Household incomes, production shocks and labour allocation

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This version 19 September 2022

How do productivity shocks affect the sectoral allocation of labour? To study the above question, we induce a production shock with a unique technology-aided agricultural program on Indian farms. Our results show farm productivity and crop incomes increase for the program recipients. The information provision also appears equally valuable to unintended farmers. We observe increases in agricultural labour earnings, but non-agricultural incomes shrink. The increase in productivity, while driving up labour demand and relieving liquidity constraints, attenuates labour allocation to the non-agricultural sector. Agricultural development programs can raise household earnings but are prone to compete in the rural labour market. (*JEL* O13, Q12, Q16)

Global poverty is primarily a predicament of low agricultural incomes among rural households in developing countries. A crucial focus of development policy is to raise the incomes of smallholder farmers by reducing yield gaps through improved access to new agricultural technologies (World Bank, 2007; Fuglie et al., 2020). There is also a big push toward antipoverty cash and assets transfers and skills-enhancing programs for altering occupational choices (e.g., Bandiera et al., 2013; Blattman et al., 2014; Bandiera et al., 2017), a complementary strategy widely believed.[1] If productivity increases in agriculture with an

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[1] See Barrientos (2012), Alderman and Yemtsov (2014), and more recently, Gehrke and Hartwig (2018) for a review of different programs across developing countries.

immediate increase in labour demand impede the reallocation of labour to the non-farm sector, the program's outcome could be ambiguous. For instance, Blattman et al. (2020) rightly highlight that the effects of grants of cash and other capital will depend on the returns to other labour market opportunities. Results of the programs vary, and many randomized evaluations in numerous countries have found no impact on incomes (Bauchet et al., 2015; Crepon et al., 2015; Blattman et al., 2020). Yet, the experimental evidence on whether and how rural households respond (compete) in the labour market to agricultural productivity shocks remains scant.

In this paper, we induce a production shock in agriculture to examine the impact of agricultural productivity growth on the sectoral allocation of labour between the farm and non-agricultural sectors. We do so by exogenously varying agricultural productivity from implementing a technology-led extension program (called electronic solutions against agricultural pests, henceforth, eSAP) to addressing production constraints. There are two vital features of the software. First, it uses its extensive crop-level database of different pests and diseases and farmer responses to benchmark the initial farming practices of every farmer. Second, dynamically personalize the material delivered to match the level and rate of progress made by each farmer. The eSAP program can be delivered in various settings (on-farm, in call centres, or through self-guided animations) and deployed through computers, tablets, or smartphones in both online and offline modes.

This paper evaluates the eSAP program deployed through tablets in on-farm delivery by an operator visiting the farms owned by the treatment households twice a month each growing season across all three program years. Our evaluation is carried out on a sample of farming households recruited for the study in the Indian state of Karnataka. We measure program impacts over five years using farm surveys at the end of six crop growing seasons.

Our empirical analysis proceeds in two steps. First, we develop an intervention offering pest and input management services using a technology-aided agricultural program. We show that the program leads to per acre crop incomes being 20.55 percent higher for the treated than their counterparts in control villages and with a 5.63 percent reduction in nonfarm incomes, on average. Pooling incomes across all four household activities for the treated, there is a net positive effect of 36.44 percent on total household incomes. Paddy productivity over the program, on average, increased by 14.99 percent relative to their counterparts in the control villages.

Unexpectedly, though consistent with the social network literature, untreated spillover households within treatment villages experienced higher agriculture productivity (14.06 percent) despite not receiving the program. The cleanest evidence of spillover observed is in the adoption of the Direct Seeded Rice (DSR) technique, with take-up rates on the order of 94 percent of the untreated farmers in the treatment village starting with the practice by the end of the program. Given water and labour shortages at peak times, our information provision is equally valuable to farmers in the spillover group.

Second, using the exogenously induced production shock, we examine the households' response to intersectoral labour allocation. The program implementation transforms labour activity choices, with treatment households devoting 4.15 percent and 3.05 percent fewer days and hours annually to nonfarm activities. The reallocation of family labour from the labour market to the family farm and the hiring of additional labour for crop cultivation show an increase of 33.58 percent (or 128 labour-days) relative to the control group. Aggregating across household labour activities, there is no significant net effect on days or hours worked, suggesting all withdrawals from nonfarm activities are fully deployed in crop cultivation with no idle work capacity. Rural households are significantly more likely to withdraw or reduce family labour sales to the nonfarm sector due to higher farm output and crop incomes.

Our paper builds on the small number of recent empirical papers studying the impact of varying agricultural productivity on sectoral factors allocation and growth. Foster and Rosenzweig (2004, 2008) show that agricultural development has a negligible effect on local nonfarm business income.[2] And villages with larger improvements in crop yields during the Green Revolution in India experienced lower manufacturing growth. Using data from the United States, Hornbeck and Keskin (2015) similarly showed that substantial agricultural growth had little long-run expansion of non-agricultural activities. In contrast, other studies report that

[2] These empirical studies build on a long-standing theoretical interest in how agricultural productivity affects structural transformation in economic development (Nurkse, 1953; Ranis and Fei, 1961). Harris and Todaro (1970) two-sector model posit that increases in agricultural productivity will raise labour's marginal productivity, driving up wages and attracting labour to agriculture. Thus, high agricultural productivity can retard industrial growth as labour relocates towards the comparative advantage sector (Matsuyama, 1992). This result contrasts with the view that agricultural productivity growth raises income per capita, generating demand for manufacturing goods and reallocating labour away from the agricultural sector (Schultz, 1953; Rostow, 1960). Higher agricultural productivity and farm incomes can relieve liquidity constraints to migration where up-front costs are barriers that prevent households from leaving rural areas (Bryan et al., 2014). The declining factor prices from increased agricultural productivity combined with forward linkages to the non-agricultural sector can also explain labour reallocation (Emerick, 2018). Bustos et al. (2016) find the effect of agricultural productivity on structural transformation depends on the factor bias of technical change.

agricultural productivity gains cause development and labour reallocation in the non-agricultural sector (Kochar, 1999; Adhvarya et al., 2013; Emerick, 2018; Colmer, 2020).

Since our experiment treats few samples in each village, we cannot get at the forces driving the general equilibrium effects highlighted in the above studies. However, we can examine the conflicting views amenable to scrutiny in a partial equilibrium setting. For instance, on the one hand, the increased demand for labour from higher agricultural production could increase wages paid to attract additional wage labour. While on the other hand, increased crop income from farm productivity increases can relieve liquidity constraints among farming households to ease transfer to non-farm activities (Bryan et al., 2014). The conclusions thus far from existing observational studies are mixed, and previous attempts to isolate productivity shocks have difficulty establishing causal impacts. We provide the first experimental evidence on households' labour market response to agricultural productivity growth by exogenously varying crop productivity.

A substantial literature has documented households' coping strategies in response to economic shocks (Morduch, 1995; Dercon, 2002; Jayachandran, 2006; Morten, 2019; Fink et al., 2020).[3] Shifting or improving access to non-farm income in response to shocks can be found in Blattman et al. (2014), Bryan et al. (2014), and more recently in Blakeslee et al. (2020). The causal evidence from Uganda shows that increasing non-agricultural production and labour supply does not diminish agricultural output or inputs (Blattman et al., 2014), or the opposite, with India's National Rural Employment Guarantee Scheme reducing farm earnings per acre and large landowners' net incomes (Muralidharan et al., 2021). Still, the experimental evidence of household non-farm labour supply response to farm productivity shocks (improvements) remains scant.

Finally, our paper is closely related to the extensive literature on digital approaches to agricultural extension (Fafchamps and Minten, 2012; Casaburi et al., 2014; Cole and Fernando, 2021; Van Campenhout et al., 2021; Bold et al., 2021; Fabregas et al., 2022). We extend this literature in two ways. First, we use novel digital intervention to relax multiple constraints along the entire crop cycle (e.g., macro- and micro-nutrient deficiency, pests, disease, water stress, etc.). The in-person digital support is fully customized to each crop plot addressing the

[3] Rural households are frequently hit by several idiosyncratic and covariate shocks. As a response, households adopt different coping strategies - ranging from social networks (Rosenzweig and Stark 1989) to compensating increase in market hours of work (Kochar 1995, 1999), temporary migration (Rosenzweig and Stark 1989), and sale of assets (Eswaran and Kotwal 1989).

time-sensitive needs of the farmers. Second, we quantify the spillover impact of a neglected technology in the presence of labour and water constraint. Like Fabregas et al. (2022), we also find sizable spillovers. However, for us, they are just as large as the direct effects, even with an intervention providing customized advice by visiting individual farms.[4]

The remainder of the paper is structured as follows. Section I presents the intervention and study design. Section II discusses the data, and section III provides the main results. Finally, Section IV concludes.

I. Intervention and study design

A. The eSAP crop health management software

Developed by a leading Indian agriculture technology firm called Tene Agricultural Solutions (TAS), the eSAP software reflects over a decade of iterative product development. It aims to leverage several posited channels through which agricultural technology may improve farm productivity. At the time of the study, eSAP supported over 100,000 farmers in the neighbouring districts of Karnataka deployed to provide information for only a few crops. With the rollout of our project, TAS began to expand its database of crop pests and diseases information to over 26 major crops grown widely in the state. According to FAO (2017), plant pests and diseases are the foremost emergencies responsible for 20-40 percent of global food production losses. It poses a significant threat to the livelihoods of vulnerable farmers in developing countries and global food security.

The interactive software includes continuous crop assessment alongside instructional videos, animation, and activities from which farmers learn through explanations and feedback. Here we highlight some of the critical design features of the software and provide a more detailed pictorial description with examples in the Online Appendix C.

First, despite an extensive corpus of complex pest management options, identifying problems and providing solutions are intricate for various pestiferous species of insects, viruses, fungi, bacteria, nematodes, weeds, and nutritional deficiencies that decrease crop production, impacting farmers' welfare. The design of the content tries to reflect current research in effective crop health management and real-time monitoring of field situations with inbuild intelligence aiding the process of decision-making based on accurate, verifiable field data.

[4] With a mobile phone-based information sharing intervention, Fabregas et al. (2022) find impact that are about half to one third of the direct treatment effect.

Second, the content is adaptive, with solutions presented to each farmer's field based on that crop's performance. This adaptation is dynamic, occurring at the beginning of the crop cycle based on a diagnostic assessment and every subsequent activity completed. The architecture for pest identification follows a unique image-based branching model. The software's unique feature is its content presented to farmers based on intuitively built pest-specific diagnoses to quantify damage and estimate the economic threshold for optimal pest management. In other words, it enables dynamic "Extension at the Right Level" for each farmer. It can cater effectively to the vast heterogeneity of pests and diseases for all major crops grown in Karnataka.

Third, eSAP enables real-time monitoring of the crop field by integrating the spatial coordinates of the field to the GIS map along with the severity of the problem. The application is built on a platform that opens a gateway for the two-way dissemination of information in real-time. It has substantial in-built intelligence for on-field decision support and protocols for intelligent surveys to gather pest and disease-related information for streams-in to be viewed over the GIS platform. As surveillance entails multiple images captured by the field device, a set of close-ups and field images along with data on the crop, crop age, pest damage, and geo-coordinates of the field are transmitted to the cloud for further use by researchers and policymakers.

Finally, high-quality images that characterize pests and their symptoms are adopted to guide users in identifying the pest intuitively. Audio assistance in the local language is provided at every step; the user need not be literate. The interactive user interface, combined with the individualization of material for each farmer, facilitates the farmer's continuous engagement with the prevailing crop health management strategies. This approach aims to boost farmer attention and engagement, provide feedback at the level of each intermediate step in solving a problem, and shorten the feedback loop between farmers facing similar pests and diseases.

As the discussion above clarifies, eSAP aims to use technology to simultaneously alleviate multiple constraints to effective extension in a scalable way. In the future, we hope to run experiments on the eSAP platform to isolate the impact of specific software components on production outcomes (such as cultivation practices, input use, labour use, or the effect of pest-specific management strategies). However, from an economist's perspective, we are more interested in studying how technology-aided extension can improve agricultural outcomes and resource allocation. Thus, this paper focuses on learning the impact of technology-aided instruction on productivity, income, and input allocation. We defer analysis of the relative impact of specific components of eSAP to future work.

The eSAP intervention – we evaluate the pests and diseases delivered in stand-alone eSAP at farmers' fields in real-time. Farmers who signed up for the program received a visit from a trained eSAP operator with a hand-held Android Tablet device with a portable printer every twelfth day to inspect their fields. The services we provided were free of charge to the treatment farmers.

A typically scheduled appointment from the eSAP operator consists of traversing for about 60 minutes every crop plot owned by the treatment farmer, marking against a crop-specific checklist of basic questions on cultural practices, taking pictures from all four coordinates for reference, and discussing the crop progress with the farmer. Here plot refers to a parcel of land with a single crop demarcated by raised bunds. If any potential problem is identified, the process can take much longer with printed prescription handed over to the farmer of any recommended solutions and contacting the dedicated network of experts at the partner agricultural institutions across Karnataka if eSAP fails to identify the problem. Each operator visits three to four farmers daily and meets the same farmer twice a month. If problems are detected, the operator follows up with the farmer over the phone until the issue is resolved. Besides, a dedicated qualified supervisor with a PhD in Agronomy was available 24/7 to monitor and coordinate the activities of the operators. The supervisor paid visits only to those farms where the eSAP reported a pest or disease as unidentified.

B. Technology and management strategies disseminated

The project promoted the adoption of the DSR technique in paddy cultivation to encourage less use of inputs such as water and labour (see Online Appendix B). These inputs have become scarcer and a major constraining factor in crop cultivation in India. The management of pests and diseases using eSAP and DSR techniques is likely to improve paddy yields and reduce the cost of production.

In the conventional transplanting system (CTS), puddling creates a hardpan below the plough zone and reduces soil permeability. It leads to high water losses through puddling, surface evaporation, and percolation. Water resources, both surface and underground, are shrinking, and water has become a limiting factor in rice production (Farooq et al., 2011). The transplanting operation of CTS cultivation has a high demand for labour for uprooting nursery seedlings, puddling fields, and transplanting seedlings into fields.

Though DSR is not a new technique, in the past, the prevalence of high weeds and lack of constraints in water and labour availability favoured the CTS technique and kept the adoption of DSR low. The DSR technique is a significant opportunity to change production practices to attain optimal plant density and high-water productivity in water-scarce areas. The advantages of the CTS technique include increased nutrient availability and weed suppression (Singh et al., 2001). Concerning crop yield, both CTS and DSR have similar results (Kukal and Aggarwal, 2002). With the deployment of eSAP for suitable management practices, the crop yield and weed and pest management under DSR can be improved apart from reducing the cost of cultivation.

The eSAP management practices include seed priming for a reduced need of a high seeding rate and better weed management using the stale seedbed technique combined with a pre-emergence herbicide, pendimethalin, applied within two days after seeding. Though rice, in general, is susceptible to various diseases, rice blasts are one of the most devastating. The impact is even severe in water-limited conditions under DSR. Poor water management practices under DSR can result in moist or dry soil instead of flooded or wet conditions, favouring dew deposition and making the environment susceptible to host and blast development (Savary et al., 2005).

Puddling in continuously flooded rice under CTS limits percolation losses in the field. It retains a saturated soil profile, inhibiting the establishment and growth of many weeds (Sahid and Hossain, 1995) and has positive consequences for nutrient availability (Wade et al., 1998). Land preparation and water management are the principal factors governing the nutrient dynamics in DSR. Nutrient deficiencies are an essential concern in DSR; thus, eSAP can assess the dynamics of macro- and micro-nutrients in DSR culture and develop appropriate management strategies to harvest maximum crop returns sustainably.

In the DSR system, soil type, weed management, and land levelling are essential. Weeds pose a severe threat to DSR by competing for nutrients, light, space, and moisture throughout the growing season. An integrated approach involving cultural practices, crop rotation, stale seedbed practices, selection of suitable seed varieties, and use of herbicide mixtures is an essential response to changes in weed community structure in DSR (Maity and Mukherjee, 2008).

Productivity in the DSR system approaches the CTS system when fertilizer is supplied at high rates (McDonald et al., 2006). However, with eSAP, we deployed nutrient management practices such as deep placement and controlled-release fertilizer to enhance paddy yield. Additional recommendations included the split application of N-fertilizer to improve N fertilizer use efficiency, reduce denitrification losses, synchronize with plant demand, and improve straw and grain yield and harvest index in DSR.

C. Sample, randomization and compliance

Our sample consists of farmers from two districts in different agroclimatic zones of Karnataka, a southwestern state of India. The two districts are Tumkur in the south and Bellary in the north. To randomize farmers into treatment, we followed a three-stage procedure (Appendix A Figure A1). In the first stage, we stratified the 58 *Gram Panchayat* (GP, an administrative unit smaller than the district) with 411 villages into farm and nonfarm based on the primary sources of income to guarantee the desired heterogeneity in terms of sectors of activity.[5]

In the second stage, after the GP was stratified and we randomly allocated the villages to treatment and control within each stratum. There are 102 villages assigned to the treatment group and 103 to the control group. In the third stage, we identified farmers who had cultivated paddy in the last three years and randomly selected 310 households from the treatment villages and 329 households from the control villages.[6] We randomize at the village rather than household level to mitigate spillovers between treatment and control households through markets or eSAP operators.

Additionally, we randomly selected 74 households (no two spillover households are from the same treatment village) from the same villages as the treatment households to capture the spillover effect of the eSAP intervention. Note that households in the spillover group live in the same village as the treatment households but do not receive any treatment. The overall attrition is low, with 6 percent at the end of the first and 2 percent at the second program year. It is split equally between treatment (3 percent) and control (4 percent) and one percent among spillover households.

[5] We conducted focus group discussions with the village elders (progressive farmers, retired government servants, elected representatives) in each of the village to identify the primary sources of household income to the village. A village is categorised as nonfarm if there was a consensus among village elders that the main source of household income collectively is not from crop cultivation.

[6] Our power calculation based on the crop yield outcomes of paddy suggested a sample size of 330 households to each control and treatment group. There was no particular reason for the number of spillover households included in the study except determined by the project budget. Eight treatment (four households with two brothers and another four with three brothers) and two control households jointly cultivated their undivided land while living separately in the same household. Thus, this reduced the household samples in both groups.

Control Group: Print Information and Awareness. Farmers in the study were aware that they were part of an experiment; that is, the awareness (control) group did not receive any visits from eSAP operators but were conscious of their crop productivity being monitored. Additionally, we designed an information brochure and a wall calendar summarising the solutions for some common pests and diseases based on the eSAP program. All households included in the study from the control villages received a printed copy of the information brochure and a wall calendar in the local language but did not receive any briefing about their contents.

Treatment Group: Print Information and Monitoring. Households in the treatment group received the same information in print outlined above and received visits from eSAP operators on their farms. The information was relayed to treatment farmers over three years with visits every twelfth day, excluding the summer months. Every twelfth day the eSAP operators, accompanied by the farmer, visit the farms to inspect the crop's health to identify the prevalence of any pest and disease, nutritional deficiencies, and weed problems. If the eSAP identifies any of these problems, we recommend appropriate management strategies to the farmers with more frequent follow-up phone calls and visits. ExpertConnect feature to connect with scientists in local Agricultural Universities is also available when the field device cannot make the diagnosis.

Spillover Group: Print Information, Awareness and Proximity. In addition to the farmers being aware that they are being monitored and receiving the print information as above (as received by both control and treatment groups), these farmers live in the same village as the treatment farmer but do not receive eSAP visits. Yet, they may be impacted by the information (spillover) received via social networks operating within the village.

II. Data

Trained research assistants, different from the eSAP operators' team, visited the sample households at their homes and farms to administer a baseline survey. We collected multiple rounds of detailed data from farm surveys during four-monthly on-farm eSAP monitoring for four years throughout the agricultural seasons (Figure 1).[7] Household surveys were conducted annually for four rounds. But the first midline household survey did not collect member-wise household data on employment but included information on livestock activity.

[7] The agricultural seasons are *kharif* (from June to September), *rabi* (from October to January), and summer.

The baseline round occurred before households were provided with the print information on brochures and wall calendars and included questions on (i) farm production, (ii) input cost, and (iii) household and demographic characteristics. We repeated this full survey for a follow-up multiple rounds of farm and household surveys.

The farm survey comprised a plot roster that recorded the output of crops in each plot for the months preceding the interview. We collected plot-level information on the type of crop produced, the area planted, output quantity and prices, and the duration of the crop produced. We collected labour hours worked, input quantity and prices, and revenues in the cost module. This information was recorded for each crop plot and every farming operation. The household roster recorded member-wise information on age, sex, education, occupation, salary, and wage incomes earned from agricultural and non-agricultural employment, and details of assets owned and livestock activity.

III. Results

A. Farm income, nonfarm work and labour allocation

This section examines how labour allocation between farm and nonfarm work responds to household income growth from the eSAP productivity shock. Most rural households spread their risk by participating in several productive activities. The activities range from crop cultivation, livestock rearing, and off-farm to nonfarm work such as carpentry, tailoring, construction, etc. Since the randomization was stratified to account for the variations in the primary source of income, we evaluate effects in different strata, reporting the heterogeneous results for the sector of activity. Following Banerjee et al. (2021), we regress different outcomes of the sector of household activity on treatment status using the specification

$$S_{ivt}^{a} = \propto + \beta_1 Treatment_{ivt} + \beta_2 Spillover_{ivt} + \gamma S_{ivo}^{a} + Y_t + \theta_{gp} + \epsilon_{ivt} \quad (1)$$

The subscripts denote household i residing in village v in time t, S_{ivt}^{a} is the sector of activity of household in three outcome variables – household income, number of labourers, and hours worked to total labour employed. $Treatment_{ivt}$ is a dichotomous variable equal to 1 if the household received the eSAP intervention. $Spillover_{ivt}$ is a dichotomous variable equal to 1 if the household lives in the treatment village but does not receive the eSAP intervention. S_{ivo}^{a} is the value of the dependent variable at the baseline, Y_t is the year fixed effects, θ_{gp} is the strata fixed effects and are included to improve efficiency because the randomization is stratified by GP. The error term ϵ_{ivt} is clustered by village, the unit of randomization. Since all eligible farmers received treatment and the take-up was high, we present the intent-to-treat (ITT) estimates that are very close to the treatment on the treated effect.

Our results in Table 1, panel A, show that households in our program participated in farming (crop cultivation, livestock, and off-farm wage labour) and nonfarm work as the four primary sources of income. At the baseline, shown at the bottom of Table 1, 63 percent of the aggregate household income is from crop cultivation, while the rest is from off-farm wage labour (10 percent) and nonfarm work (23 percent).

In Figure 2, Panel A, we show the trends in aggregate crop incomes across treatment groups. Comparing changes in earnings, the earnings responses to the eSAP intervention relative to control increase crop incomes for both treatment and spillover households. Crop income includes profits from 34 crops cultivated by the treatment group for which support was provided in the eSAP program. In the program's first year, the intervention's direct effect appears to be as large as the spillover. In Figure 2, Panel B, we show all experimental groups' crop profits over the program years. Mean profits from crop cultivation of treatment and spillover households increased with much higher expansion for those who directly received the eSAP intervention.

Several factors contributed to this profit increase: first, farmers in the treatment villages grew more output on a given crop plot (Column 1, Table 2). Second, eSAP intervention primarily reduced the paddy production cost (Table 3 and Appendix Table A6). The combined effect of the increase in revenue and reduced production costs raised the mean per acre crop income over the entire program period by ₹3182 or 20.55 percent (p =0.001) for treatment (₹2681 or 17.31 percent (p = 0.033) for spillover despite not receiving the program) relative to the control group.

Though livestock is not profitable, we observe an improvement in livestock activity only for the treatment households (Column 2, Table 1). As noted later, the positive impact is because as household members reallocated for work to their farms, they spent more time tending the animals than previously, where they had to transit for nonfarm work outside the village.

The off-farm wage incomes in Table 1, Panel A column 3, show an increase of 1.99 percent (p = 0.047) for the treatment group, while a higher figure of 4.92 percent (p = 0.001) for the spillover group relative to the control group. The treated (spillover) households increase their family labour sales to other farmers (off-farm labour). The increase in household incomes from the agricultural sector (columns 1 to 3), however, comes at the cost of the nonfarm sector (column 4), with revenues declining by 5.63 percent (p = 0.001) for treatment and 5.57 percent (p = 0.047) for spillover households relative to control households. We estimate the regression on individual household members; thus, the impact shown here is the individual's response to the treatment.

Given the employment shifts and income substitution reported above, we now examine its likely impact on the total household income. Aggregating incomes across all four activities (column 5), we observe a net positive effect of 36.44 percent or ₹74,594 per annum (p = 0.046) on total household incomes for treated households, while a null result for the spillover group relative to the control group. In Appendix Table A2, we further report the net impact of the intervention on the overall household income over program years across all activities disaggregated by sectors.[8] We can notice a contrast between the significant per acre increase (column 1 Panel A, Table 1) and null aggregate (column 1 Panels A and B, Appendix Table A2) in crop income: spillover households with fewer lands did not benefit from the within-village information overflow. Thus, it appears that, in this context, access to extension intervention leads to a change in the mix of activities but no income growth overall. The intervention, however, significantly increased the crop income of the treatment households across both program years but offset the decrease in non-farm incomes only over the entire program. The difference between treatment arms is not statistically significant at the conventional level except for livestock and off-farm labour, as shown by the p-values reported at the bottom of Panel A in the table.

In Panel B, Table 1, we examine the labour market impact of the production shock. We report labour-days employed (extensive margin) in the sectors of household activity in Panel B and Panel C, the hours worked to total labour used (intensive margin). We find an increase in the number of labour-days for workers in farming by 33.58 percent relative to control (or 128 labour-days, p = 0.001). For the spillover households, it is less precise at 24.14 percent (p = 0.078).

[8] In Appendix A, Figures A6-A8, we explore whether the analysis overlooks important heterogeneity in response to intervention, though with the caveat that our sampling design did not account for the differential land size holdings, confounding the interpretation. Here we treat spillover households as a control group that did not directly receive the treatment (and null effect for household crop income), and thus we regroup accordingly. We note two points: (a) Receiving eSAP intervention relative to the control is more profitable on large farms, decreases nonfarm incomes, and increases total household incomes. (b) For farms with less than 5 acres, receipt of eSAP intervention is regressive (except for nonfarm incomes) relative to control. The most likely candidate in the explanation for the observed impact may be the economies of scale. Though we cannot fully explain why this is the case, future studies can design interventions to study the causal effect considering the heterogeneity impact within their research design.

In columns 3 and 4, we present the changes in the employment status of individual household members in response to the production shock. The household members working as labourers on others' farms significantly increase their labour-days by 4.61 percent (column 3) for the spillover households (3 labour-days, p = 0.000). In contrast, individuals engaged in nonfarm work respond to the production shock by reducing their labour-days by 4.15 percent relative to the control (column 4 panel B) for the treatment household (14 labour-days, p = 0.000), while 3 percent (10 labour-days, p = 0.043) for the spillover households.[9] These are family members working in the urban informal sectors (i.e., auto driver, welder, carpenter, electrician, construction labour, low-skill manufacturing workers etc.).[10] Still, individuals working in the formal sector jobs, such as teachers, state transport drivers, etc., did not reallocate. Aggregating across household labour activities (column 5), there are no significant net effects on days worked, suggesting all withdrawals from nonfarm activities are fully deployed in crop cultivation with no idle work capacity.

The hours worked to total labour employed (intensive margins) in nonfarm work also declined by about 2 percent for both treatment and spillover households (Panel C, column 4). An increase in agricultural productivity resulting from the eSAP program can pull labourers out of the nonfarm sectors. In response to higher crop profits, some nonfarm labourers in the treatment and spillover households shifted to agriculture, working on their and others' farms. It is worth noting that the decrease in extensive margins in nonfarm work is despite twice the average wages paid compared to the farm wages (Table 1, last row and Online Appendix A, Figure A5).

The evidence is consistent with the prediction from the theory that agricultural production shocks, while enhancing crop productivity, can pull labour away from the non-agricultural sector (Harris and Todaro, 1970). To attract additional hired labour into farming, higher than village equilibrium wages are paid (see also Online Appendix A, Figures A2-A4). With most casual labour transactions occurring within the village, wages are determined endogenously, with negotiations happening on a case-by-case basis.

B. Program effects: unpacking the impact

[9] Note that these are individual responses. A household response to the production shock is much higher, for instance, if three members of a treatment household work in the nonfarm sector in the baseline then the impact of the production shock will be a reduction in the labour-days by 12 percent annually, assuming symmetrical response by rest of the household members. Thus, family members working in nonfarm reduce by about 43 labour-days annually which is one-third of the labour-days increase in agriculture.

[10] The focus group did not highlight any industrial or manufacturing work, which included working in agri-food processing units and agricultural machinery manufacturing, that was unpleasant or posed any health risk, unlike in the case of Ethiopia (Blattman and Dercon, 2018).

In this section, we unpack the impact of the eSAP program that increased crop incomes over the program period. On average, the experimental households owned and managed at least one paddy plot at the baseline, apart from plots growing 33 other crops. Since the intervention was at the plot level that we tracked over the program period, we present results from regression using crop-plot data. To examine this, we use a similar specification as equation 1 with the performance of paddy plot c in village v at time t as the outcome variable.

In the three panels of Table 2, we report regression results for several outcomes in columns over all the program years. In the first column, Panel A, we report crop yield (a measure of agricultural productivity) one year after the program started. In Panel B and C, we show the impact of the eSAP program after three and four years, respectively, after the program began. In the subsequent columns, we report income gains and labour allocation.

DSR adoption and agricultural productivity.–We begin by looking at the DSR technique adoption in the experimental groups. The take-up rates of DSR were zero across all experimental groups in the baseline and remained the same for the control group over the program years. In Figure 3, we show the adoption of the rest of the groups. In the first-year post-intervention, the take-up rates were similar for treatment and spillover groups at 44 percent of the paddy plots cultivated using the DSR technique. In the second year, the adoption rapidly increased for treatment villages with spillover households and lacklustre in other treatment villages, resulting in relatively lower overall adoption among the treatment group. By the end of the program, the take-up rates were on the order of 86 percent and 94 percent of the paddy plots for treatment and spillover, respectively, who were using DSR cultivation practices.

We find strong evidence of the eSAP program's impact on productivity pooling across all three program years (Table 2, columns 1). The program is very successful, showing enormous potential to raise crop yields. The direct effect size of the program reached its full potential in the first year of implementation at 23.63 percent (p = 0.000) but declined over the program years to 14.99 percent (p = 0.000) in the final year, yet still highly significant. The decline can partly be explained by the increase in mean yield from conducive weather conditions to cultivate paddy for the control farmers.[11]

[11] It may likely be that control farmers received information (underestimated impact) just like the spillover farmers but our focus group discussions in control villages did not reveal any such receipt. The zero adoption of DSR technique in the baseline among control farmers was maintained over the program years. The social network within villages appeared to be stronger than between villages.

The most exciting aspect of the intervention is quantifying the spillover impact for the households not offered the program. The paddy yield impact of the eSAP program is 21.39 percent (p = 0.000) greater for the spillover farmers in the program's first year and is analogous to the effect on treatment farmers in the rest of the program years. In an influential study, BenYishay and Mubarak (2019) on social networks show social learning from similar-looking peers as an important channel for technology diffusion. The focus group discussions with the spillover farmers on the diffusion of information indicated that they belonged to the same caste network, were more likely to talk regularly and had similar land size holding as the treatment farmers within the village. Later in this section, we provide more details on the spillover effect concerning the specifics of the DSR technique.

Is DSR technique adoption profitable?–We next examine profit – revenue minus cost – over the program years. The cost of cultivation covers the combined value of both material inputs and wage costs. The wage costs include payments to hired labour and the imputed wages for family labour. We calculated the imputed wage cost of family labour by multiplying the number of family members providing work in each operation with the (gender- and operation-specific) market wage rate. A visual inspection of Figure 2 Panel C shows the increase in mean profits for the treatment group but no increase for the spillover group relative to the control mean. The regression results in Table 2 column 2 show an increase in profits by 27.73 percent (p = 0.000) relative to control at the end of the first program year; however, the treatment's persistent effect diminishes with each program year. The spillover effect mirrors the treatment impact but is slightly lower at 21.21 percent (p = 0.048) relative to control in the program's first year and increases somewhat only in the following year.

Effect of crop production on intersectoral labour allocation.–Our surveys very carefully collect detailed data on labour days and hours, separately for hired and family labour in every agricultural operation, across all plots in the household. The impact on the hired labour-days presented in column (3) after one year of the program shows that treatment households hired 62.63 percent or 109 labour-days per acre (p = 0.000), more than the control farmers. On the other hand, spillover farmers seem to increase the family labour-days by 51.45 percent or 37 labour-days (p = 0.047) relative to control, drawing down the deployment of its household members in nonfarm activities. Along with hired labour, treatment farmers also reallocate family labour from the market to the family farm. The increase in the demand for hired labour raises the wages paid (column 4) across the program years ranging from 56 percent in the first program year to 40 percent over the entire program, which is in response to the changes in the demand for hired labour shown in column 3. More family members work on their farms for the spillover households than the treatment group relative to the control households (Online Appendix Table A3).[12]

Based on equation (1) above, we examine the effect of eSAP on nonfarm activity. The nonfarm work consists of households working in non-agricultural and self-employed activities.[13] Non-agricultural activities include welder, carpenter, building contractors, drivers etc., working outside and inside the village (producing local non-tradable goods). Owning a shop, renting out agricultural machinery and livestock, interest earned from money lending and bank deposits, etc., are categorized as self-employed nonfarm.

Two years after the program, we observe a significant decrease of 4.84 percent (p = 0.000) in household incomes for the treatment group from non-agricultural activities relative to the control group (column 6).[14] As columns (7) and (8) show, the income reduction can be explained by the reallocation of family labour away from these activities across both extensive (3.78 percent, p = 0.000) and intensive margins (3.71 percent, p = 0.000). Decreases are slightly larger for the spillover group by 4.13 percent (p = 0.000) family labour-days and 4.03 percent (p = 0.000) hours worked per labour. The program's final year also shows a similar result, with incomes from the non-agricultural activity for treatment households falling by 4.92 percent (p = 0.000) (3.75 percent (p = 0.036) for the spillover group) relative to control. Consistent with this, the family labour-days decreased along with hours worked per labour.

Turning now to self-employed nonfarm activity in columns 9 to 11, we observe a substantial income decrease of 7.32 percent (p = 0.000) for spillover households (4.45 percent (p = 0.049) for the treatment households) relative to the control group at the end of two years of the program. The income decreases for both treatment arms are mainly because of the labour reallocation to the agricultural sector. The likelihood of supplying family labour and hours sold to the labour market decreases with the eSAP intervention (columns 10 and 11).

Effect of DSR adoption on cultivation cost.–Drawing on the full input costs for each of the different agricultural operations in paddy, we report the impact of the eSAP program on the

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[12] The reallocation of family labour from the labour market and the hiring of additional labour to the family farm have been reported previously in other contexts in response to the offer of subsidized loans (Fink et al., 2020) or relaxing both demand and supply constraints in agriculture (Bold et al. 2021).

[13] Since household members work on both farm and non-agriculture at different times in the year, we do not classify a worker as either an agricultural or non-agricultural worker. Thus, we work with the number of labour-days spent by each household member in each of the sectors.

[14] In the first year of the program, we did not collect information other than crop cultivation and livestock.

various components of the input costs in Table 3. It is, however, worth keeping in mind that we show the combined effect of the eSAP and DSR techniques. We report the control means in the first column. Each cell in columns 2 and 3, based on separate regressions, shows the impact of the eSAP on the cost of input use in farming operations. All regressions control for the value of the dependent variable at the baseline and year and strata fixed effects.

With the adoption of DSR and the associated practices of seed priming, the rate of germination and emergence increased, reducing the need for high seeding rates. It significantly reduced the seed requirements by 89 percent for treatment relative to control. We can also note a slightly lower reduction (82 percent) for spillover farmers. However, farmers continued buying seedlings for transplanting, where germination and emergence of the sown seeds were poor. Since the DSR process of establishing a paddy crop is from seeds sown in the field rather than transferring seedlings from the nursery, it eliminates transplanting operation, thus saving water and labour. The negative sign (although the effect is not precisely estimated) for transplanting in Table 3 (columns 2 and 3) reflects the successful adoption of the DSR technique.

DSR technique is believed to increase weeding costs. Still, results show it had a null effect on treatment households, meaning it is not different from CTS with suitable weed management methods supported by eSAP. The weed management includes a state-seed bed technique combined with a pre-emergence herbicide applied within two days after seeding. However, with the eSAP intervention, the herbicide application did not significantly increase, thus providing some cost savings for treatment households.

As previously mentioned, the key to DSR adoption is reducing water use for irrigation. Both treatment (₹73 per acre or 86 percent (p = 0.000)) and spillover (₹70 per acre or 82 percent (p = 0.000)) households significantly reduced the use of water for irrigation. It lowered the overall production costs substantially. Since water is not traded, this cost includes only the labour cost, mostly family labour (see online Appendix Table A7).

The severity of pests and diseases increases under water-limited conditions (Bonman, 1992) while resulting in an imbalance of macro- and micro-nutrition content of the soil (Geo et al., 2006). It can drastically increase production costs with enhanced micronutrients and insecticide applications. Since nutrient deficiency is an essential concern in DSR, the eSAP intervention increased the use of micro-nutrient applications for treatment households by 37.20 percent (p = 0.035, column 2). A somewhat higher usage can also be noticed for the spillover households (39.47 percent (p = 0.044), column 2). The insecticide application increased considerably for both treatment (₹692 per acre or 28.89 percent (p = 0.000), column 2) and spillover (₹628 per acre or 26.22 percent (p = 0.000), column 3) households relative to the control.

Why did the program have such large spillovers? The two key practices that distinguish the commonly used CTS from the DSR technique are water for puddling and transplanting. Here we examine if these practices were affected by the treatment status. Since eSAP has no direct role in embracing these practices, we can isolate the impact of technology from the adoption decision of DSR. Though we showed the lower production cost previously from reduced use of water and labour, here we elaborate further on the two modifying features of the practices likely to have spread to other farmers within the village. In Table 4, we report on these features over program years. In panel A, we find that the adoption of DSR leads to a significant reduction in the number of transplanting (164 percent (p = 0.000), panel A column 5) and irrigation (175 percent (p = 0.000), panel A column 6) by the end of the program. Similar results can also be noted for the spillover group both in magnitude and significance, demonstrating the robust learning within the village from agricultural operations that are mostly observable and frequently talked about.

In panel B, we assess the impacts of DSR on the family labour hours devoted to transplanting and irrigation. We find that DSR adoption leads to a significant reduction in labour-days devoted to transplanting, with an impact size of 221 percent (column 5) for treatment farmers and a slightly higher reduction for spillovers (226 percent, column 5) in program year three. Although similar adverse effects can be observed in previous years, these are somewhat less precisely estimated. We also find a significant decrease in labour-days for irrigation among the treatment group but no significant reduction for the spillover group.

The focus groups with the spillover farmers pointed to the labour- and water-saving features of the DSR technique that appealed to them most. Once adopted, replicating the program practices was not challenging (which is not entirely a new technology) with standard observable procedures in treatment plots. It appears that the spillover effects are less about the eSAP intervention but better verbal communication within the villages. The expected payoff from using the technology increases in their proximity to the treatment farmers and the precision of the information received (Bardhan and Udry, 1999). Because of the spillover farmers' proximity to the treatment crop fields, they also communicate frequently to the treatment farmers about various farming practices. The spillover farmers who did not benefit hardly interacted with treatment farmers and were poorer and less educated, which makes them ineligible for local social network membership.

C. Cost-effectiveness of the eSAP program

Using profit and cost measures, we develop a back-of-the-envelope cost-effectiveness calculation of our eSAP intervention. We conservatively assume that the full research cost we incurred is required to implement such a treatment. The eSAP program, as delivered, had an unsubsidized cost of about ₹455 per household per month. The project paid the fee to TAS for providing the eSAP intervention (although services to farmers were free of charge), including hardware costs (₹130), staffing for visits twice a month (two hours salary) (₹250), and pro-rated fees for software development (₹75). Using our ITT estimates, we see that the average treated household gained ₹ 6,216 per month from the eSAP intervention (column 5 in Table1).[15] Note that the estimate consists of all sources of income, including decreases in nonfarm incomes. Even when implemented with high fixed costs and without economies of scale and spillovers, this generates a benefit/cost ratio of 13.68. The program, therefore, has the potential to be very cost-effective.

IV. Conclusion

Given the context of the study, results from our intervention show a positive impact on farm productivity growth and crop and household incomes. The spillover households that did not directly receive the program also benefited from productivity growth, subjecting membership to a strong within the village's social network. We find that the positive production shocks in the farm sector absorb more labour. The increase in agricultural productivity from the eSAP intervention reallocates both hired and family labour into the farm sector. Both livestock and off-farm activities benefit from labour reallocation. However, the reallocation of labour away from non-agricultural activities shrinks nonfarm incomes. Back-of-the-envelope calculations suggest that the eSAP program offers some promise to policymakers, a rewarding and scalable intervention enabling poor farmers to improve their welfare.

From a policy perspective, designing programs requires important consideration of the intersectoral links between various initiatives. The underlying assumption is that agricultural and occupational change programs are complementary because of surplus labour (Blattman et al., 2014) and/or labour exits agriculture when farm incomes increase (Johnston and Mellor, 1961; Gollin et al., 2002). However, our findings run counter, suggesting that productivity

[15] Given large spillovers observed in the treatment villages, the effects we measure are likely to be an underestimate of the direct effects of the eSAP program.

increases in agriculture increase the demand for labour which is likely to compete in the labour market. Accordingly, the results of both programs concurrently could be equivocal.

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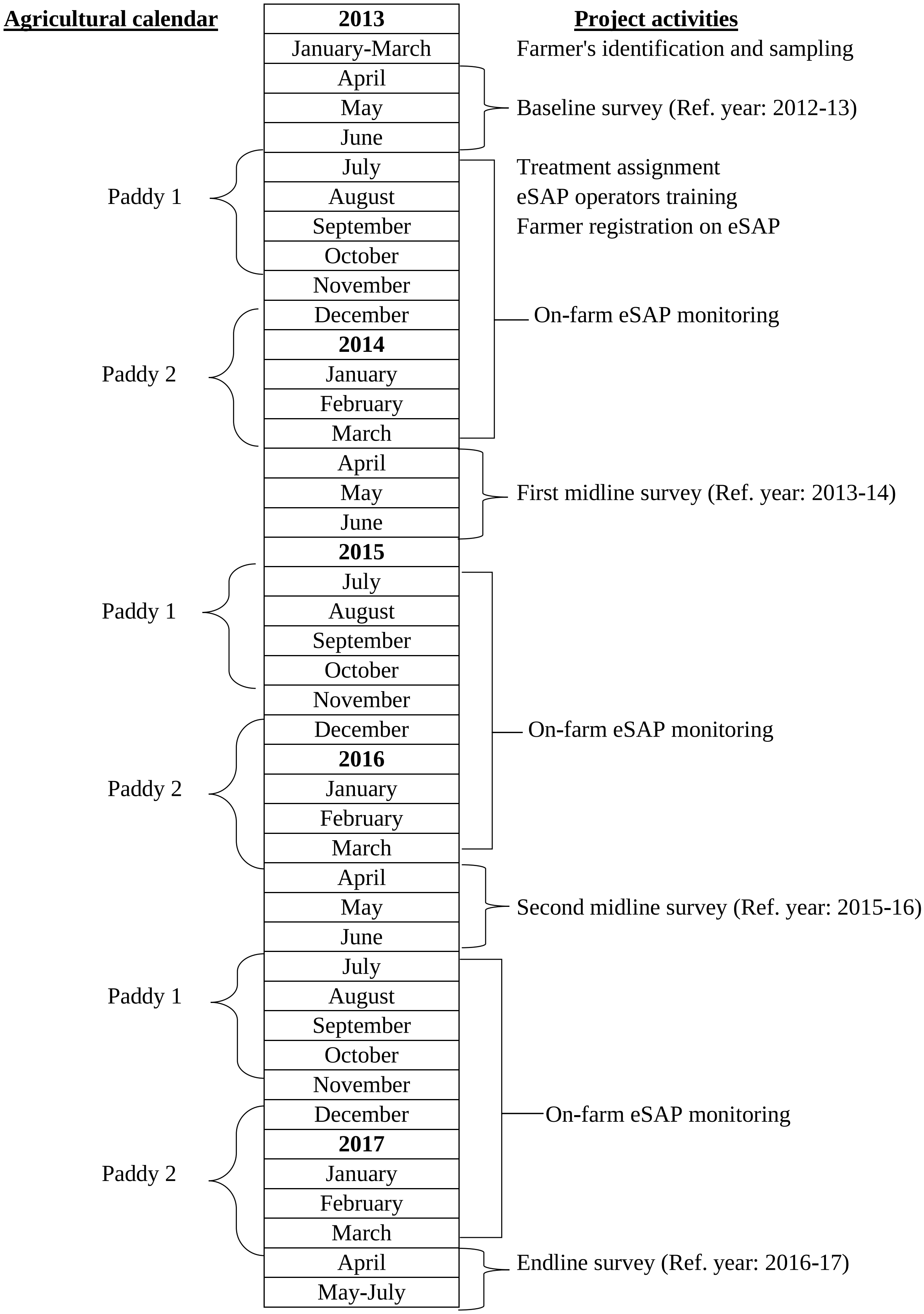

Figure 1: Project timeline

Notes: We did not conduct on-farm eSAP monitoring between July 2014 and June 2015. During the first midline survey, we did not carry out household surveys. Not all farmers grow paddy every season, which strongly depends on water availability. No plots were sold or taken out of production for the entire year over the study period.

Table 1: Impact on rural household earnings and labour market over the program

	Sector of activity				Activity across all sectors
	Crop cultivation	Livestock	Off-farm labour	Nonfarm work	
Program years included	Three years	Three years	Last two years	Last two years	Last two years
Unit of estimation	Plot	Household	Individual	Individual	Household
	(1)	(2)	(3)	(4)	(5)
Panel A: Household incomes (₹ per annum)					
Dependent variable	Crop income per acre	Livestock income	Off-farm wage income	Nonfarm income	Total income
Treatment	3,182***	15,763***	348**	-5,393***	74,594**
	(1012)	(4193)	(165)	(1822)	(33084)
	{0.010,0.079}	{0.062,0.237}	{0.001,0.032}	{0.159,0.174}	{0.139,0.154}
Spillover	2,681**	2,104	859***	-5,343**	13,875
	(1362)	(5948)	(207)	(2375)	(48436)
	{0.111, 0.590}	{0.368, 0.861}	{0.022, 0.124}	{0.746, 0.759}	{0.167,0.164}
Control mean (₹ in levels)	15,482	-25,554	17,439	95,789	204,690
R-squared	0.2097	0.2647	0.4530	0.2018	0.3031
Observations	4,250	2,753	9,041	9,041	2,041
P-values on tests of equality (Treatment=Spillover)	(0.7321)	(0.004)	(0.000)	(0.9794)	(0.1635)
Panel B: Employment of hired and family labour					
Dependent variable	Number of labour-days per acre	Number of labour-days	Number of labour-days	Number of labour-days	Number of labour-days
Treatment	128.465***	43.210**	1.377	-14.963***	2811
	(41.010)	(14.832)	(0.864)	(3.591)	(1836)
	{0.000,0.025}	{0.000,0.041}	{0.071,0.487}	{0.012,0.466}	{0.113,0.357}
Spillover	92.345*	53.911**	3.967***	-10.983**	-2796
	(53.850)	(20.791)	(0.990)	(4.562)	(5113)
	{0.000,0.040}	{0.000,0.026}	{0.000,0.367}	{0.606,0.685}	{0.705,0.786}
Control means (in levels)	382.487	135.76	86	360	7176
R-squared	0.0901	0.3124	0.4633	0.3652	0.0250
Observations	4,250	2,753	9,041	9,041	2,041
P-values on tests of equality (Treatment=Spillover)	(0.4096)	(0.668)	(0.000)	(0.241)	(0.3482)
Panel C: Total hours worked to total number employed					
Dependent variable	Hours worked to total labour per acre	Hours worked to total labour	Hours worked to total labour	Hours worked to total labour	Hours worked to total labour
Treatment	-5.382**	-705.136***	11.022	-67.718***	-46.941
	(2.221)	(228.788)	(6.915)	(20.573)	(83.539)
	{0.000,0.097}	{0.000,0.072}	{0.000,0.112}	{0.511,0.663}	{0.412,0.565}
Spillover	-7.772**	-593.027**	31.741***	-70.243***	8.897
	(2.384)	(236.821)	(7.920)	(24.260)	(103.200)
	{0.000,0.058}	{0.000,0.069}	{0.000,0.082}	{0.506,0.666}	{0.536,0.646}
Control means (in levels)	84.367	489	690	2,142	2,041
R-squared	0.1410	0.4173	0.4633	0.4605	0.5444
Observations	4,250	2,753	9,041	9,041	2,041
P-values on tests of equality (Treatment=Spillover)	(0.1313)	(0.011)	(0.000)	(0.888)	(0.5142)
Share in household income at baseline	63%	-	10%	23%	100%
Nominal wage per person per day (₹)	178	174	231	320	

Notes: Estimates in columns 1 and 2 are based on annual data pooling across all three program years and a base year. Income in Panel A is net income. Columns 3-5 include only the last two program years because detailed information was not collected except for livestock and crop cultivation. The share (%) in total household income does not include receipts from land leased out (4%). Crop income includes profits from 34 crops – paddy, cotton, sorghum, chili, bengal gram, horse gram, maize, red gram, sugarcane, sunflower, cowpea, barley, groundnut, castor, green gram, and a combination of several crops raised together. Livestock includes milk production, meat, poultry, and hire, sale and purchase of animals. Incomes from off-farm labour include wages earned by household members working on other's farms pooling across all three agricultural seasons. Nonfarm work includes household members over 18 years working in non-agricultural employment (72 different types of nonfarm work within the village and nearby towns, i.e., welder, carpenter, building contractor, driver, etc.) and self-employed nonfarm (shops, renting out of agriculture machinery and livestock, interest earned from money lending, bank and post office deposits, etc.). The number of Labour-days is calculated as the number of times the operation was completed multiplied by the number of days multiplied by the number of hours multiplied by the number of family and household labour divided by 8 working hours per day. We work with Labour-days (not days) since some agricultural operations are completed in a few hours while others take many hours. Thus, we asked the farmers for the number of hours worked and the number of days to complete each operation, which is then standardized by 8 working hours. All regressions include constant, strata fixed effects, time fixed effects, and the value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). We report unadjusted p-values (left) and p-values adjusted (right) for multiple hypothesis testing in braces. These are computed using the Romano-Wolf multiple hypothesis testing as implemented in Clarke, Romano and Wolf (2019). At the foot of each column, we report p-values on the null that the impact of the treatment is equal to the impact on the spillover group.

*** significant at the 1 percent level

** significant at the 5 percent level

* significant at the 10 percent level

Table 2: Impact on farm and nonfarm activity

Unit of estimation:	Plot					Individual					
Household activity:	Paddy cultivation					Non-agricultural activity			Self-employed nonfarm		
	Crop yield	Crop profit per acre	Hired Labour-days per acre	Wage paid for harvesting per day	Family labour-days per acre	Income	Family labour-days	Hours worked to total labour	Income	Family labour-days	Family labour hours worked to total labour
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: Impacts in first follow-up survey (one year into the program)											
Treatment	6.251***	5,424.177***	109.910***	62.914***	25.123**	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
	(1.339)	(1580.878)	(25.732)	(6.224)	(10.448)						
	{0.008,0.095}	{0.001,0.085}	{0.025,0.067}	{0.034,0.067}	{0.010,0.077}						
Spillover	5.659***	4,148.579**	21.462	54.122***	37.217**						
	(1.463)	(1954.073)	(29.204)	(6.935)	(16.626)	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
	{0.030,0.094}	{0.070,0.087}	{0.030,0.099}	{0.050,0.095}	{0.056,0.047}						
Control mean	26.447	19,557.78	175.477	119	72.336	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
R-squared	0.2393	0.1530	0.0444	0.2222	0.0367						
Observations	1,595	1,595	1,595	1,595	1,595	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
P-values on tests of equality (Treatment=Spillover)	0.4433	0.4139	0.0003	0.0762	0.3778						
Panel B: Impacts in the second follow-up survey (three years into the program)											
Treatment	5.605***	5,388.38***	107.694***	58.892***	26.781**	-2,948***	-6.734***	-53.040***	-1,274**	-2.956**	-13.734*
	(0.997)	(1320.353)	(24.014)	(5.550)	(10.985)	(713)	(2.042)	(18.116)	(629)	(1.281)	(7.393)
	{0.000,0.066}	{0.010,0.067}	{0.001,0.066}	{0.030,0.088}	{0.004,0.047}	{0.000,0.093}	{0.003,0.045}	{0.004,0.066}	{0.020,0.090}	{0.004,0.047}	{0.006,0.066}
Spillover	5.296***	4,662.848 ***	6.922	49.826***	41.509 **	-2,458**	-7.363***	-57.574***	-2,094***	-3.517**	-18.231**
	(1.116)	(1690.599)	(40.412)	(6.310)	(16.108)	(1099)	(2.445)	(20.874)	(645)	(1.395)	(8.9216)
	{0.030,0.080}	{0.010,0.095}	{0.004,0.057}	{0.005,0.047}	{0.002,0.056}	{0.006,0.090}	{0.000,0.007}	{0.001,0.098}	{0.002,0.007}	{0.004,0.007}	{0.001,0.087}
Control mean	26.374	20,488.530	195.372	128	74.549	60,815	178	1427	28,591	88	705
R-squared	0.2269	0.1556	0.0550	0.1538	0.0408	0.3134	0.5278	0.5270	0.4326	0.5486	0.5483
Observations	2,117	2,117	2,117	2,117	2,117	5,987	5,987	5,987	5,987	5,987	5,987
P-values on tests of equality (Treatment=Spillover)	0.6389	0.5796	0.0290	0.0533	0.2480	0.6390	0.7197	0.7464	0.0254	0.5496	0.5492
Panel C: Impacts in the third follow-up survey (four years into the program)											
Treatment	4.030***	3,619.755***	93.079**	52.215***	19.340**	-3,164***	-6.438***	-54.233***	-1,346**	-3.671**	-18.616**
	(0.879)	(1056.43)	(40.406)	(4.543)	(10.113)	(712)	(2.365)	(17.848)	(637)	(1.586)	(8.894)
	{0.002,0.007}	{0.004,0.006}	{0.002,0.007}	{0.001,0.008}	{0.010,0.000}	{0.000,0.058}	{0.000, 0.032}	{0.000, 0.048}	{0.020,0.095}	{0.034,0.045}	{0.002,0.068}
Spillover	3.778***	3,187.426***	15.926	44.545***	29.436**	-2,415**	-6.826**	-56.927**	-2,151***	-3.539*	-17.561
	(0.940)	(1431.569)	(48.339)	(5.711)	(14.519)	(1152)	(2.748)	(22.087)	(710)	(1.979)	(12.602)
	{0.001,0.007}	{0.001,0.005}	{0.000,0.003}	{0.000,0.002}	{0.000,0.090}	{0.273, 0.386}	{0.157, 0.522}	{0.157, 0.783}	{0.000,0.067}	{0.021,0.057}	{0.031,0.087}
Control mean	26.869	22,676.78	183.187	129	84.962	64,249	176	1412	31,303	91	730
R-squared	0.2197	0.2086	0.0480	0.1480	0.0450	0.2360	0.4223	0.4217	0.3268	0.4153	0.4149
Observations	2,572	2,572	2,572	2,572	2,572	9,041	9,041	9,041	9,041	9,041	9,041
P-values on tests of equality (Treatment=Spillover)	0.8449	0.6831	0.0603	0.0679	0.4022	0.5074	0.8473	0.8676	0.0794	0.9207	0.9210

Notes: n.a. refers to information not available. All farmers cultivate paddy 1 in the first season (few in multiple plots), but the choice of cultivation of paddy 2 in the second season varies every year depending on water availability. Since crop cultivation is an endogenous choice, we also estimate using data for only the first season. The estimates from these regressions are not very different from the results in the above table. Incomes from off-farm labour include wages earned by household members working on other's farms across all three agricultural seasons. Nonfarm work includes household members over 18 years working in non-agricultural employment (72 different types of nonfarm work within the village and nearby towns, i.e., welder, carpenter, building contractor, driver, etc.) and self-employed nonfarm (shops, renting out of agriculture machinery and livestock, interest earned from money lending, bank and post office deposits, etc.). The number of Labour-days is calculated as the number of times the operation was completed multiplied by the number of days multiplied by the number of hours multiplied by the number of family and household labour divided by 8 working hours per day. All regressions include constant, strata fixed effects, time fixed effects, and value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). We report unadjusted p-values (left) and p-values adjusted (right) for multiple hypothesis testing in braces. These are computed using the Romano-Wolf multiple hypothesis testing as implemented in Clarke, Romano and Wolf (2019). At the foot of each column, we report p-values on the null that the impact of the treatment is equal to the impact on the spillover group.

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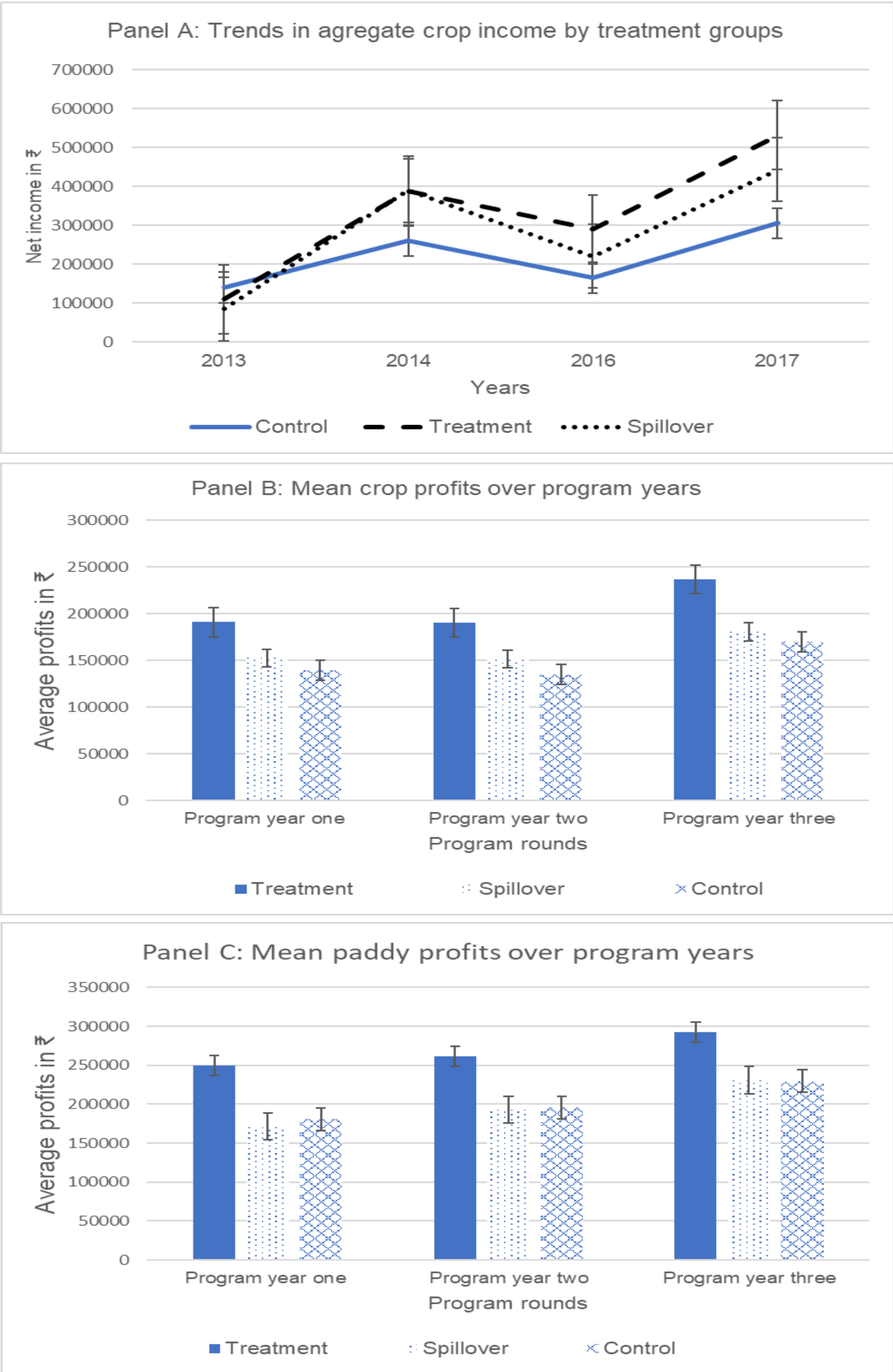

Figure 2: Farm income, crop profit, and agricultural wages

Notes: The figure in Panel A shows the trends in crop income, which is the aggregate of profits across treatment groups from each of the 34 crops grown and calculated as revenue minus cost of cultivation, including hired and family labour. Panel B shows the mean crop profits calculated as revenue minus cost, including hired and family labour over 34 crops grown. Panel C shows the mean paddy profits calculated as revenue minus cost, including hired and family labour over 34 crops grown.

Table 3: Impact on components of input costs by agricultural operations in paddy

Unit of estimation:	Plot				
Dependent variable:	Cost of input use (amount in ₹ per acre)				
	Control mean (SD)	Treatment (SE)	Spillover (SE)	P-values on tests of equality (Treatment=Spillover)	Bootstrap p-values for multiple hypothesis test (unadjusted; Holm)
Agricultural operations	(1)	(2)	(3)	(4)	(5)
Plowing	901.1232	-111.2148	-20.6307	0.0097	(0.0151,0.099)
	(600.2976)	(126.2157)	(128.2186)		{0.464,0.940}
Harrowing	877.0952	95.8912	145.2142	0.2255	(0.017,0.099)
	(736.8009)	(163.7705)	(166.533)		{0.570,0.940}
Sowing	1505.136	-1347.936**	-1243.716**	0.1022	(0.100,0.069)
	(1528.462)	(639.2051)	(642.7467)		{0.053,0.336}
Transplanting	1830.42	-57.6051	-18.3808	0.6412	(-,0.009)
	(832.8252)	(39.7036)	(85.2815)		{-,0.009}
Weeding	1985.378	545.0931	819.1578*	0.2835	(0.000,0.029)
	(3276.336)	(335.8333)	(453.9994)		{0.233,0.841}
Fertiliser application	6624.472	1007.697	971.1459	0.8515	(0.000,0.009)
	(4174.271)	(1100.365)	(1117.289)		{0.434,0.940}
Micro-nutrient application	341.054	126.896**	134.6313**	0.7155	(0.013,0.099)
	(401.1706)	(63.5976)	(65.5813)		{0.740,0.940}
Irrigation	84.7093	-73.1037***	-70.1054***	0.8738	(0.019,0.099)
	(139.9716)	(15.5289)	(20.5961)		{0.010,0.069}
Insecticide application	2396.771	692.628***	628.4669***	0.3522	(0.001,0.029)
	(1659.538)	(167.618)	(191.0625)		{0.620,0.940}
Herbicide application	213.6753	-4.2553	1.5525	0.4666	(0.063,0.118)
	(245.7279)	(5.8785)	(36.7773)		{0.038,0.217}
Harvesting	2337.816	504.762**	344.206	0.0747	(0.073,0.218)
	(1404.222)	(209.591)	(218.543)		{0.046,0.316}
Strata FE		Included	Included		
Year FE		Included	Included		
Cluster SE		Included	Included		
Observations		2572	2572		

Notes: The figures in parenthesis in column (1) are the standard deviation (SD), and figures in columns (2) and (3) are clustered standard errors (SE). Standard errors are clustered at the village level (in parentheses). Each cell in columns (2) and (3) are based on separate regressions showing the impact of eSAP intervention on the cost of input use in each of the agricultural operations. Input costs across all operations include the use of machinery, animal and human labour. If a machine or an animal is owned, then we use the year-wise going hire price to quantify the value of their services. Human labour includes the cost of both hired and family labour. We use the year-wise going wage rate to quantify the value of family labour. In column (5), we report unadjusted p-values (left) and p-values adjusted (right) for multiple hypothesis testing. These are computed using the Romano-Wolf multiple hypothesis testing as implemented in Clarke, Romano and Wolf (2019). In parenthesis, we report p-values for each operation while in braces for the spillover group.

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* significant at the 10 percent level

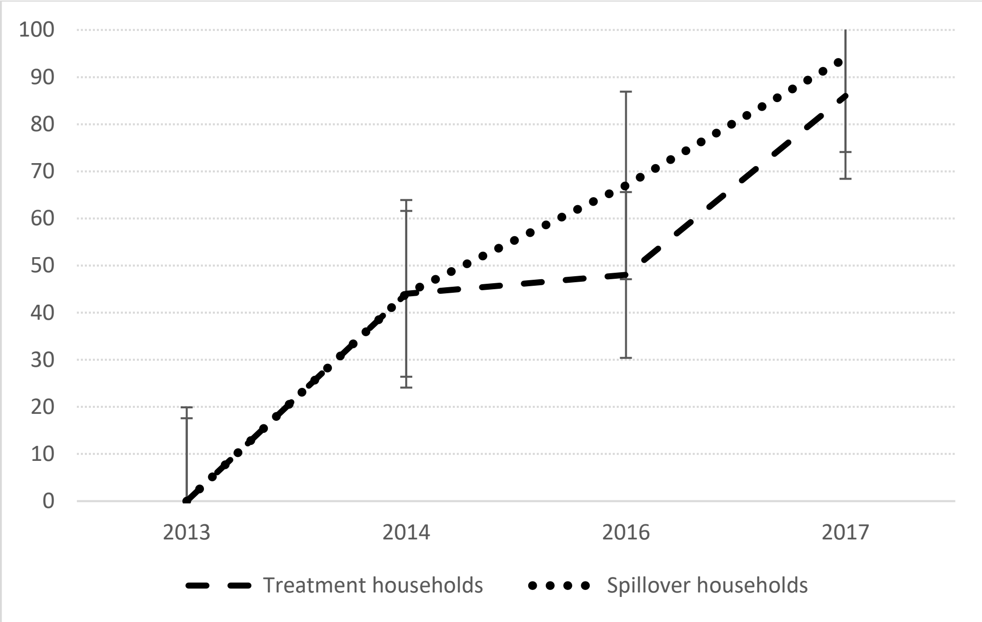

Figure 3: Percentage adoption of the DSR technique

Notes: Graph from recall survey based on the question to farmers on their paddy plots: did you adopt the DSR technique in the paddy plot? Yes 1; No 0.

Table 4: Change in farming practices from adoption of DSR technique

Unit of estimation	Plot					
	Program year one		Program year two		Program year three	
	Transplanting	Irrigation	Transplanting	Irrigation	Transplanting	Irrigation
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Number of times in each operation per acre						
Treatment	-0.482***	-16.704***	-0.475***	-14.441**	-0.486***	-15.048***
	(0.150)	(4.807)	(0.146)	(4.969)	(0.145)	(4.827)
Spillover	-0.453***	-16.676***	-0.459***	-14.496**	-0.483***	-15.365***
	(0.153)	(4.883)	(0.149)	(5.0574)	(0.147)	(4.889)
Control mean (₹ in levels)	0.318	9.256	0.309	9.518	0.295	8.557
R-squared	0.3949	0.4114	0.3548	0.3162	0.3448	0.3062
Observations	1,595	1,595	2,117	2,117	2,572	2,572
P-values on tests of equality (Treatment-Spillover)	0.2801	0.9728	0.5601	0.9394	0.9068	0.6280
Panel B: Family labour-days per acre						
Treatment	-0.269	-14.198***	-0.380*	-11.132***	-0.414**	-11.441***
	(0.254)	(4.453)	(0.213)	(3.640)	(0.193)	(3.141)
Spillover	-0.255	-1.499	-0.379*	-0.063	-0.424**	-1.479
	(0.263)	(11.051)	(0.221)	(10.389)	(0.200)	(9.399)
Control mean (₹ in levels)	0.069	12.876	0.138	11.353	0.187	9.993
R-squared	0.0367	0.0655	0.0432	0.0574	0.0427	0.0548
Observations	1,595	1,595	2,117	2,117	2,572	2,572
P-values on tests of equality (Treatment-Spillover)	0.7368	0.3189	0.9827	0.3528	0.8524	0.3521

Notes: All regressions include constant, strata fixed effects, time fixed effects, and value of the dependent variable at the baseline as controls. Standard errors are clustered at the village level (in parentheses). At the foot of each column, we report p-values on the null that the impact of the treatment is equal to the impact on the spillover group.
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