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RISK SHARING, COMMITMENT CONSTRAINTS AND SELF HELP GROUPS

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Risk Sharing, Commitment Constraints and Self Help Groups
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ABSTRACT

Evaluations of group savings and lending programs have largely focused on *average* impacts, rather than *distributional* impacts — finding modest effects on long-term economic well-being. In this paper, we exploit the randomized roll-out of a self-help group lending program in rural Bihar, India (Hoffmann et al., 2021) to demonstrate that well-functioning groups facilitate risk-sharing within rural communities. We find no impact of the program on risk-sharing, measured as a reduction in the variance of consumption growth, in the aggregate. However, the program significantly improves risk-sharing in regions where it had greater institutional capacity and was better implemented. Building on our theoretical framework, we provide evidence of a specific channel of impact: program quality and pre-existing scale improve the quality and functioning of groups, which in turn increase the insurance value of the program to communities.

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1 Introduction

There is by now a large and growing literature evaluating the impacts of group savings and lending programs (including micro-finance and self-help groups (SHGs)) in developing countries. Six of these studies, focusing mainly on micro-credit (reviewed in Banerjee et al., 2015) found modest impacts on outcomes, such as household consumption, that should reflect levels of long term economic well-being. However, the vast majority of papers that look at microfinance or savings programs have focused on the *average* impacts, and not the *distributional* impacts of such programs.

One important channel through which such programs might plausibly affect participants' welfare is by changing the variability of recipient outcomes, i.e., improving the degree of *risk sharing* among them. Feigenberg et al. (2013), for instance, study how the features and rules of microcredit programs affect the level of risk sharing that prevails within groups as well as the probability of repayment. Fischer (2013) looks at the interaction of the structure of micro-credit programs with informal risk sharing and finds that these effects could explain the limited success of micro-credit programs in stimulating successful investment. Related to risk, Attanasio et al. (2018) consider how perceived subjective uncertainty in a certain context affects the likelihood of joining a group. However, direct evidence on the impact of an intervention aimed at fostering group formation and activities on the amount of risk sharing is virtually non-existent.

In this paper, we study the impact of a group savings and lending program on risk sharing. This is important from both a theoretical and policy perspective. From a normative point of view, identifying potential benefits (or the lack thereof) of such programs that might have so far been overlooked is important, since insurance can be extremely valuable to the families and the communities targeted by the intervention. From a theoretical point of view, the study helps us understand the nature of risk-sharing in rural communities and identify existing imperfections that might prevent full risk-sharing. In particular, the program we study can provide a sensible narrative about the type of imperfection such an intervention may be correcting so as to improve risk sharing.

We focus on *Jeevika*, a women's SHG program in the eastern Indian state of Bihar. Run by the state as part of India's National Rural Livelihoods Mission (NRLM), the program combines access to finance with training curricula relating to women's empowerment, collective action and livelihoods. A *Jeevika* SHG comprises between 10 and 15 women, each of whom reside within the same residential neighbourhood (hamlet) of a village. As with other group savings and lending programs, groups meet regularly (usually weekly) and contribute a fixed amount into a group savings account. Internal savings, augmented by government grants and bank borrowing, enable loans amongst group members at an interest rate of 2% per month — a significantly lower rate than those charged by informal lenders. Decisions regarding loan recipients and amounts are made collectively by the members of each group.

Our analysis builds on a prior cluster randomized evaluation of the program between 2011 and 2014 (Hoffmann et al., 2021). *Jeevika*'s second phase commenced in 2011, and Hoffmann et al. selected an experimental sample from the set of *Gram Panchayats* (GPs) that had not been included in the program's first phase (2006-2011).[1] Following a baseline survey in 2011, the Hoffmann et al. study team randomized *Gram Panchayats* into treatment and control groups. The program was implemented in treated GPs in 2012, an endline survey was conducted in late 2014, and, finally, control GPs received access to *Jeevika* in 2015. The experimental sample included GPs from 16 blocks in 7 districts — spanning the different zones of the state to address concerns regarding the external validity of the study's findings.[2]

This first evaluation found a considerable effect of *Jeevika* on the functioning of local credit markets. In particular, Hoffmann et al. (2021) show significantly lower interest rates in treatment relative to control villages and improvements in household access to low-cost credit. Furthermore, the intervention seemed to have generated a reduction in informal loans from local moneylenders — the study documents a reduction in interest rates on loans from moneylenders, and a reduction in the reported number of moneylenders actively lending in the village. Despite these positive outcomes and substantial changes in the functioning of the local credit markets, however, the program's effect on average consumption and other measures of long term well-being seemed to be minimal (consistent with the other interventions cited above).

The lack of effects on the level of, and growth in, household consumption expenditures is perhaps unsurprising. In the early stages of the program's implementation, loan amounts are relatively small since the size of groups' endowments or resources are also relatively small. Consequently, in the first few years of their development, such group-based interventions might be more likely to help protect members from idiosyncratic shocks than to enable productive income-enhancing investments. Such improvements in risk-sharing agreements might be welfare improving both in the short and long run. In other words, one potentially important impact of the program could be on the amount of risk sharing that it can provide members of the SHG. The original study, however, did not evaluate whether the program affected the amount and modality of risk sharing.

A common strategy to study risk sharing, following the seminal work by Townsend (1994), is to examine changes in individual consumption in response to idiosyncratic income changes after controlling for the change in average income in a given risk sharing group. Perfect risk sharing, which is typically used as a benchmark, would imply that idiosyncratic income shocks are insured by the group so that, after controlling for aggregate fluctuations, these shocks should not be reflected in changes in idiosyncratic consumption.[3] Imperfect risk

[1] A *Gram Panchayat* is a group of between 2 and 4 villages.

[2] A block is a 'third-level' administrative unit in India, with the higher level units being the district and the state.

[3] A number of additional assumptions are needed for such a result to hold, including homogeneity of preferences. It is possible that, with heterogeneous aversion to risk, some households might be willing to

sharing, instead, might generate a correlation between idiosyncratic income and consumption changes.

The lack of reliable data that would allow us to measure income shocks prevents us from using this approach. We instead test whether the introduction of SHGs impacted risk sharing within groups and/or within villages where SHGs are operative using an alternative measure of risk sharing proposed by Attanasio and Székely (2004) (which develops work in Deaton and Paxson, 1994; Albarran and Attanasio, 2003). Rather than identifying the relationship between idiosyncratic income and consumption shocks, this approach looks at another implication of perfect risk sharing, namely that the distribution of marginal utilities within a risk sharing group should be unchanged over time. With power utility (as noted by Deaton and Paxson, 1994), perfect risk sharing within a group implies that the variance of log-consumption within that group is constant. Our analysis of the variance of log consumption changes within a village rejects perfect risk sharing. However, the nature of our data and the survey design allow us to dig deeper into the functioning of insurance mechanisms and propose a narrative about the imperfections that prevent optimal risk sharing.

One such narrative derives from models where full risk sharing is not achieved because of the imperfect enforceability of informal contracts, of the type considered, for instance, by Ligon et al. (2002), Albarran and Attanasio (2003) and, more recently, by Abraham and Laczó (2018). In these models, the amount of risk sharing that can be implemented in equilibrium depends on the punishment that can be imposed upon individuals that do not follow through on their commitments. If the punishment is ostracism from a group, the amount of feasible risk sharing will depend on the difference between the value of being in and outside the group. Therefore, SHG membership can improve risk sharing in the presence of enforceability problems, because exclusion from the group might imply an additional punishment for individuals that do not respect the risk sharing agreement. Moreover, variation in the quality of the groups (and therefore in the value of membership) would imply corresponding variation in the contribution of SHGs to risk sharing, as it would imply variability in the extent to which participation constraints bind. Testing for risk sharing across contexts that differ in group quality and hence the benefits of membership can thus be informative about the mechanisms and imperfections that prevent perfect risk sharing and lead to its empirical rejection.

The experimental sample drawn by Hoffmann et al. (2021) provides an opportunity to analyze such differences in quality, since it includes blocks that differed significantly in their initial administrative capacity and experience with the program. This regional difference was caused by the phasing of the program across blocks — *Jeevika* was first implemented in some parts of "Phase 1" blocks in 2006, while villages in "Phase 2" blocks did not receive access to the program until 2012. Within each phase or set of blocks, the roll-out of the program across GPs was also staggered. As a result, at the start of the study period in 2011,

absorb a larger fraction of aggregate risk and be compensated by a higher average level of consumption.

the experimental sample spanned both "Phase 1" blocks where some non-experimental GPs had already received access to the program as well as "Phase 2" blocks where almost none of the non-experimental GPs had received access to the program. In 2011, following a baseline survey within the experimental sample, experimental GPs within each block were then randomized into a 'treatment' or early roll-out group and a 'control' or late roll-out group (see Figure 1). This results in an experimental sample of GPs with no program presence in 2011 drawn from blocks with previous exposure to *Jeevika* (5 'Phase 1' blocks) as well as blocks without previous exposure (11 'Phase 2' blocks).

We show that SHGs located in blocks that had prior experience with the program differed significantly from those in other blocks. Correspondingly, distinguishing between SHGs in Phase 1 (previous exposure) and Phase 2 blocks (no exposure), we find differences in treatment effects on risk sharing, with access to SHG groups significantly reducing the variance in household consumption growth in treatment villages in Phase 1 blocks. Thus, while our findings suggest an important and previously undocumented role for the program in increasing risk sharing, they also reveal significant variation in the extent to which SHGs serve this function.[4]

Understanding the determinants of this variation is the second aim of this paper. In addition to differences in program implementation, Phase 1 blocks also differ from those in Phase 2 in initial socio-economic conditions: Phase 2 (no exposure) blocks in the sample fall in the *Kosi* region of Bihar, a region characterized by higher levels of poverty, greater dependence on agriculture, and significantly more out-migration. This complicates the interpretation of the regional heterogeneity in treatment effects that we document.

We make headway by exploiting the variation in past exposure to the program across survey blocks and exploring the role of this variation in explaining the heterogeneity in treatment effects. We find that interactions of the treatment indicator with measures of program scale (functions of the number of SHGs in each block) at the start of Phase 2 (2011) and hence prior to the initiation of the program in treatment GPs fully explain the regional variation in treatment effects between Phase 1 and Phase 2 blocks. This provides supportive evidence that the variation in treatment effects across Phase 1 and 2 blocks arises from variation in program implementation rather than underlying heterogeneity.

These same programmatic factors also have large effects on a key measure of SHG capacity – village-level SHG funds (which we obtained from rich administrative data). This in turn suggests that their effect on risk-sharing may operate through their impact on group endowments, as hypothesized by the theoretical literature on risk sharing with limited commitment cited above (Abraham and Laczó, 2018; Albarran and Attanasio, 2003). Using the interaction of the treatment indicator with these programmatic factors as instruments for village-level group savings, we provide empirical support for these models, showing that

[4]This heterogeneity of program impacts on risk sharing is not reflected in differential impacts on consumption *levels*, which are unaffected in both sub-samples.

village-level SHG endowments significantly explain the ability of SHGs to reduce the variance in consumption growth.

Our study is amongst the few that establishes the value of group-lending programs for increasing risk sharing. Additionally, our contribution to the literature lies in the support we provide for theoretical models of insurance under limited commitment and for our identification of the importance of program implementation in this regard. Thus, while most studies that examine risk reduction focus on "demand side" determinants related to socio-economic characteristics of the region such as its exposure to weather variability or the strength of insurance networks, ours is amongst the few that emphasizes that policy can play a significant role in enhancing the quality of groups and hence their insurance value to households. We emphasize, in particular, the importance of program experience for the quality of new groups. While this suggests a role for administrative capacity, we note that this could also reflect other differences.

Our empirical analysis is enabled by data from two new sources that we combine with the baseline and endline household surveys used in the previously cited initial evaluation of the project. The first is an extensive follow-up survey, conducted in 2019, of SHGs in the study region.[5] This survey provides details of SHG procedures, functioning and activities. A second data source is the government's Management Information System (MIS) for the program that provides rich data on the census of all SHGs in every village, including the year of formation and the number of members. The SHG survey includes data on SHG-stipulated monthly savings amounts while the MIS provides information on the growth in the number of SHGs in each village and detailed information on the scale of the program at the time of treatment. Combining SHG monthly savings with growth in the number of SHGs in treatment and control villages provides estimates of the magnitude of (expected) SHG internal funds at the level of the village.

This measure enables our analysis of the importance of group quality for risk sharing. As noted by Abraham and Laczó (2018), empirical research that establishes the role of groups in risk sharing is limited. This is true also of the larger literature that evaluates the impact of group lending on household consumption and other outcomes. With few exceptions, including those previously referenced (Feigenberg et al., 2013; Fischer, 2013), much of this literature examines treatment effects but provides little information on which aspects of groups explain their performance or, in most cases, the lack thereof. This paucity of evidence reflects the fact that while data on a set of household outcomes are generally available, detailed information on groups rarely is. Consequently, empirical support for the hypothesis that the magnitude of group funds facilitates risk sharing has not previously been available.

Our analysis also contributes to a growing literature that evaluates credit programs, includ-

[5]This survey was part of a large national evaluation of NRLM. Because of budget constraints, the survey, though covering all blocks of the initial survey, did not cover all villages. Details of this survey are provided in Section 3 of this paper.

ing group lending programs, which operate at scale. For microfinance, research by Breza and Kinnan (2021) establishes large effects of a reduction in activity attributable to reductions in aggregate demand and business activity. Similarly, Kaboski and Townsend (2012) find large effects of the Thai Government's microfinance program on credit, consumption and income, documenting evidence of general equilibrium effects through wages. Our finding that programs that operate at scale are characterized by significant heterogeneity in treatment effects is not new: several studies that evaluate credit and other programs that are implemented at scale also document this (Cameron et al., 2019; Bold et al., 2018; Joshi and Rao, 2018; Imbert and Papp, 2015). Our contribution to this literature lies in our focus on risk sharing, and on the empirical evidence we provide that relates treatment heterogeneity to differences in the ability of SHGs to enforce contracts through their accumulation of funds.

2 Background

In this section, we provide information on the Self Help Group intervention we will be studying and about Bihar, the context where it was implemented.

2.1 Setting

Bihar is among India's poorest states. In 2011-12, the start of our study period, Bihar's net state domestic product per capita was ₹13,149 (in constant 2004-05 prices), while the average for India overall was ₹38,048 (Government of Bihar, 2015). During the same period (2011-12), national poverty estimates indicated that 34.1% of the state's rural population was below the poverty line — higher than the national average of 25.7% for the rural population (Government of India, 2013). In addition, economic conditions vary considerably across districts, with the richest district (excluding the state capital), Munger, being more than three times as rich as the poorest, Sheohar (in terms of 2011-12 net district domestic product per capita) (Government of Bihar, 2015).

2.2 *Jeevika*: The Bihar Rural Livelihoods Project

Jeevika or the Bihar Rural Livelihoods Project is a significant part of Bihar's poverty reduction strategy, and has been operational since 2006. It is a women's self-help group (SHG) program which was subsumed into India's National Rural Livelihoods Mission (NRLM) in 2011. *Jeevika* aims to improve rural households' well-being through the formation of SHGs comprising women from disadvantaged backgrounds with a primary focus on access to finance. Women who are members of *Jeevika* SHGs attend weekly group meetings, where they are required to save.[6] Group savings, augmented by state funds and loans from formal

[6] A survey of approximately 4,800 SHGs spread over 8 states conducted as part of an evaluation of the NRLM by Kochar et al., 2021 indicates that monthly savings amounts average around ₹30 per member across the NRLM.

banks, function as a pool of funds for groups to extend loans to their members. Each SHG had access to a 'revolving fund' of ₹15,000 around 6 months after a group was formed, provided as a one-time grant to the VO they were a part of (Kochar et al., 2022). During the period studied here (2011 onwards), this was ₹50,000 after 3 months of establishing regular savings (Hoffmann et al., 2021). In addition, all SHGs were also provided around ₹30,000 (Kochar et al., 2022) as a 'Community Investment Fund (CIF)'. *Jeevika* also provides women with training and leads them through curricula relating to signature literacy, basic literacy, numeracy, empowerment and collective action, and livelihoods.

As with other state versions of the NRLM, *Jeevika* supports a hierarchy of community institutions with SHGs forming the lowest tier. All groups in a village are organized into a 'Village Organization (VO)', which enables groups to pool funds at the level of the village, providing access to larger loan amounts since SHGs can borrow from VOs and on-lend to its members. VOs are, in turn, federated into a 'Cluster Level Federation (CLF)' at the level of the cluster, a group of approximately 25 villages — enabling further pooling of funds and eventual linkages with formal banks. SHG linkage to commercial banks was limited in early years of the program, and expanded only after 2015.

Importantly, the program operates at scale, intending to benefit all target households within a village. While most states identified target households using either a household's caste or 'below poverty line' status for their programs, Bihar used geographic targeting, i.e., targeting all households in hamlets identified as having high concentrations of disadvantaged households. As a result of this strategy, the number of SHGs in Bihar was substantially higher than that in other states even as early as in 2011.[7] Both the program's federated structure and its extensive coverage in Bihar suggest its potential to affect risk sharing in the entirety of a village.

Implementing the program at scale (across villages) required significant administrative capacity at the level of the block, which was the primary administrative unit for the program. First, within each block, administrative teams (known as project facilitation teams) led the formation of SHGs, VOs and CLFs. Second, to ensure the quality of each of these institutions, project facilitation teams also trained members of each level of the federation on a continuing basis. As in other at-scale programs and with the implementation of the NRLM in other states, *Jeevika* ensured administrative capacity by phasing its growth across regions and over time.[8] Additionally, *Jeevika* also formed a cadre of 'community mobilizers' to aid its

[7]Data from the program's online Management and Information System (MIS) as of 2021 report a total of 80 million SHG members in the country. With membership restricted to one woman per household, this implies a coverage rate, based on 2011 census data, of 47.5% of India's rural households. For Bihar, however, a similar calculation suggests a coverage rate that is 20 percentage points higher, at 68% (12 million members over a base of 17 million households in 2011).

[8]The general procedure was to identify early (Phase 1) and late blocks (Phase 2), distinguished by the year of program entry. Within any block, the program was also phased across villages, with full coverage of a block taking between three and four years.

expansion — an innovative method to address capacity constraints, employed across NRLM programs. Community mobilizers, or '*Jeevika didis*' were women from existing early SHGs who were identified as having leadership potential.[9] They were then trained, for between 1 and 2 additional years, to mobilize members to form new SHGs, and to monitor and expand the capacities of existing SHGs. As apart of this process, trainees also accompanied existing team for between 6 months and 1 year. Recognizing constraints on women's mobility, members of the cadre were primarily deployed within a block. The program thus built spillovers from early to late entry villages of a block into its design, correlating the capacity to monitor SHGs and hence their quality to its existing scale.

Between 2006 and 2010, *Jeevika's* first phase spanned 44 blocks in 8 districts (Government of Bihar, 2011). This phase was seen to successfully reduce household debt burdens, and improve certain measures of women's empowerment (Datta, 2015). The program commenced its second phase in 2011, with a goal to both increase its coverage of villages within existing program blocks, and to spread its coverage to new blocks (Figure 1 describes the program's phasing). Since *Jeevika* relied on its block-level cadre of 'community mobilizers', blocks where it commenced for the first time in 2011 had far lower administrative capacity at the beginning than those blocks where the program had commenced in phase 1 (as seen in Figure 2). We leverage this difference to better understand how program impacts might vary with scale.

3 The Impact of SHG on Risk Sharing: study design

We study the impact that Self Help Groups have on risk sharing, estimating this impact using *Jeevika's* expansion in 2011 and two of its features. First, its roll-out was randomized across GPs in sixteen blocks (within seven districts) in a cluster randomized controlled trial. Second, five of these study blocks had pre-existing SHGs (phase 1 blocks) while eleven had none (phase 2 blocks) — leading to variation in initial program scale within the block. The randomized roll-out and variation in initial program scale in a block at the time of *Jeevika's* entry into a village form the basis of our identification strategy, and allow for insights into the factors that underlie the insurance value of SHGs.

3.1 Sampling and Randomization

The Hoffmann et al. (2021) study team randomly selected 180 GPs from sixteen blocks to form the experimental sample. One or two villages were selected from within each GP with probability proportional to size for data collection, while households in villages were selected by stratified random sampling (the strata being *Dalit* or *Adivasi*, and other, more privileged, caste groups). This sampling design was achieved by first selecting households from *tolas* (hamlets) where the majority of households were *Dalit* or *Adivasi*, and then from other *tolas*

[9] '*Jeevika didis*' were recruited from SHGs that had been in existence for at least a year or longer.

— since *Jeevika* used a similar strategy for recruitment into the program (Hoffmann et al., 2021). A total of 8988 households across 333 villages were sampled overall, and a baseline survey was canvassed between July and October, 2011. After the baseline data collection, the study GPs were randomized into the treatment (or early roll-out) and control (or late roll-out) groups, after stratifying the sample of GPs by block and mean outstanding high-cost ($\geq$4 % per month) debt at the GP level in 2011. As a result, each randomization stratum had a pair of, or occasionally three, GPs. [10]

3.2 Randomized Roll-out of *Jeevika*

In treated (or early roll-out) GPs, *Jeevika's* community mobilizers encouraged women to form self-help groups (SHGs) under its ambit. During this expansion, once women formed SHGs in newly treated GPs, each group was required to meet on a weekly basis, and members were expected to save ₹2 (0.04 USD) each week. After 3 months of consistent savings, SHGs became eligible to borrow upto ₹50,000 (1,073 USD) from the VO at an interest rate of 1% per month. SHG members could borrow loans from their SHG at interest rates of 2% per month (far lower than the prevailing interest rates of 5% per month in the informal market). Borrowers were individually liable for their SHG loan, but collectively liable for their SHG's loan from the VO (that the SHG was a part of). Access to *Jeevika* was rolled out in treatment GPs between January and April, 2012. An endline survey was canvassed in all study villages between July and September, 2014, following which the control (late roll-out) GPs became eligible to receive access to *Jeevika*.

During the expansion, apart from access to finance, women in SHGs also received basic literacy, numeracy and signature literacy training, and were led through empowerment and collective action curricula. In the longer term, the program has also delivered livelihood training and other development interventions, but these activities had not yet commenced during the study period (Hoffmann et al., 2021).

3.3 Data

We use the following data sources: (a) primary data on household and village outcomes in 2011 and 2014 collected by the Hoffmann et al. (2021) study team for all study villages; (b) primary data on SHG outcomes in 2019 collected by our team for 321 out of 333 of the initial study villages; (c) data from the 2011 Indian census; (d) new administrative data from the program's Management and Information System (MIS) on the census of all SHGs formed in Bihar. The MIS data includes information on the formation year and member counts of

[10] Since household sampling is stratified, with 70% of sample households being *Dalit* or *Adivasi*, and 30% being non-*Dalit*/*Adivasi*, the Hoffmann et al. (2021) study team used village level data on the number of households to construct inverse probability of sampling weights to re-constitute the caste composition of each village in certain regression specifications. These sampling weights were normalized to sum to one at the village level so that each village is given equal weight in the analysis.

each SHG. This allows us to track the growth in the number of SHGs in each village and hence measure the program's scale at the time of this study.

3.4 Differences in Baseline Characteristics Across Phases

Study villages in phase 2 blocks lie in Supaul, Saharsa and Madhepura districts, which together form the geographically and economically distinct Kosi division, named for the Kosi river that flows through it. Socio-economic differences between this region and the other districts in the state result in corresponding differences between sample villages in phase 1 and phase 2 blocks in 2011.

The Kosi region is characterized by lower income levels relative to other districts in Bihar, with Supaul and Madhepura ranked in the bottom three of the 38 districts in the state in terms of per capita Gross District Domestic Product in 2011-12 (₹8,492 and ₹8,609 respectively, compared to the state's average of ₹14,574). Among districts in our study sample, those with phase 1 blocks had an average Gross District Domestic Product in 2011-12 of ₹12,275 per capita, while those with phase 2 blocks had an average Gross District Domestic Product in 2011-12 of ₹9,766 per capita (Government of Bihar, 2016).[11] In addition, data from our study's baseline survey reveal that approximately 50% of households from the Kosi region (i.e., phase 2 blocks) report an adult member who resided outside the village for a month or more in the past year, compared to 37% in phase 1 blocks (in Table B3). The region also possessed above-average connectivity with the outside economy — Table B1 indicates that phase 2 study villages were more likely to have access to all-weather roads (75% as opposed to 68% in phase 1 study villages).

The simultaneous existence of greater connectivity, higher migration and lower incomes, suggest that collective organization within the village in the Kosi region might be more difficult than in villages in our study's phase 1 blocks (i.e., those outside the Kosi region). Correspondingly, the characteristics of SHGs formed in different regions will reflect these differences in economic conditions in addition to differences in program scale. Consistent with this, Table B3 reveals that survey villages in phase 2 blocks have higher variance in consumption expenditures at baseline (0.12 as opposed to 0.10) and are less likely to have savings (37% as opposed to 47%). This highlights the main challenge we face in ascribing causality to program scale when we analyze its effect on risk-sharing within villages — phase-based differences in program scale coincide with regional differences.

[11] However, data from our study's baseline survey in 2011 (Table B3; and from the NSS Consumption-expenditure survey in the same period) indicates that sample households in phase 2 blocks had higher consumption expenditures (₹806.07 as opposed to ₹676.95) — perhaps due to the Kosi region's greater reliance on agriculture.

3.5 Randomization Balance

Tables B4 and B5 presents balance tests to evaluate the validity of random assignment to the treatment group, both for the sample overall, and separately within phase 1 and phase 2 blocks. Columns (2) and (3) present the means in levels for the control and treatment group villages, respectively. Columns (4), (5) and (6) present normalized differences (Imbens and Rubin, 2015) between the treatment and control groups (overall, within phase 1 blocks, and within phase 2 blocks) estimated through linear regressions of the normalized outcome variable on a dummy for the treatment status and controls for randomization strata, with standard errors clustered at the GP level.[12,13] The columns also present randomization inference (Fisher, 1935; Rosenbaum, 2002) p-values.[14]

Imbens and Wooldridge (2009) indicate that linear regressions methods are sensitive to specifications when differences in covariates exceed a cut-off value of 0.25 in normalized differences. Reassuringly, none of the differences in outcomes in Table B4 exceed this threshold.

4 Risk Sharing and SHG: A Conceptual Framework

We draw on the vast literature on risk sharing in rural economies to measure the level of risk sharing within a village and to build a conceptual framework that relates the presence and the level of development of Self Help Groups to the extent of risk sharing in a village and to other observable variables. A useful starting point is a benchmark case where there is perfect within-group risk-sharing in the face of idiosyncratic shocks, such as in the social planner's problem considered in Townsend (1994). An advantage of this approach is that one can consider risk sharing *within a group*, where the definition of a group can be arbitrary, without excluding the possibility of some risk being shared with individuals outside the group, or with other groups. Furthermore, this approach focuses on consumption allocations, without requiring a stand on the specific mechanisms used to achieve such allocations. One can then characterize some of the properties of these allocations and the amount of actual risk sharing by quantifying the deviations from such a benchmark.

In the problem, the planner maximizes the expected utility of a risk sharing group q, giving each individual a *Pareto weight*, which can represent a variety of factors, such as individual wealth or position in the group. While some frictions, such as imperfectly enforceable contracts, can result in changes in the Pareto weights, they are given in this context and the theory is silent about what determines them. The only constraint group q planner faces is that of aggregate resources. Therefore, neglecting aggregate saving for notational simplicity. the planner problem can be written as maximising the following function.

[12] Implementing (Heß, 2017) in Stata

[13] Imbens and Rubin (2015) indicate that normalized differences, defined as $\hat{\Delta}_{ct} = \frac{\bar{X}_t - \bar{X}_c}{\sqrt{(s_t^2 + s_c^2)/2}}$, provide scale-free measures of differences in co-variate values.

[14] Randomization inference p-values are obtained from 500 permutations

$$W^q = \sum_{i=1}^{I_q} \lambda_i^q E_0 \sum_{t=0}^{\infty} \beta^t u(c_t^{i,q}) \tag{1}$$
$$subject\ \ to \quad \sum_i c_t^{i,q} \leq \sum_i y_t^{i,q}, \qquad \forall t.$$

The Lagrangian for this problem is given by:

$$L^q = \sum_{t=0}^{\infty} E_0 \left\{ \sum_{i=1}^{I_q} \lambda_i^q \beta^t u(c_t^{i,q}) + \theta_t^q \sum_{i=1}^{I_q} [y_t^{i,q} - c_t^{i,q}] \right\} \tag{2}$$

where θ_t^g is the (non-negative) Lagrange multiplier associated with the feasibility constraints relevant in time t (and state of the world). The first order condition w.r.t. $c_t^{i,q}$ for this problem is given by the following equation:

$$\beta^t u'(c_t^{i,q}) \lambda_i^q = \theta_t^q \qquad \forall i, t. \tag{3}$$

This equation should hold for any possible state of the world, which explains the lack of an expectation operator in it. As we mentioned above, λ_i^q is the Pareto weight given to agent i in group q and is constant over time, while θ_t^q is the multiplier associated with the resource constraint at time t in a particular state of the world for risk sharing group q. [15]

Assuming power utility to compute marginal utility, and taking log of the corresponding expression we get:

$$\ln c_t^{i,q} = \frac{1}{\gamma}(t \ln \beta - \ln \theta_t^q - \ln \lambda_i^q) \quad \forall i, t. \tag{4}$$

Considering equation (4) at time t and $t-1$ and taking the difference between these two equations we get:

$$\Delta \ln c_t^{i,q} = \frac{1}{\gamma} \ln \beta + \frac{1}{\gamma} \Delta \ln \theta_t^q \quad \forall i, t. \tag{5}$$

Equations (4) and (5) define an important implication of the perfect risk sharing model: the level equation states that individual consumption is defined by an individual fixed effect, which reflects the individual Pareto weight, and a time fixed effect, which reflects the aggregate resource constraints. The difference equation points to the fact that changes in

[15]We are abusing notation here, in that the right-hand side of the f.o.c. should be multiplied by the probability of every state of the world considered. We can assume, without loss of generality, that such a term is absorbed by the multiplier θ_t^q.

individual marginal utility (here approximated by changes in log consumption) are *only* affected by changes in aggregate resources.

These two equations also constitute the basis for Townsend (1994) tests of the model: variables reflecting idiosyncratic resources (such as the level of income in eq. (4) or changes in individual income in equation eq. (5), should not attract a significant coefficient when added to these regressions. The size and significance of the coefficients on these variables can therefore be interpreted as a measure of the deviation from perfect risk sharing.

An attractive feature of this approach is that it relies only on properties of resource allocation *within a certain group*. In this sense, the hypothesis being tested refers to the ability of a group (which is identified by the researcher and defines the resource constraint) to provide insurance to its members for a certain type of shock. The approach can therefore be used flexibly to test the existence of risk sharing within different groups.

A different approach takes eqs. (4) and (5) in another direction. Following Attanasio and Székely (2004), who develop an idea discussed in Deaton and Paxson (1994), one can take the variance of the left hand side of these two equations, within a risk sharing group. For eq. (4) one would get:

$$Var_q(\ln c_t^{i,q}) = \frac{1}{\gamma^2} Var_q(\ln \lambda_i^q) \quad \forall i, t. \tag{6}$$

where the subscript q defines the risk sharing group considered, for instance the village.

This equation stresses an important implication of perfect risk sharing: the distribution of marginal utility in a risk sharing group is kept constant and depends only on the variance of Pareto weights within a group. Taking first differences over time of this equation would yield a zero on the right-hand side, as the distribution of Pareto weights does not change over time under perfect risk sharing. In addition to the cross-sectional variance of eq. (4), one can also consider the variance of equation eq. (5).

$$Var_q(\Delta \ln c_t^{i,q}) = 0 \quad \forall i, t. \tag{7}$$

As it is clear from eq. (5), the variance of its left-hand-side should be zero, as the multiplier θ_t^g is the same for all members of the risk sharing group, reflecting the fact that the changes in log marginal utility of consumption is homogeneous within risk sharing groups.

These equations can again be used to test perfect risk sharing and, potentially, to measure deviations from it. Such an approach is particularly useful when, as in our context, one considers a number of risk sharing groups (in our case the GP included in the survey). The metric to assess deviations from perfect risk sharing and, in particular, the relationship between these deviations and observable characteristics of the risk sharing groups can be defined by the specific imperfections preventing perfect risk sharing one considers.

As noted in the introduction, one issue with applying the Townsend (1994) approach in our context to test perfect risk sharing and assess deviations from it is that our data does not contain reliable measures that could be used to identify idiosyncratic shocks. Therefore, we follow the second approach outlined above, which focuses on movements in the distribution of consumption in the risk sharing group considered.

This approach to measuring deviations from perfect risk sharing is particularly interesting because it can be related to specific imperfections that preclude complete insurance markets. Attanasio and Pavoni (2011), for instance, construct a model that relates specific form of imperfect information to certain deviations from perfect risk sharing. More generally, given a theoretical model where perfect risk sharing is prevented by a given imperfection, one can relate observed markers of such imperfection to the size of the observed deviations from perfect risk sharing.

A relevant context, which we will be using here, are models with imperfectly enforceable contracts such as that in Ligon, Thomas, and Worrall (2002). In this model, the social planner, solves a constrained efficient problem in which, in addition to a resource constraint, they face a set of the participation constraints, which guarantee that every participant does not deviate from the agreed risk sharing arrangement. Participation constraints are satisfied if the expected utility from respecting the risk sharing agreement is at least as large as that from deviating. Deviating from the risk sharing agreement implies a punishment, which consists of the exclusion from the risk sharing agreement in the future plus any additional sanctions the group can impose. In the limit, if these sanctions are very large, the planner could implement perfect risk sharing.

In this model, the constrained efficient social planner modifies the Pareto weights in eq. (1) so to make sure that the participation constraints are not violated. The characterization of equilibrium with full risk-sharing through the social planner problem does not explain the Pareto weights. These are exogenous quantities that can represent other predetermined factors, such as property rights and other sources of inequality. The model with imperfect enforceability effectively, partly endogenize changes the social planner problem's Pareto weights, so that the dynamics of the consumption allocation is governed by such changes. When the participation constraint binds, the planner effectively moves the weight given to the agent who is tempted to leave the agreement to maintain them in.

An interesting result Ligon et al. (2002) derive is that when the states of the world can be described by a discrete vector, the equilibrium can be characterised by a set of intervals. If, after the realization of the shocks, the (previous period) ratio of the marginal utilities of a generic consumer and that of the social planner, which under perfect risk sharing corresponds to the Pareto weight given to that consumer, is within the interval corresponding to that particular state of the world, appropriate transfers will be implemented to guarantee that the ratio of marginal utilities stays at the same level. If this is true for all consumers, effectively perfect risk sharing is possible in that context. If, instead, the ratio of marginal utilities is outside the relevant interval, appropriate transfers will make it move so that it will be just at one of the borders of the interval, a point at which one participant is just willing to stay in the risk sharing arrangement.In other words, if the enforceability constraints are not binding, the distribution of marginal utilities stays constant, as under perfect risk sharing. The more binding the constraints are, the tighter the intervals and more volatile the distribution of marginal utilities.

This characterization is useful for several reasons. First, an important implication is that the size of the intervals defines the amount of risk sharing that is implementable in equilibrium. If the intervals are sufficiently large so that their intersection is not empty, the system will eventually converge to perfect risk sharing. And even when this is not the case, suggesting movements in relative marginal utilities, systems with relatively large intervals would have more infrequent and smaller movements. Larger intervals will in general imply smaller movements in the distribution of marginal utilities, a measure related to the one in equation (7). Second, increases in punishments are likely to lead to increase in the size of the intervals, which is relevant in our context.[16]

Whether participation constraints bind or not depend on the strength of the enforcing mechanisms, that is on how painful is the exclusion from the risk sharing group. The intuition we use in our context is therefore that a well-developed SHG which has built a sizeable fund can be an effective enforcement mechanism that allows the implementation of more effective risk sharing agreements.

We test whether the variance of changes in consumption is smaller in villages where the program is operating, that is whether these villages are closer to full risk sharing. In addition, we hypothesize that this movement towards better risk sharing is larger in contexts where commitment to the program and hence the ability to enforce contracts is greater.

5 Village Risk Sharing

In this section we present the empirical specification we use and the basic results on the impact of the SHG intervention on risk sharing in our sample villages.

5.1 Empirical Strategy

As mentioned above, unfortunately, the survey we use does not contain good quality information on individual households' income, which prevents us from implementing tests of risk sharing such as those proposed by Townsend (1994) and others. Instead, building on the framework laid out in Section 4, we focus on the impact on the variance of the growth in household consumption between 2011 and 2014 to evaluate the impact of the self-help group

[16]These statements need some qualification when one considers the effect of changes in the distribution of income, as discussed in Attanasio (2023). When dealing with changes in sanctions the results are robust.

program on informal village risk sharing. In particular, we estimate:

$$Var_{vgb}(\triangle_{2011}^{2014}\ \log c^{ivgb}) = \alpha_0 + \alpha_1 \mathbf{T}_{gb} + \mathbf{X}_{vgb}^{'}\alpha_2 + \mathbf{S}_{gb} + \epsilon_{vgb} \tag{8}$$

where $Var_{vgb}(\triangle_{2011}^{2014}\ \log c^{ivgb})$ is the village-level variance of consumption growth between 2011 and 2014 for all sample households, h, in a village, v, in a gram panchayat, g, in block, b. $\mathbf{T}_{gb}$ is a dummy variable indicating random assignment of a gram panchayat to treatment; $\mathbf{S}_{gb}$ is a vector of strata fixed effects. In some specifications, we also control for $\mathbf{X}_{vgb}$. a vector of pre-treatment village-level variables that might affect risk sharing. Standard errors are clustered at the level of randomization, the gram panchayat. The fact that we consider the cross sectional variance of (changes in) log consumption within a village makes it clear that in our exercise the village is the relevant risk sharing group we are considering.[17] We should also add that we interpret log consumption as an approximation to the (log) of marginal utility.

In equation (8), we estimate the impact of the SHG on risk sharing *within a village*. However, this impact likely varies across villages in Phase 1 and Phase 2 blocks because of differences in socio-economic characteristics as well as differences in program scale and hence institutional capacity at the start of the experimental study. Section 2 described how *Jeevika's* institutional capacity in Phase 1 blocks far exceeded that in Phase 2 blocks at the start of the study period. Therefore, we allow treatment effects to vary across Phase 1 and Phase 2 blocks. We can perform this exercise because the randomization of the program happened *within* both Phase 1 and Phase 2 blocks. In particular, we estimate eq. (8) separately for blocks in Phase 1 or Phase 2:

$$Var_{vgb}(\triangle_{2011}^{2014}\ \log c^{ivgb}) = \beta_0^k \ + \ \beta_1^k \mathbf{T}_{gb} \ + \ \mathbf{X}_{vgb}^{'}\beta_2^k \ + \ \mathbf{S}_{gb} + \epsilon_{vgb}^k, \quad k = 1, 2 \tag{9}$$

where the superscript k indicates if the village belongs to a block in Phase 1 or Phase 2.

We next examine whether the treatment heterogeneity in Phase 1 and 2 blocks we might observe from the estimation of eq. (9) reflects the scale of the program. To do so we interact the (randomized) treatment indicator with a measure of the *scale* of the program in a given block as well as with a Phase 1/2 indicator. In particular, we estimate the following regression:

$$\begin{aligned} Var_{vgb}(\triangle_{2011}^{2014}\ \log c^{ivgb}) = \ & \theta_1 \mathbf{T}_{gb} \ + \ \theta_2\ \mathbf{T}_{gb} \times \mathbf{P}_{gb} \ + \ (\mathbf{T}_{gb} \times \mathbf{Scale}_b)^{'}\theta_3 \\ & + (\mathbf{T}_{gb} \times \mathbf{B}_b)^{'}\theta_4 \ + \ \mathbf{X}_{vgb}^{'}\theta_5 \ + \ \mathbf{S}_{gb} \ + \ \epsilon_{vgb} \end{aligned} \tag{10}$$

[17] In Table B6 and Table B7 in the Appendix, we consider the cross section variance of (changes in) log consumption within caste categories in a village, i.e., within Dalit/Adivasi and non-Dalit/Adivasi within a village. We find similar results when we consider caste categories within a village as the relevant risk sharing groups.

where $\mathbf{Scale}_b$ is a second order polynomial in the number of SHGs in a block in 2011.[18] Equation (10) differs from eq. (9) in the inclusion of the interaction between treatment and $\mathbf{Scale}_b$, which recognizes that initial program scale affects outcomes only in treated *Gram Panchayats* of a block. In addition, since the program scale variables are measured at the level of the block, this regression specification also includes the interaction of the treatment indicator with a vector of block level variables, $\mathbf{B}_b$ — the block population and the block *Dalit* and *Adivasi* population — to ensure that $\mathbf{Scale}_b$ is not merely approximating variation in block population. Finally, given the nature of the sampling strategy we discussed above and the availability of sampling probabilities, we report the results obtained with weighted and unweighted regressions.

5.2 Empirical Results

Table 1: Impact of *Jeevika* on Village Risk Sharing

	Weighted		Unweighted	
	(1)	(2)	(3)	(4)
Treatment	-0.01	-0.01	-0.01	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Controls	No	Yes	No	Yes
Obs	333	333	333	333
Clusters	179	179	179	179
Mean	0.21	0.21	0.22	0.22

Standard errors clustered at the gram panchayat level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The outcome is the village-level variance of the change in the log of monthly per capita consumption expenditure (MPCE, winsorized at 1% and 99%). All columns present the results from regressions of the outcome on a treatment dummy. Columns 1 & 2 weight household observations by their sampling weights while computing the village-level variance, while columns 3 & 4 do not. Regressions in columns 2 & 4 include controls for the village population ('000), village Dalit and Adivasi population ('000), share of temporary migrants in the village, share of households in the village with savings, whether there is a bank in the village, whether a village has a paved road, the distance of a village from the district headquarters and its square from the census.

Table 1 presents the results from the estimation of eq. (8), which indicate that the program, *Jeevika*, had no significant effect on village risk sharing overall. These results, combined with the lack of program effects on household consumption (in Hoffmann et al. (2021), reproduced in Table B8, which also shows lack of treatment effects on consumption levels in both Phase 1 and Phase 2 blocks), might suggest that the program had a very limited impact on both the level of consumption and its variability. However, the differences in program implementation we discussed above suggest that these results might hide mask considerable regional heterogeneity in treatment effects.

[18] We also experimented with alternative functions of program scale: binary, logarithmic, and linear. We also consider regressions where $\mathbf{X}_{vgb}$ is interacted with $\mathbf{P}_{gb}$. These results are in the Appendix.

Table 2: Impact of *Jeevika* on Village Risk Sharing (by program phase)

	Weighted		Unweighted	
	(1)	(2)	(3)	(4)
Panel A: Phase 1 Blocks				
Treatment	-0.03**	-0.03	-0.04***	-0.03**
	(0.01)	(0.02)	(0.01)	(0.01)
Controls	No	Yes	No	Yes
Obs	109	109	109	109
Clusters	58	58	58	58
Mean	0.19	0.19	0.21	0.21
Panel B: Phase 2 Blocks				
Treatment	0.01	0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Controls	No	Yes	No	Yes
Obs	224	224	224	224
Clusters	121	121	121	121
Mean	0.22	0.22	0.22	0.22

Standard errors clustered at the gram panchayat level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The outcome is the village-level variance of the change in the log of monthly per capita consumption expenditure (MPCE, winsorized at 1% and 99%). All columns present the results from regressions of the outcome on a treatment dummy. Columns 1 & 2 weight household observations by their sampling weights while computing the village-level variance, while columns 3 & 4 do not. Regressions in columns 2 & 4 include controls for the village population ('000), village Dalit and Adivasi population ('000), share of temporary migrants in the village, share of households in the village with savings, whether there is a bank in the village, whether a village has a paved road, the distance of a village from the district headquarters and its square from the census.

The results in Table 2 suggest that this is, indeed, the case. Distinguishing between villages located in Phase 1 blocks (with greater program experience) and those located in Phase 2 blocks (with limited program experience) we find that the lack of significant effects in Table 1 is driven by villages in phase 2 blocks. In fact, Table 2 indicates that villages in Phase 1 program blocks see a significant reduction of 0.03 in the variance of (log) consumption growth among village households (or 14% of the variance in the Phase 1 control villages), suggesting improved risk-sharing when villages have access to *Jeevika*. Moreover, results in Table B6 indicate that the variance of consumption growth in Phase 1 villages reduced amongst both Dalits/Adivasis and other groups.

These results suggest that, when implemented in blocks where adequate institutional capacity and experience has accumulated, the program was successful in facilitating risk sharing within villages. This result suggests a significant insurance value of the program, one that has not previously been documented.

As discussed above, we next investigate whether the scale of the program can explain the heterogeneity in program impacts on risk sharing between Phase 1 and Phase 2 blocks. The results from the estimation of some versions of eq. (10) are reported in Table 3.

Table 3: Intermediation Analysis or Reduced Form
Relationship between Variance of Change in Village Consumption and Program Scale

	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-0.036***	-0.044***	0.061	0.040	0.040	0.039
	(0.010)	(0.012)	(0.084)	(0.092)	(0.028)	(0.029)
Treated × Phase 2	0.042***	0.051***	-0.017	-0.001		
	(0.013)	(0.015)	(0.061)	(0.066)		
Treated × Program Scale			-0.531**	-0.486*	-0.505***	-0.485**
			(0.232)	(0.262)	(0.188)	(0.211)
Treated × Program Scale Sq			0.481**	0.420*	0.479**	0.420*
			(0.205)	(0.233)	(0.203)	(0.229)
R-squared	0.36	0.38	0.37	0.40	0.37	0.40
Additional Controls	No	Yes	No	Yes	No	Yes
Obs	333	333	333	333	333	333
Clusters	179	179	179	179	179	179
Mean (Phase 1)	0.21	0.21	0.21	0.21	0.21	0.21
Mean (Phase 2)	0.22	0.22	0.22	0.22	0.22	0.22

Robust standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Outcome is the variance of change in log MPCE at the village level between 2011 and 2014, constructed using sampling weights and by winsorizing consumption observations at 1% and 99%. Program scale is the number of SHGs in the block that a village is in in 2011 (in 1000s), which is when Jeevika rolled out in treated villages. All regressions control for the interaction between block population, block Dalit/Adivasi population, number of villages in the block, and treatment status. Columns 2, 4, 6 control for the village population (in 1000s), village Dalit and Adivasi population (in 1000s), share of temporary migrants in the village, share of village households with savings, whether there is a bank in the village, whether a village has a paved road, the distance of a village from the district headquarters and its square.

The first two columns of the table report the results of estimating eq. (9), where the coefficient on the program is allowed to take different values in Phase 1 and Phase 2 blocks. These results are a restricted version of those presented in columns (3) and (4) in Table 2.[19]

In columns (3) and (4), we add an interaction of the treatment effect with a quadratic in the scale of the program, measured by the number of SHG in the relevant block. These results suggest that the differences in treatment effects across Phase 1 and Phase 2 villages is driven by differences across these villages in pre-existing program scale. Indeed, the scale variable captures completely the difference in program impacts between Phase 1 and 2. Therefore, in column (5) and (6), we consider the scale effects on their own. These results also suggest a non-linear effect of initial program scale, with the negative effect of the pre-existing number of SHGs on the variance in village consumption tapering off as this number increases. This suggests the demands of serving very large numbers of pre-exising SHGs outweighs improvements in capacity that may result from the recruitment of administrative staff from their membership.

6 Scale, Group Quality and Contract Enforcement

In Section 5, we have shown that an intervention that introduces SHGs induces cross-sectional consumption allocations that are closer to allocations consistent with perfect risk sharing within villages. However, these effects can only be seen in blocks where SHGs have been developed for longer, possibly with better functioning infrastructure. Indeed, Table 3 shows that the impact SHGs have on village risk sharing depends on the scale of the program. We now look at possible channels that can explain this evidence.

The narrative we propose here is that the program might be reducing frictions that prevent full risk sharing and, in particular, frictions due to the imperfect enforceability of risk sharing arrangements, as discussed in Section 4. In such models, informal risk sharing can be improved by increasing the punishment that can be imposed upon deviations from the informal arrangements. In the case we are considering, exclusion from the SHGs can become more salient and painful as the group grows and its savings funds become large. In this section, we provide the basis for this narrative with a discussion of the program's scale and its relation to features of the SHGs.

As described previously (in Section 3 and in Figure 1), GPs in the study sample were randomized into a treatment group, which received access to *Jeevika* in 2012 ('early roll-out'), and a control group, which received access to the program after the study's 2014 endline survey ('late roll-out'). In 2012, treatment GPs in the study sample spanned Phase 1 and Phase 2 blocks, which differed significantly in their numbers of pre-existing SHGs. As

[19] A larger set of regressions are in Appendix Table B10, where the variance measure is computed using sampling weights. Similar results are obtained with the in Appendix Table B9, where the variance measure is computed without using sampling weights.

a result, the institutional capacity available to aid the formation of new SHGs and ensure their quality also differed across phases. Figure 2 indicates that in 2010, while Phase 1 blocks had 186 SHGs per 100,000 people, Phase 2 blocks had only 0.26 SHGs per 100,000 people.

Using data from a follow-up 2019 survey of a sample of SHGs in 246 study villages (out of a total of 333), we provide descriptive evidence of differences in the quality of Phase 1 and Phase 2 SHGs that mirror differences in institutional capacity across blocks in the two Phases, as well as other differences among the two regions.

The first panel in Table 4 suggests that SHGs in both Phase 1 and Phase 2 blocks differ only slightly in member attributes. All SHGs, regardless of region, adhere to program guidelines regarding the number of members in each SHG and to the targeting of the program towards *Dalits* and *Adivasis*. Sample SHGs in both regions have close to twelve members on average, 65% of whom are *Dalit* or *Adivasi*. While women SHG members (on average aged around 38) in villages across blocks have low levels of education, those in Phase 1 blocks are relatively more educated. Members in Phase 1 blocks have completed 1.8 years of education on average, while those have only completed one year of education, with this difference being statistically significant. The second panel in Table 4 indicates that while there are differences in the number of meetings attended in the preceding year and in the regularity of attendance, neither of these differences are statistically significant. Overall, approximately 84% of groups meet on a regular basis with SHGs reporting an average of around 36 meetings in the preceding year.

Measures of the quality of groups formed, however, suggest significant differences between SHGs in Phase 1 and Phase 2 blocks. A first measure of quality is the *Panchsutra* score, an overall index used internally by the program to evaluate SHGs and determine their eligibility for incremental benefits such as access to bank loans. Our analysis uses a measure of this score reported in the 2019 survey.[20] The last row in this panel reveals a significantly higher *Panchsutra* score for SHGs in Phase 1 blocks (with an average score of 2.8 out of a maximum of 5) relative to blocks in the Phase 2 (with an average score of 2.3).

The *Panchsutra* score takes lending and savings activity into account, and so it is not surprising that differences in this score are mirrored by differences in these activities (as seen in Table 4's third panel). While not all these differences are statistically significant, they are all negative and some of them are significant at conventional levels. In particular, SHG members in Phase 2 have significantly smaller monthly savings and fewer loans per member. Additionally, SHGs in Phase 1 blocks are significantly more likely than those in Phase 2 blocks to impose penalties on members so as to enforce savings and loan repayments. Only

[20]The program bases this score on an SHG's adherence to the five norms of the program: regular meetings, savings, lending, repayment and the maintenance of books of account. Correspondingly, the 2019 survey reports an index based on whether the SHG reports the following: weekly meetings, weekly savings, maintenance of all required registers, lending activity in the year prior to the survey year, and the existence of a system for collecting penalties for delayed repayment.

Table 4: SHG Characteristics Across Program Phase in 2019

	Means			Difference
	Obs	Phase 1 Blocks	Phase 2 Blocks	in Means
SHG Characteristics				
No. Members	1217	11.65	11.81	0.16 (0.16)
Dalit/Adivasi Members	1217	65.21%	65.44%	0.23 (2.43)
Members' Education (Years)	1217	1.80	1.05	-0.75*** (0.08)
Members' Age	1217	38.11	37.89	-0.22 (0.37)
SHG Functioning				
Meet Irregularly?	1217	13.50%	16.65%	3.15 (6.16)
Meetings Attended (Last Year)	1217	36.97	35.63	-1.34 (2.94)
SHG Panchsutra Score	1217	2.76	2.31	-0.45* (0.22)
SHG Savings and Loans				
Times Saved (Last Year)	1217	39.58	36.95	-2.62 (3.06)
Monthly Savings Amount per member	1217	₹42.41	₹39.14	-3.27** (1.21)
Cumulative SHG Savings per member	1209	₹2,012.64	₹1,972.43	-40.22 (181.29)
Loans per Member (Overall)	1217	2.71	2.27	-0.43 (0.51)
Loan Amount per Member (Overall)	1217	₹14,958.78	₹11,016.58	-3942.20 (3325.88)
Loans per Member (Last Year)	1217	0.48	0.29	-0.19** (0.08)
Loan Amount per Member (Last Year)	1217	₹4,069.58	₹2,350.53	-1719.04 (1140.40)
Commitment				
Missing Savings Penalty?	1217	16.50%	5.88%	-10.62 (9.64)
One-time Default Penalty?	1217	37.75%	13.10%	-24.65*** (6.60)
Repeat Defaulter Penalty?	1217	47.50%	15.18%	-32.32*** (7.70)

Standard errors clustered at the panchayat level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Data from a random sample of SHGs in 246 study villages surveyed in 2019

6% of SHGs in Phase 2 blocks reported a penalty for missed savings, in contrast to 17% of SHGs in phase 1 blocks. Differences in the imposition of penalties for loan default are greater — while the percentage of SHGs in Phase 2 blocks reporting penalties on one-time and repeat defaulters was just 13% and 15%, respectively, the corresponding percentages for SHGs in phase 1 blocks were about thrice as high (38% and 47% respectively).

It is worth noting that SHGs (separately in treatment GPs and in control GPs) in Phase 1 and Phase 2 blocks were formed around the same time. Thus, these differences in their activity are not a function of age effects, but rather reflect regional differences including differences in the stage of implementation of the program in the block. We note, also, that though differences in the use of sanctions across Phase 1 and Phase 2 SHGs are suggestive of differences in their ability to penalize members who do not adhere to contractual terms, they may also simply reflect the fewer financial transactions reported in Phase 2 SHGs.

Taken together, the evidence in this section suggests that groups formed in Phase 2 program blocks, which both lacked experience with the program prior to 2011 and were in a geographically distinct (Kosi) region, had lower quality than those formed in phase 1 blocks even as late as 2019. These differences in quality, as reflected in reduced savings and lending activities, are matched by observed differences in the ability of SHGs to enforce contractual terms. This, in turn, likely affects the growth of the program in the village, reducing its contribution to village risk sharing. A caveat is that since we only consider cross-sectional differences across the two phases in 2019 here, these differences likely reflect both those arising out of differences in initial program scale as well as other regional differences and so should only be seen as suggestive of the mechanism proposed.

7 Village Risk Sharing and Group Quality

In models where full risk sharing is prevented by the difficulty to enforce informal contracts and risk sharing agreements, the ability a group has to impose penalties can determine the amount of risk sharing that is feasible to achieve, And the ability to enforce contracts is likely to be determined by the harshness of the punishment that can be imposed on those that do not respect the terms of the contract. In the context of SHGs, exclusion from the group is a likely punishment and the harshness of such a punishment is determined by the quality of what the group can offer. As we have seen in the previous section, after being formed, groups accumulate resources, in the form of saving amounts, that can be used to provide risk sharing. Moreover, a group with a good institutional support. possibly deriving from the presence of other groups in the same village, can help a group to run smoothly and provide its members better services.

In what follow we relate the amount of risk sharing that we observe in a village to the the SHG total amount of resources, measured by the size of their saving account. Obviously, such an amount might be associated with better risk sharing for a variety of reasons, which are not necessarily linked to the mechanism (imperfect enforceability) through which we hypothesize risk sharing is determined. In particular, SHG savings is the result of household choices and therefore can be endogenous to risk sharing. Therefore, in this section, we use an IV approach where we instrument the size of the saving accounts a SHG controls with the randomization of the introduction of the SHG program. In a sense, we can interpret the evidence provided in section 5 as the reduced form of such an exercise. We now present the first stage of such an approach, which relates our measure of the value of SHG to their participants, that is the size of the saving account, to the randomization instrument, interacted with the scale of the program, exploiting the heterogeneity we have documented. We then present the second stage of this approach, relating risk sharing to the our measure of SHG saving, appropriately instrumented.

7.1 Program Scale and Group Savings

Our measure of the value of SHG savings in a village , with which we capture the value of exclusion from an SHG, is the total accumulated SHG savings at the start of 2015. In the absence of the exact accumulated value, we turn to a measure of a SHG's 'corpus' used by banks to calculate SHGs' loan eligibility. This measure is the product of a group's monthly savings rate, the number of its members, and its years of operation.[21] Administrative data provide the required information on the number of SHGs in the village, the total membership of each SHG, and the year of formation. Aggregated over the SHGs in existence in the village provides a measure of the total endowment of village SHGs which we denote by $\mathbf{V}_{vgb}$. The first stage equation is:

$$\mathbf{V}_{vgb} = \delta_1 \mathbf{T}_{gb} + \delta_2 \mathbf{T}_{gb} \times \mathbf{Scale}_b + \delta_3 \mathbf{T}_{gb} \times \mathbf{B}_b + \mathbf{X}'_{vgb}.\delta_4 + \mathbf{S}_{gb} + u_{vgb} \tag{11}$$

We report regression results with the same set of basic and expanded controls previously used. Table 5 presents the results from the estimation of versions of the first stage, eq. (11), while in Table B11 we present results using alternative measures of and functional forms for program scale. As we might expect, the regression in column (1) indicates that earlier access to *Jeevika*, i.e., treatment, leads to a significant increase in accumulated village SHG savings. Treated villages have ₹593,000 more (or 2.7 times more) in accumulated savings by 2015. Given the heterogeneity in program impact on risk-sharing between program phases, interacting the treatment indicator with an indicator for a village being in a phase 2 block indicates that treated villages in phase 1 blocks saw a larger increase in accumulated resources, consistently with our discussion in Section 6. Column (2) indicates that access to the program significantly increased village pooled resources by 2015 to a larger extent in phase 1 blocks (by ₹967,000 phase 1 blocks and ₹691,000 in phase 2 blocks, in 2015 rupees).

[21]While data on monthly savings is unavailable, we use information on this rate from the 2019 survey to estimate the mean monthly savings of SHGs, allowing for variation across blocks and by year of formation within each block.

Table 5: Relationship between Accumulated SHG Savings in a Village and Program Scale

	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.972***	0.855***	0.686	0.691	0.240	0.119
	(0.263)	(0.230)	(0.582)	(0.458)	(0.257)	(0.224)
Treated × Phase 2	-0.274*	-0.274*	-0.359	-0.457		
	(0.159)	(0.148)	(0.516)	(0.396)		
Treated × Program Scale			3.093**	2.889***	3.648**	3.620***
			(1.385)	(1.063)	(1.510)	(1.152)
Treated × Program Scale Sq			-3.680**	-3.657***	-3.717**	-3.747***
			(1.645)	(1.238)	(1.680)	(1.293)
R-squared	0.52	0.70	0.53	0.71	0.53	0.71
F-statistic	44.60	25.72	33.29	24.55	38.95	25.94
Additional Controls	No	Yes	No	Yes	No	Yes
Obs	333	333	333	333	333	333
Clusters	179	179	179	179	179	179
Mean (Phase 1)	0.19	0.19	0.19	0.19	0.19	0.19
Mean (Phase 2)	0.23	0.23	0.23	0.23	0.23	0.23

Robust standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Outcome is the total group savings accumulated across all SHGs at the village level by 2015 (in 10,00,000 ₹). Program scale is the number of SHGs in the block that a village is in in 2011 (in 1000s), which is when Jeevika rolled out in treated villages. All regressions control for the interaction between block population, block Dalit/Adivasi population, number of villages in the block, and treatment status. Columns 2, 4, 6 control for the village population (in 1000s), village Dalit and Adivasi population (in 1000s), share of temporary migrants in the village, share of village households with savings, whether there is a bank in the village, whether a village has a paved road, the distance of a village from the district headquarters and its square.

As with previous results on the variance of consumption growth in Table 3, columns (3)-(6) add measures of pre-existing program scale interacted with the treatment indicator to the base regressions. Qualitatively, these results indicate that an increase in program scale increases the accumulated savings in a village by 2015. These results remain statistically significant when we drop the interaction between the treatment indicator and the indicator for a village being in a phase 2 block. In addition, the fact that the results in Tables 3 and 5 are similar is consistent with the argument that existing program scale affects consumption growth through SHG savings, i.e., the summary statistic measuring SHG quality and, therefore, its value to SHG members.

7.2 Risk Sharing, Group Quality and Program Scale

The preceding sections suggest that the program's scale underlies the regional heterogeneity in the impact of *Jeevika* on risk-sharing. We have also shown that *Jeevika* affects SHG quality and, indirectly, the value of SHGs to their members. This value, in turn, should allow well-functioning SHGs (and the villages where they are located) to achieve more efficient risk sharing. If so, the argument that SHG quality improves risk sharing can be supported through regressions of our measure of risk-sharing, i.e., the village-level variance of the growth in household consumption between 2011 and 2014, on SHG resources, appropriately instrumented to take into accounts its likely endogeneity. Assuming that the initial program scale determines the program's impact on risk-sharing only through its impact on SHG quality and resources, it is a valid instrument for accumulated SHG savings and can be used to establish the effect of SHG quality on risk sharing.

Having provided evidence that our proxy of the value that SHGs can impose as a punishment is related to our proposed instruments, we proceed with our second stage, which relates our measure of risk sharing to the value of SHGs' savings. In particular, the second-stage instrumental variables regression relates the variance of consumption growth to total savings accumulated by all SHGs in a village by the end of the evaluation period, $\mathbf{V}_{vgb}$.Interactions of treatment with a quadratic in the number of 2011 SHGs in the block serve as instruments in the estimating equation:

$$\begin{aligned} Var_{vgb}(\triangle_{2011}^{2014}\ \log\ c^{ivgb}) = \ & \gamma_1 \widehat{\mathbf{V}}_{vgb} \ + \ \gamma_2 \mathbf{T}_{gb} \ + \ \gamma_3 \mathbf{T}_{gb} \times \mathbf{B}_b \ + \ \mathbf{X}^{'}_{vgb}\gamma_4 \\ & + \mathbf{S}_{gb} + \epsilon_{vgb} \end{aligned} \tag{12}$$

Results from a two-stage least squares estimation of eq. (12) are in Table 6. The instrument is the interaction between an indicator for treatment status and a function of the initial number of self help groups in a block. For completeness, we report results using both weighted and unweighted quantities, and results obtained adding a set of controls to the basic specification. Across all columns, we see that an increase in total village-level SHG resources reduces the variance of household consumption growth between 2011 and the end of the study period. These results are robust to the form of instrument used, and to the inclusion of additional

Table 6: Impact of village SHG savings on variance of change in consumption (IV)

	Unweighted		Weighted	
	(1)	(2)	(3)	(4)
Village SHG Savings in 2015 ('00000)	-0.066**	-0.075*	-0.083**	-0.099**
	(0.033)	(0.040)	(0.040)	(0.044)
Additional Controls	No	Yes	No	Yes
Obs	333	333	333	333
Clusters	179	179	179	179
Olea and Pflueger (2013) F-statistic	7.366	8.428	7.366	8.428
Critical Values (% worst case bias)				
τ=5%	21.553	20.248	21.444	20.292
τ=10%	13.387	12.661	13.327	12.686
τ=20%	8.825	8.410	8.791	8.424
τ=30%	7.124	6.821	7.099	6.831

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Village-level cumulative SHG savings ('0,00,000) in 2015 is instrumented by Treatment status, Treatment × Program Scale, and Treatment × Program Scale Squared.
In columns (1) and (2), the variance of change in consumption All regressions control for block population, block Dalit/Adivasi population, number of villages in the block, and their interactions with treatment status. In addition, even columns control for the village population (in 1000s), village Dalit and Adivasi population (in 1000s), share of village households with temporary migrants, share of village households with savings, whether there is a bank in the village, whether a village has a paved road, the distance of a village from the district headquarters and its square from the census.

controls. Overall, Table 6 establishes that an increase in the scale of the program within a village significantly reduces the variance of consumption growth within a village, moving the village economy closer to full risk sharing.

These results suggest both the importance of participation constraints and, through our choice of instruments, the importance of SHG quality in reducing these constraints. Consequently, the results establish that SHGs play an important role in helping insure households against idiosyncratic shocks, but only when the quality of SHGs, as reflected in their resource endowments, can be assured.

8 Discussion and Conclusion

In this paper, we find that well functioning self-help groups facilitate risk-sharing within rural communities. Our study is the first, to the best of our knowledge, to look at the effect of SHGs on risk sharing. And yet, as the groups are institutions that help and promote social interactions and connections, risk sharing, which can have important welfare and productivity consequences, is an important dimension that should be considered. In addition to the impact of *well-functioning* SHG on risk sharing, we also propose a possible narrative, supported by empirical evidence, about a specific imperfection of informal risk sharing that SHGs might be helping to fix: the lack of enforceability of informal insurance contracts.

The *well-functioning* qualification to the impact of the *Jeevika* intervention was justified by the fact that while our analysis finds no impact on risk sharing (as measured by changes in the cross section within village variance of log consumption) for the sample as a whole, this masks substantial heterogeneity in the institutional quality of SHGs. Dividing the sample into GPs lying in Phase 1 (where the GPs were of better quality, as we show in Section 6), and Phase 2 blocks (where SHG capacity was not as well developed), we find that the program significantly improved risk sharing in the former but not in the latter.

In particular, Phase 1 blocks are distinguished from Phase 2 blocks by having access to experienced community cadres, who facilitated the formation of groups, fostering higher initial program administrative capacity. We measure the difference in this 'experience' or administrative capacity across blocks by the number of SHGs formed in the block prior to the start of the study (in 2011). Our analysis then relates the variation in impacts across program-phases to differences in administrative capacity and experience across blocks, and we show this affects the quality of the program in study villages. We then use this relationship to identify the effects of program scale, and finally show that the heterogeneity we observe reflects underlying variation in scale.

The relationship between program scale and risk sharing constitutes the basis of our mediation analysis of the program impacts. We argue that the establishment of SHGs reduces the imperfect enforceability of informal insurance contracts, which has been proposed in the literature as a possible explanation for deviations from perfect risk sharing (Ligon et al., 2002; Abraham and Laczó, 2018). Self-enforcing risk sharing contracts might depend on the harshness of the punishment that can be imposed upon deviants. In many contexts, punishment can be enforced by exclusion from a risk sharing or other type of groups. The harshness of such an exclusion would then depend on the value and level of the activities in the group from which the member would be excluded. We proxy the value of these activities by total GP SHG savings and, to avoid endogeneity problems, we instrument savings by measures of program scale. We then show that risk sharing improvements are linked to the size of the SHG's savings.

Our study is amongst the few to establish the value of group-lending programs for increasing risk sharing while providing a plausible mediation analysis of the impacts we document. In addition, in building the mediation analysis to explain the effect of the program on risk sharing, we contribute to the literature on program scale and implementation by documenting the relationship between program quality and scale on side and the quality and functioning of groups, on the other. This evidence has obvious policy implications and provides an additional set of considerations to assess the usefulness of SHGs.

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A Figures

Figure 1: *Jeevika's* Phased Roll-out and the Experimental Sample

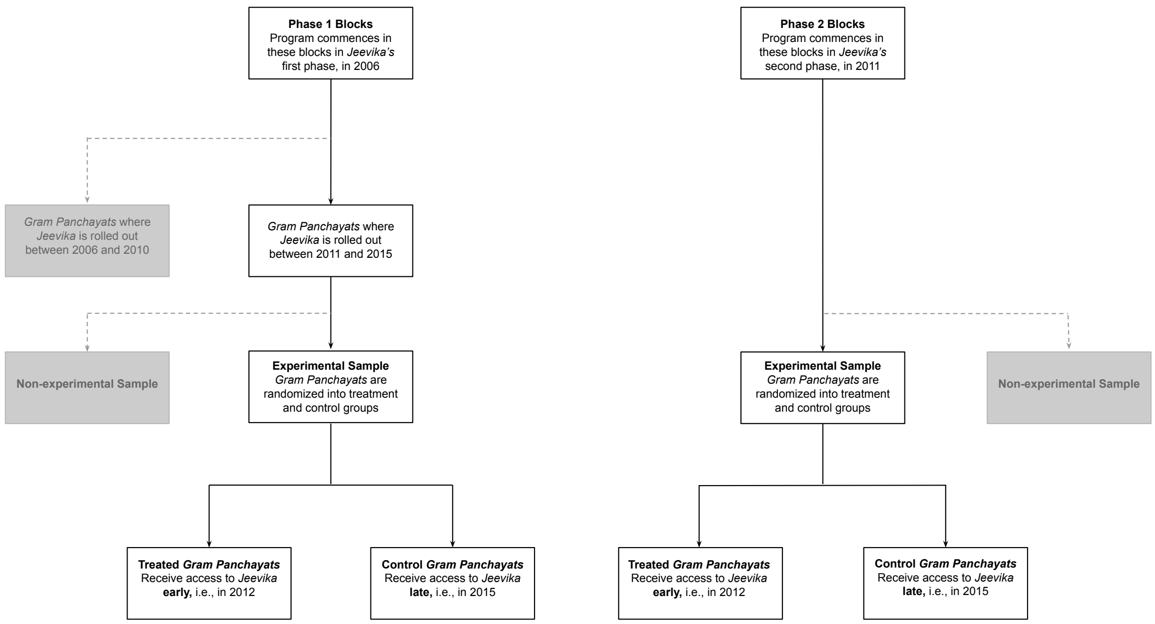
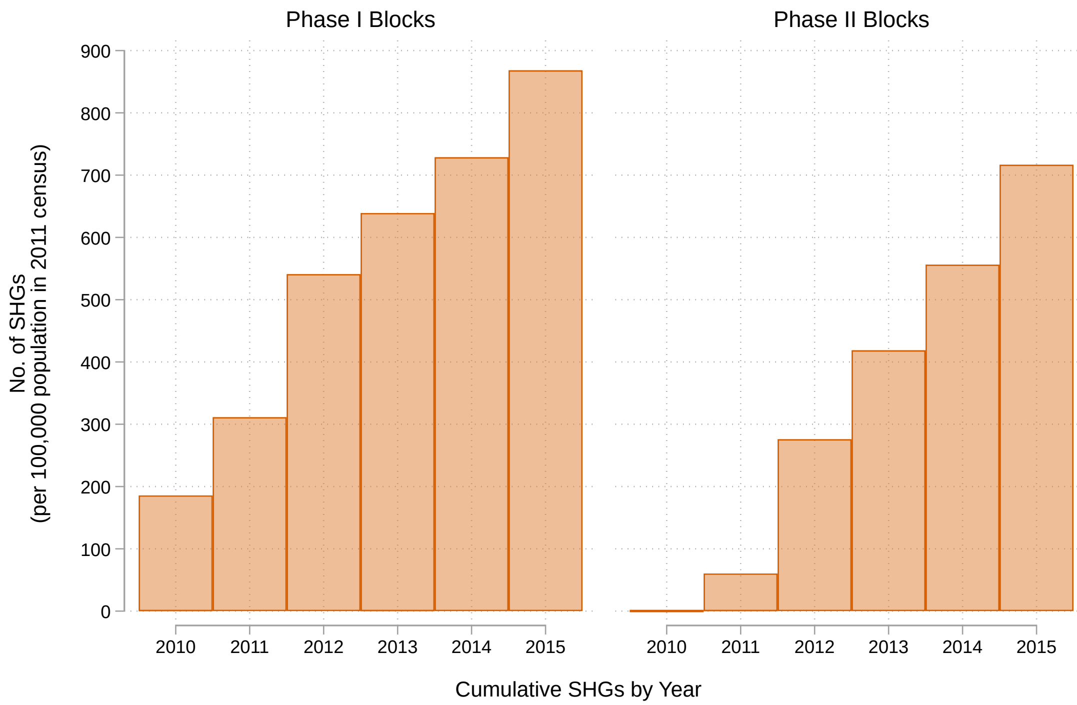
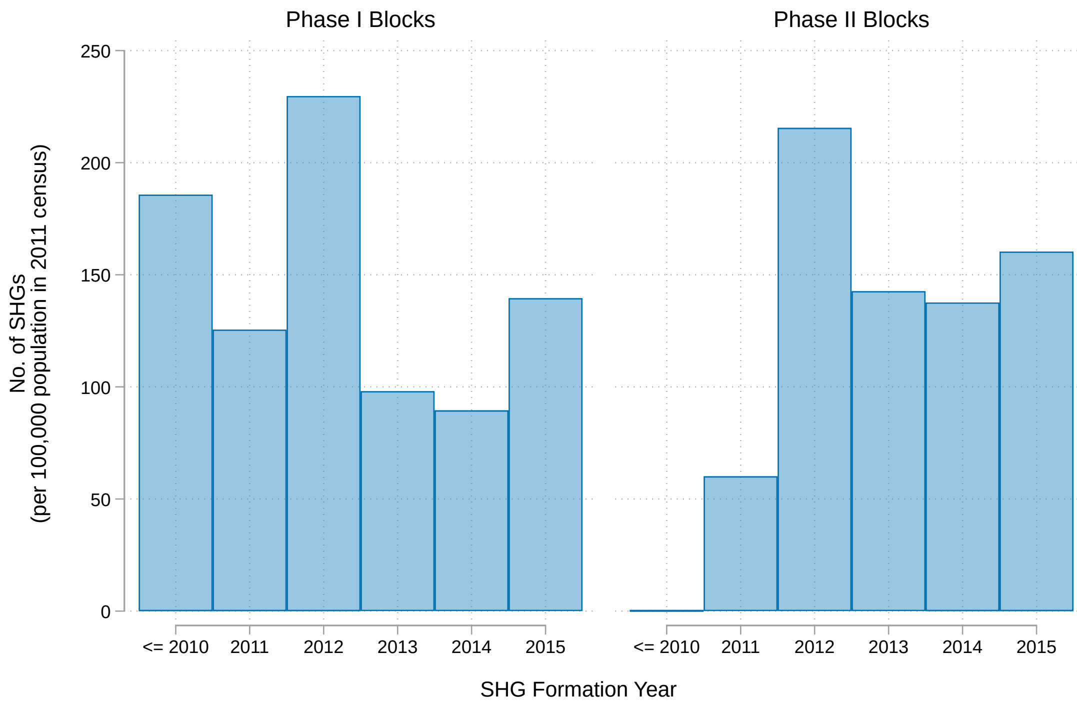


Figure 2: Cumulative No. of SHG



Source: *Jeevika* MIS data

Figure 3: SHGs Formed in Each Year



Source: *Jeevika* MIS data

B Additional Tables

Table B1: Baseline Characteristics Across Program Phases, Census 2011

	Means			Difference
	Obs	Phase I Blocks	Phase II Blocks	in Means
Village Characteristics				
Num of HHs	8295	398.74	786.39	387.64***
				(50.45)
Population	8295	2207.65	3990.65	1783.00***
				(241.70)
Dalit/Adivasi Population	8295	455.27	694.47	239.20***
				(47.00)
Dalit/Adivasi %	8286	24.46%	16.64%	-7.82***
				(1.50)
Village Area (Ha)	8295	199.11	396.70	197.59***
				(20.75)
Distance to District HQ	8295	33.27	31.12	-2.15
				(4.10)
Net Sown Area (%)	8295	140.50	285.82	145.32***
				(17.99)
Irrigated Area/Net Sown Area (%)	8255	63.33%	55.31%	-8.03**
				(3.48)
Amenities				
Bank Branch	8295	5.44	10.08	4.64***
				(1.06)
Govt. Primary School	8295	81.03%	85.19%	4.16
				(3.18)
ASHA	8295	74.11%	77.98%	3.87
				(3.33)
Mobile Phone Coverage	7815	48.91%	41.55%	-7.36***
				(1.06)
Public Bus Access	8295	14.73%	17.63%	2.90
				(3.16)
All Weather Roads	8295	61.47%	62.35%	0.87
				(5.32)
PDS shop	8295	37.17%	63.10%	25.93***
				(5.21)
Domestic Power Supply	8295	67.82%	43.69%	-24.13***
				(5.92)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Standard errors clustered at the block level

Table B2: Summary Statistics

	Obs (1)	Mean (2)	Std. Dev (3)
Village Pop ('000)	333	4.68	3.62
No. of HHs in Village	333	918.16	724.02
Village Dalit/Adivasi Pop ('000)	333	0.92	0.86
Dist to District HQ (kms)	333	32.36	17.65
Bank branch in Village? (%)	333	15.02	35.78
All-weather Road? (%)	333	79.88	40.15
Phase 2 Village? (%)	333	67.27	46.99
Variance of consumption growth (weighted, All HHs)	333	0.21	0.10
Variance of consumption growth (unweighted, All HHs)	333	0.22	0.08
Variance of consumption growth (Non-Dalit/Adivasi HHs)	296	0.22	0.13
Variance of consumption growth (Dalit/Adivasi HHs)	324	0.21	0.09
Cumulative SHG Savings (₹'000,000)	333	0.53	0.59
No. of SHGs in Block (in 2011)	333	0.36	0.30

Table B3: Baseline Characteristics Across Program Phases, Baseline Survey

	Means			Difference
	Obs	Phase I Blocks	Phase II Blocks	in Means
Village Characteristics				
Num of HH	333	735.56	1007.01	271.45***
				(77.29)
Population	333	3906.65	5058.62	1151.97***
				(397.56)
Dalit/Adivasi Population	333	761.88	993.17	231.29***
				(83.64)
Bank in Village	333	17.43%	13.84%	-3.59
				(4.71)
Distance to Dist HQ (km)	333	27.18	34.88	7.70***
				(2.43)
Consumption Var	333	0.11	0.14	0.02**
				(0.01)
Household Characteristics				
Land-owner	8988	43.80%	45.48%	1.68
				(2.60)
Dalit/Adivasi?	8988	32.01%	32.54%	0.52
				(3.20)
HH Size	8988	5.62	5.40	-0.22**
				(0.09)
Female Head?	8988	14.16%	12.87%	-1.28
				(1.39)
Any Male Migrants?	8988	37.14%	44.52%	7.38***
				(2.24)
Assets and Liabilities				
Any Savings?	8988	46.65%	37.09%	-9.55***
				(3.29)
Any Loan?	8988	66.38%	68.37%	1.99
				(2.09)
Productive Assets	8988	-0.07	0.04	0.11***

				(0.02)
Consumer Durables	8988	0.06	-0.03	-0.08***
				(0.03)
Real Consumption				
MPCE	8973	₹671.58	₹799.63	128.05***
				(18.33)
Food PC	8973	₹480.28	₹599.54	119.26***
				(11.98)
Non-Food PC	8973	₹219.98	₹237.63	17.65*
				(9.96)
Delicacy Share (%)	8985	16.80%	19.84%	3.04***
				(0.41)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B4: Baseline Village Characteristics Across Treatment and Control Villages

	Means			Normalized Differences [RI p-value]		
	Obs (1)	Control (2)	Treatment (3)	All (4)	Phase I (5)	Phase II (6)
Num of HH	333	896.71	940.26	0.06 [0.614]	0.020 [0.928]	0.057 [0.566]
Population	333	4555.26	4811.68	0.07 [0.524]	0.013 [0.956]	0.068 [0.451]
Dalit/Adivasi Pop	333	904.66	930.66	0.02 [0.878]	0.121 [0.444]	0.017 [0.832]
Bank in Village	333	16%	14%	-0.08 [0.503]	-0.212 [0.399]	-0.079 [0.912]
Dist. to Dist HQ (km)	333	32.87	31.84	-0.08 [0.229]	-0.242 [0.008]	-0.083 [0.954]
Consumption Var	333	0.13	0.13	-0.09 [0.349]	-0.190 [0.283]	-0.094 [0.697]

Table B5: Baseline Household Characteristics Across Treatment and Control Villages

	Means			Normalized Differences [RI p-value]		
	Obs	Control	Treatment	All	Phase I	Phase II
	(1)	(2)	(3)	(4)	(5)	(6)
Household Characteristics						
Land-owner	8988	45.58%	44.25%	-0.02	0.03	-0.02
				[0.654]	[0.742]	[0.434]
Dalit/Adivasi?	8988	32.34%	32.39%	-0.01	0.02	-0.01
				[0.882]	[0.847]	[0.804]
HH Size	8988	5.46	5.48	-0.01	-0.01	-0.01
				[0.859]	[0.754]	[0.966]
Female Head?	8988	13.93%	12.64%	-0.04	-0.11	-0.04
				[0.284]	[0.072]	[0.933]
Any Male Migrants?	8988	43.71%	40.45%	-0.07	-0.07	-0.07
				[0.070]	[0.324]	[0.176]
Assets and Liabilities						
Any Savings?	8988	38.32%	42.18%	0.08	0.24	0.08
				[0.146]	[0.037]	[0.930]
Any Loan?	8988	67.37%	68.08%	0.03	-0.02	0.03
				[0.409]	[0.783]	[0.232]
Productive Assets	8988	0.01	-0.01	-0.02	-0.03	-0.02
				[0.188]	[0.300]	[0.357]
Consumer Durables	8988	-0.01	0.01	0.03	0.05	0.03
				[0.208]	[0.198]	[0.540]
Real Consumption						
MPCE (ln)	8970	₹764.18	₹751.62	-0.02	-0.05	-0.02
				[0.653]	[0.517]	[0.886]
Food PC (ln)	8970	₹562.91	₹558.44	-0.01	-0.02	-0.01
				[0.834]	[0.883]	[0.894]

Non-Food PC (ln)	8969	₹236.83	₹226.91	-0.04	-0.05	-0.04
				[0.418]	[0.466]	[0.634]
Delicacy Share (%)	8985	18.94%	18.75%	-0.02	-0.05	-0.02
				[0.641]	[0.488]	[0.890]
Attrition						
Attrition	8988	2.82%	2.94%	0.01	-0.06	0.01
				[0.761]	[0.316]	[0.291]

Table B6: Impact of *Jeevika* on Village Risk Sharing

	non-Dalit/Adivasi		Dalit/Adivasi	
	(1)	(2)	(3)	(4)
Treatment	-0.02	-0.02	-0.01	-0.01
	(0.01)	(0.02)	(0.01)	(0.01)
Controls	No	Yes	No	Yes
Obs	294	294	324	324
Clusters	172	172	177	177
Mean	0.23	0.23	0.21	0.21

Standard errors clustered at the gram panchayat level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The outcome is the village-level variance of the change in the log of monthly per capita consumption expenditure (MPCE, winsorized at 1% and 99%). All columns present the results from regressions of the outcome on a treatment dummy. Columns 1 & 2 weight household observations by their sampling weights while computing the village-level variance, while columns 3 & 4 do not. Regressions in columns 2 & 4 include controls for the village population ('000), village Dalit and Adivasi population ('000), share of temporary migrants in the village, share of households in the village with savings, whether there is a bank in the village, whether a village has a paved road, the distance of a village from the district headquarters and its square from the census.

Table B7: Impact of *Jeevika* on Village Risk Sharing (by Program Phase)

	non-Dalit/Adivasi		Dalit/Adivasi	
	(1)	(2)	(3)	(4)
Panel A: Phase 1 Blocks				
Treatment	-0.03*	-0.05**	-0.04***	-0.04*
	(0.02)	(0.02)	(0.01)	(0.02)
Controls	No	Yes	No	Yes
Obs	99	99	106	106
Clusters	58	58	57	57
Mean	0.20	0.20	0.21	0.21
Panel B: Phase 2 Blocks				
Treatment	-0.01	-0.01	0.00	0.00
	(0.02)	(0.02)	(0.01)	(0.01)
Controls	No	Yes	No	Yes
Obs	195	195	218	218
Clusters	114	114	120	120
Mean	0.24	0.24	0.21	0.21

Standard errors clustered at the gram panchayat level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The outcome is the village-level variance of the change in the log of monthly per capita consumption expenditure (MPCE, winsorized at 1% and 99%). All columns present the results from regressions of the outcome on a treatment dummy.
Regressions in columns 2 & 4 include controls for the village population ('000), village Dalit and Adivasi population ('000), share of village households with temporary migrants, share of village households with savings, whether there is a bank in the village, whether a village has a paved road, the distance of a village from the district headquarters and its square from the census.

Table B8: Impact of *Jeevika* on Household Consumption

	(1) MPCE (ln)	(2) Food PC (ln)	(3) Non-food PC (ln)	(4) Home PC (ln)	(5) Delicacy (%)	(6) Growth MPCE
Panel A: Overall						
Treatment	0.02	0.00	0.03	0.00	0.00	-0.04
	(0.02)	(0.01)	(0.02)	(0.01)	(0.00)	(0.04)
Obs	8822	8817	8822	8817	8822	8947
Clusters	179	179	179	179	179	179
R-squared	0.16	0.16	0.18	0.16	0.09	0.07
Mean	6.84	6.46	5.73	6.46	0.27	0.61
Panel B: Program Phase Heterogeneity						
Treatment	0.00	-0.01	-0.01	-0.01	-0.00	-0.02
	(0.02)	(0.03)	(0.04)	(0.03)	(0.01)	(0.05)
Treatment × Phase 2	0.03	0.01	0.06	0.01	0.00	-0.03
	(0.03)	(0.03)	(0.05)	(0.03)	(0.01)	(0.07)
Obs	8822	8817	8822	8817	8822	8947
Clusters	179	179	179	179	179	179
R-squared	0.16	0.16	0.18	0.16	0.09	0.07
Mean (Phase 1)	6.78	6.35	5.75	6.35	0.26	0.59
Mean (Phase 2)	6.87	6.51	5.72	6.51	0.27	0.62

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The unit of observation is the household. Outcomes in columns 1-4 are monthly per capita consumption expenditures, overall, and by specific types. The outcome in column 5 the share of total food expenditure going to non-staple nutritious food, while the outcome in column 6 is the growth in household consumption expenditure between 2011 and 2014.

All regressions use sampling weights to reconstitute the village caste composition.

Table B9: Intermediation Analysis or Reduced Form
Relationship between Variance of Change in Village Consumption and Program Scale (Unweighted)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Program Scale (Log)						
Treated	-0.036***	-0.044***	0.223	0.186	0.132**	0.181***
	(0.010)	(0.012)	(0.182)	(0.196)	(0.055)	(0.053)
Treated × Phase 2	0.042***	0.051***	-0.028	-0.002		
	(0.013)	(0.015)	(0.050)	(0.056)		
Treated × Program Scale (ln)			-0.044	-0.042	-0.032**	-0.041***
			(0.028)	(0.030)	(0.012)	(0.013)
R-squared	0.36	0.38	0.37	0.39	0.37	0.39
Panel B: Program Scale (Linear)						
Treated			0.004	-0.015	-0.011	-0.005
			(0.081)	(0.085)	(0.024)	(0.025)
Treated × Phase 2			-0.012	0.008		
			(0.064)	(0.067)		
Treated × Program Scale			-0.099	-0.106	-0.082**	-0.117***
			(0.105)	(0.107)	(0.035)	(0.038)
R-squared	0.36	0.38	0.36	0.39	0.36	0.39
Additional Controls	No	Yes	No	Yes	No	Yes
Obs	333	333	333	333	333	333
Clusters	179	179	179	179	179	179
Mean (Phase 1)	0.21	0.21	0.21	0.21	0.21	0.21
Mean (Phase 2)	0.22	0.22	0.22	0.22	0.22	0.22

Robust standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Outcome is the village-level variance of the change in a household's log MPCE between 2011 and 2014. Consumption observations are winsorized at 1% and 99%. Program scale is the number of SHGs in the block that a village is in in 2011 (in 1000s), which is when Jeevika rolled out in treated villages. All regressions control for the interaction between block population, block Dalit/Adivasi population, number of villages in the block, and treatment status.

Columns 2, 4, 6 control for the village population (in 1000s), village Dalit and Adivasi population (in 1000s), share of temporary migrants in the village, share of village households with savings, whether there is a bank in the village, whether a village has a paved road, the distance of a village from the district headquarters and its square from the census.

Table B10: Intermediation Analysis or Reduced Form
Relationship between Variance of Change in Village Consumption and Program Scale (Weighted)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Program Scale (log)						
Treated	-0.031**	-0.039**	0.553**	0.457*	0.092	0.125
	(0.012)	(0.015)	(0.260)	(0.267)	(0.074)	(0.077)
Treated × Phase 2	0.037**	0.045**	-0.141*	-0.103		
	(0.017)	(0.019)	(0.072)	(0.075)		
Treated × Program Scale			-0.088**	-0.078**	-0.025*	-0.033**
			(0.038)	(0.039)	(0.015)	(0.017)
R-squared	0.29	0.32	0.32	0.35	0.31	0.34
Panel B: Program Scale (linear)						
Treated	-0.031**	-0.039**	0.153	0.103	-0.020	-0.024
	(0.012)	(0.015)	(0.116)	(0.118)	(0.032)	(0.033)
Treated × Phase 2	0.037**	0.045**	-0.140	-0.103		
	(0.017)	(0.019)	(0.089)	(0.089)		
Treated × Program Scale			-0.252*	-0.226	-0.049	-0.079
			(0.143)	(0.143)	(0.044)	(0.050)
R-squared	0.29	0.32	0.31	0.34	0.31	0.34
Additional Controls	No	Yes	No	Yes	No	Yes
Obs	333	333	333	333	333	333
Clusters	179	179	179	179	179	179
Mean (Phase 1)	0.21	0.21	0.21	0.21	0.21	0.21
Mean (Phase 2)	0.22	0.22	0.22	0.22	0.22	0.22

Robust standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Outcome is the village-level variance of the change in a household's log MPCE between 2011 and 2014. Consumption observations are winsorized at 1% and 99%. Program scale is the number of SHGs in the block that a village is in in 2011 (in 1000s), which is when Jeevika rolled out in treated villages. All regressions control for the interaction between block population, block Dalit/Adivasi population, number of villages in the block, and treatment status.

Columns 2, 4, 6 control for the village population (in 1000s), village Dalit and Adivasi population (in 1000s), share of temporary migrants in the village, share of village households with savings, whether there is a bank in the village, whether a village has a paved road, the distance of a village from the district headquarters and its square from the census.

Table B11: First Stage
Relationship between Accumulated SHG Savings in a Village and Program Scale

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Program Scale (Log)							
Treated	0.593***	0.967***	0.858***	-0.307	-0.103	-0.135	-0.203
	(0.166)	(0.263)	(0.230)	(1.102)	(0.872)	(0.340)	(0.314)
Treated × Phase 2		-0.276*	-0.281*	0.053	-0.031		
		(0.159)	(0.148)	(0.346)	(0.288)		
Treated × Program Scale				0.193	0.145	0.170**	0.159**
				(0.162)	(0.127)	(0.074)	(0.065)
R-squared	0.52	0.52	0.69	0.53	0.69	0.53	0.69
F-statistic	54.75	44.28	25.59	37.67	24.29	45.30	25.98
Panel B: Program Scale (Linear)							
Treated	0.593***	0.967***	0.858***	1.109*	1.158**	0.624***	0.508***
	(0.166)	(0.263)	(0.230)	(0.643)	(0.498)	(0.165)	(0.145)
Treated × Phase 2		-0.276*	-0.281*	-0.394	-0.528		
		(0.159)	(0.148)	(0.542)	(0.429)		
Treated × Program Scale				-0.198	-0.415	0.374*	0.339*
				(0.796)	(0.622)	(0.220)	(0.205)
R-squared	0.52	0.52	0.69	0.52	0.69	0.52	0.69
F-statistic	54.75	44.28	25.59	36.70	23.82	44.47	25.49
Obs	333	333	333	333	333	333	333
Clusters	179	179	179	179	179	179	179
Mean (Phase 1)	0.19	0.19	0.19	0.19	0.19	0.19	0.19
Mean (Phase 2)	0.23	0.23	0.23	0.23	0.23	0.23	0.23

Robust standard errors in parentheses.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Outcome is the total group savings accumulated across all SHGs at the village level by 2015 (in 1,000,000 ₹). Program scale is the number of SHGs in the block that a village is in in 2011 (in 1000s), which is when Jeevika rolled out in treated villages.

All regressions control for the interaction between block population, block Dalit/Adivasi population, number of villages in the block, and treatment status. Columns 3, 5, 7 control for the village population (in 1000s), village Dalit and Adivasi population (in 1000s), share of village households with temporary migrants, share of village households with savings, whether there is a bank in the village, whether a village has a paved road, the distance of a village from the district headquarters and its square (from the census).

Table B12: Impact of village SHG savings on variance of change in consumption (IV)

	Log Instrument		Linear Instrument		Quadratic Instrument	
	(1)	(2)	(3)	(4)	(5)	(6)
Unweighted						
Village SHG Savings in 2015 ('00000)	-0.049	-0.069	-0.036	-0.049	-0.066**	-0.075*
	(0.035)	(0.046)	(0.034)	(0.045)	(0.033)	(0.040)
Additional Controls	No	Yes	No	Yes	No	Yes
Obs	333	333	333	333	333	333
Clusters	179	179	179	179	179	179
Olea and Pflueger (2013) F-statistic	10.122	9.314	8.964	7.658	7.366	8.428
Critical Values (% worst case bias)						
τ=5%	9.859	7.729	10.799	8.485	21.553	20.248
τ=10%	6.915	5.674	7.472	6.121	13.387	12.661
τ=20%	5.204	4.476	5.538	4.741	8.825	8.410
τ=30%	4.554	4.027	4.801	4.219	7.124	6.821
Weighted						
Village SHG Savings in 2015 ('00000)	-0.055	-0.087*	-0.041	-0.069	-0.083**	-0.099**
	(0.041)	(0.052)	(0.043)	(0.055)	(0.040)	(0.044)
Additional Controls	No	Yes	No	Yes	No	Yes
Obs	333	333	333	333	333	333
Clusters	179	179	179	179	179	179
Olea and Pflueger (2013) F-statistic	10.122	9.314	8.964	7.658	7.366	8.428
Critical Values (% worst case bias)						
τ=5%	9.859	7.729	10.799	8.485	21.553	20.248
τ=10%	6.915	5.674	7.472	6.121	13.387	12.661
τ=20%	5.204	4.476	5.538	4.741	8.825	8.410
τ=30%	4.554	4.027	4.801	4.219	7.124	6.821

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Village-level cumulative SHG savings ('000,000) in 2015 is instrumented by Treatment status and Treatment × Program Scale in all columns. All regressions control for block population, block Dalit/Adivasi population, number of villages in the block, and their interactions with treatment status. In addition, even columns control for the village population (in 1000s), village Dalit and Adivasi population (in 1000s), share of village households with temporary migrants, share of village households with savings, whether there is a bank in the village, whether a village has a paved road, the distance of a village from the district headquarters and its square from the census.