate seasonal migration in face of adverse rain shocks (there is a positive and strongly significant correlation between the probabilities to borrow and to migrate in a given year). This in turn opens the possibility to smooth consumption. Unfortunately, given that the questionnaire collected food consumption information about the week preceding the survey, the data are not ideal to capture those effects, as the surveys were carried right after the harvest (between January and March) when rice stocks are still plenty. Yet, the questionnaire did ask about food security throughout the year. In particular, for each month of the year before the survey, we asked if the household had enough to eat. On average, households have enough food during 10 months per year, and 38% of them suffer hunger for at least one month (the most frequent hungry months being August and July). Table 13 regresses the number of months with enough food over the monsoon deficit variable, using a fixed-effect Poisson count model. I find that food security decreases rapidly with monsoon deficit. Yet, SHG members are much less dependent on the quality of monsoon and enjoy a much more stable consumption profile over the year (see the graphical representation of the estimated relation in appendix). On average, they go hungry about 11% less often during the year following a one standard-deviation monsoon shock. The effect is especially strong for the poorest households. Hence, it appears that SHGs help households to smooth consumption across months when there is food shortage. This can be the consequence of the income-generating preventive migration highlighted above as well as of the increase in borrowing one year after a bad monsoon highlighted in the credit section.

In short, SHGs help households to make better inter-temporal choices in occupation and consumption, which can have large health and economic benefits over the long-run given the adverse consequences of consumption volatility (e.g. Branca et al., 1993; Rao et al., 2009). This result also echoes the findings of Duflo et al. (2015).

Table 12: Migration

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All households			Land ≤ median			Land > median		
	probability	income	remitt.	probability	income	remitt.	probability	income	remitt.
A. Linear relationship									
Rain deficit (D)	0.0388**	0.307**	0.114	0.0257	0.158	-0.124	0.0600**	0.537**	0.476**
	(0.0177)	(0.153)	(0.127)	(0.0227)	(0.195)	(0.168)	(0.0269)	(0.233)	(0.186)
D x SHG	0.0303***	0.272***	0.101	0.0722***	0.649***	0.391***	-0.0226	-0.202	-0.251**
	(0.0104)	(0.0917)	(0.0755)	(0.0135)	(0.119)	(0.0981)	(0.0155)	(0.137)	(0.113)
B. Quadratic relationship									
D	0.0173	0.141	0.0706	-0.0123	-0.141	-0.301	0.0464	0.431	0.489**
	(0.0201)	(0.175)	(0.150)	(0.0257)	(0.224)	(0.197)	(0.0305)	(0.264)	(0.220)
D_squared	-0.00219	-0.0347	-0.0438	0.00174	-0.00471	0.00265	0.00941	0.0710	0.0136
	(0.00671)	(0.0581)	(0.0504)	(0.00924)	(0.0802)	(0.0704)	(0.0104)	(0.0897)	(0.0767)
D x SHG	0.0155	0.140	0.0327	0.0432***	0.392***	0.248**	-0.0226	-0.203	-0.240**
	(0.0107)	(0.0942)	(0.0806)	(0.0146)	(0.128)	(0.111)	(0.0156)	(0.138)	(0.117)
D_sq. x SHG	0.0363***	0.323***	0.168***	0.0519***	0.457***	0.257***	-0.000205	0.00603	-0.0542
	(0.00840)	(0.0725)	(0.0600)	(0.0110)	(0.0944)	(0.0798)	(0.0131)	(0.114)	(0.0923)
Observations	3088	3087	3088	1612	1612	1612	1476	1475	1476
p-value: joint sig. _D	0.687	0.702	0.686	0.891	0.743	0.203	0.0774	0.0704	0.0300
p-value: joint sig. _DxSHG	0.000	0.000	0.0064	0.000	0.000	0.000	0.344	0.336	0.0663

OLS FE estimation. Clustered standard errors in parentheses (*p<0.10, **p<0.05, ***p<0.01). Dependent variables: (1): dummy=1 if at least one seasonal migrant in household; (2): ln (total income from seasonal migration +1); (3): ln (total remittances from seasonal migration +1).
All equations include a constant, time and household fixed effects, and control for household size.

Table 13: Food security: number of months with enough food last year

	(1)	(2)	(3)	(4)	(5)	(6)
	All households		Land ≤ median		Land > median	
Rain deficit (D)	-0.0234**	-0.135***	-0.0126	-0.141***	-0.0342***	-0.127***
	(0.00919)	(0.0278)	(0.0132)	(0.0402)	(0.0125)	(0.0387)
D_squared		-0.0366***		-0.0436***		-0.0297***
		(0.00789)		(0.0115)		(0.0108)
D x SHG	0.00791	0.0891***	0.00767	0.106**	0.00781	0.0719
	(0.00709)	(0.0345)	(0.0112)	(0.0518)	(0.00902)	(0.0456)
D_sq. x SHG		0.0285**		0.0361**		0.0217
		(0.0112)		(0.0169)		(0.0146)
Observations	3005	3005	1587	1587	1418	1418
p-value: joint sig. _D		0.000		0.0007		0.00224
p-value: joint sig. _DxSHG		0.0357		0.101		0.272

Poisson FE estimation. Clustered standard errors in parentheses (*p<0.10, **p<0.05, ***p<0.01).
All equations include a constant, time and household fixed effects, and control for household size.

8 Conclusion

In developing countries, most poor households experience extremely variable income because of a large exposure to climatic, economic and policy shocks, combined with a lack of appropriate insurance devices. Extreme weather events, in particular, are projected to become more frequent in a warming climate, leaving rain-fed agriculture and large populations in developing countries at risk. Policymakers need a better understanding of the magnitude of the impacts on rural households, the distribution across income groups, as well as the potential coping strategies available.

It is well established in the literature that recurring income shocks, as well as traditional risk-mitigating strategies and coping mechanisms, can be very costly for poor households. In this context, reliable access to finance in general and credit in particular can potentially bring welfare-improving opportunities to smooth household consumption. Although (or perhaps because) the argument is theoretically well-accepted, there is not much empirical evidence about the impact of microfinance on the possibility to cope with (climate-related) income shocks.

The present paper studies the effect of monsoon intensity on credit access, seasonal migration and food security of rural households in Jharkhand, India. Using first-hand panel data about members of Self-Help Groups (SHGs) and control households, I show that all households' agricultural production and income are very sensitive to rainfall shocks, which therefore represents large exogenous income shocks that cannot be dealt with through inter-household transfers or other informal insurance mechanisms. Interestingly, while credit dries up dramatically for control households during the bridge period after a bad monsoon, I find that

SHG members enjoy a stable access to credit over time. That is, local savings and credit associations such as SHGs keep playing their crucial buffer role even in case of (largely covariate) weather shocks, thanks to their collection of regular deposits, their strong repayment performance and their linkage with external commercial banks for additional funding.

Moreover, I show that SHG credit encourages seasonal migration immediately after the realization of a bad monsoon, in order to substitute low-yield rice cultivation for alternative temporary occupations outside of the household. In line with the predictions of a simple occupational-choice model in a risky rural environment, this effect is especially strong for the poorest households, who lack savings to finance migration direct costs and have a lower opportunity cost of migration. Finally, I find evidence that SHG members enjoy higher food security over the year. To my knowledge, this is one of the first papers to provide direct evidence about the impact of microcredit on the ability to deal with climatic shocks.

I conclude that Indian SHGs are useful and effective credit instruments for rural households, which appear very resilient to covariate weather shocks. Despite the fact that they are not designed as insurance tools, they offer significant seasonal smoothing possibilities to members, with potentially substantial medium and long-term benefits to members. They help households to make better inter-temporal choices in occupation and consumption. My findings have potentially important policy implications, with extreme weather events projected to become more frequent in a warming climate. Interestingly, and in contrast to the widespread adoption of microcredit, attempts at introducing explicit microinsurance arrangements have met with very limited success. This may require a rethinking of development strategies aimed at reducing risk. Rather than trying to create formal insurance products from scratch, building on the success of local credit and savings associations may be a better option. In particular, there may be ways to change the way microcredit operates, at the margin, to further improve households' insurance. For instance, the Indian SHGs' policy of forced savings, though central to their resilience, might nevertheless be too rigid in order to play an effective insurance role over multiple years in case of important adverse shocks. Well-established SHGs could explore the possibility to relax the regular savings constraint during periods of economic hardships.

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A Descriptive statistics about the sample

Table 14: Sample villages and district

Region	District	Village	Type
Northeast	Banka†	Fattapathar	Member
Northeast	Banka†	Kanibel	Member
Northeast	Banka†	Devhar	Control
Northeast	Banka†	Bagmunda	Member
Northeast	Dumka	Gwalshimla	Member
Northeast	Dumka	Sitasal	Member
Northeast	Dumka	Tetriya	Member
Northeast	Dumka	Barhet	Control
Northeast	Dumka	Ranga	Control
Central	Hazaribagh	Bigha	Member
Central	Hazaribagh	Debo	Member
Central	Hazaribagh	Ranik	Member
Central	Hazaribagh	Rupin	Control
Central	Koderma	Garhai	Member
Central	Koderma	Irgobad	Member
Central	Koderma	Saanth	Member
Central	Koderma	Lariyadih	Control
Southeast	E. Singhbhum	Haldipokhar	Member
Southeast	E. Singhbhum	Murasai	Member
Southeast	E. Singhbhum	Pukhuria	Member
Southeast	E. Singhbhum	Pathar Banga	Control
Southeast	W. Singhbhum	Baihatu	Member
Southeast	W. Singhbhum	Chandra Jarki‡	Member
Southeast	W. Singhbhum	Kera	Member
Southeast	W. Singhbhum	Mermera	Member
Southeast	W. Singhbhum	Unchibita	Member
Southeast	W. Singhbhum	Jarki	Control
Southeast	W. Singhbhum	Nakti	Control
Southwest	Gumla	Jaldega	Member
Southwest	Gumla	Semra	Member
Southwest	Gumla	Umra	Member
Southwest	Gumla	Kurum	Control
Southwest	Khunti	Banabira	Member
Southwest	Khunti	Bhandara	Member
Southwest	Khunti	Udikel	Member
Southwest	Khunti	Irud	Control
Southwest	Khunti	Kamra	Control

Notes: † Bihar. ‡ Chandra Jarki replaced Kera in round 3 due to insecurity reasons.

Table 15: District poverty (data from 2001 Census if not otherwise indicated)

District	Population (thousands)	BPL households[1]	SC (%)	ST (%)	Female literacy (%)	Infant mortality (‰)	Households electrified (%)[2]
Banka	1,608.8	215,784	12.4	4.7	28.7	56	4.7
Dumka	1,759.6	125,701	7.3	39.9	32.3	47	7.7 / 20.4
Hazaribagh	2,277.5	222,810	15.0	11.8	42.8	46	34.7 / 57.2
Koderma	499.4	51,282	14.4	0.8	33.6	46	21.7 / 31.2
E. Singhbhum	1,983.0	117,918	4.7	27.8	57.3	36	47.4 / 67.1
W. Singhbhum	2,082.8	152,560	4.9	53.4	34.4	54	16.5 / 22.5
Gumla	1,346.8	87,546	5.0	68.4	39.9	60	5.1 / 6.8
Khunti	2,785.1	207,187	5.2	41.8	51.7	45	29.9 / 48.1

Notes: [1] 2002-07, official BPL list from the Government of Jharkhand (Bihar for Banka).
[2] Figures on the right are from a household survey by the Ministry of Health and Family Welfare in 2002-04.

Table 16: Baseline village characteristics and balance check

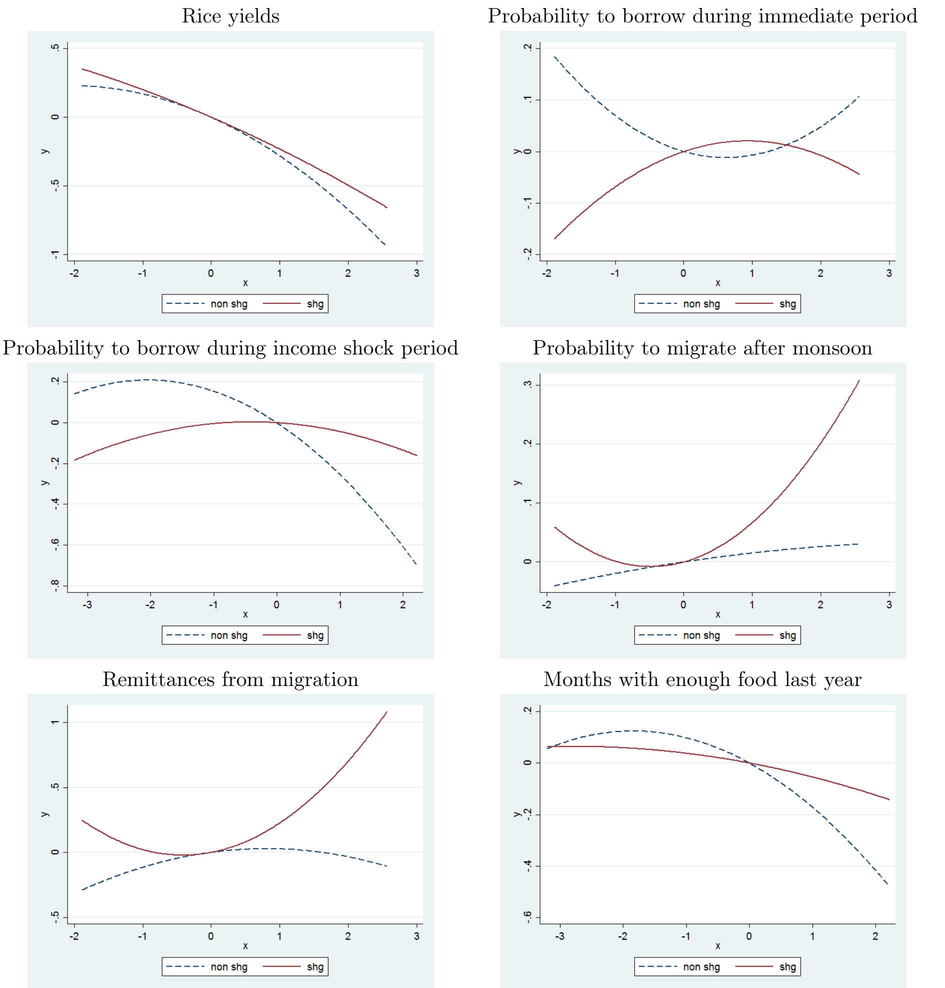
	control villages	treated villages	p-value treated = control
Population (# households)[1]	167.4	166.4	0.977
SC population(%)[1]	0.107	0.114	0.891
ST population(%)[1]	0.473	0.464	0.958
Landless population (%)[1]	0.246	0.300	0.577
Illiterate population (%)[1]	0.663	0.642	0.589
Female illiterate population (%)[1]	0.774	0.767	0.862
Farming population (%)[1]	0.352	0.366	0.892
Working gender-parity index[1]	0.472	0.512	0.785
Unemployment (%)[1]	0.408	0.353	0.591
Female unemployment (%)[1]	0.588	0.560	0.850
Caste / tribe fractionalization[2,4]	0.583	0.512	0.504
Language fractionalization[2,4]	0.347	0.358	0.888
Religious fractionalization[2,4]	0.402	0.298	0.246
Hinduism is main village religion[3]	0.637	0.596	0.761
All-weather road reaches village[3]	0.266	0.196	0.586
Electricity available in village[3]	0.403	0.439	0.840
Irrigated land (%)[3]	13.33	13.34	0.999
Distance to nearest bank (km)[3]	6.028	7.284	0.506
Distance to nearest primary health center (km)[3]	5.083	5.909	0.551
Distance to nearest fair price shop (km)[3]	2.611	4.509	0.272
Distance to nearest market (km)[3]	5.111	5.727	0.628
Distance to nearest rail station (km)[3]	23	20	0.780
Presence of a bus stop in village[3]	0.278	0.205	0.655
Distance to nearest bus stop (km)[3]	2.917	3.557	0.587
Presence of a primary school in village[3]	0.778	0.773	0.973
Presence of a middle school in village[3]	0.278	0.364	0.592
Presence of a secondary school in village[3]	0	0.0455	0.366
Distance to nearest secondary school (km)[3]	8.333	7.182	0.559
observations	12	24	

Sources of data: [1] Census of India 2001. [2] Using round 1 data of our own household survey. [3] Data from our own village survey. [4] Probability that two randomly-drawn individuals belong to different groups (commonly known as ethno-linguistic fractionalization index): $f = 1 - \sum_{i=1}^{n} s_i^2$, where s_i refers to the sample share of the ith group.

Table 17: Baseline household characteristics used as control variables in the regressions and balance check (round 1 data)

	Members (M)	Nonmembers (NM)	p-value M=NM	Controls (C)	p-value C=(NM+M)
A. Household characteristics					
Scheduled caste (SC)	0.139	0.057	0.000	0.061	0.073
Scheduled tribe (ST)	0.364	0.412	0.153	0.449	0.099
Hindu	0.670	0.671	0.982	0.626	0.235
Below official poverty line	0.529	0.484	0.197	0.439	0.079
Head's age	42.8	45.5	0.001	45.0	0.306
Mother's age	38.5	40.2	0.039	40.2	0.332
Head's years of education	3.41	3.10	0.218	2.82	0.114
Mother went to school	0.189	0.169	0.461	0.124	0.062
Own some land	0.936	0.876	0.002	0.965	0.009
Land owned (acres)	1.95	1.74	0.241	1.85	0.966
Number of babies aged 0-5 years	1.03	0.84	0.008	0.94	0.085
Number of children aged 6-17 years	1.72	1.46	0.008	1.58	0.845
Number of adults	3.06	3.04	0.893	3.13	0.521
observations	467	386		198	

B Graphical representation of the main significant quadratic relationships estimated in the text



The graphs draw the functions $\hat{y} = \hat{\rho}_1 D + \hat{\rho}_2 D^2$ for non shg and $\hat{y} = (\hat{\rho}_1 + \hat{\beta}_1)D + (\hat{\rho}_2 + \hat{\beta}_2)D^2$ for shg, over the relevant range of the deficit variable. Since they abstract from intercepts, they should not be used to read levels.

C Robustness test: instrumental variable

In this section, I check the robustness of the main findings of the paper through an instrumental variable strategy. I instrument (original) SHG membership by the interaction between the proportion of landless households in each village from the 2001 census data and each household's scheduled caste (SC) status. Those two variables are predetermined and can safely be considered as exogenous. Although they each separately could have some direct impact on outcomes such as migration and consumption, their interaction is arguably a good instrument. As explained in section **??**, the NGO PRADAN targeted the poorest villages to establish SHGs, with land ownership being a crucial indicator. Hence, the 2001 proportion of landless people influences the probability that the village got treated in 2002 and therefore the probability of being an SHG member.[30] It is not very likely to affect directly the reactions to shocks of SHG members, because it does not correlate with their individual land ownership (correlation of -0.005, p-value of 0.84). That means that, if selection into SHGs were orthogonal to landlessness, the correlation would not be above 30% anyway. In fact, it turns out that SHG members are less likely to be landless (see table **??**), which explains that the correlation is approximately zero. Yet, such a variable affecting all households in the village might not be a valid instrument in presence of externalities at the village level. This is why we interact it by the SC status of each household. As from table **??**, SC is a strong determinant of SHG membership within villages that have been targeted by the program (and obviously not in other villages). Again, while the SC status might influence most outcomes, there is no reason why SC households in villages with a

[30]The average proportion of landless people in the 2001 population in treated villages is 31% (median of 32%), while it is 25% in other villages (median of 20%).

high baseline landless population should behave differently than the average SC household, besides their much higher probability of being part of an SHG. That is, the exclusion restriction is likely to hold.

I start by regressing the SHG variable on the instrument - the proportion of landless households in the village population taken from the 2001 census data interacted by each household's SC status - and a set of exogenous controls as well as district fixed effects, using round 2 data (2004) given that all variables are time invariant. The results are shown in the three first columns of table 18. As expected, controlling for the base effect of the landless population and SC status, the instrument is a strong predictor of membership. Using the full specification (column 3), I then predict the $S\hat{H}G$ variable, which gives for each household the probability of being an SHG member based only on the interaction between its exogenous caste identity and the NGO's program placement policy. The $S\hat{H}G$ variable thus removes self-selection determinants. I then construct the variable D x $S\hat{H}G$, which is a valid instrument for the interaction between the exogenous rain deficit variable (D) and the endogenous SHG variable (Wooldridge, 2010). Columns 4 to 6 show the results of the first-stage regression and confirm the strong correlation and significance of the instrument. The two instruments are strong, with Kleibergen-Paap Wald F statistics consistently above 13 and largely above the 10% Stock-Yogo critical value of 7.03. Table 19 gives the second-stage results, with and without household fixed effects. Although precision naturally decreases, IV estimates are consistently larger than their fixed-effects OLS counterparts. This might be because the instrument focuses on SC households who are the most disadvantaged to start with. In any case, I conclude that the previous results were unlikely to suffer from an upward bias. Besides, an endogeneity test fails to indicate that the SHG and D x SHG variables are endogenous (p-value=0.8).

Table 18: Two-stage least squares: first stage (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	SHG member			Rain deficit x SHG		
2001 landless population	0.498**	0.391*	0.479**			
x SC status	(0.222)	(0.226)	(0.230)			
Rain deficit x $S\hat{H}G$				1.038***	1.047***	1.035***
				(0.0185)	(0.040)	(0.0403)
Time fixed-effects	-	-	-	no	yes	yes
District fixed-effects	no	yes	yes	no	yes	yes
Other control variables	no	no	yes	no	no	yes
Observations	1051	1051	1048	3009	3009	3007
R^2	0.029	0.043	0.092	0.514	0.514	0.519

All equations include a constant and control for SC status and 2001 landless population.
Other control variables are a list of predetermined household- and village-level variables.
Columns 1-3 use 2004 data and columns 4-6 use all years. *p<0.10, **p<0.05, ***p<0.01.

Table 19: Migration and food security: IV estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	mig. probability		mig. income		mig. remittances		months with enough food		
A. All households									
D	0.0236	0.0251	0.177	0.172	0.0112	-0.0245	-0.0714***	-0.0676**	-0.0488**
	(0.0265)	(0.0324)	(0.234)	(0.333)	(0.197)	(0.248)	(0.0227)	(0.0292)	(0.0210)
D x SHG	0.0577*	0.0559	0.513*	0.519	0.281	0.350	0.0989**	0.0921	0.0574
	(0.0340)	(0.0431)	(0.302)	(0.449)	(0.255)	(0.289)	(0.0450)	(0.0594)	(0.0389)
SHG	0.0629		0.546		-0.197		0.115		0.0507
	(0.101)		(0.886)		(0.749)		(0.0805)		(0.0698)
Observations	3007	3009	3007	3009	3007	3009	3007	3009	3007
B. Land ≤ median									
D	0.0271	0.0221	0.184	0.119	-0.119	-0.195	-0.0907**	-0.0819	-0.0551**
	(0.0349)	(0.0492)	(0.307)	(0.323)	(0.261)	(0.385)	(0.0358)	(0.0527)	(0.0244)
D x SHG	0.0705*	0.0779	0.618*	0.711*	0.372	0.503	0.176**	0.156*	0.0976***
	(0.0417)	(0.0592)	(0.370)	(0.364)	(0.315)	(0.429)	(0.0712)	(0.0877)	(0.0374)
SHG	0.0705		0.506		-0.180		0.203		0.0727
	(0.128)		(1.157)		(1.057)		(0.128)		(0.0873)
Observations	1604	1604	1604	1604	1604	1604	1604	1604	1604
Household FE	no	yes	no	yes	no	yes	no	yes	no
District FE	yes	-	yes	-	yes	-	yes	-	yes
Other control var.	yes	-	yes	-	yes	-	yes	-	yes

Col. 1-6: OLS estimation; variables definition above. Col. 7-8: OLS estimation; log(nb. of months with enough food last year).
Col. 9: Poisson estimation; nb. of months with enough food. Clustered standard errors in parentheses (*p<0.10, **p<0.05, ***p<0.01).
All equations include a constant. Other control variables are a list of predetermined household- and village-level variables.