PRELIMINARY DRAFT

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Incentivizing Social Learning for the Diffusion of Climate-Smart Agricultural Techniques

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Abstract

Unsustainable land use is a key threat to both economic development and environmental conservation in developing countries. We implement a randomized controlled trial in arid Burkina Faso to test the effectiveness of subsidizing the adoption of sustainable land management practices (SLMPs). We do so in the context of a so-called cascade training program, in which some farmers are trained in SLMP implementation, who are expected to subsequently disseminate their newly acquired knowledge and expertise in their social networks. Offering adoption payments is expected to solve two barriers for SLMP adoption – the (perceived) lack of private profitability, and insufficient diffusion of the technical implementation information from the trained farmers to their peers. We find that, within one agricultural season, peers of the trained farmers ask for advice more frequently from the trained farmers, and adopt significantly more SLMPs when offered financial payments conditional on adoption. Simultaneously, trained farmers increase their effort to communicate knowledge and adopt more practices themselves regardless of whether they have a direct financial stake in the adoption decision of their peers or not.

Keywords: Land degradation, agricultural extension, sustainable land management.

1 Introduction

Unsustainable land use is a threat to both economic development and environmental conservation. This holds true especially for arid Sub-Saharan Africa, where soil erosion and soil depletion are major threats to agricultural viability in the long run (FAO and ITPS, 2015), and where continued agricultural conversion of forested areas contributes to both global warming and biodiversity loss (World Bank, 2008; FAO, 2019). Although various so-called sustainable land management practices (SLMPs) are available to increase (long-run) agricultural productivity and reverse soil degradation (Liniger *et al.*, 2011b), adoption rates remain typically low. Two of the most important explanations for this low take-up are a lack of information about their existence and implementation (Conley and Udry, 2010; Jack, 2011), and concerns about short-run implementation cost and long-run private returns (Jack, 2011; Beaman and Dillon, 2018). By definition, the societal benefits of sustainable techniques exceed the private benefits, as the agent adopting them only reaps a small (and oftentimes negligible) share of the environmental gains these technologies give rise to. Farmers may be reluctant to invest in technologies of which the up-front costs may be considerable, and of which the private returns are uncertain and materialize in the (distant) future. Society, however, may be willing to subsidize the adoption of these technologies, because the societal private discount rate is typically smaller than the private one, and because the social benefits of adoption exceed its private costs.

In this paper we study whether a subsidy for the adoption of sustainable land management practices increases take-up, and whether (and to what extent) it can help overcome the above two key barriers – limited (or even negative) perceived private profitability, as well as the lack of information. We cooperated with the government of Burkina Faso and implemented a randomized controlled trial (RCT) to estimate the impact of offering farmers financial compensation conditional on the adoption of up to nine different SLMPs. The core of the intervention is a so-called cascade training scheme (Banerjee *et al.*, 2013; BenYishay and Mobarak, 2018; Kondylis *et al.*, 2017; Sseruyange and Bulte, 2018). Government extension workers provide farmers with information on both the benefits of adopting each of the SLMPs as well as on how to implement them. Upon completion of the training, the trained farmers were encouraged to actively disseminate their newly acquired knowledge and expertise among other farmers in their existing social network who, in turn, may or may not have decided to adopt one or more technologies. Referring to the former farmers as the contact farmers and the latter as their peer farmers, our main intervention consisted of offering financial compensation to the peer farmers depending on the number of technologies they adopted.

We hypothesize that the conditional adoption subsidies are effective because they help overcome the two key adoption barriers discussed above – the (perceived) lack of private profitability, and/ or the lack of information on technology implementation. That conditional adoption subsidies improve the cost-benefit ratio of technology adoption, is straightforward. As such, our intervention can be viewed as an example of a "Payments for Ecosystem Services" (PES) scheme – a policy that aims to stimulate the private provision of nature conservation by offering financial compensation conditional on actual environmental service delivery (Wunder, 2007; Engel *et al.*, 2008; Engel, 2016). PES schemes have been shown to be effective at inducing forest and water conservation (Jayachandran *et al.*, 2017; Börner *et al.*, 2017); our study contributes to this literature by testing the effectiveness of PES on the diffusion of sustainable land management practices. More importantly, however, we also hypothesize that offering conditional adoption payments increases downstream demand for information on technology implementation, and hence ameliorates the transfer of information.

Whether farmers receive all relevant information regarding SLMP benefits and implementation know-how is especially important in the context of cascade training programs. These programs have been developed as an alternative to the traditional model of government agricultural extension services because of essentially two reasons (BenYishay and Mobarak, 2018). First, large-scale dissemination of information on new agricultural technologies is challenging in Sub-Saharan Africa, as the available resources are oftentimes insufficient for a nation-wide coverage of high-quality government extension services. Second, the standard extension services' approach of top-down information provision, from an extension worker to a farmer, does not always succeed in convincing the latter of the desirability of adopting the new technology – oftentimes because of doubts whether the new technology is sufficiently well suited for the local agronomic circumstances. Cascade training systems may be able to alleviate (if not overcome) both issues. They hold the promise of being both more efficient as well as more effective than the traditional diffusion model. They may be more efficient as relatively few farmers need to be trained directly. And they may also be more effective, as information provided by a fellow farmer from the same region may be perceived as more reliable and better adapted to the local agronomic conditions than the information provided by (non-local) government extension workers.

By now there is widespread agreement among development economists that leveraging social ties to disseminate information on new technologies is a promising avenue to foster technology adoption (Foster and Rosenzweig, 1995; Krishnan and Patnam, 2014; Takahashi *et al.*, 2019). Indeed, a number of studies have documented that information provided by farmers within one's own social network is more successful in disseminating new agricultural technologies than via governmental extension services (Bandiera and Rasul, 2006; Conley and Udry, 2010; Krishnan and Patnam, 2014; Miller and Mobarak, 2015; Vasilaky and Leonard, 2018). However, there is also ample evidence that the social learning process cannot be taken for granted, as contact farmers may not face sufficient incentives to actively disseminate their knowledge and expertise. BenYishay and Mobarak (2018) show that providing contact farmers with information about new technologies does not automatically translate into technology adoption by their fellow peer farmers within their respective village. And Kondylis *et al.* (2017) show that even if contact farmers are provided with demonstration tools, they still exert little effort in reaching out to their peer farmers in their networks.

In this paper we aim to gain more insight into the role of financial compensation in improving the transmission of information in the cascade training approach. We do so by varying the direct incentives for contact farmers to transfer their knowledge and expertise to their peers. More specifically, we implement two treatment arms (in addition to the control group). In both treatment arms financial compensation is offered as a function of the number of SLMPs that are present, at endline, on a treatment farmer's land. The amount paid, for any number of SLMPs present at endline, is also the same in both treatments. The only difference between the two treatments is with respect to the (initial) allocation of the payment. In one treatment arm the amount earned is disbursed, in full, to the peer farmer; in the other the amount is split, 80-20, between the peer and contact farmer. Our two treatment arms thus generate exogenous variation in the *direct* financial stakes a contact farmer has in stimulating adoption by their peer farmers, and hence they may or may not provide differential incentives for peer farmer SLMP adoption. The two treatments may have differential outcomes because in the 80-20 treatment contact farmers have a direct stake in inducing their peer farmer to adopt, and hence the contact may be more eager to share their newly acquired knowledge and expertise on SLMP with his peers. But then the initial allocation of the funds may well differ from the final allocation. If the market for information is efficient, the initial allocation of the surplus may not affect the actual amount of information transferred.

The fact that (i) financial compensation is offered to farmers in our two treatment arms (not to the farmers in the control group) and (ii) the treatment arms differ in the initial allocation of the amount offered allows us to not only estimate the impact of offering conditional payments on SLMP adoption, but also on the role financial compensation plays in the dissemination of SLMP information. We consider both input and output measures of information transfer. The output indicators pertain to the possible differential impacts of the peer and split payment schemes on actual peer farmer technology adoption – the number of SLMPs adopted, as well as (potential differences in) the types of technologies adopted. But our set of output indicators also include measures of the extent to which a lack of information is considered a barrier to adoption, such as the share of peer farmers mentioning lack of information as a reason for not having adopted specific SLMPs. The input indicators of communication effort include the frequency with which the peer and contact farmers met to discuss SLMP adoption, and the frequency with which the peer farmers asked their contact farmers for advice. But we also test for differences in the levels of SLMP adoption by the contact. The program did not allow for financial compensation to the contact farmers for their own SLMPs adoption. Offering contact farmers a financial stake in the adoption by their peer farmers may have induced them to increase verbal information dissemination efforts, but it may also have induced them to adopt more technologies themselves – as a teaching device (by turning their land into demonstration plots), or in an attempt of leading by example.

We find strong evidence that conditional payments increase peer farmer technology adoption in our cascade training program. Compared to the control group, offering financial compensation conditional on technology adoption results in increased technology adoption of 0.5 additional units. Offering financial payments obviously improves the cost-benefit ratio of SLMP adoption, but we also find that they increase the downstream demand for knowledge and expertise. More specifically we find that offering financial compensation for downstream adoption resulted in more frequent meetings between peer and contact farmers, in peer farmers' being more prone to reach out to their contact farmers to ask for advice, and in contact farmers being more likely to adopt SLMP technologies themselves too (even though in none of the three treatment groups they received compensation for their own rate of technology adoption). We also find that, at endline, "a lack of information" is mentioned less frequently as a barrier to adoption in the paid treatment arms than in the control group.

We thus find that offering financial compensation for downstream adoption results in an increased demand for contact farmers' knowledge and expertise, and we thus also observe that the supply of information is increased too – because of the reduced importance of a lack of information as a barrier to adoption. Interestingly, however, we find no statistically significant differences on neither any of the output nor on the input measures of communication, between the peer payment treatment arm and the split payment treatment arm. This is an interesting outcome as we find that if the downstream demand for information is sufficiently strong, supply will follow – independent of whether the supplier of information is rewarded directly for supplying information, or not. This result is reminiscent of the Coase theorem, which can be formulated in the current context as "given the surplus generated by transferring knowledge, the amount of information provision is independent of the initial allocation of the surplus".

We are not the first to explore how financial incentives affect information transmission in cascade training programs. BenYishay and Mobarak (2018) offer financial compensation to contact farmers dependent on their peer farmers' rate of adoption, and find that contact farmers disseminate their knowledge more actively and more of their peers adopt the promoted practices. Our 80-20 split payment scheme is similar to BenYishay and Mobarak (2018)'s treatment in this aspect. Our second treatment arm (in which peer farmers receive the full amount) sheds light on the question whether, for the same amount of surplus transferred, it is more efficient to stimulate downstream demand for information (by offering peer farmers the full payment), or to stimulate information supply (by giving contact farmers a direct stake in downstream adoption). Sseruyange and Bulte (2018) make use of a financial literacy cascade training program among farmers in Uganda, and vary whether or not contact farmers receive money depending on their peer farmers' test scores on a financial literacy test. Offering contact farmers money as a function of their peers' knowledge acquisition substantially improves peer farmers' test scores, but also those of the contact farmers themselves. Providing contact farmers with a direct stake in transferring information to peer farmers does not only increase their dissemination effort, but it also incentivizes them to pay more attention at the contact farmer training session. Shikuku *et al.* (2019) experiment with a private in-kind reward and social recognition as incentives for contact farmers to improve their knowledge and their dissemination effort about a set of SLM techniques. They find that the private incentive increased the information dissemination effort by contact farmers, but they also find that contact farmers themselves did not adopt them, and that peer farmers did not become more aware of SLMPs. However, they observe that social recognition increase all three measures. Improved knowledge of peer farmers still did not clearly lead to higher experimentation with the practices by peer farmers. Berg *et al.* (2017) show that financial incentives to contact farmers can foster knowledge transmission to those peers that are not socially close. We complement this line of research by testing whether, in the context of conditional adoption subsidies, rewarding contact farmers for peer farmer adoption increases information dissemination and/or technology uptake.

The remainder of this paper is organized as follows. Section 2 provides a brief description of the research context, and as well as the experimental design. Section 3 presents the empirical framework, and section 4 presents the results. Section 5 concludes the paper.

2 Program Description and Experimental Design

2.1 The Cascade Dissemination Program

Our study is embedded in a large scale environmental project implemented by the government of Burkina Faso, with financial support by the World Bank, the African Development Bank, and the Climate Investment Fund (CIF). One of the aims of this so-called

Forest Investment Program (FIP) is to reduce the dependence of rural communities on (the unsustainable) utilization of nearby forest areas. Forest conservation is threatened by agricultural encroachment on the forest fringe, resulting from an increased demand for land (Pouliot *et al.*, 2012). Population growth is one of the factors resulting in an increased demand for land; low and oftentimes decreasing productivity on existing agricultural lands is another (Goldstein and Udry, 2008; Etongo *et al.*, 2015). Productivity can be enhanced by implementing so-called Sustainable Land Management Practices (SLMPs), such as the use of specific types of inputs, or by taking measures aimed at reducing soil depletion and erosion (Liniger *et al.*, 2011a).

In cooperation with the FIP we identified nine of the most promising SLMPs, which were subsequently to be promoted in targeted areas throughout the country (see table 1). These practices span three agricultural domains: agronomy, agro-sylvo-pastoralism, and agro-forestry. The agronomy-oriented SLMPs focus on maintaining land productivity by conserving soil nutrients and retaining rainwater on farmers' plots. They include planting seeds in purposely prepared pits, constructing earth and/or stone bunds on plot perimeters, or building adequate structures for composting. The SLMPs in the agro-sylvo-pastoral domain consist of producing and storing fodder from residues of agricultural production, from forest residues or from direct cultivation of forage crop. These practices enhance the value of agricultural production and reduce the herding pressure on nearby lands. Finally, practices in agroforestry aim to improve soil and water management by conserving tree and shrub cover on agricultural plots, to improve nutrient recycling and to reduce soils' exposure to direct sunlight. All nine SLMPs are expected to improve short-term growing conditions as well as agricultural resilience to climate change, and are especially well-suited for low-input agriculture in arid countries (Liniger *et al.*, 2011b).

The intervention to promote these nine SLMPs was rolled out in 32 *communes* (municipalities) across 5 different regions. These regions are Boucle du Mouhoun, Centre Sud, Centre Ouest, Est and Sud-Ouest (see fig. 1), and were selected because they are among the FIP's target areas. The core of the intervention is a cascade training model that was implemented as follows (see fig. 2). In early June 2019, at the beginning of the growing season, ten so-called contact farmers were invited from each of the 32 communes to par-

[1] Or Integrated Crop and Livestock Management.

Table 1: Overview of SLMPs promoted by the FIP project

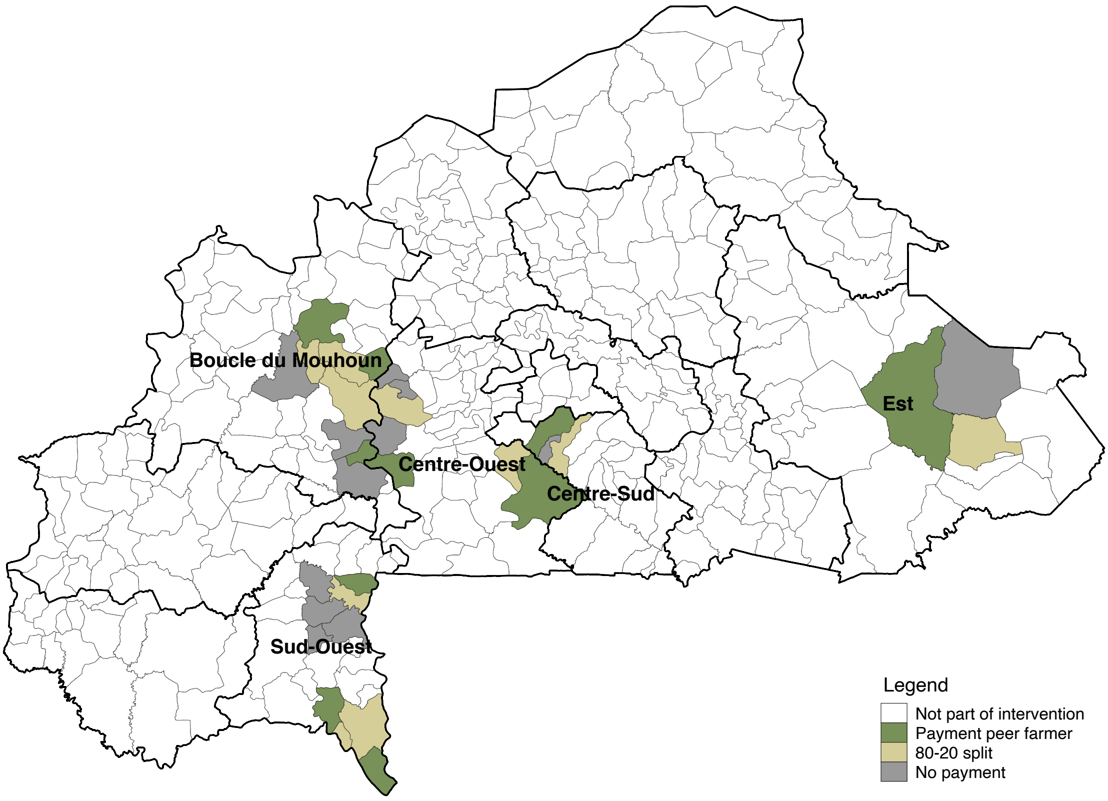
Group	**Practice**
Agronomy	Zaï (pit planting)
	Stone and earth bunds
	Heap and pit composting
Agro-sylvo-pastoral [1]	Mowing and conservation of natural fodder
	Forage crop cultivation
	Use of agricultural and wood by-products
Agroforestry	Controlled clearing
	Assisted natural regeneration
	Living hedges

ticipate in a four-day training in their respective commune organized by the Ministry of Agriculture and implemented by government extension workers on the nine key SLMPs described above.[2] The selection of the 320 contact farmers was done by the FIP project team. Those farmers had previously participated in activities organized by the FIP and were selected, based on their role and reputation within their village, to serve as entry points for the diffusion of the practices within their respective communities. Before the actual training, the contact farmers were informed of the general set-up of the intervention – that they themselves would receive training on nine SLMPs that are considered effective in raising agricultural yields in the long-run, and that they would be expected to actively transfer the knowledge and expertise they would acquire during the training to fellow farmers in their village. They were asked to provide the names of five "peer farmers" in their village who would be expected to be particularly interested in the usage and adoption of (some of) the SLMPs, and whom they would be willing to disseminate their acquired knowledge and expertise to (to help them implement the recommended practices). That means that, in each of the 32 communes there were 10 contact farmers and 50 peer farmers participating in the program.

The training of the contact farmers was set up as follows. On the first day, the contact farmers received information regarding the benefits of each of the nine SLMPs as well as necessary conditions that are required for each SLMP to be effective. The last three days of the training were dedicated to practical training of the nine SLMPs on demonstration

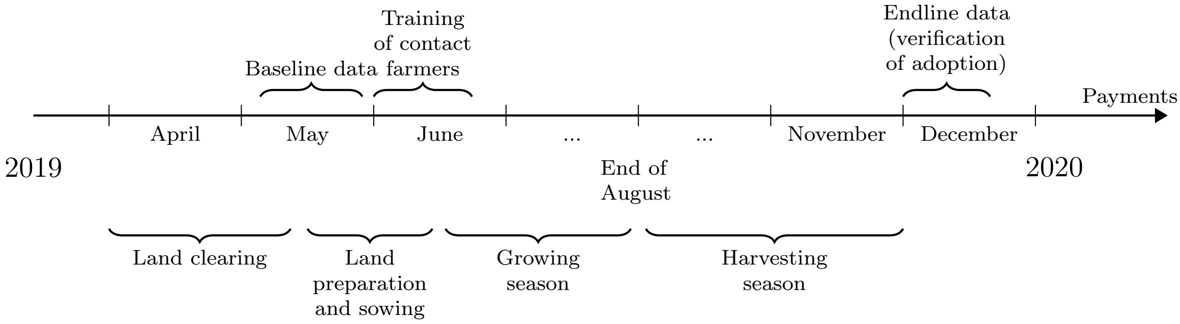
[2]In preparation to that, the extension workers themselves had received a refresher training in late April 2019 by experts of the FIP on the nine SLMPs.

Figure 1: Communes involved in SLMP promotion.



plots. At the end of the training, the contact farmers received SLMP implementation kits containing agricultural equipment (including a wheelbarrow, a pickaxe, a shovel, a fork, and a bundler) as well as inputs (like seeds and plants). These tools were distributed to the contact farmers by the project team to facilitate their own adoption of SLMPs, but they were also intended to be used to help fellow commune members, the peer farmers, to also adopt and implement SLMPs. Moreover, each contact farmer was also provided with a knowledge refresher and dissemination kit, which included a cheat sheet summarizing all important information on the benefits and implementation of each of the nine SLMPs. To evaluate the effectiveness of the training and quantify the learning amongst contact farmers, we administered a test at the beginning and the end of the training on the content that was taught during the training. After the training, all 320 contact farmers were sent back to the their villages. Before they left, however, the government extension workers emphasized, once more, the importance of disseminating the newly acquired knowledge and expertise to their fellow community members. They were explicitly told the project team would visit them as well as their five peers, at the end of the agricultural season, to evaluate the outcomes of the dissemination and SLMP adoption process.

Figure 2: Timeline of data-collection and program enrollment.



2.2 Experimental Design

Our RCT consisted of two treatment arms, and hence three treatment groups (including a control group). The implementation of the cascade training and dissemination program, as described in the previous section, was identical for all three treatment groups. The two treatment arms differ from the control group in whether or not financial compensation was offered conditional on the number of SLMPs adopted by peer farmers at endline. Farmers in the control group did not receive any payments. The total amount of money to be disbursed in the treatment groups was a function of the number of SLMPs present, at endline, on each peer farmer's land (as verified by independent SLMP adoption verification teams); the payment scheme is presented in table 2. The two treatments differed from each other in how the total payment was split. In one treatment arm the relevant amount was disbursed, in full, to the peer farmer, whereas in the other treatment arm the amount was split, 80-20, between the peer farmer and her contact farmer. We will refer to these two treatment arms as, respectively, the "peer payment" treatment and the "payment 80-20 split" treatment.

Table 2: The total amount of money disbursed as a function of the number of SLMPs present on a peer farmer's land.

# of SLMPs adopted	Payment	
0	0 FCFA	
1-3	30,000 FCFA	(≈ \$ 50)
4-6	40,000 FCFA	(≈ \$ 68)
7-9	50,000 FCFA	(≈ \$ 85)

Before discussing the assignment into the treatments in more detail, three remarks are in order regarding the payment scheme presented in table 2. First, the amounts of money offered, are sizeable. Depending on the number of SLMPs present at endline, payments are equivalent to 5-8% of the average total annual agricultural production of a farming household (≈ \$ 960 (WB, 2016, p. 52)) or 40-70% of annual per capital food consumption (≈ \$ 120 (WB, 2016, p 29.)). Therefore these payments constitute considerable amounts of money for farmers in Burkina Faso.

Second, payments are conditional on the number of SLMPs present on a peer farmer's land at endline – those SLMPs that have newly been adopted during the agricultural season, as well as those that had been adopted prior to the start of the project. This rule was imposed by the FIP, because it considered that imposing additionality was unfair vis-a-vis the farmers who already adopted SLMPs prior to the start of the intervention.

Third, the bracket payments have been set such that the average payment per SLMP is decreasing in the cumulative number adopted. Absent fixed setup costs, one would expect the marginal costs of adopting SLMPs would increase. When considering which of the remaining SLMPs to adopt, the farmer is expected to order them from lowest to highest, and then to choose the cut-off technology that maximizes her net revenues of technology adoption. However, fixed set-up costs are likely to be present too, as it requires spending time and effort on acquiring information on the range of available technologies. These fixed costs can be substantial (Liniger *et al.*, 2011a; Giger *et al.*, 2018). While the cascade dissemination scheme is intended to reduce these costs, they are unlikely to be zero. We therefore decided to provide slightly stronger incentives for the first technology bracket than for the second and the third. Note that, dependent on whether or not there are non-negligible fixed set-up costs, the choice of the compensation function affects the incentives to adopt, but it does not affect the internal validity of our RCT.

Randomization was implemented at the level of communes, stratified by region. While randomization at the village level would have increased our RCT's statistical power, we were unable to do so because of fairness and implementation issues. Government extension services are organized at the commune level, and hence within-commune randomization faces the risk of incorrect treatment implementation (with extension workers servicing different villages within their commune inadvertently diffusing information about the differential treatment of peer and contact farmers between villages). While randomization at the commune level is costly in terms of power, it has the advantage of a lower likelihood of treatment spillovers – thus making it more likely that the SUTVA assumption is met. Of the 32 communes, we decided to assign 10 to each of the two treatment groups, and 12 to the control group.[3] Contact farmers in the two treatment arms were asked to communicate the presence of the financial incentive and to hand to their peers a pre-printed notification that contains the name of the peer, the village name, and the details of the financial incentive.[4]

2.3 Hypotheses

Our experimental design allows us to estimate two effects. First, it allows us to estimate the impact of offering financial compensation on SLMP adoption. Second, because we vary how the payment, conditional on peer farmer adoption, is split (everything for the peer farmer, or an 80-20 split between the peer and the contact farmer) affects the dissemination of information, and hence, possibly also the number of SLMPs adopted.

The neoclassical predictions are straightforward. First, the usage of SLMPs is expected to be beneficial for the farmer adopting them, but their adoption may be less than perfect because of incomplete knowledge about the practice or (perceived) risks of implementing them (Karlan *et al.*, 2014). Offering farmers payments conditional on their adoption is thus

[3]Following List *et al.* (2011) and using z to denote the number of treatments (in addition to the control group), statistical power is maximized by assigning a share of $1/(z+\sqrt{z})$ of the available treatment units to each of the treatments, and hence a share of $\sqrt{z}/(z+\sqrt{z})$ of the available units to the control group. Intuitively, because the control group is used as a reference outcome for the test of the effectiveness of either treatment, the joint statistical power of the two treatment effects is maximized by (slightly) oversampling the control group. Because of indivisibilities we approximate this optimal allocation by assigning 10 treatment units to each of the treatment groups, and 12 to the control group.

[4]In our endline survey, enumerators also verified whether farmers still had these materials (tools for adoption from FIP and notifications) at hand or not. 98% of contact farmers could show the tools to the enumerator and 96% of contact farmers still had the notifications. As for the peer farmers, 89% of them had the notifications at endline. This rate was balanced across the treatment groups.

expected to increase take-up, as the conditional payments increase the cost-effectiveness of the SLMPs (Foster and Rosenzweig, 1995; Koundouri *et al.*, 2006). Second, offering peer farmers financial incentives to adopt SLMPs increases the benefits of adoption, and hence the demand of peer farmers for the knowledge and expertise of the contact farmer increases too (Conley and Udry, 2010; Dupas, 2014). Offering adoption payments to the peer farmers increases their willingness to pay for more detailed information on how to implement the SLMP technologies. In turn, the contact farmer faces financial incentives to actively provide the required knowledge and expertise (BenYishay and Mobarak, 2018; Sseruyange and Bulte, 2018). With undistorted markets for information, the contact farmer's incentives to share information is independent of the initial allocation of the budget (100% for the peer farmers, or 80% to the peer farmers and 20% for the contact farmers). Hence, the initial allocation of the payments will affect neither the SLMP adoption rates by the peer farmers, nor the knowledge transfer from the contact farmer to their peer farmer. The alternative hypothesis is that the market frictions affect the efficient transfer of information, and hence providing the contact farmer with a direct stake in SLPM adoption by the contact farmer is expected to result in higher actual adoption rates.

3 Empirical Framework

3.1 Identification strategy

We use the following reduced-form linear model to capture the impact of financial incentives on adoption of SLMPs, with pooled treatment groups:

$$y^1_{icr} = \alpha + \beta y^0_{icr} + \tau T_{cr} + \gamma' X_{icr} + \delta' W_{cr} + R_r + \epsilon_{icr}. \qquad (1)$$

Here, y^t_{icr} ($t \in \{0, 1\}$) is the value of the outcome variable of interest observed for farmer i, living in commune c in region r, at either baseline ($t = 0$) or endline ($t = 1$). Conditioning the regression on the lagged dependent variable typically results in more precise treatment estimates than standard difference-in-difference models (McKenzie, 2012).[5] The vector of

[5]This modelling approach is typically referred to as the ANCOVA specification. The key difference with standard dif-in-dif models is that in the latter β is restricted to be equal to 1, whereas in equation eq. (1) β can be estimated freely. The extent to which ANCOVA outperforms dif-in-dif thus depends on

baseline farmer level controls is captured by X_{icr} and includes the age, gender, education of the farmer, the number of adult household members, an index of household durable goods, the total size of agricultural area, the number of plots and the number of eroded plots managed by the farmer, the use of hired labour, non-agricultural household income, and the contact farmers' knowledge score after the training. The vector of baseline commune level controls, W_{cr}, includes the share of farmers in the commune who have any practices in place at baseline and its quadratic term. These term controls for strategic considerations in technology adoption (Bandiera and Rasul, 2006). A farmer might postpone her own adoption of practices if there are many other farmers experimenting and she can learn from others' experiences about the practices. On the other hand, she is more likely to adopt and learn from her own experience if few other farmers adopt them. Next, R_r is the strata (region) fixed effect, and ϵ_{icr} is an idiosyncratic error term, clustered at the level of randomization – the commune level (Abadie *et al.*, 2017).

Last but not least, T_{cr} is a dummy variable capturing the treatment status of the commune where farmer i resides in. We implement two types of analyses. The first and most important one is when we estimate the pooled impact of offering conditional adoption payments on the dependent variable of interest. In that case, T_{cr} in eq. (1) is a dummy variable that takes on value one if the commune a household resides in has been assigned to either of the treatment groups, and zero otherwise. In that case, τ captures the average intention-to-treatment impact of offering conditional payments. τ could also be a vector of coefficients capturing the effect of the full payment treatment and the split payment treatment relative to the control group. In this case, T_{cr} is a vector of two dummies. The first of them takes up the value of 1 when the commune is assigned to the full payment scheme and of 0 otherwise. Similarly, the second dummy indicates if the commune was assigned to the split payment treatment.

Even though our outcome variables of interest are predominantly non-negative integers (e.g. the number of SLMPs in place at endline) or binary variables (e.g., having adopted a specific SLMP, yes or no), we estimate eq. (1) using Ordinary Least Squares (OLS). We mainly do so for simplicity of interpretation. However, we also test the robustness of these results, by rerunning the key specifications using probit and negative binomial

whether the coefficient on the lagged dependent variable differs from 1.

models and reporting the results in the Appendix. Another benefit of the OLS estimator is that its results are comparable to those of the Seemingly Unrelated Regressions we will implement. We estimate eq. (1) separately for the adoption of individual SLMPs, but we also complement them with the estimation of the corresponding seemingly unrelated regression (SUR) model. This system of equations allows for correlation in the error terms across equations for the same individual, but not across individuals (Wooldridge, 2010). Indexing by s the individual SLMPs, this implies $\text{cov}(\epsilon_{icr,s_1}, \epsilon_{icr,s_2}) = \sigma_{s_1,S_2}$ for $s_1 \neq s_2$ or that there are unobserved factors for a given farmer which similarly influence the adoption decision of the SLMPs. Using SUR, we regard the adoption decision of the SLMPs as related decisions through unobserved factors and include more information in the estimation of the model.

3.2 Data and Descriptive Statistics

This study relies primarily on two rounds of household survey data collection: a baseline and one follow up. Figure 2 outlines the timeline of survey collections relative to the implementation of the interventions. We collected baseline information in May 2019 following the invitation of contact farmers to the training event and the nomination of peer farmers by their contact farmer, and before the training event. This baseline survey contains information on household socio-demographic characteristics, ownership of durable assets, agricultural production, social capital, and household head behavioral traits for both contact and peer farmers. During this survey, farmers had to indicate up to five plots where the adoption of the SLMPs would be verified at baseline.[6] We inspect the same five plots at endline to determine the payments for SLMPs adoption. This detail was explicitly announced to farmers at the time of contract signing. The five plots were also geo-referenced and their names and coordinates were also indicated on the notification for the farmer, which were handed out to the contact farmers at the end of their training. Overall, the baseline sample included 1914 farmers, 319 contact and 1595 peer farmers.[7]

Table 3 summarizes the results of the balance tests across the three treatment arms on

[6]During data collection at baseline, survey enumerators were accompanied by government extension workers who had training in the SLMPs and were able to identify the presence of the SLMPs on the plots.

[7]We were unable to reach and survey one contact farmer and the corresponding 5 peer farmers in the East region due to security concerns. With 10 contact farmers, each suggesting five peers, per commune, the sample size should have been 1600 peer and 320 contact farmers overall.

peer farmer household characteristics. On average, household heads in the sample are in their 40s, tend to be male, uneducated, living in poor housing conditions[8] and, on average, manage two plots. The pairwise t-tests show that farmers characteristics are generally balanced across the treatment groups. However, we do find some significant differences across treatment arms in the gender and the education of household head, as well as in the number and the total area of plots managed by the farmers. These imbalances are not caused by multiple hypothesis testing as the joint orthogonality test rejects that these differences are jointly zero. We include these characteristics as control variables in our treatment effect estimations as they are expected to influence the management of agricultural plots.

We also show differences between contact and peer farmers in table A3 in the Appendix. The table shows that similarly to leader farmers in BenYishay and Mobarak (2018) and contact farmers in Kondylis *et al.* (2017), our contact farmers are in a better position to understand the benefits of SLMPs. Contact farmers are, on average, older, more likely to be educated, wealthier, likely to have hired labor for agricultural production, own larger cultivable plots, and have experience with more SLMPs at baseline. This is consistent with the FIP's goal of selecting farmers who are more likely to be good transmitters of knowledge given their education and experience. When comparing balance of contact farmer characteristics across treatment arms (table A2 in the Appendix), we find significant differences along contact farmer gender, education, and housing quality. We control for the lack of balance of these characteristics in our regressions.

[8]This is a measure of whether the habitat of the household is deprived. That is, whether the floor, the wall or the roof is made of rudimentary materials. The variable proximates the level of poverty through housing.

Table 3: Baseline characteristics and balance tests for peer farmers

	(1) No payment		(2) Payment Peer Farmer		(3) Payment 80-20		(4) Total		T-test P-value			Normalized difference		
Variable	N/[Clusters]	Mean/SE	N/[Clusters]	Mean/SE	N/[Clusters]	Mean/SE	N/[Clusters]	Mean/SE	(1)-(2)	(1)-(3)	(2)-(3)	(1)-(2)	(1)-(3)	(2)-(3)
Age	600	42.382	500	40.542	495	41.002	1595	41.377	0.148	0.205	0.545	0.169	0.128	-0.042
	[12]	(0.978)	[10]	(0.837)	[10]	(0.397)	[32]	(0.477)						
Female respondent (0/1)	600	0.140	500	0.176	495	0.210	1595	0.173	0.301	0.053*	0.273	-0.099	-0.186	-0.086
	[12]	(0.036)	[10]	(0.025)	[10]	(0.031)	[32]	(0.018)						
Has some primary education (0/1)	600	0.298	500	0.320	495	0.234	1595	0.285	0.683	0.050**	0.031**	-0.047	0.144	0.191
	[12]	(0.033)	[10]	(0.033)	[10]	(0.022)	[32]	(0.018)						
Adults in houshold	600	12.217	500	11.084	495	11.679	1595	11.695	0.333	0.651	0.436	0.170	0.077	-0.092
	[12]	(1.012)	[10]	(0.817)	[10]	(0.766)	[32]	(0.508)						
Deprived house (0/1)	600	0.875	500	0.802	495	0.893	1595	0.858	0.258	0.721	0.178	0.200	-0.056	-0.253
	[12]	(0.042)	[10]	(0.065)	[10]	(0.053)	[32]	(0.030)						
Asset Index (PCA)	600	-0.058	500	-0.174	495	-0.191	1595	-0.136	0.479	0.470	0.962	0.052	0.058	0.008
	[12]	(0.362)	[10]	(0.388)	[10]	(0.484)	[32]	(0.229)						
Association membership (0/1)	600	0.635	500	0.614	495	0.727	1595	0.657	0.654	0.159	0.064*	0.043	-0.197	-0.241
	[12]	(0.071)	[10]	(0.063)	[10]	(0.046)	[32]	(0.036)						
Hired labor in previous agri. season (0/1)	600	0.595	500	0.550	495	0.475	1595	0.544	0.509	0.163	0.316	0.091	0.241	0.150
	[12]	(0.085)	[10]	(0.092)	[10]	(0.088)	[32]	(0.050)						
Number of plots under the control of the farmer	600	1.802	500	1.516	495	1.760	1595	1.699	0.051*	0.844	0.119	0.366	0.049	-0.297
	[12]	(0.109)	[10]	(0.104)	[10]	(0.130)	[32]	(0.068)						
Number of eroded plots	600	2.588	500	2.294	495	2.451	1595	2.453	0.191	0.549	0.485	0.211	0.097	-0.110
	[12]	(0.150)	[10]	(0.200)	[10]	(0.178)	[32]	(0.100)						
Landholdings (ha)	600	5.168	500	4.018	495	5.712	1595	4.976	0.014**	0.554	0.030**	0.269	-0.107	-0.396
	[12]	(0.540)	[10]	(0.254)	[10]	(0.942)	[32]	(0.374)						
Number of SLMPs adopted at baseline	600	2.367	500	2.234	495	2.444	1595	2.349	0.488	0.918	0.347	0.096	-0.056	-0.150
	[12]	(0.240)	[10]	(0.282)	[10]	(0.253)	[32]	(0.145)						
Contact farmer is family member (0/1)	599	0.474	500	0.400	495	0.412	1594	0.432	0.156	0.289	0.878	0.149	0.125	-0.025
	[12]	(0.030)	[10]	(0.046)	[10]	(0.066)	[32]	(0.027)						
Income from agricultural production (IHS transformed)	600	13.086	500	12.894	495	12.409	1595	12.815	0.269	0.347	0.553	0.092	0.227	0.158
	[12]	(0.155)	[10]	(0.175)	[10]	(0.896)	[32]	(0.284)						
Household has income from non-agricultural activities (0/1)	600	0.538	500	0.494	495	0.519	1595	0.518	0.229	0.739	0.733	0.089	0.038	-0.050
	[12]	(0.036)	[10]	(0.041)	[10]	(0.068)	[32]	(0.027)						
F-test of joint significance (p-value)									0.079*	0.000***	0.000***			
F-test, number of observations									1099	1094	995			

Notes: *Notes*:The value displayed for t-tests are the differences in the means across the groups. Standard errors are clustered at commune level and fixed effects are included at region level in all estimation regressions. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Following the baseline survey, contact farmers were trained by government extension agents in the first two weeks of June 2019. At this stage, farmers in the region had begun land clearing or even land preparation for the following main agricultural season. Before and after the training session, we measured the knowledge of contact farmers on the three groups of SLMPs. Since treatment status was announced after the test, our measure of their knowledge is not affected by the treatment.

The endline survey was administered seven months after the baseline, in December 2019, after the harvest season. Overall, 99.3% of the baseline households were surveyed again in this round (see table A5 in the Appendix) which implies that potential bias from systemic attrition is negligible. The survey contained similar modules as the baseline.

Our main outcome variables from the endline survey capture SLMP adoption and the extent to which contact and peer farmers communicated. To measure SLMP adoption, we count the number of practices that enumerators could verify at least on plot of the farmer. We capture interactions between contact and peer farmers by asking how frequently they had met to discuss the SLMPs, how frequently the contact farmers had verified if SLMPs were correctly adopted on the plot of the peers, and how often peer farmers had asked their contact farmers for advice on the practices. These answers were transformed into binary variables that indicate if the frequency was at least once per month or not.

4 Results

4.1 Can Money Buy Sustainable Farming?

We start our discussion by addressing the central question of this study – whether the financial incentives and their structure have accelerated the adoption of SLMPs by peer farmers. This reflects the role of financial incentives in increasing the benefits of downstream practice adoption. Column 1 of table 4 estimates the treatment effects on the number of SLMPs when we pool peer farmers in the two treatment groups with financial incentives ("payment peer farmer" and "payment 80-20 split") and compare them to peer farmers in the control group. The estimated effect is positive and significant at the 5% level. It indicates that offering financial payments overall increases the number of SLMPs adopted by 0.51 – an effect size of 0.29 standard deviations relative to the control. These results, however, do not differentiate between the two treatment arms in our study.

Column 3 of table 4 breaks out the two treatment arms to investigate how each of the incentive structures performed. We observe a positive effect of offering the peers the full payment conditional on adopting or self-experimenting with the GDTs. The point estimate is comparable to those observed in column 1 and significant at the 5%level. The second treatment group, where the contact farmers receive 20 percent of the payments offered conditional on the adoption by the peer farmers also reports positive and meaningful coefficient sizes, though none of the coefficients is significant at conventional statistical levels.

Despite this, we cannot reject the null hypothesis that the estimated effect for the "payment peer farmer" and for the "payment 80-20 split" are statistically equal. This means the final adoption by peer farmers is not affected by how we structure the payment between contact and peer farmers. Following this results, we present our next set of evidence on the adoption decision of peer farmers with the "payment peer farmer" and "payment 80-20 split" groups pooled together.

Financial incentives increase the number of adopted practices on average, but do we observe more adoption by farmers who were close to the thresholds of the non-linear payment schemes at baseline? We study this question in column 2 of table 4 where we interact the binary treatment indicator with the number of practices adopted at baseline. The estimated interactions show that farmers who adopted at least one, but not many practices are the ones who decide to adopt more SLMPs in response to the payments. This suggests that farmers with low but positive baseline practice adoption tried to capitalize on their baseline experience with SLMPs and were more willing to adopt new practices to reach the next payment bracket (from \$ 50 to \$ 68). On average, those with two or three practices at baseline successfully adopt close to one SLMP more than those with zero baseline SLMP, over the agricultural season. We do not observe significant adoption of additional technologies for farmers with a high number of SLMPs adopted at baseline potentially because of increasing marginal costs of doing so. Surprisingly, we also do not observe a significant response to the payments incentives from farmers who were not adopting any of the SLMPs promoted at baseline and whose marginal increase in payments from adopting a new practice would be the highest (\$ 50).

We have seen that the financial incentives induced more adoption of SLMPs by the peer farmers with few baseline practices adopted, and the next natural question is whether these farmers focused on a particular set of practices, for instance practices with the least cost to adopt. We answer this question by estimating if the financial incentives affected the adoption decision of individual SLMPs. Table 5 shows the seemingly unrelated regressions estimation results of the effects of the payments incentives on the likelihood of adopting each practice. The results suggest that the increase in overall adoption is not driven by a small group of practices as estimates show positive and significant treatment effects for almost all practices, except for the use of agricultural and wood by-products as fodder and controlled clearing of agricultural plots. We even observe positive and significant effects on the adoption of agronomic practices, which are perceived as labor intensive, and on the adoption of assisted natural regeneration and living hedges, which require investments in protecting existing trees and in planting shrubs (Liniger *et al.*, 2011a). The point estimates range from 3 to 15 percentage points increase in adoption rates as a result of the payment incentives. These results suggest that farmers possibly adopted the practices that they deemed beneficial for them as the growing conditions are heterogeneous across farmers. In addition, farmers do not seem to trade-off the adoption of agronomy and agroforestry practices in favor of others. The only SLMP for which we see a negative treatment effect is the use of agricultural and wood by-products as fodder. To the extent that increased natural fodder and forage crops provide enough forage to feed livestock, this may reflect a shift within integrated crop and livestock management practices.

Table 4: Treatment effects on the number of Sustainable Land Management Practices (SLMPs) adopted at endline for peer farmers

	# of SLMPs adopted at endline		
	(1)	(2)	(3)
Payment	0.515**	-0.151	
	(0.233)	(0.342)	
Payment peer farmer			0.556**
			(0.263)
Payment 80-20			0.466
			(0.300)
Heterogeneity Baseline SLMPs			
Payment × One SLMP		0.458**	
		(0.218)	
Payment × Two SLMP		0.959**	
		(0.362)	
Payment × Three SLMP		0.910**	
		(0.419)	
Payment × Four SLMP		0.596	
		(0.431)	
Payment × Five SLMP		-0.056	
		(0.475)	
Payment × Six SLMP		1.413	
		(1.068)	
Payment × Seven SLMP		0.045	
		(1.111)	
Constant	-5.766**	-4.845*	-6.101**
	(2.739)	(2.838)	(2.975)
Observations	1564	1564	1564
R^2	0.335	0.343	0.335
p(Treat1=Treat2)			0.78
Observations	1564	1564	1564
Baseline outcome	Yes	Yes	Yes
Covariates included	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes
Control mean	2.97	2.97	2.97
Control standard deviation			

Standard errors in parentheses
We cluster standard errors at commune level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Treatment effects for each SLMP - Seemingly unrelated regression

	Agronomy SLMPs			Int. Crop & Livestock Manag. SLMPs			Agroforestry SLMPs		
	Zai	Heap and pit composting	Stone and earth bounds	Mowing and conservation of natural fodder	Forage crop cultivation	Use of agricultural and wood by-products	Controlled clearing	Assisted natural regeneration	Living hedges
Payment	0.026**	0.080***	0.105***	0.131***	0.040***	-0.057**	-0.006	0.135***	0.085***
	(0.013)	(0.023)	(0.024)	(0.021)	(0.015)	(0.024)	(0.025)	(0.024)	(0.016)
Constant	-0.302	-0.505	-1.354***	-1.419***	-0.682***	0.198	0.100	-1.549***	-0.207
	(0.188)	(0.332)	(0.353)	(0.312)	(0.219)	(0.357)	(0.370)	(0.351)	(0.237)
Observations	1564	1564	1564	1564	1564	1564	1564	1564	1564
Baseline outcome included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p<0.10, ** p<0.05, *** p<0.01.
We cluster standard errors at commune level and control for region fixed effects.
As covariates we include the age of the respondent, indicators for whether the respondent is female, has some primary education, hired agricultural labor in the previous season.
In addition, we include the number of adults in the household, an asset index, the number of plots controlled by the farmer, the number of eroded plots, overall landholdings, the number SLMPs adopted at baseline, income from agricultural production (IHS transformed), and whether the household has any non-agricultural income.
Lastly, we control for the knowledge of SLMPs of the contact farmer at baseline.

4.2 Contact farmers' efforts to disseminate practices

Having established the impact of the payments at the third stage of the cascade training scheme, we next analyze the changes in the outcomes connected to the second stage. Recall that payments in both treatment groups depend on the adoption rate of the peer farmer and peer farmers get either the full payment or 80% in these groups, so that peer farmers are directly incentivized to increase their own adoption. Contact farmers have explicit financial stake in the adoption decision of their peers only in the "payment 80-20 split" group, but might also gain a stake in the decision of the peer in the "payment peer farmer" group if the contact and the peer farmer successfully negotiate a sharing of the payments amongst them. In such case, the contact farmer will have stronger incentive to transfer knowledge about the practices by having frequent meetings to discuss details of the practices and by implementing the practices on their own plots to demonstrate their implementation and to lead by example. We investigate these two forms of knowledge transfer activities by the contact farmers in this section.

First, we estimate the effect of financial incentives on the number of practices adopted by contact farmers in table 6. Column 1 and 2 repeat the estimates on peer farmers for comparison and column 3 and 4 present the estimates for contact farmers. The estimation results for contact farmers in panel A, where farmers in the "payment peer farmer" and "payment 80-20 split" group are pooled together, show that in communities where the payments incentives were introduced, contact farmers adopted more SLMPs than the control communities. This result mimic the findings on the peer farmers discussed in the previous section. On average contact farmers in the treatment group adopt 0.44 more SLMPs than those in the control group. This effect size corresponds to 11% of the mean or 25% of the standard deviation in the control group, and is significant at the 10% level.

When we estimate the treatment effects amongst contact farmers separately for the two treated groups in Panel B, the points estimates for the separate treatments, though estimated imprecisely, appear larger when payments are split than when payments are made only to the peer farmer. We cannot reject the null that the two treatment effects are equal, either. These results suggest that offering payments to peers led to more experimentation with the promoted technologies by contact farmers themselves. However, we fail to conclude that offering direct financial stake to contact farmers in their peers' adoption decision leads to statistically more experimentation by the contacts than when only peer farmers are entitled to the payments.

In order to better understand how the financial incentives led to more adoption of SLMPs by both peer farmers and contact farmers, we investigate whether contact and peer farmers also communicated frequently about the practices. In table 7, we summarize the estimation results on various measures of communication between farmers. The outcome measures are all binary variables which indicate if farmers engaged in the particular information sharing activities more frequently than once per month. Column 1 shows that offering payments incentives led to 14 percentage points increase in the share of peer farmers who had frequent meetings with the contact farmer to talk about the practices, a 40 percent increase compared to the control group. When we break these results down by the two treatment groups (column 2), we observe similar magnitudes of effects for both treatments, also comparable to the effects measured when the two treatment groups are pooled. However the effects are not measured as precisely when we separate the two treatment groups. The coefficient on the "payment peer farmer" treatment is significant at 5% but We fail to reject the null hypothesis for the "payment 80-20 split" treatment.

In columns 3 and 4, we report the treatment effect results on the share of peer farmers who turned to their contact farmers for advice on the practices more than once per month. The results suggests that the payment incentives led to 11 percentage points increase in the likelihood of peer farmers asking their contact farmers for advice more than once per month, which corresponds to 31% of the mean or 22% of the standard deviation in the control group. Again, when the treatment is broken down in the two treatment groups, the measured affects are no longer significant at conventional levels.

We observe similar treatment effects on the likelihood of contact farmers frequently verifying SLMPs adoption in the plots of their peers. The results reported in columns 5 and 6 suggest that the overall payment incentives led to 11 percentage point increase in the likelihood of contact farmers verifying if peer farmers adopted the practices correctly on the cultivated plots more often than once per month. These results are consistent with the effects we observe on the other measures of dissemination effort. Estimating these effects separately for the "payment peer farmer" and "payment 80-20 split" groups again yields similar treatment effects, but neither of the coefficients on the two treatment is significant at conventional level. Furthermore, we cannot reject the null hypothesis that the treatment effects are statistically equal for the two treatment groups. This applies across all three indicators of communication efforts reported in this table.

More practices adopted by contact farmers and more exchange between contact and peer farmers in response to the financial incentives are important findings that complement those of BenYishay and Mobarak (2018). Although point estimates for the "payment peer farmer" were slightly smaller than those of the "payment 80-20 split" group and not statistically significant, they were always positive and large relative to the mean and standard deviation in the control group. In addition, they were not statistically different from the estimates of the other group in any case. This suggests that contact farmers increased their dissemination efforts in the "payment peer farmer" group even if they were not directly entitled to a payment for the peer farmers' adoption decision, an indication that peer farmers have likely provided a financial stake to the contact farmer in exchange for information. Namely, we find that contact farmers can be indirectly incentivized to disseminate by increasing peer farmers' willingness to pay for such information, not only directly as in BenYishay and Mobarak (2018).

4.3 Did more intensive dissemination improve knowledge?

Given that the financial incentives increased communication efforts from both the peers and the contact farmers, we expect that peer farmers gained more knowledge on the practices, and decided to adopt them. Although we did not administer a test on the practices during the endline data collection, we asked peer farmers why they did not implement specific SLMPs. Based on respondents' answers, we calculate the share of non-adopted practices for which "lack of knowledge" was indicated as the main reason. Since this variable represents the share among non-adopted practices, it does not capture that farmers in the treatment group adopt more practices and only reflects changes in the relative importance of non-adoption reasons. We estimate the treatment effects on this variable for peer farmers and report the results in table 8.

Result show that the share of non-adopted practices for which "lack of knowledge" was a binding constraint is smaller in the treatment groups. The point estimates are strongly consistent across specifications and they are statistically indistinguishable between treatment arms. The observed effect is a 10-12 percentage point reduction, a large effect relative to the corresponding share in control group (25%) and in terms of standardized effect size (0.4 standard deviation).

These results suggest that a key mechanism through which the payment incentives led to the increased adoption of SLMPs, in our cascade training scheme, is by increasing information exchange between contact farmers and their peers, which subsequently led to an increase in the peer farmers' stock of knowledge on the technologies.

Table 6: Treatment effects on the number of Sustainable Land Management Practices (SLMPs) adopted at endline by producer type

	# of SLMPs adopted	
	Peer farmers	**Contact farmers**
	(1)	(2)
	Panel A: Pooled treatment	
Payment	0.512**	0.436*
	(0.233)	(0.243)
Constant	-5.772**	-0.981
	(2.736)	(3.831)
	Panel B: Payment structure treatment	
Payment peer farmer	0.554**	0.367
	(0.263)	(0.293)
Payment 80-20	0.463	0.514
	(0.300)	(0.335)
Constant	-6.109**	-0.437
	(2.972)	(3.809)
p(Treat1=Treat2)	0.776	0.713
Observations	1564	313
Covariates included	Yes	Yes
Baseline outcome	Yes	Yes
Region fixed effects	Yes	Yes
Control mean	2.784	3.900
Control standard deviation	1.670	1.746

Notes: * p<0.10, ** p<0.05, *** p<0.01.
We cluster standard errors at commune level and control for region fixed effects. As covariates we include the age of the respondent, indicators for whether the respondent is female, has some primary education, hired agricultural labor in the previous season. In addition, we include the number of adults in the household, an asset index, the number of plots controlled by the farmer, the number of eroded plots, overall landholdings, the number SLMPs adopted at baseline, income from agricultural production (IHS transformed), and whether the household has any non-agricultural income. Lastly, we control for the knowledge of SLMPs of the contact farmer at baseline.

Table 7: Treatment effects on contact and peer farmers' communication about SLMPs.

	Farmers met to discuss SLMPs		**Peer farmer asked for advice**		**Contact farmer verified SLMP adoption**	
	(1)	(2)	(3)	(4)	(5)	(6)
Payment	0.139**		0.114*		0.112*	
	(0.063)		(0.063)		(0.064)	
Payment peer farmer		0.139**		0.098		0.101
		(0.064)		(0.064)		(0.072)
Payment 80-20		0.140		0.133		0.125
		(0.088)		(0.087)		(0.089)
Constant	-1.200	-1.196	-1.439	-1.310	-1.408*	-1.318
	(0.919)	(0.972)	(0.887)	(0.944)	(0.801)	(0.864)
Observations	1563	1563	1563	1563	1563	1563
Adjusted R^2	0.076	0.075	0.077	0.077	0.082	0.082
p(Treat1=Treat2)		0.989		0.686	.	0.804
Covariates included	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Control mean		0.408		0.356		0.336
Control standard deviation		0.492		0.479		0.473

Standard errors in parentheses
We cluster standard errors at commune level and control for region fixed effects.
As covariates we include the age of the respondent, indicators for whether the respondent is female, has some primary education, hired agricultural labor in the previous season.
In addition, we include the number of adults in the household, an asset index, the number of plots controlled by the farmer, the number of eroded plots, overall landholdings, the number SLMPs adopted at baseline, income from agricultural production (IHS transformed), and whether the household has any non-agricultural income.
Lastly, we control for the knowledge of SLMPs of the contact farmer at baseline.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Treatment effects on the share of non-adopted SLMPs with lack of knowledge as the main barrier to adoption

	% of Non-adopted SLMPs for which knowledge is the main barrier			
	(1)	(2)	(3)	(4)
Payment	-0.107**	-0.121***		
	(0.041)	(0.034)		
Payment peer farmer			-0.124***	-0.126***
			(0.042)	(0.041)
Payment 80-20			-0.090*	-0.114***
			(0.053)	(0.041)
Constant	0.289***	-0.353	0.292***	-0.308
	(0.042)	(0.585)	(0.042)	(0.614)
Observations	1583	1563	1583	1563
Adjusted R^2	0.105	0.137	0.107	0.136
p(Treat1=Treat2)			0.49	0.79
Covariates included	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Control mean				0.25
Control standard deviation				0.28

Standard errors in parentheses
We cluster standard errors at commune level and control for region fixed effects. As covariates we include the age of the respondent, indicators for whether the respondent is female, has some primary education, hired agricultural labor in the previous season. In addition, we include the number of adults in the household, an asset index, the number of plots controlled by the farmer, the number of eroded plots, overall landholdings, the number SLMPs adopted at baseline, income from agricultural production (IHS transformed), and whether the household has any non-agricultural income. Lastly, we control for the knowledge of SLMPs of the contact farmer at baseline.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

5 Conclusion

Adoption of sustainable agricultural practices in arid Sub-Saharan Africa is hindered by limited knowledge about the practices and by the low (perceived) private profitability. Cascade training programs, in which some farmers – the so-called contact farmers – are trained by government extension workers in the benefits and usage of new agricultural techniques and who are subsequently asked to disseminate their newly acquired knowledge and expertise among fellow – or peer – farmers in their local social network, have been developed to overcome the information barrier.

In this paper we argue that in the context of sustainable land management practices, aimed at conserving soils and water to reduce the need for new land clearing, conditional adoption payments can help overcome both the perceived lack of profitability barrier as well as the information barrier. Offering conditional compensation on downstream adoption is likely to improve the new technology's perceived cost-benefit ratio, as well as the transfer of the contact farmer's newly acquired knowledge and expertise to her peer farmers. Offering payments for downstream SLMP adoption increases the demand for knowledge and expertise, but it is an open question whether this will also translate in improved information transfer from the contact to the peer farmer.

In this paper we analyzed to what extent payments, conditional on downstream adoption, are effective in inducing increased SLMP adoption, and also in improving knowledge dissemination. In the context of a cascade training program We implemented a field experiment with three treatment groups. The contact farmers in the control group received the training, and were subsequently asked to disseminate the newly acquired knowledge to peer farmers in their network. Our two treatments consisted of offering financial compensation based on SLMP adoption by the peer farmers in these treatment groups. The two treatments only differed in the initial allocation of the payment. In the one treatment arm the peer farmer received the full amount whereas in the other treatment the payment was split, 80-20, between the peer and the contact farmer.

We find that peer farmers adopted significantly more practices when there is a financial incentive. Contact farmers also increased their dissemination effort and adopted more practices themselves, likely for demonstration purposes and to lead by example. We do not find that these effects depend on how the payment is structured between trained and peer farmers, suggesting that improved profitability and demand for more information are driving these findings.

The findings of the experiment provide important lessons for technology dissemination. BenYishay and Mobarak (2018), Sseruyange and Bulte (2018), and Shikuku *et al.* (2019) find that incentives are important to facilitate knowledge transfer by the trained farmer in a cascade training scheme, while we show that dissemination could also be improved due to increasing demand for information by peer farmers when they have a financial stake. Improving cost-benefit outcomes and transferring knowledge can be complementary goals in policies aimed at disseminating new technologies, which can both be achieved by a single financial incentive (similarly to Dupas (2014)). Also note that farmers have responded within one agricultural season to the incentives. Wider adoption and experimentation with the practices in the short-run can improve their long-run adoption to the extend that learning by doing provides important experiences for farmers to adopt the practices, to further improve the use of the practices, and to further disseminate these practices to non-adopters.

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A Appendix

Table A1: Differences across treatment groups (at baseline)

Variable	(1) No payment N/[Clusters]	(1) No payment Mean/SE	(2) Payment Peer Farmer N/[Clusters]	(2) Payment Peer Farmer Mean/SE	(3) Payment 80-20 N/[Clusters]	(3) Payment 80-20 Mean/SE	(4) Total N/[Clusters]	(4) Total Mean/SE	T-test P-value (1)-(2)	T-test P-value (1)-(3)	T-test P-value (2)-(3)	Normalized difference (1)-(2)	Normalized difference (1)-(3)	Normalized difference (2)-(3)
Age	720	42.844	600	41.208	594	41.902	1914	42.039	0.160	0.385	0.346	0.151	0.087	-0.063
	[12]	(0.887)	[10]	(0.770)	[10]	(0.462)	[32]	(0.440)						
Female respondent (0/1)	720	0.146	600	0.175	594	0.215	1914	0.177	0.375	0.046**	0.173	-0.080	-0.182	-0.102
	[12]	(0.033)	[10]	(0.025)	[10]	(0.028)	[32]	(0.017)						
Has some primary education (0/1)	720	0.324	600	0.357	594	0.256	1914	0.313	0.431	0.057*	0.013**	-0.070	0.149	0.218
	[12]	(0.032)	[10]	(0.031)	[10]	(0.027)	[32]	(0.019)						
Adults in houshold	720	12.460	600	11.312	594	11.928	1914	11.935	0.318	0.649	0.434	0.167	0.076	-0.092
	[12]	(0.973)	[10]	(0.817)	[10]	(0.788)	[32]	(0.501)						
Deprived house (0/1)	720	0.868	600	0.773	594	0.891	1914	0.845	0.163	0.677	0.105	0.249	-0.069	-0.313
	[12]	(0.045)	[10]	(0.068)	[10]	(0.056)	[32]	(0.032)						
Asset Index (PCA)	720	0.083	600	-0.024	594	-0.077	1914	-0.000	0.490	0.419	0.868	0.049	0.069	0.023
	[12]	(0.342)	[10]	(0.382)	[10]	(0.456)	[32]	(0.219)						
Association membership (0/1)	720	0.662	600	0.657	594	0.749	1914	0.688	0.850	0.166	0.109	0.012	-0.189	-0.202
	[12]	(0.065)	[10]	(0.058)	[10]	(0.045)	[32]	(0.034)						
Hired labor in previous agri. season (0/1)	720	0.608	600	0.570	594	0.492	1914	0.560	0.588	0.182	0.306	0.078	0.235	0.157
	[12]	(0.086)	[10]	(0.091)	[10]	(0.088)	[32]	(0.050)						
Number of plots under the control of the farmer	720	1.843	600	1.565	594	1.798	1914	1.742	0.058*	0.841	0.136	0.338	0.051	-0.274
	[12]	(0.112)	[10]	(0.103)	[10]	(0.135)	[32]	(0.069)						
Number of eroded plots	720	2.665	600	2.352	594	2.522	1914	2.522	0.189	0.573	0.453	0.213	0.097	-0.116
	[12]	(0.163)	[10]	(0.207)	[10]	(0.191)	[32]	(0.106)						
Landholdings (ha)	720	5.362	600	4.382	594	5.997	1914	5.252	0.023**	0.489	0.041**	0.217	-0.122	-0.346
	[12]	(0.499)	[10]	(0.260)	[10]	(0.966)	[32]	(0.370)						
Number of SLMPs adopted at baseline	720	2.557	600	2.388	594	2.643	1914	2.531	0.427	0.874	0.290	0.115	-0.059	-0.170
	[12]	(0.233)	[10]	(0.293)	[10]	(0.261)	[32]	(0.147)						
Income from agricultural production (IHS transformed)	720	13.178	600	12.992	594	12.455	1914	12.895	0.249	0.333	0.520	0.093	0.243	0.176
	[12]	(0.150)	[10]	(0.153)	[10]	(0.921)	[32]	(0.290)						
Household has income from non-agricultural activities (0/1)	720	0.556	600	0.508	594	0.539	1914	0.536	0.128	0.776	0.684	0.095	0.034	-0.061
	[12]	(0.033)	[10]	(0.037)	[10]	(0.070)	[32]	(0.027)						
F-test of joint significance (p-value)									0.096*	0.000***	0.000***			
F-test, number of observations									1320	1314	1194			

Notes: *Notes*:The value displayed for t-tests are the differences in the means across the groups. Standard errors are clustered at commune level and fixed effects are included at region level in all estimation regressions. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table A2: Differences across treatment groups of contact farmers (at baseline)

	(1) No payment		(2) Payment Peer Farmer		(3) Payment 80-20		(4) Total			T-test P-value			Normalized difference	
Variable	N/[Clusters]	Mean/SE	N/[Clusters]	Mean/SE	N/[Clusters]	Mean/SE	N/[Clusters]	Mean/SE	(1)-(2)	(1)-(3)	(2)-(3)	(1)-(2)	(1)-(3)	(2)-(3)
Age	120	45.158	100	44.540	99	46.404	319	45.351	0.654	0.415	0.186	0.062	-0.124	-0.184
	[12]	(1.071)	[10]	(0.893)	[10]	(1.435)	[32]	(0.654)						
Female respondent (0/1)	120	0.175	100	0.170	99	0.242	319	0.194	0.929	0.107	0.094*	0.013	-0.166	-0.179
	[12]	(0.028)	[10]	(0.037)	[10]	(0.032)	[32]	(0.019)						
Has some primary education (0/1)	120	0.450	100	0.540	99	0.364	319	0.451	0.149	0.332	0.022**	-0.180	0.175	0.353
	[12]	(0.060)	[10]	(0.045)	[10]	(0.070)	[32]	(0.035)						
Adults in houshold	120	13.675	100	12.450	99	13.172	319	13.135	0.395	0.730	0.509	0.160	0.069	-0.096
	[12]	(1.038)	[10]	(0.933)	[10]	(0.989)	[32]	(0.566)						
Deprived house (0/1)	120	0.833	100	0.630	99	0.879	319	0.784	0.031**	0.545	0.017**	0.463	-0.128	-0.576
	[12]	(0.066)	[10]	(0.087)	[10]	(0.068)	[32]	(0.045)						
Asset Index (PCA)	120	0.788	100	0.725	99	0.496	319	0.678	0.672	0.313	0.477	0.032	0.140	0.108
	[12]	(0.289)	[10]	(0.394)	[10]	(0.361)	[32]	(0.194)						
Association membership (0/1)	120	0.800	100	0.870	99	0.859	319	0.840	0.330	0.405	0.863	-0.187	-0.154	0.033
	[12]	(0.055)	[10]	(0.056)	[10]	(0.053)	[32]	(0.031)						
Hired labor in previous agri. season (0/1)	120	0.675	100	0.670	99	0.576	319	0.643	0.998	0.330	0.308	0.011	0.205	0.194
	[12]	(0.096)	[10]	(0.090)	[10]	(0.092)	[32]	(0.053)						
Number of plots under the control of the farmer	120	2.050	100	1.810	99	1.990	319	1.956	0.215	0.844	0.337	0.247	0.063	-0.189
	[12]	(0.153)	[10]	(0.138)	[10]	(0.173)	[32]	(0.089)						
Number of eroded plots	120	3.050	100	2.640	99	2.879	319	2.868	0.272	0.700	0.389	0.230	0.102	-0.144
	[12]	(0.266)	[10]	(0.283)	[10]	(0.268)	[32]	(0.155)						
Landholdings (ha)	120	6.333	100	6.198	99	7.423	319	6.629	0.810	0.414	0.255	0.025	-0.196	-0.204
	[12]	(0.586)	[10]	(0.516)	[10]	(1.236)	[32]	(0.465)						
Number of SLMPs adopted at baseline	120	3.508	100	3.160	99	3.636	319	3.439	0.304	0.766	0.208	0.223	-0.087	-0.292
	[12]	(0.238)	[10]	(0.373)	[10]	(0.333)	[32]	(0.177)						
Income from agricultural production (IHS transformed)	120	13.640	100	13.483	99	12.684	319	13.294	0.436	0.285	0.406	0.107	0.322	0.270
	[12]	(0.188)	[10]	(0.150)	[10]	(1.045)	[32]	(0.332)						
Household has income from non-agricultural activities (0/1)	120	0.642	100	0.580	99	0.636	319	0.621	0.288	0.964	0.586	0.126	0.011	-0.115
	[12]	(0.047)	[10]	(0.053)	[10]	(0.091)	[32]	(0.036)						
F-test of joint significance (p-value)									0.000***	0.001***	0.000***			
F-test, number of observations									220	219	199			

Notes: *Notes*:The value displayed for t-tests are the differences in the means across the groups. Standard errors are clustered at commune level and fixed effects are included at region level in all estimation regressions. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table A3: Differences in contact and Peer farmers (at baseline)

	(1) Contact farmer		(2) Peer farmer		(3) Total		T-test P-value	Normalized difference
Variable	N/[Clusters]	Mean/SE	N/[Clusters]	Mean/SE	N/[Clusters]	Mean/SE	(1)-(2)	(1)-(2)
Age	319	45.351	1595	41.377	1914	42.039	0.000***	0.366
	[32]	(0.654)	[32]	(0.477)	[32]	(0.440)		
Female respondent (0/1)	319	0.194	1595	0.173	1914	0.177	0.216	0.056
	[32]	(0.019)	[32]	(0.018)	[32]	(0.017)		
Has some primary education (0/1)	319	0.451	1595	0.285	1914	0.313	0.000***	0.358
	[32]	(0.035)	[32]	(0.018)	[32]	(0.019)		
Adults in houshold	319	13.135	1595	11.695	1914	11.935	0.000***	0.209
	[32]	(0.566)	[32]	(0.508)	[32]	(0.501)		
Deprived house (0/1)	319	0.784	1595	0.858	1914	0.845	0.002***	-0.205
	[32]	(0.045)	[32]	(0.030)	[32]	(0.032)		
Asset Index (PCA)	319	0.678	1595	-0.136	1914	-0.000	0.000***	0.359
	[32]	(0.194)	[32]	(0.229)	[32]	(0.219)		
Association membership (0/1)	319	0.840	1595	0.657	1914	0.688	0.000***	0.395
	[32]	(0.031)	[32]	(0.036)	[32]	(0.034)		
Hired labor in previous agri. season (0/1)	319	0.643	1595	0.544	1914	0.560	0.000***	0.200
	[32]	(0.053)	[32]	(0.050)	[32]	(0.050)		
Number of plots under the control of the farmer	319	1.956	1595	1.699	1914	1.742	0.000***	0.302
	[32]	(0.089)	[32]	(0.068)	[32]	(0.069)		
Number of eroded plots	319	2.868	1595	2.453	1914	2.522	0.000***	0.281
	[32]	(0.155)	[32]	(0.100)	[32]	(0.106)		
Landholdings (ha)	319	6.629	1595	4.976	1914	5.252	0.000***	0.343
	[32]	(0.465)	[32]	(0.374)	[32]	(0.370)		
Number of SLMPs adopted at baseline	319	3.439	1595	2.349	1914	2.531	0.000***	0.738
	[32]	(0.177)	[32]	(0.145)	[32]	(0.147)		
Income from agricultural production (IHS transformed)	319	13.294	1595	12.815	1914	12.895	0.000***	0.177
	[32]	(0.332)	[32]	(0.284)	[32]	(0.290)		
Household has income from non-agricultural activities (0/1)	319	0.621	1595	0.518	1914	0.536	0.002***	0.205
	[32]	(0.036)	[32]	(0.027)	[32]	(0.027)		
F-test of joint significance (p-value)							0.000***	
F-test, number of observations							1914	

Notes: *Notes*:The value displayed for t-tests are the differences in the means across the groups. Standard errors are clustered at commune level and fixed effects are included at region level in all estimation regressions. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table A4: Knowledge of contact farmers of SLMPs (at baseline)

Variable	(1) No payment N	(1) No payment Mean/SE	(2) Payment Peer Farmer N	(2) Payment Peer Farmer Mean/SE	(3) Payment 80-20 N	(3) Payment 80-20 Mean/SE	(4) Total N	(4) Total Mean/SE	T-test Difference (1)-(2)	T-test Difference (1)-(3)	T-test Difference (2)-(3)	Normalized difference (1)-(2)	Normalized difference (1)-(3)	Normalized difference (2)-(3)
Agronomy (in percent)	120	0.912	99	0.914	98	0.893	317	0.907	-0.002	0.019	0.021*	-0.028	0.207	0.256
		(0.009)		(0.008)		(0.008)		(0.005)						
Integrated crop and livestock management (in percent)	120	0.748	99	0.718	98	0.732	317	0.734	0.030	0.016	-0.014	0.207	0.113	-0.097
		(0.013)		(0.015)		(0.015)		(0.008)						
Agroforestry (in percent)	120	0.655	99	0.668	98	0.665	317	0.662	-0.012	-0.009	0.003	-0.093	-0.072	0.021
		(0.010)		(0.015)		(0.015)		(0.008)						
Total score (in percent)	120	0.775	99	0.769	98	0.765	317	0.770	0.006	0.010	0.005	0.073	0.141	0.053
		(0.006)		(0.009)		(0.009)		(0.005)						

Notes: The value displayed for t-tests are the differences in the means across the groups.
***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table A5: Attrition rates across treatment arms

	(1) No payment		(2) Payment Peer Farmer		(3) Payment 80-20		(4) Total		T-test Difference			Normalized difference		
Variable	N	Mean/SE	N	Mean/SE	N	Mean/SE	N	Mean/SE	(1)-(2)	(1)-(3)	(2)-(3)	(1)-(2)	(1)-(3)	(2)-(3)
Attrited (0/1)	720	0.006	600	0.005	594	0.010	1914	0.007	0.001	-0.005	-0.005	0.008	-0.052	-0.059
		(0.003)		(0.003)		(0.004)		(0.002)						

Notes: The value displayed for t-tests are the differences in the means across the groups. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

Table A6: Treatment effects on SLMP adoption

	Agronomy SLMPs			Int. Crop & Livestock Manag. SLMPs			Agroforestry SLMPs		
	Zai	Heap and pit composting	Stone and earth bounds	Mowing and conservation of natural fodder	Forage crop cultivation	Use of agricultural and wood by-products	Controlled clearing	Assisted natural regeneration	Living hedges
Payment peer farmer	0.010	0.094***	0.098***	0.138***	0.110***	-0.106***	0.004	0.119***	0.085***
	(0.015)	(0.026)	(0.028)	(0.025)	(0.017)	(0.028)	(0.030)	(0.028)	(0.019)
Payment 80-20	0.043***	0.063**	0.115***	0.123***	-0.043**	0.001	-0.018	0.153***	0.086***
	(0.016)	(0.028)	(0.029)	(0.026)	(0.018)	(0.030)	(0.031)	(0.029)	(0.020)
Constant	-0.177	-0.566	-1.300***	-1.472***	-1.251***	0.596	0.020	-1.425***	-0.203
	(0.198)	(0.348)	(0.372)	(0.328)	(0.226)	(0.374)	(0.390)	(0.369)	(0.250)
Observations	1564	1564	1564	1564	1564	1564	1564	1564	1564
Baseline outcome included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p<0.10, ** p<0.05, *** p<0.01.
We cluster standard errors at commune level and control for region fixed effects.
As covariates we include the age of the respondent, indicators for whether the respondent is female, has some primary education, hired agricultural labor in the previous season.
In addition, we include the number of adults in the household, an asset index, the number of plots controlled by the farmer, the number of eroded plots, overall landholdings, the number SLMPs adopted at baseline, income from agricultural production (IHS transformed), and whether the household has any non-agricultural income.
Lastly, we control for the knowledge of SLMPs of the contact farmer at baseline.

Table A7: Negative binomial results with pooled treatment

	# of SLMPs adopted at endline	
	(1)	(2)
No payment	2.629***	2.568***
	(0.188)	(0.188)
Payment	3.042***	2.997***
	(0.213)	(0.161)
Observations	1584	1564
Covariates included	No	Yes
Baseline outcome	Yes	Yes
Region fixed effects	Yes	Yes

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

Table A8: Probit results with pooled treatment

	Agronomy SLMPs			Int. Crop & Livestock Manag. SLMPs			Agroforestry SLMPs		
	Zai (1)	Heap and pit composting (2)	Stone and earth bounds (3)	Mowing and conservation of natural fodder (4)	Forage crop cultivation (5)	Use of agricultural and wood by-products (6)	Controlled clearing (7)	Assisted natural regeneration (8)	Living hedges (9)
Payment	0.028	0.077	0.097^{*}	0.132^{**}	0.032	-0.060	-0.005	0.126^{*}	0.085^{***}
	(0.027)	(0.052)	(0.057)	(0.054)	(0.049)	(0.061)	(0.102)	(0.067)	(0.021)
Observations	1564	1564	1564	1564	1564	1564	1564	1564	1564
Baseline outcome included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Covariates included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors in parentheses

We cluster standard errors at commune level and control for region fixed effects.

As covariates we include the age of the respondent, indicators for whether the respondent is female, has some primary education, hired agricultural labor in the previous season.

In addition, we include the number of adults in the household, an asset index, the number of plots controlled by the farmer, the number of eroded plots, overall landholdings, the number SLMPs adopted at baseline, income from agricultural production (IHS transformed), and whether the household has any non-agricultural income. Lastly, we control for the knowledge of SLMPs of the contact farmer at baseline.

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