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The spillover effects of seed producer groups on non-member farmers in mid-hill communities of Nepal

by
Kate Vaiknoras
Catherine Larochelle
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Authors:
Kate Vaiknoras, Catherine Larochelle, Jeffrey Alwang

ISBN 978-92-9266-012-3
Printed June 2020

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Acknowledgements

Funding for this research was provided by IFAD and supplemented in various ways with resources from the College of Agriculture and Life Sciences, Virginia Polytechnic and State University. The IFAD-funded Consortium for Unfavorable Rice Environments (CURE) provided access to data and background reports that were helpful in the completion of this project. The authors especially thank Dr David Johnson, former director of CURE for his guidance. The International Rice Research Institute (IRRI) provided logistical support and access to background data.

The authors acknowledge support with data collection from iDE Nepal and faculty and students from the Institute of Agriculture and Animal Science (IAAS) in the Lamjung district, Nepal. We are particularly grateful for contributions from Arun Limbu, Bal Krishna Thapa and Rakesh Kothari from iDE Nepal; Rajkumar Pandey and Rajesh Pandey from the Child Health and Environment Save Society Nepal (CHESS Nepal); Bhaba Tripathi from IRRI; Bishnu Bilas Adhikari from IAAS; and the enumerators and drivers who helped us complete our field work. We also acknowledge contributions of seed producer group executive committee members who participated in our focus groups and the households and village leaders who took the time to participate in our surveys.

Dr Fabrizio Bresciani and Dr Aslihan Arslan were instrumental in the design and conduct of the study. Dr Arslan provided numerous insights throughout the study and provided insightful comments on intermediate drafts. We thank Dr George Norton (Virginia Tech) for his helpful comments and suggestions and participants in a workshop hosted by the International Center for Tropical Agriculture in Vietnam during August 2019.

About the authors

Kate Vaiknoras recently graduated with her PhD from the Department of Agricultural and Applied Economics at Virginia Tech; she also has a MS in agricultural and applied economics from Virginia Tech and a BA in economics from Smith College. Her research examines adoption of agricultural technologies, particularly improved seed varieties, and the impact that adoption has on household outcomes. She has extensive experience in developing and conducting household surveys.

Catherine Larochelle has been a faculty member in the Department of Agricultural and Applied Economics at Virginia Tech since 2011. She held the positions of research associate and research assistant professor and is now a tenure-track faculty since 2015. Her research focuses on assessing the impact of agricultural research and programmes on yield, poverty, food security and nutrition. She has researched and published on issues related to food demand, farm productivity, risk management strategies, factors driving and constraining technology adoption, and gender decision making, among others. Catherine recently studied the adoption and disadoption of iron-biofortified bean varieties and the impact of their adoption on yield, bean consumption and bean sales among Rwandan rural households. Catherine has been extensively involved in graduate student advising and teaches courses on international agricultural development and trade and agricultural production and consumption economics at Virginia Tech.

Jeffrey Alwang is professor in the Department of Agricultural and Applied Economics at Virginia Tech. He received his PhD from Cornell University in 1989 and has taught and conducted research on agricultural and rural development at Virginia Tech since then. His research focuses on policies to alleviate poverty in rural areas, development of rural economies and assessment of impacts of technologies, policies and programmes on rural residents. His recent projects have assessed impacts of new agricultural technologies (Bangladesh, China, Ecuador, Egypt, Ethiopia, Peru, Rwanda, Uganda); strategies to engage poor producers in modern value chains (Ecuador, Jordan, Indonesia); use of information and communications technologies to promote technology adoption (Ecuador, Rwanda); and child labor, schooling and poverty (Jordan, Zimbabwe).

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Abstract

Rice farmers in the mid-hills region of Nepal are vulnerable to drought, which can drastically reduce yields. Stress-tolerant rice varieties (STRVs) can mitigate this vulnerability, as can having a high seed replacement rate (SRR) and using best management practices (BMPs) in rice cultivation. In 2013, IFAD established and trained 12 seed producer groups (SPGs) across three districts in Nepal to improve local access to STRV seed. This paper presents propensity-score weighted regressions used to estimate the spillover effects of SPGs on the adoption of STRVs and BMPs and the SRR of non-member households in villages with an SPG, or that are next to a village that had an SPG, compared to randomly selected villages in the region. Non-member households in SPG villages are 18 percentage points more likely to have grown an STRV for at least one season, 15 percentage points more likely to have grown an STRV in 2018 and 23 percentage points more likely to have grown an STRV in 2017, compared to non-member households in randomly selected villages. Non-member households in adjacent villages are 19 percentage points more likely to have grown an STRV in 2017 compared to those in randomly selected villages. Non-members in SPG villages also have a higher SRR and are more likely to follow some BMPs compared to non-members in randomly selected villages. Results show that SPGs have the potential to improve the resilience of their local communities in the face of climate change.

1. Introduction

Rice is the staple food for billions of people in Asia; however, over half of the rice land on the continent is in unfavourable environments that are vulnerable to weather shocks, such as drought and flood, and suffer from low productivity (Manzanilla, Johnson and Castillo, 2017). One such unfavourable environment is the mid-hills region of Nepal, where upland farmers lack irrigation, use poor crop management practices and rely heavily on recycled seed of old varieties, all of which contribute to low yield and can exacerbate vulnerability to climate shocks. Seed that is not replaced frequently can harbor microorganisms, including nematodes, fungi, viruses, or bacteria, causing diseases and low productivity. Some of these diseases are seedborne and will pass to the next generation of seed (Gonzales and Huelma, 2013). Poor management can reduce yields and old varieties often lack tolerance to adverse climate conditions.

Some of these challenges can be addressed through agricultural technologies, such as stress-tolerant rice varieties (STRVs), best management practices (BMPs) and replacing seed frequently with high-quality seed. High-quality seed can improve yield by 5-20 per cent (IRRI Rice Knowledge Bank, 2012). STRVs are bred to withstand climatic stress conditions better than non-STRVs, mitigating potential production losses. For instance, drought-tolerant varieties have higher yields under reduced rainfall compared to other varieties. The Consortium for Unfavorable Rice Environments (CURE), an IFAD project developed in 2002 with support from the Asian Development Bank, promotes STRVs, BMPs and seed replacement in several Asian countries, including Nepal, to increase yield and reduce environmental vulnerability of rice crops. In Nepal, CURE took over after the IFAD Technical Assistance Grant (TAG) 706, which operated from 2005 to 2008, ended. IFAD TAG 706, in collaboration with the Nepal Agriculture Research Council (NARC) and the Institute of Agriculture and Animal Science (IAAS) located in the Lamjung district, Nepal, validated over 30 improved technologies for rice and other crops in Nepal's mid-hills region. Participatory varietal selection was conducted on upland and rainfed rice, leading to high demand for seed among participating farmers. However, supply of these varieties was insufficient to meet demand, a reflection of the weakness of the national seed system. According to the NARC, the amounts of quality rice seed available was insufficient (Gauchan et al., 2014). As a result, the seed replacement rate (SRR) was around 12 per cent, much lower than the recommended rate of 25-30 per cent, and the informal seed sector in which farmers save and trade seeds within their social networks accounted for about 90 per cent of rice seed planted. The remaining 10 per cent comes from public agencies, the private sector and community-based seed production (Gauchan et al., 2014).

To facilitate multiplication of these newly validated rice varieties, IFAD TAG 706, and later the CURE project, along with the Gates Foundation-funded Stress Tolerant Rice for Africa and South Asia project, established 12 seed producer groups (SPGs) between 2007 and 2013 in the neighboring Lamjung, Tanahu and Gorkha districts1 in the Western development region of Nepal (figure 1). These districts were chosen because they are prone to drought and are close to the IAAS.

[1] Three SPGs were also established in Bajhang district in the Far Western development region, but these groups received far less support and monitoring than those in Lamjung, Tanahu, and Gorkha and are not part of this study.

Figure 1. SPG locations and districts, Nepal

Source: own analysis from survey data

SPGs are community-based organisations in which members are trained in rice seed production and sales, including STRVs. The SPGs were established in drought-prone villages with road accessibility, recommended by extension agents from the District Agricultural Development Office (DADO) and where rainfed lowland rice is cultivated each year. Local farmers volunteered to join the groups. SPG members received two trainings per year on rice cultivation practices. IAAS, DADO and NARC provide seed inspection services so that SPGs can sell their seed as either truthfully labeled, which requires IAAS inspection, certified, which requires inspection by DADO, or foundation seed, which requires inspection by NARC. Many SPGs sell their seed to Sundar Cooperative, which was the first cooperative that SPG established. In addition to operating its own SPG, Sundar Cooperative collects and sells seed from other SPGs. The SPGs can also sell seed independently to other cooperatives, NGOs and agroveterinary businesses (commonly called agrovets) that sell seed. Although the CURE programme ended in 2013, many of the SPGs remain highly active, while others have ceased operating or have only a few active members remaining.

Previous studies find that SPGs and other forms of seed production are beneficial for producers (Katungi et al., 2011; Tebeka et al., 2017; Mishra et al., 2016; Winters, Simmons and Patrick, 2010; Simmons, Winters and Patrick, 2005). Katungi et al. (2011) found that farmer-based bean seed production in Kenya was profitable for producer farmers, despite the higher costs of producing bean seed over grain. Tebeka et al. (2017) examined community-based seed multiplication of common bean in Ethiopia and found that producing and selling seed was more profitable than producing and selling grain. Contracts to produce hybrid maize seed and broiler chickens benefited smallholder farmers in Indonesia by improving returns to farm capital, although contracts to produce rice seed did not increase returns (Simmons, Winters and Patrick, 2005). In Nepal, Mishra et al. (2016) found that farmers who entered into contracts with private seed companies for production of high-yielding rice varieties earned higher profits than those who produced such varieties without contracts. While the existing literature has documented the direct effects of SPGs and other forms of organized seed production, such as contracts, there is little or no research examining the spillover effects, also called 'indirect effects', of seed production.

Evidence of spillover effects is documented for different types of development programmes. In the health sector, Miguel and Kremer (2004) investigated the direct and indirect impacts of deworming among children of school age in Kenya. Schools were randomly selected into treatment and control groups, and within treatment schools some students were randomly assigned deworming medicine, while others served as controls. Untreated students in the treatment and neighboring schools had better health and greater school participation compared to students in the control schools, which the authors argued was due to treatment spillover effects of the reduced presence of worms in the environment. Janssens (2011) evaluated the direct and spillover effects of a women's empowerment programme in India on child immunization using instrumental variables to address participation selection bias. She found higher immunization rates among participant children, compared to children in control villages, as well as spillover effects on immunization rates of non-participant children in the programme villages. Thome et al. (2013) found evidence of spillover effects on the value of local agricultural production, arising from general equilibrium impacts of a cash transfer programme in Kenya. Wanjala and Muradian (2013) documented the spillover effects from the Millennium Villages Project in Kenya on production margins and household income.

The overarching goal of this paper is to estimate the spillover effects of SPGs onto non-members in SPG villages and nearby villages on the adoption of STRVs, SRR and use of BMPs in rice cultivation. We hypothesize that through interactions with SPG members, non-members in neighborhood communities will gain knowledge and awareness about these agricultural technologies, which, in turn, will stimulate adoption. Failing to account for these spillover effects can drastically underestimate the impact of a programme (Winters, Maffioli and Salazar, 2011).

A difficulty in estimating programme impacts in a quasi-experimental setting such as this is to establish a valid counterfactual. Since information is available on the criteria used to select villages for the establishment of the SGPs, two propensity-score weighted regression adjustment (RA) estimation methods are used to control for potential village selection bias. The weighted RA estimation methods allow for multivalued treatment effects, which we need to quantify the spillover effects of SPGs that occur at two levels: 1) to non-members in SPG villages and 2) to non-members in adjacent villages. The weighted RA estimation methods involve estimating the treatment model first, from which propensity scores are generated and used as weights in the outcome model. These estimation methods improve the balance between treated and untreated groups and are considered 'doubly-robust', as they are valid if either the treatment or outcome model is correctly specified (Wooldridge, 2010). While these methods reduce bias arising from observed village characteristics, unobserved bias could arise if all factors that influence village selection are not observed. Several village-level covariates influencing village selection are included, and statistical tests are used to examine whether unobserved factors are likely to bias the results.

This research provides evidence on the effectiveness of community-based seed production to protect communities from drought and other climate stressors through the spread of agricultural technologies and guides the scaling up of similar IFAD-funded or other projects. This research will also inform policy makers in Nepal and other Asian countries that wish to increase the supply and adoption of improved agricultural technologies through SPGs.

2. Data

2.1. Data source

Data were collected in two stages. In the first stage, a SPG leader focus group survey was fielded. Three to six executive committee members from each of the 12 SPGs established by CURE participated. The SPG leader survey was conducted in September-October 2018 and gathered information on the rice varieties grown by the SPG, type of training provided by CURE and the quantity of seed produced and sold in the 2017/2018 season. Last, the survey participants were asked about current challenges faced by the SPGs and what resources could help overcome these challenges. Interviews with the SGP executive committee members were conducted first to inform the design of the household and community questionnaires.

In the second stage, household and community surveys were administered simultaneously in November-December 2018. Enumeration teams were comprised of current or recently graduated agriculture students. Most graduate students had previous survey experience and had worked previously with our partner organisation, iDE Nepal. The household survey began with a household roster, followed by a module on STRV adoption. Households were asked if they had heard of each of the improved drought-tolerant varieties grown by SPGs. If households reported having heard of the variety, they were asked when they first heard of it, if they had ever grown it, in which season they first grew it and where they obtained their initial planting material.

The bulk of the remaining survey collected detailed information on rice cultivation during the 2018 monsoon season, which is the main rice season in Nepal and runs from June to November. Some information on rice cultivation in the 2017 monsoon season was also collected. The plot roster module collected information on all plots cultivated in the 2018 monsoon season, such as plot size, land ownership, crops grown and whether the crops have suffered from insufficient water availability in the past five years. For plots under rice cultivation, additional questions were asked regarding irrigation, fertilizer and pesticide use as well as paid and unpaid labor. The next survey module collected information on rice varieties grown during the 2018 monsoon season, including the source of planting material, the year the household first grew the variety and whether they consider the variety improved or local and drought-tolerant. Plot-level information was then collected by variety, since more than one rice variety can be grown in a plot. Farmers reported area cultivated, quantity of seed planted, method of planting and quantity harvested for each variety in a plot. The remaining survey modules asked about household social capital, access to agricultural extension and asset ownership. GPS coordinates were also collected.

For the community survey, we interviewed village leaders about the amenities and services available in the villages, including distance to the nearest asphalt road, agrovet and DADO. We also asked about adoption of STRVs in the village and whether local names were used for any of the STRVs varieties to assist with rice varietal identification.

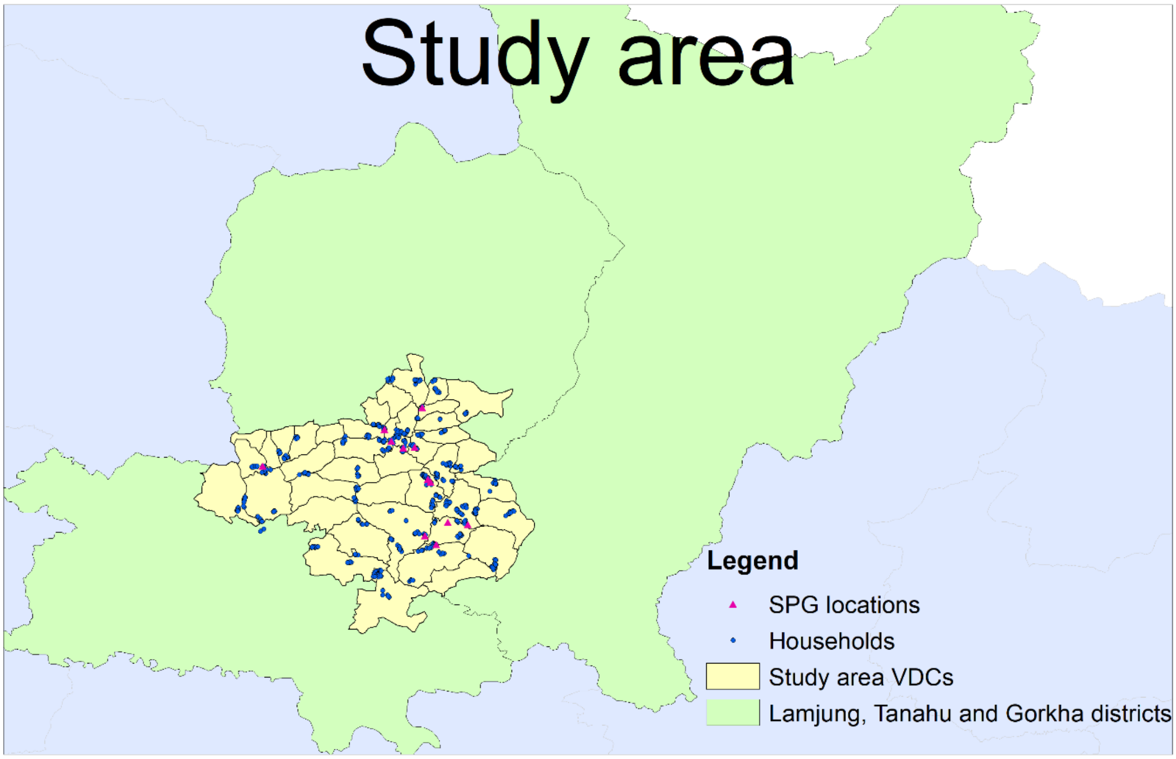
Household GPS coordinates were combined with various spatial datasets to create variables that can control for villages being selected for the establishment of a SPG and explain our outcomes of interest. We used the Landsat data (National Center for Atmospheric Research Staff, 2018) to calculate the Normalized Difference Vegetation Index (NDVI), a measure of the extent of green vegetation that ranges from -1 (a body of water) to 1 (rain forest). The distance from the household dwellings to the nearest road and IAAS as well as the elevation and slope of land were also calculated using a geographical information system.

2.2. Sample selection

The household and community surveys were conducted in 75 villages in Lamjung, Tanahu and Gorkha districts. These 75 villages include the 12 SPG villages. One village that is adjacent to each SPG village was also randomly selected to capture spillover effects onto neighboring villages. A list of adjacent villages and their approximate populations was provided by a local organisation that assisted with sampling, Child Health and Environment Save Society Nepal (CHESS Nepal); adjacent villages were those next to or sharing a border with the SPG villages. One adjacent village was selected for each SPG village using probability proportion to population size. The remaining 51 villages were randomly selected to represent the rice-growing households in the study area, which is shown by the yellow area in figure 2. The study area encompassed Village Development Committees (VDCs)2 that contained the SPG villages and VDCs that are adjacent to SPG VDCs or that connected them into a continuous area. Forty-one VDCs were included. This study area covers a realistic range for the dissemination of SPG seeds while also including villages that vary by distance to SPGs, access to roads, elevation and other factors that could affect adoption of STRVs.

[2] VDCs are administrative units in Nepal that are smaller than districts but larger than villages.

Figure 2. Study area location within the Lamjung, Tanahu and Gorkha districts



Source: own analysis from survey data

The number of villages to randomly select in each district was determined using probability proportion to size, based on population, and lead to 11 villages in Gorkha, 18 in Lamjung and 22 in Tanahu districts. Because lists of villages were available, we selected wards rather than villages (a VDC contains nine wards and a ward contains about 3-6 villages) using proportional to population size sampling. For each ward, staff from CHESS Nepal collected the lists of villages and their approximate number of rice-growing households. One village per ward was randomly sampled, again using proportional to population size sampling. Once the 75 villages (51 randomly selected villages, 12 SPG villages and 12 adjacent villages to SPG) were selected, CHESS Nepal staff collected the names of all rice-growing households in each village. Twelve households were randomly selected[3] and interviewed in each village, for a total of 900 households. The locations of the SPGs and sampled households4 are shown in figure 2. The 75 villages are located in 37 of the 41 VDCs in our study area; thus, the sample covers a wide range of the study area.

2.3. Rice variety identification

The success of the study relies on households accurately identifying the rice varieties they cultivated, particularly the STRVs. Prior to conducting the household survey, local extension agents, agrovets and other individuals knowledgeable about rice production were asked about farmers' ability to identify varieties. All reported that farmers were well aware of the official names of varieties they cultivate, particularly the more recently released improved varieties, including the STRVs. They stated that the only problem that could arise was from farmers in different villages having different names for local varieties. To assist proper varietal identification during data collection, we prepared a list of variety names that enumerators could select from. This list came from the SPG leader survey and documents on rice varieties (Crop Development Directorate, 2015). For varieties that households reported were not on our pre-defined list, local experts were used to help identify whether they were improved, hybrid or STRV; these answers were compared

[3] We randomly selected 12 households and five alternates.
[4] Some households appear to be outside the study area VDCs; this is likely due to fuzziness of border boundaries on the ground.

with farmer's own classifications. Identification of STRVs is most crucial, and we feel confident that households were able to correctly identify them.

3. Conceptual and empirical framework

3.1. Theory of spillover mechanisms

Adapting the theories of spillover mechanisms in Benjamin-Chung et al. (2015), we hypothesize that spillover effects from SPGs can occur through social proximity and general equilibrium effects. Social proximity refers to a change in behaviours among non-members that arise from their connections with SPG members. Benjamin-Chung et al. (2015) considered learning/imitation and norm-setting effects to be two types of social proximity. In the case of learning/imitation effects, non-members learned the new varieties and BMPs from SPG members, either by talking with them or observing them, and then imitated their behaviours. SPG members could also establish new social norms about rice cultivation practices, influencing the behaviours of non-members. General equilibrium effects refer to programmes that affect equilibrium prices through changes in supply and demand. In this case, the establishment of SPGs has increased the supply of STRVs and other improved rice varieties, which could potentially lower the price of seeds.

To estimate the spillover effects of SPGs, three groups are compared: non-members in SPG villages, non-members in villages adjacent to SPG villages and non-members in randomly selected villages. We hypothesize that spillover effects will reach neighboring villages, since the agricultural technologies considered are highly transferrable (Winters, Maffioli and Salazar, 2011). We also assume that spillover effects in randomly selected villages are negligible due to lack of connections with SPG members, given that these villages are located far from SPG villages. Thus, to estimate the SPG spillover effects, we compare the outcomes of non-members in SPG villages and adjacent villages to those of non-members in randomly selected villages, which represent the control group.

We hypothesize that non-members in SPG villages and nearby villages will have higher STRVs adoption rates and SRR than non-members in randomly selected villages due to their social proximity to SPG members and general equilibrium effects. For the use of BMPs, spillover effects are expected to arise primarily through learning/imitation and norm-setting effects. We expect spillover effects to be greater for practices that are more 'visible', easier and cheaper to implement and most profitable. For example, crop rotation can be more easily observed than a less visible practice, such as rice seed cleaning and drying. We hypothesize that non-members in SPG villages will more likely adopt BMPs than non-members in randomly selected villages, but the increased BMP usage may not spread among non-members in adjacent villages, or may be limited to a subset of practices, because changes in behaviours from learning/imitation and norm-setting may not extend as easily across villages compared to rice seed.

3.2. Econometric strategy

The challenge in estimating the indirect effects of SPGs is that villages were not chosen randomly for the establishment of SPGs. SPG villages, and possibly adjacent villages, might vary systematically compared to randomly selected villages. If some of this variance is correlated with the outcome variables, then the estimates of the spillover effect would be biased. To correct for village selection bias and ensure that villages are comparable, we use two weighted regression estimators, namely the augmented inverse-probability weighted (AIPW) estimator and the inverse-probability weighted RA (IPWRA) estimator. We also estimate unweighted RA estimators, as is commonly done in the treatment effect estimators literature (Haile et al., 2017; Smale et al., 2018).

RA estimates the outcome model specified in equation (1), where the outcome variable (Y_i) is regressed on a vector of covariates (X_{vi}), which vary by village (v), household (i) and a vector of village covariates that influence treatment assignment (Z_v).

$$Y_i = f(X_{vi}, Z_v, \beta) + \epsilon_{vi} + \epsilon_v \quad (1)$$

β represents a vector of coefficients to be estimated. The error terms ϵ_{vi} and ϵ_v are the household and village-level error terms, which are assumed to be independent and, in our models, robust to heteroskedasticity. The outcome model is estimated separately for each treatment level, which is, in our case, the three type of villages. The multivalued treatment variable is specified as $SPG_v = 0$ for control villages (i.e. those that were randomly selected), SPG_v = 1 if v is adjacent to an SPG village and SPG_v = 2 if v is an SPG village. The second step of RA involves averaging the predicted outcomes over all observations for each outcome model (i.e. when SPG_v = 0, 1 and 2). The third step of the RA consists of calculating the difference between the predicted average outcome of the two treatment groups (SPG_v = 1 and 2) and the control group (SPG_v = 0), which gives the average spillover effect for each type of village.

Weighted estimators work similarly to the RA estimator but add the weighting, which involves the following steps. First, the treatment probability model is estimated using a multinomial logit model, where the multivalued treatment variable is regressed on a set of village characteristics represented by the vector Z_v in equation (2):

$$SPG_v = h(Z_v, \Lambda) + w_v \qquad (2)$$

The error term w_v includes any village heterogeneity in treatment not captured by Z_v, and Λ is a vector of parameters to be estimated. Then, the generalized propensity score is calculated with the conditional probability that a village receives each level of treatment (SPG_v = 0, 1 and 2) given Z_v. The outcome regression models (in IPWRA) for each treatment level or the predicted outcomes (in AIPW) for each treatment level are then weighted by the inverse of the propensity scores for the respective treatment level (McCaffrey et al., 2013). The Z_v vector includes only village-level variables because SPGs were established based on village characteristics.

Weighted estimators create a more balanced dataset based on observable characteristics than RA or other unweighted regression methods, such as an ordinary least squares (OLS) or logit model, making treatment and control observations more comparable to each other and further reducing the bias that arises from observables (Austin, 2011). Weighted estimators are called ‘doubly robust’ because they only require that either the outcome model or the treatment model be correctly specified to obtain consistent estimates (Wooldridge, 2010). Moreover, the weighted estimators are more efficient and robust than RA, assuming either the outcome model or the treatment model is well-specified. Both IPWRA and AIPW have been used in the recent literature to evaluate the impacts of agricultural interventions. Smale et al. (2018) used multivalued AIPW and IPWRA estimators to evaluate the effects of improved and hybrid sorghum adoption on yields, household sorghum purchases and dietary diversity. Esposti (2017) used multivalued AIPW to estimate the impacts of the Common Agricultural Policy on farm production choices of Italian farmers. Haile et al. (2017) used the AIPW estimator to determine the effects of participatory action research in Malawi. Finally, Cavatassi et al. (2011) used inverse propensity-score weighted least squares (a different type of weighted estimator) to evaluate the impacts of Plataformas, a programme in Ecuador that links smallholder potato producers with agricultural support service providers.

Weighted regression estimators rely on two assumptions: overlap and unconfoundedness. The overlap assumption requires that the values of the weighting variable Z_v are similar enough between treatment and control villages that these villages can be meaningfully compared. We assess the overlap assumption by examining the distribution of the propensity scores for treatment and control groups. When a group has a high density of propensity scores in the same range as the other groups, there is a high level of overlap (Imbens and Wooldridge, 2009).

The unconfoundedness assumption stipulates that there are no unobserved village characteristics that correlate with being selected for the establishment of an SPG and the outcomes of interest. We control for observed characteristics known to influence the selection of SPG villages, but if unobserved characteristics exist, then selection bias could arise. A common way to assess the validity of the unconfoundedness assumption is to verify that the weighting models properly balance the distributions of the covariates between each treatment group, meaning that each treatment group has a similar mean and variance for the observed characteristics (Esposti, 2017; Haile et al., 2017). We do this using a balance test derived by Imai and Ratkovic (2014).

3.3. Variables

This section discusses outcome variables (Y_i), weighting variables (Z_v) and control variables (X_{vi}). Table 1 defines outcomes of interest related to spillover effects of SPGs (descriptive statistics for these variables are presented in table A1). STRV adoption behaviour was examined for three time periods: 1) the 2017 monsoon season, 2) the 2018 monsoon season and 3) in any season past or present. Analysis of three periods allows examination of whether the indirect effects of SPGs have become stronger or weaker over time. The SRR is calculated as the percentage of seed grown by the household in 2018 that came from formal seed sources (Gauchan et al., 2014). In this region, the most common formal seed types are certified or truthfully labeled seed. Our list of BMPs comes from interviews with SPG executive committee members and includes practices for which SPG members were trained. These practices range from the beginning (pre-transplanting) to the end (post-harvest processing) of the rice season and include cleaning rice seed prior to planting, using lower seeding rate and planting seedlings when they are 18-22 days old. In addition, members were taught that chemical fertilizer requirements vary with soil quality but that they can apply any quantity of organic fertilizer. For weed and pest management, members were trained to rogue (i.e. pick through the crop and pull out weeds and damaged plants) their rice fields throughout the season. During post-harvest practice, SPG members were trained to test the moisture of their seed prior to storage. Finally, they were trained on cropping patterns, specifically to plant legumes and/or vegetables on rice plots after having harvested rice. This can be beneficial because planting legumes fixes nitrogen into the soil and because legumes and vegetable consumption is nutritious.

Table 1. Dependent variables and their description

Outcome variable	**Description**
STRV adoption	Household has grown an STRV in the current or previous season (1 = yes; 0 = no)
STRV 2018 adoption	Household grew an STRV in 2018 monsoon season (1 = yes; 0 = no)
STRV 2017 adoption	Household grew an STRV in 2017 monsoon season (1 = yes; 0 = no)
SRR	SRR of rice at the household level, measured by the % of rice seed grown in the 2018 monsoon season that was certified or truthfully labeled seed
Use of BMPs	*Household practiced the following in 2018 monsoon season*
Clean rice seed prior to planting	Household cleaned seed prior to planting, either by floating it in water and removing seeds that float to the top and/or picking through it to remove damaged seeds (1 = yes; 0 = no)
Seeding rate	Quantity of rice seed planted in kg/ha
Age of seedlings	Age of seedlings when they were transplanted into rice fields (in days)
Organic fertilizer	Quantity of organic fertilizer applied in kg/ha
Chemical fertilizer	Quantity of chemical fertilizer applied in kg/ha
Roguing	Number of times the household rogued their rice fields
Moisture testing	Household checked moisture of seed prior to storage, either by using a moisture control machine or by biting the seed to determine if it snaps in half (1 = yes; 0 = no)
Legume cultivation	Household grew lentils (1 = yes; 0 = no)
Vegetable cultivation	Household grew vegetables (1 = yes; 0 = no)

The vector Z_v includes village-level variables likely to have influenced the selection of villages for the establishment of SPGs (table 2). Proximity to roads was an explicit criterion for SPG location; we therefore include distance from the village centre to the nearest asphalt road in minutes travel time using the most common mode of transportation. Similarly, we include distance from the village centre to DADO, as extension agents may have been more likely to recommend villages near their offices. We also control for distance to the nearest agrovet, since it may be easier for villages nearby agrovets to sell their seeds, and thus, could have been considered more likely to sustain a successful SPG. Distances from village centre to the nearest asphalt road, DADO and agrovets were obtained from the community survey. In addition, farmers must cultivate rice every year for a village to be considered for a SPG. While rice is grown each monsoon season in all the selected villages (SPG, adjacent and randomly selected), we include a few agroecological variables to control for suitability of rice production. These include NDVI, elevation[5] and slope, calculated based on household dwelling coordinates and then averaged at the village level. Household distance by road to IAAS campus in minutes is averaged at the village level and included as a regressor, since IAAS helped launch and support the SPG programme. IAAS implementers may have been more familiar with, and thus more likely to recommend, nearby villages.

Covariates in the X_{vi} vector include one village characteristic and several household characteristics that could be correlated with both treatment and the outcome variables (table 2). The village-level variable used as a control is a dummy variable equal to one if the village had a farmer association 6-10 years ago, around the time of the SPG establishment. We initially included this variable as a covariate in the $Z_v$vector but it was unbalanced. Since we believe it is important to control for the presence of a farmer association, as it can improve access to information and influence the outcomes of interest (Beyene and Kassie, 2015; Foster and Rosenzweig, 2010), we include this covariate in the X_{vi} vector. Moving the unbalanced variable to the control vector did not change results substantially.

Table 2. Village and household level covariates

Variable	**Description**
Weighting variables ($\mathrm{Z_v}$) – explain selection of villages for the establishment of SPGs	
Elevation	Village average elevation
NDVI	Village average NDVI
Slope	Village average slope
IAAS	Village average distance to IAAS (in minutes) traveling by car
DADO	Distance from the village centre to the nearest DADO office (in km)
Agrovet	Distance from the village centre to the nearest agrovet (in minutes), traveling using the most popular mode of transportation
Asphalt road	Distance from the village centre to the nearest asphalt road (in minutes), traveling by the most popular mode of transportation
Control variables ($\mathrm{X_{vi}}$)	
SPG member	A household member has been a member of an SPG (1 = yes; 0 = no)
Sex	Sex of household head (1 = female; 0 = male)
Age	Age of household head
Education	Household head completed at least primary education (1 = yes; 0 = no)
Land owned	Land owned (in ha) in 2008
Wealth index quintile	Wealth index created using polychoric principal components analysis based on asset ownership and housing characteristics in 2008
Distance to road	Distance from household to the nearest road (in metres)
Farmer's association	The village had a farmer's association six years ago (1 = yes; 0 = no)

A number of household characteristics were also included. The first is whether any household member has ever been a member of a SPG. Controlling for membership is essential to separate the direct effect of SPGs from the spillover effects. The age, sex and education of the household head were also included, as these traits could influence access to information and other resources

[5] We used values for elevation that were captured by survey tablets during data collection. We also have elevation data available that was captured in ArcGIS at household coordinates. These two sets of values are similar to one another, and using one over the other does not change the main results of this paper.

related to the outcomes of interest. Households whose head is more educated may be more likely to replace rice seed according to the recommended rate and adopt improved varieties and BMPs, since they likely have greater access and ability to process information. Education enters the models as a binary variable equal to one if the household head has completed at least primary education. The number of adults in the household aged 15 and older is included as a measure of household labor availability, as labor availability could influence rice cultivation decisions, including what varieties and practices to use. Household wealth in 2008 was included to avoid any potential endogeneity problem that could arise if SPGs have influenced wealth over time. Two variables were used to reflect wealth: 1) a wealth index, created using polychoric principal components analysis based on housing characteristics and asset ownership in 2008; and 2) land owned in 2008. Wealthier households and households owning more land may be more likely to replace rice seed and to adopt new varieties, as they have a greater ability to purchase seeds and have access to more resources that may promote adoption (Feder, Just and Zilberman, 1985). Finally, distance to the nearest road can influence household rice cultivation by affecting how easy it is for households to access new planting material and inputs as well as information.

3.4. Robustness checks

Several robustness checks were conducted to assess the sensitivity to model and treatment variable specification. A first robustness check involves estimating unweighted OLS or logit models, depending on the nature of the outcome variable, controlling for variables in Z_v and X_{vi} and using as treatment variable distance to the nearest SPG, measured in km and then in minutes travel time. Having two measures of distance to the nearest SPG serves as a sensitivity check of the results to the treatment variable specification. Moreover, using a continuous variable sheds light on how far spillovers effects can occur. Spillovers could potentially reach beyond adjacent villages, particularly for adoption of STRVs, as the transfer of seeds can occur along marketing channels and extend past neighboring villages.

We also estimate the direct effects of SPGs using RA, where the treatment variable is a dummy variable equal to one if a household member has ever been a member of an SPG and zero if the household is not a member and lives a randomly selected village. It is more difficult to deal with the problem of participation selection bias when examining the direct effects of SPGs because members volunteered to join SPGs. Therefore, it is possible that SPG members differ from non-members in terms of ability or entrepreneurship. Given the difficulty in finding suitable instrumental variable to correct for this bias, we use RA to address selection on observables only. Despite this potential issue, examining the direct effects of SPGs can shed light on whether the magnitudes of the estimated indirect effects are plausible by serving as upper bounds for spillover effects. For example, if SPG members did not follow recommended BMPs, then it is unlikely that SPGs would have an impact on the adoption of BMPs among non-members based on our conceptual framework of how spillover effects arise.

4. Findings

4.1. SPG focus group analysis

The focus group discussion with SPG executive members provided extensive descriptive information that supports the understanding of the context for the econometrics findings. The SPGs vary in how active they were as of 2018. Nine SPGs still actively produced and sold rice seed (one in Gorkha, two in Tanahu and six in Lamjung), while three SPGs did not sell rice seed in 2018 (two in Gorkha and one in Tanahu). All SPGs had active members (figure 3), even those that did not produce/sell rice in the 2017/2018 season (figure 4). Membership numbers ranged from 7 to 75. Most members live in the same village as their SPG, though some SPGs have members from neighboring villages.

The active SPGs produced between 200 kg and 16 mt of rice seed in 2017 for sale in 2018. However, not all members of the active SPGs sold rice seed in 2018 (the number ranged from 7 to 52). Seven of the twelve groups had their own or a shared storage facility. The three inactive SPGs in 2018 did not have storage facilities.

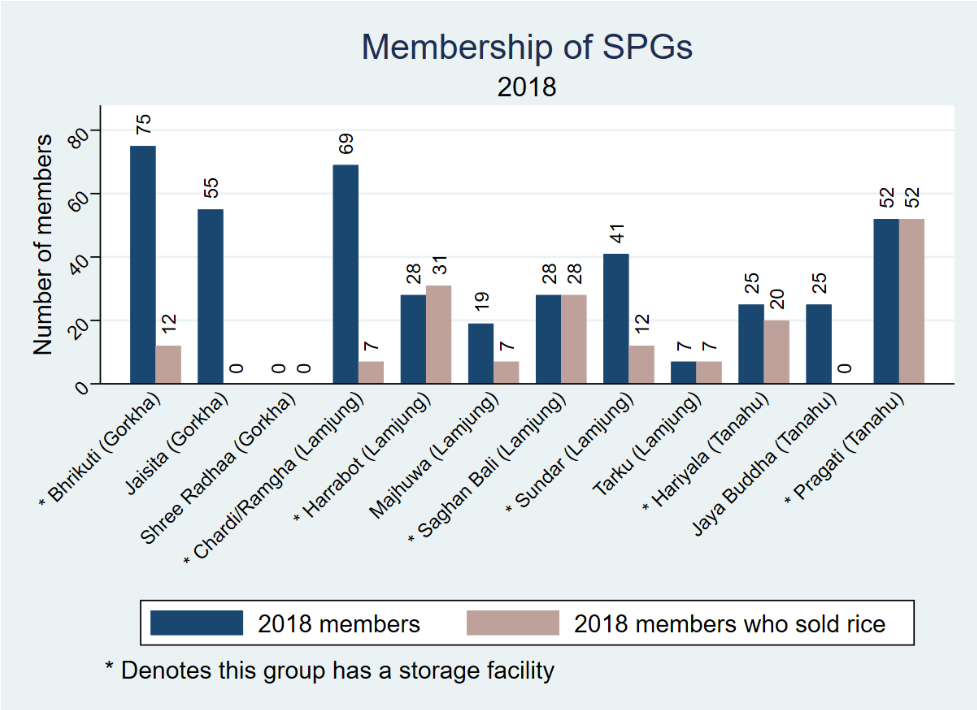
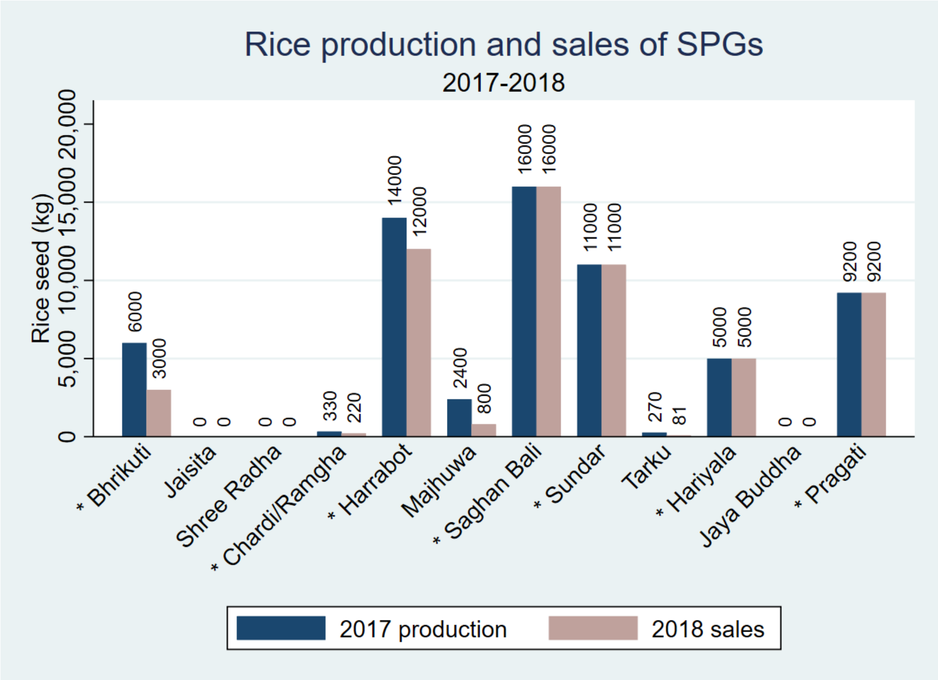


Figure 3. 2018 SPG membership

Source: own analysis from focus group data

Not all SPGs provided information for the year prior (2016 production/2017 sales), but it appears that production in 2016/2017 was higher than in 2017/2018. Bhrikuti produced over 9,000 kg; Saghan Bali produced 21,500 kg; Sundar produced 20,500 kg; Pragati produced 15,000 kg. Even two of the smaller SPGs produced more seeds in 2016/2017 than 2017/2018: Jaya Buddha produced 1,800 kg and Chardi/Ramgha produced 20,000 kg. We do not have information as to why 2016 production tended to be higher than 2017 production.

Figure 4. SPG production and sales in 2017/2018



Source: own analysis from focus group data

We collected a list of all the rice seed varieties SPGs had ever produced. It includes nine drought-tolerant varieties (Sukkha-1, Sukkha-2, Sukkha-3, Sukkha-4, Sukkha-5, Sukkha-6, DRR 44, Hardinath and Radha-4) and one submergence tolerant variety (Swarna Sub-1). Members also grew Sabitri, Ramdan and Loktantra, which are varieties suitable for rainfed conditions but are not considered drought-tolerant (Adhikari, 2017). Additional varieties produced and sold by SPGs are Makwanpur, Sunaula Sagunda, CR Sub-1, Kirbhan Sub-1, Chait-5, Radha-9, Bindeswore and Mansuli, which are other improved varieties.

SPGs most commonly sold seed from their storage facilities directly to farmers, DADOs located in district capitals and Sundar Cooperative. Only two SPGs sold to agrovets in 2018. Two agrovets reported that they used to purchase rice seeds from the SPGs but recently stopped because they can buy cheaper seed from producers in the plains, or terai region, particularly from the nearby Chitwan district.

SPG executive members also reported rice cultivation practices learned from their IAAS trainings. They were trained on many topics, including nursery bed preparation, seeding rate, land preparation, weeding, input use, seed cleaning and storage. Respondents also reported that, prior to training, SPG members did not follow many of these practices. The list of BMP outcome variables in table 1 was based on this information and information obtained from the IAAS staff (Bishnu Bilas Adhikari) responsible for training SPG members.

SPG executive members were asked about challenges to rice cultivation and sales. The two most commonly listed cultivation problems were lack of labor and machinery. These are exacerbated by the high level of migration from rural areas to urban areas in Nepal and to other countries. The biggest problem, however, related to finding consistent seed buyers. Some SPGs used to sell to Sundar Cooperative but said that Sundar no longer purchases their seed. Respondents from Sundar noted that a lack of labor made it challenging to manage their cooperative. This problem relates to what the agrovets reported: seed production is cheaper in the terai and SPGs face competition from seed producers there. Two of the more remote, inactive groups (Jaisitar and Shree Radha) also noted transportation difficulties for selling seed.

4.2. Econometrics results

4.2.1. Statistical test results

Propensity score overlap graphs are presented in the Appendix. For each treatment level (0-2), a high proportion of villages from each group are in the area of common support (i.e. the area where all groups have an above zero density of propensity scores), indicating that the overlap assumption is met and our villages are comparable (Imbens and Wooldridge, 2009).

The Imai and Ratkovik test used to assess covariate balance between groups can only be estimated with binary treatment variable (Imai and Ratkovic, 2014). To test for covariate balance, treatment was specified in three ways: 1) SPG villages vs. randomly selected villages (excluding adjacent villages); 2) adjacent villages vs. randomly selected villages (excluding SPG villages); and 3) SPG and adjacent villages vs. randomly selected villages. For each specification, we fail to reject the null hypothesis that the treatment model balances covariates between treatment groups (p = 0.178, p = 0.390 and p = 0.999, respectively). This provides evidence that covariates are well balanced and that unconfoundedness assumption holds (Haile et al., 2017; Smale et al., 2018).

4.2.2. STRV adoption and seed replacement ratio

The RA, IPWRA and AIPW estimators indicate that living in a village with an SPG raises the probability that non-members have adopted an STRV at some point in the past by 17-18 percentage points above non-members in randomly selected villages (table 3), indicating the presence of spillover effects within villages where SPGs were established. There is no evidence of spillover effects on STRV adoption among non-members in adjacent villages. In 2018, non-members in SPG villages were about 15 percentage points more likely to have adopted STRVs than non-members in randomly selected villages (though the IPWRA results were not significant). The spillover effect on STRV adoption in SPG villages was stronger in 2017 than in 2018. The spillover effect of SPG on 2017 STRV adoption was also significant in adjacent villages. SPGs raised STRV adoption by 23-24 percentage points and 19-22 percentage points (depending on the estimators) for non-members in SPG villages and adjacent villages, respectively, compared to non-members in randomly selected villages. It is not surprising that spillover effects were greater in 2017 compared to 2018, as SPGs sold a higher quantity of seed in 2017 than 2018. The conceptual framework predicts that spillover effects on adoption will extend as far as SPG seed is commonly sold, which is likely in adjacent villages. The results suggest that spillover effects may extend farther in years of high production.

Table 3. Spillover effects of SPGs on STRV adoption and SRR, by village type

	Adopted in any season (1 = yes)			Adopted in 2018 (1 = yes)			Adopted in 2017 (1 = yes)			SRR (0-100)		
	RA	IPWRA	AIPW	RA	IPWRA	AIPW	RA	IPWRA	AIPW	RA	IPWRA	AIPW
SPG vill.	0.17***	0.18***	0.18***	0.15***	0.13	0.15***	0.23***	0.24***	0.23***	52.01***	52.38**	52.59***
	(0.04)	(0.04)	(0.04)	(0.06)	(0.09)	(0.06)	(0.06)	(0.06)	(0.06)	(19.60)	(20.57)	(19.57)
Adj. vill.	0.02	0.06	0.02	0.11	0.17*	0.12	0.19*	0.22***	0.19**	-3.05	-10.05	-3.09
	(0.07)	(0.11)	(0.07)	(0.07)	(0.10)	(0.07)	(0.10)	(0.07)	(0.10)	(13.01)	(13.18)	(13.69)
N	872	872	872	872	872	872	872	872	872	869	869	869

Note: */**/*** denotes statistical significance at 10%/5%/1% respectively. Standard errors, reported in parentheses, are robust to heteroskedasticity. Results provide comparison between SPG villages/adjacent villages and randomly selected villages (considered the control group). Spillover effects are interpreted as percentage changes in the likelihood for binary outcome variables.

Source: own analysis from survey data. Full regression results are available upon request to the authors.

All three estimators reveal that SRR is 52 percentage points higher for non-members in SPG villages compared to non-members in randomly selected villages. This large spillover effect is likely due to the lower cost, either explicit or implicit, of accessing new rice seeds for households living in SPG villages. While spillover effects on SRR of non-members in adjacent villages were expected, there is no evidence that this occurred in 2018. However, these results are in line with the previous finding that SPGs did not stimulate STRV adoption in adjacent villages in 2018; it would be interesting to determine if SPGs had an effect on SRR in 2017, but we did not collect this information.

4.2.3. Best management practices

According to the weighted estimators, non-members in SPG villages plant between 56 kg (IPWRA estimate) and 59 kg (AIPW estimate) less seeds per hectare compared to non-members in randomly selected villages (table 4). Non-members in SPG villages also rogue their rice fields one additional time compared to non-members in control villages. However, there are no spillover effects on these two BMPs for non-members in adjacent villages, suggesting that changes in behaviour due to learning/imitation is limited to those villages in close proximity to SPG members. The RA estimator suggests that non-members in SPG villages are 25 percentage points more likely to test seed moisture prior to storage compared to non-members in control villages. This estimate is significant at the 10 per cent level, while the weighted estimators are not statistically significant. The RA, IPWRA, AIPW estimators reveal that non-members in adjacent villages are 13 per cent more likely to test seed moisture compared to non-members in randomly selected villages. Testing moisture is easy and can be done at no cost by biting the seed. Non-members in SPG villages are 16-17 percentage points more likely to grow lentils during the monsoon season compared to non-members in randomly selected villages, suggesting that SPG members have influenced the cultural practices of non-members living nearby.

Table 4. Spillover effects of SPGs on seeding rate, roguing, moisture testing and legume cultivation, by village type

	Seeding rate (kg/ha)			Number of time rice fields were rogued			Tested seed moisture prior storage (1 = yes)			Grew legumes in 2018 (1 = yes)		
	RA	IPWRA	AIPW	RA	IPWRA	AIPW	RA	IPWRA	AIPW	RA	IPWRA	AIPW
SPG Vill.	-59.60 (28.90)	-56.40 (26.35)	-59.37 (23.83)	1.16 (0.35)	1.26 (0.40)	1.16 (0.35)	0.25 (0.15)	0.23 (0.14)	0.24 (0.15)	0.17 (0.04)	0.16 (0.04)	0.16 (0.04)
		**	**	***	***	***	*			***	***	***
Adj. Vill.	23.84 (24.49)	25.26 (26.35)	23.83 (24.55)	0.03 (0.23)	-0.04 (0.23)	0.04 (0.23)	0.13 (0.03)	0.13 (0.04)	0.13 (0.03)	-0.10 (0.10)	-0.13 (0.08) *	-0.11 (0.10)
							***	***	***			
N	868	868	868	872	872	872	871	871	871	872	872	872

Note: */**/*** denotes statistical significance at 10%/5%/1% respectively. Standard errors, reported in parentheses, are robust to heteroskedasticity. Results provide comparison with SPG villages/adjacent villages to randomly selected villages. Spillover effects are interpreted as percentage changes in likelihood for binary outcome variables.

Source: own analysis from survey data

There is no evidence of significant SPG spillover effects on non-members in SPG villages and adjacent villages for the probability that a household cleans seeds prior to planting, the age of seedlings at the time of transplantation and the quantity of chemical fertilizer applied to rice fields (table 5). Cleaning seeds prior to planting and the quantity of chemical fertilizers applied are practices that are more difficult to observe, limiting the opportunity to learn by imitation, which could explain the absence of spillover effects.

Table 5. Spillover effects of SPGs on probability of cleaning seeds, quantity of chemical fertilizer applied to rice fields and age of seedlings at time of transplantation[6], by village type

	Cleaned seeds (1 = yes)			Chemical fertilizer (kg/ha)			Age of seedlings (days)		
	RA	IPWRA	AIPW	RA	IPWRA	AIPW	RA	IPWRA	AIPW
SPG Village	0.01	0.01	0.00	95.75	135.87	-303.89	-1.63	-1.16	-1.67
	(0.04)	(0.12)	(0.04)	(66.05)	(75.96)	(252.72)	(1.55)	(1.53)	(1.55)
Adj. Village	-0.05	-0.02	-0.04	-308.66	-202.31	95.26	0.26	0.55	-0.24
	(0.07)	(0.12)	(0.07)	(256.38)	(172.0)	(66.32)	(0.75)	(0.75) *	(0.75)
N	868	868	868	866	866	866	854	854	854

Note: */**/*** denotes statistical significance at 10%/5%/1% respectively. Standard errors, reported in parentheses, are robust to heteroskedasticity. Results provide comparison of households in SPG villages/adjacent villages to those in randomly selected villages. Spillover effects are interpreted as percentage changes in likelihood for binary outcome variables. For the age of seedlings regression, one randomly selected village had to be dropped because its propensity score was too low for estimation.

Source: own analysis from survey data

4.3. Robustness checks

4.3.1. Distance to SPGs

To assess the sensitivity of the results to the treatment variable specification and explore how far SPG spillover effects might travel, we estimated unweighted regressions with distance to the nearest SPG, in kilometres and travel time in minutes, as treatment variables. The regressions include the same weighting variables (Z_v) and control variables (X_{vi}) as previously. We used OLS for continuous outcome variables, a logit model for binary outcome variables and a fractional logit model for outcome variables measured as a percentage.

The two distance variables have significant and negative effects on STRV adoption at any point in time, in 2018 and in 2017. Living 1 km (minute in travel time) farther from an SPG reduces the probability that a non-member has adopted an STRV at any point in time by 2.1 percentage points (0.2 percentage points) (table 6). One additional kilometre (minute in travel time) from a SPG reduces the probability of STRV adoption by 1.9 percentage points (0.1 percentage points) in 2018 and 1.5 percentage points (0.1 percentage points) in 2017 among non-members. This provides additional evidence that living nearby SPGs has spillover effects on STRV adoption rates of non-members and indicates that our findings are robust to treatment variable specification. The spillover effect of SPGs on the SRR in 2018 is not significant when using distance in kilometres or minutes to the nearest SPG as treatment variable. This is in line with the weighted results that suggest that SPGs spillover effects on SRR do not extend beyond SPG villages, at least in 2018.

[6] We had two additional BMPs: the quantity of organic fertilizer applied to rice fields and the probability that a household grows vegetables. However, these models would not converge.

Table 6. Effect of distance to SPGs in kilometres and minutes travel time on STRV adoption, SRR and use of BMPs

	One additional km from SPG	One additional minute in travel time from SPG
	Coefficient or marginal effect (standard error)	Coefficient or marginal effect (standard error)
Adopted STRV (1 = yes)	-0.021 (0.005) ***	-0.002 (0.001) ***
Adopted STRV in 2018 (1 = yes)	-0.019 (0.005) ***	-0.001 (0.001) *
Adopted STRV in 2017 (1 = yes)	-0.015 (0.005) ***	-0.001 (0.001) **
SRR (0-100)	0.12 (0.45)	-0.08 (0.05)
Cleaned rice seed prior to planting (1 = yes)	0.003 (0.005)	0.000 (0.001)
Seeding rate (kg/ha)	-1.476 (0.829) *	-0.097 (0.103)
Age of seedlings (days)	-0.008 (0.04)	-0.007 (0.004) *
Organic fertilizer (kg/ha)	5.899 (98.412)	8.41 (12.06)
Chemical fertilizer (kg/ha)	0.150 (1.547)	-0.200 (0.170)
Roguing (number of times per season)	-0.002 (0.008)	-0.001 (0.001)
Tested moisture (1 = yes)	-0.003 (0.004)	-0.000 (0.001)
Cultivated legume (1 = yes)	-0.000 (0.003)	-0.000 (0.001)
Cultivated vegetable (1 = yes)	-0.004 (0.005)	-0.000 (0.000)

Note: */**/*** denotes statistical significance at 10%/5%/1% respectively. Standard errors, reported in parentheses, are robust to heteroskedasticity. Results are presented as coefficients for continuous outcome variables, and marginal effects for regressions were estimated by logit or the fractional logit model.

Source: own analysis from survey data

Using distance to SPGs as treatment variables suggests that there is no SPG spillover effects on use of BMPs (table 6). Spillover effects of SPGs on adoption of BMPs may be more localized, reaching only non-members closely connected to SPG members. This follows the theory that knowledge about BMPs is most likely to spread through social proximity, resulting in localized spillover effects only. This finding is also consistent with our RA, IPWRA and AIPW results, which suggests no spillover effects on BMP adoption among non-members in adjacent villages, except for testing moisture.

4.3.2. Effects on SPG members

To provide evidence of the direct effects of SPGs on STRV adoption, SRR and use of BMPs among members, we used RA estimators where the treatment variable is a binary variable equal to one if a household member has ever been a member of an SPG and zero if the household is not a member and lives in a randomly selected village. We did not include non-member households who live in SPG or adjacent villages, as they have benefitted from spillover effects of the SPGs. We do not control for membership selection bias due to the difficulty in finding valid instrumental variables. Therefore, we do not claim that these results represent the causal impact of being a SPG member, but rather we examine the significance and magnitude of the direct effects as another mean of assessing the plausibility of the spillover effects of SPGs.

We find that SPG members are 20, 29 and 24 percentage points more likely to have grown an STRV at any time in the past, in 2018 and in 2017, respectively, than non-members in randomly selected villages (table 7). In line with expectations, the magnitude of the direct effects is similar to the estimated indirect effect of SPGs on STRV adoption of non-members in SPG villages in 2017 (23-24 percentage points) but higher than the estimated indirect effects in 2018 (15 percentage points) or in any previous season (17-18 percentage points). SPG members also have an SRR that is 10 percentage points higher than non-members in randomly selected villages, but the effect is significant at the 10 per cent level only. This estimate is smaller in magnitude and estimated with less precision than the SPG spillover effect on SRR among non-members in SPG village (52 percentage points), although the confidence intervals for these estimates overlap, and thus, are not statistically different. Descriptive analysis of the data indicates that 11.5 per cent of SPG members continue to cultivate local varieties compared to 11.0 per cent of non-members in SPG villages, 6.8 per cent of non-members in adjacent villages and 23.7 per cent of non-members in randomly selected villages. Local varieties are valued for their taste and importance in festivals, so it is not surprising that SPG members would want to maintain cultivation of local rice varieties. This could lower the estimated direct effects of SPG on SRR of members.

Table 7. Averaged direct effects of SPGs on STRV adoption, SRR, use of BMPs of members, estimated using RA

	Direct effects (std errors)
Adopted STRV (1 = yes)	0.20 (0.11) *
Adopted STRV in 2018 (1 = yes)	0.29 (0.09) ***
Adopted STRV in 2017 (1 = yes)	0.24 (0.06) ***
SRR (0-100)	10.38 (7.12) *
Cleaned rice seed prior to planting (1 = yes)	-0.10 (0.06)
Seeding rate (kg/ha)	-21.26 (8.23) **
Age of seedlings (days)	-1.00 (0.59) *
Organic fertilizer (kg/ha)	7711.98 (3162.73) **
Chemical fertilizer (kg/ha)	-62.96 (50.26)
Roguing (number of times per season)	0.46 (0.13) ***
Tested moisture (1 = yes)	0.14 (0.06) **
Cultivated legume (1 = yes)	0.21(0.06) ***
Cultivated vegetable (1 = yes)	0.27 (0.07) ***

Note: */**/*** denotes statistical significance at 10%/5%/1% respectively. Standard errors, reported in parentheses, are robust to heteroskedasticity. Different effects are interpreted as percentage changes in likelihood for binary outcome variables.

Source: own analysis from survey data

SPG members plant 21 kg of seed per hectare fewer than non-members in randomly selected villages. This direct effect is smaller in magnitude than the estimated indirect effect on seedling rate of non-members in SPG villages; although the direct and indirect effects do not vary statistically (based on 95% confidence intervals). SPG members also rogue their rice fields an additional 0.5 times, on average, over non-members in randomly selected villages. The direct effect of SPGs on roguing is smaller in magnitude but statistically equivalent to the spillover effects (based on 95% confidence intervals) on non-members in SPG villages, which indicates that non-members in SPG villages rogue their rice fields one additional time compared to non-member households in randomly selected villages. SPG members are 14 per cent more likely to test seed moisture prior to storage compared to non-members in randomly selected villages, which is similar in magnitude to the spillover effect on non-members in adjacent villages. SPG members are 21 percentage points more likely to grow lentils and 27 percentage points more likely to grow vegetables than non-members in randomly selected villages. This direct effect for growing lentils is similar to the indirect one for non-members in SPG villages. SPG members also transplant seedlings when they are, on average, one day younger and use an additional 6,000 kg/ha of organic fertilizer on rice plots compared to non-members in randomly selected villages. However, the direct effect of SPG membership on chemical fertilizer is not significant. For age of seedlings, organic and chemical fertilizer use, we found no evidence of spillover effects. Increasing organic fertilizer use could be costly for farmers, which explains why this practice has not spilled over for farmers producing grains. In the case of seedling age, it could be that SPG members transplant seedlings one day earlier than non-members, but there is a lack of spillover effects because this practice is not easily visible to other farmers.

5. Conclusions

The spillovers from SPGs are important. Our econometric analysis provides evidence that the SPGs had several spillover effects, benefiting non-member rice farmers in local and adjacent communities. This includes higher STRV adoption rates and increased SRR among non-members in SPG villages and increased STRV adoption for non-members in adjacent villages in 2017 compared to non-members in randomly selected villages. We also found that SPGs induced greater use of some BMPs but not all, including reduced seeding rates, increased roguing and increased legume cultivation among non-members in SPG villages compared to non-members in randomly selected villages. Non-members in adjacent villages were also more likely to test seed moisture prior to storage than non-members in randomly selected villages. We hypothesize that legume cultivation and roguing may have spread because they are highly visible practices, while seeding rates and seed moisture checking may have spread because they are easy to implement and have no-cost. However, more research is needed to understand how and why some BMPs have spread and caught on locally, while others have not. The spillover of BMPs was not an explicit goal of the project, so limited geographical spillover might be expected.

This study provides evidence that a short-term programme to establish and support SPGs can have long-lasting impacts. In this case study, SPG members have continued to produce and sell seed and use BMPs. Technology transfer also occurred, generating spillover benefits onto non-member households in SPG and adjacent villages. This indicates that an analysis of only the direct effects of the SPGs established through the CURE project would have significantly underestimated its benefits. SPGs that introduce climate-smart technologies can help directly improve resilience to climate change through the technologies they produce and through spillover effects. Members of future established SPGs could be explicitly encouraged to share their knowledge of BMPs to enhance project benefits.

Spillovers of BMPs are less prominent than those from the seed technologies themselves. Future programmes might emphasize outreach and combined group-specific training with events, such as field days and farmer interchanges, to promote the spread of disembodied technologies, such as BMPs.

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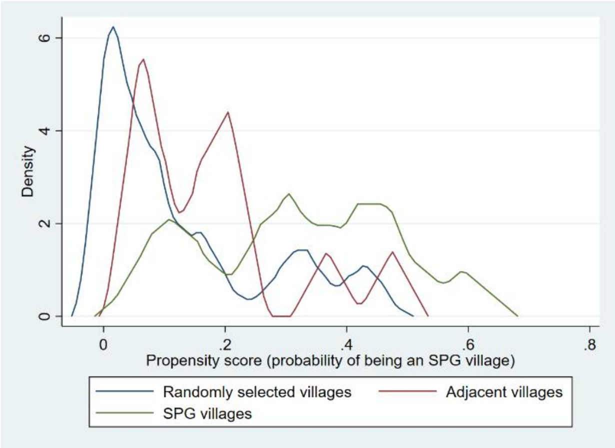
Appendix

Table A1. Means (standard deviations) for all outcome variables, comparing non-members in randomly selected villages with non-members in adjacent villages and non-members in SPG villages

Outcome variable	Non-members in randomly selected villages (group 0)	Non-members in adjacent villages (group 1)	Non-members in SPG villages (group 2)	Statistically significant differences
STRV adoption (1 = adopted)	0.40 (0.49)	0.50 (0.50)	0.59 (0.49)	5% difference 0 vs. 1; 1% difference 0 vs. 2
STRV adoption 2018 (1 = adopted)	0.26 (0.44)	0.33 (0.47)	0.36 (0.48)	10% difference 0 vs. 1 and 2
STRV adoption 2017 (1 = adopted)	0.19 (0.40)	0.29 (0.45)	0.27 (0.45)	5% difference 0 vs. 1
SRR (0-100)	52.36 (44.75)	51.56 (44.71)	64.62 (42.81)	5% difference 2 vs. 0 and 1
Clean rice seed prior to planting (1 = cleaned)	0.59 (0.49)	0.63 (0.49)	0.66 (0.48)	
Seeding rate (kg/ha of land)	93.84 (84.38)	106.57 (101.19)	80.91 (70.79)	5% difference 1. vs. 2
Age of seedlings (days)	27.03 (4.12)	26.26 (2.90)	26.31 (3.47)	5% difference 0 vs. 1; 10% difference 0 vs. 2
Organic fertilizer (kg/ha of land)	7 360.56 (8871.94)	8 224.78 (8773.98)	8 939.27 (9358.47)	
Chemical fertilizer (kg/ha of land)	128.69 (150.53)	152.55 (232.67)	133.53 (88.05)	
Roguing (number of times per season)	1.46 (0.81)	1.45 (0.78)	1.53 (0.74)	
Moisture testing (1 = tested)	0.14 (0.35)	0.17 (0.37)	0.18 (0.38)	
Legume cultivation (1 = grown)	0.41 (0.49)	0.39 (0.49)	0.51 (0.50)	10% difference 2 vs. 0 and 1
Vegetable cultivation (1 = grown)	0.10 (0.30)	0.05 (0.21)	0.10 (0.30)	1% difference 1 vs. 2

Source: own analysis from survey data

Figure A1. Propensity score overlap graph: SPG village



Source: own analysis from survey data

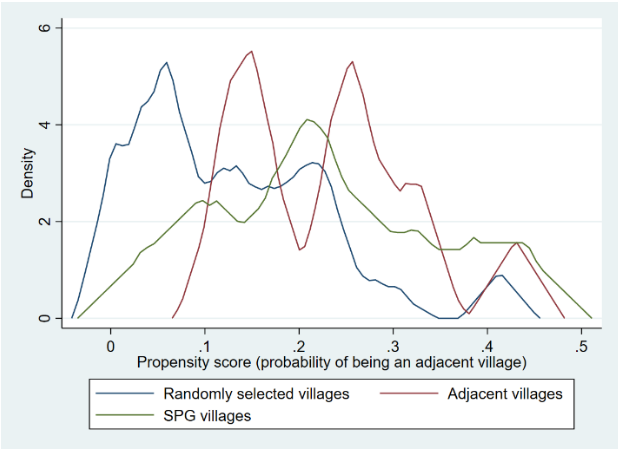
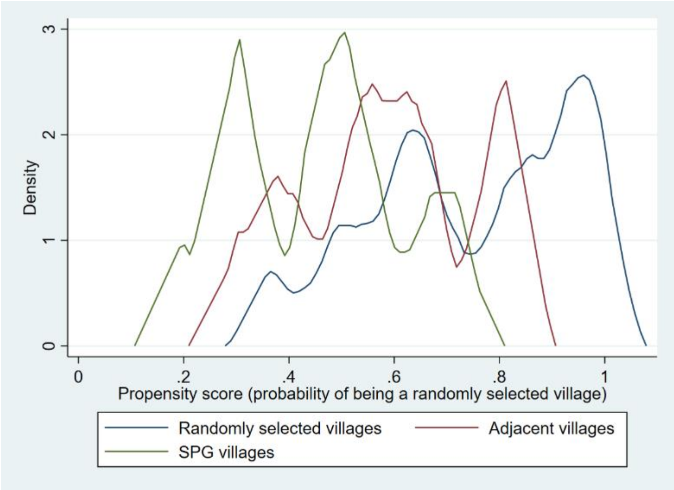


Figure A2. Propensity score overlap graph: SPG adjacent village

Source: own analysis from survey data

Figure A3. Propensity score overlap graph: Randomly selected villages



Source: own analysis from survey data

IFAD

International Fund for Agricultural Development
Via Paolo di Dono, 44 - 00142 Rome, Italy
Tel: +39 06 54591 - Fax: +39 06 5043463
Email: ifad@ifad.org
www.ifad.org

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ISBN 978-92-9266-012-3
9 789292 660123