amse
école d'économie d'aix-marseille
aix-marseille school of economics

Working Papers / Documents de travail

Coping with shocks: the impact of Self-Help Groups on migration and food security

Timothée Demont

WP 2020 - Nr 16

Coping with shocks: the impact of Self-Help Groups on migration and food security

Timothée Demont*

Aix-Marseille Univ., CNRS, EHESS, Centrale Marseille, IRD, AMSE

May 11, 2020

*timothee.demont@univ-amu.fr. I received helpful comments from Jean-Marie Baland, Rohini Somanathan, Xavier Giné, Catherine Guirkinger, Wouter Gelade, Nicolas Berman, Roberta Ziparo, as well as seminar participants at AMSE (Marseille), CRED (Namur), IIES (Stockholm) and ISI (Delhi). I also want to thank the NGO PRADAN (Delhi), and in particular Sanjay Prasad and Amit Kumar, for outstanding assistance in data collection and cleaning. This work was supported by the European Research Council (project AdG-230290-SSD) and the French National Research Agency (grant ANR-17-EURE-0020). This study is registered in the AEA RCT Registry and the unique identifying number is: AEARCTR-0005570.

Abstract This paper asks whether local savings and credit associations help poor rural households hit by climatic shocks. Combining data from an original field experiment with meteorological data, I investigate how Self-Help Groups (SHGs) allow households to cope with rainfall shocks in villages of East India over a seven-year period. I show that SHGs withstand large rainfall shocks remarkably, and that credit flows are very stable in treated villages. As a result, treated households experience a higher food security during the lean season following a drought and increase seasonal migration to mitigate future income shocks. These results imply that small-scale financial institutions like SHGs help to finance temporary risk management strategies and to cope with important covariate income shocks such as droughts.

Keywords: Microfinance, weather shocks, risk management, seasonal migration, food security.

JEL Classification Numbers: O13, O15, G21, Q54

1 Introduction

Most poor households living in rural areas of developing countries experience strongly volatile income streams due to their large exposure to climatic, economic and policy 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). Likewise, 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.

This paper studies whether Self-Help Groups (SHGs), a versatile model of local savings and credit associations, can help households to cope with large covariate income shocks such as droughts in villages of East India.[1] SHGs represent one of the most successful and sustainable microfinance instruments in the world, which spread widely throughout rural India and beyond (in stark contrast with more complex microinsurance products, for instance).[2] It is therefore very important to

[1]Indian agriculture, which still accounts for 16% of GDP and 49% of employment, is extremely dependent on erratic monsoon rainfall given the low irrigation coverage and the effects of climate change (Gadgil and Gadgil, 2006; World Bank, 2006; Asada and Matsumoto, 2009; Prasanna, 2014; Government of India, 2018). As a consequence, rainfall shocks have been repeatedly 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., 2012, 2013; Gaurav, 2015).

[2]Today, there are about 8.7 million bank-linked SHGs in India (NABARD, 2018). This

understand how far such simple, yet complex, deeply rooted and widely accepted informal institutions can go in 'insuring' poor households against income shock, including when those are largely covariate. By offering relatively cheap and flexible credit, and by combining internal accumulating savings with external credit taken jointly from commercial banks, SHGs present interesting characteristics in this respect.

While risk and income 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.[3] Second, poor households are disproportionately likely to lack the necessary human, physical, and financial capital to manage shocks. Third, developing countries and rain-fed agriculture are disproportionately vulnerable to global climate change (World Bank, 2010; IPCC, 2014; FAO, 2016). And weather-related income shocks, because of their covariate nature, are particularly difficult to deal with through informal insurance arrangements among local communities.

The rapid expansion of microcredit in many parts of the world could thus be expected to have helped otherwise-constrained poor users to develop ex-post risk-coping or ex-ante risk-mitigating strategies in order to manage weather-related

represents a remarkable achievement, especially given the general acknowledgment that standard microfinance products remain more suited to urban and peri-urban areas than to the rural world. More details about the SHG model are given in section 2.

[3]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).

income shocks. Despite the importance of the question, there is surprisingly little direct evidence 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. More recently, microinsurance products, such as index-based weather insurance, have been developed to address risk directly. However, evidence about the demand and impact of such products has been disappointing, mostly because of the cost, complexity, rigidity and substantial basis risk of most insurance contracts (see Cole et al., 2013; Karlan et al., 2014; Platteau et al., 2017).[4]

The present paper exploits data from a long-run 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, in order to evaluate the changes in their living standards.[5] Estimating the effect of the treatment at the village level (intent-to-treat framework), I present three main findings. First, I show that, despite being hit as strongly on the agricultural front (with an estimated general 20% drop in rice yields), treated household enjoy a higher food security in case of droughts. On average, they experience a 50% lower loss of adequate food consumption during the year following a negative monsoon shock. Second, I show that, despite being village-based and small-scale institutions, SHGs are robust sources of credit in presence of covariate shocks. While credit access virtually dries up in control villages one year after a bad monsoon,

[4] In last years, the 'microinsurance promise' has been losing impetus even among policy circles. 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.

[5] See Baland et al. (2020) for the original impact evaluation.

reflecting strong credit rationing from informal lenders during the lean season, households in treated villages enjoy a steady access to credit, and are even able to borrow counter-cyclically. They use this credit in part to finance consumption during the lean (or 'hungry') season, thus improving food security through the seasonal adjustment of liquidity. Third, I find that treated households increase seasonal migration immediately after a bad monsoon (by an estimated 35-40%), as a strategy to diversify income and mitigate future shocks. The effect is partly explained by the greater credit availability offered by SHGs, which helps facing the direct costs as well as the income risk of migration. Other aspects of SHGs, such as the expansion of peer networks, are also helping to curb non-monetary costs through support and learning.

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 small-scale, local, and poor-oriented credit institutions such as SHGs can contribute to the management of covariate shocks, with very important health and economic consequences. Moreover, this is one of the few papers investigating the impact of microfinance on seasonal migration.

There are, however, several related papers in the literature. First, there is an extensive literature on risk coping and risk 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 those stem 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 less likely to experience hunger and more likely to retain their job in the 6 to 12 months following the intervention. Beaman et al. (2014) report on another field experiment on savings and credit groups in Mali, which 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), exploiting observational panel data from Tanzania, show that households respond to transitory income shocks – a dummy variable indicating a 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. Following an instrumental variable approach, Kaboski and Townsend (2005) show that microfinance institutions, providing savings services and emergency consumption loans in Thailand, decrease 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.[6] Yet, households having access to microcredit are less likely to

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

sell productive assets in response to health shocks. Finally, in a field experiment that randomly provided access to a bank account to Indian villagers, Somville and Vandewalle (2019) find that treated households smooth food consumption better, thanks to pro-cyclical saving on the account. Third, a few recent papers have studied the link between microfinance and seasonal migration. Contrary to this paper, Khandker et al. (2010), using cross-sectional survey data, show that the probability of seasonal migration and microfinance membership are negatively correlated. By contrast, 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 season increased seasonal migration among rural households, leading to improvements in household consumption and food security.[7] Interestingly, I find similar results, while SHG credit is not earmarked in any way for migration.[8] My results thus indicate that seasonal migration is a well-known mitigation strategy, though it is often unworkable because of the lack of appropriate credit and networks. Moreover, by exploiting a long panel, I am able to link such migration to the occurrence of explicit and objective income shocks.

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 and food security in section 5, followed by credit in section 6, and finally migration in section 7.

[7]A scale-up of the intervention failed to induce migration and replicate such positive effects. The authors argue that the failure is partly explained by administrative changes in the program and the government's strategic reaction, leading to delivery issues and mistargeting.

[8]In fact, PRADAN, the partner NGO, was rather expecting the opposite effect (as in Khandker et al., 2010).

2 The SHG program and the context

2.1 The context and intervention

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 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, with average yields around 1,800 kg per hectare – 25% below the national average according to the Directorate of Economics and Statistics (2016 data).

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 (see section 3). Global warming, in particular, is making monsoon rains increasingly erratic (Singh et al., 2014; Loo et al., 2015). The agriculture in the state suffers from such 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).

In 2002, the NGO PRADAN launched a large program of creation of women-only SHGs. It established a list of potential intervention villages (based on their high poverty incidence), located in four geographic clusters covering the entire state of Jharkhand.[9] 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 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). By January 2004 (when the first survey wave took place), there were between 1 and 10 (4 on average) active SHGs in treated villages and none in control villages. Over time, some of those initial SHGs went defunct and some others were created, including a limited number in control villages. However, by the last survey wave (January 2009), treated villages were still much more likely to have SHGs, with an average of 5 groups against 1 in control villages. Likewise, in the last round, 47.5% of the households in treated villages had borrowed from an SHG over the last two years, against 18.4% in control villages.

[9]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.

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

SHGs are groups of women from the same village and homogeneous backgrounds, who voluntarily come together to save and borrow small amounts on a regular basis. The formation of the groups starts by some initial training and capacity building from the NGO. Each group then chooses a name and distributes the roles of president, secretary, cashier, and accountant.[10] It also sets the 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[11], and potential sanctions 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.

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

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

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

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 a delay.[12] 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 absorbs the loss with the defaulting member's savings and, if needed, the collective 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.[13] In particular, SHGs can allow members to borrow in response to

[12]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.

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

negative income shocks, in order to manage inter-temporal liquidity and/or finance risk-mitigating strategies. Several features of SHGs are important to underline in this respect. First, SHGs are meeting weekly 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 simultaneously and SHGs are potentially able to insure at least partially against all sorts of income shocks, including covariate weather shocks.[14] Finally, SHGs certainly go beyond mere credit and savings activities. They constitute strong groups of peers meeting regularly, which constitute powerful information, support, and collective-action networks (see for instance Desai and Joshi, 2013; Casini et al., 2015; Baland et al., 2020).

3 Data

3.1 Household data

The sample selection occurred at the end of 2003, i.e. about one year and a half after the creation of the first SHGs, s.t. all groups were stabilized and fully operational. In each treated village, 18 SHG member households were randomly

ROAs ranging from 1.4 to 7.5% for a sample of SHGs in Andra Pradesh and Karnataka. Several studies confirm the longevity and high rate of socia inclusion of SHGs, such as Gaiha and Nandhi (2008) and Baland et al. (2019).

[14]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.

selected from PRADAN's lists, together with 18 nonmembers. In the control villages, 18 households were randomly selected.[15] The full sample therefore consists in 1080 households, which were surveyed three times, in 2004, 2006, and 2009.

The questionnaire took the form of Living Standards Measurement Survey, recording detailed information about household demographics, consumption, asset ownership, credit, labor market participation and self-employment, migration, land ownership and agriculture, among other items. 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 village and household levels. It shows that there is no statistically-significant difference between treated and control villages (and that point estimates are very similar), which validates the randomization of villages.

The overall attrition rate across rounds is very limited, at 6.7%.[16] The vast majority (77%) of the households have been interviewed in all survey rounds and 90% have been interviewed at least twice.

3.2 Rainfall

I retrieve historical rainfall data from the Global Precipitation Climatology Center, which provides monthly precipitation at 0.25-degree spatial resolution ($\sim 25km^2$). I compute two measures of monsoon quality, which, when interacted with

[15]Nonmember and control households were selected following a standard random-walk procedure.

[16]One of the reasons for this attrition is the Naxalite rebellion in the region, which prohibited the survey team from visiting a treated village for security reasons in the last survey wave. Excluding that village, the average attrition rate is only 5%. Results are fully robust to its exclusion.

treatment, will be the key explanatory variables in the empirical analysis. They both focus on the rain between June and August, which corresponds to the core monsoon period and concentrates more than 70% of yearly rainfall on average. It is also the period that is crucial for (rain-fed) agriculture, residual rain being scattered over the rest of the year.[17]

The first measure (*Rain*) is simply the natural log of the cumulative monsoon rainfall in every village-year. Given the presence of village or household fixed effects in the regression equation (see below), this measure can be interpreted (roughly speaking) as the percentage *deviation* from the mean village rainfall.[18] Second, I construct a rainfall shock indicator ($Rain\_shock$) in the following way. I start by computing a z-score measure of standardized precipitation deficit for each village-year, i.e. the monsoon precipitation deficit from the long-term village average divided by the long-term village standard deviation[19]:

$$Rain\_def_{vy} = \frac{Precip\_avg_v - Precip_{vy}}{\sigma(Precip)_v}$$

[17]The most important rains for the cultivation of rice - the main staple food - in the study area come in June-July, when rice needs to be transplanted in flooded fields. Asada and Matsumoto (2009) find a significant correlation coefficient of 0.36 between the rainfall in July and kharif rice production in Bihar and Jharkhand, higher than for any other month. Gadgil and Rupa Kumar (2006) confirm that the monsoon onset (June-July) has a large and significant influence on kharif rice production, but explain that if rain picks up in August, the damage to output can still be limited through delayed sowing. In my data, I find a very strong and significant raw correlation of 0.45 between cumulative rainfall in the June-August period and annual rice yields.

[18]This continuous rainfall 'shock' measure is used for instance in Maccini and Yang (2009) and Vanden Eynde (2018).

[19]Village means and standard deviations of monsoon precipitation are calculated over a rolling window corresponding to the twenty years immediately preceding each round, which is considered as the relevant rainfall history for farmers. This measure is close to the "Standardized Precipitation Index" (the most commonly used indicator worldwide for detecting and characterizing meteorological droughts) developed by McKee et al. (1993), and is used for instance in Cole et al. (2012).

where v and y stand for village and year, respectively. Then, I define

$$Rain\_shock_{vy} = \mathbb{1}(Rain\_def_{vy} \geq 0.5).$$

That is, *Rain_shock* takes value 1 if the monsoon is at least 0.5 standard deviation below the village's historical norm, corresponding to a (mild) drought happening once every 3 years on average, and 0 otherwise.[20]

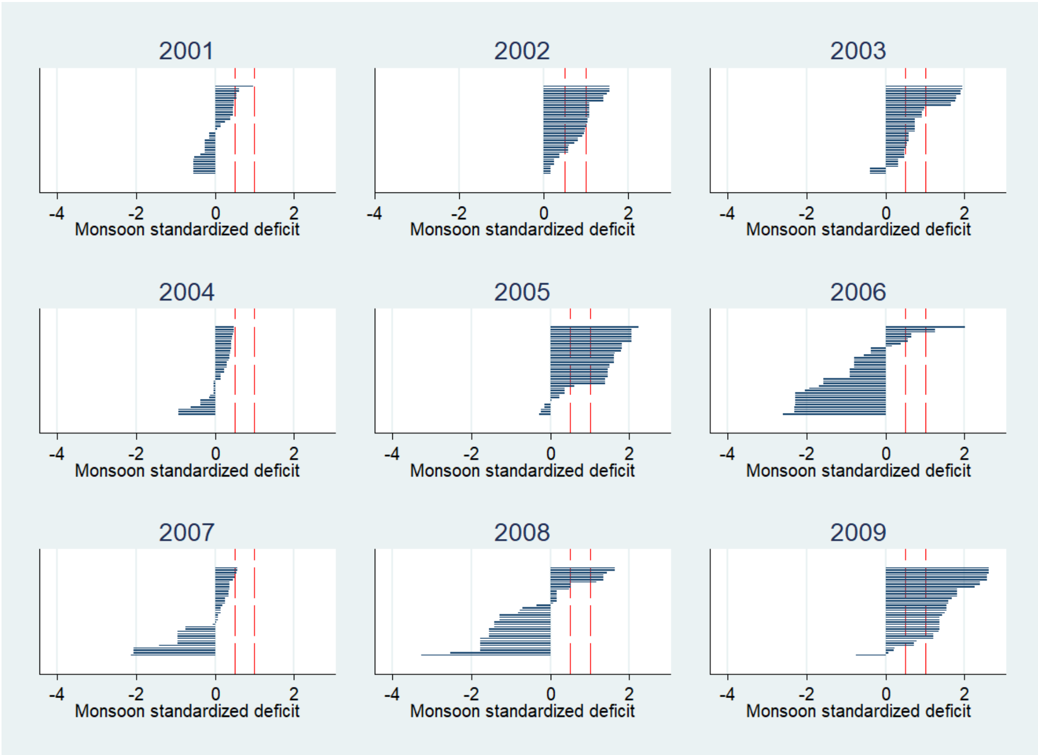
Figure 1 shows substantial variation in the sample distribution of the *Rain_def* variable, both across villages and over time. Roughly speaking, 2009, 2005, and 2002 were bad monsoon years (2009 and 2005 being officially recognized ex-post as a drought year for the whole state of Jharkand), while 2006 and 2008 received relatively generous rainfall (though, as the graph makes it clear, this was not the case for all villages). During the other years of the survey period, average precipitations were closer to average, though with important inter-village variation. Indeed, thanks to the stratification strategy, the sample includes villages in all agro-climatic zones composing the state of Jharkhand.

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

[20]One standard deviation of the sample distribution of monsoon rainfall corresponds to about 25 cm on average. The maximum and minimum standardized precipitation deficits observed over the sample period are respectively 2.61 and -3.27, see figure 1. In appendix C, I show that all results are qualitatively robust to using a more restrictive definition of a drought, namely a rain deficit larger than 1 standard deviation (corresponding to severe droughts happening once every 5 years on average). Yet, the lower variation in this restrictive shock variable (see figure 1) implies generally less precise estimates.

Figure 1: Village-level standardized deficit of monsoon rainfall (z-scores) during study period



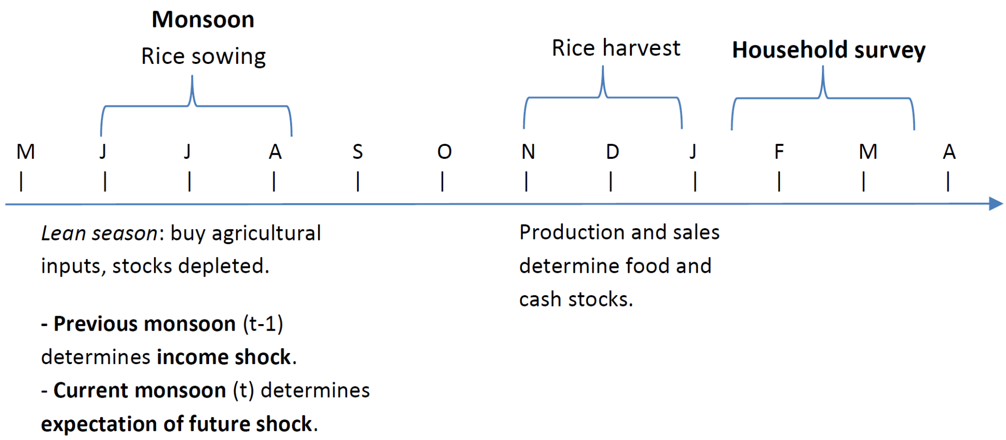
Data: GPCC. Dashed lines indicate rain shocks (deficits larger than 0.5 and 1 std deviation).

unpredictable at the start of the season.[21] Thus, rainfall shocks are exogenous and unanticipated, spread over space, and their incidence is balanced between treated and control villages thanks to the stratified randomization of villages. Figure 2 sketches the timing of events over the year as well as their potential consequences on outcomes of interest. The strongest income shock is expected to hit one year

[21]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 villages).

after a bad monsoon, when stocks are depleted and farmers still have to wait several months before the new harvest. By contrast, expectations about future shocks are formed immediately after a bad monsoon. Hence, some outcomes – e.g. agriculture, migration – are expected to react to the last monsoon (t), while others – e.g. food security, transfers – are expected to react to the monsoon before (t-1).

Figure 2: Timing of events over the year



My approach is to estimate the impact of SHGs at the village level, irrespective of households' actual membership (intention-to-treat estimates, or ITT), following a simple difference-in-difference strategy. I compare the average reaction to shocks of the households living in treated villages (in which SHGs were created in 2002) to the same reaction in control villages, from potentially different baseline levels. This ITT approach, while it gives the impact of SHG *access* and not participation, has the advantages of avoiding any bias stemming from self-selection of SHG members, and to factor in potential spillovers from member to non-member households within treated villages.[22]

[22]Because of self-selection into SHGs, member and non-member households will tend to represent different sub-samples of the village population, thus confounding the estimated effect of

My baseline specification takes the following form:

$$Y_{ivt} = \alpha + \rho Rain_{vt} + \beta(Rain_{vt} * Treat_v) + \gamma \boldsymbol{H}_{it} + \lambda_t + \eta_{v/i} + \epsilon_{ivt}, \tag{1}$$

where Y_{ivt} is the outcome of interest (agricultural production, food security, credit, transfers, migration) for household i in village v and year t, $Rain_{vt}$ are the measures of monsoon quality, defined in the previous section, for village v and year t or t-1 (as explained above, the relevant rainfall might be t or t-1 depending on outcomes), and $Treat_v$ is a dummy variable taking value one if household i lives in a treatment village (given that this measure is time-invariant, the base level is absorbed by the village or household fixed effects). The coefficient β is the main coefficient of interest, measuring the relative difference between households in treated and control villages in case of rainfall shocks (controlling for any normal-time difference). This coefficient therefore estimates 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% on average). $\boldsymbol{H}_{it}$ is a vector of control variables at the household level, including the household size in equivalent adults[23], official scheduled caste or tribe and below-poverty-line statuses, head's education and age (in a quadratic fashion), and land ownership category (land size between the 25^{th} and the 75^{th} percentile or larger than the 75^{th} percentile of the district-round distribution). Finally, λ_t are round (year) fixed

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.

[23]I use the equivalence scale proposed by Townsend (1994), who computes adult male 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 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.

effects that account for economy-wide shocks and $\eta_{v/i}$ are village or household fixed effects (all results are presented using both specifications), which account for villages' fixed characteristics or households' fixed characteristics (including at the village level) and average behavior. In the specification with household fixed effects, $\boldsymbol{H}$ is replaced by the household size in equivalent adults only. Throughout, standard errors are clustered at the household level in order to account for the correlation of standard errors and potential heteroskedasticity. In order to adequately represent the village population from which they are drawn, observations are weighted in order to control for the different sampling probabilities between SHG and non-SHG households in treated and control villages.

5 Agriculture and food security

Most of the households in the sample are small landholders (94% own some land, of average size below 2 acres), who by and large practice a subsistence agriculture with limited marketable surplus. Rice, in particular, often represents the main source of food and agricultural 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.[24]

[24]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

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 seem to be 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

	Means in case of		
	good monsoon	bad monsoon	P-value†
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	

Good and bad monsoons refer to June-August rainfall in year t 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 the monsoon quality, and that my rain (shock) variables are indeed identifying important productivity or income shocks.[25] In columns 1 and 2, I estimate a 0.33-0.36 elasticity of rice yields – 10% more rain leading to a 3-4% increase in yields. Looking at the interaction term, I find that treated villages are equally affected,

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.

[25]In appendix C, I also provide a specification test, in which I replace rain of the current year (t) by rain of the next year (t+1) and show that future rain has no effect on current agricultural outcomes.

which was expected given that there is not much one can do against bad rain when cultivating rain-fed rice (except, of course, carrying out risk-mitigating investments such as irrigation, which are too complex and costly given the size and scope of SHGs). Focusing on negative shocks, panel B shows that a monsoon deficit of at least one standard deviation leads to a very large and significant drop in yields of more than 20%, implying a big income shock. Recalling that home-grown rice represents the basis of food consumption in the sample villages, columns 3 and 4 look at the distance to 'self-sufficiency' in rice.[26] I find that a rainfall shock leads to a loss of self-sufficiency of about 5 percentage points, or 12%. Finally, a bad monsoon also affects negatively market participation (from already very low levels in normal times), implying lower cash earnings. In columns 5 and 6, I find that rainfall shocks lead on average to a reduction of 1.5 percentage points, or 75%, in the proportion of rice home production sold on the market.

All in all, the above results confirm that most households in the sample are net buyers and strongly negatively affected by a bad monsoon.[27]

[26]In rural India, the minimum nutritional requirement for a typical adult is usually set at 2,400 calories per day (though some studies set it as low as 1,800), out of which about 70% come from cereals and rice in particular (Deaton and Drèze, 2009). Therefore, beyond a yearly per-capita production of 135 kg of raw rice (corresponding to a daily per-capita consumption of 0.4 kg, or about 1,300 calories), a household can be roughly considered self-sufficient and net seller. In practice, I compute a measure of rice production per capita, normalizing household size by the equivalence scale suggested by Townsend (1994). I then construct a sufficiency gap ratio for each household as: $\max\left(0; \frac{135 - per\_capita\_rice\_production}{135}\right)$. On average, households in the sample are 44% below the self-sufficiency threshold.

[27]In appendix B, I show that local agricultural prices react mildly to local rain conditions, reflecting the relatively 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 infrastructure to store rice from one year to the next. Following a 10% decrease in local monsoon rainfall, the local farm-gate price of rice (received by producers) increases by 3% on average (its market price – measured several weeks later – increasing by a lower 0.4%), while the local market prices of tomatoes and onions decrease by 4% and 1% respectively – reflecting the fact that rice and vegetables are complement and that vegetables are superior goods in the context (see table 15). However, it is clear that these modest price effects will far from compensate the large quantity variations, even for the few net sellers in the sample.

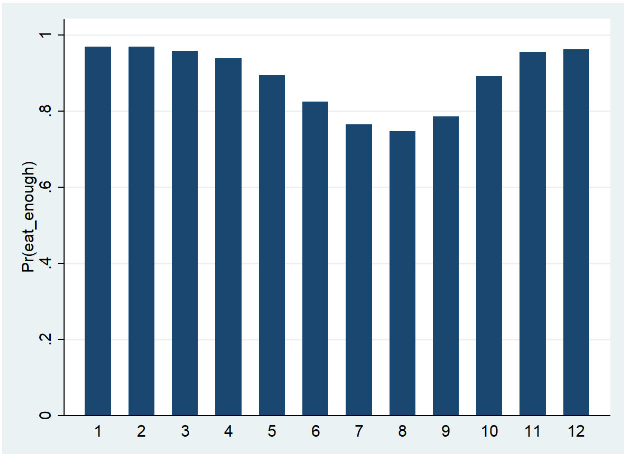
Table 2: Rice production

	(1)	(2)	(3)	(4)	(5)	(6)
	Log yields (kg/acre)		Sufficiency gap ratio		Proportion sold	
Relevant monsoon episode:			*t*			
A. Log rainfall						
Rain	0.329**	0.355**	-0.0398	-0.0429	0.0184	0.0220
	(0.148)	(0.156)	(0.0466)	(0.0476)	(0.0145)	(0.0150)
$Rain * Treat$	-0.116	-0.115	-0.0432	-0.0287	-0.0109	-0.0145
	(0.167)	(0.177)	(0.0527)	(0.0544)	(0.0151)	(0.0157)
B. Negative rainfall shock (drought)						
$Rain\_shock$	-0.204***	-0.210***	0.0500**	0.0439*	-0.0145**	-0.0151**
	(0.0752)	(0.0790)	(0.0225)	(0.0236)	(0.00685)	(0.00714)
$Rain\_shock * Treat$	0.121	0.118	0.00968	0.0102	0.00237	0.00340
	(0.0879)	(0.0928)	(0.0265)	(0.0276)	(0.00738)	(0.00787)
Village FE	yes	no	yes	no	yes	no
Household FE	no	yes	no	yes	no	yes
Observations	2421	2424	3189	3193	2444	2448
Mean of dep. var. in control group	741	741	0.41	0.41	0.02	0.02
Mean of dep. var. in treated group	671	671	0.45	0.45	0.03	0.03

OLS estimation. Std errors clustered at the household level in parentheses (*p<0.10, **p<0.05, ***p<0.01).
Observations are weighted in order to account for different sampling probabilities.
All equations include a constant, round (time) fixed effects, and household controls / family size (with hh. FE).
sufficiency gap ratio is calculated for each household as: $\max\left(0; \frac{135 - per\_capita\_rice\_production}{135}\right)$.

Building on the previous discussion, and remembering that Jharkhand is the Indian state with the second highest level of hunger and malnutrition prevalence (Menon et al., 2008), a key dimension of household welfare in case of rain shocks is food security. Ideally, in order to study intra-year variation of food security, weekly or at least monthly food consumption – especially regarding the lean season – would be needed. Unfortunately, given that the three surveys took place once year in January-March, i.e. right after the kharif harvest, the food consumption data of this study are not really able to capture those effects. Yet, the questionnaire did ask about food security throughout the year: for each month of the year preceding the survey, households were asked if there was enough to eat, s.t. all members could enjoy 3 meals per day. Households declare having enough food during 10.7 months per year on average, with 34% of them suffering hunger for at least one month. As can be seen clearly from figure 3, food security decreases gradually with the time since the last rice harvest, reaching its lowest in the June-September period – which, as explained above, corresponds to the bridge period where the income shock is expected to hit the strongest.

Figure 3: Food security across months



Data: own household survey (3 waves pooled).

Table 3 shows that food security depends heavily on monsoon abundance, with an estimated average elasticity of 0.5. However, it is significantly more stable for treated households, who are suffering about half less variation of food consumption on average. After a negative shock in particular, control households lose on average 1.6 months of adequate food, while the loss is limited to about 0.9 month for treated households (a 59% reduction). Columns 3 and 4 report on the consumption of animal proteins during the week before the survey.[28] Unlike staple (rice) consumption, such superior goods can be expected to be affected even a few weeks after harvest, through harvest-determined cash earnings from rice sales

[28]Animal proteins include eggs, fish and different types of meat. I compute the monetary value of aggregate consumption using village median of reported prices.

or expectations of lower future income (future need to buy cereals on the market). Animal protein consumption is low in the sample, with only 35% reporting a positive quantity. I find that it strongly depends on monsoon, with an estimated elasticity of almost 2. This is likely to have important impacts on nutritional status (though I have no data to check the persistence of such consumption over the year). Here again, treated households enjoy a much more stable consumption, especially after a negative shock.

Hence, it appears that SHGs help households to ensure an adequate and smoother level of food consumption across months when harvests are low and prices high. This in turn can have large health and economic benefits over the long-run given the adverse consequences of food consumption volatility (e.g. Branca et al., 1993; Alderman et al., 2006; Dercon and Sanchez, 2008; Maluccio et al., 2009; Rao et al., 2009; Ampaabeng and Tan, 2013). The next sections are devoted to explaining how treated households manage to smooth food consumption after a drought, despite suffering as severe agricultural losses.

6 Credit

This section focuses on credit, which is expected to be an important channel through which the consumption-smoothing 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 all loans taken during the two years preceding each survey wave, including the date of borrowing, which will be useful to identify mechanisms.Indeed, credit might be taken 'immediately' after rain shocks, for

Table 3: Food security

	(1)	(2)	(3)	(4)
	Months with enough food		Log animal protein cons. (+1)	
Relevant monsoon episode:	*t-1*		*t*	
A. Log rainfall				
$Rain$	4.518***	4.706***	1.965***	1.741***
	(0.786)	(0.812)	(0.505)	(0.508)
$Rain * Treat$	-1.847**	-2.319***	-0.984*	-0.842
	(0.863)	(0.885)	(0.577)	(0.585)
B. Negative rainfall shock (drought)				
$Rain\_shock$	-1.564***	-1.554***	-0.963***	-0.844***
	(0.267)	(0.268)	(0.269)	(0.270)
$Rain\_shock * Treat$	0.559**	0.636**	0.627**	0.578*
	(0.282)	(0.282)	(0.315)	(0.320)
Village FE	yes	no	yes	no
Household FE	no	yes	no	yes
Observations	3169	3173	3189	3193
Mean of dep. var. in control group	10.6	10.6	1130	1130
Mean of dep. var. in treated group	10.8	10.8	1180	1180

OLS estimation. Std errors clustered at the household level in parentheses (*p<0.10, **p<0.05, ***p<0.01).
Observations are weighted in order to account for different sampling probabilities.
All equations include a constant, round (time) fixed effects, and household controls / family size (with hh. FE).
Animal protein consumption is the annualized monetary value of eggs, fish and meat consumption.

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). On the other hand, lenders might be reluctant to grant credit if they expect lower future incomes for borrowers or themselves. Moreover, credit can be very useful one year after, i.e. during the following lean season. As explained above, it corresponds to the hungry period in rural Jharkhand, when the relative scarcity is the highest, 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, given that the major traditional sources of credit are relatives and bigger farmers from the same community. Moreover, given that traditional lenders often require to start repaying immediately, it might be harder to take credit after a bad shock.

As a consequence, households are expected to need more credit in the second half of the year, at least in reaction to rainfall shocks. In the data, the average probability to borrow between January and May is 28%, against 47% between June and December. The analysis below will therefore focus on that relevant period. On average, households take 1,230 INR of credit between June and December, corresponding to about 6% of total annual income (the sum of all remunerations received plus the net value of agricultural production over the year).

Table 4 displays immediate and lean-season treatment effects for both the probability to borrow and the total amount borrowed (both outcomes deliver similar insights, indicating that most of the action takes place at the extensive margin).[29]

[29]Because the distribution of credit is right-skewed and presents an important mass at zero, I regress the log of amounts plus one. Alternative estimation techniques, such as a Poisson regression on levels, give very similar results. In appendix C, I show that results are virtually

What comes out very clearly is that access to credit is extremely volatile for control households and stable for treated households, and that the effects are, as expected, much stronger for the lean-season period. For control households, I estimate a 1.4 elasticity between rainfall and amounts borrowed in the immediate period, which doubles to 3 in the lean season – indicating that credit is divided by 3 one year after a monsoon that was just 20% below average. By contrast, treated households appear to enjoy a very stable, slightly countercyclical, access to credit, as their coefficient more than compensates controls'. When focusing on negative shocks, I estimate that a drought leads one year later to a probability of borrowing that is 18 percentage points (more than 40%) lower for control households and 4 percentage points *higher* for treated households.

Table 4: Credit (June to December)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Borrowing probability				Log total credit (+1)			
	Immediately		Lean season		Immediately		Lean season	
Relevant monsoon episode:	t		t-1		t		t-1	
A. Log rainfall								
Rain	0.214***	0.218***	0.544***	0.495***	1.453**	1.449**	3.359***	2.908**
	(0.0798)	(0.0810)	(0.164)	(0.168)	(0.600)	(0.605)	(1.146)	(1.159)
$Rain * Treat$	-0.221**	-0.220**	-0.584***	-0.559***	-1.698***	-1.636**	-3.731***	-3.423***
	(0.0861)	(0.0879)	(0.168)	(0.172)	(0.642)	(0.651)	(1.155)	(1.166)
B. Negative rainfall shock (drought)								
$Rain\_shock$	-0.145***	-0.143***	-0.182***	-0.183***	-0.958***	-0.917***	-1.183***	-1.176***
	(0.0419)	(0.0423)	(0.0578)	(0.0588)	(0.315)	(0.318)	(0.422)	(0.430)
$Rain\_shock * Treat$	0.139***	0.137***	0.218***	0.223***	0.970***	0.919***	1.414***	1.414***
	(0.0462)	(0.0468)	(0.0546)	(0.0553)	(0.344)	(0.347)	(0.385)	(0.389)
Village FE	yes	no	yes	no	yes	no	yes	no
Household FE	no	yes	no	yes	no	yes	no	yes
Observations	3189	3193	3189	3193	3188	3192	3188	3192
Mean of dep. var. in control group	0.396	0.396	0.396	0.396	1340	1340	1340	1340
Mean of dep. var. in treated group	0.488	0.488	0.488	0.488	1203	1203	1203	1203

OLS estimation. Std errors clustered at the household level in parentheses (*p<0.10, **p<0.05, ***p<0.01).
Observations are weighted in order to account for different sampling probabilities.
All equations include a constant, round (time) fixed effects, and household controls / family size (with hh. FE).

unchanged when rain in t and t-1 are included in the same equation ('horse-race' specification).

In sum, while the access to credit is strongly pro-cyclical for poor households in Indian villages, the presence of SHGs ensures a stable, potentially counter-cyclical, access. Given that the need for credit is theoretically inversely related to last year's rainfall quantity, the observed relation in control villages suggests credit rationing from informal lenders. As a matter of fact, more than half of the loans to non-SHG members come from neighbors and relatives (see table 16 in B), 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 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, SHG members take the overwhelming majority of their loans from SHGs, and their credit availability is 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.

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 2, the main reasons are 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, and that such pool is being complemented by external loans from commercial banks.[30] 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 that

[30] In appendix B, I provide further evidence about the resilience of SHGs. First, I show that, even after a bad monsoon, members keep saving regularly and the modal behavior remains taking out roughly the same amount of annual credit than one's own annual savings. Second, I show that repayment rates on SHG loans keep being high after shocks, but that there is higher flexibility in the form of delays.

can meet most individual credit needs thanks to the collection of regular deposits and borrowing from commercial banks.

The availability of credit in periods of covariate income shocks is all the more important that private transfers also dry up in those periods. The questionnaire asked about all transfers received and given, in cash or kind, from/to any other household. In table 5, 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, with an average loss of 30%. Transfers given, lower to start with, shrink even more, by 70% on average. This is strongly indicative evidence that informal insurance mechanisms fail to cope with such shocks in the villages of the sample, which is expected since most households are affected. Moreover, the fact that treated households are as affected as control households seem to suggest that there is neither crowding out nor crowding in of informal insurance in this context.

Table 5: Private transfers

	Means in case of		
	no rain shock in t-1	rain shock in t-1	P-value†
A. All households			
Transfers received	3,116	2,314	0.008
Transfers given	897	283	0.000
Net transfers	2,215	2,030	0.578
Observations	2314	872	
B. Treated households			
Transfers received	3,008	2,277	0.024
Transfers given	906	241	0.000
Net transfers	2,088	2,040	0.895
Observations	1850	694	

† Two-sided t-test for difference in means.

I now try to link explicitly credit availability and food security after income shocks. First, although credit is of course fungible, the questionnaire recorded borrowing purposes, grouped into 6 broad categories: consumption, business /

work, health, education, social events, other. The three first categories represent the bulk of declared purposes. It is interesting to note that the proportion of credit for consumption purpose (out of total credit) goes up very significantly one year after a drought, from 23 to 34%, well above any other category (see table 6). That is, in case of shocks, households borrow mostly to finance consumption, which becomes the first motive.

Table 6: Distribution of loan purposes

	Means in case of		
	no rain shock in t-1	rain shock in t-1	P-value†
Proportion of credit for...			
consumption	0.228	0.339	0.000
business / work	0.303	0.296	0.771
health	0.331	0.282	0.054
education + social + other	0.129	0.077	0.002
Observations	1037	457	

† Two-sided t-test for difference in means.

Second, in appendix B, I replicate table 4 focusing only on credit for a consumption purpose (see table 18). The estimated treatment effect for the lean season increases (and disappears for the immediate period, during which food security is not an issue). Finally, despite obvious endogeneity concerns, I plug credit in the food security equation. In order to be as close as possible to the causal mechanism, I focus on negative shocks and credit taken between June and September, i.e. the hungry months identified in figure 3. The two first columns of table 7 show that credit significantly helps achieving higher food security after a drought. Columns 3 and 4 show that the estimated treatment effect is lower once controlled for credit, suggesting that at least part of it indeed goes through this credit channel. Yet, there remains an independent treatment effect, which indicates that there are other channels at play.

Table 7: Food security and credit

	(1)	(2)	(3)	(4)
Relevant monsoon episode:			*t-1*	
$Rain\_shock$	-1.659***	-1.850***	-2.046***	-2.273***
	(0.283)	(0.306)	(0.338)	(0.355)
$Rain\_shock * Treat$			0.531*	0.603**
			(0.283)	(0.283)
$Credit\_junsep$	-0.0379**	-0.0710***	-0.0388**	-0.0726***
	(0.0183)	(0.0249)	(0.0183)	(0.0249)
$Credit\_junsep * Rain\_shock$	0.123**	0.181***	0.116**	0.171***
	(0.0483)	(0.0548)	(0.0486)	(0.0554)
Village FE	yes	no	yes	no
Household FE	no	yes	no	yes
Observations	3168	3172	3168	3172
Mean of dep. var. in control group	10.6	10.6	10.6	10.6
Mean of dep. var. in treated group	10.8	10.8	10.8	10.8

OLS estimation. Std errors clustered at the household level in parentheses (*p<0.10, **p<0.05, ***p<0.01).
Observations are weighted in order to account for different sampling probabilities.
All equations include a constant, round (time) fixed effects, and household controls / family size (with hh. FE).
$Credit\_junsep$ is the log of the sum of all amounts borrowed in June to September last year (+1).

Such additional channels might include the adoption of risk-mitigating strategies. As a matter of fact, credit needs to be repaid and is therefore only a temporary solution, offering liquidity during the most constrained season. Hence, alternative income-generating activities must be developed in order to sustain a higher level of consumption. In this respect, it is interesting that credit for business /work purposes, unlike consumption credit, responds much more strongly immediately after a bad monsoon than during the lean season (see table 19 in appendix B). Such credit might help financing risk-mitigating activities in expectation of the future income shock.

7 Labor supply and seasonal migration

This section focuses on labor supply decisions as a way to diversify sources of income and mitigate expected agricultural income shocks. Many households complement agricultural income with some kind of off-season labor activity, such as casual labor or handicraft. In my sample, only 10% of households perform exclusively a farming activity. Given the limited options at home, casual labor activities often have to take place away from the village, through seasonal migration. Therefore, the two issues of labor supply and migration are closely linked.

Seasonal migration in Jharkhand mostly takes place in post-monsoon winter months (September-November) and/or in the post-harvest summer months (March-June). It can be distress migration, especially in winter months one year after a bad monsoon, when food availability is lowest as food stock is depleted and the next harvest is still several months away (*ex-post coping strategy*). For some households, it can also be a recurrent, planned strategy to complement agricultural income (*ex-ante risk-mitigating strategy*). Yet, many households of our sample do not migrate: on average, only 14% of the households send at least one migrant in any year.

The foremost reason is that migration involves many different costs. There are direct, monetary costs that are both fixed, such as transportation costs, and variable, such as living costs (Gollin et al., 2014; Angelucci, 2015; Bryan and Morten, 2019). There are also indirect, opportunity costs, such as not being able to cultivate one's own agricultural land – though, as explained above, seasonal migration in the study area mostly happens during the off-season. Another source of utility cost associated with migration is income risk: migrants may not find work at destination or may have to work for lower wages than expected (Harris and Todaro, 1970; Bryan et al., 2014). Finally, there are non-monetary cost for migrants, reflecting a preference for staying in the village because of material reasons (e.g. safety, comfort, collective support, control over household members) or psychological reasons (e.g. ambiguity or loneliness aversion, habits, socio-cultural norms). Several studies have shown in similar contexts that those non-monetary costs can be very large and might in fact represent the main barrier to migration (Lagakos et al., 2018; Imbert and Papp, 2020).

Seasonal migrants in the sample are defined as household members who have been out of the household in order to work for maximum six months during the year preceding the survey. Table 8 presents some basic statistics at the migrant-level. 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. In terms of occupation, the big majority (70%) are casual wage workers outside agriculture (at brick kilns, construction sites, etc.). Seasonal migration appears to be profitable: migrants get an average daily wage of 66 rupees, which compares favorably with the average daily wage of 56 rupees that laborers get at home (median wages are respectively 60 vs. 50). Yet, it is also riskier: the coefficient of variation of migrants' wage is 54%, against 45% for non-migrant laborers. The median total income earned during migration is 5,000 rupees, but a non-trivial fraction (7%) of labor migrants fail to earn any income, which highlights again the riskiness of the migration enterprise. At the end of the migration spell, each migrant brings back home remittances of about 3,200 rupees on average (in addition to what might have been potentially transfered while away). Finally, the big majority of migrants (79%) are males, and are either the head of the household (31% of the cases) or a son (48% of the cases).

In table 9, I show that treated households supply significantly more labor (out-

Table 8: Seasonal labor migration: descriptive statistics

	Mean (std dev.)	Median	Min	Max
Duration (months)	3.4 (1.5)	4	1	6
Daily wage (INR)	65.7 (35.3)	60	0	300
Total income earned abroad (hundreds INR)	59.54 (47.29)	50	0	360
Remittances brought home (hundreds INR)	30.16 (34.07)	20	0	42

Migrant-level data (587 observations).

side of their farm), which translates into higher labor income, immediately after witnessing a bad monsoon. As explained above, such wage work is mostly performed through seasonal migration, which is shown in table 10. While control households do not (or cannot) increase migration, treated households are 5 percentage points (35%) more likely to migrate, and enjoy a more than 40% increase in total migration income and remittances the year of a bad monsoon.

Table 9: Labor supply

	(1)	(2)	(3)	(4)
	Number of laborers		Log labor income	
Relevant monsoon episode:			t	
A. Log rainfall				
$Rain$	0.0494	0.0527	0.0154	0.0512
	(0.174)	(0.175)	(0.135)	(0.134)
$Rain * Treat$	-0.318	-0.313	-0.315**	-0.265*
	(0.194)	(0.195)	(0.153)	(0.152)
B. Rainfall shock				
$Rain\_shock$	-0.118	-0.105	-0.0453	-0.0648
	(0.0900)	(0.0897)	(0.0739)	(0.0723)
$Rain\_shock * Treat$	0.204**	0.213**	0.142*	0.146*
	(0.103)	(0.102)	(0.0860)	(0.0856)
Village FE	yes	no	yes	no
Household FE	no	yes	no	yes
Observations	3189	3193	2845	2848
Mean of dep. var. in control group	1.81	1.81	14,558	14,558
Mean of dep. var. in treated group	1.82	1.82	15,333	15,333

OLS estimation.
Std errors clustered at the household level in parentheses (*p<0.10, **p<0.05, ***p<0.01).
Observations are weighted in order to account for different sampling probabilities.
All equations include a constant, round (time) fixed effects and hh. controls / size (with hh. FE).

The above findings indicate that treated households are much better able to

Table 10: Seasonal migration

	(1)	(2)	(3)	(4)	(5)	(6)
	Migration probability		Log total mig. income (+1)		Log total remittances (+1)	
Relevant monsoon episode:				t		
A. Log rainfall						
Rain	0.0381	0.0321	0.400	0.355	0.375	0.307
	(0.0459)	(0.0463)	(0.418)	(0.424)	(0.376)	(0.379)
$Rain * Treat$	-0.0885*	-0.0921*	-0.710	-0.704	-0.657	-0.665
	(0.0501)	(0.0506)	(0.449)	(0.456)	(0.406)	(0.411)
B. Rainfall shock						
$Rain\_shock$	-0.0274	-0.0203	-0.277	-0.224	-0.291	-0.233
	(0.0246)	(0.0248)	(0.220)	(0.222)	(0.198)	(0.200)
$Rain\_shock * Treat$	0.0455	0.0490*	0.409*	0.426*	0.448**	0.467**
	(0.0278)	(0.0281)	(0.247)	(0.250)	(0.224)	(0.227)
Village FE	yes	no	yes	no	yes	no
Household FE	no	yes	no	yes	no	yes
Observations	3189	3193	3188	3192	3188	3192
Mean of dep. var. in control group	0.133	0.133	984	984	421	421
Mean of dep. var. in treated group	0.141	0.141	1129	1129	569	569

OLS estimation. Std errors clustered at the household level in parentheses (*p<0.10, **p<0.05, ***p<0.01).
Observations are weighted in order to account for different sampling probabilities.
All equations include a constant, round (time) fixed effects, and household controls / family size (with hh. FE).

diversify income sources through seasonal migration in order to mitigate future income shocks, which echoes the results of Bryan et al. (2014). It is natural to think that those additional earnings from wage activities abroad explain another part of the higher food security observed in section 5. Although I have no data about food security during the year following the detected increase in migration, a back-of-the-envelope calculation shows that the estimated migration treatment effect after a drought implies that the income of treated households increases by 450 INR on average thanks to seasonal migration, which roughly corresponds to half a month of food.[31]

This is likely to be another positive consequence of credit availability (see previous section), though some other aspects of SHGs are probably at work too. First, credit might help treated households to pay for the direct sunk costs of migration,

[31] In the sample, the modal monthly expenditures on food are 789 INR.

even though I showed that the strongest credit effects were not observed immediately after rain shocks but rather during the lean season.[32] Indeed, I do find evidence of a direct effect of credit on migration (see table 20 in appendix). As in the case of food security, credit seems to explain a share of the treatment effect, though not all (table 21). Second, higher *expected* availability of credit in treated villages might also be very important to reduce the important income risk from migration (such as in Bryan et al., 2014). For instance, SHGs can act as consumption credit, informal insurance and support providers for women left behind, in case migrating husbands fail to send money for some time. Unfortunately, it is harder to show evidence about this channel involving expectations and depending on migration failure.

A third effect of SHGs, going beyond credit, might be to decrease non-monetary costs of migration through network and peer effects, which have been shown to matter a lot in migration decisions (McKenzie and Rapoport, 2010; Hiwatari, 2016; Chort, 2017; Kinnan et al., 2018). For instance, (husbands of) SHG members could migrate together or share contacts and tips at destination. In table 11, I show that the probability to migrate is strongly positively correlated with the own experience of previous migration (row 1), which seems to come partly from learning by previously non-migrating households (row 2). It is also strongly positively correlated with the existence of a migration network at the village level (row 3), confirming the importance of peer effects in migration decisions. The village network matters non only contemporaneously but seem to persist over time (row 4), pointing again at the importance of experience and learning (from peers in this case). Moreover,

[32]Interestingly, I find a small and insignificant treatment effect on migration or labor during the lean season, which would correspond to 'desperate' reactions occurring *after* being hit by the income shock.

the households who are members of SHGs seem to benefit greatly from an additional network, composed of the other members of their particular group (rows 5 and 6). The treatment is therefore expected to have increased migration by making own experimentation and learning easier, as well as by expanding peer networks (as another source of learning, through information exchange and imitation).[33] This is likely to explain another share, potentially large, of the treatment effect. Finally, SHGs could act as 'monitoring' devices during husbands' absence, thus encouraging migration (such as in Chen, 2006; de Laat, 2014), though I have no evidence supporting this hypothesis.[34]

Table 11: Probability to migrate: correlation matrix

Sample:	All waves	2 last waves
(1) Someone in hh. migrated in previous wave	-	0.153 (0.000)
(2) Someone in hh. migrated in R2 but nobody migrated in R1[†]	-	0.073 (0.042)
(3) Proportion of hh. in village who migrated in current wave[‡]	0.189 (0.000)	0.169 (0.000)
(4) Proportion of hh. in village who migrated in previous wave[‡]	-	0.062 (0.004)
SHG members only:		
(5) Someone in same SHG migrated in current wave[‡]	0.138 (0.000)	0.132 (0.000)
(6) Someone in same SHG migrated in previous wave[‡]	-	0.072 (0.022)

Significance level (p-value) between parentheses. [†] Estimated on last wave only. [‡] Excluding current household.

[33]Several studies have shown the importance of giving the opportunity to households to experiment with effective but uncertain technologies to boost adoption rates (e.g. Foster and Rosenzweig, 1995; Dupas, 2014; Bryan et al., 2014). The particular role of peer effects has been highlighted in Bandiera and Rasul (2006) and Conley and Udry (2010), among others.

[34]Related to this point, Bargain et al. (2020) show that, in Indonesia, male migration is higher in households where the wife's bargaining power is stronger because limited commitment issues are less binding in that case. A number of papers in the literature have pointed out that, because of the support of the group, improved financial capacities and the ability to formulate individual projects, female empowerment is a major consequence of the participation to SHGs (e.g. Desai and Joshi, 2013; Deininger and Liu, 2013; Datta, 2015; Baland et al., 2019, 2020).

8 Conclusion

In developing countries, most poor households experience a large income volatility 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, and of 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 very little direct empirical evidence about the impact of microcredit on the possibility to cope with (climate-related) income shocks.

The present paper studies how does the monsoon quality affect credit access, seasonal migration and food security of rural households in Jharkhand, East India, and what is the impact of Self-Help Groups (SHGs) in this context. SHGs are groups of women from the same village and homogeneous backgrounds, who voluntarily come together to save and borrow small amounts on a regular basis. To answer this question, the paper combines meteorological data with original panel data from a long-run field experiment that randomized access to SHGs at the village level and measured changes in the living standards of a sample of households between 2004 and 2009.

I show that all households' agricultural production and income are very sensitive to monsoon deficits, which represent 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 lean season following a bad monsoon, I find that treated households enjoy a stable access to credit over time. Hence, 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. I then show that treated households increase seasonal migration immediately after the realization of a bad monsoon, in order to mitigate the future agricultural income shock through temporary profitable occupations away from home. Such migration is a direct result of SHG credit, which facilitates the payment of sunk costs and attenuates the income risk related to migration. It also results from a side-effect of SHGs, which is that they constitute peer networks in which information exchanges and collective experimentation can take place. Finally, I find that the combination of SHG credit and migration earnings allow treated households to 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 two very important and topical issues: dealing with climatic shocks and encouraging seasonal migration. It shows that SHGs are useful and effective credit instruments for rural households, which appear very resilient to covariate weather shocks. Even though they are not designed as insurance tools, they offer significant seasonal smoothing possibilities to members, with potentially large 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, given that weather shocks are ubiquitous and expected to increase in future due to climate change, with very important health and economic consequences for millions of poor farmers. 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 design new formal insurance products for poor small-scale farmers in developing countries – which are likely to remain too costly, complex, rigid and risky in most cases –, building on the success of local credit and savings associations such as SHGs may be a better option. In particular, there may be ways to change the way microcredit operates, at the margin, to further improve households' risk management. 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.

References

Alderman, Harold, John Hoddinott, and Bill Kinsey, "Long term consequences of early childhood malnutrition," *Oxford Economic Papers*, July 2006, *58* (3), 450–474.

Ampaabeng, Samuel K. and Chih Ming Tan, "The long-term cognitive consequences of early childhood malnutrition: The case of famine in Ghana," *Journal of Health Economics*, 2013, *32* (6), 1013–1027.

Angelucci, Manuela, "Migration and Financial Constraints: Evidence from Mexico," *The Review of Economics and Statistics*, March 2015, *97* (1), 224–228.

Asada, Haruhisa and Jun Matsumoto, "Effects of rainfall variation on rice production in the Ganges-Brahmaputra Basin," *Climate Research*, 2009, *38*, 249–260.

Baland, Jean-Marie, Rohini Somanathan, and Lore Vandewalle, "Socially disadvantaged groups and microfinance in India," *Economic Development and Cultural Change*, 2019, *67* (3), 537–569.

_ , Timothée Demont, and Rohini Somanathan, "Child Education and Labour Decisions of Long-Run Microfinance Participants in Rural India," *Economic Development and Cultural Change*, October 2020, *forthcoming.*

Bandiera, Oriana and Imran Rasul, "Social Networks and Technology Adoption in Northern Mozambique," *Economic Journal*, October 2006, *116* (514), 869–902.

Bargain, Olivier, Jordan Loper, and Roberta Ziparo, "Women's Empowerment and Husband's Migration: Evidence from Indonesia," Working Paper, AMSE 2020.

Beaman, Lori, Dean S. Karlan, and Bram Thuysbaert, "Saving for a (not so) Rainy Day: A Randomized Evaluation of Savings Groups in Mali," CEPR Discussion Papers 10206, C.E.P.R. Discussion Papers October 2014.

Beegle, Kathleen, Rajeev H. Dehejia, and Roberta Gatti, "Child labor and agricultural shocks," *Journal of Development Economics*, October 2006, *81* (1), 80–96.

Branca, F, G Pastore, T Demissie, and A Ferro-Luzzi, "The nutritional impact of seasonality in children and adults of rural Ethiopia," *European journal of clinical nutrition*, December 1993, *47* (12), 840—850.

Bryan, Gharad and Melanie Morten, "The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia," *Journal of Political Economy*, 2019, *127* (5), 2229–2268.

_ , Shyamal Chowdhury, and Ahmed Mushfiq Mobarak, "Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh," *Econometrica*, 2014, *82* (5), 1671–1748.

Casini, Paolo, Lore Vandewalle, and Zakhi Wahhaj, "Public Good Provision in Indian Rural Areas: the Returns to Collective Action by Microfinance Groups," *World Bank Economic Review*, August 2015, *lhv041*, 1–41.

CGAP, "Sustainability of Self-Help Groups in India: two analyses," Occasional Paper 12, Consultative Group to Assist the Poor August 2007.

Chen, Joyce J., "Migration and Imperfect Monitoring: Implications for Intra-Household Allocation," *American Economic Review*, May 2006, *96* (2), 227–231.

Chort, Isabelle, "Migrant Network and Immigrants' Occupational Mismatch," *The Journal of Development Studies*, 2017, *53* (11), 1806–1821.

Cole, Shawn, Andrew Healy, and Eric Werker, "Do voters demand responsive governments? Evidence from Indian disaster relief," *Journal of Development Economics*, 2012, *97* (2), 167 – 181.

_ **, Xavier Gine, Jeremy Tobacman, Petia Topalova, Robert Townsend, and James Vickery**, "Barriers to household risk management : evidence from India," *American Economic Journal: Applied*, 2013, *5* (1), 104–135.

Conley, Timothy G. and Christopher R. Udry, "Learning about a New Technology: Pineapple in Ghana," *American Economic Review*, March 2010, *100* (1), 35–69.

Cruz, R.V., H. Harasawa, M. Lal, S. Wu, Y. Anokhin, B. Punsalmaa, Y. Honda, M. Jafari, C. Li, and N. Huu Ninh, "Asia," in M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden, and C.E. Hanson, eds., *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge University Press, 2007, pp. 469–506.

Datta, Upamanyu, "Socio-Economic Impacts of JEEViKA: A Large-Scale Self-Help Group Project in Bihar, India," *World Development*, 2015, *68*, 1 – 18.

Dave, Harishkumar R. and Hans Dieter Seibel, "Commercial Aspects of Self-Help Group Banking in India: A Study of Bank Transaction Costs," Working Papers 2002,7, University of Cologne, Development Research Center 2002.

de Laat, Joost, "Household allocations and endogenous information: The case of split migrants in Kenya," *Journal of Development Economics*, 2014, *106* (C), 108–117.

Deaton, Angus and Jean Drèze, "Food and Nutrition in India: Facts and Interpretation," *Economic & Political Weekly*, 2009, *XLIV* (7), 42–65.

Deininger, Klaus and Yanyan Liu, "Economic and Social Impacts of an Innovative Self-Help Group Model in India," *World Development*, 2013, *43* (C), 149–163.

Demirgüç-Kunt, Asli, Leora Klapper, Dorothe Singer, Saniya Ansar, and Jake Hess, "Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution," Technical Report, The World Bank 2018.

Dercon, Stefan, "Growth and shocks: evidence from rural Ethiopia," *Journal of Development Economics*, August 2004, *74* (2), 309–329.

_ **and Alan Sanchez**, "Children and the Food Price Crisis.," Young Lives Policy Brief 5, University of Oxford September 2008.

_ **and Pramila Krishnan**, "In Sickness and in Health: Risk Sharing within Households in Rural Ethiopia," *Journal of Political Economy*, August 2000, *108* (4), 688–727.

_ **, John Hoddinott, and Tassew Woldehanna**, "Shocks and Consumption in 15 Ethiopian Villages, 1999–2004," *Journal of African Economies*, December 2005, *14* (4), 559–585.

Desai, Raj M. and Shareen Joshi, "Collective Action and Community Development: Evidence from Self-Help Groups in Rural India," *The World Bank Economic Review*, 2013.

Dupas, Pascaline, "Short-Run Subsidies and Long-Run Adoption of New Health Products: Evidence From a Field Experiment," *Econometrica*, January 2014, *82* (1), 197–228.

Fafchamps, Marcel and Susan Lund, "Risk-sharing networks in rural Philippines," *Journal of Development Economics*, August 2003, *71* (2), 261–287.

FAO, "Climate Change and Food Security: Risks and Responses," Technical Report, Rome: FAO 2016.

Foster, Andrew D and Mark R Rosenzweig, "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture," *Journal of Political Economy*, December 1995, *103* (6), 1176–1209.

Gadgil, Sulochana and K. Rupa Kumar, "The Asian monsoon - agriculture and economy," in Bin Wang, ed., *The Asian Monsoon*, Berlin, Heidelberg: Springer Praxis Book, 2006, pp. 651–683.

— **and Siddhartha Gadgil**, "The Indian Monsoon, GDP and Agriculture," *Economic and Political Weekly*, November 2006, *41* (47), 4887–4895.

Gaiha, Raghav and Mani Arul Nandhi, "Microfinance, Self-Help Groups and Empowerment in Maharashtra," in Raghbendra Jha, ed., *The Indian Economy Sixty Years After Independence*, London: Palgrave Macmillan UK, 2008, pp. 179–199.

Gaurav, Sarthak, "Are Rainfed Agricultural Households Insured? Evidence from Five Villages in Vidarbha, India," *World Development*, 2015, *66* (C), 719–736.

Gollin, Douglas, David Lagakos, and Michael E. Waugh, "The Agricultural Productivity Gap," *The Quarterly Journal of Economics*, 2014, *129* (2), 939–993.

Government of India, "Climate, Climate Change and Agriculture (chapter 6)," in "Economic Survey of India, 2017-18" 2018.

Groppo, Valeria and Kati Kraehnert, "Extreme Weather Events and Child Height: Evidence from Mongolia," *World Development*, 2016, *86* (C), 59–78.

Hallegatte, Stephane, Adrien Vogt-Schilb, Mook Bangalore, and Julie Rozenberg, *Unbreakable : Building the Resilience of the Poor in the Face of Natural Disasters*, Washington, DC: World Bank, 2017.

Harris, John R and Michael P Todaro, "Migration, Unemployment & Development: A Two-Sector Analysis," *American Economic Review*, March 1970, *60* (1), 126–142.

Hiwatari, Masato, “Social networks and migration decisions: The influence of peer effects in rural households in Central Asia,” *Journal of Comparative Economics*, 2016, *44* (4), 1115–1131.

Imbert, Clement and John Papp, “Costs and Benefits of Rural-Urban Migration: Evidence from India,” *Journal of Development Economics*, 2020, *forthcoming.*

IPCC, “Climate Change 2014: Impacts, Adaptation, and Vulnerability,” in Intergovernmental Panel on Climate Change, ed., *Fifth Assessment Report*, Cambridge University Press, 2014.

Islam, Asadul and Pushkar Maitra, “Health shocks and consumption smoothing in rural households: Does microcredit have a role to play?,” *Journal of Development Economics*, 2012, *97* (2), 232 – 243.

Jacoby, Hanan G and Emmanuel Skoufias, “Risk, Financial Markets, and Human Capital in a Developing Country,” *Review of Economic Studies*, July 1997, *64* (3), 311–35.

Jensen, Robert, “Agricultural Volatility and Investments in Children,” *American Economic Review*, May 2000, *90* (2), 399–404.

Kabeer, Naila and Helzi Noponen, “Social and economic impacts of PRADAN’s Self-Help Group Microfinance and Livelihoods Promotion Program,” Working Paper 11, Imp-Act March 2005.

Kaboski, Joseph P. and Robert M. Townsend, "Policies and Impact: An Analysis of Village-Level Microfinance Institutions," *Journal of the European Economic Association*, 03 2005, *3* (1), 1–50.

Karlan, Dean and Jonathan Zinman, "Expanding Credit Access: Using Randomized Supply Decisions to Estimate the Impacts," *Review of Financial Studies*, 2010, *23* (1).

_ , Robert Osei, Isaac Osei-Akoto, and Christopher Udry, "Agricultural Decisions after Relaxing Credit and Risk Constraints," *The Quarterly Journal of Economics*, 2014, *129* (2), 597–652.

Kazianga, Harounan and Christopher Udry, "Consumption smoothing? Livestock, insurance and drought in rural Burkina Faso," *Journal of Development Economics*, April 2006, *79* (2), 413–446.

Khandker, Shahidur R., M.A. Baqui Khalily, and Hussain A. Samad, "Seasonal Migration to Mitigate Income Seasonality: Evidence from Bangladesh," *Journal of Development Studies*, October 2010, *48* (8), 1063–1083.

Kinnan, Cynthia, Shing-Yi Wang, and Yongxiang Wang, "Access to Migration for Rural Households," *American Economic Journal: Applied Economics*, October 2018, *10* (4), 79–119.

Kochar, Anjini, "Explaining Household Vulnerability to Idiosyncratic Income Shocks," *American Economic Review*, May 1995, *85* (2), 159–64.

Lagakos, David, Ahmed Mushfiq Mobarak, and Michael E. Waugh, "The Welfare Effects of Encouraging Rural-Urban Migration," NBER Working Papers 24193, National Bureau of Economic Research, Inc January 2018.

Loo, Yen Yi, Lawal Billa, and Ajit Singh, "Effect of climate change on seasonal monsoon in Asia and its impact on the variability of monsoon rainfall in Southeast Asia," *Geoscience Frontiers*, 2015, *6* (6), 817 – 823. Special Issue: Geoinformation techniques in natural hazard modeling.

Maccini, Sharon and Dean Yang, "Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall," *American Economic Review*, June 2009, *99* (3), 1006–26.

Maluccio, John A., John Hoddinott, Jere R. Behrman, Reynaldo Martorell, Agnes R. Quisumbing, and Aryeh D. Stein, "The Impact of Improving Nutrition During Early Childhood on Education among Guatemalan Adults," *The Economic Journal*, 2009, *119* (537), 734–763.

McKee, T. B., N. J. Doesken, and J. Kleist, "The relationship of drought frequency and duration of time scales," in "Eighth Conference on Applied Climatology" American Meteorological Society Anaheim CA January 1993, pp. 179–186.

McKenzie, David and Hillel Rapoport, "Self-Selection Patterns in Mexico-U.S. Migration: The Role of Migration Networks," *The Review of Economics and Statistics*, November 2010, *92* (4), 811–821.

Menon, P., A. Deolalikar, and A. Bhaskar, "India state hunger index: Comparisons of hunger across states," Technical Report, International Food Policy Research Institute, Washington, D.C. 2008.

Morduch, Jonathan, "Income Smoothing and Consumption Smoothing," *Journal of Economic Perspectives*, Summer 1995, *9* (3), 103–14.

NABARD, "Annual Report 2017-18," Technical Report, National Bank for Agriculture and Rural Development, Mumbai 2018.

Platteau, Jean-Philippe, Ombeline De Bock, and Wouter Gelade, "The Demand for Microinsurance: A Literature Review," *World Development*, 2017, *94*, 139 – 156.

Prasanna, V., "Impact of monsoon rainfall on the total foodgrain yield over India," *Journal of Earth System Science*, Jun 2014, *123* (5), 1129–1145.

Premand, Patrick and Renos Vakis, "Do shocks affect poverty persistence? Evidence using welfare trajectories from Nicaragua," *Well-Being and Social Policy*, 2010, *6* (1), 95–129.

Rao, Shobha, Asawari N Kanade, Chittaranjan S Yajnik, and Caroline H D Fall, "Seasonality in maternal intake and activity influence offspring's birth size among rural Indian mothers—Pune Maternal Nutrition Study," *International Journal of Epidemiology*, 2009, *38* (4), 1094–1103.

Rosenzweig, Mark R and Hans P Binswanger, "Wealth, Weather Risk and the Composition and Profitability of Agricultural Investments," *Economic Journal*, January 1993, *103* (416), 56–78.

Singh, D., M. Tsiang, B. Rajaratnam, and N. S. Diffenbaugh, "Observed changes in extreme wet and dry spells during the South Asian summer monsoon season," *Nature Climate Change*, June 2014, *4*, 456–461.

Somville, Vincent and Lore Vandewalle, "Access to Banking, Savings and Consumption Smoothing in Rural India," IHEID Working Papers 09-2019, Economics Section, The Graduate Institute of International Studies June 2019.

Tiwari, Sailesh, Hanan G. Jacoby, and Emmanuel Skoufias, "Monsoon Babies: Rainfall Shocks and Child Nutrition in Nepal," *Economic Development and Cultural Change*, 2017, *65* (2), 167–188.

Townsend, Robert, "Risk and Insurance in Village India," *Econometrica*, May 1994, *62* (3), 539–91.

Vanden Eynde, Oliver, "Targets of Violence: Evidence from India's Naxalite Conflict," *The Economic Journal*, 2018, *128* (609), 887–916.

World Bank, *Overcoming Drought*, The World Bank, 2006.

_ , "Development and Climate Change," World Development Report 2010, The World Bank 2010.

A Descriptive statistics about the sample

Table 12: 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 13: Baseline summary household-level statistics and balance check

		Control Group		Treatment-Control		
	Obs.	Mean	(std. err.)	Coeff.	(std. err.)	p-value
Head's years of education	1,051	2.93	(0.35)	0.35	(0.44)	0.437
Spouse's years of education	841	0.75	(0.16)	0.26	(0.22)	0.240
Scheduled caste (SC)	1,051	0.061	(0.022)	0.045	(0.041)	0.281
Scheduled tribe (ST)	1,051	0.430	(0.109)	-0.053	(0.130)	0.683
Below official poverty line	1,050	0.444	(0.067)	0.061	(0.067)	0.374
Land owned (acres)	1,048	1.758	(0.275)	0.159	(0.275)	0.566
Hindu	1,051	0.650	(0.082)	0.030	(0.100)	0.767
Head's age	1,048	44.78	(1.359)	-0.04	(1.577)	0.978
Spouse's age	850	38.79	(1.273)	-0.21	(1.428)	0.886
Household size	1,051	5.73	(0.264)	-0.09	(0.336)	0.786
Participation rate to last Lokh Sabah elections (%)	1,051	55.3	(6.08)	-2.06	(6.95)	0.769

Data source: own 2004 household survey. Standard errors clustered at the village level in parentheses. Observations weighted according to sampling probabilities.

Table 14: Baseline summary village-level statistics and balance check

		Control Group		Treatment-Control		
	Obs.	Mean	(std. err.)	Coeff.	(std. err.)	p-value
20-year (1990-2009) average annual precipitation (mm)[1]	36	1468	(1051)	46.3	(127.8)	0.719
Rain shock t (see def. in data section)[1]	36	0.25	(0.127)	-0.01	(0.155)	0.949
Rain shock t-1 (see def. in data section)[1]	36	0.50	(0.148)	-0.06	(0.180)	0.740
Population (# households)[2]	36	178.8	(70.8)	49.8	(86.1)	0.567
SC population(%)[2]	36	0.115	(0.038)	-0.009	(0.046)	0.839
ST population(%)[2]	36	0.427	(0.111)	0.014	(0.135)	0.916
Landless population(%)[2]	36	0.229	(0.073)	0.080	(0.089)	0.374
Illiterate population(%)[2]	36	0.666	(0.030)	-0.031	(0.036)	0.396
Female illiterate population(%)[2]	36	0.783	(0.030)	-0.024	(0.037)	0.513
Farming population(%)[2]	36	0.416	(0.079)	-0.058	(0.096)	0.553
Working gender-parity index[2]	36	0.521	(0.109)	0.025	(0.133)	0.852
Unemployment (%)[2]	36	0.344	(0.074)	-0.016	(0.090)	0.859
Female unemployment (%)[2]	36	0.526	(0.109)	-0.001	(0.132)	0.992
Caste / tribe fractionalization[3]	36	0.557	(0.078)	-0.028	(0.095)	0.768
Language fractionalization[3]	36	0.345	(0.060)	0.023	(0.072)	0.757
Religious fractionalization[3]	36	0.371	(0.064)	-0.080	(0.077)	0.308
Hinduism is main village religion[4]	36	0.631	(0.098)	-0.013	(0.119)	0.912
All-weather road reaches village[4]	36	0.227	(0.088)	-0.042	(0.107)	0.698
Electricity available in village[4]	36	0.330	(0.129)	0.097	(0.156)	0.540
Irrigated land (%)[4]	36	12.5	(3.43)	-0.06	(4.17)	0.989
Distance to nearest bank (km)[4]	36	8.02	(1.73)	-1.25	(2.10)	0.556
Distance to nearest primary health center (km)[4]	36	4.31	(1.02)	1.13	(1.25)	0.372
Distance to nearest market (km)[4]	36	5.17	(0.92)	0.09	(1.13)	0.934
Presence of a bus stop in village[4]	36	0.292	(0.122)	-0.72	(0.149)	0.633
Presence of a primary school in village[4]	36	0.75	(0.106)	0.05	(0.129)	0.701
Presence of a middle school in village[4]	36	0.292	(0.122)	0.108	(0.148)	0.4790
Distance to nearest secondary school (km)[3]	34	7.75	(1.35)	-0.95	(1.64)	0.565

Data sources: [1] GPCC, [2] Census of India 2001, [3] own 2004 household survey, [4] own 2004 village survey.
Standard errors in parentheses. Fractionalization indexes give the probability that two randomly-drawn individuals belong to different groups: $f = 1 - \sum_{i=1}^{n} s_i^2$, where s_i refers to the sample share of the ith group.

B Supplementary material

B.1 Agriculture: price channel

Table 15: Agricultural market prices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Rice (farm-gate)		Rice (market)		Tomatoes (market)		Onions (market)	
Rain	-1.269**		-0.393*		1.476*		0.971**	
	(0.502)		(0.216)		(0.757)		(0.370)	
Rain_shock		0.651***		0.200*		-0.739**		-0.532**
		(0.227)		(0.105)		(0.317)		(0.206)
Observations	2513	2513	3030	3030	2860	2860	2861	2861
Mean of dep. var.	4.9	4.9	9.9	9.9	6.2	6.2	13.3	13.3

Farm-gate and market prices are the median prices reported by producers and consumers (respect.) in each village-round.
OLS estimation. All equations include a constant, round (time) and village fixed effects.
Std errors clustered at the village level in parentheses (*p<0.10, **p<0.05, ***p<0.01).

B.2 Credit

Table 16: 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

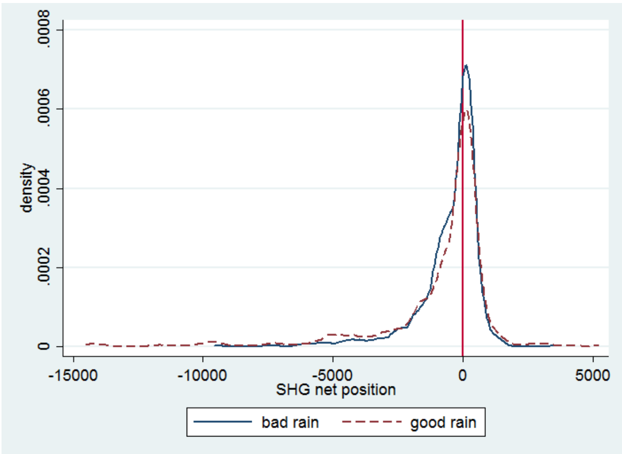
Figure 4 displays the the distribution of the net annual position of SHG members - i.e. the sum of the regular deposits over the year (excluding loan repayment) minus the sum of loans, one year after a monsoon below or above median.[35] Strikingly, the distributions appear very similar in good and bad years.[36] Moreover,

[35]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.

[36]A fixed-effect regression of SHG net position on rain deficit of the form of equation (1) gives positive and insignificant estimates.

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.

Figure 4: Net SHG position and monsoon intensity in t-1: Kernel density estimate



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 17 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 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 17: Borrowing: average loan repayment performance

	Bad monsoon in t-1		Good monsoon 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

Good and bad monsoons refer to June-August rainfall in year t-1 respectively above and below the historical district average. † 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).

Table 18: Credit (June to December) for consumption purpose

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Borrowing probability				Log total credit (+1)			
	Immediately		Lean season		Immediately		Lean season	
Relevant monsoon episode:	t		t-1		t		t-1	
A. Log rainfall								
Rain	-0.00106	0.00515	0.197**	0.218**	-0.0847	-0.0817	1.213*	1.293*
	(0.0494)	(0.0510)	(0.0974)	(0.100)	(0.330)	(0.334)	(0.650)	(0.664)
$Rain * Treat$	-0.0142	-0.0163	-0.257**	-0.292***	-0.0969	-0.0697	-1.398**	-1.565**
	(0.0554)	(0.0574)	(0.107)	(0.109)	(0.372)	(0.379)	(0.693)	(0.700)
B. Negative rainfall shock (drought)								
$Rain\_shock$	-0.0215	-0.0232	-0.0352	-0.0391	-0.0983	-0.0883	-0.240	-0.260
	(0.0251)	(0.0256)	(0.0359)	(0.0367)	(0.164)	(0.165)	(0.238)	(0.243)
$Rain\_shock * Treat$	0.0178	0.0213	0.0926***	0.106***	0.0975	0.101	0.486**	0.555**
	(0.0297)	(0.0305)	(0.0352)	(0.0354)	(0.195)	(0.198)	(0.223)	(0.223)
Village FE	yes	no	yes	no	yes	no	yes	no
Household FE	no	yes	no	yes	no	yes	no	yes
Observations	3189	3193	3189	3193	3188	3192	3188	3192
Mean of dep. var. in control group	0.102	0.102	0.102	0.102	167	167	167	167
Mean of dep. var. in treated group	0.155	0.155	0.155	0.155	200	200	200	200

OLS estimation. Std errors clustered at the household level in parentheses (*p<0.10, **p<0.05, ***p<0.01).
Observations are weighted in order to account for different sampling probabilities.
All equations include a constant, round (time) fixed effects, and household controls / family size (with hh. FE).

Table 19: Credit (June to December) for business / work purpose

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Borrowing probability				Log total credit (+1)			
	Immediately		Lean season		Immediately		Lean season	
Relevant monsoon episode:	t		t-1		t		t-1	
A. Log rainfall								
Rain	0.123**	0.126**	0.129	0.0802	0.812*	0.825*	0.685	0.369
	(0.0583)	(0.0583)	(0.105)	(0.105)	(0.428)	(0.429)	(0.725)	(0.716)
$Rain * Treat$	-0.148**	-0.150**	-0.184	-0.145	-1.031**	-1.033**	-1.039	-0.774
	(0.0626)	(0.0632)	(0.113)	(0.114)	(0.458)	(0.463)	(0.770)	(0.771)
B. Negative rainfall shock (drought)								
$Rain\_shock$	-0.0769**	-0.0810***	-0.0766*	-0.0743*	-0.535**	-0.561**	-0.428	-0.411
	(0.0299)	(0.0299)	(0.0396)	(0.0408)	(0.223)	(0.224)	(0.288)	(0.296)
$Rain\_shock * Treat$	0.0882***	0.0887***	0.0776**	0.0684*	0.621**	0.620**	0.481*	0.430
	(0.0336)	(0.0338)	(0.0388)	(0.0398)	(0.247)	(0.250)	(0.273)	(0.279)
Village FE	yes	no	yes	no	yes	no	yes	no
Household FE	no	yes	no	yes	no	yes	no	yes
Observations	3189	3193	3189	3193	3188	3192	3188	3192
Mean of dep. var. in control group	0.102	0.102	0.102	0.102	167	167	167	167
Mean of dep. var. in treated group	0.155	0.155	0.155	0.155	200	200	200	200

OLS estimation. Std errors clustered at the household level in parentheses (*p<0.10, **p<0.05, ***p<0.01).
Observations are weighted in order to account for different sampling probabilities.
All equations include a constant, round (time) fixed effects, and household controls / family size (with hh. FE).

B.3 Migration and credit

Table 20: Seasonal migration and credit

	(1)	(2)	(3)	(4)	(5)	(6)
	Migration probability		Log total mig. income (+1)		Log total remittances (+1)	
Relevant monsoon episode:				t		
$Rain\_shock$	-0.00891	0.00696	-0.0812	0.0137	-0.0624	0.0563
	(0.0164)	(0.0166)	(0.147)	(0.151)	(0.131)	(0.134)
$Credit\_sepnov$	-0.00674**	-0.000132	-0.0633**	-0.0154	-0.0529**	-0.0111
	(0.00304)	(0.00393)	(0.0268)	(0.0352)	(0.0236)	(0.0322)
$Credit\_junsep * Rain\_shock$	0.0143***	0.00992*	0.0992**	0.0817*	0.0994***	0.0644
	(0.00480)	(0.00561)	(0.0396)	(0.0492)	(0.0366)	(0.0447)
Village FE	yes	no	yes	no	yes	no
Household FE	no	yes	no	yes	no	yes
Observations	3189	3193	3188	3192	3188	3192
Mean of dep. var. in control group	0.133	0.133	984	984	421	421
Mean of dep. var. in treated group	0.141	0.141	1129	1129	569	569

OLS estimation. Std errors clustered at the household level in parentheses (*p<0.10, **p<0.05, ***p<0.01).
Observations are weighted in order to account for different sampling probabilities.
All equations include a constant, round (time) fixed effects, and household controls / family size (with hh. FE).

Table 21: Seasonal migration and credit

	(1)	(2)	(3)	(4)	(5)	(6)
	Migration probability		Log total mig. income (+1)		Log total remittances (+1)	
Relevant monsoon episode:				t		
$Rain\_shock$	-0.0404	-0.0271	-0.373*	-0.285	-0.383*	-0.279
	(0.0250)	(0.0253)	(0.223)	(0.228)	(0.202)	(0.204)
$Rain\_shock * Treat$	0.0412	0.0451	0.382	0.395	0.419*	0.444*
	(0.0278)	(0.0281)	(0.246)	(0.250)	(0.224)	(0.227)
$Credit\_sepnov$	-0.00663**	0.0000952	-0.0623**	-0.0134	-0.0519**	-0.00887
	(0.00303)	(0.00393)	(0.0268)	(0.0353)	(0.0236)	(0.0322)
$Credit\_junsep * Rain\_shock$	0.0141***	0.00942*	0.0968**	0.0772	0.0967***	0.0594
	(0.00480)	(0.00562)	(0.0396)	(0.0492)	(0.0365)	(0.0448)
Village FE	yes	no	yes	no	yes	no
Household FE	no	yes	no	yes	no	yes
Observations	3189	3193	3188	3192	3188	3192
Mean of dep. var. in control group	0.133	0.133	984	984	421	421
Mean of dep. var. in treated group	0.141	0.141	1129	1129	569	569

OLS estimation. Std errors clustered at the household level in parentheses (*p<0.10, **p<0.05, ***p<0.01).
Observations are weighted in order to account for different sampling probabilities.
All equations include a constant, round (time) fixed effects, and household controls / family size (with hh. FE).

C Robustness tests

Table 22: Rice production: specification test (rain t+1)

	(1)	(2)	(3)	(4)	(5)	(6)
	Log yields (kg/acre)		Sufficiency gap ratio		Proportion sold	
A. Log rainfall						
R	0.219	0.207	-0.00698	-0.0113	0.0139	0.0125
	(0.160)	(0.170)	(0.0520)	(0.0522)	(0.0147)	(0.0151)
$Rain * Treat$	-0.237	-0.177	0.0545	0.0606	-0.0274**	-0.0243**
	(0.155)	(0.164)	(0.0506)	(0.0513)	(0.0118)	(0.0124)
B. Rainfall shock						
$Rain\_shock$	-0.0836	-0.0815	0.0114	0.00321	-0.0128	-0.00913
	(0.0940)	(0.0988)	(0.0327)	(0.0329)	(0.0107)	(0.0111)
$Rain\_shock * Treat$	0.0817	0.0494	-0.0349	-0.0335	0.0136	0.0111
	(0.0891)	(0.0934)	(0.0312)	(0.0313)	(0.00896)	(0.00927)
Village FE	yes	no	yes	no	yes	no
Household FE	no	yes	no	yes	no	yes
Observations	2421	2424	3189	3193	2444	2448
Mean of dep. var. in control group	741	741	0.41	0.41	0.02	0.02

OLS estimation. Std errors clustered at the household level in parentheses (*p<0.10, **p<0.05, ***p<0.01).
Observations are weighted in order to account for different sampling probabilities.
All equations include a constant, round (time) fixed effects, and household controls / family size (with hh. FE).
sufficiency gap ratio is calculated for each household as: $\max\left(0; \frac{135 - per\_capita\_rice\_production}{135}\right)$.

Table 23: Food security: extreme shocks

	(1)	(2)	(3)	(4)
	Months with enough food		Animal protein consumption	
Relevant monsoon episode:	*t-1*		*t*	
Rain_shock	-1.145***	-1.237***	-462.6***	-411.2**
	(0.317)	(0.320)	(162.7)	(163.9)
$Rain\_shock * Treat$	0.531	0.652*	224.8	176.6
	(0.338)	(0.342)	(189.7)	(191.6)
Village FE	yes	no	yes	no
Household FE	no	yes	no	yes
Observations	3169	3173	3180	3184
Mean of dep. var. in control group	10.6	10.6	1130	1130
Mean of dep. var. in treated group	10.8	10.8	1180	1180

OLS estimation. Std errors clustered at the household level in parentheses (*p<0.10, **p<0.05, ***p<0.01).
Observations are weighted in order to account for different sampling probabilities.
All equations include a constant, round (time) fixed effects, and household controls / family size (with hh. FE).
Animal protein consumption is the annualized monetary value of eggs, fish and meat consumption.

Table 24: Credit (June to December): horse-race specification

	(1)	(2)	(3)	(4)
	Borrowing probability		Log total credit (+1)	
A. Log rainfall				
$Rain_t$	0.156*	0.168**	1.111*	1.170*
	(0.0829)	(0.0842)	(0.614)	(0.620)
$Rain_t * Treat$	-0.152*	-0.156*	-1.284*	-1.270*
	(0.0914)	(0.0931)	(0.671)	(0.679)
$Rain_{t-1}$	0.456***	0.404**	2.714**	2.265*
	(0.168)	(0.172)	(1.156)	(1.171)
$Rain_{t-1} * Treat$	-0.485***	-0.463**	-2.902**	-2.634**
	(0.176)	(0.180)	(1.186)	(1.198)
B. Negative rainfall shock				
$Rain\_shock_t$	-0.104**	-0.102**	-0.696**	-0.658**
	(0.0432)	(0.0435)	(0.319)	(0.321)
$Rain\_shock_t * Treat$	0.0874*	0.0838*	0.641*	0.589*
	(0.0479)	(0.0483)	(0.349)	(0.351)
$Rain\_shock_{t-1}$	-0.138**	-0.140**	-0.898**	-0.909**
	(0.0597)	(0.0606)	(0.429)	(0.437)
$Rain\_shock_{t-1} * Treat$	0.184***	0.192***	1.166***	1.194***
	(0.0565)	(0.0569)	(0.390)	(0.393)
Village FE	yes	no	yes	no
Household FE	no	yes	no	yes
Observations	3189	3193	3188	3192
Mean of dep. var. in control group	0.396	0.396	1340	1340
Mean of dep. var. in treated group	0.488	0.488	1203	1203

OLS estimation.
Std errors clustered at the household level in parentheses (*p<0.10, **p<0.05, ***p<0.01).
Observations are weighted in order to account for different sampling probabilities.
All equations include a constant, round (time) fixed effects,
and household controls / family size (with hh. FE).

Table 25: Credit (June to December): extreme shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Borrowing probability				Log total credit (+1)			
	Immediately		Lean season		Immediately		Lean season	
Relevant monsoon episode:	t		t-1		t		t-1	
$Rain\_shock$	0.00348	-0.000292	-0.213***	-0.224***	-0.0250	-0.0499	-1.327***	-1.390***
	(0.0415)	(0.0416)	(0.0644)	(0.0649)	(0.304)	(0.304)	(0.458)	(0.461)
$Rain\_shock * Treat$	0.0296	0.0286	0.223***	0.228***	0.299	0.292	1.407***	1.428***
	(0.0456)	(0.0459)	(0.0680)	(0.0684)	(0.330)	(0.331)	(0.478)	(0.479)
Village FE	yes	no	yes	no	yes	no	yes	no
Household FE	no	yes	no	yes	no	yes	no	yes
Observations	3189	3193	3189	3193	3188	3192	3188	3192
Mean of dep. var. in control group	0.396	0.396	0.396	0.396	1340	1340	1340	1340
Mean of dep. var. in treated group	0.488	0.488	0.488	0.488	1203	1203	1203	1203

OLS estimation. Std errors clustered at the household level in parentheses (*p<0.10, **p<0.05, ***p<0.01).
Observations are weighted in order to account for different sampling probabilities.
All equations include a constant, round (time) fixed effects, and household controls / family size (with hh. FE).

Table 26: Seasonal migration: extreme shocks

	(1)	(2)	(3)	(4)	(5)	(6)
	Migration probability		Log total mig. income (+1)		Log total remittances (+1)	
Relevant monsoon episode:			*t*			
$Rain\_shock$	-0.0152	-0.0205	-0.131	-0.159	-0.124	-0.151
	(0.0243)	(0.0248)	(0.214)	(0.219)	(0.193)	(0.197)
$Rain\_shock * Treat$	0.0471*	0.0550**	0.334	0.365	0.306	0.360*
	(0.0267)	(0.0271)	(0.234)	(0.239)	(0.210)	(0.214)
Village FE	yes	no	yes	no	yes	no
Household FE	no	yes	no	yes	no	yes
Observations	3189	3193	3188	3192	3188	3192
Mean of dep. var. in control group	0.133	0.133	984	984	421	421
Mean of dep. var. in treated group	0.141	0.141	1129	1129	569	569

OLS estimation. Std errors clustered at the household level in parentheses (*p<0.10, **p<0.05, ***p<0.01).
Observations are weighted in order to account for different sampling probabilities.
All equations include a constant, round (time) fixed effects, and household controls / family size (with hh. FE).