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Coping with shocks: how Self-Help Groups impact food security and seasonal migration

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Abstract Combining seven years of household data from an original field experiment in villages of Jharkand, East India, with meteorological data, this paper investigates how Indian Self-Help Groups (SHGs) enable households to withstand rainfall shocks. I show that SHGs operate remarkably well under large covariate shocks. While credit access dries up in control villages one year after a bad monsoon, reflecting strong credit rationing from informal lenders, credit flows are counter-cyclical in treated villages. Treated households experience substantially higher food security during the lean season following a drought and increase their seasonal migration to mitigate expected income shocks. Credit access plays an important role, together with other SHG aspects such as peer networks. These findings indicate that local self-help and financial associations can help poor farmers to cope with climatic shocks and to implement risk management strategies.

Keywords: Microfinance, credit, climatic shocks, risk management, resilience, seasonal migration, food security.

JEL Classification Numbers: O13, O15, G21, Q54

1 Introduction

In developing countries, most poor, rural households experience strongly volatile income streams due to their high exposure to a variety of shocks, including climatic events. For instance, about half of agricultural households in the world report a substantial loss in crops or livestock during the previous five years, with only a minority of them receiving any kind of compensation (Demirgüç-Kunt et al., 2018). An estimated 26 million people fall into poverty each year because of natural disasters (Hallegatte et al., 2017). A probably 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.

While risk and income volatility exist everywhere, they are especially problematic for poor populations in developing countries. First, risk is costlier for households close to subsistence, because a small negative shock can tip them into malnutrition and underdevelopment traps.¹ Second, poor households are disproportionately likely to lack the necessary human, physical, and financial capital to mitigate such shocks (Castells-Quintana et al., 2018). Third, developing countries are disproportionately vulnerable to global climate change, especially those relying heavily on rain-fed agriculture (IPCC, 2022). Weather-related income shocks, because they tend to affect the entire local community, are especially difficult to deal

¹For instance, even short episodes of child under-nutrition can cause long-lasting damage to health and human capital, inability to afford schooling for a prolonged period can lead to school drop-out, and delaying treatment of illnesses can increase morbidity and future health costs. Several studies show that uninsured income shocks can lead to adverse human development outcomes such as reduced 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).

with through informal insurance arrangements. According to FAO et al. (2018), climate variability and extremes are a key driver behind the recent rise in global hunger. The issue is particularly pronounced in India, which ranks 94 out of 107 countries in the last Global Hunger Index (von Grebmer et al., 2020). Indian agriculture, which still accounts for 16% of GDP and 49% of national employment, is very dependent on erratic monsoon rains given the low irrigation coverage and the effects of climate change (Asada and Matsumoto, 2009; Prasanna, 2014; Government of India, 2018; IPCC, 2022). Rainfall shocks have repeatedly been found to largely affect the welfare of rural households in India (Cole et al., 2013; Gaurav, 2015; Carpena, 2019). Therefore, finding effective policies to cope with climate change and fight malnutrition and in India is extremely important and urgent.

This paper explores whether Indian Self-Help Groups (SHGs), a widespread versatile model of community-based savings and credit associations, can help households to cope with large covariate income shocks such as droughts in villages of Jharkhand, East India.² The state of Jharkhand is one of the poorest and most rural Indian states, suffering from some of the highest levels of hunger and malnutrition prevalence (Swaminathan et al., 2019). In 2002, the NGO PRADAN started to progressively introduce SHGs in villages chosen for their high poverty levels and the absence of any NGO or microfinance institution. A list of 36 villages spread over the entire state were randomized into a treatment group, where the SHG program was implemented, and a control group, where no intervention took place. A random sample of a bit more than 1,000 households from those villages

²SHGs represent the most important source of microfinance in India today, both in terms of outreach and total loan disbursements, with about 8.7 million bank-linked SHGs in India (NABARD, 2018). This represents a remarkable achievement, especially given the general acknowledgment that standard microfinance products remain more suited to urban and peri-urban areas than to the rural world. Section 2 gives more details about how SHGs work concretely.

was then surveyed three times between 2004 and 2009, in order to estimate the impact of SHG creation at the village level (intent-to-treat framework). Combining these data with historical monthly precipitation data, I obtain three main findings.

First, I show that, despite being hit just as strongly on the agricultural front (with an estimated general 20% drop in rice yields), treated households enjoy much greater food security in times of drought. On average, they gain more than one month of adequate food consumption during the year following a negative monsoon shock. This is a remarkable contribution of SHGs in a context where hunger and malnutrition rates have been stubbornly high in recent years.

Second, I find that local credit markets are also strongly affected by rainfall, as moneylenders and other traditional sources strongly ration credit after a negative shock. By contrast, SHGs, despite being village-based and small-scale institutions, prove to be robust sources of credit under covariate shocks. I show that households in treated villages enjoy 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 seasonal adjustment of liquidity.

Third, I find that treated households diversify income by strongly increasing seasonal migration immediately after observing a bad monsoon (by an impressive 50-60%). Importantly, since the income shock is expected to hit one year after a drought, this does not correspond to distress migration, but rather to a strategy to mitigate *expected* shocks. The effect is partly explained by the greater credit availability offered by SHGs, which helps them face both the direct costs and the income risk involved in migration. Other aspects of SHGs, such as expanded peer networks, also help to curb non-monetary costs through support and learning.

To my knowledge, this is one of the first papers to provide direct causal evidence on how community-based microfinance institutions enable households to react to large, objective, and exogenous climatic shocks. It shows that small-scale, local, and pro-poor institutions such as SHGs can contribute to the management of climatic shocks, significantly increasing households' resilience and adaptive capacity, with major health and economic consequences.³

The paper is related to several strands of the literature. 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 those stemming from weather events (Paxson, 1993; Townsend, 1994; Dercon and Krishnan, 2000; Dercon et al., 2005; Kazianga and Udry, 2006; Maccini and Yang, 2009; Groppo and Kraehnert, 2016; Tiwari et al., 2017). Given imperfect risk-sharing mechanisms, the ability of households to insure against shocks has often been shown to crucially depend on their wealth and access to formal credit markets (Udry, 1990; Rosenzweig and Wolpin, 1993; Jalan and Ravallion, 1999).

More recently, microinsurance products, such as index-based weather insurance, have been developed to address risk directly. However, the available evidence shows that the demand for and the impact of such products have been very disappointing, mainly because of the large costs, complexity, rigidity, and basis risk of most insurance contracts, as well as farmers' behavioral biases (see Cole et al., 2013; Karlan et al., 2014; de Janvry et al., 2014; Platteau et al., 2017; Wong et al., 2020; Ahmed et al., 2020). As a consequence, microinsurance, while it can

³As will be emphasized later, given the nature of SHGs, this should be considered as the impact of a bundled intervention, including microfinance, but also solidarity networks, collective action platforms, and female empowerment.

be a useful complement in some particular contexts, has failed to spread widely and deeply in developing countries and has shown very limited capacity to protect poor households.⁴

Microcredit has traditionally been considered mostly as a means to start a business or to meet big lump-sum expenses, which explains why there is so little direct evidence concerning its ‘insurance’ aspect. Some papers provide indirect evidence, though with important limitations. In a very different context (urban areas of South Africa), Karlan and Zinman (2010) implement a randomized evaluation of the impact of high-rate, high-risk consumption loans, and find that treated households are less likely to report experiencing hunger or a job loss in the 6 to 12 months following the intervention. Another field experiment in Indian villages show that households with access to bank accounts smooth food consumption better, thanks to pro-cyclical saving on the account (Somville and Vandewalle, 2019). Some papers have shown that credit access is generally linked to lower consumption volatility, though relying on observational data and subjective assessments of shocks, with potentially serious selection and recall issues (Kaboski and Townsend, 2005; Beegle et al., 2006; Islam and Maitra, 2012).⁵

This paper also adds to a recent literature studying the determinants of seasonal migration and the potential role of microfinance. Migration is costly and there are numerous barriers to migration, especially for poorer households who are

⁴In recent years, the ‘microinsurance promise’ has been losing impetus even in 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, steadily reduced 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.

⁵It is worth to note that Islam and Maitra (2012) analyze self-declared *health* shocks, which are expected to be better insured through informal means because they are idiosyncratic and not covariate as weather shocks (Townsend, 1994; Kochar, 1995).

often most vulnerable to climate risk. The inability to migrate – and the potential for populations to become trapped in marginal or vulnerable locations – thus represents an important, and relatively neglected, policy concern (Dercon, 2014; Castells-Quintana et al., 2018). Khandker et al. (2010), using cross-sectional survey data, show that the probability of seasonal migration is negatively correlated with microfinance membership in Bangladesh, a finding opposite to the present paper. 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 increases seasonal migration among rural households, leading to improvements in household consumption and food security.⁶ Interestingly, I find similar results in a situation where SHG credit is not earmarked in any way for migration.⁷ My results thus suggest that seasonal migration can be a desirable strategy to mitigate expected shocks, though often unfeasible due to 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.

Closest to this paper is Christian et al. (2019), who show that the participation to a rural livelihoods program based on SHGs partly mitigated the losses from a strong tropical storm that hit the Bay of Bengal in 2013. Although the topic and setting are very close to this paper, there are important differences. First, Christian et al. (2019) exploit a natural experiment, relying on the spatial variation in the intensity of the rainfall shock and the staggered roll-out of the livelihood program, which imply very different assumptions to draw causal infer-

⁶A 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.

⁷In fact, PRADAN, the partner NGO, expected the opposite effect.

ence. Moreover, the cyclone led to a range of public and private emergency relief programs, which can confound part of the effects. Second, a one-shot climate disaster, involving extensive damage due to flooding and strong winds, may involve very different responses. For instance, the principal issue in that case is to rebuild capital assets after being hit, while, in my setting, a large part of the effects go through the adoption of mitigating strategies ex-ante. Moreover, migration, the main risk-mitigating strategy identified in this paper, might be impaired because of infrastructure destruction. Third, the livelihood program studied by Christian et al. (2019) is more intensive and broader in scope, as it involves technical assistance and training by public and private sectors, as well as grants to the poorest households. Interestingly though, both our studies coincide on the conclusion that Indian SHGs can play a role of (partial) insurance against climatic shocks of different nature and in different contexts.

The remainder of the paper is organized as follows. Some background information is given in section 2. Sections 3 and 4 describe the data and the empirical strategy. The results are then presented: agriculture and food security in section 5.1, credit in section 5.2, and migration in section 5.3.

2 The SHG program and the context

2.1 The context and the policy intervention

Jharkhand is one of the poorest Indian states, with a rural poverty rate estimated at as high as 41% in 2012 by the Planning Commission. The female literacy rate is as low as 55%, ten percentage points below the national average, according

to the 2011 Indian census. The state is mostly rural, with 76% of its 33 million inhabitants living in rural areas. Its population consists of about 26% tribals and 12% scheduled castes, known to be the most vulnerable groups in Indian society. Villages are very isolated on average, their inhabitants living chiefly on subsistence agriculture and seasonal labor. Rain-fed paddy is by far the predominant crop in the state, with average yields of 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 of above 1,000 mm, is not considered as suffering from chronic drought. Nevertheless, it is characterized by a 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 is making monsoon rains increasingly erratic (Singh et al., 2014; Loo et al., 2015; FAO et al., 2018), to the detriment of the state’s agriculture, which also suffers from low irrigation coverage (5.3% of agricultural area in 2014). As a result, households’ food security needs can only be met through own cultivation for at most six months of the year (Kabeer and Noponen, 2005), and Jharkhand is suffering from one of the highest levels of hunger and malnutrition prevalence in India (IIPS, 2015; Swaminathan et al., 2019). 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 2002, the NGO PRADAN launched a large program to create women-only SHGs. It established a list of potential intervention villages (based on their high

poverty rate), located in four geographic clusters covering the entire state of Jharkhand.⁸ From that list, 36 villages were randomly selected (9 in each cluster) and allocated to either treatment or control groups. In treated villages, the program was explained in public village meetings and groups of between 10 and 20 interested women were created. By the time of the first survey (January 2004), there were between 1 and 10 active SHGs (4 on average) in treated villages, covering between 5 and 45% of the village population (24% on average). There were none in control villages. Over time, some of those initial SHGs became defunct and others were created, including a limited number in control villages. However, at the time of 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 (corresponding to average population coverage rates of 32% in treated villages and 9% in control villages). Likewise, in the last wave, 80% of the households in treated villages who were members of SHGs in the first wave were still active members, while only 15% of the households in control villages had joined SHGs.⁹ Importantly, no other microfinance institution was present in any of the villages during the entire period of the study.

Appendix A provides the full list of villages surveyed, as well as basic descriptive statistics and balance checks. Given that no baseline data is available, I use basic

⁸Within geographical clusters located around their offices, PRADAN chooses to work with relatively disadvantaged communities and poor villages with no history of NGO intervention. 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 non-agricultural land and almost 90% live in thatched huts or are squatters.

⁹Because individual membership and changes in membership are likely to be endogenous, the empirical analysis will estimate the impact of the original assignment to treatment at the village level, irrespective of households' actual membership (see section 4). The (limited) contamination of the control control group will therefore generally imply an underestimation of the true treatment effects.

village characteristics measured at the first wave (2004), as well as matched village data from the 2001 Indian census. On average, villages in the sample are very small (less than 200 households), isolated (80% have no all-weather road reaching the village, two thirds have no electricity) and poor (half of their population belong to scheduled castes or tribes, one fourth are landless, two thirds are illiterate). Importantly, there is no statistically-significant difference between treated and control villages (and point estimates are very similar), indicating that the random selection of villages was successful.

2.2 The organization of SHGs and their potential role against shocks

SHGs represent one of the most successful and sustainable microfinance vehicles in the world. They were initially promoted by the National Bank for Agriculture and Rural Development of India in the 1990s as women’s collectives to promote microcredit, but also more general political participation and female empowerment. They have quickly spread widely throughout rural India and have become a central piece of the National Rural Livelihood Mission, the flagship program of the government of India to alleviate poverty and promote self-employment among the rural poor.

SHGs are groups of women from the same village and homogeneous backgrounds¹⁰, who voluntarily come together to save and borrow small amounts on a regular basis (one important rule imposed by PRADAN is only one member per household). The group formation starts with some initial training from the NGO.

¹⁰Demont (2016) shows that SHGs display assortative matching properties in the same context.

Each group then chooses a name and nominates a president, secretary, cashier, and accountant.¹¹ It also sets rules such as weekly meeting times, minimum contributions per member at each meeting (usually 5 or 10 INR, i.e. 0.5-1 USD per month), the interest rate charged on loans to group members¹², 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 can access bank loans (the group is then said to be *linked*). At that point, groups are autonomous and the NGO's intervention 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 back part of the principal. Interest earned on internal loans remains within the group and becomes part of its pool of funds. Members who do not yet have a loan can apply for one to the group. Loans are individual but require group consent, and repayment is public. There is strong peer pressure for due repayment, so as to preserve the group's resources. Yet the group is generally flexible and understanding when a member is not able to pay the weekly installment and asks for an extension.¹³ The savings and interest revenues of the group help to

¹¹The roles of president, secretary, cashier usually rotate; the accountant can be external.

¹²In practice, there is virtually no deviation from the interest rate of 2% monthly, suggested by the NGO. However, interest rates can sometimes be higher for very large amounts because they require extra group borrowing from the bank.

¹³A study by CGAP (2007) calculated an average Portfolio at Risk > 90 days for PRADAN

cushion irregular cash flows and adjust to urgent and unexpected situations, while respecting bank loan repayment terms. If a member fails to repay or to come to meetings for a prolonged period, group representatives will visit her home to encourage her to go back to paying. In (rare) cases of actual default, the group absorbs the loss using the defaulting member's savings and, if needed, the collective pool of funds.

SHGs can potentially allow members to borrow in response to negative income shocks, in order to manage inter-temporal liquidity and/or finance risk-mitigating strategies. Several features of SHGs stand out in this respect. First, SHGs meet weekly and there is no fixed order for loan taking (unlike ROSCAs for instance). That is, members can ask for any amount at any time, provided that (i) the group agrees and (ii) the money is available. Second, as outlined above, 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, as already explained, SHGs certainly go beyond mere credit and savings activities. They involve cohesive 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; Kumar et al., 2021).

SHGs of about 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." Consistent with this, I observe extremely few outright defaults in the data.

¹⁴Note that even large rainfall shocks are certainly not fully covariate, since members are heterogeneous in terms of land ownership, main occupation, assets, family structure, etc.

In sum, the bank-linked SHG model provides access to flexible 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.¹⁵ However, how far such simple, deep-rooted, and widely accepted informal institutions can go toward ‘insuring’ poor households against income shocks, including those resulting from extreme climate events, remains an open question.

3 Data

3.1 Household living standards

The sample was selected at the end of 2003, i.e. about eighteen months after the creation of the first SHGs, to ensure that all groups were stabilized and fully operational. In each treated village, 18 SHG member households were randomly selected from PRADAN’s lists, together with 18 non-members households. In the control villages, 18 households were randomly selected.¹⁶ The full sample therefore consists of 1080 households, which were surveyed three times, in 2004, 2006, and 2009.

The questionnaire took the form of a Living Standards Measurement Survey,

¹⁵CGAP (2007) estimates that the average cost of promoting and supporting SHGs in India is around 18 USD per member (20 USD for PRADAN groups), and that the average return on assets after adjusting for loan loss provisions is around 9% (16% for PRADAN groups). Deducting the costs borne 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.” Several other studies confirm the longevity and high rate of social inclusion of SHGs (e.g. Gaiha and Nandhi, 2008; Deininger and Liu, 2013; Baland et al., 2019).

¹⁶Non-member and control households were selected following a standard random-walk procedure.

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 took place during the same period of the year, namely January-March, just after the winter-season harvest. Appendix A provides basic descriptive statistics at the household level and balance checks across treatment groups. I focus on time-invariant household characteristics measured at the first wave (2004). Households in the sample have six members and heads with less than primary-school education on average, and about half of them belong to scheduled castes or tribes. There is no statistically-significant difference between households living in treated and control villages.

The overall attrition rate across rounds is very limited. The vast majority (80%) of households were interviewed in all survey waves and 92% were interviewed at least twice.¹⁷ Importantly, the probability of being interviewed in all waves is not significantly different between treated and control villages (after removing the treated village that had to be dropped in the last wave due to insecurity reasons). In order to maximize variation and ensure consistency across specifications with and without fixed effects, the empirical analysis focuses on the sample of households observed at least two times, which represents 97% of all observations.¹⁸

3.2 Rainfall

Rainfall quantity is crucial for the households in the sample. Most of them are small landholders (94% own some land, on average less than 2 acres), who

¹⁷One entire treated village could not be surveyed in the last wave due to serious Naxalite activism in the region at the time. Excluding that village, more than 82% of households have been surveyed three times.

¹⁸In Appendix C, I show that results are fully robust to using the fully-balanced sample of households observed in all three waves (88% of observations).

by and large practice subsistence agriculture with limited marketable surplus. If rainfall matters for all crops, in the region, it is especially the case for rice, which is also the main source of food and agricultural income for most households. 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). The region cultivates only kharif rice, which is planted during the monsoon and harvested in November-December, i.e. just before the survey.¹⁹

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 treatment, will be the key explanatory variables in the empirical analysis. They both focus on rainfall between June and August, the core monsoon period with more than 70% of yearly rainfall on average. This is also the period that is crucial for agriculture in the region, residual rain being scattered over the rest of the year.²⁰

The first measure (*'Rain'*) is simply the natural log of the cumulative monsoon

¹⁹By contrast, rabi crops are harvested in Spring and do not rely directly on monsoon rains. In Jharkhand, rabi cultivation is relatively limited and is unevenly distributed geographically, mainly because of underinvestment in irrigation facilities. For instance, wheat, the main rabi crop, is only cultivated by 23% of the sample. As a result, rabi production at best only slightly mitigates shocks to the main kharif production. It also implies a longer recall period and complicates shock identification, as rabi crops rely on both residual soil moisture from the monsoon season and partial irrigation.

²⁰The 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 rainfall in June-July has the largest and most 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.

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.²¹ Second, I construct an explicit 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 (\overline{Precip}) divided by the long-term village standard deviation (σ)²²:

$$Rain_def_{vt} = \frac{\overline{Precip}_v - Precip_{vt}}{\sigma_v},$$

where v and t stand for village and year, respectively. Then, I define my indicator of interest as:

$$Rain_shock_{vt} = \mathbf{1}(Rain_def_{vt} \geq 0.5).$$

That is, *Rain_shock* takes value 1 if the monsoon is at least 0.5 standard deviation below the village’s historical norm – which corresponds to a (mild) drought happening once every 3 years on average – and 0 otherwise.²³

Figure 1 shows substantial variation in the sample distribution of the *Rain_def*

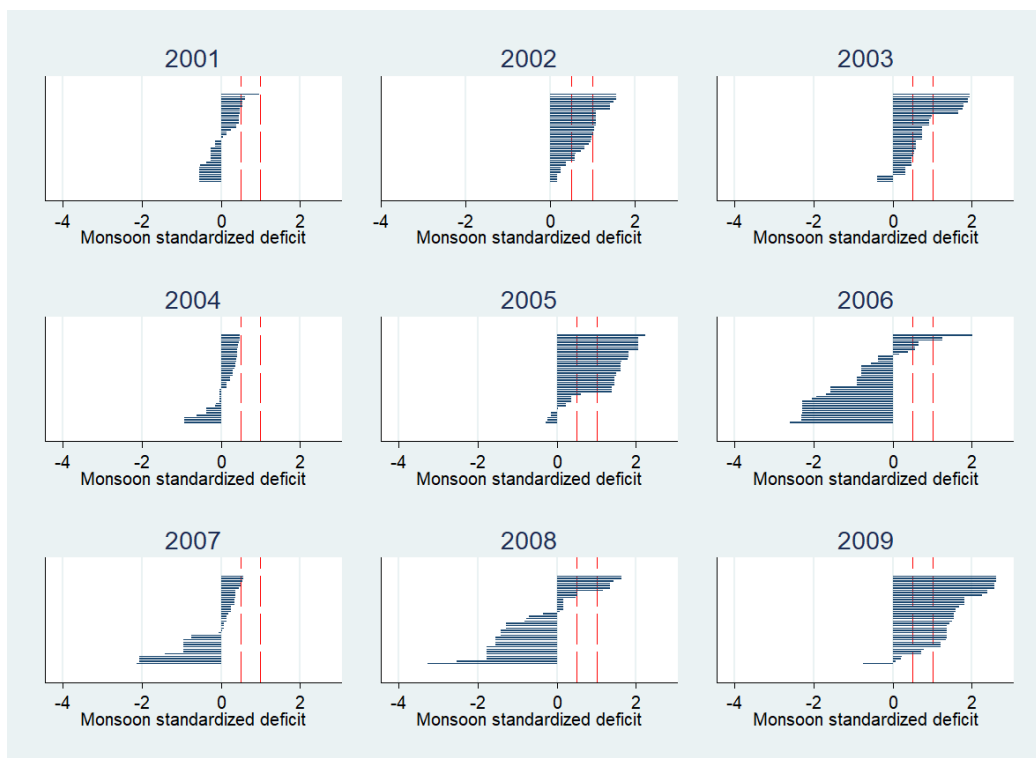
²¹This continuous rainfall ‘shock’ measure is used for instance in Maccini and Yang (2009) and Vanden Eynde (2018).

²²Village 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).

²³One 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 the main results are qualitatively robust to a more restrictive drought definition, namely a rain deficit larger than 1 standard deviation (corresponding to severe droughts happening once every 5 years on average). However, the lower variation in this restrictive shock variable (see Figure 1) generally leads to less precise estimates.

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 drought years for the whole state), while 2006 and 2008 saw relatively generous rainfall (though not in all villages, as the graph makes clear). During the other years of the survey period, precipitations were closer to the mean, though with marked inter-village variation. Indeed, thanks to the stratification strategy, the sample includes villages in all the agro-climatic zones within Jharkhand.

Figure 1: Monsoon standardized deficit (z-score) at the village level during study period



Data from GPC. Dashed lines indicate droughts (deficits larger than 0.5 and 1 std deviation).

Finally, Table 1 shows that the *Rain_shock* indicator indeed captures large and significant shocks to rice production in the sample. The average produc-

tion and sales are respectively 25% and 40% lower in village-years experiencing a (mild) drought compared to village-years with normal or good conditions. Households are also 9 percentage point less likely to produce a positive quantity, half of which being explained by a higher crop failure probability and the other half being explained by households temporarily exiting agriculture. There does not seem to be adaptation at the intensive margin in the conditional area sown. Rice production is overwhelmingly aimed at home consumption in all years, though market participation is twice lower after a negative shock. Finally, households are more than 25% less likely to be self-sufficient in rice after a drought.²⁴

Table 1: Average rice production, by rain shock

	Means in cases of		P-value*
	no rain shock	rain shock	
Yields (kg/acre)	734.2	581.2	0.00
Total production (kg)	727.5	541.6	0.00
Probability of producing a quantity >0	0.82	0.73	0.00
Probability of a complete crop failure [†]	0.01	0.05	0.00
Total sown area (acres)	1.26	1.15	0.05
Total sown area if >0 (acres)	1.51	1.52	0.90
Total quantity sold if prod. >0 (kg)	60.7	36.4	0.01
Probability of selling on market if prod. >0	0.14	0.07	0.00
Production for home consumption (%)	96.6	98.3	0.00
Probability of being self-sufficient [‡]	0.41	0.30	0.00
Observations	1,420	1,647	

Notes: Three household survey waves pooled; rain shock refers to a June-August rainfall at least 0.5 standard deviation below the village's historical average.

* 2-sided t-test for differences in means. [†] Crop failure is defined as a zero harvest despite a positive area sown. [‡] Self-sufficiency is defined as an annual rice production greater than 135kg per capita.

The above statistics make it evident that most households in the sample are

²⁴In 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 especially rice (Deaton and Drèze, 2009). Therefore, above 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 considered roughly self-sufficient and a net seller. I compute a measure of rice production per capita, normalizing household size by the equivalence scale suggested by Townsend (1994).

net buyers and strongly negatively affected by a bad monsoon.²⁵ The next sections turn to the econometric estimation of the impact of SHGs to mitigate such rainfall shocks.

4 Empirical analysis

4.1 Outcomes of interest

The empirical analysis of this paper will focus on the following outcomes: food security, credit, and income diversification through seasonal migration. Table 2 provides descriptive statistics on all the outcome variables used in the empirical analysis.

4.1.1 Food security

Given the above discussion about how agricultural outcomes are affected by rainfall and recalling that home-grown rice is the staple food in the sample villages, a key dimension of household welfare in presence of rain shocks is food security. The steady access to a sufficiently nutritious diet is a key factor affecting human nutritional status, child development and health. According to FAO et al. (2018), “poor access to food increases the risk of low birth weight and stunting in children,

²⁵In Appendix B, I show that local agricultural prices react moderately 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 – probably reflecting a decrease in the demand for vegetables due to the negative income effect from the rice price increase (see Table 16). However, it is clear that these modest price effects will not nearly compensate for the large quantity variations, even for the few net sellers in the sample.

Table 2: Outcomes of interest: descriptive statistics

	All households (N=3,067)			Treated households (N=2,438)			Control households (N=629)		
	Mean	Std Dev.	Median	Mean	Std Dev.	Median	Mean	Std Dev.	Median
<i>Food security variables</i>									
Yields (kg/acre)	625.6	543.3	480.0	610.0	523.8	477.8	682.0	605.7	500.0
Months with enough food last year	10.63	2.29	12.00	10.70	2.23	12.00	10.40	2.47	12.00
Probability of food shortage	0.35	0.48	0.00	0.34	0.47	0.00	0.39	0.49	0.00
Animal protein consumption (INR)	1,050.9	2,009.8	0.0	1,058.0	2,003.9	0.0	1,023.7	2,033.6	0.0
<i>Credit variables</i>									
Probability of borrowing in Jan.-May	0.28	0.45	0.00	0.30	0.46	0.00	0.20	0.40	0.00
Probability of borrowing in June-Dec.	0.47	0.50	0.00	0.49	0.50	0.00	0.40	0.49	0.00
Probability of borrowing from SHG in June-Dec.	0.27	0.44	0.00	0.31	0.46	0.00	0.09	0.29	0.00
Total credit in June-Dec. (INR)	936.3	2,074.2	0.0	943.9	2,013.5	0.0	906.9	2,297.5	0.0
SHG share in total credit in June-Dec.	0.53	0.49	1.00	0.59	0.48	1.00	0.23	0.42	0.00
Avg int. rate on loans taken in June-Dec. (% monthly)	3.08	3.73	2.00	2.74	3.32	2.00	4.65	4.91	3.00
Private transfers received (INR)	2,490.7	5,851.4	70.0	2,471.7	5,741.3	100.0	2,564.1	6,262.4	0.0
Private transfers sent (INR)	436.1	2,125.9	0.0	429.5	2,002.7	0.0	461.5	2,550.2	0.0
<i>Seasonal work migration variables</i>									
Number of laborers in household	1.82	1.19	2.00	1.82	1.18	2.00	1.82	1.21	2.00
Labor income (INR)	9,672.0	10,808.3	6,600.0	9,729.8	10,789.5	6,700.0	9,447.5	10,886.7	6,300.0
Probability of seasonally migrating	0.15	0.36	0.00	0.15	0.36	0.00	0.14	0.34	0.00
Total income from seasonal migration (INR)	963.0	2,933.4	0.0	984.6	2,971.5	0.0	879.8	2,782.0	0.0
Total savings brought home from seas. migration (INR)	448.5	1,488.6	0.0	456.3	1,509.3	0.0	418.2	1,406.8	0.0

Notes: The three data waves are pooled. For all continuous variables, I remove the top 1% of observations to avoid the undue influence of very large values.

which are associated with higher risk of overweight and obesity later in life.”

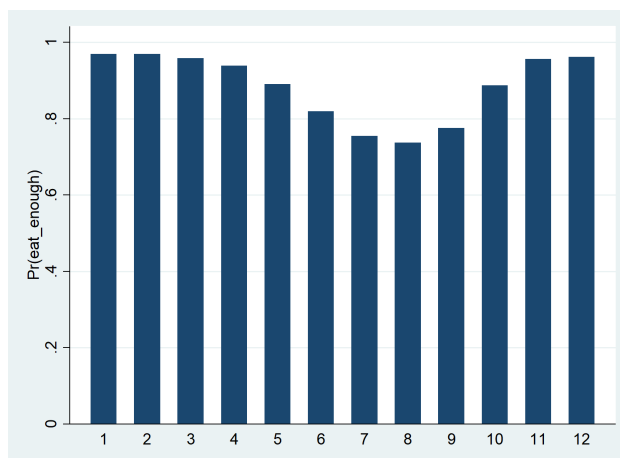
India performs very poorly on a wide range of nutrition indicators. In the most recent Global Hunger Index (von Grebmer et al., 2020), India ranks 94 out of 107 countries. According to the National Family Health Survey (IIPS, 2015), the country exhibits particularly high rates of stunting (38%), wasting (21%) and anemia (59%) among children under 5 years, and underweight (23%) and anemia (53%) among adult women. In Jharkhand, the same statistics are much worse, with rates of stunting, wasting and anemia of respectively 45%, 29% and 70% among children under 5, and with 31% and 65% of adult women being respectively underweight and anemic. Jharkhand is indeed one of the states with the highest levels of hunger and malnutrition prevalence in India (Swaminathan et al., 2019). Alarmingly, very little progress has been done over the last decades, with several indicators actually worsening.

Raghunathan et al. (2021) show that the level and volatility of food prices and rural incomes are important determinants of food security in India, both between

and within years. They estimate that as much as 63–76% of the rural poor could not afford a recommended diet in 2011. Likewise, Carpena (2019) shows that droughts negatively impact not only the quantity but also the quality of household diets in rural India, coming primarily from the reduction of household market and non-market income.

It is therefore crucial to understand whether SHGs can help to smooth food consumption across seasons, and in particular when production is lower and prices are higher following a drought. Ideally, intra-year variation in food availability should be assessed on the basis of weekly or at least monthly food consumption, especially regarding the lean season. Unfortunately, given that the three surveys were carried once a year in January-March, i.e. shortly after the kharif harvest, the available food consumption data are not really able to capture these effects. However, the questionnaire did ask about food availability throughout the year: for each month of the previous year, households were asked if there was enough food for all members to enjoy 3 meals per day. While this measure is certainly imperfect and might be sensitive to some behavioral biases (e.g. selective memory or ex-post rationalization), it is probably a good proxy on average to rank households in terms of food vulnerability. It is easy to understand for respondents, for whom the memory of the painful experience of hunger is certainly long-lasting. Moreover, aggregate statistics make sense given the environment. On average, the households declare that food was sufficient during 10.6 months per year, with 35% of them suffering hunger for at least one month. As can be seen clearly from Figure 2, food security decreases gradually with time since the last rice harvest, reaching its lowest point in the June-September period – which, as explained above, corresponds to the bridge period where the income shock is expected to hit hardest.

Figure 2: Food security across months



Data: own household survey (3 waves pooled).

4.1.2 Credit

Credit is expected to be an important channel for any potential role of SHGs. The survey collected data on all loans taken during the two years preceding each survey wave, including the date of borrowing, useful to identify mechanisms. Loans might be taken ‘immediately’ after rain shocks, for instance to finance agricultural expenditure to take advantage of a good monsoon or, conversely, 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. Credit can also be especially useful one year later, i.e. during the following lean season. As explained above, this is the period of maximum hunger in rural Jharkhand, when relative scarcity is the highest, and households are expected to seek credit to see them through to the next harvest, especially following a negative rain shock. However, this might be a period of acute credit shortage if traditional lenders suffered bad harvests themselves,

given that the major traditional sources of credit are relatives, neighbors and bigger farmers from the same community (see Table 18 in Appendix B for a description of the local credit market). Moreover, given that traditional lenders often demand an immediate start for repayment, it might be harder to take loans after a bad shock.

As a consequence, households are expected to need more credit in the second half of the year, especially when there was a bad monsoon one year before. In the data, the average probability of borrowing between January and May is 28%, against 47% between June and December. The analysis below therefore focuses on the latter period. On average, households take 936 INR (a bit more than 10 USD) of credit between June and December, corresponding to about 5% of their total annual income (the sum of all remunerations received plus the net value of agricultural production over the year). On average, households borrow about as much in treated as in control villages. However, there is a big difference in the composition of such credit, as SHGs appear to largely crowd out traditional sources when they are present in the village. In treated villages, 31% of the households take at least one SHG loan between June and December, and SHG credit accounts for almost 60% of total credit on average. In control villages, the corresponding figures are only 9% and 23%.²⁶ This is also reflected in a much lower average interest rate paid on loans taken in treated villages (SHG loans being much cheaper than moneylenders', see Table 18). Indeed, as a rule, only current group members can borrow from SHGs. Moreover, there is no evidence of substantial spillovers to other villagers, as less than 4% of non-member households living in

²⁶As a reminder, a small number of SHGs entered control villages from wave 2, see section 2.1.

treated villages report borrowing from SHG, for an average value of 34 INR. This different composition of credit sources might imply a very different volatility of credit availability and conditions in periods of shocks.

4.1.3 External labor supply and migration

Supplying labor outside the farm can be an important way to diversify income sources and mitigate expected agricultural income shocks. Indeed, many households complement agricultural income with some kind of off-season labor activity, such as casual labor or handicrafts. In my sample, only 10% of households are exclusively involved in farming. 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 occurs in the post-monsoon winter months (September-November) and, to a lower extent, 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 due to depleted stocks 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 in the sample do not migrate: on average, only 15% of the households send at least one member into seasonal migration.

The foremost reason is that migration involves many different costs. There are direct monetary costs, 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 occurs during the off-season. Another utility cost associated with migration is income risk: migrants may not find work on arrival or may have to work for lower wages than expected (Harris and Todaro, 1970; Bryan et al., 2014). Finally, there are non-monetary costs for migrants, reflecting a preference for staying in the village for 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 these non-monetary costs can be very high 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 absent from the household for working purposes for a maximum of six months during the year preceding the survey (beyond six months, they were considered as permanent migrants). Table 3 presents some basic statistics about all migration spells observed in the sample. On average, migration episodes last 3.4 months. By far the most frequent destination is West Bengal, a neighboring state that is a major agricultural producer and home to large manufacturers, especially in the Calcutta region. Other frequent destinations include New Delhi, Maharashtra, and elsewhere in Jharkhand. In terms of occupation, most (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-negligible fraction (7%) of labor migrants fail to earn any income, highlighting again the riskiness of migration. At the end of the migration, each migrant brings back home 3,000 rupees on average (in addition to possible remittances while away). Finally, most migrants (79%) are males, and are either the head of the household (31%) or a son (48%).

Table 3: Seasonal labor migration: descriptive statistics at the migration-spell level (N=587)

	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
Savings brought home (hundreds INR)	30.16	34.07	20	0	42

4.2 Econometric strategy

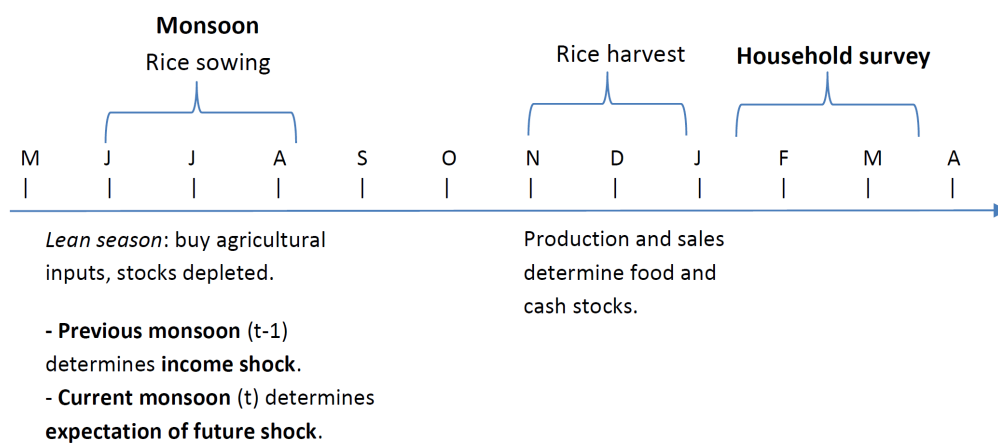
Although average rainfall is predictably different from place to place, the deviation of each year’s rainfall from its local mean is serially uncorrelated and largely unpredictable at the start of the season.²⁷ That is, rainfall shocks are exogenous and unanticipated, spread over space, and their incidence is balanced between treated and control villages thanks to the stratified randomization of villages.

Figure 3 sketches the timing of events over the year as well as their potential consequences on outcomes of interest. The income shock is expected to hit one year

²⁷As 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. Given the erratic nature of rainfall in Jharkhand, this is highly unlikely in this context. In particular, it is very hard to predict the timing of the monsoon onset and the distribution of rainfall, two crucial parameters for agricultural outcomes. Moreover, rainfall does not appear to be serially correlated in the data (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 observing a bad monsoon. Hence, some outcomes – e.g. agriculture (obviously), or migration decisions (if based on expectations) – are expected to react to the last monsoon (t), while others – e.g. food security and transfers, which depend primarily on current income – are expected to react to the monsoon before ($t-1$).

Figure 3: 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), using a difference-in-difference specification. 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, controlling for potentially different baseline levels. This ITT approach, while it reveals the impact of SHG *access* and not actual participation, has the advantages of avoiding any bias stemming from the self-selection of SHG members, and of factoring in potential spillovers from member

to non-member households within treated villages.²⁸

My baseline specification takes the following form:

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

where Y_{ivt} is the outcome of interest (agricultural production, food security, credit, transfers, migration) for household i in village v and year t , $Rain_{vt}$ is a measure of monsoon quality as 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). Coefficient β is the main coefficient of interest, measuring the relative difference between households in treated and control villages under rainfall shocks (controlling for any normal-time difference). This coefficient therefore estimates the average effect of having access to SHGs at the village level, allowing for the fact that part of the population does not directly participate in the intervention (70% on average). \mathbf{H}_{it} is a vector of control variables at the household level, including household size in equivalent adults²⁹, official scheduled caste or tribe and below-poverty-line statuses, head's

²⁸Because 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 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. For instance, Demont (2016) shows that, in this context, the development of microfinance might result in lower access to credit in treated villages for households who are not member of SHGs, because the riskiness of moneylenders' borrower pool increases given adverse selection – an effect which is particularly salient when default risk increases after a drought. Likewise, section 5.2 shows that private transfers between households in the village are also affected.

²⁹I 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 Maharashtra): for adult males, 1.0; for adult females, 0.9; for males

education and age (in a quadratic fashion), and land ownership category (land size between the 25th and the 75th percentile or larger than the 75th percentile of the district-round distribution). Finally, λ_t are round (year) fixed effects that account for economy-wide shocks and $\eta_{v/i}$ are village or household fixed effects (all results are presented using both specifications) that account for villages' fixed characteristics or households' fixed characteristics (including at the village level) and average behavior. In the specification with household fixed effects, \mathbf{H} is replaced by household size in equivalent adults only. Throughout, standard errors are clustered at the village level (i.e. treatment level) to account for the intra-cluster correlation of standard errors and potential heteroskedasticity. Because of the low number of clusters (36), I always report both the cluster-robust standard errors (using the standard sandwich variance estimator) as well as the wild cluster bootstrap correction proposed by Cameron et al. (2008) for situations when large-sample assumptions might fail to hold (using the procedure developed by Roodman et al. 2019).

5 Results

5.1 Food security

Table 4 first confirms that rice production in the study area is very sensitive to the monsoon intensity, and that my rain and shock variables are indeed identifying important agricultural productivity shocks. In columns 1 and 2, I estimate

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, though it could vary quicker through migration.

a 0.5 elasticity of rice yields – 10% more rain leading to a 5% increase in yields.³⁰ Looking at the interaction term, I find that treated villages are just as strongly impacted, which was expected given that not much can be done to combat poor rainfall when cultivating rain-fed rice (risk-mitigating investments such as irrigation are too complex and costly for 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 30%, implying a large expected income shock. Columns 3 and 4 show that food security depends heavily on monsoon intensity, with an estimated average elasticity close to one (0.9). However, it is significantly more stable for treated households, who suffer less than half as much variation in food consumption on average. After a negative shock, control households lose 2 months of sufficient food on average, while the loss is only one month for treated households. Using a dichotomous version of the previous variable, I estimate in columns 5 and 6 that a drought increases the probability to suffer hunger for at least one month by 28-29 percentage points on average. Again, the SHG treatment significantly decreases this probability, by 13-14 percentage points on average. When removing households who declare to have never enough throughout the year (a potential recall bias), results are slightly stronger (not reported here). Finally, I try to go beyond quantity outcomes and study the quality of the diet. As explain above, short-term food data collected a few weeks after the harvest have a limited capacity to detect the impact of rain shocks on the quality and variety of the diet. Yet, one category

³⁰Yields are the quantity harvested in last November-December, divided by the area cultivated (in kilograms per acre). Other outcomes, such as rice production or sales, follow the same pattern.

of food, animal proteins, can be considered as a superior good in this context.³¹ Unlike staple food, it can be potentially affected even a few weeks after harvest, through harvest-determined cash earnings from rice sales or expectations of lower future income (e.g. future need to buy cereals on the market). Animal protein consumption is low in the sample, with only 35% reporting a positive quantity. It is however a powerful provider of iron and thus an important component of the fight against widespread anemia. In columns 7 and 8, I find that animal protein consumption in January-March depends strongly on the last monsoon's intensity, with an estimated elasticity of 1.7. This is likely to strongly impact nutritional status, though my data does not permit me to check the persistence of the effect over the year. Here again, treated households enjoy much more stable consumption, especially after a negative shock, which leaves their animal protein consumption almost unchanged.

Hence, it appears that SHGs help households to ensure that there is adequate and steadier food consumption across months when harvests are low and prices are high. This in turn can provide large health and economic benefits in the long run, given the adverse consequences of food consumption volatility (e.g. Branca et al., 1993; Alderman et al., 2006; Maluccio et al., 2009; Rao et al., 2009; Ampaabeng and Tan, 2013; FAO et al., 2018). The next sections are devoted to explaining how treated households manage to smooth food consumption after a drought, despite suffering just as severe agricultural losses.

³¹Animal proteins include eggs, fish, and different types of meat. I compute the monetary value of aggregate consumption using the village median of reported prices.

Table 4: Rice yields and food security

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Relevant monsoon episode:</i>	Log rice yields	Log rice yields	Months enough food	Months enough food	Proba. food shortage	Proba. food shortage	Log animal prot. cons.	Log animal prot. cons. (+1)
	<i>t</i>	<i>t</i>	<i>t-1</i>	<i>t-1</i>	<i>t-1</i>	<i>t-1</i>	<i>t</i>	<i>t</i>
A. Log rainfall								
<i>Rain</i>	0.509** (0.199) [0.027]	0.521** (0.205) [0.030]	6.012*** (1.656) [0.002]	6.053*** (1.699) [0.003]	-0.895*** (0.196) [0.004]	-0.858*** (0.208) [0.006]	1.756*** (0.519) [0.001]	1.706*** (0.512) [0.002]
<i>Rain * Treat</i>	-0.133 (0.212) [0.564]	-0.158 (0.218) [0.514]	-3.301* (1.717) [0.067]	-3.526* (1.758) [0.040]	0.453** (0.198) [0.010]	0.449** (0.213) [0.028]	-0.896 (0.525) [0.106]	-0.897* (0.517) [0.096]
B. Negative rainfall shock (drought)								
<i>Rain_shock</i>	-0.322*** (0.100) [0.006]	-0.322*** (0.101) [0.009]	-2.111*** (0.491) [0.000]	-2.111*** (0.506) [0.000]	0.298*** (0.0650) [0.002]	0.289*** (0.0655) [0.002]	-0.862*** (0.231) [0.002]	-0.832*** (0.233) [0.003]
<i>Rain_shock * Treat</i>	0.0730 (0.106) [0.499]	0.0636 (0.109) [0.610]	1.022* (0.511) [0.070]	1.079* (0.524) [0.066]	-0.141* (0.0675) [0.061]	-0.145* (0.0694) [0.053]	0.627** (0.268) [0.029]	0.619** (0.266) [0.028]
Village FE	✓		✓		✓		✓	
Household FE		✓		✓		✓		✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2337	2340	3063	3067	3063	3067	3063	3067
Mean of dep. var. in control group	741	741	10.4	10.4	0.390	0.390	1130	1130

Notes: This table reports OLS estimates of the ITT effect of SHGs on the outcomes listed at the top of the columns. Yields are the quantity harvested divided by the area cultivated (in kilograms per acre) and are defined only for households who cultivated a positive area. Animal proteins consumption is the monetary value of the total consumption of eggs, fish, and meat. All equations include a constant and household controls (restricted to family size with household FE). Robust standard errors clustered at the village level are reported in round brackets. P-values of wild cluster bootstrap tests (999 replications, Webb weight) are reported in square brackets. Stars are reported when *both* corrections indicate statistical significance (* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$).

5.2 Credit

This section focuses on credit, which is expected to be an important channel for the consumption-smoothing effect of SHGs. I test the hypothesis that SHGs bring easier access to credit, even in periods of low rainfall, and that this credit is directly related to higher food security.

Table 5 displays immediate and lean-season treatment effects on credit. Columns 1-8 report quantity effects, showing both the probability of borrowing and the total amount borrowed from all sources between June and December. Both outcomes deliver similar insights, indicating that most of the action takes place at the extensive margin.³² What emerges very clearly is that borrowing is

³²For the ease of interpreting coefficients in terms of elasticities and to deal with the positive

strongly positively related to rainfall quality for control households. Moreover, the effects are, as expected, stronger for the ‘lean-season’ period than the ‘immediate’ period. In control villages, the elasticity between rainfall and amounts borrowed is 1.4-1.6 in the immediate period, which doubles to 3.2-3.3 in the lean season – indicating that total credit is divided by 3 one year after a monsoon that was just 20% below average. By contrast, treated households appear to enjoy a robust access to credit, which allows them to borrow counter-cyclically in response to shocks, as their coefficients more than compensate for controls’. Focusing on negative shocks (panel B), I estimate that, one year after a drought, the probability of borrowing is 19 percentage points (almost 50%) lower for control households, but 6 percentage points *higher* for treated households. The last two columns of Table 5 show that the equilibrium interest rate increases sharply in control villages after a shock, but much more modestly in treated villages. This price effect is however not significant in presence of household fixed effects, as few households take multiple loans in those periods when credit is expensive, especially in control villages. In the interest of space, I do not report results for the immediate period, for which I do not find any price effects.

Given that the demand for credit is theoretically higher in case of a negative income shock, the observed evolution of the credit quantity exchanged in control villages after a drought suggests severe rationing from traditional lenders. Actually, more than half of the loans taken by households who are not member of SHGs come from neighbors and relatives (see Table 18), who are likely to be affected by the

asymmetry of the distribution of credit, I regress the log of amounts plus one. A Poisson regression on levels give very similar results. In Appendix, I show that results are virtually unchanged when rainfall in both t and $t-1$ are included in the same equation (‘horse-race’ specification in Table 17).

Table 5: Credit (June to December)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Borrowing probability				Log total credit (+1)				Interest rate	
	Immediately		Lean season		Immediately		Lean season		Lean season	
<i>Relevant monsoon episode:</i>	t		t-1		t		t-1		t-1	
A. Log rainfall										
<i>Rain</i>	0.219*** (0.0708) [0.006]	0.238** (0.0741) [0.013]	0.551* (0.274) [0.019]	0.557* (0.276) [0.021]	1.443** (0.515) [0.021]	1.576** (0.530) [0.016]	3.243* (1.734) [0.028]	3.309* (1.750) [0.030]	-8.386** (3.215) [0.033]	-5.384 (3.182) [0.168]
<i>Rain * Treat</i>	-0.284*** (0.0755) [0.004]	-0.302*** (0.0790) [0.002]	-0.659** (0.290) [0.020]	-0.692** (0.291) [0.023]	-2.099*** (0.567) [0.003]	-2.201*** (0.582) [0.001]	-3.975** (1.819) [0.016]	-4.227** (1.822) [0.021]	7.059* (3.028) [0.068]	3.492 (3.010) [0.298]
B. Negative rainfall shock (drought)										
<i>Rain_shock</i>	-0.147** (0.0512) [0.011]	-0.154** (0.0522) [0.012]	-0.192** (0.0792) [0.029]	-0.197** (0.0796) [0.038]	-0.949** (0.347) [0.016]	-0.990** (0.353) [0.021]	-1.241** (0.502) [0.027]	-1.275** (0.497) [0.025]	1.995** (0.840) [0.034]	1.722 (0.979) [0.227]
<i>Rain_shock * Treat</i>	0.174*** (0.0564) [0.007]	0.181*** (0.0571) [0.009]	0.247*** (0.0843) [0.003]	0.260*** (0.0848) [0.007]	1.172*** (0.386) [0.006]	1.204*** (0.390) [0.009]	1.539*** (0.529) [0.014]	1.628*** (0.525) [0.010]	-1.918** (0.823) [0.039]	-1.237 (0.924) [0.304]
Village FE	✓		✓		✓		✓		✓	
Household FE		✓		✓		✓		✓		✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3063	3067	3063	3067	3062	3066	3062	3066	1126	1130
Mean of dep. var. in control group	0.396	0.396	0.396	0.396	1.333	1.333	1.333	1.333	4.65	4.65

Notes: This table reports OLS estimates of the ITT effect of SHGs on the outcomes listed at the top of the columns. All equations include a constant and household controls (restricted to family size with household FE). Robust standard errors clustered at the village level are reported in round brackets. P-values of wild cluster bootstrap tests (999 replications, Webb weight) are reported in square brackets. Stars are reported when *both* corrections indicate statistical significance (*p<0.10, **p<0.05, ***p<0.01).

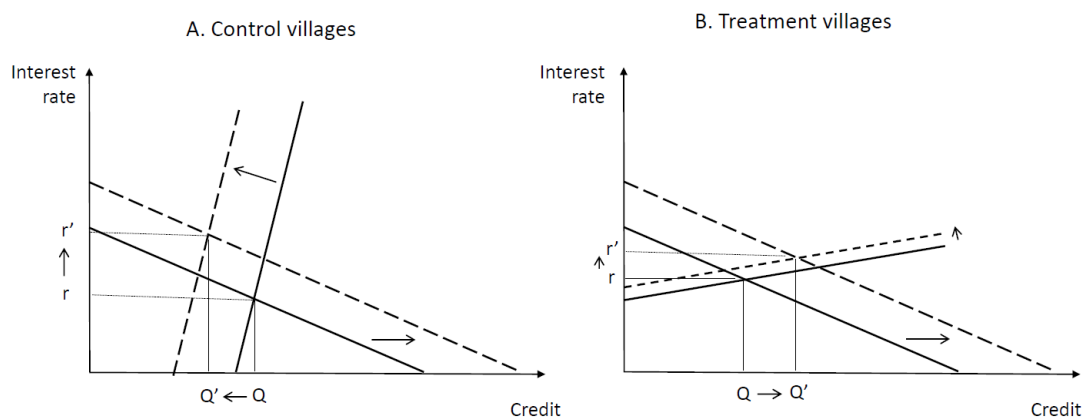
same rain shock. Even moneylenders, the main source of credit for non-members, are often larger farmers living in the same village or its neighborhood and therefore not generally insulated from local rain shocks. Moreover, such ‘professional’ lenders might anticipate lower repayment rates and be more reluctant to lend after a shock.³³ By contrast, treated villages take the majority of their loans from SHGs, and their access to credit is unaffected by rain shocks.

Figure 4 represents two credit markets that plausibly correspond to treatment and control village situations, and are consistent with the above findings. A negative income shock implies a shift rightwards of the demand for credit in all villages. In control villages, the credit supply is not very elastic and strongly shifts leftwards

³³See Demont (2016) for a discussion about the riskiness of moneylenders’ business in the same context.

after a negative rain shock, which results in a large reduction of the equilibrium credit quantity and a sharp increase in the equilibrium interest rate (see panel A in Figure 4). In treated villages, the presence of SHGs implies a more liquid credit market, with a more elastic supply and a smaller shift leftwards after a shock.³⁴ As a result, in treated villages, the equilibrium quantity of credit increases and the equilibrium interest rate increases only slightly after a shock.

Figure 4: Credit market equilibria in treated and control villages after a shock



The arrows indicate the effect of a negative rainfall shock.

In a nutshell, while access to credit is strongly pro-cyclical for poor households in Indian villages, the presence of SHGs ensures stable, even counter-cyclical, access.³⁵ 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 the event of adverse rainfall shocks. Different factors explain why SHGs are able to continue lending when there are major and largely covariate shocks. As mentioned in sec-

³⁴The fact that SHG credit supply is more elastic than traditional lenders' is also consistent with the fact that there is a significantly higher within-village volatility of the interest rates paid on moneylenders' loans than on SHG loans.

³⁵It is worth recalling that SHG loans are essentially only available to current SHG members, such that ITT estimates are probably underestimating the counter-cyclical use of credit by SHG members.

tion 2, the main reasons are that SHG members do not borrow from their *current* money but from a pool of accumulated savings growing over time, and this pool is complemented by external loans from commercial banks.³⁶ 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 can meet most individual credit needs through regular deposit collecting and borrowing from commercial banks.

The availability of credit under covariate income shocks is all the more important since private transfers also tend to dry up in these periods. The questionnaire asked about all transfers received and made, in cash or in kind, from/to any other household. Those transfers mostly come from relatives, with intergenerational transfers between parents and children making up about half of the cases, and transfers to/from other relatives accounting for another 40%. The main purposes of the transfers are family events (about 50% of the cases) – like marriage (including dowry), births and funerals –, festivals (13%), durable goods acquisition / investment (13%), and consumption (about 10%). Table 6 shows that, during the year starting 6 months after and ending 18 months after a bad monsoon, all households in the sample receive significantly less transfers, with an average loss of 25%. Transfers made, lower to start with, shrink even more, by 70% on average. This is strongly indicative of the fact that informal insurance mechanisms are not able to cope with such shocks, which is not surprising since most households living locally are affected.³⁷ Interestingly, treated households are as affected as control

³⁶In Appendix B, I provide further evidence of the resilience of SHGs. First, I show that, even after a bad monsoon, members keep saving regularly and the modal behavior remains taking an amount of annual credit roughly equal to own annual savings. Second, I show that repayment rates on SHG loans remain high after shocks, but that there is higher flexibility on extended terms.

³⁷Most relatives live in the same village or nearby, as permanent migration is very limited in the sample. Indeed, only 21% of the households declare having at least one relative living outside

households, which suggests that there is neither crowding out nor crowding in of informal insurance in this context.

Table 6: Private transfers

	Means in cases of		P-value [†]
	no rain shock in t-1	rain shock in t-1	
Transfers received	2,923	2,224	0.013
Transfers made	892	290	0.000
Net transfers	2,017	1,933	0.786
Observations	2,212	847	

Notes: Rain shock refers to a June-August rainfall at least 0.5 standard deviation below the village’s historical average. [†] Two-sided t-test for difference in means. I remove the top percentile of the conditional distribution of positive amounts to avoid the undue influence of very large values.

I now try to explicitly link 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. Interestingly, the proportion of credit for consumption purposes goes up very significantly one year after a drought, from 23 to 34%, above all other categories (see Table 7). That is, under shocks, households seem to borrow primarily to finance consumption. I also observe a significant reduction of the share of ‘non-necessary’ credit, e.g. to finance expenses related to social events, which echoes the results on transfers.

Second, in Appendix B, I replicate Table 5 distinguishing between credit for consumption and business / work purposes (see Table 20). Interestingly, for consumption loans, the estimated treatment effect disappears for the immediate period – during which food security is not an issue, while it remains significant and strong for the lean season. I observe the opposite for business loans, where treatment ef-

of the village.

Table 7: Distribution of loan purposes (June-December)

Proportion of credit for...	Means in cases of		P-value [†]
	no rain shock in t-1	rain shock in t-1	
consumption	0.232	0.341	0.000
business / work	0.308	0.297	0.652
health	0.324	0.285	0.127
education + social + other	0.133	0.077	0.001
Observations	984	444	

Notes: Rain shock refers to a June-August rainfall at least 0.5 standard deviation below the village's historical average. [†] Two-sided t-test for difference in means. I remove the top percentile of the conditional distribution of positive credit amounts to avoid the undue influence of very large values.

fects are larger for the immediate period – when treated households undertake mitigating strategies such as seasonal migration (see section 5.3). Finally, despite obvious endogeneity concerns, I plug credit as a control variable into the food security equation. To get as close as possible to the causal mechanism, I focus on negative shocks and credit taken between June and September (in logs), i.e. the months of greatest hunger identified in Figure 2. The two first columns of Table 8 show that credit in general significantly helps to ensure greater food security after a drought. Columns 3 and 4 show that the estimated treatment effect decreases once credit is controlled for, suggesting that part of such effect operates through the credit channel. I estimate that treated households suffer 40% less hunger than control households once the pure credit effect is separately accounted for (against 50% earlier). The fact that there remains an independent treatment effect indicates that there are certainly other channels at play beyond credit (in line with the various missions of SHGs highlighted in the introduction).

Such additional channels include the adoption of risk-mitigating strategies. Indeed, 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 to sustain a higher level of consumption. Credit, in

Table 8: Food security and credit

	(1)	(2)	(3)	(4)
	Months with enough food			
<i>Relevant monsoon episode:</i>	<i>t-1</i>			
<i>Rain_shock</i>	-1.579*** (0.289) [0.000]	-1.635*** (0.293) [0.000]	-2.288*** (0.474) [0.000]	-2.364*** (0.476) [0.000]
<i>Rain_shock * Treat</i>			0.931* (0.481) [0.074]	0.975* (0.485) [0.065]
<i>Credit_junsep</i>	-0.0164 (0.0117) [0.154]	-0.0369** (0.0159) [0.016]	-0.0169 (0.0115) [0.149]	-0.0376** (0.0158) [0.020]
<i>Credit_junsep * Rain_shock</i>	0.104** (0.0405) [0.009]	0.142*** (0.0464) [0.000]	0.0940** (0.0381) [0.012]	0.126*** (0.0435) [0.005]
Village FE	✓		✓	
Household FE		✓		✓
Year FE	✓	✓	✓	✓
Observations	3062	3066	3062	3066
Mean of dep. var. in control group	10.4	10.4	10.4	10.4

Notes: This table reports OLS estimates of the ITT effect of SHGs on the outcome listed at the top of the columns. *Credit_junsep* is the logarithm of the cumulative amount of credit taken between June and September (+1). All equations include a constant and household controls (restricted to family size with household FE). Robust standard errors clustered at the village level are reported in round brackets. P-values of wild cluster bootstrap tests (999 replications, Webb weight) are reported in square brackets. Stars are reported when *both* corrections indicate statistical significance (*p<0.10, **p<0.05, ***p<0.01).

particular business loans (see Table 20), might help finance risk-mitigating activities in expectation of the impending income shock.

5.3 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. In Table 9, I show that treated households supply significantly more labor outside of their farm in bad-monsoon years, which translates into higher labor income (by 10% on average).³⁸ As explained above, most of this wage work is undertaken through seasonal migration, which is analyzed separately in Table 10. I find very sizable treatment effects. While control households do not (or cannot) increase migration immediately after a bad monsoon, treated households are 6 percentage points (about 50%) more likely to migrate. As a result, they enjoy an increase in total migration income and savings of about 60%.

The above findings indicate that treated households are better able to diversify income sources, through seasonal migration, in order to mitigate impending income shocks, which echoes the results of Bryan et al. (2014). It can be assumed that additional earnings from waged activities away from home are another explanation for the higher food security observed in section 5.1. Although I have no data on food security during the year following the detected increase in migration, a back-of-the-envelope calculation indicates that the estimated migration treatment effect after a drought implies that seasonal migration increases the gross income of treated households by about 600 INR on average, which corresponds to more

³⁸Unfortunately, I do not have the precise starting date of the jobs taken, such that these data correspond to the total labor supplied over the year (some of it potentially before the monsoon).

Table 9: External labor supply

	(1)	(2)	(3)	(4)
	Number of laborers		Log labor income (+1)	
<i>Relevant monsoon episode:</i>			<i>t</i>	
A. Log rainfall				
<i>Rain</i>	0.0895 (0.166) [0.471]	0.0810 (0.152) [0.445]	0.553 (0.544) [0.308]	0.554 (0.485) [0.222]
<i>Rain * Treat</i>	-0.333 (0.196) [0.103]	-0.334* (0.177) [0.082]	-1.384* (0.711) [0.068]	-1.432** (0.612) [0.041]
B. Rainfall shock				
<i>Rain_shock</i>	-0.111 (0.0996) [0.252]	-0.107 (0.0878) [0.216]	-0.420 (0.379) [0.303]	-0.402 (0.323) [0.206]
<i>Rain_shock * Treat</i>	0.193 (0.113) [0.103]	0.200* (0.0993) [0.079]	0.700 (0.445) [0.138]	0.707* (0.378) [0.087]
Village FE	✓		✓	
Household FE		✓		✓
Year FE	✓	✓	✓	✓
Observations	3063	3067	3062	3066
Mean of dep. var. in control group	1.81	1.81	14,558	14,558

Notes: This table reports OLS estimates of the ITT effect of SHGs on the outcome listed at the top of the columns. All equations include a constant and household controls (restricted to family size with household FE). Robust standard errors clustered at the village level are reported in round brackets. P-values of wild cluster bootstrap tests (999 replications, Webb weight) are reported in square brackets. Stars are reported when *both* corrections indicate statistical significance (*p<0.10, **p<0.05, ***p<0.01).

Table 10: Seasonal migration

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Relevant monsoon episode:</i>	Migration probability		Log mig. income (+1)		Log mig. savings (+1)	
	<i>t</i>					
A. Log rainfall						
<i>Rain</i>	0.0230 (0.0548) [0.638]	0.0157 (0.0574) [0.677]	0.283 (0.481) [0.531]	0.216 (0.509) [0.607]	0.229 (0.447) [0.579]	0.197 (0.477) [0.627]
<i>Rain * Treat</i>	-0.129** (0.0557) [0.027]	-0.127** (0.0562) [0.021]	-1.122** (0.486) [0.031]	-1.076** (0.493) [0.039]	-0.947** (0.408) [0.034]	-0.926* (0.423) [0.052]
B. Negative rainfall shock (drought)						
<i>Rain_shock</i>	-0.0217 (0.0282) [0.468]	-0.0157 (0.0305) [0.622]	-0.246 (0.248) [0.380]	-0.194 (0.268) [0.496]	-0.239 (0.241) [0.343]	-0.205 (0.262) [0.450]
<i>Rain_shock * Treat</i>	0.0751** (0.0326) [0.034]	0.0730* (0.0337) [0.064]	0.660** (0.282) [0.028]	0.629** (0.291) [0.050]	0.610** (0.252) [0.042]	0.592** (0.265) [0.049]
Village FE	✓		✓		✓	
Household FE		✓		✓		✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	3063	3067	3062	3066	3062	3066
Mean of dep. var. in control group	0.133	0.133	984	984	421	421

Notes: This table reports OLS estimates of the ITT effect of SHGs on the outcomes listed at the top of the columns. All equations include a constant and household controls (restricted to family size with household FE). Robust standard errors clustered at the village level are reported in round brackets. P-values of wild cluster bootstrap tests (999 replications, Webb weight) are reported in square brackets. Stars are reported when *both* corrections indicate statistical significance (*p<0.10, **p<0.05, ***p<0.01).

than 22 days worth of food.³⁹

It is very likely that this is another positive consequence of credit availability listed in the previous section, though other aspects of SHGs are probably at work too. First, credit might help treated households to pay for the direct sunk costs of migration, even though the strongest credit treatment effects are not observed immediately after rain shocks but rather during the lean season (see Table 5).⁴⁰ Indeed, I do find evidence of a strong and positive direct effect of credit on migration after a rain shock (see Table 11). As in the case of food security, credit

³⁹In the sample, the modal monthly expenditure on food is 789 INR.

⁴⁰Interestingly, 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.

explains a share of the treatment effect, but not all.

Table 11: Migration and credit

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Migration probability	Log mig. income	Log mig. income (+1)	Log mig. income (+1)	Migration probability	Log mig. income (+1)	Log mig. income (+1)	Log mig. income (+1)
<i>Relevant monsoon episode:</i>	<i>t</i>							
<i>Rain_shock</i>	-0.00470 (0.0200) [0.782]	0.0128 (0.0212) [0.498]	-0.0475 (0.173) [0.747]	0.0714 (0.186) [0.632]	-0.0555 (0.0295) [0.119]	-0.0355 (0.0325) [0.381]	-0.500* (0.260) [0.078]	-0.350 (0.284) [0.331]
<i>Rain_shock * Treat</i>					0.0666* (0.0325) [0.087]	0.0641* (0.0336) [0.059]	0.594* (0.280) [0.051]	0.560* (0.290) [0.091]
<i>Credit_jundec</i>	-0.00330 (0.00214) [0.109]	0.000514 (0.00252) [0.750]	-0.0242 (0.0181) [0.150]	0.00378 (0.0211) [0.799]	-0.00335 (0.00212) [0.090]	0.000392 (0.00252) [0.802]	-0.0247 (0.0179) [0.143]	0.00274 (0.0210) [0.808]
<i>Credit_jundec * Rain_shock</i>	0.0125*** (0.00318) [0.001]	0.00842** (0.00315) [0.028]	0.0947*** (0.0275) [0.002]	0.0668** (0.0273) [0.043]	0.0121*** (0.00315) [0.002]	0.00798** (0.00315) [0.011]	0.0919*** (0.0272) [0.003]	0.0630** (0.0271) [0.025]
Village FE	✓		✓		✓		✓	
Household FE		✓		✓		✓		✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3062	3066	3061	3065	3062	3066	3061	3065
Mean of dep. var. in control group	0.133	0.133	0.133	0.133	0.133	0.133	0.133	0.133

Notes: This table reports OLS estimates of the ITT effect of SHGs on the outcome listed at the top of the columns. *Credit_jundec* is the logarithm of the cumulative amount of credit taken between June and December (+1). All equations include a constant and household controls (restricted to family size with household FE). Robust standard errors clustered at the village level are reported in round brackets. P-values of wild cluster bootstrap tests (999 replications, Webb weight) are reported in square brackets. Stars are reported when *both* corrections indicate statistical significance (*p<0.10, **p<0.05, ***p<0.01).

Second, the higher *expected* availability of credit in treated villages might also play an important role in reducing the income risk from migration (such as in Bryan et al., 2014). For instance, SHGs can offer consumption credit and provide informal insurance and support for women left behind, should migrating husbands fail to send money for some time. Unfortunately, evidence regarding this channel is harder to collect, since it involves expectations and depends on migration failure.

A third effect of SHGs, going beyond credit, might lie in decreasing 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 their destination. Table 12 shows that the probability of migrating is strongly positively correlated

with own experience of previous migration (row 1), which seems to come partly from learning for households who have not previously migrated (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 and it has a lasting effect (row 4), pointing again to the importance of experience and learning (from peers in this case). Moreover, 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 facilitating personal experience and learning, as well as by expanding peer networks (as another source of learning, through information exchange and imitation).⁴¹ This likely accounts for another, potentially large, part 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 to support this hypothesis.⁴²

6 Conclusion

In developing countries, most poor households experience substantial income volatility because of their high exposure to shocks, combined with a lack of ap-

⁴¹Several studies have shown the importance of giving households the opportunity 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.

⁴²Related 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 have pointed out that, because of the support of the group, improved financial capability, and the ability to formulate individual projects, female empowerment is a major consequence of participation in SHGs (e.g. Desai and Joshi, 2013; Deininger and Liu, 2013; Datta, 2015; Baland et al., 2019, 2020; Kumar et al., 2021).

Table 12: Probability of migrating: correlation matrix

Sample:	All waves	2 last waves
(1) Someone in hh. migrated in previous wave	-	0.144 (0.000)
(2) Someone in hh. migrated in wave 2 but nobody migrated in wave 1 [†]	-	0.089 (0.014)
(3) Proportion of hh. in village who migrated in current wave [‡]	0.196 (0.000)	0.180 (0.000)
(4) Proportion of hh. in village who migrated in previous wave [‡]	-	0.045 (0.040)
<i>SHG members only:</i>		
(5) Someone from own SHG migrated in current wave [‡]	0.160 (0.000)	0.156 (0.000)
(6) Someone from own SHG migrated in previous wave [‡]	-	0.063 (0.052)

Notes: This table reports the Pearson correlation between the probability of having at least one seasonal migrant in the household and the variable listed in each row. Significance levels (p-values) in parentheses. [†] Estimated on last wave only. [‡] Excluding current household.

propriate 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 provide welfare-improving opportunities to smooth household consumption. Although (or perhaps because) the argument is theoretically well-accepted, however, there is very little direct empirical evidence on how microcredit impacts the capacity to cope with (climate-related) income shocks.

Self-Help Groups (SHGs) represent one of the most successful and sustainable microfinance programs in the world and constitute a key anti-poverty strategy in South Asia. However, their impact on consumption-smoothing in the face of income shocks has not previously been evaluated. The present paper studies how SHGs impact the effects of monsoon intensity on the access to credit, seasonal migration, and food security of rural households in Jharkhand, East India. The

paper combines meteorological data with original panel data from a long-term 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. While credit access dries up in control villages one year after a bad monsoon, reflecting strong credit rationing from informal lenders during the lean season, I find that treated households enjoy stable access to credit over time and can even borrow counter-cyclically. That is, SHGs continue playing their crucial buffer role even under (largely covariate) weather shocks, thanks to their collecting of regular deposits, their strong repayment performance, and their links with external commercial banks. I then show that treated households increase seasonal migration immediately after observing a bad monsoon, to mitigate the future agricultural income shock (expected to hit about one year later) 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 and experience exchanges can take place. Finally, I find that the combination of SHG credit and migration earnings allows treated households to enjoy much greater food security over the year.

To my knowledge, this is one of the first papers to provide direct causal evidence on the role of microcredit to tackle two very important and topical challenges: dealing with climatic shocks and encouraging profitable seasonal migration.

It shows that SHGs, which appear very resilient to covariate weather shocks, are useful and effective credit instruments for rural households. Even though they are not designed as insurance tools, they offer members significant seasonal smoothing opportunities, with potentially large medium- and long-term benefits to members. They appear to significantly increase households' resilience and adaptive capacity in the face of changing climate variability and increasing extremes. As emphasized in the text, given the nature of SHGs, this should in fact be considered as the impact of a bundled intervention, including microcredit but also solidarity networks, collective action platforms, and female empowerment.

My findings have potentially important policy implications. Weather shocks are ubiquitous and expected to increase in future due to climate change, with major 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 community-based financial associations such as SHGs may be a better option. In particular, there may be ways to marginally change the way microcredit operates to further enhance households' risk management. For instance, SHGs' policy of forced savings, though central to their resilience, may nevertheless be too rigid to play an effective insurance role over multiple years under major adverse shocks. Well-established SHGs could profitably explore the possibility of relaxing the regular savings constraint during periods of economic hardship.

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A Descriptive statistics on the sample

Table 13: 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	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.

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

	Obs.	Control Group		Treatment-Control		
		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	36	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 i th group.

Table 15: Baseline summary household-level statistics and balance check

	Obs.	Control Group		Treatment-Control		
		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
Annual rice production (kg)	1,050	554.9	(46.7)	-10.6	(62.3)	0.865
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 in 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.

B Supplementary material

B1 Agricultural prices

Table 16: Agricultural market prices

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Rice (farm-gate)		Rice (market)		Tomatoes (market)		Onions (market)	
<i>Rain</i>	-1.269**		-0.393*		1.476*		0.971**	
	(0.502)		(0.216)		(0.757)		(0.370)	
<i>Rain_shock</i>		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).

B2 Credit

Table 17: Credit (June to December): horse-race specification

	(1)	(2)	(3)	(4)
	Borrowing probability		Total credit (log)	
<i>Rain_shock_t</i>	-0.102**	-0.108**	-0.665**	-0.697**
	(0.0460)	(0.0465)	(0.302)	(0.304)
	[0.035]	[0.029]	[0.045]	[0.043]
<i>Rain_shock_t * Treat</i>	0.117**	0.121**	0.826**	0.837**
	(0.0519)	(0.0524)	(0.344)	(0.347)
	[0.044]	[0.037]	[0.023]	[0.035]
<i>Rain_shock_{t-1}</i>	-0.154*	-0.158*	-1.009*	-1.030**
	(0.0784)	(0.0776)	(0.492)	(0.479)
	[0.075]	[0.063]	[0.066]	[0.0135]
<i>Rain_shock_{t-1} * Treat</i>	0.204**	0.216**	1.240**	1.328**
	(0.0822)	(0.0819)	(0.506)	(0.497)
	[0.041]	[0.024]	[0.042]	[0.041]
Village FE		✓	✓	
Household FE			✓	✓
Year FE		✓	✓	✓
Observations		3063	3067	3067
Mean of dep. var. in control group		0.396	0.396	0.396

Notes: This table reports OLS estimates of the ITT effect of SHGs on the outcomes listed at the top of the columns. All equations include a constant and household controls (restricted to family size with household FE). Robust standard errors clustered at the village level are reported in round brackets. P-values of wild cluster bootstrap tests (999 replications, Webb weight) are reported in square brackets. Stars are reported when *both* corrections indicate statistical significance (*p<0.10, **p<0.05, ***p<0.01).

Table 18 shows how the credit market looks like in the villages of this study, by reporting average statistics on all loans taken by the households in the sample between 2004 and 2009 (with a gap in 2006 given that respondents were asked about all loans taken in the two years preceding each survey wave). Formal bank loans are extremely rare, reflecting the local market imperfections. Households traditionally borrow from moneylenders, neighbors, and relatives. SHG loans represent a much cheaper option, which is essentially only available to SHG members (who basically substitute SHG for all other sources). They are also clearly more easily available (though they generally involve lower amounts), being more than twice more frequent than all other sources combined (while SHG member households represent less than half the sample overall).

Table 18: 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

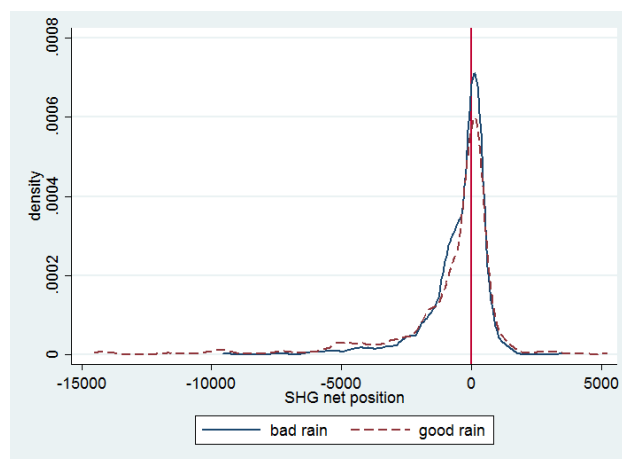
Figure 5 displays the distribution of the net annual position of SHG members - i.e. the sum of regular deposits over the year (excluding loan repayment) minus the sum of loans, one year after a monsoon below or above median.⁴³ Strikingly, the distributions appear very similar in good and bad years.⁴⁴ Moreover, both distributions are centered around zero, s.t. the most frequent pattern is to fully

⁴³SHGs keep two separate accounts for each member, one for regular deposits and one for loans taken and repaid. Only if there is a problem of repayment is the savings account used to absorb the debt.

⁴⁴A fixed-effect regression of SHG net position on rain deficit of the form of equation (1) gives positive and insignificant estimates.

collateralize SHG loans over the year: more than half of SHG members display a net position of 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 not the case for all members, as there is an important mass of net contributors to the group and an even larger mass of net borrowers.

Figure 5: Net SHG position and monsoon intensity in t-1: Kernel density estimate



Another aspect of SHG resilience is the evolution of repayment performance (though groups break even with savings alone, as shown above, at least for the modal member). Table 19 displays statistics concerning repayment performance. While outright defaults are extremely rare in our data, delays in repayment are common. I observe that a bad monsoon negatively affects promptness in repayment of SHG loans but not of other loans. In fact, other loans tend to be repaid better when rainfall is poor, likely due to moneylenders' stricter selection of borrowers and harsher loan recovery practices in periods of funding scarcity. This is in line with the fact that the contractual term of these loans decreases sharply in bad years. As

a consequence, even with an extended repayment period, the availability of savings means that rainfall shocks have no major consequence on SHGs' sustainability.

Table 19: 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 1 if (repayment time > contractual term) when the loan is repaid or if (time elapsed from the date of borrowing > contractual term) when the loan is not repaid, and is equal to 0 otherwise.

Table 20: Borrowing probability (June to December), by purpose

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Consumption purpose				Business / work purpose			
	Immediately		Lean season		Immediately		Lean season	
<i>Relevant monsoon episode:</i>	t		t-1		t		t-1	
A. Log rainfall								
<i>Rain</i>	0.00452 (0.0453) [0.915]	0.0175 (0.0457) [0.699]	0.211* (0.109) [0.019]	0.229** (0.112) [0.018]	0.115** (0.0440) [0.022]	0.130** (0.0452) [0.019]	0.111 (0.102) [0.314]	0.0959 (0.115) [0.435]
<i>Rain * Treat</i>	-0.0136 (0.0539) [0.827]	-0.0295 (0.0548) [0.624]	-0.311** (0.119) [0.010]	-0.349*** (0.120) [0.002]	-0.190*** (0.0562) [0.005]	-0.198*** (0.0574) [0.005]	-0.187 (0.120) [0.138]	-0.177 (0.132) [0.208]
B. Negative rainfall shock (drought)								
<i>Rain_shock</i>	-0.0221 (0.0231) [0.362]	-0.0284 (0.0234) [0.243]	-0.0374 (0.0308) [0.267]	-0.0408 (0.0306) [0.228]	-0.0766*** (0.0235) [0.010]	-0.0843** (0.0247) [0.020]	-0.0699** (0.0295) [0.040]	-0.0697** (0.0302) [0.045]
<i>Rain_shock * Treat</i>	0.0208 (0.0283) [0.482]	0.0294 (0.0286) [0.321]	0.110*** (0.0312) [0.001]	0.120*** (0.0315) [0.001]	0.106*** (0.0333) [0.004]	0.111*** (0.0343) [0.005]	0.0816** (0.0371) [0.045]	0.0796* (0.0381) [0.067]
Village FE	✓		✓		✓		✓	
Household FE		✓		✓		✓		✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3063	3067	3063	3067	3063	3067	3063	3067
Mean of dep. var. in control group	0.396	0.396	0.396	0.396	1333	1333	1333	1333

Notes: This table reports OLS estimates of the ITT effect of SHGs on the outcomes listed at the top of the columns. All equations include a constant and household controls (restricted to family size with household FE). Robust standard errors clustered at the village level are reported in round brackets. P-values of wild cluster bootstrap tests (999 replications, Webb weight) are reported in square brackets. Stars are reported when *both* corrections indicate statistical significance (*p<0.10, **p<0.05, ***p<0.01).

C Robustness checks

C1 Fully balanced panel

Table 21: Rice yields and food security: balanced panel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Relevant monsoon episode:</i>	Rice yields (log)		Months with enough food		Proba. of food shortage		Animal protein cons. (log)	
	<i>t</i>		<i>t-1</i>		<i>t-1</i>		<i>t</i>	
A. Log rainfall								
<i>Rain</i>	0.460** (0.191) [0.025]	0.485** (0.203) [0.028]	6.389*** (1.717) [0.001]	6.356*** (1.745) [0.001]	-0.865*** (0.206) [0.003]	-0.852*** (0.209) [0.002]	1.676*** (0.449) [0.004]	1.681*** (0.449) [0.000]
<i>Rain * Treat</i>	-0.111 (0.204) [0.600]	-0.133 (0.220) [0.549]	-3.731** (1.788) [0.018]	-3.747** (1.816) [0.026]	0.434** (0.208) [0.024]	0.436** (0.213) [0.037]	-0.894* (0.454) [0.042]	-0.936** (0.447) [0.045]
B. Negative rainfall shock (drought)								
<i>Rain_shock</i>	-0.286*** (0.0964) [0.007]	-0.296*** (0.100) [0.012]	-2.261*** (0.519) [0.000]	-2.262*** (0.525) [0.000]	0.300*** (0.0629) [0.001]	0.298*** (0.0630) [0.000]	-0.798*** (0.212) [0.006]	-0.801*** (0.215) [0.006]
<i>Rain_shock * Treat</i>	0.0459 (0.103) [0.676]	0.0440 (0.109) [0.698]	1.172** (0.537) [0.049]	1.202** (0.544) [0.045]	-0.143** (0.0649) [0.037]	-0.149** (0.0657) [0.035]	0.622** (0.257) [0.021]	0.638** (0.253) [0.026]
Village FE	✓		✓		✓		✓	
Household FE		✓		✓		✓		✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2163	2166	2777	2781	2777	2781	2777	2781
Mean of dep. var. in control group	734	734	10.4	10.4	0.381	0.381	1115	1115

Notes: This table reports OLS estimates of the ITT effect of SHGs on the outcomes listed at the top of the columns. All equations include a constant and household controls (restricted to family size with household FE). Robust standard errors clustered at the village level are reported in round brackets. P-values of wild cluster bootstrap tests (999 replications, Webb weight) are reported in square brackets. Stars are reported when *both* corrections indicate statistical significance (*p<0.10, **p<0.05, ***p<0.01).

Table 22: Credit: balanced panel

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Borrowing probability				Total credit (log)			
	Immediately	Lean season	Lean season	Lean season	Immediately	Lean season	Lean season	Lean season
<i>Relevant monsoon episode:</i>	t	t	t-1	t-1	t	t	t-1	t-1
A. Log rainfall								
<i>Rain</i>	0.235** (0.0790) [0.013]	0.248** (0.0801) [0.013]	0.497* (0.263) [0.038]	0.508* (0.260) [0.029]	1.570** (0.573) [0.022]	1.647** (0.572) [0.035]	2.870* (1.666) [0.046]	2.982* (1.650) [0.036]
<i>Rain * Treat</i>	-0.320*** (0.0857) [0.005]	-0.331*** (0.0876) [0.001]	-0.686** (0.278) [0.015]	-0.694** (0.277) [0.018]	-2.355*** (0.630) [0.004]	-2.409*** (0.634) [0.004]	-4.217** (1.740) [0.017]	-4.304** (1.735) [0.012]
B. Negative rainfall shock (drought)								
<i>Rain_shock</i>	-0.156*** (0.0524) [0.010]	-0.159** (0.0528) [0.012]	-0.170** (0.0801) [0.049]	-0.175** (0.0792) [0.050]	-1.001*** (0.359) [0.008]	-1.018*** (0.359) [0.008]	-1.086** (0.509) [0.044]	-1.132** (0.497) [0.036]
<i>Rain_shock * Treat</i>	0.190*** (0.0583) [0.007]	0.193*** (0.0585) [0.010]	0.258*** (0.0844) [0.002]	0.260*** (0.0847) [0.003]	1.286*** (0.400) [0.006]	1.296*** (0.400) [0.006]	1.645*** (0.530) [0.003]	1.656*** (0.526) [0.007]
Village FE	✓		✓		✓		✓	
Household FE		✓		✓		✓		✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	2777	2781	2777	2781	2776	2780	2776	2780
Mean of dep. var. in control group	0.401	0.401	0.401	0.401	1387	1387	1387	1387

Notes: This table reports OLS estimates of the ITT effect of SHGs on the outcomes listed at the top of the columns. All equations include a constant and household controls (restricted to family size with household FE). Robust standard errors clustered at the village level are reported in round brackets. P-values of wild cluster bootstrap tests (999 replications, Webb weight) are reported in square brackets. Stars are reported when *both* corrections indicate statistical significance (*p<0.10, **p<0.05, ***p<0.01).

C2 Extreme shocks ($Rain_def_{vt} \geq 1$)

Table 23: Seasonal migration: balanced panel

	(1)	(2)	(3)	(4)	(5)	(6)
<i>Relevant monsoon episode:</i>	Migration probability		Mig. income (log)		Mig. savings (log)	
	<i>t</i>					
A. Log rainfall						
<i>Rain</i>	0.0102 (0.0581) [0.872]	0.00904 (0.0607) [0.899]	0.179 (0.514) [0.721]	0.156 (0.539) [0.782]	0.191 (0.469) [0.698]	0.167 (0.504) [0.750]
<i>Rain * Treat</i>	-0.135** (0.0551) [0.024]	-0.132** (0.0564) [0.048]	-1.176** (0.480) [0.041]	-1.134* (0.493) [0.051]	-0.952* (0.437) [0.065]	-0.923* (0.453) [0.077]
B. Negative rainfall shock (drought)						
<i>Rain_shock</i>	-0.0112 (0.0308) [0.713]	-0.00955 (0.0323) [0.765]	-0.159 (0.272) [0.554]	-0.142 (0.283) [0.496]	-0.187 (0.258) [0.676]	-0.172 (0.274) [0.583]
<i>Rain_shock * Treat</i>	0.0758** (0.0322) [0.031]	0.0730** (0.0330) [0.055]	0.656** (0.280) [0.040]	0.627** (0.286) [0.048]	0.600** (0.268) [0.047]	0.577* (0.277) [0.068]
Village FE	✓		✓		✓	
Household FE		✓		✓		✓
Year FE	✓	✓	✓	✓	✓	✓
Observations	2777	2781	2776	2780	2777	2781
Mean of dep. var. in control group	0.134	0.134	1004	1004	428	428

Notes: This table reports OLS estimates of the ITT effect of SHGs on the outcomes listed at the top of the columns. All equations include a constant and household controls (restricted to family size with household FE). Robust standard errors clustered at the village level are reported in round brackets. P-values of wild cluster bootstrap tests (999 replications, Webb weight) are reported in square brackets. Stars are reported when *both* corrections indicate statistical significance (*p<0.10, **p<0.05, ***p<0.01).

Table 24: Food security and migration: extreme shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Relevant monsoon episode:</i>	Months with enough food		Probab. of food shortage		Migration probability		Mig. income (log)	
	<i>t-1</i>							
	<i>t</i>							
<i>Ext_rain_shock</i>	-1.692** (0.736) [0.030]	-1.731** (0.751) [0.040]	0.232** (0.0906) [0.036]	0.236** (0.0923) [0.045]	-0.0164 (0.0282) [0.643]	-0.0200 (0.0309) [0.620]	-0.138 (0.244) [0.658]	-0.160 (0.267) [0.617]
<i>Ext_rain_shock * Treat</i>	1.127 (0.745) [0.216]	1.201 (0.761) [0.204]	-0.118 (0.0918) [0.255]	-0.129 (0.0955) [0.240]	0.0701** (0.0292) [0.019]	0.0749** (0.0303) [0.044]	0.543** (0.248) [0.049]	0.569* (0.258) [0.060]
Village FE	✓		✓		✓		✓	
Household FE		✓		✓		✓		✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3063	3067	3063	3067	3063	3067	3062	3066
Mean of dep. var. in control group	10.4	10.4	0.390	0.390	0.133	0.133	984	984

Notes: This table reports OLS estimates of the ITT effect of SHGs on the outcomes listed at the top of the columns. All equations include a constant and household controls (restricted to family size with household FE). Robust standard errors clustered at the village level are reported in round brackets. P-values of wild cluster bootstrap tests (999 replications, Webb weight) are reported in square brackets. *p<0.10, **p<0.05, ***p<0.01.