The Role of Extension and Sustainable Soil Management in Smallholder Agriculture – Evidence from Ethiopia –

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Summary

Rising demand for agricultural commodities coupled with population growth, climate change, declining soil fertility, environmental degradation and rural poverty in the developing world call for strategies to sustainably intensify agricultural production. Sustainable intensification refers to increasing production from the same area of land while reducing its negative environmental consequences. Most of the adverse conditions are particularly prevalent in Sub-Saharan Africa (SSA), where rates of undernutrition are the highest worldwide, while agricultural productivity is still far below global averages. An important factor in explaining productivity deficits among smallholders in SSA is the slow adoption of new agricultural technologies. Recently, governments and international donors especially concentrate on the promotion of 'system technologies', i.e. packages of technologies that should be applied jointly due to synergistic effects. Yet, evidence shows that farmers delay in particular the uptake of system technologies, and tend to scatter practices across plots instead of combining them on the same plot. Hence, analyzing how to effectively enhance the adoption of technology packages is crucial, but still understudied. In addition, comprehensive studies on the plot- and household level effects of system technologies that use micro data from farmer surveys are still scarce when it comes to impacts beyond traditional outcomes, such as crop yields and income, but important to understand the consequences of adoption for farmers.

This dissertation addresses these gaps by studying the adoption and effects of 'Integrated Soil Fertility Management' (ISFM). ISFM is a system technology comprised of a set of site-specific soil fertility practices which should be applied in combination. Its core is the integrated use of organic and inorganic fertilizers with improved seeds. Practices should be adapted to local conditions, accompanied by a general improvement of agronomic techniques and, depending on the context, by other technologies such as crop rotation, agroforestry or reduced tillage. The general aim of ISFM is an improvement of the soil's fertility by replenishing its nutrient stocks and organic matter level. Enhanced soil fertility is likely to improve food security, incomes, and ultimately, livelihoods of the rural population depending on small-scale agriculture. In addition, healthier and more fertile soils can contribute to restoring and conserving natural resources by providing crucial ecosystem services, such as the storage of soil carbon, erosion control and the prevention of further deforestation. Thus, they can make an important contribution to the sustainable intensification of smallholder agricultural systems. However, ISFM commonly also goes along with increased demand for capital and labor, which often prevents smallholders from adopting it. In addition, ISFM is considered knowledge-intensive, as combining

several practices and adapting them to local conditions requires at least a basic understanding of biological processes.

Against this background, the dissertation addresses two broad research objectives: Firstly, to assess the role of 'farmer-to-farmer' and non-traditional forms of agricultural extension to enhance knowledge and adoption of ISFM as a pathway to sustainable intensification. And secondly, to assess the productivity and welfare implications of adopting ISFM practices at the plot and household level. The thesis comprises three essays. The first essay concentrates on knowledge and adoption of ISFM as a complex agricultural technology, while the second and third essay analyze the effects of ISFM at the plot, respectively household level. All three essays build on primary data collected among 2,382 farm households in the three Ethiopian regions Amhara, Oromia and Tigray. The research was carried out in cooperation with the 'Integrated Soil Fertility Management Project' (ISFM+ project) of the German Agency for International Cooperation (GIZ), launched in 2015 in 18 districts in the three highland regions.

The first essay focusses on the role of agricultural extension in the dissemination of ISFM. In recent decades, decentralized and participatory extension models have become dominant in SSA. In these 'famer-to-farmer' approaches, only a few 'model farmers' are trained directly by extension agents and should then train other farmers, often organized in groups. From there, information should trickle down to all other households in a community. Yet, evidence suggests that information diffusion is a complex process and does not automatically reach all farmers. On the contrary, knowledge is likely to be transmitted incompletely from model farmers to extension group members and from there to 'ordinary' farmers. This applies in particular to complex system technologies, where farmers have to learn about each individual practice as well as the necessity of applying them jointly. In this article, we assess the effects of a farmer-to-farmer extension model and an additional intervention in form of a video on farmers' knowledge and adoption of ISFM. We implemented a cluster randomized controlled trial, using 161 microwatersheds (mws) as primary units of randomization. 72 mws received the farmer-to-farmer extension treatment, with model farmers who maintain ISFM demonstration plots and train so-called 'farmer research and extension groups' as core elements. 36 out of these treatment mws received an additional video intervention, explaining the underlying reasons for adopting the ISFM package, and featuring documentaries on successful ISFM adoption. 89 mws did not receive any intervention and serve as control group. In each of the three groups, 15 households per mws were randomly selected to be included in the sample. Findings show that farmer-to-farmer extension, both alone and in combination with video, increases ISFM adoption, both of its individual components as well as their combined adoption on the same plot. Effects are stronger for farmers who are involved in group-based extension activities, but exist to a weaker extent also for farmers in the same communities who are not involved. On average, we find no significant additional effect of the video intervention on adoption. However, the video does show a significant additional effect for farmers in treatment mws who are not members of extension groups, in particular when it comes to the integrated use of the practices on the same plot. Further, while both farmer-to-farmer extension alone and in combination with the video induce gains in ISFM knowledge, effects are significantly stronger for the combined treatment. A causal mediation analysis reveals that increases in knowledge explain part of the treatment effects on adoption. Overall, these results suggest that farmer-to-farmer extension can effectively foster technology adoption; both among extension group members as well as among non-members residing in the same communities, probably a sign of information spillovers. Yet, for the non-members, providing complementary information via video seems a valuable method to counterbalance incomplete information diffusion and ultimately, foster the adoption of complex system technologies such as ISFM.

Essay two analyzes of the effects of different combinations of ISFM practices on land productivity, net crop value, labor demand, labor productivity and financial returns to unpaid labor at the plot level. To date, evidence on the profitability of ISFM in smallholder settings is scarce, in particular when it comes to labor investments. The study differs from previous research by looking into a broader range of outcome indicators, and into the effects of distinct combinations of inorganic fertilizer, organic fertilizer and improved seeds. We employ a multinomial endogenous switching model to account for endogeneity, and data from over 6,000 teff, wheat and maize plots. Results show that both partial and complete ISFM adoption lead to significant increases in land productivity and net crop value, in particular when improved seeds are used. On average, the largest effect on land productivity stems from adopting complete ISFM, i.e. improved varieties with inorganic fertilizer *and* organic fertilizer, followed by the combinations containing only one fertilizer type. Analyses for two different agroecological zones suggest that in moister regions, complementing improved varieties with inorganic fertilizer is most important, while in drier regions, enhancing it with organic fertilizer is crucial, most probably due to its water-retaining effect. Regarding net crop value, average effects of combining improved seeds with either one or both fertilizer types are similar, despite the larger effect of the complete package on land productivity; probably due to reduced input costs when only one of the two fertilizer types is used. Further, as expected, ISFM is related to higher labor demand, but also significantly increases labor productivity and financial returns to labor. Hence, despite the additional demand for labor and capital, results suggest that ISFM can be a profitable technology for smallholders, at least when assessed at the plot level.

The third essay complements the picture on ISFM effects by analyzing its impacts at the household level. This is important since additional demand for resources associated with a technology (package) may imply a reallocation of labor from one income-generating activity to another, leaving net effects for a household uncertain. Therefore, we study whether adopting ISFM on at least one teff, wheat or maize plot increases income obtained from these crops, as well as total household income and household labor demand, and whether ISFM adoption is related to the probability of pursuing other economic activities. In addition, we assess impacts on food security, measured by self-reported incidences of food deprivation. Further, the essay analyzes effects on children's education as indicator for longer-term welfare, assessed by the enrollment rate of children in primary school age, the average number of absent school days and average educational expenditure. On the one hand, additional labor requirements may increase the work burden for children, with possible negative effects for their education. On the other hand, if ISFM is related to income gains, it might also lead to additional investments in education. We apply the inverse probability weighting regression adjustment method to account for selection bias, with propensity score matching as robustness check, and account for dissimilar agroecological potential by running disaggregated analyses for moist and dry regions. Results show that ISFM adoption for main cereal crops is related to increased income per capita obtained from these crops in both agroecological zones. Effects sizes of a rather lax definition of ISFM – having used improved seeds in combination with at least either organic or inorganic fertilizer – and a stricter definition, which comprises both fertilizer types, are very similar. A reason for that might be the additional costs associated with using two instead of only one fertilizer type; or because the synergistic potential of their joint use does not materialize immediately. Yet, only in the moister regions, higher crop income seems to translate into higher household income per capita, while it does not in the dry region. This might be because the share of income from these crops in total household income is not important enough in the latter subsample. Yet, in the dry region, ISFM adoption for main cereals also leads to a lower probability of achieving income from other crops and off-farm activities, probably an effect of resource reallocation (in particular labor). Moreover, we find a food security-enhancing effect of ISFM only for the moister areas, but not for the dry region. In both subsamples, ISFM adoption is related to increased demand for household labor. Yet, despite the higher labor demand, we find no indication for increased school absenteeism or even reduced enrollment rates of children, and no effects on educational expenditure. By contrast, ISFM adoption is associated with higher primary school enrollment the moist agroecology. Hence, only for areas where ISFM adoption is related to gains in overall household income, we also find positive effects on other welfare indicators, such as food security and education. All in all, these results suggest that broader welfare effects of agricultural innovations have to be evaluated within the complex system of households' income diversification strategies.

Overall, this dissertation contributes to the state of research by drawing a more comprehensive picture of the effects of ISFM in resource-constrained and diversified smallholder systems, as well as of interventions to foster the adoption of ISFM, or system technologies in general. Firstly, results imply that farmer-to-farmer and other, not traditional forms of agricultural extension have the potential to increase knowledge and adoption of complex innovations. Yet, extension systems still have to overcome shortcomings and find ways to be more inclusive, probably by means of an effective and creative mix of interventions. And secondly, findings suggest that ISFM can be a profitable technology for farmers, but also requires more resources. When evaluating broader impacts of its adoption, it is important to account for heterogeneous conditions and contexts.

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List of acronyms

ACME	Average Causal Mediation Effect
ADE	Average Direct Effect
AME	Average Marginal Effect
ATET	Average Treatment Effect on the Treated
ATT	Average Treatment Effect on the Treated
C	Control group
DA	Development Agent
DAP	Di-Ammonium Phosphate
ETB	Ethiopian Birr
FREG	Farmer Research and Extension Group
FTC	Farmer Training Center
GIZ	German Agency for International Cooperation
HH	Household
IF	Inorganic Fertilizer
IPW	Inverse Probability Weighting
IPWRA	Inverse Probability Weighting Regression Adjustment
IS	Improved Seeds
ISFM	Integrated Soil Fertility Management
ISFM+ project	Integrated Soil Fertility Management Project of GIZ
ITT	Intent-to-treat Effect
K	Potassium
MESR	Multinomial Endogenous Switching Regression
MWS/mws	Microwatershed
N	Nitrogen
OF	Organic Fertilizer
OLS	Ordinary Least Squares
P	Phosphor
PSM	Propensity Score Matching
RA	Regression Adjustment
RCT	Randomized Controlled Trial
S	Sulfur
SDG	Sustainable Development Goals
SLMP	Sustainable Land Management Programme
SOM	Soil Organic Matter
SSA	Sub-Saharan Africa
T1	Treatment group 1
T2	Treatment group 2
TLU	Tropical Livestock Unit

1. General introduction

1.1 Background and research objectives

1.1.1 The need for a sustainable intensification of agriculture

The rising demand for agricultural commodities, coupled with an increasing global competition for land between food production and other economic activities, put an enormous pressure on food systems and the natural resource base. Agricultural expansion and related land use change are recognized as the most important drivers of land degradation as well as biodiversity loss, which has occurred at an unprecedented rate during the past 50 years (IPBES, 2019). Most likely, climate change will exacerbate this process by adversely affecting terrestrial ecosystems and further contributing to land degradation. At the same time, climate change is intensified itself by massive global land use change through the release of greenhouse gas emissions (IPCC, 2019). In addition to environmental sustainability, achieving stable food security remains a major global challenge. After decades of steady decrease, the prevalence of hunger has stagnated in recent years the at a level of around 11 percent of the global population being undernourished (FAO, 2019). The 'twin-challenge' of eradicating hunger while preserving and restoring the natural resource base is addressed in the framework of the Sustainable Development Goals (SDGs). Through SDG 2, the global community commits to "end hunger, achieve food security and […] promote sustainable agriculture" by 2030, while SDG 15 states to "protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests […] halt and reverse land degradation and halt biodiversity loss" (UN, 2015).

This 'twin-challenge' is particularly urgent in Sub-Saharan Africa (SSA), which is currently experiencing a rise in the prevalence of undernourishment, estimated to affect around 23 percent of the population (FAO, 2019). The region also faces the most rapid population growth, with its population projected to at least double by 2050 (UN, 2019). Currently, agricultural production growth cannot keep pace with these demographic trends. For example, the demand for cereals will approximately triple until the mid of this century, whereas present consumption levels already depend to a considerable extent on imports (Van Ittersum et al., 2016). Climate change is likely to put agricultural systems in SSA under additional strain. Though spatial effects are not entirely clear yet, most evidence suggests that increased climate variability and climate change will have particularly adverse effects in regions that are already prone to food insecurity, including large parts of SSA (Wheeler & von Braun, 2013).

In past decades, much of the agricultural production growth in SSA happened through an expansion in area, rather than an increase in productivity. Though progress can be noted in some areas within SSA, yields still lag substantially behind global averages, and also behind estimated averages for maximum attainable yields in a given region (FAO, 2020; Mueller et al., 2012). To a considerable extent, this ‘yield gap’ can be attributed to the slow adoption of agricultural innovations in SSA. Whereas in Asia and Latin America the development and use of improved technologies such as fertilizers, new crop varieties and irrigation has contributed to substantial productivity gains, Africa is lagging behind its ‘Green Revolution’. Recently, external input application is accelerating gradually, but use and intensities are generally still far below optimal levels (Sheahan & Barrett, 2017). An average farmer outside of SSA, for example, applies almost 15 times more fertilizer per hectare than the average SSA farmer (Vanlauwe et al., 2014).

Given the comparatively low rates of input use, farmers in SSA depend decisively on their soils and the nutrients provided by them. Some parts of SSA have favorable climate and soil conditions. Yet, for a long time, agricultural systems have been largely based on nutrient mining, resulting in a steady decline of nutrient stocks, soil carbon, and deteriorating soil health. An estimated 65% of SSA’s land area can be classified as degraded, i.e. characterized by physical, chemical and biological deterioration, including top soil erosion, compaction, loss of organic matter, salinization, acidification, and consequently, low soil fertility (Zingore et al., 2015). Soils are particularly nutrient-depleted in densely populated areas, where regeneration through fallow periods is not viable and nutrient recycling through organic and inorganic fertilizer application is insufficient (Vanlauwe et al., 2014; Zingore et al., 2015). Poor soil status is often closely intertwined with rural poverty via self-reinforcing negative feedback loops (Tittonell & Giller, 2013). Research shows that poverty prevents many smallholders from investing in an improvement of their soils’ fertility (Barrett & Bevis, 2015). As land and labor productivity decrease with deteriorating soils, rural dwellers typically try to cope with this by farming their land even more intensively, or making increased use of nearby natural resources, which further aggravates soil degradation and, over time, poverty (Barbier & Hochard, 2018).

Large parts of the scientific community agree that these intertwined challenges of environmental degradation, climate change, food insecurity and rural poverty need to be tackled conjointly by a sustainable intensification of agriculture. *Sustainable intensification* refers to increasing agricultural production on the same area of land, while at the same time, reducing its negative environmental impact (Godfray, 2010; Pretty et al., 2011). Accordingly, agricultural output growth should not happen by further expanding the agricultural area, but by increasing yields on underperforming lands – which are often managed by small-scale farmers in developing countries (Garnett et al., 2013; Mueller et al., 2012; Pretty, 2018; Tilman et al., 2011). However, the concept of sustainable intensification does not provide a 'one-size-fits-all' solution. It rather describes a goal, while recognizing that the means are context-, region- and time-specific. Acknowledging the large heterogeneity of smallholder types and conditions, there is also a multitude of pathways towards sustainable intensification, and most likely no technology or management system will be the best solution forever (Garnett et al., 2013; Pretty, 2018; Vanlauwe et al., 2014). Further, understanding the term 'sustainable' in its most commonly used sense, agricultural systems need to be viable from an environmental, economic, as well as a social perspective. Thus, apart from preserving land and natural resources, sustainable agriculture needs to provide economic benefits to farmers while being socially inclusive, i.e. acceptable and feasible for a large number of different smallholders.

1.1.2 Integrated Soil Fertility Management as means to sustainable intensification

Substantial evidence on yield gaps in SSA suggests that there is much potential to increase agricultural productivity by restoring degraded soils and replenishing nutrient stocks (Mueller et al., 2012; Sanchez et al., 2009; Tittonell & Giller, 2013; Vanlauwe et al., 2014). There is a general consensus that much higher levels of inorganic fertilizer are needed to catalyze sustainable intensification in SSA, as well enhanced use of plant genetic resources (Jayne et al., 2019). In this regard, two crucial elements of sustainable intensification are the increase of resource use efficiency and the substitution of technologies (Foley et al., 2011; Pretty, 2018). *Increasing efficiency* refers to making better use of on-farm resources and external inputs, thus, allowing less waste of valuable nutrients and escape of agrochemicals across farm boundaries. For example, efficiency gains can accrue from precise dosing and targeting of fertilizers, recycling on-farm organic resources, and from the simultaneous use of organic and inorganic nutrient sources due to synergistic effects. *Substitution* refers to the replacement of less suited technologies by improved ones. For instance, traditional seeds may be substituted by improved crop varieties that better convert nutrients into biomass, are more drought-tolerant and locally adapted to increase pest and disease tolerance. Another example are standard blanket fertilizers, which are increasingly replaced by inorganic fertilizers that address area-specific nutrient constraints in order to improve crop response (Pretty, 2018; Vanlauwe et al., 2015).

The 'Integrated Soil Fertility Management' (ISFM) approach subsumes these key elements of sustainable intensification (Jayne et al., 2019), and is increasingly promoted by governments and international donors across SSA. ISFM is a ‘system technology’ that aims at enhancing soil fertility and agricultural productivity through adequate nutrient and input management while maximizing their use efficiency. The core of this technology package is the integrated use of improved seeds with organic and inorganic fertilizers, adapted to local conditions (Vanlauwe et al., 2010). Depending on the local context, core ISFM technologies should be complemented by other practices such as cereal-legume intercropping, agroforestry, reduced tillage or lime application to correct soil acidity (Vanlauwe et al., 2015). And lastly, ISFM comprises a general improvement of agronomic techniques, such as timely weeding, line seeding or microdosing of fertilizers and other inputs.

Higher-yielding crop varieties are seen as main drivers of an ‘African Green Revolution’, because they can improve agricultural output per area and increase farmers’ resilience to shocks (Sanchez et al., 2009; Takahashi, Muraoka, et al., 2019). Yet, their potential can only be fully realized when matched with adequate soil management strategies and nutrient application (Sanchez, 2002). Organic and inorganic fertilizers comprise different compositions of nutrients and/or carbon and hence, address soil fertility constraints in a complementary manner. Further, the soil’s responsiveness to mineral fertilizers is often considerably inhibited by low levels of soil organic matter (SOM) and soil moisture (Marenya & Barrett, 2009; Place et al., 2003; Vanlauwe et al., 2010). Organic fertilizer provides additional nutrients, and can, over time, help to improve SOM levels and soil moisture, which both regulate the solubility and thus, the availability of added nutrients for crop uptake (Marenya & Barrett, 2009). Efficient use of inorganic fertilizers, in turn, enhances on-farm biomass production of both crops and residues, and consequently, the availability of organic materials for resource recycling (Vanlauwe et al., 2013).

Summing up, ISFM builds on a combination of methods from organic and conventional agriculture. Even though some proponents advocate for a pure organic approach as pathway towards truly sustainable agriculture, recent evidence suggests that it will probably be unable to raise food production sufficiently (Keating et al., 2013; Meemken & Qaim, 2018). Though organic has shown to be less polluting than conventional agriculture when measured per unit of land, this is not true when measured per unit of output due to lower average yields on a given area of land (Meemken & Qaim, 2018). Considering the imperative of not further expanding the agricultural frontier and the urgent need to enhance food security, a well-managed mix of organic farming practices and moderate levels of agrochemicals, as proposed by ISFM, seems the most viable approach towards a sustainable intensification of agriculture in SSA.

1.1.3 Enhancing the use of Integrated Soil Fertility Management

Against this background, a crucial question is how to enhance the use of ISFM among small-scale farmers. Two key points are identified in the literature. Firstly, adoption of technologies requires an *enabling environment*. In many parts of SSA, the increasing fragmentation of farms coupled with insecure land tenure makes investments in new technologies unattractive and unviable for farmers, while inadequate infrastructure impedes access to capital, seed and input markets. Hence, restructuring and strengthening infrastructure and institutions are indispensable to promote sustainable soil management practices (Foley et al., 2011; Jayne et al., 2019; Vanlauwe et al., 2014). Another decisive element with respect to an enabling environment is how knowledge and innovation systems need to be designed, which is especially relevant for relatively complex system technologies. Since ISFM is a flexible concept, it requires at least a basic understanding of biological processes, and the adaptation of practices to local agroecological conditions. In this regard, Pretty (2018) emphasizes the need for new 'knowledge economies' built on social capital, in which knowledge is best created and spread locally and collectively.

In recent decades, governments across SSA refocused on the agricultural sector, including substantial investments and a restructuring of extension systems (Berhane et al., 2018; Ragasa & Niu, 2017; Swanson, 2008). The core of extension is the transfer of agricultural knowledge to farmers. Yet, in the past, most extension systems in SSA showed limited success in spurring large-scale adoption of agricultural innovations. In fact, shortcomings like high bureaucratic burden, high financial costs and weak institutions often led to an undersupply of trainings, limited geographic coverage and the exclusion of marginalized farmers (Anderson & Feder, 2007). In many countries, extension now follows a more decentralized and participatory approach, involving farmers as active stakeholders in the technology innovation and transfer process rather than perceiving them as mere recipients. In these 'farmer-to-farmer' models, extension agents train only few 'model' or 'contact farmers' who pass on their knowledge to other farmers, often organized in groups, where technologies should be further developed and adapted to local needs in a participatory and experiential way. From there, information should eventually reach the broader rural population via information sharing (Swanson, 2008; Takahashi, Muraoka, et al., 2019). In line with the sustainable intensification paradigm, these developments often go along with a change from a pure output-growth to a more holistic perspective, promoting technologies that achieve productivity increases and sustainable use of natural resources at the same time (Swanson, 2008). In addition, extension systems increasingly incorporate non-traditional ways of spreading agricultural information, in particular via media and other information and communication technologies, such as mobile phones, radio programs or videos (Aker, 2011). This leads to the first overall research objective of this dissertation:

(1) To assess the potential of farmer-to-farmer and non-traditional forms of extension to enhance knowledge and adoption of ISFM as a pathway to sustainable intensification.

A second main determinant of adoption are the *incentives* farmers face. As Vanlauwe et al. (2014: 17) state, smallholders' engagement will ultimately be determined by the profitability of a technology package, while "its [environmental] sustainability will not necessarily be *their* immediate concern". This holds even more true considering that small-scale farmers are often present-biased, as poverty impedes investing in strategies that might only pay off in the longer run, or being overly concerned with environmental issues (Jayne et al., 2019). Farmers are probably more likely to adopt a technology package that offers (immediate) positive economic returns, including gains in productivity, profitability and overall welfare. In particular, system technologies such as ISFM typically go along with additional labor as well as capital input, so that farmers will likely adopt only if these additional investments pay off (Jayne et al., 2019). Consequently, the second broad research objective of this dissertation is:

(2) To assess the productivity and welfare implications of adopting ISFM practices at the plot and household level.

1.2 Research gaps and questions

1.2.1 Research objective 1

The first essay of this dissertation addresses the role of extension in fostering knowledge and adoption of complex agricultural technologies such as ISFM. A considerable body of literature concludes that providing training to farmers enhances their knowledge and adoption of technologies (e.g. De Brauw et al., 2018; Feder et al., 2004; Fisher et al., 2018; Godtland et al., 2004; Kondylis et al., 2017; Nakano et al., 2018; Ogutu et al., 2018; Takahashi, Mano, et al., 2019). Yet, evidence is less clear when it comes to diffusion to peers, a crucial determinant of success of farmer-to-farmer extension. While a series of studies finds positive effects of training some farmers on their neighbors' knowledge or behavior (Fisher et al., 2018; Nakano et al., 2018; Takahashi, Mano, et al., 2019), others suggest that neither knowledge (Feder et al., 2004; Rola et al., 2002; Tripp et al., 2005) nor technology diffusion (Kondylis et al., 2017; Van den Berg & Jiggins, 2007) to peers takes place. Niu and Ragasa (2018) observe that while knowledge transmission from extension agents to lead farmers and from there to other farmers occurs, important pieces of information get lost along the way due to selective attention of both communicators and recipients. Yet, other research suggests that incomplete information transmission can be counterbalanced by reminders of commonly neglected information (Hanna et al., 2014). Overall, the available evidence shows that farmer-to-farmer technology dissemination is a multifaceted process that does not occur automatically. It is reasonable to assume that this is particularly true in the case of system technologies, i.e. sets of technologies that should be used in combination, where farmers have to learn about each individual practice as well as the importance of applying them jointly. While there is an emerging strand of literature on farmer-to-farmer extension, studies do mostly not focus on the integrated uptake of system technologies, despite the high policy relevance. In addition, there is hardly any evidence on how incomplete information spillovers from extension beneficiaries to their neighbors can be counterbalanced by additional interventions. This leads to the first set of research questions of this thesis:

(1) Does farmer-to-farmer extension and an additional intervention in form of a video increase knowledge and adoption of ISFM?
(2) Do the interventions have differential effects on farmers who are actively involved in extension activities and non-involved farmers in the same communities?
(3) Do gains in ISFM knowledge increase its adoption?
(4) Which forms of knowledge are particularly relevant?

The first essay addresses these questions by means of a randomized controlled trial (RCT) and data from 2,382 farm households in the Ethiopian highlands. In addition to the experimental set-up, matching techniques and a causal mediation analysis are used to answer the research questions.

1.2.2 Research objective 2

The second and third essays focus on the effects of ISFM adoption at the plot and household level, respectively. There is a well-established body of literature on the plot- and household-level impacts of individual or combined uptake of a large variety of agricultural or natural resource management practices (e.g. Abro et al., 2017, 2018; Becerril & Abdulai, 2010; Di Falco et al., 2011; Jaleta et al., 2016; Kassie et al., 2010; Khonje et al., 2015, 2018; Manda et al., 2016; Noltze et al., 2013; Takahashi & Barrett, 2014; just to mention a few); some of which analyze technology combinations that can be classified as ISFM, such as intercropping, conservation tillage or improved seeds (Arslan et al., 2015; Kassie et al., 2015; Teklewold et al., 2013). However, relatively few studies using micro-level data look into the combined use of organic and inorganic fertilizers with improved seeds, the core ISFM technologies, and those that exist

(Adolwa et al., 2019; Wainaina et al., 2018) only estimate effects on productivity, crop or household income. Yet, as concluded in a recent review article by Takahashi, Muraoka, et al. (2019), more evidence on ISFM beyond these traditional yield and income effects is needed. This is particularly important since ISFM usually goes along with substantial investments of capital and labor for the purchase, preparation, transportation and application of inputs. Moreover, much of the evidence on the yield-enhancing effects of ISFM stems from well-managed trial fields rather than plots managed by 'regular' smallholders. Since ISFM is considered knowledge- and management-intensive, effects achieved by the latter might differ from those achieved under best agricultural practices on trial plots (Jayne et al., 2019). Hence, in order to draw a more comprehensive picture on the impacts of ISFM in resource-constrained smallholder systems, evidence on the profitability of additional resource investments is required. The second article of the thesis addresses this research gap with the following question:

(5) What are the plot-level effects of ISFM adoption on land productivity and net crop value, as well as on labor demand, labor productivity and financial returns to labor?

More precisely, the paper focusses on the effects of organic fertilizer, inorganic fertilizer, improved crop varieties and combinations thereof on 6,247 wheat, maize and teff[1] plots managed by 2,040 Ethiopian farm households. The study distinguishes between two different agroecological zones, and uses a multinomial endogenous switching model to tackle issues with self-selection.

Lastly, it is important to assess the broader implications of adopting a capital- and labor-intensive system technology at the household level. Since farm households commonly diversify their livelihoods between different agricultural and non-agricultural economic activities, adopting ISFM for some crops might imply reallocation effects of household resources (in particular labor), as suggested by Takahashi and Barrett (2014) for example. Hence, net implications for a household are not clear, even if ISFM goes along with productivity increases. For instance, household food security can be influenced by both farm and off-farm income (Babatunde & Qaim, 2010). Hence, while agricultural productivity gains associated with a technology can positively influence food security, this effect might be muted if technology adoption withdraws resources from other economic activities. Another issue of concern are possible effects on children's education, which are hardly addressed in studies on technology adoption (with the

[1] Teff is a small cereal grain (annual grass) originating from the Northern Ethiopian highlands. While it is hardly grown in other parts of the world, it presents a major staple in Ethiopian and Eritrean diets (Baye, 2010).

exception of Takahashi & Barrett, 2014). On the one hand, increased demand for household labor may increase children's work burden, with potential negative effects for their education. On the other hand, income gains may induce higher investments in human capital formation and thus, positive effects on children's education. In order to create more evidence on welfare effects at the household level related to ISFM, the third article of this dissertation focusses on the following:

(6) What are the effects of ISFM adoption on crop, household and off-farm income, as well as on food security, labor demand and children's education?

This essay uses data from 2,059 maize, wheat and teff growing households in two agroecological zones in Ethiopia, and distinguishes between a rather lax and a stricter definition of ISFM. The inverse probability weighting regression adjustment method is used, and propensity score matching as robustness check.

1.3 Study context

1.3.1 Agriculture in Ethiopia

The data used in this dissertation come from Ethiopia. With around 108 million inhabitants, Ethiopia has the second largest population in Africa, which continues to grow by 2.6% annually (CIA, 2020). Despite considerable economic growth of around 10% annually in recent years, one quarter of the population still lives below the national poverty line, while over 20% of the population are undernourished and 38% of children under age five suffer from stunting (FAO, 2020). Although services have recently surpassed agriculture in terms of GDP share, the sector remains of tremendous importance, accounting for over 35% of the country's GDP and being the major income source for around three fourths of the population (CIA, 2020). Three cereal crops – maize, wheat and teff – account for 56% of the country's cultivated area and present the main staples in rural diets (CSA, 2019). Despite the importance of the sector and substantial output growth in recent years, agricultural yields remain comparatively low, with average cereal yields below 2.5 tons per hectare, and are not at par with population growth (FAO, 2020).

Land degradation and reduced soil fertility are among the most serious problems to the Ethiopian agriculture. In 2007, 85% of the land in Ethiopia was classified as degraded to some degree (Gebreselassie et al., 2016). Among the major causes of soil degradation are the expansion of cultivated areas into marginal lands, excessive deforestation and inappropriate agricultural land use practices, such as burning of rangelands, overgrazing, improper crop rotations, insufficient fallow periods, intensive tillage or unbalanced use of mineral fertilizer

(Gebreselassie et al., 2016). As one of the consequences, many soils in Ethiopia lack key nutrients like nitrogen, phosphorus, potassium, sulfur and zinc, in addition to suffering from waterlogging, alkalinity or acidity (Haileslassie et al., 2004).

In order to restore degraded lands, combat low agricultural productivity and prevent further environmental deterioration, the Ethiopian government has implemented the ‘Sustainable Land Management Programme’ (SLMP) in cooperation with international donors across large parts of the country’s highland area (Schmidt & Tadesse, 2019). In the past three decades, the SLMP focused on the stabilization of hillsides through physical soil conservation measures at the watershed and landscape scales. Building on these achievements, the focus has recently shifted to an intensification of smallholder farming practices. With the 2017 Ethiopian ‘Soil Health and Fertility Improvement Strategy’, the promotion of ISFM has become a national policy to improve soil fertility and food security of a bulging population (MoANR, 2017).

These initiatives are accompanied by unprecedented investments in the agricultural extension system. Nowadays, Ethiopia counts with one of the largest public extension systems in Africa in terms of public budget share, and has the worldwide highest extension-agent-to-farmer ratio (Berhane et al., 2018). Further, the system has undergone a reorientation from a centralized ‘top-down’ towards a supposedly more inclusive ‘bottom-up’ model. This decentralized, participatory approach builds on model farmers and grassroots farmer groups as key elements for technology innovation and dissemination (ATA, 2014; Berhane et al., 2018).

1.3.2 The GIZ-ISFM+ project

Against this background, in 2015 the German Agency for International Cooperation (GIZ) launched the ‘Integrated Soil Fertility Management Project’ (ISFM+ project) in three Ethiopian highland regions: Amhara, Oromia and Tigray.[2] The project is executed under the ‘Soil Protection and Rehabilitation for Food Security’ program through the Special Initiative ‘One World – No Hunger’ of the German Federal Ministry of Economic Cooperation and Development (BMZ, 2015; GIZ & MoANR, 2015). The overarching goal of the ISFM+ project is to promote the wider use of ISFM practices to improve soil fertility and productivity; and consequently, to increase crop yields, in particular for the three main staples wheat, teff and maize. The ISFM+ project is a component of GIZ’s contribution to the SLMP[3] and only operates in districts (in

[2] Initially, the project was planned as a three-year program until the end of 2017. By now, it has been extended until the end of 2023 and operates in a fourth region, Southern Nations, Nationalities, and Peoples' Region (SNNPR).

[3] Beginning of 2018, the SLMP has been replaced by the successor project named ‘Sustainable Use of Rehabilitated Land for Economic Development’ (SURED).

Ethiopia called Woredas) where physical land rehabilitation measures have been successfully introduced (GIZ & MoANR, 2015). The project works in close cooperation with the Ethiopian Ministry for Agriculture and Natural Resources. One package of interventions concentrates on capacity building among government agricultural advisory staff. Eventually, these local experts are responsible for transmitting ISFM knowledge to farmers. The main target population of the project consists of small-scale farmers in the three regions, the vast majority of which grow staple crops for subsistence (GIZ, 2016; GIZ & MoANR, 2015).

In accordance with the national policy, model farmers present the cornerstone of the project's decentralized 'participatory learning and extension approach' for ISFM dissemination at the farm level. Model farmers are trained by public extension agents and maintain ISFM demonstration plots on their farms. Further, each model farmer is responsible for leading a so-called 'Farmer Research and Extension Group' (FREG) in his or her community as core entity to discuss and experiment with ISFM practices, and conducts field days to visit demonstration sites at least twice per harvest cycle (GIZ, 2016).[4] In addition, the project works with various local stakeholders to improve supply chains for necessary inputs in all project Woredas, e.g. for improved seeds, fertilizers or lime.

1.4 Study design and data

1.4.1 Research design and sampling

All essays of this thesis build on data from farmers in ISFM+ project Woredas. In order to pursue the first research objective, an RCT was implemented. The experimental set-up, sampling strategy and data collection were done in close cooperation with the ISFM+ project, as well as the University of Mannheim.

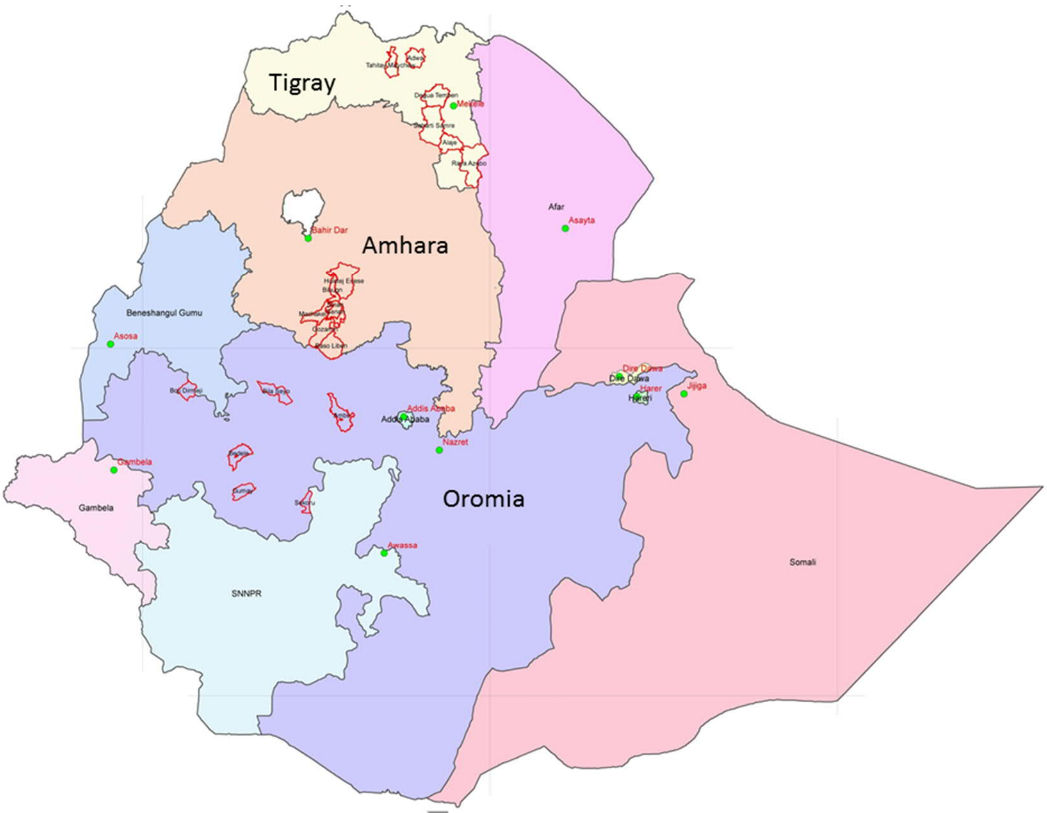
The primary units of randomization are microwatersheds (mws), which are typical implementation units of natural resource related projects in Ethiopia. These are natural topographic entities, which typically consist of an agglomeration of up to 300 households sharing a common rainwater outlet. Target mws were selected during planning workshops in the early phase of the project, based on the following criteria: (1) benefiting from the SLMP, (3) no/minimal previous exposure to soil fertility interventions, and (3) targeting six Woredas in each of the three regions Amhara, Oromia and Tigray. Out of a total sampling frame of 161 mws, 72 were randomly selected to benefit from the ISFM+ project (treatment mws), stratified by region and Woreda. Hence, in each of the three regions, six Woredas are targeted, and within each Woreda, four mws were randomly selected by means of a lottery. The remaining 89 serve as control mws and

[4] Further details on the project's interventions are presented in chapter 2.

are located in the same Woredas. In addition to the ISFM+ interventions, in early 2017, half of the 72 treatment mws were randomly chosen to receive a video treatment. The video treatment consisted of a one-time video screening conducted in public venues, which primarily featured information on *why* ISFM with all its components is important.[5] Summing up, the RCT contains 36 mws that only received the extension treatment, 36 mws that received the extension plus the additional video treatment, and 89 control mws.

The sampling frame for the farmer survey consisted of all households in the 161 mws, from which approximately 15 households per mws were randomly drawn from administrative lists. This resulted in a total sample of 2,416 households, of which 2,382 could be re-interviewed in the follow-up data collection and thus, constitute the base sample used in this dissertation. In addition, data on infrastructure, (extension) service provision and climate were gathered during key informant interviews at the Woreda and mws levels in 2018. Figure 1.1 shows the location of the study Woredas within the three regions (red framed areas).

Figure 1.1. Map of Ethiopia depicting the location of the 18 study Woredas within the three regions.



Source: GIZ-ISFM+ project Ethiopia.

[5] Further details on the video treatment are presented in chapter 2.

1.4.2 Data

Two rounds of data were collected among the sampled households. The first round was gathered in early 2016 as RCT baseline by researchers from the University of Mannheim. The second wave of data collection was led by the author of this dissertation among the same rural households in the first half of 2018. All three essays mainly use data from the second wave, and make use of baseline data as control variables (detailed descriptions in the respective chapters).

Data in both rounds were gathered using a structured questionnaire during tablet-based face-to-face interviews with household heads or their spouses. Prior to the data collection, an intensive ten-day enumerator training took place, with both a classroom and a field module. Questionnaire contents were thoroughly translated into the three local languages Amharic, Afaan Oromo and Tigrigna, and pretested in several rounds. Each of the 40 enumerators was a proficient speaker of at least one of the languages and assigned to the respective team. In each region, two survey teams collected the data, supervised by team leaders who reported to the local survey manager and the author as overall coordinators.

Both survey rounds contained modules on household socio-demographic characteristics, income and assets, subjective food security level, social relationships, farming practices and agricultural production data for the preceding cropping seasons (2015 in the baseline and 2017 in the follow-up survey), as well as exposure to agricultural extension. As far as possible, data were assessed in the same way during follow-up, although the mode of measurement was adapted for some variables. Moreover, the second-round-questionnaire added detailed modules on ISFM knowledge and participation in the interventions.

1.5 Thesis outline

The remainder of this thesis is organized as follows: Chapter two presents the first essay, which analyzes the effects of farmer-to-farmer and video-based extension on knowledge and adoption of ISFM using an experimental research design. Chapter three presents the second essay, focusing on the effects of different ISFM practices and their combinations on land productivity, net crop value and different labor outcomes at the plot level. Chapter four contains the third essay, which assesses the household-level effects of ISFM adoption on income, food security, labor and children's education. The last section summarizes the main findings, draws overall conclusions and puts them into the broader context of current debates on agricultural extension and technology adoption, and also highlights some limitations of the studies and scope for future research.

2. Knowledge and adoption of complex agricultural technologies – Evidence from an extension experiment[6]

Abstract

The slow adoption of new agricultural technologies is an important factor in explaining persistent productivity deficits and poverty among smallholders in Sub-Saharan Africa. Farmer-to-farmer extension models aim to diffuse technology information from extension agents to model farmers and farmer group members, and then further on to other community members. Yet, only few studies investigate how to design modalities for information transmission effectively, in particular for complex and knowledge-intensive technology packages. In this study we assess the effects of farmer-to-farmer extension and an additional video intervention on the adoption of 'Integrated Soil Fertility Management' (ISFM) among 2,382 small-scale farmers in Ethiopia using a randomized controlled trial. We find that both extension-only and extension combined with video induce ISFM adoption and gains in knowledge. While effects are stronger for active participants, we find evidence that information diffuses to community members not actively participating in the extension activities. The additional video intervention shows a significant complementary effect for these non-actively involved farmers, in particular when it comes to the *integrated* adoption of the full technology package.

Key words: Integrated Soil Fertility Management (ISFM), system technology, technology diffusion, farmer-to-farmer extension, selective attention, rural development

[6] This essay is co-authored by Adrien Bouguen (AB), Markus Frölich (MF) and Meike Wollni (MW). I, Denise Hörner (DH), developed and implemented the video intervention, collected the follow-up data in 2018, performed the analysis, interpreted results and wrote the paper. MW assisted at various stages of the research; MW and MF contributed to interpreting results, writing and revising the paper. MF and AB developed the original RCT research design in collaboration with the GIZ-ISFM+ project, did the initial sampling and collected the baseline data in 2016.

2.1 Introduction

The slow adoption of new agricultural technologies is an important factor in explaining persistent productivity deficits and poverty among the rural population in developing countries, especially in Sub-Saharan Africa (SSA). Lack of technological innovation and underinvestment in soils – an essential productive asset of smallholder farmers in SSA – is viewed as a major cause for self-reinforcing poverty traps in rural areas (Barrett & Bevis, 2015). Recent evidence shows that farmers delay in particular the uptake of integrated system technologies, i.e. packages of agricultural practices that should be jointly applied in order to deploy their full productivity-enhancing potential (Noltze et al., 2012; Sheahan & Barrett, 2017; Ward et al., 2018). Integrated system technologies are typically knowledge-intensive, as they require the understanding of at least basic underlying biological functions and processes and the adaptation of practices to local agri-environmental conditions (Jayne et al., 2019; Vanlauwe et al., 2015). While information and knowledge constraints are frequently cited barriers to the adoption of agricultural innovations in general (Aker, 2011; Foster & Rosenzweig, 1995; Magruder, 2018), they are likely to play a key role in explaining incomplete or non-adoption of complex system technologies (Takahashi, Muraoka, et al., 2019).

Agricultural extension services aim at transferring knowledge to farmers in order to bridge knowledge and capacity gaps. Previous literature has pointed out that extension systems in developing countries are frequently subject to a series of shortcomings, such as high bureaucratic burden, excessive costs of direct trainings, limited geographic coverage, and exclusion of marginalized, resource-poor households (Aker, 2011; Anderson & Feder, 2007). In recent decades, this has given rise to the introduction of decentralized approaches, especially in SSA, where extension agents train a small number of selected farmers (usually referred to as 'contact', 'lead' or 'model farmers') in the application of new techniques on their farms. These model farmers are then expected to pass their knowledge on to other farmers in the village, who are usually organized in groups to facilitate participatory and experiential learning processes. This goes along with a shift in perspective from a "top-down" to a more inclusive "bottom-up" strategy by involving farmers as active stakeholders in the technology transfer process and is often referred to as 'farmer-to-farmer extension' (Takahashi, Muraoka, et al., 2019). Eventually, exposure to on-farm demonstrations, trained model farmers and group members is supposed to spur broader adoption of technological innovations in the community (Gautam, 2000; Swanson, 2008), which is supported by a general recognition that farmers learn from each other (Foster & Rosenzweig, 1995; Krishnan & Patnam, 2014), and in particular from more progressive farmers (Maertens, 2017).

A growing body of literature has analyzed the effectiveness of decentralized extension models in facilitating innovation and knowledge diffusion. There is now substantial evidence that directly training selected farmers spurs knowledge and adoption among them (Davis et al., 2012; De Brauw et al., 2018; Feder et al., 2004; Fisher et al., 2018; Godtland et al., 2004; Kondylis et al., 2017; Nakano et al., 2018; Ogutu et al., 2018; Takahashi, Mano, et al., 2019), and some evidence that subsequent diffusion to other farmers takes place (Fisher et al., 2018; Nakano et al., 2018; Takahashi, Mano, et al., 2019). On the other hand, several studies conclude that knowledge gains among trained individuals hardly trickle down to neighboring farmers (Feder et al., 2004; Rola et al., 2002; Tripp et al., 2005), and that increased technology adoption among trained farmers does little to change the behavior of non-trained peers (Kondylis et al., 2017; Van den Berg & Jiggins, 2007). A relatively new strand of research focuses more explicitly on the determinants of diffusion processes in farmer-to-farmer extension set-ups. These studies find that successful diffusion is shaped by model farmers' motivation and familiarity with the technology (Fisher et al., 2018), incentives attached to information dissemination (BenYishay & Mobarak, 2019; Shikuku et al., 2019), the social distance between communicators and target farmers (BenYishay & Mobarak, 2019; Shikuku, 2019) as well as other context-specific forms of social capital prevalent in the communities (Pamuk et al., 2014). In addition, some studies suggest that farmers need to learn from multiple sources before they adopt (Beaman et al., 2018; Fisher et al., 2018).

Most of the above studies, however, focus on the adoption of (several) individual practices, while recent extension efforts in SSA increasingly concentrate on integrated system technologies (Takahashi, Muraoka, et al., 2019). In the case of knowledge-intensive system technologies, adoption and diffusion processes are likely to become even more complex, since knowledge on each individual practice as well as on the importance of applying them jointly needs to be transmitted. For the case of a complex technology, Niu and Ragasa (2018) document substantial information losses along the transmission chain from extension agents to farmers. They show that even though knowledge is transmitted, important dimensions get lost along the chain due to selective attention: given the mental costs associated with processing new information, individuals tend to neglect information that they consider less important. On the other hand, literature suggests that reminders of commonly neglected knowledge dimensions can help to offset teaching and learning failures (Hanna et al., 2014; Niu & Ragasa, 2018).

In the current study, we analyze the effects of farmer-to-farmer extension on knowledge and adoption of an integrated system technology using a randomized controlled trial. We expand the emerging body of experimental literature investigating information and technology diffusion in rural settings in developing countries in several ways. First, we focus on the integrated adoption of a complex system technology, rather than on the uptake of individual practices, an issue of increasing importance in rural SSA and largely understudied to date (Jayne et al., 2019; Sheahan & Barrett, 2017; Takahashi, Muraoka, et al., 2019). Secondly, we analyze the effectiveness of information spillovers as a key principle of farmer-to-farmer extension models. We do so by estimating differential effects for those who actively participate in the extension activities and those who at most benefit indirectly. Thirdly, we evaluate whether an additional intervention in form of a video can offset incomplete information diffusion likely to occur in farmer-to-farmer extension set-ups and thus, foster the wider adoption of an integrated system technology. The video intervention is intended to remind farmers of commonly neglected knowledge dimensions, in particular emphasizing the importance of the holistic concept of the system technology (joint application of practices), and additionally explains the underlying principles of the components. Finally, we explicitly focus on the role of different types of knowledge, including knowledge on the underlying principles, as potential drivers of adoption using a causal mediation analysis.

Our study is implemented in the context of a large-scale farmer-to-farmer extension program promoting 'Integrated Soil Fertility Management' (ISFM) in three rural regions of Ethiopia. ISFM is a knowledge-intensive system technology widely promoted in SSA as a strategy to sustainably intensify agricultural productivity (Jayne et al., 2019), enhance rural livelihoods and combat land degradation, caused by excessive deforestation and inappropriate agricultural land use practices, such as overgrazing, improper crop rotations, insufficient fallow periods or intensive tillage (Barrow, 1991). A fundamental feature of ISFM is the integrated use of improved seeds together with inorganic and organic soil amendments, in order to enhance both nutrient availability and the soil's capacity to absorb nutrients. In addition, ISFM aims at a general improvement of agronomic techniques adapted to local conditions (Place et al., 2003; Vanlauwe et al., 2010).

The remainder of this article is structured as follows: In the next section we provide an outline of the context and the conceptual model of our study. Subsequently, we describe the experimental design, empirical data and estimation strategy. In the results section, we first assess the impact of the interventions on ISFM adoption, before analyzing treatment effects on knowledge as potential impact pathway. The last chapter discusses implications of our findings and concludes.

2.2 Setting and conceptual framework

2.2.1 Study context

Our study is conducted in three Ethiopian highland regions; Amhara, Oromia, and Tigray. Agriculture presents the main income source for almost three-fourths of the Ethiopian population (CIA, 2020). Improving agricultural production on smallholder family farms is therefore considered an important pathway to improving rural livelihoods. Five cereals – teff[7], maize, wheat, barley and sorghum – are the most important staple food crops, both in terms of production and consumption (CSA, 2019; Taffesse et al., 2011). Despite the importance of the sector and substantial output growth in recent years, productivity remains comparatively low with average cereal yields below 2.5 metric tons per hectare (FAO, 2020). Land degradation and declining soil fertility are among the most serious problems for Ethiopian smallholder agriculture. In the past decade, the Ethiopian government has responded to these challenges with considerable investments in the extension system, estimated to around 2% of the agricultural GDP (Spielman et al., 2010). At the same time, rural advisory services have undergone substantial structural changes, away from a centralized top-down approach – typically only reaching few, rather resource-rich farmers – towards a more decentralized outreach program (Belay, 2003).

In mid-2015, the German Agency for International Cooperation (GIZ) launched the 'Integrated Soil Fertility Management Project' (ISFM+ project) in Amhara, Oromia and Tigray.[8] During the initial phase of the ISFM+ project from 2015 to 2018, the use of five so-called 'quickwin technologies' was promoted for all major cereal crops, since the combination of these practices is expected to boost yields within a relatively short period of time. The quickwin package consists of the following practices: *Compost*, prepared of crop residues or other plant materials and animal dung, is supposed to increase soil organic matter, thus improving nutrient supply, soil biota as well as water holding capacity. *Blended fertilizer* refers to inorganic fertilizers that are aligned to a specific location's soil type and therefore provide a balanced nutrient supply. It is commonly composed of nitrogen (N), phosphor (P), potassium (K), sulfur (S), zinc and boron and should replace the widely used standard fertilizer Di-ammonium phosphate (DAP). *Improved seeds* should increase biomass production of both grain and residues and are distributed to model farmers by the project for all major crop types. *Line seeding* is promoted to replace the common practice of broadcasting seeds. It reduces competition for space,

[7] Teff is a small cereal grain originating from the Northern Ethiopian highlands. While it is hardly grown in other parts of the world, it presents a major staple in Ethiopian and Eritrean diets (Baye, 2010).

[8] The ISFM+ project is a component of GIZ's contribution to the Ethiopian 'Sustainable Land Management Programme' (SLMP) and only operates in districts, where physical land rehabilitation measures (stabilization of hillsides, erosion control measures) have been successfully introduced by the SLMP. Beginning of 2018, the SLMP has been replaced by the successor program named 'Sustainable Use of Rehabilitated Land for Economic Development' (SURED).

nutrients and water among plants, and thus, leads to more vigorous crop growth. At the same time, line seeding allows to target inputs directly to the plants, and hence, reduce required amounts and enhance efficiency. *Lime* application is promoted in regions where soils suffer from acidity in order to normalize its pH value. In our research area, this applies to Amhara and Oromia, but not to Tigray.

Substantial positive impacts of ISFM on soil fertility and crop yields are well documented by studies using micro-level survey data (Adolwa et al., 2019), and in particular numerous experimental field trials (Agegnehu et al., 2016; Gnahoua et al., 2017; Nezomba et al., 2015; Vanlauwe et al., 2012). For the study regions Amhara and Oromia, results from 280 agricultural plots combining improved seeds, blended fertilizer, compost, line seeding and lime show average grain yield increases of 80% compared to fields managed with common farmers' practices (MoANR, 2017).

2.2.2 Conceptual framework

As pointed out earlier, the key feature of ISFM is the combined use of a range of different practices. Hence, it is pivotal for farmers to learn about each of the individual components as well as the necessity of applying them jointly. This is, however, frequently neglected by farmers, which may be a result of learning gaps. This shortcoming can be conceptualized as a learning failure in the framework of selective attention theory (Schwartzstein, 2014). Hanna et al. (2014) as well as Niu and Ragasa (2018) developed a set of assumptions based on Schwartzstein's (2014) model of selective attention that are relevant for the context of agricultural technology adoption: First, a new technology comes along with a set of parameters that are unknown and must be learned by a farmer, e.g. through trainings, visits, or farmer-to-farmer extension. Yet, farmers often do not consider all aspects equally important and therefore, a priori, attach different weights to these. Second, paying attention involves costs, because learning requires capacities in the form of mental energy and time, and individuals need to economize these resources. Third, farmers seek to maximize their net payoffs, resulting from expected yields minus attentional (and other) costs. Consequently, even when full information on a new technology is readily available through trainings, field demonstrations or on neighbors' fields, farmers may not be able to pay attention to each of its parameters due to resource boundaries, and therefore need to decide which dimensions to focus on.

In the case of a system technology that requires learning about several individual practices, a resource-constrained farmer might – consciously or unconsciously – base the decision which components to focus on not only on how important she or he considers a certain practice, but also on its level of complexity. Since learning more complex technologies requires more cognitive energy, payoff-maximizing farmers will only learn them when they are sufficiently convinced of their benefits, but otherwise disregard. Knowledge dimensions that have been neglected from the beginning are often continuously ignored throughout the further process of experimentation and implementation, simply because farmers initially did not pay attention to them, due to low perceived importance or high perceived complexity. In that sense, a learning failure essentially stems from a failure to notice (Niu & Ragasa, 2018). As a result, farmers may persistently stick to suboptimal choices or applications of technologies, if they do not get reminded of the ignored parts. Conversely, reminders of neglected dimensions of a technology (package) may help to overcome this learning failure and alter farmers' behavior (Hanna et al., 2014; Niu & Ragasa, 2018).

The ISFM technology package promoted in our study area consists of several individual components. Yet, due to a failure to notice the importance of each individual – and in particular the more complex – components, we expect learning and teaching along the knowledge transmission chain from extension staff to model farmers to extension group members and other farmers to occur incompletely and therefore, lead to incomplete adoption. Consequently, in order to overcome this potential 'failure to notice', farmers' attention needs to be drawn to each of the individual practices and to the need for their integrated adoption. To do so, we designed a video intervention to complement the farmer-to-farmer extension approach, which provides farmers with information on *why* each component is important, that is, explanations about the underlying principles and mechanisms of ISFM, and emphasizes the positive synergy effects of applying the practices jointly.

Previous research has shown that video as information delivery channel has the potential to induce behavioral changes in farming communities (Bernard et al., 2014; Van Mele, 2006; Zossou et al., 2010), can increase the effectiveness of standard extension activities (Gandhi et al., 2009; Van Campenhout et al., 2017; Vasilaky et al., 2018) and even trigger knowledge increases in areas not explicitly mentioned in the videos (Van Campenhout et al., 2017). While extension activities often aim at providing awareness for improved practices and instructions on how to implement them, they frequently disregard the importance of providing sufficient information on *why* certain practices are beneficial (Anderson & Feder, 2007; Rogers, 1995). Yet, individuals' "competence to decide whether or not to adopt" a technology can be facilitated by being well informed about their underlying principles and mechanisms due to enhanced capacity of appraising consequences of adoption (Rogers, 1995: 166).

Building on these considerations, we derive a set of hypotheses for the context of ISFM knowledge diffusion and adoption in our experimental set-up. Firstly, we expect farmers to learn about ISFM through the extension intervention, and therefore hypothesize:

H1: ISFM adoption and knowledge will increase through the extension activities, both of its individual components and the integrated package.

Further, we expect that farmers in treatment communities who are not actively involved in the extension activities (i.e. as model farmer or extension group member) benefit from information spillovers that occur via farmer-to-farmer communication or by observing neighbors' behavior, and therefore assume that:

H1a: Due to information spillovers, ISFM adoption and knowledge will also increase among farmers not directly involved in extension activities.

Yet, farmers that 'only' learn via informational spillovers are more likely to pick up incomplete pieces of information (primarily what they consider most important, or what is easier to grasp), which lets us hypothesize:

H1b: Since information spillovers occur incompletely, increases in ISFM adoption and knowledge will be lower for farmers not directly involved in extension activities.

We expect the additional video treatment to make farmers aware of potentially neglected knowledge dimensions, which is particularly beneficial for those who do not directly learn via extension. Thus, we hypothesize:

H2: The additional video intervention counteracts incomplete information spillovers and therefore leads to higher ISFM knowledge and adoption.

H2a: The additional 'video effect' will be stronger for farmers that are not directly involved in extension activities.

Ultimately, since we expect that more complete knowledge fosters adoption, we hypothesize that:

H3: Increases in ISFM adoption are (partly) channeled through gains in ISFM knowledge triggered by the interventions.

2.3 Experimental design

This study builds on a randomized controlled trial (RCT) with two treatment arms and a control group. The first treatment consists of an extension intervention; the second treatment combines the extension intervention with a video intervention. We used microwatersheds (mws) as units of randomization, which are common implementation units for natural resource related interventions in Ethiopia. These are water catchment areas, i.e. natural hydrological entities defined by the topography of the land, typically consisting of around 250 to 300 households in one or several communities that share a common rainwater outlet.

2.3.1 Treatment description

The core elements of the extension intervention are the following: In each treatment mws, three so-called 'farmer research and extension groups' (FREG) were formed, each consisting of 16 or 17 members, leading to a total of around 50 FREG members per mws. FREG farmers were selected in a non-random manner by extension agents and village heads, based on farmers' interest and social involvement. The FREGs conduct regular meetings, typically once or twice per month, to discuss on agricultural topics. Each group is led by three of its members, called 'model farmers', that are appointed based on their reputation and farming skills in a participatory process with FREG members and extension staff. Some of the model farmers or FREG members may be replaced from season to season, but this is not defined in a fixed way. The central activity of model farmers is the establishment and maintenance of demonstration plots. For this purpose, model farmers receive trainings on ISFM from public extension agents and are provided with all necessary inputs. Demonstration plots are on-farm trials on which the package of ISFM practices is applied, next to plots that are managed according to traditional farming practices. Hence, the benefits of ISFM in comparison to traditional practices, such as yield improvements, become clearly visible to farmers (cp. Figures A 2.1 to A 2.3 in Appendix A 2). In each mws, 'farmer field days' are conducted twice per harvest cycle; at critical stages around mid-season and just before harvest. During these field days, model farmers share and discuss their experience with FREG members (from their own and other FREG groups in the mws); extension agents are present to complement information. Field day activities are mainly targeted at FREG members, although in some communities, other farmers do also participate. Overall, the extension treatment aims at creating awareness and know-how about ISFM through a knowledge sharing process from extension agents (in Ethiopia called 'development agents') to model farmers, and from model farmers to other FREG members. Through that entry point, information should diffuse to the broader population of farmers in the communities. Hence, this model heavily relies on peer-to-peer learning.

The video intervention has been designed to provide an additional stimulus for adoption by exposing farmers to information about the ISFM concept, in order to overcome potential knowledge gaps on key dimensions of the approach. The movie is composed of two parts: A narrative and documentary part which presents the example of a farmer couple who has successfully implemented the ISFM quickwin technologies and visibly increased yields, serving as (potential) role models for treated farmers. These main characters explain their experience with implementation, emphasizing benefits and successes, but also critically discussing their initial reluctance and problems they have faced. In the narratives, particular emphasis was put on the fact that ISFM is a package approach and therefore, practices need to be combined on the same plot. Given the cultural, linguistic as well as agroecological differences between Tigray, Amhara and Oromia, three different farmer couples were featured in the versions for the respective region. Previous research has underlined the importance of tailoring information to specific local conditions, as well as framing messages in a way that an audience can relate to them, which is best achieved by presenting credible role models from similar backgrounds (BenYishay & Mobarak, 2019; Bernard et al., 2015, 2014; Jensen, 2010). Major agroecological differences between the three study regions exist with respect to soil acidity. While soil acidity is high in Amhara and Oromia making the promotion of lime crucial, soils in the intervention areas in Tigray do not suffer from acidity. Accordingly, lime application is not featured in the movie version for Tigray. Beyond these local adaptations, all three versions strictly follow the same script in order to convey the same messages. The second component of the film consists of animations that visualize processes taking place in the soil – such as hydrological cycles, the 'work' of roots, soil organic matter, microorganisms and nutrients. Complex soil processes and the relationship between the ISFM components, soil fertility and improved yields are presented in a simplified way. Ultimately, farmers should gain a better understanding on why the integrated use of all techniques is important to improve soil fertility and productivity.

2.3.2 Sampling and randomization strategy

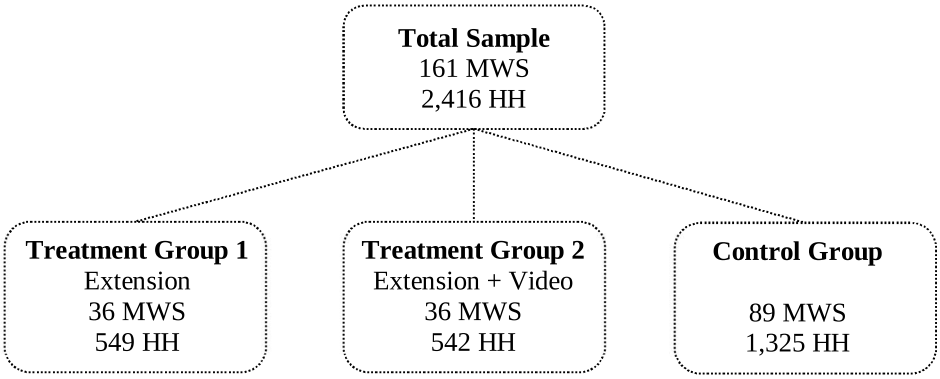
Since the participatory extension approach draws on the establishment of community-based farmer groups and demonstration sites, we applied a cluster randomization approach using microwatersheds (mws) as sampling units. The full sampling frame consists of 161 mws located in 18 districts (in Ethiopia called Woredas), equally distributed among the three regions Tigray, Amhara and Oromia.[9] From this list, a sample of treatment mws was drawn randomly – stratified by region and Woreda – so that in each Woreda four mws were selected, resulting in a total of 72 treatment mws. The total number of 72 treatment mws was given by the capacity constraint of the ISFM+ project. Half of the 72 treatment mws were assigned to the additional video intervention. Consequently, 36 mws received the extension treatment only (in the following

[9] The list of target mws was compiled based on the criteria (i) benefiting from the Sustainable Land Management Programme and (ii) no/minimal previous exposure to soil fertility interventions.

referred to as T1), and another 36 mws received the extension treatment plus the additional video intervention (T2). The remaining 89 mws serve as control group (C).

For the survey we randomly sampled 15 households in each treatment and control mws. For this purpose, complete lists of households living in the respective mws were compiled from administrative village lists of registered households. Thus, in treatment mws, the proportions of non-FREG and FREG farmers in the sample should on average represent their distribution in the population. Figure 2.1 graphically depicts our full original sample, consisting of 2,416 households.

Figure 2.1. Diagrammatic illustration of the full sample.



Note: MWS stands for microwatershed, HH for household.
Source: Own illustration.

2.3.3 Treatment implementation

The ISFM+ project was launched by the German Agency for International Cooperation (GIZ) in mid-2015. Yet, in the first months of operation, the project's main activities were establishing partnerships and conducting planning workshops, while the implementation of the above described extension intervention on a broad scale started in the 2016 main cropping season. Since then, extension activities in T1 and T2 mws are on-going, regionally aligned with the course of the main harvest cycle.

The video screenings were conducted in T2 mws in early 2017, around six weeks prior to the start of the main growing season. Typically, the video was shown in public spaces such as farmer training centers, health posts or schools, and followed by group discussions facilitated by extension agents. In each of the T2 mws, the 15 households from our sample were invited by village heads a few days prior to the screenings orally and with written invitation cards. In the case of double-headed households we invited both spouses, otherwise only household heads.[10]

2.4 Data and empirical strategy

2.4.1 Data

In order to assess the interventions' impact, two rounds of survey data were collected. A baseline survey took place in early 2016, shortly after the launch of the ISFM+ project in mid-2015. The timing of the survey may raise concerns about baseline data being influenced by first project activities. While this cannot be ruled out completely, it appears very unlikely because all structured extension activities in the treatment mws started only in 2016. The endline survey took place in early 2018 among the same rural households. Data in both rounds were collected through tablet-based face-to-face interviews with the household head or spouse, using a structured questionnaire. Our attrition rate was remarkably low, since 2,382 (98.6%) of the 2,416 baseline sample households could be re-interviewed during endline, and we cannot detect any non-random patterns in this.

The surveys covered modules on household socio-demographic characteristics, income and assets, food security level, social relationships, farming practices and agricultural production data for the preceding cropping season, as well as exposure to agricultural extension. During endline, we assessed most information in the same way as in the baseline to maintain comparability. Yet, for some variables, including key outcome variables, we had to adapt the mode of measurement, because the information collected at baseline was not detailed enough for the planned analyses. For the main outcome variables, the adoption of ISFM practices, enumerators cross-checked self-reported data whenever possible. In order to verify information on compost production, farmers were asked to show their compost pits or heaps to enumerators, who assessed their size with a measurement tape. Furthermore, in addition to questions on the final compost product (such as color, texture or odor), detailed questions on the production process were posed in order to assess compost quality. We asked, for example, which ingredients were used, how much time the composting process took, whether and how often materials were turned, whether the pit/heap was covered, or if tubes for aeration were used.[11] To confirm which kind of inorganic fertilizers farmers applied, enumerators checked the labels on (empty) fertilizer bags from

[10] After the endline data collection, the video became freely available for extension staff to be used in T1 as well as control communities.

[11] Since the survey took place *after* the 2017 season, it was not possible for enumerators to inspect the finished or nearly-finished compost, which is why we need to rely on farmers' self-reports.

the previous season.[12] In addition, they showed pictures of different types of fertilizer granulate to farmers in order to identify the correct product.[13] For lime, stored bags were checked as well. In order to verify the use of improved seeds, the survey contained detailed questions on the name of the seed, its original source and for how long it had been reused[14].

In the endline survey, we further added questions on awareness of and participation in ISFM+ extension activities. In addition to the household-level questionnaire, we included two individual-level modules administered to the household head as well as the spouse (in case the household was not single-headed), covering questions on the video content, as well as a detailed knowledge exam. For the knowledge part, we first assessed farmers' awareness by asking them which ISFM components they actively remembered, and in a second step, letting enumerators read through a list of practices and record which techniques respondents remembered by name.[15] Subsequently, questions on their underlying principles and purpose ('principles knowledge') as well as their mode of implementation ('how-to knowledge') were posed. We combined different types of knowledge questions, including open questions, multiple choice tasks and correct/incorrect statements (or a neutral "don't know" option) to minimize fatigue effects (for details of the knowledge exam, see Appendix B 2.1). Enumerators were intensively trained and supervised during a ten-day training period. Questionnaire contents were carefully translated into the three local languages Amharic, Afaan Oromo and Tigrigna and pre-tested in several rounds.

In addition to the farm household survey, we administered two community level questionnaires to key informants at the Woreda and mws levels, in order to collect data on infrastructure, extension exposure, rainfall and temperature, as well as other contextual characteristics.

2.4.2 Descriptive statistics and balance at baseline

Table 2.1 depicts descriptive statistics for selected variables at baseline using data from the balanced panel of 2,382 households, including tests for covariate balancing between the three treatment groups to verify the success of the randomization process. Table 2.1 shows those variables that are used as additional covariates in the adoption and knowledge regressions,

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[12] Most farmers keep even empty fertilizer bags to use them for other purposes, e.g. to sit on them or to store other things.

[13] During pre-testing, we found out that it is common for farmers to call any kind of inorganic fertilizer "DAP", irrespective of whether it is really Di-ammonium phosphate or a different fertilizer type (e.g. NPK or NPS blends). Recognizing by pictures turned out to be an easy task for farmers.

[14] If seeds had been reused for more than four seasons, they are no longer considered improved, because improved traits get lost over generations.

[15] Inspired by Kondylis et al. (2015), we included a placebo practice ("seeding in circles") in this list to get a sense for possible response bias, which does not appear to threaten our results since yes-answers regarding this practice are close to zero.

Table A 2.1 in Appendix A 2 presents further balance checks on selected household, farming and community characteristics.

On average, household heads are 47 years old and have slightly over two years of schooling (Panel A, Table 2.1). 85% of the sample households are male-headed. The mean household consists of 5.3 members, of which three are age 15 and above. Around 19% of households earn income from a non-farm family business or wage employment, respectively. Farmers are involved in around 4.5 local organizations. Access to communication technologies is limited, as only 29% of smallholders own a radio, and 52% a mobile phone. On average, a household possesses livestock equivalent to 3.4 tropical livestock units. Whereas around 73% of households consider themselves eligible for a formal credit (from a bank, governmental institution or microcredit institute), roughly 34% contracted a credit in the year preceding baseline, with a small imbalance between farmers in T1 and C. According to a food insecurity score, which is based on self-reported incidents of food shortage, around 28% of the sample households can be classified as food insecure at baseline. Average walking distances from farmers' homestead to the closest farmer training center, paved road and market are 33, 27, respectively 74 minutes. Farmers in the control group seem to live somewhat further away from the nearest road than T2 farmers, and from the nearest market than farmers in both treatment groups.

On average, smallholders manage 1.3 ha of land (Panel B, Table 2.1). The vast majority (94%) cultivates at least one of the main crops teff, wheat, barley, maize or sorghum. At baseline, farmers on average adopted 1.4 out of the five quickwin technologies, with treatment farmers somewhat more than control farmers (1.5 vs. 1.3). Looking at the individual quickwin components, this imbalance seems to stem from a more widespread use of improved seeds among T1 than C households (64% vs. 53%), and line seeding among treatment compared to control farmers (52% vs. 39%).[16] Compost was used by around 36% of smallholders at baseline. While the use of blended fertilizer and lime was very limited (adoption rates of 1.4% and 0.8%), 70% of households used Di-ammonium phosphate (DAP) fertilizer during the first survey round. On average, farmers had 5.5 conversations with a development agent in the year before baseline, and around 27% participated in at least one agricultural training, with treatment more often than control farmers (30% and 34% vs. 23%).

Overall, households in the three groups seem largely balanced on a series of socio-demographic and economic indicators. Yet, they exhibit a few differences regarding agricultural production-related characteristics, which need to be considered in our outcome estimation

[16] Yet, line seeding was assessed on a more general level during baseline, asking farmers how they usually plant crops, but not at the plot level.

framework. Moreover, ISFM practices are not necessarily new to farmers, since some were used prior to the interventions, though mostly to a modest extent.

Finally, Panel C of Table 2.1 and Panel C of Table A 2.1 (Appendix A 2) show that there are no significant differences regarding a set of community level indicators related to climate, extension provision (other than from the ISFM+ project) or input supply.

Table 2.1. Baseline descriptive statistics and balance between treatment groups.

	Overall	T1	T2	C	T1 - T2	T1 - C	T2 - C
Panel A: Household characteristics							
Age HH head (in years)	47.03	46.27	47.32	47.22	-1.05	-0.95	0.10
	[14.61]	[14.61]	[14.54]	[14.64]	(1.02)	(0.85)	(0.94)
Gender HH head (1=male)	0.85	0.86	0.84	0.85	0.02	0.01	-0.00
					(0.02)	(0.02)	(0.02)
Education HH head	2.15	2.19	2.42	2.03	-0.23	0.15	0.39
(grades completed)	[3.36]	[3.36]	[3.61]	[3.24]	(0.37)	(0.32)	(0.28)
Non-farm family business	0.19	0.21	0.18	0.18	0.03	0.02	-0.00
(1=yes)					(0.04)	(0.03)	(0.03)
Off-farm wage employment	0.19	0.18	0.23	0.18	-0.05	-0.00	0.05
(1=yes)					(0.03)	(0.02)	(0.03)
No. of HH members	3.06	3.08	3.11	3.03	-0.03	0.05	0.08
over age 14	[1.31]	[1.34]	[1.31]	[1.29]	(0.11)	(0.10)	(0.08)
No. of organizations involved	4.47	4.53	4.38	4.49	0.15	0.05	-0.1
(0-12)	[1.87]	[1.91]	[1.78]	[1.90]	(0.21)	(0.19)	(0.18)
Basic assets score (0-4)	1.84	1.79	1.91	1.83	-0.13	-0.04	0.09
	[0.89]	[0.84]	[0.90]	[0.90]	(0.10)	(0.09)	(0.09)
No. of TLU owned	3.39	3.26	3.48	3.42	-0.22	-0.16	0.06
	[2.83]	[2.61]	[2.93]	[2.87]	(0.29)	(0.26)	(0.25)
Radio owned (1=yes)	0.29	0.27	0.29	0.30	-0.02	-0.03	-0.01
					(0.03)	(0.03)	(0.03)
Cellphone owned (1=yes)	0.52	0.53	0.53	0.51	-0.00	0.02	0.02
					(0.04)	(0.03)	(0.04)
Contracted any credit (1=yes)	0.34	0.38	0.35	0.32	0.03	0.06**	0.03
					(0.04)	(0.03)	(0.06)
Eligible for formal credit	0.73	0.71	0.73	0.75	-0.02	-0.04	-0.02
(1=yes)					(0.05)	(0.04)	(0.05)
HH is food insecure (1=yes)	0.28	0.26	0.25	0.30	0.01	-0.03	-0.05
					(0.05)	(0.04)	(0.04)
Walking dist. to nearest FTC	33.30	33.34	32.94	33.42	0.40	-0.09	-0.48
(min)	[25.55]	[26.21]	[25.31]	[25.40]	(3.84)	(3.03)	(3.29)
Walking dist. to nearest	27.36	25.56	22.34	30.14	3.22	-4.58	-7.80**
(all-season) road (min)	[29.47]	[23.66]	[25.98]	[32.50]	(3.34)	(3.02)	(3.56)
Walking dist. to nearest	74.17	67.03	67.91	79.65	-0.88	-12.63*	-11.74*
market (min)	[48.15]	[44.82]	[46.86]	[49.31]	(7.84)	(6.96)	(6.47)

Panel B: Agricultural production characteristics							
Total land size (in ha)	1.34	1.37	1.40	1.30	-0.03	0.07	0.10
	[1.11]	[1.16]	[1.18]	[1.06]	(0.18)	(0.15)	(0.14)
Grows main crop (1=yes)	0.94	0.94	0.95	0.93	-0.01	0.01	0.02*
					(0.01)	(0.02)	(0.01)
No. of adopted quickwins	1.40	1.51	1.53	1.30	-0.02	0.21*	0.23**
(0-5)	[0.99]	[1.00]	[0.97]	[0.99]	(0.14)	(0.13)	(0.11)
Compost applied (1=yes)	0.36	0.34	0.39	0.37	-0.05	-0.03	0.02
					(0.06)	(0.05)	(0.05)
Blended fertilizer applied	0.014	0.009	0.021	0.014	-0.011	-0.004	0.007
(1=yes)					(0.011)	(0.007)	(0.011)
Improved seeds used (1=yes)	0.57	0.64	0.59	0.53	0.04	0.11**	0.07
					(0.06)	(0.05)	(0.05)
Plants crops usually in lines	0.45	0.52	0.52	0.39	-0.00	0.13*	0.13*
(1=yes)					(0.09)	(0.07)	(0.07)
Lime applied (1=yes)	0.008	0.009	0.009	0.007	0.000	0.002	0.003
					(0.007)	(0.005)	(0.005)
DAP applied (1=yes)	0.70	0.76	0.74	0.66	0.02	0.09*	0.07
					(0.05)	(0.05)	(0.05)
Used irrigation (1=yes)	0.19	0.17	0.19	0.20	-0.03	-0.03	-0.00
					(0.05)	(0.04)	(0.04)
Last season was bad (1=yes)	0.48	0.46	0.45	0.51	0.02	-0.04	-0.06
					(0.08)	(0.07)	(0.07)
No. of times talked to DA	5.53	5.76	6.42	5.07	-0.66	0.69	1.35
in past year	[10.97]	[11.06]	[14.35]	[9.20]	(1.23)	(0.90)	(1.06)
Attended agric. training	0.27	0.30	0.34	0.23	-0.03	0.08**	0.11***
in past year (1=yes)					(0.05)	(0.04)	(0.04)
Panel C: Community level characteristics							
Mean annual temperature	20.56	20.45	20.40	20.68	0.05	-0.23	-0.28
2017 (°C)	[4.10]	[4.21]	[4.24]	[4.00]	(1.00)	(0.82)	(0.83)
Mean annual rainfall	1108.84	1140.53	1140.11	1083.12	0.42	57.40	56.98
2017 (mm)	[396.23]	[381.88]	[380.26]	[406.66]	(90.84)	(77.59)	(77.13)
Distance to Woreda	14.62	13.66	15.52	14.65	-1.86	-0.99	0.87
capital (km)	[15.42]	[16.31]	[13.69]	[15.69]	(3.67)	(3.27)	(2.85)
N	2,382	539	532	1,311	1,071	1,850	1,843

Note: HH stands for household. Basic asset score comprises the following: HH has modern roof, improved stove, modern lighting, toilet facility. TLU=Tropical livestock unit. Calculation of food insecurity score based on self-experienced events of food insecurity, based on Household Food Insecurity Access Scale (HFIAS). FTC stands for farmer training center. Main crops are teff, wheat, barley, maize, sorghum. DA stands for development agent. Temperature and rainfall measured assessed at endline. For means, standard deviations in brackets; for mean comparisons, robust standard errors in parentheses, clustered at the mws level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

2.4.3 Key outcome variables

Since our key concern is the increase in ISFM adoption, we measure how many ISFM practices households adopted in the preceding harvest cycle (2017), and therefore assess the *number of ISFM technologies adopted*, ranging from 0 to 5. We use this variable despite the fact that lime is not relevant in one of the regions (and thus, no farmers in Tigray reach a value of 5), but provide robustness checks verifying that implications do not change, if we exclude lime and employ a 0 to 4 measure instead. Since the complementary use of the practices is pivotal to

ISFM, our second main outcome is the *integrated adoption of the full ISFM package*. We assess this with a binary variable that measures whether a farmer has used all four quickwin practices in combination on at least one plot.[17] Here we exclude the use of lime, since adoption would otherwise always be zero in Tigray. To check sensitivity of our results with respect to this definition, we also use several alternative measures. Firstly, a variable that equals 1 when at least four out of five practices (including lime) are adopted. Secondly, a measure for the joint adoption of compost, blended fertilizer and line seeding, that is, excluding improved seeds, which might possibly be concentrated around a certain crop type. And lastly, a region-specific measure that requires all five practices to be adopted in Amhara and Oromia, but only four in Tigray. Furthermore, we are interested in the adoption of the individual ISFM quickwin components, which are *compost*, *blended fertilizer*, *improved seeds*, *line seeding* and *lime*. For each technology, we define a dummy variable taking the value of 1 if the household has applied the respective practice in the 2017 main cropping season on any plot and for any crop type.

Furthermore, we assess effects on the *quantity of compost* farmers produce, measured in cubic meter per hectare of cropland managed by the household. Moreover, since the contribution of compost to soil fertility improvement depends on its quality, we calculate a *compost quality index*, ranging from 0 to 9, based on farmers' self-reported information. The index is composed of six questions on the compost production process and three questions on the compost end product (see Appendix B 2.2 for details).

We are also interested in the effect of our treatments on ISFM knowledge as potential impact pathway to adoption. We construct an *overall ISFM knowledge* score based on questions on each of the individual ISFM components (excluding questions on lime). It ranges from 0 to 1, with 1 standing for full knowledge, i.e. having answered all questions correctly. Since the number of questions is not the same for all practices, we first calculate a knowledge score for each component individually and then combine it to an overall score, so that each ISFM dimension is included with the same weight in that indicator. Farmers who were not aware of a practice in the first place, were immediately given a value of zero in the respective follow-up questions. Since the aim of the video treatment was to increase farmers' knowledge on *why* ISFM is important (and not on *how* to implement it), we also construct two individual indicators for *principles* and *how-to knowledge*, depending on whether a question was on the purpose (the 'why') of a technology, or its mode of implementation (the 'how-to'), which also range from 0 to 1. For the how-to score, we give twice the weight to knowledge on how to correctly produce

[17] We restrict these analyses to plots planted with main crops, i.e. wheat, maize, teff, barley and sorghum, which are the main focus of the interventions.

compost, since this is a more complicated process than the implementation of the other ISFM practices. For the principles score we weigh all ISFM components equally, and include one indicator for the general understanding of the necessity to integrate organic and inorganic soil inputs.[18] For our analyses, we use the household heads' knowledge score.

2.4.4 Estimation strategy for intent-to-treat effect using RCT design

In order to assess the effects of our experimental interventions on ISFM adoption and knowledge, we estimate regressions of the following form:

$$Y_{i1} = \alpha + \beta T_i 1 + \lambda T_i 2 + \varepsilon_j + \epsilon_{ij} \qquad (2.1)$$

where Y_{i1} denotes the respective outcome variable for household or individual *i*, measured at endline. $T_i 1$ is a dummy variable indicating whether farm household *i* lives in mws *j* assigned to the extension intervention, and $T_i 2$ indicates whether household *i* lives in an extension mws *j* that has additionally been randomly selected for the video screening. ε_j represents a cluster level error term, and ϵ_{ij} the individual level error term. In order to allow for arbitrary correlation of households and individuals within clusters, standard errors are clustered at the mws level.

Although treatment indicators should be orthogonal to further explanatory variables due to randomization, we will re-estimate all models including additional covariates in order to increase precision of our estimates and to control for small-sample imbalances in our sample:

$$Y_{i1} = \alpha + \beta T_i 1 + \lambda T_i 2 + \gamma X_{i0} + \varphi W_{j1} + \nu Y_{i0} + \varepsilon_j + \epsilon_{ij} \qquad (2.2)$$

In these models, X_{i0} represents a vector of control variables related to farmer and household characteristics captured at baseline, while with W_{j1}, we add indicators for rainfall, temperature and remoteness measured at the community level. If available, we include the baseline level of outcome Y_{i0} in the equation in order to reduce the overall variance, since we assume some degree of path dependency on previously gained experience with a technology. This treatment effect model is appropriate in our case, since for some outcomes, baseline and endline measures are not completely identical, or baseline data is not available at all.[19] In addition, this specification has been shown to be more powerful than the difference-in-difference estimator in the presence of relatively low autocorrelation, which can at least be stated for some of our outcome

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[18] This is based on the respondent agreeing with the following statement: "The soil needs both organic and inorganic inputs to be healthy and fertile".

[19] Baseline data is available for adoption of compost, blended fertilizer, improved seeds and lime. Regarding blended fertilizer, we additionally control for ex-ante use of any inorganic fertilizer, since during time of baseline, blended fertilizer was largely unavailable; instead, farmers used the widely available DAP fertilizer (cp. Table 2.1). In the two years between baseline and endline, supply-side structures changed in the way that more blended fertilizer factories were set up in Ethiopia and NPS/NPK fertilizer blends largely replaced other inorganic fertilizer types. Line seeding can only be proxied, since it was assessed on a more general level during baseline, asking farmers how they *usually* plant crops, but not at the plot level. Knowledge variables were not measured in the baseline survey.

variables (De Brauw et al., 2018; McKenzie, 2012a). Our main estimators of interest are β and λ; in order to evaluate the additional impact of the video intervention, we also run a test of equality of the two coefficients.

2.4.5 Differential effects for members and non-members of 'farmer research and extension groups'

In the previous section, the intent-to-treat effect (ITT) of the randomly allocated interventions was identified, which measures the average effect of living in a randomly assigned T1 or T2 mws, irrespective of actual treatment participation. ITT estimates are of particular interest for policy makers, since in reality, participation is never expected to be perfect, and in our case not even intended.

In this section, we seek to disentangle the effects for FREG members and the remaining population in treatment communities. That is, beyond average effects, we are interested in potentially differential effects of the treatments on the primary beneficiary group, i.e. FREG members, and those who might only benefit indirectly, i.e. non-FREG farmers. Let the binary variable *F* indicate whether an observation is FREG member or not. The ITT can thus be decomposed as

$$E[Y^1 - Y^0] = E[Y^1 - Y^0|F = 1] \cdot Pr(F = 1) + E[Y^1 - Y^0|F = 0] \cdot Pr(F = 0) \quad (2.3)$$

By randomized allocation, the ITT is identified as

$$E[Y^1 - Y^0] = E[Y|Z = 1] - E[Y|Z = 0] \quad (2.4)$$

where the binary variable *Z* refers to the randomization of the mws, i.e. *Z* = 1 for treatment mws and *Z* = 0 for control mws. By randomized allocation, the effects for FREG members and non-members would be analogously identified, where, however, FREG membership is unknown for control farmers since the groups are formed as part of the intervention.

Since FREG membership is not randomized, we need to consider that FREG members and non-members are likely to be different. For identification of the separate effects we need to use quasi-experimental methods and rely on a selection-on-observables assumption, where we assume that conditional on a set of baseline covariates *X*, the potential outcomes do not differ between members and non-members (see e.g. Frölich & Sperlich, 2019), i.e.

$$Y^0 \coprod F|X, Z = 1 \quad (2.5)$$

where the symbol $\coprod$ denotes statistical independence. Basically, this assumption says that we can control for all systematic differences between members and non-members by controlling for *X*. Because of randomized allocation of *Z,* it is also natural to assume conditional independence in the control group

$$Y^0 \amalg F|X, Z = 0 \tag{2.6}$$

where F refers to the hypothetical membership in the control mws, i.e. the latent membership type of each observation corresponding to member status if it had been randomly allocated to treatment. With random allocation of Z, we also have

$$F \amalg Z|X \tag{2.7}$$

for baseline covariates X, i.e. covariates not causally affected by the intervention, and thus obtain

$$Y^0 \amalg (F, Z)|X \tag{2.8}$$

This implies that we can identify the ITT on members as

$$E[Y^1 - Y^0|F = 1] = E[Y|F = 1, Z = 1] - \int E[Y|X, Z = 0] \cdot dF_{X|F=1,Z=1} \tag{2.9}$$

and we can estimate this by matching, using the two groups of observations: (F = 1, Z = 1) and (Z = 0). It is also straightforward to show that propensity score matching can be used, where the propensity score is defined as belonging to the former of these two groups, conditional upon belonging to any of these two groups.

Analogously, we can identify the ITT on non-members as

$$E[Y^1 - Y^0|F = 0] = E[Y|F = 0, Z = 1] - \int E[Y|X, Z = 0] \cdot dF_{X|F=0,Z=1} \tag{2.10}$$

In the propensity score matching approach for members and non-members we control for farmer and household covariates X, which are assumed to influence the decision to become a FREG member. The set of covariates used is not exactly identical to the covariates in the previous subsection as they serve a different purpose. Here, the covariates X are important in order to reduce (or hopefully) eliminate the bias due to systematic differences between FREG and non-FREG members, where the problem arises because FREG membership status is not observable in control mws. In the previous subsection, on the other hand, bias was not a concern because of the randomized assignment of treatment, and covariates were only included for efficiency reasons and any finite sample imbalances. (The results are robust to the choice of control variables, though. Results available upon request.)

Propensity score matching is implemented via probit regression and subsequent one-nearest neighbor regression without replacement. That is, to each FREG member in the treatment group the closest observation from the control mws is matched, which we refer to as ‘matched controls’. We proceed analogously for the non-members.

2.4.6 Causal mediation analysis

In order to assess the importance of additional knowledge as potential impact pathway to adoption, we apply a causal mediation analysis, following De Brauw et al. (2018), Frölich and Huber

(2017) and Imai et al. (2011). The aim is to estimate the average effect of our treatments T_i that is occurring through changes in knowledge as a mediating variable $M_i(T_i)$ that are triggered by the treatment. The causal mediation effect can be written as

$$\delta_i(t) \equiv Y_i\big(t, M_i(1)\big) - Y_i\big(t, M_i(0)\big) \tag{2.11}$$

in which $t = 0, 1$ denotes the treatment status. By holding the treatment status otherwise constant at t and therefore eliminating all other causal mechanisms, $\delta_i(t)$ isolates the change in the outcome Y_i that stems from changing the mediator M_i from the control to the treatment condition.

The direct effect of the treatment $\zeta_i(t)$, that is, the portion of the treatment effect not explained by the mediator, can be identified by changing the treatment status from 0 to 1, while fixing the effect of the mediator at t:

$$\zeta_i(t) \equiv Y_i\big(1, M_i(t)\big) - Y_i\big(0, M_i(t)\big) \tag{2.12}$$

When averaging over all observations, the average causal mediation effect (ACME) is given by $\delta(t)$, and the average direct effect (ADE) is estimated by $\zeta(t)$, while the sum of the two $\delta(t) + \zeta(t)$ represents the total average treatment effect.

Two ignorability assumptions have to be made in order to estimate the ACME and the ADE (Frölich & Huber, 2017). Firstly, treatment assignment is assumed to be independent of potential outcomes and mediators, conditional on baseline confounders. This exogeneity assumption holds due to randomization. The second imposes a selection-on-observables assumption, which states that when we control for actual treatment status and observed pre-treatment characteristics, the mediating variable is statistically independent of potential outcomes. This assumption is called sequential ignorability and implies that no unobserved confounders exist that affect both our outcome and the mediator. Subsequently, we can estimate the ACME and ADE by sequentially estimating the following equations:

$$M_{i1} = \alpha_2 + \beta_2 T_i1 + \lambda_2 T_i2 + \gamma_2 X_{i0} + \varphi_2 W_{j1} + \nu_2 Y_{i0} + \varepsilon_{2i} \tag{2.13}$$

$$Y_{i1} = \alpha_3 + \beta_3 T_i1 + \lambda_3 T_i2 + \xi M_{i1} + \gamma_3 X_{i0} + \varphi_3 W_{j1} + \nu_3 Y_{i0} + \varepsilon_{3i} \tag{2.14}$$

The ACME of knowledge for T1 is given by $\hat{\beta}_2\hat{\xi}$, where β_2 represents the effect of T1 on the mediator variable, and ξ the effect of the mediator on the outcome measure. Similarly, $\hat{\lambda}_2\hat{\xi}$ gives the ACME of knowledge for T2.[20] Due to sequential ignorability, non-correlation between the error terms ε_{2i} and ε_{3i} is assumed, denoted by $\rho = 0$. Yet, since we can reasonably think of

[20] Note that this formal description of causal mediation analyses assumes to fit linear regressions, in which both the outcome and the mediating variable are continuous measures. When the outcome is binary (as it is the case for the integrated adoption of the full ISFM package), the product of coefficients does not correspond to the ACME (Hicks & Tingley, 2011; Imai et al., 2010). Methods to correctly estimate mediation effects for binary outcomes and continuous mediators have been developed and are applied accordingly (Hicks & Tingley, 2011).

potential unobservable confounders that affect both knowledge and adoption (e.g. farmers' level of motivation or commitment) and would consequently bias our ACME estimates, we perform sensitivity tests in which we relax the assumption of $\rho = 0$ and re-estimate equations (2.13) and (2.14) for different hypothetical values of ρ.

2.5 Results

In this section, first we briefly present a descriptive overview of farmers' participation in the interventions. Subsequently, we present and discuss ITT results on the effects of our interventions. Finally, we examine the contribution of gains in knowledge as potential impact pathways to adoption.

2.5.1 Treatment participation

Among the two treatment groups, 82 farmers (8% of T1 and T2) were active model farmers in the 2017 cropping season, that is, they were leading members of a FREG and responsible for the implementation and maintenance of an ISFM demonstration plot, for which they were provided with inputs from the project. In addition to model farmers, we find 120 farmers (around 12% of T1 and T2) that are active FREG members, meaning they belong to a FREG and have participated in field day activities along the course of the preceding season. In addition, 77 (8%) of the treatment farmers who are no FREG members state to have participated in a field day in 2017, plus 39 (3%) of control group farmers. Regarding the visit of demonstration plots, 55 treatment farmers (6% of T1 and T2) not belonging to a FREG report to have visited a demonstration site on their own behalf, i.e. independently of a field day, in addition to 39 farmers in the control group (3% of C). Consequently, although to a low extent, we find indications of treatment spillovers both within and across groups, which also means our ITT estimates might suffer from a slight downward bias due to 'contamination' of the control group.

Compliance in the video intervention was remarkably high, 499 (94%) of T2 households attended the screenings. Considering that in double-headed households we invited both spouses to the sessions, compliance at the individual level was 83%, equal to 804 participants.

2.5.2 ISFM adoption decision

Aggregated adoption measures

Columns (1) to (6) of Table 2.2 show the ITT effects of the two treatment arms on our first core outcome, the number of adopted ISFM quickwin technologies (0-5) obtained with three different regression specifications.[21] Since the dependent variable essentially is a count variable, we estimate a Poisson model. Yet, considering that it can also be perceived as either an underlying continuous or ordered process, we also estimate a linear as well as an ordered probit model to underline the robustness of our findings.

Table 2.2. ITT effects on number of adopted ISFM technologies and integrated adoption of the full ISFM package.

	Number of ISFM technologies adopted						Integrated adoption of full ISFM package	
	OLS		Poisson		Oprobit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T1	0.683***	0.448***	0.688***	0.468***	0.542***	0.529***	0.103**	0.084***
	(0.184)	(0.080)	(0.178)	(0.088)	(0.136)	(0.085)	(0.043)	(0.025)
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.016	0.001
T2	0.840***	0.569***	0.822***	0.551***	0.671***	0.671***	0.137***	0.109***
	(0.174)	(0.079)	(0.164)	(0.088)	(0.134)	(0.086)	(0.043)	(0.024)
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.000
Test T1=T2 (p-value)	0.432	0.175	0.431	0.354	0.412	0.160	0.485	0.360
Endline control mean	2.222						0.152	
Additional controls	No	Yes	No	Yes	No	Yes	No	Yes
(Pseudo) R-squared	0.071	0.531	0.016	0.122	0.025	0.223	0.023	0.271
Observations	2,382	2,382	2,382	2,382	2,382	2,382	2,160	2,160

Note: Poisson and probit models (Columns (3), (4), (7) and (8)) show average marginal effects (AME). Number of ISFM technologies adopted ranges from 0 to 5. Integrated adoption of full ISFM package is a dummy variable. Additional baseline control variables at household level are age, gender and education (in completed years) of HH head; whether HH participated in off-farm work or a non-farm business activity; number of HH members above age 14; walking distances to nearest farmer training center, paved road and market (in min); number of local organizations involved; use of irrigation, total land size in ha, tropical livestock units (TLU), a basic assets score, a food insecurity score, whether HH is eligible for formal credit and has contracted a credit in the last farming season; whether HH had a below-average preceding farming season; number of times HH had contact with a development agent and whether HH has participated in agricultural training; whether HH grew main crops (teff, wheat, barley, maize, sorghum) and used any kind of inorganic fertilizer. Community level covariates are rainfall, temperature, and distance to Woreda capital (in km). Two region dummies for Oromia and Amhara included. Tests of equality of T1 and T2 are Wald tests. Robust standard errors in parentheses, clustered at the mws level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

The results of all models indicate positive and highly statistically significant effects of both treatments on the number of adopted practices, which are robust to the inclusion of baseline control variables. Furthermore, all models lead to larger point estimates for T2 compared to T1. From the linear model we see that farmers in T1 adopt additional .683 practices, while households in T2 communities on average adopt .840 more practices than those in the control group. When we include further baseline covariates, these coefficients drop to .448 and .569, respectively (Columns (1) and (2)).[22] Columns (3) and (4) present the average marginal effects (AME) of the Poisson coefficients, which are well in line with the point estimates of the linear model

[21] In the following, we always relay on the 0-5 measure when referring to the number of adopted practices, i.e. including lime. Yet, implications of our results do not change when using the 0-4 measure (excluding lime), see Table A 2.2 (Appendix A 2).

[22] In the following, we will always revert to the estimates of the second specification when interpreting our results, since conditioning on further control variables – and in particular the baseline value of the respective outcome (respectively its best available proxy) – should unarguably increase precision of the results.

and can equally be interpreted as additional practices adopted. Finally, results of the ordered specifications provide further evidence for positive and highly statistically significant effects of both the extension-only and the extension-plus-video treatment (Columns (5) and (6)).[23] Yet, across all specifications, p-values of the test of equality of T1 and T2 (.432, .175, .431, .354, .412, .160) indicate that the average difference between the two treatment groups with regard to the number of adopted ISFM practices is not statistically significant.

Columns (7) and (8) of Table 2.2 depict the AME of being assigned to T1 and T2 on the integrated adoption of the full quickwin package, using a probit regression. As outlined earlier, we define integrated adoption as having adopted all four practices (compost, blended fertilizer, improved seeds, line seeding) together on at least one (main crop) plot.[24] The estimated ITT effects are positive and statistically significant. The AME indicate that households in T1 are on average 8.4 percentage points more likely than control group households to adopt the full set of practices on the same plot, while the likelihood for farmers in T2 is 10.9 percentage points above the control group mean. However, again we do not detect a statistically significant difference between the effect sizes of T1 and T2 (p-values of equality tests .485 and .360, Columns (7) and (8)).

In order to test whether the estimated treatment effects might be driven by the 82 model farmers in our sample that have been trained by development agents and provided with inputs, we re-estimate the ITT models on the two adoption outcomes excluding these 82 model farmers. We find that all treatment effects remain highly statistically significant with only a slight decrease in magnitude and can therefore conclude that the interventions affect farmers in treatment communities beyond model farmers (Table A 2.4, Appendix A 2).

Adoption of individual components

In order to shed light on which components are the main drivers of increased ISFM adoption, we subsequently examine the effects of the two treatment arms on the decision to adopt each of the five practices individually. We assess households' decision to adopt each quickwin technology using binary probit models for each practice.[25]

[23] Since the coefficients of the ordered probit regressions cannot be interpreted in a straightforward way, we stick to interpreting results obtained from the OLS and Poisson models, relying on the ordered models as robustness checks. In addition, the assumption of parallel regressions underlying ordered probit models is violated which makes these results less reliable (Cameron & Trivedi, 2009).

[24] Yet, in Table A 2.3 (Appendix A 2) we show results for the three alternative specifications of this measure. Although effect sizes naturally vary with the choice of this measure, results remain qualitatively unaltered.

[25] A multivariate probit model may be favored over five individual binary models to test several binary outcomes within one regression framework, since it is usually more efficient (Capellari & Jenkins, 2003). We find very similar estimates and standard errors with the mvprobit, and therefore opt for using the binary probit models, which allow for easier computation of AME and inclusion of covariates.

Table 2.3 presents the AME of being assigned to the two treatments on the decision to adopt compost, blended fertilizer, improved seeds, line seeding and lime. Our primary estimates indicate that both the extension-only and the combined intervention exert positive and statistically significant effects on the decisions to adopt compost, improved seeds, line seeding and lime. In contrast, effects for blended fertilizer are not significant (T1) or do not remain significant with the inclusion of additional controls (T2).

When assessing the effects of our interventions on five different, even if interrelated, outcomes, we are concerned that the observed effects in reality cannot be attributed to the interventions, but are rather detected by chance due to multiple outcome testing (Duflo et al., 2008). To account for the probability of false discoveries, we therefore follow Sankoh et al. (1997) and Aker et al. (2016) and use a version of the Bonferroni correction, which corrects for inter-outcome correlations for families of outcomes (cp. Appendix B 2.3). Although this procedure is less conservative than other corrections and presents a rather approximate fix, it is nonetheless informative regarding the sensitivity of our findings (McKenzie, 2012b; Sankoh et al., 1997). With this form of adjustment, p-values of the estimated coefficients of both T1 and T2 increase (respectively remain), above the .10 threshold for blended fertilizer and improved seeds, while results for compost, line seeding and lime remain significant for both treatment arms.

Table 2.3. ITT effects on adoption of individual ISFM components.

	Adopted compost		Adopted blended fertilizer		Adopted improved seeds		Adopted line seeding		Adopted lime	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
T1	0.150***	0.143***	0.097	0.039	0.129**	0.065*	0.157***	0.091***	0.222***	0.214***
	(0.057)	(0.028)	(0.062)	(0.042)	(0.058)	(0.036)	(0.057)	(0.029)	(0.042)	(0.029)
Unadjusted p-value	0.008	0.000	0.118	0.348	0.027	0.070	0.006	0.002	0.000	0.000
Adjusted p-value	0.025	0.000	0.334	0.749	0.092	0.225	0.022	0.007	0.000	0.000
T2	0.219***	0.192***	0.111**	0.046	0.129**	0.067*	0.204***	0.112***	0.254***	0.239***
	(0.054)	(0.025)	(0.055)	(0.037)	(0.058)	(0.040)	(0.057)	(0.030)	(0.042)	(0.028)
Unadjusted p-value	0.000	0.000	0.043	0.218	0.027	0.093	0.000	0.000	0.000	0.000
Adjusted p-value	0.000	0.000	0.132	0.539	0.092	0.291	0.000	0.000	0.000	0.000
Robust to Adjustment?	**Yes**		**No**		**No**		**Yes**		**Yes**	
Test T1=T2 (p-value)	0.282	0.116	0.842	0.884	0.998	0.963	0.490	0.537	0.452	0.387
Endline control mean	0.405		0.596		0.574		0.624		0.040	
Additional controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
(Pseudo) R-squared	0.027	0.361	0.009	0.220	0.014	0.257	0.033	0.388	0.137	0.336
Observations	2,382	2,382	2,382	2,382	2,382	2,382	2,382	2,382	1,464	1,464

Note: Average marginal effects (AME) of probit models. For lime, Tigray is excluded since it is not recommended in this region and adoption is zero. Additional controls identical to those listed in notes of Table 2.2. Bonferroni-adjusted p-values taking into account correlations between outcomes. Tests of equality of T1 and T2 are Wald tests. Robust standard errors in parentheses, clustered at the mws level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

For these robust results, the estimated effect sizes of the extension-plus-video intervention are larger than those of the extension-only intervention, which is in line with the findings on the aggregated ISFM adoption measures. However, again we fail to detect any statistically significant differences between the effects of T1 and T2 on technology adoption (p-values of equality tests .116, Column (2); .537 Column (8); .387 Column (10)). For compost, the AME of T1 suggests that farmers in the extension treatment are on average 14.3 percentage points more likely to adopt than farmers in the control group. For T2, the AME indicates an increased likelihood of compost adoption of 19.2 percentage points (Column (2)). Column (8) reports the AME for T1 and T2 regarding the adoption of line seeding, suggesting an increased likelihood to sow in lines of over 9 respectively 11 percentage points. Columns (9) and (10) show the AME for lime adoption, indicating that farmers in Amhara and Oromia who are assigned to T1 are on average around 21.4 percentage points more likely to adopt lime than those in the control group. Similarly, being assigned to T2 goes along with a likelihood to adopt lime that is about 23.9 percentage points above the control group mean. These effects seem substantial, considering that in the control group only 4% of households adopt.

In summary, our results indicate significant ITT effects of the extension intervention on the adoption of ISFM, both on aggregated measures as well as on some of its individual components. Yet, despite consistently larger point estimates, we do not find significant evidence for an additional ‘video effect’.

Compost quantity and quality

Table 2.4 depicts ITT estimates on compost quantity and compost quality. Recognizing that we might introduce some sort of bias (since these values are only observed for compost-producing households), this appears still useful to provide insights on treatment effects regarding agronomic quality, as the production of organic fertilizer is a central component of ISFM.

Columns (1) and (2) of Table 2.4 show negative, yet statistically insignificant coefficients for both T1 and T2 regarding the amount of compost produced. In contrast, Columns (3) and (4) show robustly significant positive effects of both treatments on our measure of compost quality, with no significant difference regarding their effect sizes (p-value of equality test .888). Hence, we can conclude that farmers in T1 and T2 mws are not only more likely to be compost producers, but that they also produce qualitatively *better* compost, once they have decided to produce.

Table 2.4. ITT effects on compost quantity and compost quality.

	Compost quantity		Compost quality	
	(1)	(2)	(3)	(4)
T1	-1.259	-0.718	0.547**	0.423***
	(1.303)	(1.179)	(0.216)	(0.126)
p-value	0.336	0.544	0.013	0.001
T2	-1.667	-1.238	0.614***	0.443***
	(1.298)	(1.014)	(0.211)	(0.124)
p-value	0.201	0.224	0.004	0.001
Test T1=T2 (p-value)	0.757	0.694	0.787	0.888
Endline control mean	8.342		4.365	
Additional controls	No	Yes	No	Yes
(Pseudo) R-squared	0.004	0.083	0.030	0.277
Observations	1,178	1,178	1,127	1,127

Note: Subsample of compost producers only; reduced sample size for compost quality due to missing information. Compost quantity measured in m^3 per ha of crop land. Compost quality is an index ranging from 0 to 9. Additional controls identical to those listed in notes of Table 2.2. Tests of equality of T1 and T2 are Wald tests. Robust standard errors in parentheses, clustered at the mws level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Differential effects for FREG members

As described above, the ITT estimates represent the average effects of living in a treatment mws. Considering the video treatment, we expect the ITT to be very close to the treatment-on-the treated effect, given the high compliance in the screenings (94% at household level). Yet, with regards to the extension intervention, the definition of actual compliance is not as straightforward. Recall that the core idea of the extension treatment is to spur ISFM adoption via peer-to-peer learning and the success of the intervention relies on information-sharing. For our analyses, this means that a large proportion of farmers in T1 and T2 have essentially not actively attended any extension activities. In fact, among the 1,071 farmers in T1 and T2, only 202 (19%) are FREG members, i.e. the primary target group of the extension activities, and of those 82 are model farmers. Consequently, the remaining 869 farmers (81%) might only benefit from the extension treatment through spillover effects. Hence, we are interested in whether the extension treatment has an effect on ISFM adoption beyond FREG membership – or whether the estimated ITT is solely concentrated among FREG farmers –, and whether the additional video treatment might influence FREG members and non-FREG members differently. To do so, we use the approach outlined in section 4.5.[26]

Table 2.5 reports that in both subsamples, treatment effects of the two interventions regarding the number of adopted ISFM practices remain positive and statistically significant. Yet,

[26] We find a high level of common support with our matching algorithm, since only one treated observation is off support. See Table A 2.5 for first-stage propensity score matching regression results and Figures A 2.4 and A 2.5 for histograms of the estimated propensity score (Appendix A 2). In Tables A 2.6 and A 2.7 in Appendix A 2 we provide balance checks between the treatment groups for the constructed FREG and non-FREG samples and find that they are well balanced (with only few exceptions).

both the linear and the Poisson specification indicate that the effects of the treatments are substantially larger in the FREG than in the non-FREG sample. While in the non-FREG sample, being assigned to T1 on average increases the number of applied technologies by .278, this coefficient is 1.232 in the FREG sample. Similarly, T2 is estimated to increase average adoption by .483 practices in the non-FREG sample, but by 1.117 technologies in the FREG sample (OLS results in Columns (1) to (4)).[27] Further, for non-FREGs, coefficients of the combined treatment are larger than those of the extension-only treatment, a difference which is estimated to be significant in both the OLS and the Poisson model, and points towards a reinforcing effect of the video for this group of farmers (p-values of equality tests .018 and .028, Columns (2) and (6)).

Similarly, we examine the differential effects in the two subsamples regarding the integrated adoption of the technology package. Columns (9) to (12) of Table 2.5 report that T1 does no longer carry a statistically significant coefficient in the non-FREG sample, while in the FREG sample, this effect stays significant at the 1% level, indicating that for FREG farmers T1 increases the likelihood of integrated adoption by around 28 percentage points on average in comparison to their matched controls. In contrast, if extension is complemented by the video intervention, the coefficient of the treatment variable (T2) is statistically significant in both subsamples. In the FREG sample, extension-plus-video increases the likelihood of integrated adoption compared to the matched control observations by 23 percentage points. For non-FREG farmers assigned to T2, the likelihood to adopt all practices in combination is on average over 8 percentage points higher compared to their matched controls.

These findings let us draw the following two conclusions: Firstly, the effect of the extension treatment is substantially larger for FREG members – even after taking into account that they may be the better farmers anyways. This is expected because they are the farmers directly benefitting from the extension activities. Yet, the extension intervention does show a positive influence also on non-FREG farmers when it comes to the number of adopted ISFM practices at the household level, pointing towards the presence of diffusion effects.[28] However, most

[27] The AME estimates of the Poisson specification (Columns (5) to (8) of Table 2.5) are fairly close to the OLS estimates and are therefore not explicitly discussed.

[28] Some farmers in treatment mws state to have attended a field day or visited a demonstration plot on their own behalf, even though they do not belong to a FREG (cp. section 5.1). Hence, to further substantiate the hypothesis of diffusion effects beyond actual extension participation, we rerun our initial analyses excluding all treatment farmers that have participated in *any* extension activity in *any* way and find that our positive treatment effects persist (results available upon request). Farmers in control mws might have also received ISFM information by communicating with extension staff at the Woreda or Kebele level. Being aware of potential endogeneity, we perform another specification in which we control for contact with extension agents and likewise find that the significant treatment effects persist (results available upon request).

interestingly, our findings indicate that extension alone does not significantly affect non-FREG farmers when it comes to *integrated* adoption, i.e. using the practices together on the same plot. By contrast, it seems that the video intervention has a significant complementary effect for non-FREG farmers, in particular when it comes to the combined adoption of the practices.

Table 2.5. ITT effects on number of adopted ISFM technologies and integrated adoption of the full ISFM package, FREG- and non-FREG samples separately.

	Number of ISFM technologies adopted								Integrated adoption of full ISFM package			
	OLS				Poisson							
	Non-FREG		FREG		Non-FREG		FREG		Non-FREG		FREG	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
T1	0.322*	0.278***	1.257***	1.232***	0.329*	0.293***	1.260***	1.228***	0.030	0.034	0.273***	0.280***
	(0.193)	(0.080)	(0.200)	(0.123)	(0.194)	(0.088)	(0.193)	(0.128)	(0.048)	(0.024)	(0.058)	(0.048)
p-value	0.097	0.001	0.000	0.000	0.090	0.001	0.000	0.000	0.528	0.161	0.000	0.000
T2	0.550***	0.483***	1.140***	1.117***	0.540***	0.478***	1.161***	1.131***	0.079*	0.084***	0.231***	0.231***
	(0.181)	(0.082)	(0.184)	(0.137)	(0.173)	(0.086)	(0.183)	(0.147)	(0.046)	(0.025)	(0.066)	(0.043)
p-value	0.003	0.000	0.000	0.000	0.002	0.000	0.000	0.000	0.082	0.001	0.001	0.000
Test T1=T2 (p-value)	0.289	0.018	0.578	0.394	0.289	0.028	0.576	0.449	0.351	0.081	0.561	0.334
Endline control mean	2.444		2.775		2.444		2.775		0.168		0.225	
Additional controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
(Pseudo) R-squared	0.031	0.496	0.224	0.570	0.006	0.094	0.030	0.077	0.007	0.285	0.059	0.299
Observations	1,606	1,606	400	400	1,606	1,606	400	400	1,606	1,606	400	400

Note: Poisson and probit models (Columns (5) to (12)) show average marginal effects (AME). Number of ISFM technologies adopted ranges from 0 to 5. Integrated adoption of full ISFM package is a dummy variable. Additional controls identical to those listed in notes of Table 2.2. Tests of equality of T1 and T2 are Wald tests. Robust standard errors in parentheses, clustered at the mws level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

2.5.3 ISFM knowledge

Treatment effects on knowledge

Columns (1) and (2) of Table 2.6 depict ITT estimates on the overall knowledge indicator. The positive and significant estimates in Column (2) show that T1 on average seems to increase overall ISFM knowledge by around 3.6 percentage points, while T2 increases farmers' knowledge by almost 7 percentage points in comparison to the control group mean. The p-value of .016 indicates that extension-plus-video has a significantly stronger effect on knowledge than extension alone and thus, points towards an additional effect of the video regarding ISFM knowledge formation. We also assess the ITT effects on the two distinct domains, principles and how-to knowledge. Regarding principles knowledge, Column (4) of Table 2.6 shows that the positive coefficient of extension alone does not remain statistically significant with the introduction of further covariates, whereas extension combined with video on average increases this knowledge indicator by 5.4 percentage points on a highly significant level. How-to knowledge seems to be positively affected by both T1 and T2, with no statistical difference regarding their effect sizes (p-value of equality test .206 Columns (6)).

Table 2.6. ITT effects on different knowledge outcomes.

	ISFM Knowledge					
	Overall		Principles knowledge		How-to knowledge	
	(1)	(2)	(3)	(4)	(5)	(6)
T1	0.050***	0.036***	0.030*	0.020	0.068***	0.052***
	(0.015)	(0.013)	(0.016)	(0.014)	(0.015)	(0.013)
p-value	0.001	0.006	0.062	0.152	0.000	0.000
T2	0.082***	0.068***	0.063***	0.054***	0.091***	0.073***
	(0.013)	(0.011)	(0.014)	(0.011)	(0.016)	(0.013)
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Test T1=T2 (p-value)	0.027	0.016	0.037	0.013	0.204	0.206
Endline control mean	0.448		0.522		0.382	
Additional controls	No	Yes	No	Yes	No	Yes
R-squared	0.034	0.219	0.012	0.155	0.048	0.221
Observations	2,334	2,334	2,334	2,334	2,334	2,334

Note: All models show treatment effects on household heads' knowledge, using OLS regressions. Knowledge scores range from 0 to 1. Additional controls are age, gender, education (in completed years), whether respondent participated in off-farm work or a non-farm family business, whether HH adopted the ISFM quickwin package at baseline, whether HH has a cell phone and radio, number of times HH had contact with a development agent, whether it has participated in agricultural training, number of local organizations involved, and walking distance to nearest farmer training center. Two region dummies for Oromia and Amhara included. Tests of equality of T1 and T2 are Wald tests. Robust standard errors in parentheses, clustered at the mws level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Differential effects for FREG members

Next, we follow our earlier approach and disaggregate the sample into a FREG and a non-FREG sample (Table 2.7). We find that the significant difference between the effect sizes of T1 and T2 on overall knowledge persists in the non-FREG, but not in the FREG sample, as the p-values of the tests of equality of T1 and T2 (.011, and .188) in Columns (2) and (4) indicate. In the non-FREG sample, the coefficient of extension alone on overall knowledge is positive, but not significant, while for the combined intervention it is highly statistically significant.

Similarly, extension alone does not show a significant effect on principles knowledge in the non-FREG sample, while extension-plus-video does (Columns (5) and (6)). In the FREG sample, both T1 and T2 affect principles knowledge positively on a highly significant level (Columns (7) and (8)).

Regarding knowledge on how to implement ISFM, both extension-only and extension-plus-video exert a positive influence for FREG members, with no statistical difference in their effect size (Columns (11) and (12)). For non-FREG farmers, both T1 and T2 significantly increase how-to knowledge compared to their matched controls. The effect of the combined treatment seems to increase this knowledge indicator significantly stronger than extension-only, albeit this difference between T1 and T2 is only significant at the 10% level (p-value of equality test .098, Column (10)). Further analyses reveal that this effect mainly stems from improved knowledge on how to produce compost among this group of farmers. This is fairly surprising, since the video did not convey any information on *how* to implement any of the practices. Yet, it may be that increased awareness and understanding of why ISFM is beneficial induced further knowledge-seeking processes on the mode of compost production among non-FREG farmers.

Table 2.7. ITT effects on different knowledge outcomes, FREG- and non-FREG samples separately.

	ISFM Knowledge											
	Overall				Principles knowledge				How-to knowledge			
	Non-FREG		FREG		Non-FREG		FREG		Non-FREG		FREG	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
T1	0.011	0.012	0.131***	0.125***	-0.006	-0.001	0.090***	0.081***	0.025*	0.026**	0.179***	0.177***
	(0.015)	(0.013)	(0.025)	(0.021)	(0.018)	(0.016)	(0.029)	(0.026)	(0.013)	(0.012)	(0.027)	(0.024)
p-value	0.450	0.371	0.000	0.000	0.719	0.929	0.003	0.002	0.064	0.031	0.000	0.000
T2	0.047***	0.047***	0.150***	0.154***	0.033**	0.040***	0.132***	0.129***	0.051***	0.050***	0.158***	0.163***
	(0.013)	(0.012)	(0.021)	(0.020)	(0.016)	(0.014)	(0.027)	(0.024)	(0.014)	(0.013)	(0.020)	(0.019)
p-value	0.001	0.000	0.000	0.000	0.036	0.005	0.000	0.000	0.001	0.000	0.000	0.000
Test T1=T2 (p-value)	0.013	0.011	0.413	0.188	0.030	0.013	0.172	0.089	0.103	0.098	0.440	0.554
Endline control mean	0.465		0.508		0.541		0.577		0.398		0.440	
Additional controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.012	0.140	0.150	0.254	0.005	0.105	0.074	0.180	0.016	0.135	0.201	0.305
Observations	1,573	1,573	395	395	1,573	1,573	395	395	1,573	1,573	395	395

Note: All models show treatment effects on household heads' knowledge, using OLS regressions. Knowledge scores range from 0 to 1. Additional controls identical to those listed in notes of Table 2.6. Tests of equality of T1 and T2 are Wald tests. Robust standard errors in parentheses, clustered at the mws level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Causal mediation analysis

Our findings provide evidence that both extension-only as well as extension-plus-video increase farmers' knowledge about ISFM. Moreover, the video has triggered additional gains in knowledge, especially among those farmers that do not actively participate in the activities of the extension intervention. In particular, the video has shown success in understanding *why* the ISFM practices are important. Therefore, we seek to understand the contribution that these gains in ISFM knowledge make to the adoption decision. To do so, we conduct a causal mediation analysis, in which we use first the overall, and subsequently both the how-to and the principles knowledge indicator as mediating variables.

Panel A of Table 2.8 suggests positive and highly statistically significant effects of all knowledge variables on both the number of adopted technologies as well as integrated adoption, while the effects of T1 and T2 remain highly statistically significant. Looking at the coefficient sizes, how-to knowledge appears to have a stronger effect on adoption than principles knowledge.

Panel B presents the estimated ACME and ADE of T1 for all three mediators and both adoption outcomes separately, Panel C the corresponding effects for T2. Regarding overall knowledge, which comprises knowledge on both why and how to implement ISFM, Columns (2) and (8) show that for both outcome variables, on average around 11% of the treatment effect of T1 and 16 to 17% of the effect of T2 can be explained by gains in knowledge.

Looking at the two different knowledge types, on average, gains in principles knowledge do not seem to significantly contribute to the effect of T1 on both adoption variables (Panel B, Columns (3), (4), (9) and (10)). In contrast, for the combined treatment (T2), the ACME is significant, albeit relatively small, for both outcome indicators. Estimates show that on average, around 6.9% respectively 6.4% of the effect of T2 on the number of adopted practices and on integrated adoption are driven by an increase in principles knowledge (Panel C, Columns (4) and (10)).

The ACME for how-to knowledge is robustly significant for both treatments and both outcome variables (Columns (5), (6), (11) and (12)). The effect sizes indicate that on average, increases in how-to knowledge triggered through T1 account for 16.1% respectively 23.0% of its total effect on adoption, while 17.5% respectively 23.3% of the effect of T2 seem to be transmitted through how-to knowledge gains (Columns (6) and (12)).

Hence, in line with the results presented earlier (Table 2.6), both extension-only and extension combined with video induce increases in understanding *how* to implement ISFM, and these increases partly account for higher ISFM adoption. In contrast, only the combined treatment leads to robustly significant gains in understanding *why* ISFM works, which accounts for a small, but significant portion of the T2 effect on adoption.

Since the sequential ignorability assumption we made to identify causal mediation effects is unjustifiably strong, we perform a sensitivity test to assess how severely our ACME estimates may be biased due to potential correlation $\rho \neq 0$ of the error terms of equations (2.13) and (2.14). Figures A 2.6 to A 2.17 in Appendix A 2 depict the ACME for both mediators and both treatment variables as functions of varying values for ρ. Results show that only relatively large negative correlations between the error terms would imply a strong impact of the knowledge mediators on both adoption outcomes. Yet, a positive correlation of error terms appears far more plausible, since unobservables determining additional unexplained knowledge should also positively affect unexplained adoption. In fact, when we estimate the correlation between error terms of equations (2.13) and (2.14) for both knowledge and both adoption variables, we find positive, but fairly small correlations never exceeding ρ = .003 for the number of adopted practices, and ρ = .089 for integrated adoption. Hence, our estimated ACMEs should be considered upper bounds.

Table 2.8. ITT and knowledge effects on number of adopted ISFM technologies and integrated adoption of the full ISFM package, ADE of treatments and ACME of overall, principles and how-to knowledge as mediating variables.

	Number of ISFM technologies adopted						Integrated adoption of full ISFM package					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Coefficient Estimates												
T1	0.546***	0.406***	0.643***	0.437***	0.480***	0.380***	0.084**	0.074***	0.098**	0.081***	0.070*	0.066***
	(0.163)	(0.075)	(0.175)	(0.080)	(0.162)	(0.075)	(0.042)	(0.025)	(0.042)	(0.026)	(0.041)	(0.024)
T2	0.609***	0.490***	0.744***	0.542***	0.568***	0.479***	0.108**	0.097***	0.125***	0.106***	0.098**	0.089***
	(0.161)	(0.074)	(0.171)	(0.077)	(0.157)	(0.074)	(0.043)	(0.024)	(0.043)	(0.024)	(0.042)	(0.023)
Overall knowledge score	2.909***	1.443***					0.398***	0.254***				
	(0.180)	(0.147)					(0.050)	(0.057)				
Principles knowledge score			1.663***	0.760***					0.227***	0.114***		
			(0.142)	(0.109)					(0.039)	(0.039)		
How-to knowledge score					3.102***	1.422***					0.483***	0.344***
					(0.193)	(0.157)					(0.056)	(0.057)
(Pseudo) R-squared	0.214	0.559	0.144	0.545	0.223	0.557	0.052	0.282	0.038	0.274	0.065	0.293

Table 2.8. ITT and knowledge effects on number of adopted ISFM technologies and integrated adoption of the full ISFM package, ADE of treatments and ACME of overall, principles and how-to knowledge as mediating variables *(continued)*.

	Number of ISFM technologies adopted						Integrated adoption of full ISFM package					
	Overall		Principles		How-to		Overall		Principles		How-to	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel B: ACME and ADE Estimates of T1												
ACME (T1)	0.147***	0.051***	0.050*	0.015	0.212***	0.073***	0.019**	0.009**	0.004	0.002	0.034***	0.020***
	(0.044)	(0.019)	(0.027)	(0.011)	(0.049)	(0.020)	(0.008)	(0.004)	(0.005)	(0.002)	(0.010)	(0.006)
ADE (T1)	0.553***	0.410***	0.651***	0.441***	0.488***	0.383***	0.094**	0.077***	0.107**	0.085***	0.079*	0.069***
	(0.153)	(0.080)	(0.165)	(0.085)	(0.153)	(0.078)	(0.045)	(0.027)	(0.045)	(0.028)	(0.045)	(0.026)
Total effect (T1)	0.700***	0.460***	0.700***	0.456***	0.700***	0.457***	0.109**	0.085***	0.111**	0.086***	0.108**	0.086**
	(0.163)	(0.080)	(0.168)	(0.083)	(0.161)	(0.079)	(0.045)	(0.028)	(0.045)	(0.028)	(0.045)	(0.027)
Share of T1 effect explained by knowledge	20.9%	**11.0%**	7.1%	3.2%	30.2%	**16.1%**	17.3%	**11.1%**	4.0%	2.1%	31.6%	**23.0%**
Panel C: ACME and ADE Estimates of T2												
ACME (T2)	0.240***	0.097***	0.105***	0.041***	0.281***	0.102***	0.038***	0.020***	0.017***	0.008**	0.049***	0.028***
	(0.042)	(0.019)	(0.025)	(0.010)	(0.052)	(0.022)	(0.008)	(0.006)	(0.005)	(0.003)	(0.011)	(0.007)
ADE (T2)	0.616***	0.493***	0.751***	0.546***	0.575***	0.483***	0.125***	0.106***	0.142***	0.115***	0.115**	0.097***
	(0.152)	(0.079)	(0.161)	(0.082)	(0.148)	(0.078)	(0.048)	(0.027)	(0.049)	(0.027)	(0.048)	(0.026)
Total effect (T2)	0.856***	0.590***	0.856***	0.586***	0.855***	0.585***	0.155***	0.122***	0.155***	0.121***	0.154**	0.120***
	(0.160)	(0.078)	(0.165)	(0.080)	(0.159)	(0.080)	(0.048)	(0.027)	(0.049)	(0.027)	(0.048)	(0.026)
Share of T2 effect explained by knowledge	28.0%	**16.4%**	12.3%	**6.9%**	32.8%	**17.5%**	24.9%	**16.9%**	11.2%	**6.4%**	32.1%	**23.3%**
Additional controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	2,334	2,334	2,334	2,334	2,334	2,334	2,116	2,116	2,116	2,116	2,116	2,116

Note: Causal mediation estimates for overall, principles, and how-to knowledge variables on number of practices adopted (OLS specification) and integrated adoption of full ISFM package (probit specification, AME shown). ACME stands for average causal mediation effect, ADE for average direct effect. Additional controls identical to those listed in notes of Tables 2.2 and 2.6. Robust standard errors in parentheses, clustered at the mws level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

2.6 Discussion and conclusion

Our results show that farmers in the treated communities have clearly learned about ISFM through the extension intervention. As hypothesized, farmer-to-farmer extension has significantly increased ISFM knowledge and adoption of individual components and the full package (hypothesis 1). Effective farmer-to-farmer extension depends on information spillovers between farmers, since only a relatively small fraction of farmers actively takes part in extension activities. As expected, we find that ISFM knowledge and adoption – at least of individual practices – also increases among farmers not actively participating in extension activities (H1a). This points towards the existence of information spillovers from FREG farmers to their peers, that occur either through active information-sharing or through observation and imitation. These results provide support for the rationale of farmer-to-farmer extension models and contradict previous research finding weak evidence for diffusion effects (Feder et al., 2004; Kondylis et al., 2017; Rola et al., 2002; Tripp et al., 2005). However, we also find that increases in ISFM knowledge and adoption are substantially lower for non-participating farmers, supporting our hypothesis (H1b). In particular when it comes to the *integrated* adoption of all technologies on the same plot, the extension-only treatment seems to do little for non-FREG farmers. Further, for non-FREG farmers, knowledge increases through extension-only are modest and mostly limited to gains in *how-to* knowledge (as opposed to *principles* knowledge). In line with selective attention theory, we argue that information loss occurs in the knowledge transmission process from actively participating farmers to their peers in communities so that only some pieces of knowledge are passed on or picked up, likely leading to incomplete adoption.

Regarding the individual ISFM components, we find significant treatment effects on the adoption of compost, line seeding and lime, while impacts on adoption of blended fertilizer and improved seeds are not robust to conditioning on baseline covariates or p-value adjustment. This can be explained by the fact that farmers are probably less uncertain about these two technologies. Blended fertilizer and improved seeds are relatively unambiguous practices, since the benefits of mineral fertilizer and quality seeds are rather common knowledge among farmers. For these two technologies, supply and liquidity shortages appear to be much more decisive than information constraints. About 50% of respondents mention financing problems as major obstacle to adoption for both practices, followed by a lack of (timely) availability (around 20%), while knowledge constraints are hardly mentioned. In addition, the use of improved seeds and mineral fertilizer is heavily promoted by the overall advisory system, which equally affects control farmers. In contrast, compost, line seeding and lime are less straightforward technologies, both in terms of their benefits and their application. The purpose and use of lime are largely unknown to farmers (around 60% have never heard of it), and often perceived rather skeptically. The production of good-quality compost is not a trivial process and needs to be learned. The benefits of line seeding are often unclear to farmers; since usually less seeds and fertilizer are used when crops are planted in rows, they commonly associate it with lower yields. In addition, compost preparation and application as well as line seeding are labor-intensive technologies (around 46% respectively 65% of farmers mention labor or time constraints as major obstacles). Hence, farmers need to be sufficiently convinced of their benefits in order to be willing to reallocate labor to these activities and gather knowledge on how to implement them. Consequently, information interventions appear more crucial for these knowledge- and labor-intensive practices.

In line with our second main hypothesis, results suggest that the video provides a significant additional effect on overall ISFM knowledge, and especially on understanding *why* ISFM is beneficial. These effects are particularly pronounced for non-FREG farmers. This provides evidence that the video intervention indeed contributed to counterbalance incomplete information transmission by drawing farmers' attention to dimensions of the ISFM technology package they might not have noticed before or that are not transmitted via farmer-to-farmer extension at all. By contrast, on average we do not find evidence for a significant complementary effect of the video on adoption of the integrated package or any individual component, despite larger effect sizes of the combined over the extension-only treatment. However, for the group of non-FREG farmers, extension in combination with video has a significantly stronger effect on the adoption of ISFM practices than extension alone (H2a). In particular, as opposed to extension alone, the combined treatment does positively affect the *integrated* adoption of ISFM practices among this group.

We further hypothesized that increases in ISFM adoption are (partly) caused by gains in ISFM knowledge induced through our interventions (hypothesis 3). In fact, we find evidence that possessing ISFM knowledge is positively associated with adoption. A causal mediation analysis reveals that higher knowledge on ISFM does partly account for the ITT effects of our interventions on ISFM adoption. Both knowledge types, how-to and principles, contribute to explaining treatment effects on adoption. These results suggest that a better understanding of ISFM as a package consisting of several important and complementary technologies might indeed have positively influenced the decision to adopt the full package in an integrated manner, especially for those farmers that are excluded from the extension activities but did take part in the video intervention. Yet, all in all we conclude that increases in knowledge only partially explain the effects of our experimental treatments, which is in line with previous studies finding effects of extension on adoption that are only modestly explained by gains in knowledge (De Brauw et al., 2018; Kondylis et al., 2017). The limited explanatory effect of knowledge as impact channel might to some extent be attributed to imperfect measurement that knowledge assessments are prone to, in the sense that with our questions we might have missed to capture some adoption-relevant dimensions of knowledge, which the treatments may have altered (Laajaj & Macours, 2017). Yet, as Kondylis et al. (2017) argue in the context of adoption of sustainable land management practices, knowledge constraints might simply not be the most decisive barrier to adoption, but rather a lack of awareness of their productivity benefits. In line with this, our treatments may have played a more crucial role in influencing farmers' awareness of the environmental and in particular the yield-enhancing benefits of ISFM, which has been shown to be an important driver of adoption (Knowler & Bradshaw, 2007). Testimonies of the farmers about improvements of yields and their livelihoods presented in the video might have further increased the credibility of information obtained via the extension intervention.

Interestingly, for the group of non-FREG farmers, we find some evidence that the additional video intervention triggered gains in knowledge on *how* to implement ISFM practices, albeit no explicit how-to messages were conveyed in the video. Further analyses reveal that these gains mostly stem from improved knowledge on the process of compost production, probably the most complex ISFM component. A possible explanation is that the video spurred how-to knowledge seeking processes. Increased awareness of ISFM and understanding why it is beneficial might have encouraged farmers to gather information on its mode of implementation, in particular on compost. This fits our argumentation in line with selective attention theory that additional information is especially needed for more complicated practices, which farmers might otherwise disregard if they are not sufficiently convinced of their importance.[29]

All in all, providing information via video seems a valuable method to complement farmer-to-farmer extension. It appears particularly helpful to increase awareness and knowledge among those who are excluded from extension groups, oftentimes more marginalized farmers that have a higher likelihood to be bypassed by more formal information diffusion chains. In line with this, Bernard et al. (2016) find that video extension presents a cost-effective complement to

[29] In line with van Campenhout et al. (2017), another plausible explanation is that the video triggers affirmative processes, activating and making farmers feel more confident about latent knowledge they already possess, even in areas not explicitly mentioned in the video.

other extension interventions and is especially beneficial for female farmers, who typically have less access to agricultural information in traditional (male-dominated) extension systems (Kondylis et al., 2016). The high compliance in the video screenings underlines that farmers generally perceive video as an appealing format of information provision, which is in line with previous studies (e.g. Bernard et al., 2014). Whereas in our case we only treated our 15 sample households in each mws, the use of video might easily be scaled up by conducting repeated screenings and admitting any interested farmer to participate. While most costs occur during video production and for the purchase of equipment, variable costs are low. Further, video screenings are relatively simple to conduct, also in more remote geographical areas. Thus, video can have the potential to achieve substantial outreach at a relatively low cost. However, its success in reaching those groups that are otherwise typically excluded from extension still depends upon these farmers knowing that a screening is going to happen, which is certainly more difficult to achieve outside of an experimental setting in which we explicitly invited the sampled farmers. Screening videos during other community events or festivities might at least increase the chance of reaching more and different types of farmers.

A central question of experimental studies is to what extent findings are replicable or generalizable to other contexts or populations. In our three study regions, land rehabilitation measures had been implemented previously under the 'Sustainable Land Management Programme'. Building on these achievements, it is possible that smallholders in the area have higher capacities to address issues of soil fertility and productivity increase, which might not be the case in other contexts. Yet, although a replication of our interventions in other settings or with different populations may require adaptations, an advantage of our study regarding external validity is the comparatively large sample size spread over three regional states, that in part differ quite substantially regarding agroecological, farming, cultural and other characteristics.

Scaling up extension approaches that support rural households in the adoption of agricultural innovations will play a key role in reducing rural poverty and fostering development in SSA and beyond. Integrated system technologies have the potential to increase yields while conserving the natural resource base at the same time, but require the transmission of complex information. Our results can help to design more effective farmer-to-farmer extension approaches, in particular, harnessing the potential of complementary interventions to close information gaps and thereby fostering wider adoption of complex agricultural technologies.

Appendix A 2

Table A 2.1. Further baseline and endline descriptive statistics and balance between treatment groups.

	Overall	T1	T2	C	T1- T2	T1-C	T2- C
Panel A: Household characteristics (baseline)							
HH head married (1=yes)	0.83	0.84	0.83	0.83	0.00	0.01	0.00
					(0.03)	(0.02)	(0.02)
Literacy HH head (1=yes)	0.56	0.53	0.56	0.57	-0.03	-0.04	-0.01
					(0.04)	(0.03)	(0.03)
No. of HH members	5.34	5.27	5.34	5.37	-0.07	-0.10	-0.03
	[2.07]	[2.11]	[2.07]	[2.06]	(0.19)	(0.16)	(0.15)
TV owned (1=yes)	0.02	0.01	0.02	0.02	-0.01	-0.01	0.00
					(0.01)	(0.01)	(0.01)
Received remittances (1=yes)	0.10	0.09	0.10	0.11	-0.01	-0.02	-0.01
					(0.02)	(0.02)	(0.02)
Received support from social programs (1=yes)	0.20	0.17	0.21	0.22	-0.05	-0.05	-0.00
					(0.06)	(0.05)	(0.06)
Panel B: Agricultural production characteristics (baseline)							
Reduced tillage practiced (1=yes)	0.07	0.09	0.05	0.06	0.04	0.03	-0.01
					(0.03)	(0.03)	(0.02)
Manure applied (1=yes)	0.49	0.51	0.48	0.48	0.03	0.02	-0.00
					(0.04)	(0.04)	(0.04)
Urea applied (1=yes)	0.64	0.70	0.66	0.60	0.04	0.10*	0.06
					(0.06)	(0.06)	(0.05)
Intercropping applied (1=yes)	0.17	0.19	0.18	0.16	0.01	0.03	0.02
					(0.05)	(0.04)	(0.04)
Grown green manure crops (1=yes)	0.02	0.03	0.03	0.02	0.00	0.01	0.01
					(0.01)	(0.01)	(0.01)
Experienced shock in last season (1=yes)	0.82	0.80	0.79	0.83	0.01	-0.03	-0.04
					(0.05)	(0.04)	(0.04)
Av. perception of change in soil fertility	1.88	1.88	1.90	1.86	-0.03	0.00	0.03
(1-decreased, 2-same, 3-increased)	[0.69]	[0.69]	[0.69]	[0.68]	(0.10)	(0.08)	(0.07)

Table A 2.1. Further baseline and endline descriptive statistics and balance between treatment groups *(continued)*.

Panel C: Community level characteristics (endline)							
MWS receives agric. support from other development organizations (1=yes)	0.34	0.36	0.31	0.34	0.06	0.03	-0.03
					(0.11)	(0.10)	(0.09)
No. of agricultural trainings in mws (apart from ISFM+)	3.24	3.18	3.98	2.97	-0.80	0.21	1.00
	[2.63]	[2.75]	[3.53]	[2.02]	(0.75)	(0.50)	(0.63)
Agri-input dealer in Kebele (1=yes)	0.63	0.61	0.70	0.61	-0.09	0.01	0.09
					(0.11)	(0.10)	(0.09)
Seed enterprise in Kebele (1=yes)	0.12	0.14	0.11	0.11	0.03	0.03	-0.01
					(0.08)	(0.07)	(0.06)
N	2,382	539	532	1,311	1,071	1,850	1,843

Note: HH stands for household. MWS stands for microwatershed. Kebele is the lowest administrative unit in Ethiopia. For means, standard deviations in brackets. For mean comparisons, robust standard errors in parentheses, clustered at the mws level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A 2.2. ITT effects on number of adopted ISFM technologies, using alternative 0-4 measure.

	Number of ISFM technologies adopted (0-4)					
	OLS		Poisson		Oprobit	
	(1)	(2)	(3)	(4)	(5)	(6)
T1	0.541***	0.326***	0.543***	0.341***	0.446***	0.397***
	(0.169)	(0.078)	(0.165)	(0.087)	(0.139)	(0.093)
p-value	0.002	0.000	0.001	0.000	0.001	0.000
T2	0.662***	0.418***	0.650***	0.406***	0.558***	0.527***
	(0.157)	(0.079)	(0.149)	(0.089)	(0.135)	(0.094)
p-value	0.000	0.000	0.000	0.000	0.000	0.000
Test T1=T2 (p-value)	0.483	0.282	0.482	0.468	0.462	0.217
Endline control mean	2.199					
Additional controls	No	Yes	No	Yes	No	Yes
(Pseudo) R-squared	0.051	0.505	0.010	0.107	0.018	0.225
Observations	2,382	2,382	2,382	2,382	2,382	2,382

Note: Poisson models (Columns (3) to (4)) show average marginal effects (AME). Number of ISFM technologies adopted excludes lime and ranges from 0 to 4. Additional controls identical to those listed in notes of Table 2.2. Tests of equality of T1 and T2 are Wald tests. Robust standard errors in parentheses, clustered at the mws level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A 2.3. ITT effects on integrated adoption of the full ISFM package, using alternative measures.

	Integrated adoption of full ISFM package					
	At least 4 out of 5		3 out of 3		Region-specific	
	(1)	(2)	(3)	(4)	(5)	(6)
T1	0.152***	0.123***	0.113**	0.095***	0.062***	0.062***
	(0.044)	(0.027)	(0.048)	(0.028)	(0.017)	(0.014)
p-value	0.001	0.000	0.017	0.001	0.000	0.000
T2	0.188***	0.148***	0.156***	0.124***	0.075***	0.064***
	(0.042)	(0.024)	(0.047)	(0.025)	(0.021)	(0.014)
p-value	0.000	0.000	0.001	0.000	0.000	0.000
Test T1=T2 (p-value)	0.466	0.375	0.429	0.336	0.481	0.876
Endline control mean	0.157		0.185		0.033	
Additional controls	No	Yes	No	Yes	No	Yes
(Pseudo) R-squared	0.039	0.274	0.025	0.269	0.042	0.238
Observations	2,160	2,160	2,160	2,160	2,160	2,160

Note: Average marginal effects (AME) of probit models. In Columns (1) to (2), full ISFM package is a dummy variable defined as adopting at least four out of five practices (including lime). In Columns (3) to (4), full package is a dummy variable defined as adopting all three practices (compost, blended fertilizer, line seeding). In Columns (5) to (6), full package is a dummy variable defined as adopting all five practices in Amhara and Oromia (including lime), but only four in Tigray. Additional controls identical to those listed in notes of Table 2.2. Tests of equality of T1 and T2 are Wald tests. Robust standard errors in parentheses, clustered at the mws level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A 2.4. ITT effects on number of adopted ISFM technologies and integrated adoption of the full ISFM package, excluding model farmers.

	Number of ISFM technologies adopted						Integrated adoption of full ISFM package	
	OLS		Poisson		Oprobit			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
T1	0.582***	0.390***	0.582***	0.404***	0.460***	0.463***	0.077*	0.066***
	(0.183)	(0.076)	(0.176)	(0.085)	(0.136)	(0.082)	(0.042)	(0.024)
p-value	0.002	0.000	0.001	0.000	0.001	0.000	0.068	0.005
T2	0.737***	0.526***	0.717***	0.508***	0.597***	0.629***	0.106**	0.091***
	(0.178)	(0.081)	(0.166)	(0.086)	(0.138)	(0.090)	(0.044)	(0.025)
p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.015	0.000
Test T1=T2 (p-value)	0.441	0.128	0.440	0.234	0.393	0.102	0.552	0.374
Endline control mean	2.222						0.152	
Additional controls	No	Yes	No	Yes	No	Yes	No	Yes
(Pseudo) R-squared	0.054	0.525	0.012	0.121	0.019	0.221	0.015	0.271
Observations	2,300	2,300	2,300	2,300	2,300	2,300	2,078	2,078

Note: Poisson and probit models (Columns (3), (4), (7) and (8)) show average marginal effects (AME). Number of ISFM technologies adopted ranges from 0 to 5. Integrated adoption of full ISFM package is a dummy variable. 82 model farmers from treatment groups excluded. Additional controls identical to those listed in notes of Table 2.2. Tests of equality of T1 and T2 are Wald tests. Robust standard errors in parentheses, clustered at the mws level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A 2.5. Probit regression results for calculation of propensity score to predict FREG membership, used for matching with potential FREG members in control group.

	FREG membership
Gender HH head (1=male)	-0.464**
	(0.221)
Age HH head (in years)	-0.003
	(0.004)
No. of months per year HH head away	-0.041
	(0.058)
HH head married (1=yes)	0.260
	(0.216)
Education HH head (grades completed)	0.035**
	(0.014)
HH head participates in off-farm wage employment (1=yes)	0.096
	(0.138)
No. of HH members	0.017
	(0.027)
No. of organizations involved (0-12)	0.005
	(0.026)
Father of HH head important in community (1=yes)	0.132
	(0.103)
Walking distance to nearest FTC (min)	-0.000
	(0.002)
No. of times talked to DA in past year	0.012***
	(0.004)
Attended agric. training in past year (1=yes)	0.774***
	(0.095)
Basic assets score (0-4)	0.015
	(0.055)
Radio owned (1=yes)	-0.177*
	(0.105)
Food insecurity score (0-12)	-0.071***
	(0.018)
Received support from social programs (1=yes)	0.168
	(0.117)
Total land size (in ha)	0.125***
	(0.040)
No. of TLU owned	-0.025
	(0.019)
No. of adopted quickwins (0-5)	0.173***
	(0.046)
Grows main crop (1=yes)	0.257
	(0.315)
Constant	-2.103***
	(0.424)
Pseudo R-squared	0.180
Observations	1,513

Note: Probit regression results for calculation of propensity score for FREG membership. HH stands for household. FTC stands for farmer training center. DA stands for development agent. TLU stands for tropical livestock unit. For further variable definitions see notes of Table 2.1. Robust standard errors in parentheses. Baseline variables used. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A 2.6. Balance between treatment groups in FREG sample, composed of actual FREG members in treatment communities and matched controls.

	T1	T2	C	T1- T2	T1-C	T2- C
Gender HH head (1=male)	0.90	0.91	0.91	0.00	-0.01	0.00
	(0.04)	(0.03)	(0.02)	(0.05)	(0.05)	(0.04)
Age HH head (in years)	42.02	45.79	43.18	-3.77*	-1.16	2.61
	(1.43)	(1.34)	(0.98)	(1.95)	(1.72)	(1.64)
No. of months HH head away	0.05	0.12	0.08	-0.07	-0.03	0.04
	(0.03)	(0.09)	(0.05)	(0.09)	(0.06)	(0.10)
HH head married (1=yes)	0.87	0.93	0.90	-0.06	-0.03	0.03
	(0.06)	(0.02)	(0.02)	(0.06)	(0.06)	(0.03)
Education HH head (grades completed)	3.49	3.57	3.48	-0.08	0.01	0.09
	(0.59)	(0.47)	(0.31)	(0.75)	(0.66)	(0.56)
HH head part. in off-farm wage employment (1=yes)	0.15	0.16	0.14	-0.01	0.00	0.02
	(0.03)	(0.04)	(0.02)	(0.05)	(0.04)	(0.05)
No. of HH members	5.73	5.83	5.91	-0.10	-0.17	-0.07
	(0.27)	(0.21)	(0.13)	(0.34)	(0.30)	(0.25)
No. of organizations involved (0-12)	5.51	5.00	5.39	0.51	0.12	-0.40
	(0.35)	(0.24)	(0.19)	(0.42)	(0.39)	(0.30)
Father of HH head important in community (1=yes)	0.78	0.73	0.78	0.05	0.00	-0.05
	(0.05)	(0.05)	(0.03)	(0.07)	(0.06)	(0.06)
Walking dist. to nearest FTC (min)	31.11	30.75	33.44	0.35	-2.34	-2.69
	(3.54)	(4.06)	(2.12)	(5.35)	(4.10)	(4.53)
No. of times talked to DA in past year	9.85	11.75	9.23	-1.90	0.62	2.52
	(2.24)	(1.69)	(1.37)	(2.79)	(2.61)	(2.16)
Attended agric. training in past year (1=yes)	0.63	0.61	0.60	0.01	0.03	0.01
	(0.07)	(0.05)	(0.04)	(0.08)	(0.08)	(0.06)
Basic assets score (0-4)	1.97	2.21	2.10	-0.24*	-0.13	0.11
	(0.10)	(0.09)	(0.08)	(0.13)	(0.12)	(0.11)
Radio owned (1=yes)	0.30	0.43	0.34	-0.14**	-0.05	0.09
	(0.05)	(0.05)	(0.04)	(0.07)	(0.06)	(0.06)
Food insecurity score (0-12)	1.49	0.96	1.23	0.53	0.26	-0.27
	(0.35)	(0.28)	(0.17)	(0.44)	(0.38)	(0.33)
Received support from social programs (1=yes)	0.19	0.23	0.22	-0.03	-0.03	0.01
	(0.05)	(0.06)	(0.03)	(0.08)	(0.06)	(0.07)
Total land size (in ha)	1.48	1.83	1.65	-0.35	-0.18	0.17
	(0.15)	(0.30)	(0.11)	(0.33)	(0.19)	(0.31)
No. of TLU owned	3.78	4.68	4.22	-0.90	-0.43	0.47
	(0.31)	(0.45)	(0.28)	(0.54)	(0.41)	(0.53)
No. of adopted quickwins (0-5)	2.66	2.71	2.63	-0.05	0.02	0.07
	(0.21)	(0.17)	(0.10)	(0.27)	(0.23)	(0.20)
Grows main crop (1=yes)	0.99	1.00	1.00	-0.01	-0.01	0.00
	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
N	94	106	200	200	294	306

Note: Total no. of observations N=400. HH stands for household. FTC stands for farmer training center. DA stands for development agent. TLU stands for tropical livestock unit. For further variable definitions see notes of Table 2.1. Robust standard errors in parentheses, clustered at the mws level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A 2.7. Balance between treatment groups in non-FREG sample, composed of actual non-FREG farmers in treatment communities and matched controls.

	T1	T2	C	T1- T2	T1-C	T2- C
Gender HH head (1=male)	0.88	0.88	0.88	0.00	0.00	-0.01
	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)	(0.02)
Age HH head (in years)	45.83	46.11	46.30	-0.27	-0.46	-0.19
	(0.74)	(0.85)	(0.59)	(1.12)	(0.94)	(1.03)
No. of months HH head away	0.12	0.10	0.09	0.01	0.02	0.01
	(0.05)	(0.03)	(0.02)	(0.06)	(0.05)	(0.04)
HH head married (1=yes)	0.86	0.86	0.86	0.00	0.00	-0.01
	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)	(0.02)
Education HH head (grades completed)	1.98	2.28	2.07	-0.30	-0.09	0.21
	(0.27)	(0.25)	(0.16)	(0.37)	(0.31)	(0.30)
HH head part. in off-farm wage employment (1=yes)	0.12	0.18	0.15	-0.06	-0.03	0.03
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
No. of HH members	5.32	5.39	5.40	-0.08	-0.08	-0.01
	(0.15)	(0.15)	(0.09)	(0.21)	(0.17)	(0.17)
No. of organizations involved (0-12)	4.40	4.31	4.36	0.09	0.04	-0.05
	(0.15)	(0.16)	(0.12)	(0.22)	(0.19)	(0.20)
Father of HH head important in community (1=yes)	0.67	0.66	0.65	0.01	0.02	0.01
	(0.03)	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)
Walking dist. to nearest FTC (min)	33.30	33.33	34.79	-0.03	-1.49	-1.46
	(2.85)	(2.87)	(1.79)	(4.02)	(3.34)	(3.36)
No. of times talked to DA in past year	5.12	4.88	5.22	0.24	-0.10	-0.34
	(0.68)	(0.77)	(0.50)	(1.02)	(0.84)	(0.91)
Attended agric. training in past year (1=yes)	0.25	0.28	0.26	-0.04	-0.02	0.02
	(0.04)	(0.04)	(0.02)	(0.05)	(0.04)	(0.04)
Basic assets score (0-4)	1.77	1.87	1.83	-0.10	-0.06	0.04
	(0.08)	(0.08)	(0.05)	(0.12)	(0.09)	(0.10)
Radio owned (1=yes)	0.28	0.26	0.28	0.02	0.00	-0.02
	(0.03)	(0.03)	(0.02)	(0.04)	(0.03)	(0.04)
Food insecurity score (0-12)	2.41	2.37	2.48	0.04	-0.08	-0.12
	(0.25)	(0.25)	(0.16)	(0.35)	(0.29)	(0.29)
Received support from social programs (1=yes)	0.16	0.20	0.18	-0.05	-0.02	0.02
	(0.04)	(0.05)	(0.03)	(0.07)	(0.05)	(0.06)
Total land size (in ha)	1.35	1.28	1.32	0.06	0.03	-0.03
	(0.14)	(0.10)	(0.06)	(0.17)	(0.15)	(0.11)
No. of TLU owned	3.20	3.32	3.30	-0.13	-0.10	0.03
	(0.24)	(0.18)	(0.15)	(0.30)	(0.28)	(0.24)
No. of adopted quickwins (0-5)	2.25	2.20	2.24	0.05	0.01	-0.05
	(0.13)	(0.11)	(0.09)	(0.17)	(0.16)	(0.14)
Grows main crop (1=yes)	0.95	0.96	0.97	-0.01	-0.02	-0.01
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
N	416	387	803	803	1,219	1,190

Note: Total no. of observations N=1,606. HH stands for household. FTC stands for farmer training center. DA stands for development agent. TLU stands for tropical livestock unit. For further variable definitions see notes of Table 2.1. Robust standard errors in parentheses, clustered at the mws level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Figure A 2.1. ISFM demonstration plot for maize, next to traditional practices.

Source: GIZ-ISFM+ project Ethiopia.

Figure A 2.2. ISFM demonstration plot for wheat, next to traditional practices.

Source: GIZ-ISFM+ project Ethiopia.

Figure A 2.3. ISFM demonstration plot for teff, next to traditional practices.

Source: GIZ-ISFM+ project Ethiopia.

Figure A 2.4. Histogram of estimated propensity score used for matching FREG members in treatment communities with control observations, using nearest-neighbor matching.

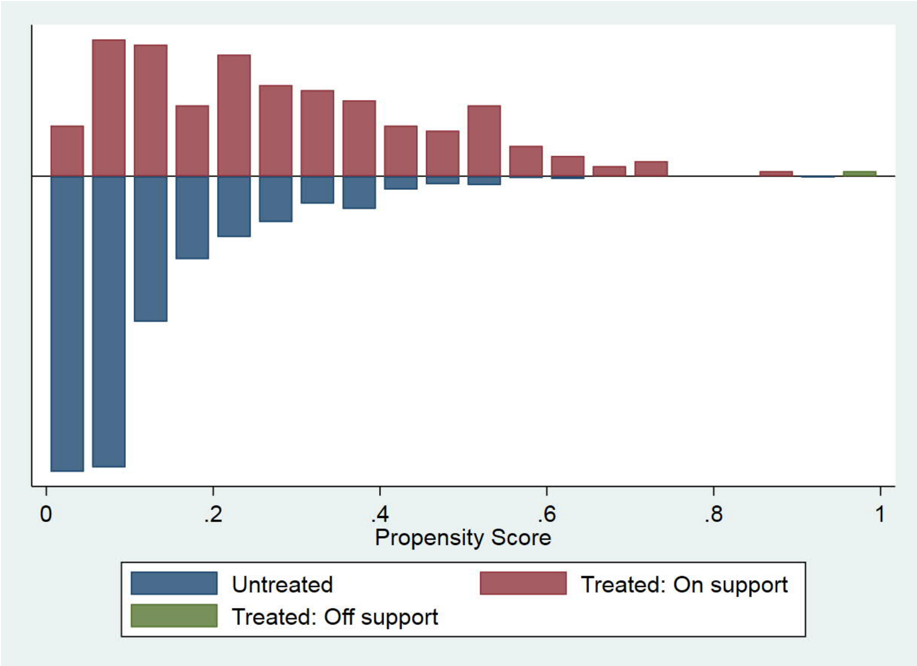


Figure A 2.5. Histogram of estimated propensity score used for matching non-FREG members in treatment communities with control observations, using nearest-neighbor matching.

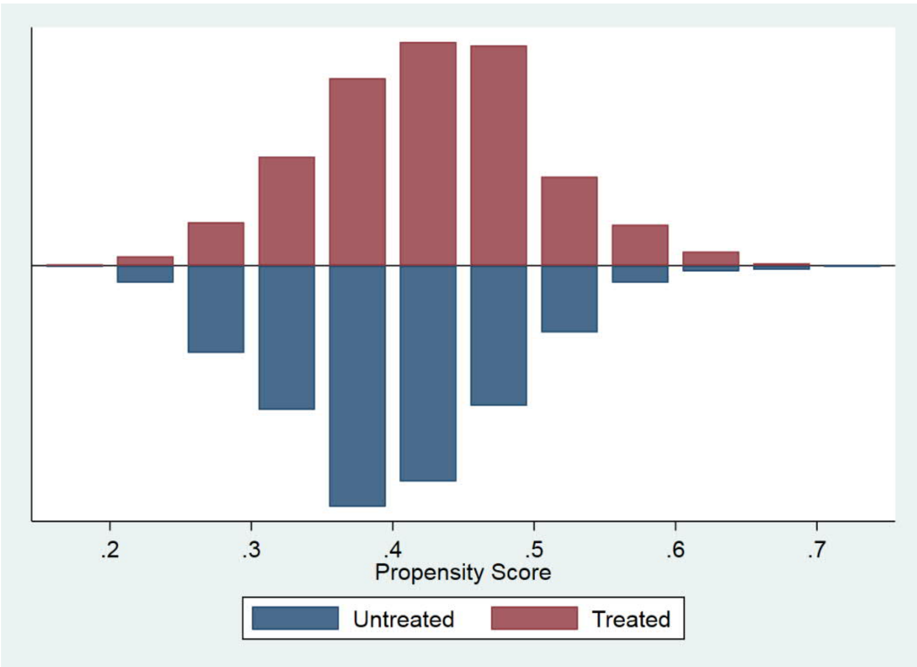


Figure A 2.6. Sensitivity test ACME overall knowledge (T1), no. of adopted practices.

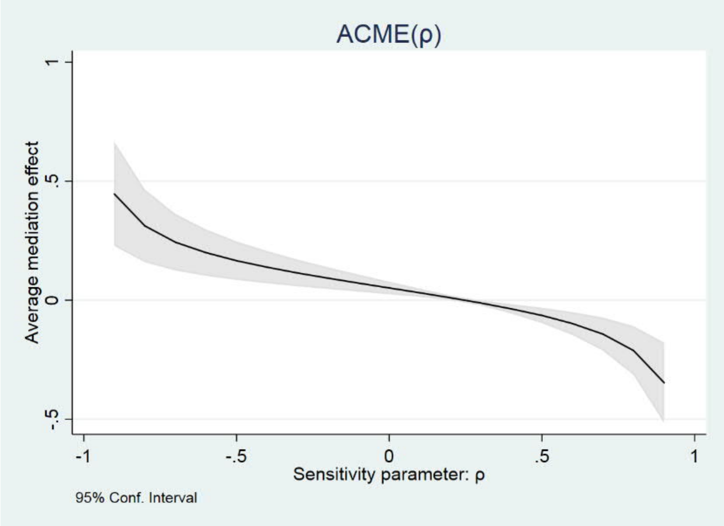


Figure A 2.7. Sensitivity test ACME overall knowledge (T2), no. of adopted practices.

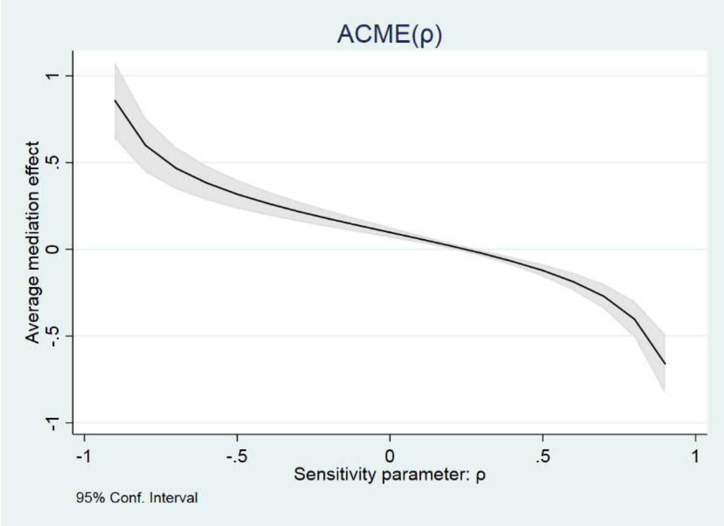


Figure A 2.8. Sensitivity test ACME overall knowledge (T1), integr. adoption.

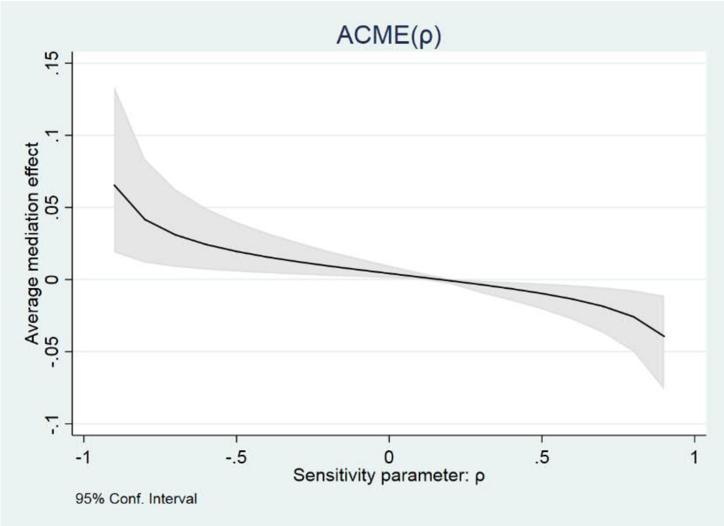


Figure A 2.9. Sensitivity test ACME overall knowledge (T2), integr. adoption.

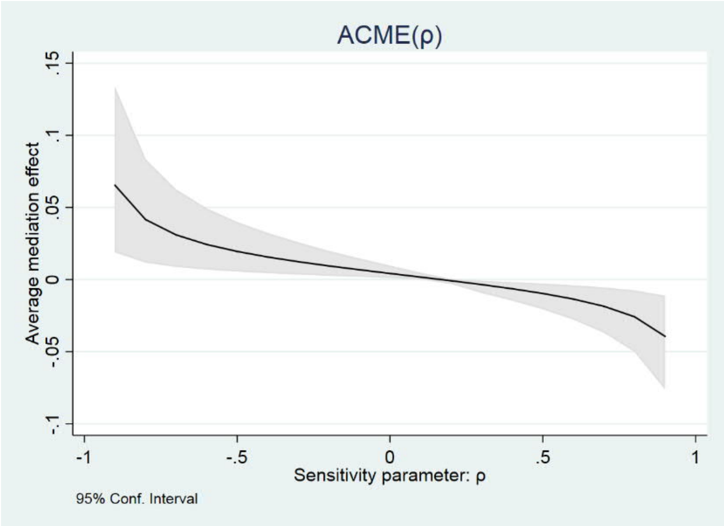


Figure A 2.10. Sensitivity test ACME prin. knowledge (T1), no. of adopted practices.

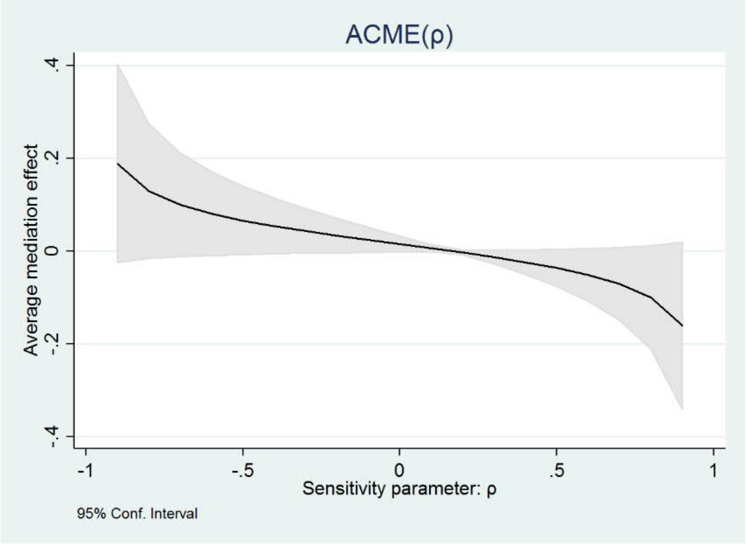


Figure A 2.11. Sensitivity test ACME prin. knowledge (T2), no. of adopted practices.

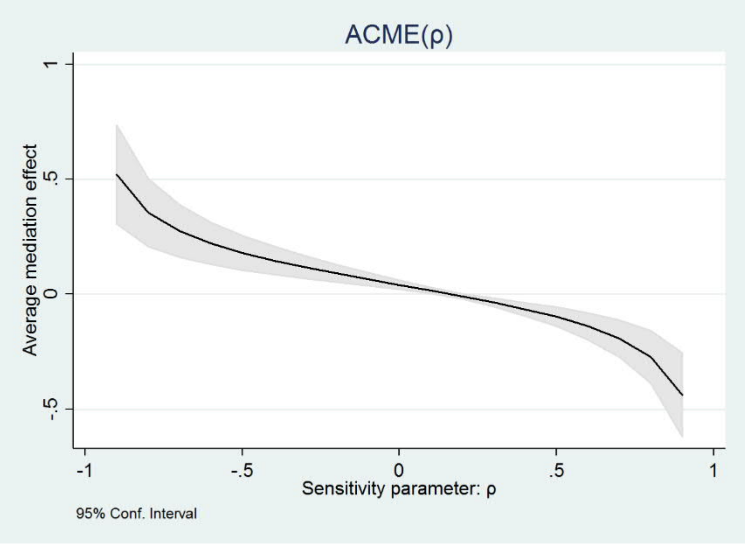


Figure A 2.12. Sensitivity test ACME prin. knowledge (T1), integr. adoption.

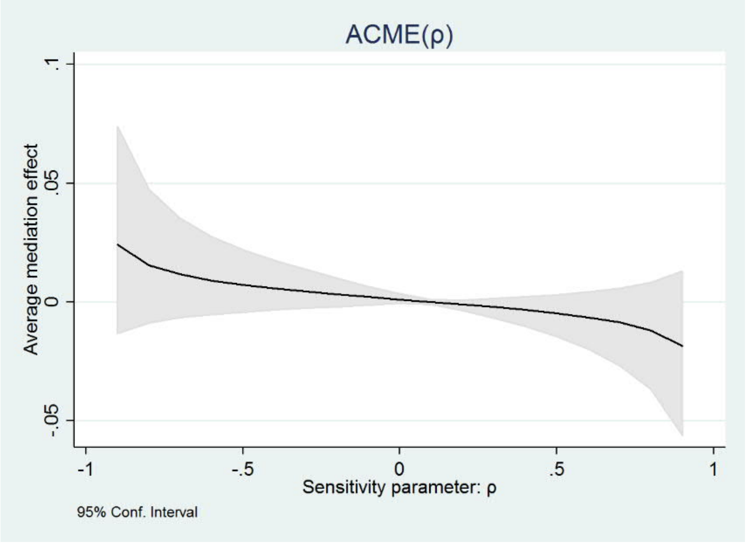


Figure A 2.13. Sensitivity test ACME prin. knowledge (T2), integr. adoption.

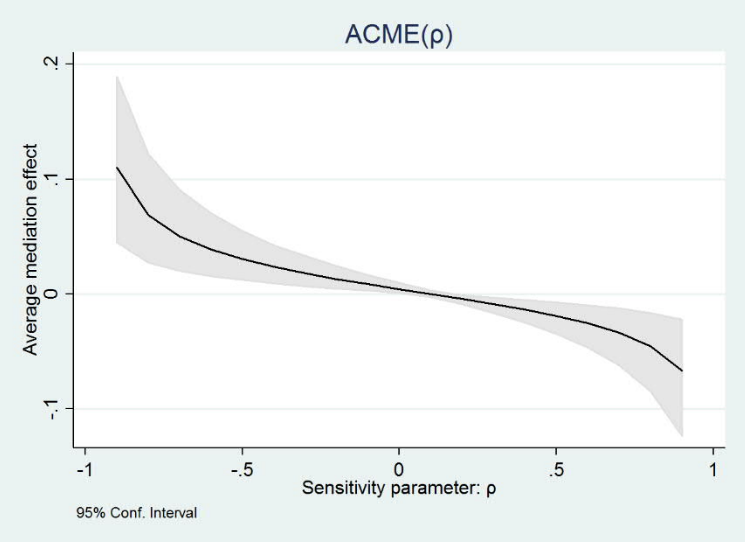


Figure A 2.14. Sensitivity test ACME how-to knowledge (T1), no. of adopted practices.

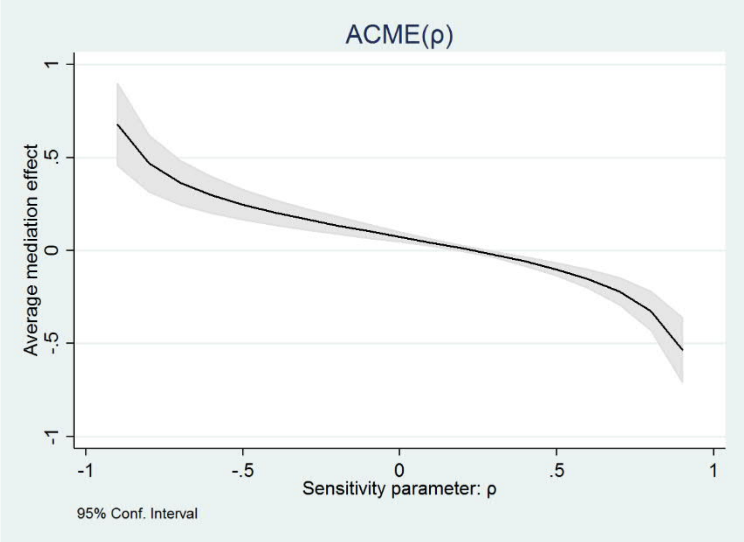


Figure A 2.15. Sensitivity test ACME how-to knowledge (T2), no. of adopted practices.

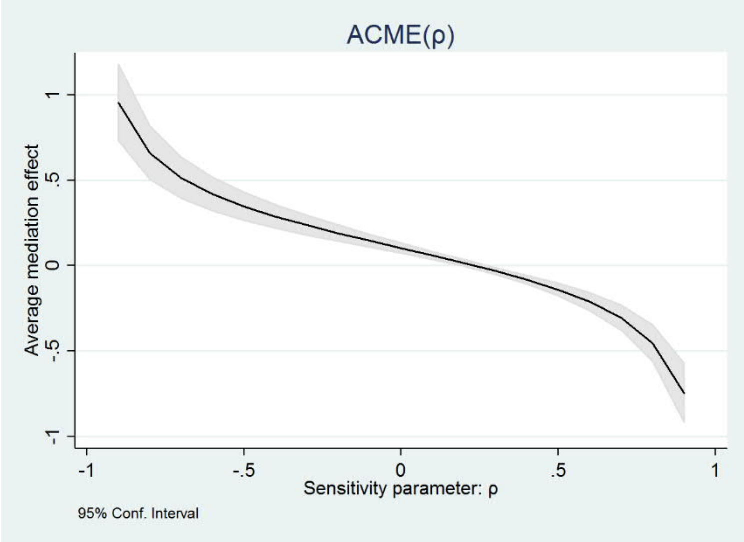


Figure A 2.16. Sensitivity test ACME how-to knowledge (T1), integr. adoption.

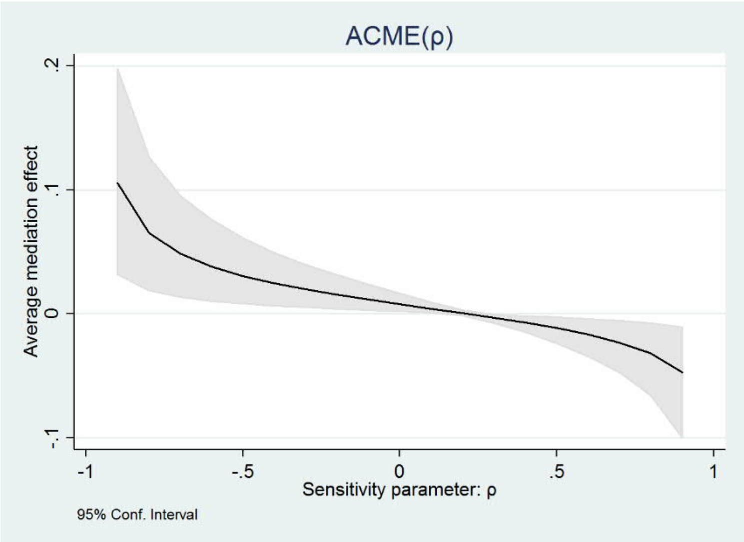
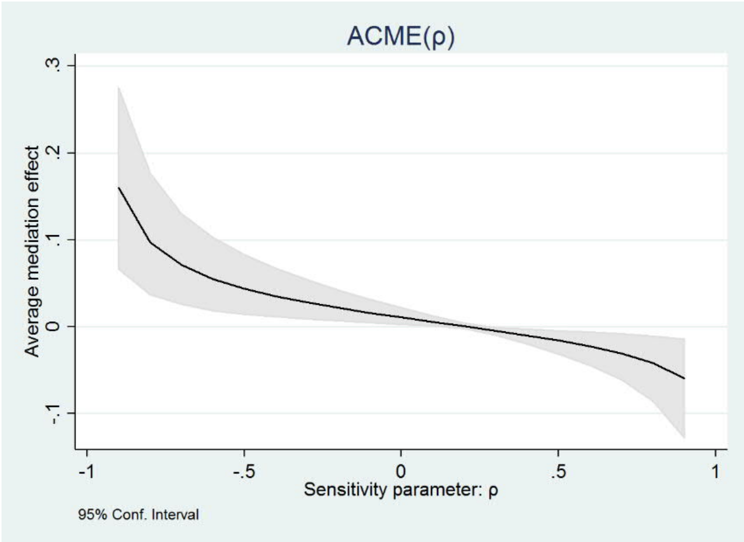


Figure A 2.17. Sensitivity test ACME how-to knowledge (T2), integr. adoption.



Appendix B 2

B 2.1 Knowledge exam

Known by memory

K1.) What are the most important components of integrated soil fertility management?
(open question)

Known by name

K2.) Which of the following technologies have you heard of before this interview?
(list of several ISFM technologies read out)

How-to knowledge

K3.) Imagine you buy improved seeds for wheat. For how many cropping seasons could you reuse them until you should purchase new ones?

Up to four cropping seasons *(correct)*
Five to eight cropping seasons
I can use them endlessly, no need to purchase again
Don't know

K4.) What are the three most important ingredients if you want to produce good-quality compost? *(open question; correct if mentions at least one nitrogen- and one carbon-rich material)*

K5.) What is the optimal sequence of layers to produce improved compost?
(choose the correct out of three pictures)

K6.) In order to produce good-quality compost, how many days should you wait at least until you turn the material? *(open question; correct: 30; acceptable range 25 to 35)*

K7.) In order to produce good-quality compost, how many times should you turn the materials in the pit or heap until the composting is finished? *(open question; correct: 3)*

K8.) If you seed maize in lines, how wide should the distance between lines usually be?
(open question, assessed with measurement tape; correct: 75 to 80 cm; acceptable range: 65 to 90 cm)

K9.) If you seed faba beans in lines, how wide should the distance between lines usually be?
(open question, assessed with measurement tape; correct: 30 to 40 cm; acceptable range: 25 to 45 cm)

Principles knowledge

K10.) For which purpose/benefit should you use improved seeds?
(open question; correct if mentions at least two correct points, i.e. one beyond "higher crop yield")

K11.) What are the major advantages of blended fertilizer (NPS+/NPK+) over DAP fertilizer? Which statements are correct?

K11_1.) Blended fertilizer contains a greater number of nutrients than DAP. *(correct)*
K11_2.) Nutrient supply is better balanced in blended fertilizer than in DAP. *(correct)*
K11_3.) Blended fertilizer directly improves soil structure.
K11_4.) Blended fertilizer is more suitable for your location's soil type than DAP. *(correct)*
K11_5.) Blended fertilizer controls weeds and pathogens.

K12.) Why is it important to use compost/organic fertilizer?
(open question; correct if mentions at least three correct points, i.e. two beyond "higher crop yield")

K13.) What are the major advantages of line seeding over broadcasting? Which statements are correct?

K13_1.) Line seeding reduces the crops' competition for space, nutrients and water. *(correct)*
K13_2.) Seeding a crop in lines is faster than broadcasting.
K13_3.) Line seeding reduces soil acidity.
K13_4.) With line seeding usually less seeds are needed. *(correct)*
K13_5.) With line seeding less fertilizer is needed because it can be targeted directly to the roots. *(correct)*
K13_6.) Line seeding makes weeding and harvesting easier. *(correct)*
K13_7.) Line seeding has no advantages.

K14.) Why is it important to use inorganic fertilizer and compost at the same time? Which statements are correct?

K14_1.) It is always better to apply inorganic fertilizer only.
K14_2.) Because the soil needs both organic and inorganic nutrient sources to be healthy and fertile. *(correct)*
K14_3.) Less seeds are needed when using inorganic and organic fertilizer at the same time.

K15.) What are the important characteristics of a fertile soil?
(open question; correct if mentions at least three correct points)

K16.) What are the benefits of applying inorganic fertilizer in lines or by band/microdosing? Which statements are correct?

K16_1.) It has no benefits.
K16_2.) It is faster than broadcasting.
K16_3.) It leads to less leaching of nutrients because they are directly targeted to the roots. *(correct)*

B 2.2 Compost quality index

Compost production process, comprises six components:

(1) Input mix: considered appropriate if farmers use at least three different materials to produce their compost, of which at least one is rich in nitrogen and one in carbon
(2) No. of times compost was turned: correct if compost was turned three times
(3) Days waited until compost was turned for the first time: correct is 30 day (acceptable range 25 to 35 days)
(4) Days until compost was finished: correct is 90 days (acceptable range 75 to 120 days)
(5) Stick or tube used for aeration of compost pit/heap? correct if yes
(6) Compost pit/heap covered? correct if yes

Compost end product, comprises three components:

(1) Compost color: correct if dark brown or black
(2) Compost odor: correct if described as good or neutral smell
(on a scale from 1=very bad smell to 4=good smell (like good quality soil))
(3) Compost texture: correct if almost or fully decomposed
(on a scale from 1=not at all decomposed to 5=fully decomposed)

B 2.3 Formula p-value correction

$$p_{adj} = 1 - (1 - p(k))^{g(k)}$$

Where $g(k) = M^{(1-r(.k))}$, with

M as the number of tested outcomes in a family,

$r(.k)$ as mean correlation among all outcomes other than outcome k, and

$p(k)$ as the unadjusted p-value for the k^{th} outcome.

Source: McKenzie (2012b), based on Sankoh et al. (1997) and used in Aker et al. (2016).

3. Does Integrated Soil Fertility Management increase returns to land and labor? Plot-level evidence from Ethiopia[30]

Abstract

Integrated Soil Fertility Management (ISFM) is widely promoted to enhance soil fertility, yields and livelihoods among smallholders, and ultimately combat environmental degradation. Its core is the combined use of organic and inorganic fertilizers with improved crop varieties. Yet, farmers face adoption barriers, such as additional monetary and labor investments. To date, much of the evidence on ISFM effects comes from experimental field trials instead of micro-level farmer data. In particular, studies on labor outcomes are scarce, but important to assess the viability of ISFM in smallholder settings. This study addresses this gap by providing a comprehensive analysis of ISFM effects on land productivity, net crop value, labor demand, labor productivity and returns to unpaid labor using survey data from over 6,000 teff, maize and wheat plots and 2,000 households in Ethiopia. We employ a multinomial endogenous switching model to account for endogeneity from observed and unobserved heterogeneity. We find that both partial and complete ISFM adoption lead to significant increases in land productivity and net crop value, in particular when improved seeds are used. In moister regions, complementing improved varieties with inorganic fertilizer seems most important, while in drier regions, enhancing it with organic fertilizer appears crucial. ISFM is related to higher labor demand, but also significantly increases labor productivity and financial returns to labor. These findings imply that ISFM can contribute to improve farmers' livelihoods by breaking the nexus between low productivity, environmental degradation and poverty.

Key words: Technology adoption, land productivity, labor productivity, crop value, rural development, agroecological heterogeneity

[30] This essay is co-authored by Meike Wollni. DH collected the data, performed the analysis, interpreted results and wrote the paper. MW contributed at various stages of the research, including interpretation of result, writing and revising the paper.

3.1 Introduction

Achieving stable food security is still one of the major challenges the global community has to face, even more in the light of on-going population growth, projected to be particularly strong in Sub-Saharan Africa (SSA) (UN, 2017). However, agricultural productivity in many African countries remains low and agricultural growth in the past was often attributed to an expansion in area rather than an intensification of production, resulting in severe threats for ecosystems and a depletion of the natural resource base. Climate change and increasing competition for land further exacerbate the pressure on the environment as well as on food systems, and call for strategies that increase food production in a sustainable way on the same (or even smaller) area of land (Godfray, 2010). One of the major bottlenecks to a sustainable intensification of agricultural productivity is the high level of land degradation, mainly caused by excessive deforestation and unsuitable agricultural practices (Barrow, 1991). Land degradation commonly goes along with a loss in soil fertility, resulting in yield deficits which are particularly threatening to the livelihoods of rural communities in developing countries (Barrow, 1991).

Both land degradation and low soil fertility can be causes of self-reinforcing negative feedback loops for the rural poor (Barbier & Hochard, 2018; Barrett & Bevis, 2015). Studies show that high levels of degradation are likely to decrease agricultural labor productivity; as coping mechanisms, farm households try to farm their land even harder, or increasingly capitalize nearby natural resources, which over time aggravates environmental deterioration (Barbier & Hochard, 2018). Along the same lines, low initial soil fertility has been shown to prevent farmers from investing in an improvement of the soil's productive capacity, which may lead to a steady decrease of both land and labor productivity. Hence, strategies to overcome these downward spirals of land degradation, poor soil fertility and low land as well as labor productivity are urgently needed.

The concept of 'Integrated Soil Fertility Management' (ISFM) is a system technology that has been promoted by governments and donors in SSA to tackle soil degradation and improve productivity and livelihoods among smallholder farmers. ISFM consists of a set of soil fertility practices including the integrated application of inorganic and organic fertilizers and the use of improved seeds, coupled with the knowledge on how to adapt these practices to a specific local context (Vanlauwe et al., 2010). Hence, it is important to understand ISFM as a site-specific concept that may vary according to local conditions, for instance with respect to locally available organic materials, water-harvesting practices or measures to correct soil acidity (Vanlauwe et al., 2015). Additionally, ISFM aims at a general improvement of agronomic techniques, like targeted application of seeds and fertilizers, and the complementary use of practices such as cereal-legume intercropping, reduced tillage, or agroforestry (Place et al., 2003). Yet, the use of ISFM is still limited since smallholder farmers face a series of barriers to adoption. Apart from knowledge constraints, ISFM involves substantial up-front investments of labor and capital (Hörner et al., 2019; Jayne et al., 2019; Takahashi, Muraoka, et al., 2019).

The positive effects of ISFM on soil fertility and yields are well documented by a comprehensive series of studies using experimental field trials (Agegnehu et al., 2016; Bationo et al., 2012; Gnahoua et al., 2017; Nezomba et al., 2015; Tabo et al., 2007; Vanlauwe et al., 2012; Zingore et al., 2008). However, in most of these cases, field trials are managed according to best practices in terms of input quantities, timing and agronomic management (Jayne et al., 2019), while studies on combinations of key ISFM practices using micro-level data from farmer surveys are scarce (with the exception of Adolwa et al. (2019)).

A well-established body of literature deals with plot- or household level effects of green-revolution, sustainable agricultural intensification or soil conservation practices on crop output, income or similar measures, mostly using matching or switching techniques to tackle endogeneity (e.g. Abro et al., 2017, 2018; Barrett et al., 2004; Di Falco et al., 2011; Jaleta et al., 2016; Kassie et al., 2008, 2010, 2015; Khonje et al., 2015, 2018; Manda et al., 2016, 2018; Noltze et al., 2013; Takahashi & Barrett, 2014; Teklewold et al., 2013, 2016). Some of these studies analyze combinations of practices that can be classified as part of ISFM, e.g. legume intercropping, conservation tillage and improved varieties in Teklewold et al. (2013), Kassie et al. (2015) or Arslan et al. (2015). There are also studies specifically analyzing the effects of organic and inorganic fertilizers. For instance, Kassie et al. (2009) show that both chemical fertilizer as well as compost lead to yield gains for major cereal crops in semi-arid areas of Ethiopia, but the effect of compost outperforms that of inorganic fertilizer and is consequently more profitable for farmers, although the authors do not analyze their joint use. Similarly, Asfaw et al. (2016) find that both inorganic fertilizer and improved seeds, as well as organic fertilizer go along with increased crop productivity and income in Niger, but do also not estimate the joint effect of all practices. In general, few studies look into the combined impact of inorganic and organic fertilizers with improved seeds, the core concept of ISFM. Interestingly, Wainaina et al. (2018) find that improved seeds coupled with chemical fertilizer have no significant effect on income among Kenyan maize farmers, nor is there an effect when the package is enhanced by organic manure. Yet, when improved varieties are combined with organic manure only, income effects are positive, and even more so when the two technologies are complemented by reduced tillage. One study by Adolwa et al. (2019) explicitly assesses the effect of ISFM on maize yields among farmers in two regions in Ghana and Kenya. They find positive effects of partial or full ISFM adoption on crop yields, albeit increasing the number of adopted ISFM components does not further enhance yields. However, the authors do not analyze interactions of particular ISFM practices, but only look at partial or complete adoption in terms of number of components, nor do they analyze effects on labor outcomes.

As Takahashi, Muraoka, et al. (2019) conclude in their recent review article, to date evidence on ISFM is mostly limited to its effects on yields or, at best, income. By contrast, studies looking into other outcomes, in particular the returns to unpaid family, labor are scarce. This is problematic considering that ISFM is often linked to higher labor investments, which are mostly covered by unpaid household labor and not accounted for in traditional outcome measures. Hence, it remains unclear whether yield benefits make up for additional labor input and thus, whether ISFM overall is a profitable technology.

This study aims at filling this gap by providing comprehensive evidence on the effects of ISFM in resource-constrained smallholder settings. We assess plot-level effects of organic fertilizer, inorganic fertilizer, improved seeds and combinations thereof on land productivity and net crop value as well as labor demand, labor productivity and financial returns to unpaid labor. To do so, we use survey data from 2,040 households and 6,247 maize, wheat and teff plots in the Ethiopian highlands. We employ a multinomial endogenous switching model to address issues of self-selection stemming from different technology choices. We differ from previous studies mainly by assessing effects of distinct combinations of ISFM practices and looking into a broader range of outcome indicators. To the best of our knowledge, no study has yet addressed labor demand, labor productivity and financial returns to labor in the context of ISFM adoption. Finally, since previous studies point towards the importance of accounting for differences in climatic, soil and other conditions (Adolwa et al., 2019; Jayne et al., 2019; Kassie et al., 2008, 2010; Marenya & Barrett, 2009), we look into heterogeneous treatment effects for two different agroecological zones.

The remainder of this article proceeds as follows: The next section outlines the ISFM concept and its potential effects on yields and labor in more detail. Subsequently, we describe the study context and data used for analysis as well as our estimation framework, followed by the empirical results. The last section discusses findings and draws conclusions.

3.2 The concept and implications of ISFM

The first core ISFM principle – the combined use of organic and inorganic fertilizers – is based on several arguments. Firstly, in many smallholder environments, neither of the two is available or affordable in adequate quantities. Secondly and more importantly, both sources comprise different sets of nutrients and/or carbon, which consequently address different soil fertility constraints in a complementary manner. Organic inputs alone, when applied at realistic levels, are unlikely to release enough nutrients to raise yield levels sufficiently on depleted African soils (Vanlauwe et al., 2010, 2015). On the other hand, marginal productivity of inorganic fertilizers, i.e. the additional crop yield per unit of fertilizer applied, is often substantially reduced on degraded soils that exhibit low levels of soil organic matter (SOM), low soil moisture, or high deficiencies of other yield-limiting nutrients (Barrett & Bevis, 2015; Jayne et al., 2019; Place et al., 2003; Vanlauwe et al., 2015). More precisely, both soil moisture as well as SOM levels – the latter closely linked to soil carbon stocks – regulate the solubility and hence, the availability of added inorganic nutrients for plant uptake. Recycling organic resources presents a strategy to improve SOM levels in the medium to long term, conserve soil moisture and supply additional nutrients, which can substantially increase the soil's responsiveness to chemical fertilizers (Marenya & Barrett, 2009). Efficient use of inorganic fertilizers, in turn, can itself contribute to increasing the availability of organic materials and consequently, building organic matter through enhanced on-farm biomass production (Vanlauwe et al., 2013). Hence, the ISFM concept goes beyond substitution effects, but claims substantial positive interactions and complementarities between inorganic and organic nutrient sources with the potential to increase crop productivity and long-term soil health (Place et al., 2003).

In terms of local adaptation of inorganic nutrient application, Vanlauwe et al. (2015) argue that crop response to fertilizers is often suboptimal, as many inorganic fertilizers are not suited to specific nutrient deficiencies prevailing in an area. In fact, the most commonly applied fertilizers used in SSA consist of the macronutrients nitrogen (N), phosphorus (P) or potassium (K), which fail to replenish secondary or micronutrients, such as sulfur (S), boron, calcium, zinc, or iron, that are particularly often lacking in densely populated areas where fallow periods are insufficient (Chianu et al., 2012; Vanlauwe et al., 2015). Hence, enriching standard fertilizers with locally deficient nutrients is important to increase their yield response.

The second core principle of ISFM is the use of crop varieties with locally required improved traits, such as higher-yielding, drought- or disease tolerant seeds, to ensure adequate matching of nutrient supply with demand, higher resilience to shocks, and increased production potential (Vanlauwe et al. 2015). Improved crop varieties are seen as key technology for boosting agricultural productivity and have proven positive effects on crop yields and welfare in numerous studies (Takahashi, Muraoka, et al., 2019), but need to go along with adequate soil management strategies to deploy their full productivity-enhancing potential (Sanchez, 2002).

Building on these theoretical ISFM premises, we expect that the use of ISFM practices will lead to enhanced land productivity. In particular, we hypothesize that the full integrated package will have the strongest effect due to the synergistic potential of organic fertilizer, inorganic fertilizer and improved seeds. Yet, for smallholder farmers, the application of ISFM may involve substantial opportunity costs in terms of financial resources, such as for the purchase of improved seeds and mineral fertilizers, and in terms of time, since in particular the preparation and transportation of bulky organic fertilizers and the targeted application of inputs are labor-intensive activities (Jayne et al., 2019; Takahashi, Muraoka, et al., 2019). We therefore expect ISFM adoption to increase labor demand. Furthermore, the effects on net crop value as well as on labor productivity and returns to unpaid labor are ambiguous, as they depend on whether increased land productivity makes up for higher input costs and labor demand.

3.3 Materials and methods

3.3.1 Study area and context

Around three-fourths of the Ethiopian population reside in rural areas and depend on agriculture as their main livelihood (CIA, 2020). Three cereal crops – maize, wheat and teff – make up for over half of the country's cultivated area and represent main staples in rural diets, but agricultural productivity remains comparatively low with average cereal yields of below 2.5 metric tons per hectare (CSA, 2019; FAO, 2020). In addition, over a quarter of the rural population lives below the national poverty line (FAO, 2020). Despite considerable prevention efforts, land degradation and declining soil fertility are still among the most severe threats to the Ethiopian agricultural sector and the livelihoods of smallholder farmers (Nyssen et al., 2015).

In order to combat environmental degradation, low agricultural productivity and rural poverty, the Ethiopian government, in cooperation with international donor agencies, has implemented a large-scale campaign to prevent further erosion and restore natural resources in large parts of the country's highland area over the past three decades (Schmidt & Tadesse, 2019). The core of the 'Sustainable Land Management Programme' (SLMP) was the stabilization of hillsides through physical soil conservation measures. Building on the SLMP achievements, the main focus has now been shifted to the intensification of smallholder farming practices. In 2017, ISFM has been integrated into the 'Ethiopian Soil Health and Fertility Improvement Strategy' (MoANR, 2017).

Against this background, in mid-2015 the German Agency for International Cooperation (GIZ) launched the 'Integrated Soil Fertility Management Project' (ISFM+ project) in areas where erosion control measures had already been introduced via the SLMP. The project's main goal is the promotion of ISFM practices among small-scale farmers, in particular for the three main staples wheat, maize and teff. It is implemented in close cooperation with the Ethiopian Ministry of Agriculture and Natural Resources, local extension staff, and farmers themselves via a community-based participatory extension strategy (Hörner et al., 2019). The ISFM+ project operates in 18 districts (in Ethiopia called Woredas) in the three Ethiopian highland regions Amhara, Oromia and Tigray.

Woredas within the three regions differ along agroecological characteristics. In terms of altitude, they cover the 'wenya dega' (1500 to 2,300 m a.s.l.) as well as 'dega' zones (over 2,300 to 3,200 m a.s.l.). In terms of rainfall, all districts in Tigray are classified as dry (less than 900 mm of annual rainfall), while those in Amhara and Oromia cover moist (over 900 to 1,400 mm) and wet (over 1,400 mm) zones, pointing towards substantial agroecological heterogeneity (Hurni, 1998).[31]

3.3.2 Sampling and data collection

We base our analysis on primary data from households residing in ISFM+ project Woredas. In order to rigorously assess the project's effectiveness in inducing ISFM adoption, the extension interventions have been implemented as a randomized controlled trial (RCT) (Hörner et al., 2019). Since the interventions were implemented in a community-based way, the primary randomization units of the RCT were microwatersheds, which are typical implementation entities for natural resource related projects in Ethiopia. Microwatersheds are water catchment areas, usually comprising 200 to 300 households in one or more villages that share a common rainwater outlet. In each of the three regions, six Woredas were selected, and within each Woreda, four treatment microwatersheds were randomly assigned. Furthermore, a total of 89 microwatersheds in the same Woredas did not receive any intervention and thus, serve as control microwatersheds. In each of the 161 microwatersheds, approximately 15 households were then randomly chosen from administrative lists to be included in the sample. While the total sample consists of 2,382 farm households, we restrict our analysis to those farmers that grow maize, wheat or teff on at least one of their plots, leading to a sample of 6,247 plots managed by 2,040 farm households.

[31] The average altitude of our study districts in Amhara is 2,450 m a.s.l., the average annual rainfall is 1,229 mm; in Oromia: 1,992 m a.s.l and 1,426 mm; and in Tigray: 2,130 m a.s.l and 661 mm.

We conduct our empirical analyses using the RCT endline data collected in treatment and control microwatersheds. Data were gathered in the first half of 2018 using tablet-based structured questionnaires. Amongst others, we collected detailed plot-level data on agricultural technology adoption, labor input and crop output in retrospective for the 2017 main cropping season. In addition, community-level data was assessed during interviews with key informants at the Woreda and microwatershed levels.

3.3.3 Description of treatment variable

Our treatment variable of interest is the adoption of ISFM practices. We focus on the three core practices of ISFM, i.e. the use of organic and inorganic fertilizers as well as improved varieties.[32] To account for differences in locally available resources, organic fertilizer refers to having applied either animal manure, compost, mulching or green manuring on a plot. Regarding inorganic fertilizer, the most common compound fertilizer types used in our sample are NPS fertilizers (in few cases NPK), mostly enriched with one or several locally deficient nutrients such as boron, zinc or iron.[33] These locally adapted 'blended fertilizers' have mostly replaced Diammonium-Phosphate (DAP), previously used as main compound fertilizer (ATA, 2019).[34] Improved seeds refer to higher-yielding open-pollinated (wheat and teff) or hybrid (maize) varieties, which in some cases also carry improved traits regarding disease (mostly wheat) or drought resistance (mostly maize). As we are particularly interested in the combined effects, we account for six possible practices and packages farmers can choose from: organic fertilizer only (OF), inorganic fertilizer only (IF), organic and inorganic fertilizers jointly (OF + IF)[35], organic fertilizer plus improved seeds but no inorganic fertilizer (OF + IS), inorganic fertilizer plus improved seeds but no organic fertilizer (IF + IS), and the full ISFM package (OF + IF + IS).[36]

[32] We leave aside additional, locally-varying components of ISFM in order to reduce the number of possible combinations of practices and hence, reduce analytical complexity to a reasonable level.

[33] In our definition of inorganic fertilizers, we refer to these 'compound' fertilizers which supply at least three key nutrients, as opposed to so-called 'straight' fertilizers containing only one nutrient type, such as Urea.

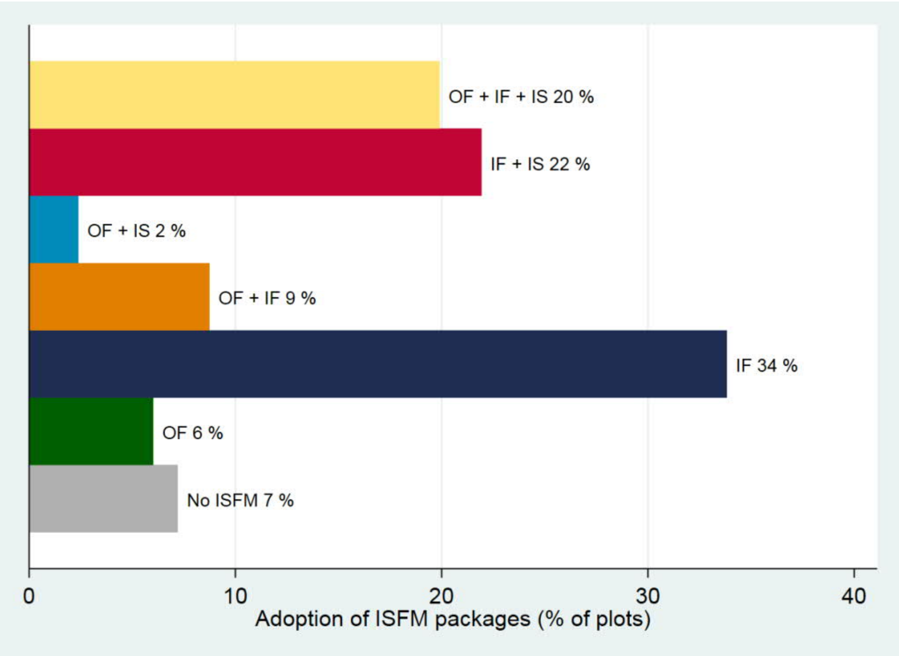
[34] In Ethiopia, the predominant belief in the past was that DAP supplemented by Urea fertilizer supply all necessary nutrients, resulting in blanket recommendations for the whole country. With the introduction of the 'Ethiopian Soil Information System' in 2012, currently the whole country is being mapped with regards to local availability and deficiencies of soil nutrients, which has led to area-specific fertilizer recommendations (ATA, 2019).

[35] In options one to three, OF, IF or OF + IF are coupled with the use of local landraces instead of improved seeds.

[36] We exclude plots on which only improved seeds were used, i.e. without organic or inorganic fertilizer, which is the case on only 58 plots. This small sub-sample size results problematic for econometric estimations, in particular that of heterogeneous treatment effects.

Figure 3.1 depicts the distribution of our treatment variable, the partial or complete adoption of the ISFM package. On around 7% of plots, none of the three technologies is used, while on about 6% respectively 9%, organic fertilizer is used solely (OF) or in combination with inorganic fertilizer (OF + IF). The most common practice is inorganic fertilizer, which is used in isolation (IF) on 34% of all fields. The least common combination of practices is OF + IS, applied on only 2% of plots, while farmers supplement improved seeds with inorganic fertilizer only (IF + IS) on 22% of their fields. The full ISFM package (OF + IF + IS) is used on 20% of maize, wheat and teff plots. These results confirm findings by Lambrecht et al. (2015): while farmers indeed engage in ISFM activities, adoption of components occurs rather sequentially than simultaneously, and large-scale complete adoption is yet to be attained.

Figure 3.1. Adoption of ISFM packages at the plot level.



Note: OF stands for organic fertilizer only, IF for inorganic fertilizer only, IS for improved seeds, while + indicates joint adoption of components.

3.3.4 Description of outcome variables

Our first core outcome variable is *land productivity*, measured as crop output in kilogram per hectare (kg/ha) over the three main cereal crops maize, wheat and teff.[37] Secondly, we assess the effects of ISFM adoption on profitability, defined as *net crop value* in Ethiopian Birr per hectare (ETB/ha). To do so, we calculate the monetary value of farmers' crop produce minus all costs for inputs such as seeds, fertilizers, pesticides and costs for hired labor. Since input

[37] In order to obtain more accurate data, we assessed this information using a broad range of local measurement units for both land area and yield quantities, and then converted into standard measurement units using conversion factors acquired from key informants at the community level, as well as from the Ethiopian Central Statistical Agency.

and output prices vary between study districts, we use price information obtained at the Woreda level.[38] It is important to note that we do not study true economic profit, but rather 'quasi profits', since we do not value owned land, equipment or household labor monetarily. *Labor demand* was assessed in detail by asking respondents which household member and how many hired or exchange laborers had been involved in farming activities during each of the following cropping stages: land preparation and sowing, 'general cultivation' (includes e.g. weeding, application of most inputs), and harvesting and threshing. Following Di Falco et al. (2011), we convert labor input into adult male equivalents with the factors 0.8 for adult females and 0.3 for children. Assuming one labor-day has about seven hours, we calculate labor demand in labor-days per hectare (labor-days/ha). Next, we are interested in effects on *labor productivity,* which describes the amount of crop output in kilogram produced per labor-day (kg/labor-day). Ultimately, we calculate the *returns to unpaid labor*[39] in Ethiopian Birr per labor-day (ETB/labor-day). Table 3.1 provides descriptive statistics of all outcome variables. In addition to full sample statistics, we distinguish between those plots on which the full package (OF + IF + IS) is used and those on which ISFM is only partially or not at all applied.

Table 3.1. Descriptive statistics of all outcome variables.

	Not adopted complete ISFM		Adopted complete ISFM			Full sample	
Outcome variables	Mean	SD	Mean	SD	p	Mean	SD
Land productivity (kg/ha)	1948.35	1648.89	3092.43	2035.11	0.000	2175.99	1791.64
Land productivity maize (kg/ha)	2914.05	2149.41	3514.53	2193.36	0.000	3146.82	2185.69
Land productivity wheat (kg/ha)	2432.35	1541.14	2544.20	1503.52	0.224	2455.83	1533.55
Land productivity teff (kg/ha)	1188.78	865.38	1701.50	1062.15	0.000	1209.24	879.57
Net crop value (ETB/ha)	17598.05	13939.66	18635.12	14299.35	0.020	17804.40	14016.92
Labor demand (labor-days/ha)	139.38	68.24	169.23	80.65	0.000	145.32	71.87
Labor productivity (kg/labor-day)	15.49	13.68	20.16	13.23	0.000	16.41	13.72
Returns to unpaid labor (ETB/labor-day)	151.87	186.55	133.56	125.52	0.001	148.24	176.26
N	5,004		1,243			6,247	

Note: SD stands for standard deviation. Exchange rate during survey period: 1 US-$ ~ 27 ETB; p-value indicates statistical significance of differences in means between those who adopt complete ISFM and those who do not.

[38] Regarding wages for hired laborers, we follow Vandercasteelen et al. (2016) and use average daily wage rates for each production activity over all microwatersheds in a Woreda.

[39] Including household and non-monetarily rewarded labor from outside the household.

3.3.5 Econometric framework

When modelling the effects of adoption of a certain technology (package) on outcomes of interest, one has to deal with potential endogeneity stemming from farmers' self-selection into different plot management regimes. Farmers' choice of technology might be influenced by both observed and unobserved factors, which at the same time may be correlated with outcomes such as yields or labor input. In order to address these issues and to disentangle the effects of ISFM adoption, we follow Teklewold et al. (2013) and Kassie et al. (2015) and employ a multinomial endogenous switching regression model (MESR). This approach allows for the modelling of alternative choices of technologies and their combinations, and thus, allows capturing interactions between different options in the selection process (Mansur et al., 2008; Wu & Babcock, 1998).[40]

The MESR entails a two-step simultaneous estimation procedure. The first stage estimates farmers' selection of alternative ISFM technologies (and their combinations) using a multinomial logit model which accounts for inter-relationships between alternatives. In the second stage, effects of the individual or combined ISFM practices on land productivity, net crop value as well as on labor demand, labor productivity and returns to labor are estimated via ordinary least squares (OLS), including selectivity correction terms obtained from the first stage.

Multinomial selection model

The analysis takes place at the plot level. Farmers are assumed to adopt a package of ISFM practices that maximizes their utility over all alternative combinations. We consider a latent model for the unobserved expected utility U_{jik}^{*} that farmer *i* derives from adopting ISFM combination *j* (with $j = 1, 2, ..., 7$) on plot *k* (Kassie et al., 2015; Teklewold et al., 2013):

$$U_{jik}^{*} = \beta_j X_{jik} + \varepsilon_{jik} \tag{3.1}$$

in which X_{jik} is a vector of observed household, plot and location characteristics, while ε_{jik} are unobserved factors. While farmers' utility is not observable, their adoption decision *I* is. A rational farmer is expected to choose technology *j*, and not any alternative combination *m*, if:

$$I = \begin{cases} 1 \; if \, U_{1ik}^{*} > max_{m \neq 1}(U_{mik}^{*}) \; or \; \eta_{1ik} < 0 \\ \vdots \qquad \qquad \vdots \qquad \qquad \vdots \\ J \; if \, U_{Jik}^{*} > max_{m \neq J}(U_{mik}^{*}) \; or \; \eta_{Jik} < 0 \end{cases} \quad for \; all \; m \neq j \tag{3.2}$$

[40] Bourguignon et al. (2007) show that the model provides a fairly good correction for endogeneity in the outcome equation even if the independence of irrelevant alternatives (IIA) assumption is violated in the selection process.

with $\eta_{jik} = max_{m \neq j}(U^*_{mik} - U^*_{jik}) < 0$, which implies that the ith farmer will adopt ISFM combination *j* on plot *k* if it provides greater expected utility than any alternative *m* (Bourguignon et al., 2007).

Assuming an independent and identical Gumbel distribution of ε, the probability that farmer *i* with characteristics *X* adopts technology package *j* on plot *k* is expressed by a multinomial logit model, which is estimated using maximum likelihood (McFadden, 1973).

$$P_{jik} = Pr(\eta_{jik} < 0 | X_{jik}) = \frac{exp(\beta_j X_{jik})}{\sum_{m \neq 1}^{J} exp(\beta_m X_{jik})} \quad (3.3)$$

Multinomial endogenous switching model

In the second stage, the relation between the outcome variables and a set of explanatory variables *Z* is estimated for each of the ISFM choices, i.e. OF *(j = 2)*, IF *(j = 3)*, OF + IF *(j = 4)*, OF + IS *(j = 5)*, IF + IS *(j = 6)* and OF + IF + IS *(j = 7)*, in which *j = 1* (no ISFM) is the reference category. For all outcomes Q, the equations for each possible adoption regime *j* is given as follows:

$$\begin{cases} Regime\ 1: Q_{1ik} = \alpha_1 Z_{1ik} + u_{1ik} & if\ I = 1 \\ \quad\vdots \qquad\qquad \vdots & j = 2, 3, 4, 5, 6, 7 \\ Regime\ J: Q_{Jik} = \alpha_J Z_{Jik} + u_{Jik} & if\ I = J \end{cases} \quad (3.4)$$

in which Q_{jik} denotes the outcome of farmer *i* on plot *k* in regime *j*, and u_{jik} the error terms distributed with $E(u_{jik}|XZ) = 0$ and $var(u_{jik}|XZ) = \sigma^2$. Q_{jik} is only observed if package *j* is used on plot *k*. If the error terms *u* are correlated with those from the first stage ε, OLS estimates in equation (3.4) are likely to be biased. In order to obtain consistent estimates of α_j, we have to augment outcome equations (3.4) by including selection correction terms (Bourguignon et al. 2007):

$$\begin{cases} Regime\ 1: Q_{1ik} = \alpha_1 Z_{1ik} + \sigma_1 \hat{\lambda}_{1ik} + \omega_{1ik} & if\ I = 1 \\ \quad\vdots \qquad\qquad \vdots \qquad\qquad \vdots & \\ Regime\ J: Q_{Jik} = \alpha_J Z_{Jik} + \sigma_J \hat{\lambda}_{Jik} + \omega_{Jik} & if\ I = J \end{cases} \quad (3.5)$$

where ω_{jik} is the error term with an expected value of zero, σ_j the covariance of the ε's and *u's*, and λ_j the inverse Mills ratio computed from the estimated probabilities in (3.3) as:

$$\lambda_{jik} = \sum_{m \neq j}^{J} \rho_j \left[\frac{\hat{P}_{mik} ln(\hat{P}_{mik})}{1 - \hat{P}_{mik}} + ln(\hat{P}_{jik}) \right] \quad (3.6)$$

with ρ_j denoting the correlation coefficients of ε and u. In this multinomial choice framework, *J-1* selection correction terms have to be included, i.e. one for each alternative technology choice. In order to account for heteroscedasticity arising from the generation process of λ, standard errors are bootstrapped.

We base the empirical specification of the variables included in X and Z on previous theoretical and empirical adoption literature (e.g. Kassie et al., 2009, 2015; Khonje et al., 2018; Knowler & Bradshaw, 2007; Marenya & Barrett, 2009; Teklewold et al., 2013, 2019; Wollni et al., 2010). Table 3.2 provides an overview of all plot and household-level characteristics included in the models as explanatory variables. In addition, we include total labor use in the models for land productivity and net crop value.

For the model to be identified correctly, it is important to use at least one selection instrument, i.e. a variable that directly affects the adoption decision, but not the outcome variables (except via adoption). This instrumental variable is included in X, but not in the Z variables. Building on the RCT design, we employ the random assignment to the ISFM+ project interventions as an instrument, which fulfils the necessary properties of a valid instrumental variable (Angrist et al., 1996). Firstly, exposure to the treatment is random, which is satisfied given the experimental set-up. Secondly, exposure to the treatment indeed influences the uptake of ISFM practices. And finally, outcomes are not directly affected by the random assignment to the ISFM+ project interventions, but only through ISFM adoption. Tables A 3.1 and A 3.2 in Appendix A 3 confirm that these assumptions hold in the empirical case, as living in an ISFM+ community significantly influences ISFM uptake, while it does not affect any of the outcome variables beyond ISFM adoption.

Estimating average treatment effects

Finally, the above described estimation procedure is used to compute the average treatment effects on the treated (ATT), hence, the expected effects of applying a certain ISFM package on a plot. To do so, one has to obtain a valid counterfactual, i.e. the outcome a farmer would obtain on an ISFM plot, assuming she or he had not adopted any ISFM practice. Following a well-established approach in the impact literature (e.g. Di Falco et al., 2011; Kassie et al., 2015; Teklewold et al., 2013), we estimate actual and counterfactual cases as follows:

Adopters with adoption (observed in sample)

$$E\left(Q_{jik} \middle| I = j\right) = \alpha_j Z_{jik} + \sigma_j \hat{\lambda}_{jik} \tag{3.7}$$

Non-adopters with non-adoption (observed in sample)

$$E(Q_{1ik}|I = 1) = \alpha_1 Z_{1ik} + \sigma_1 \hat{\lambda}_{1ik} \tag{3.8}$$

Adopters with non-adoption (counterfactual)

$$E(Q_{1ik}|I = j) = \alpha_1 Z_{jik} + \sigma_1 \hat{\lambda}_{jik} \tag{3.9}$$

Non-adopters with adoption (counterfactual)

$$E\left(Q_{jik}\middle|I = 1\right) = \alpha_j Z_{1ik} + \sigma_j \hat{\lambda}_{1ik} \tag{3.10}$$

Equations (3.7) and (3.8) model the actual expected outcomes for ISFM adopters and non-adopters, respectively, which are observed in the data. By contrast, equations (3.9) and (3.10) represent the counterfactual outcomes; that is, the outcomes that adopters would achieve without adoption, and that non-adopters would achieve under adoption. The ATT is calculated as the difference between equations (3.7) and (3.9):

$$ATT = E\left(Q_{jik}\middle|I = j\right) - E(Q_{1ik}|I = j) = Z_{jik}\left(\alpha_j - \alpha_1\right) + \hat{\lambda}_{jik}(\sigma_j - \sigma_1) \tag{3.11}$$

The first term (Z_{jik}) on the right-hand side of equation (3.11) models the expected change in adopters' mean outcomes assuming their characteristics and endowments had the same returns as those of non-adopters, while the second term $(\hat{\lambda}_{jik})$ corrects for selection bias originating from unobserved factors.

Table 3.2. Descriptive statistics of all explanatory variables used in analysis.

	Not adopted complete ISFM		Adopted complete ISFM			Full sample	
	Mean	SD	Mean	SD	p	Mean	SD
Panel A: Household characteristics							
Gender HH head (1 = male)	0.86		0.90		0.002	0.88	
Age HH head (in years)	48.84	14.29	47.51	13.35	0.031	48.21	13.87
HH head has formal education (1 = yes)	0.39		0.42		0.191	0.40	
No. of HH members	5.26	2.03	5.31	1.81	0.541	5.28	1.93
No. of TLU owned	3.57	3.01	4.50	3.02	0.000	4.01	3.05
Farm size (in ha)	1.36	1.07	1.38	0.95	0.743	1.37	1.02
HH has access to formal credit (1 = yes)	0.59		0.63		0.050	0.61	
No. of social organizations HH is involved	3.20	1.92	3.68	1.91	0.000	3.43	1.93
Talked to extension agent (1 = yes)	0.49		0.67		0.000	0.58	
Walking distance to nearest FTC (in min)	33.24	25.57	31.04	23.65	0.044	32.20	24.71
Walking distance to nearest village market (in min)	75.31	49.85	67.03	43.13	0.000	71.42	46.99
Agri-input dealer in Kebele (1 = yes)	0.60		0.63		0.194	0.62	
HH lives in ISFM+ community (1 = yes)	0.42		0.54		0.000	0.48	
Pest and disease stress (1 = yes)	0.12		0.11		0.858	0.12	
Weather stress (drought/flood/frost/storm) (1 = yes)	0.35		0.28		0.001	0.32	
Average annual rainfall (in mm)	1054.63	457.96	1203.19	361.75	0.000	1124.40	422.03
N	1,082		958			2,040	

Panel B: Plot characteristics							
Plot distance from homestead (in min)	14.92	22.15	4.91	11.20	0.000	12.93	20.83
Plot owned (1 = yes)	0.68		0.83		0.000	0.71	
Plot size (in ha)	0.24	0.21	0.20	0.18	0.000	0.23	0.20
Footslope (1 = yes)	0.46		0.46		0.873	0.46	
Hillslope (1 = yes)	0.13		0.11		0.065	0.12	
Shallow soil (1 = yes)	0.21		0.16		0.000	0.20	
Deep soil (1 = yes)	0.52		0.60		0.000	0.53	
Poor soil quality (1 = yes)	0.26		0.14		0.000	0.23	
Good soil quality (1 = yes)	0.36		0.49		0.000	0.38	
Herbicide used (1 = yes)	0.33		0.09		0.000	0.28	
Pesticide used (1 = yes)	0.13		0.17		0.000	0.14	
Lime used (1 = yes)	0.02		0.11		0.000	0.04	
Urea used (1 = yes)	0.68		0.93		0.000	0.73	
Maize plot (1 = yes)	0.25		0.64		0.000	0.33	
Wheat plot (1 = yes)	0.26		0.28		0.190	0.27	
Teff plot (1 = yes)	0.49		0.08		0.000	0.41	
N	5,004		1,243			6,247	

Note: SD stands for standard deviation. HH stands for household; FTC stands for farmer training center; TLU stands for tropical livestock unit; Kebele is the lowest administrative unit in Ethiopia; formal credit refers to bank, microfinance institution, government or agri-input dealer; footslope/hillslope compared to midslope; shallow/deep soil compared to medium soil depth; poor soil/good soil compared to average soil quality; p-value indicates statistical significance of differences in means between those who adopt complete ISFM and those who do not.

3.4 Empirical results

3.4.1 Average treatment effects in the full sample

Table 3.3 depicts the average treatment effects on the treated plots for each of the six ISFM combinations.[41] Results show that, averaged over the three crop types, adoption of all individual as well as combined ISFM practices leads to increased land productivity.[42] In the case of fertilizer use without improved seeds, we find that inorganic fertilizer is associated with more pronounced yield gains than organic fertilizer when the two are applied in isolation (546 kg/ha vs. 320 kg/ha), while the ATT of their combined use is only modestly higher than that of inorganic fertilizer alone (603 kg/ha). Combining any kind of fertilizer with improved seeds increases the magnitude of the ATT substantially. This is not surprising considering that improved seeds for all crop types carry higher-yielding traits. On average, the full ISFM package leads to the highest yield effect (1,561 kg/ha). While the ATT magnitude of the combination IF + IS (1,300 kg/ha) is relatively close to that of the complete package, the package OF + IS on average leads

[41] Since the ATT of ISFM adoption on yield- and labor-related outcomes are our primary interest in this article, we do not discuss the empirical results of the adoption and outcome equations; Tables A 3.3 to A 3.8 in Appendix A 3 show estimation results of the first and second stage regressions.

[42] Small sub-sample sizes for some categories of the treatment variable do not allow separate estimations for each crop type. While averaging productivity over different crop types makes the interpretation of the absolute magnitude of results less straightforward, relative effect sizes still provide important implications. Focusing on aggregated effects for main food crops in subsistence agriculture settings, while controlling for crop types grown, is also supported by other studies (Di Falco et al., 2011; Kassie et al., 2010).

to smaller, but still substantial effects (947 kg/ha). The treatment effects of these three packages reflect average changes in land productivity between 66% and 138% compared to the hypothetical yields that farmers would achieve under traditional farming practices (no ISFM) on the same plots.

Looking at net crop value suggests that on average, the combinations OF + IF + IS (6,995 ETB/ha) and OF + IS (6,868 ETB/ha) lead to the highest increase in profitability for farmers, followed by the IF + IS package (6,457 ETB/ha). These effects are equivalent to mean increases of 67% to 82% in comparison to the counterfactual scenarios of no ISFM on the same plots. Overall, effects of the three packages that involve improved seeds on net crop value are quite similar, despite the smaller effect of the OF + IS combination on land productivity. This is most likely the case because farmers do hardly incur expenses for organic fertilizer, which is typically sourced on-farm. In contrast, inorganic fertilizer use involves substantial monetary costs that on average do not seem to be compensated by its additional yield effect. Regarding the use of fertilizers without improved seeds, organic fertilizer alone is associated with the smallest, yet positive and significant effect on net crop value (1,851 ETB/ha), reflecting the finding that OF alone is related to the smallest yield increase. The use of inorganic fertilizer alone as well as combined with organic fertilizer lead to higher average effects on net crop value (4,932 ETB/ha and 3,723 ETB/ha). Hence, here it seems that the stronger effect of inorganic fertilizer on land productivity outweighs the additional expenses, compared to the use of organic fertilizer alone.

Table 3.3. Average ISFM adoption effects on the treated plots.

ISFM combination	Land productivity (kg/ha)			Net crop value (ETB/ha)			Labor demand (labor-days/ha)			Labor productivity (kg/labor-day)			Returns to unpaid labor (ETB/labor-day)			N
	ATT		p	ATT		p	ATT		p	ATT		p	ATT		p	
OF	320.30	(65.70)	0.000	1850.53	(494.39)	0.000	9.81	(3.19)	0.002	1.53	(0.31)	0.000	6.76	(3.44)	0.050	376
IF	545.95	(20.80)	0.000	4932.26	(213.93)	0.000	6.10	(1.00)	0.000	4.27	(0.17)	0.000	35.49	(1.69)	0.000	2,113
OF + IF	602.65	(40.03)	0.000	3722.66	(417.61)	0.000	24.21	(2.73)	0.000	3.26	(0.24)	0.000	13.96	(3.07)	0.000	546
OF + IS	947.24	(122.33)	0.000	6868.43	(850.03)	0.000	24.39	(6.10)	0.000	5.22	(0.59)	0.000	36.19	(4.24)	0.000	149
IF + IS	1299.74	(35.57)	0.000	6456.63	(245.32)	0.000	26.71	(1.34)	0.000	8.43	(0.25)	0.000	37.21	(1.91)	0.000	1,370
OF + IF + IS	1560.61	(38.66)	0.000	6995.02	(245.24)	0.000	40.38	(1.73)	0.000	8.06	(0.19)	0.000	31.56	(1.77)	0.000	1,243

Note: Exchange rate during survey period: 1 US-$ ~ 27 ETB; reduced sample size stems from logarithmic transformation of outcomes during estimation procedure; standard errors in parentheses; p-values indicate statistical significance of ATT.

As expected, using any of the ISFM practices as well as any combination thereof is associated with an increase in labor demand. On average, applying only organic fertilizer on a plot increases labor requirements by around 10 labor-days/ha, while using inorganic fertilizer leads to around 6 additional labor-days/ha. The difference in ATT magnitude between OF and IF is likely to be explained by the fact that both transportation and application of organic inputs are more cumbersome compared to inorganic fertilizers, which are applied in much lower quantities.[43] More detailed analyses reveal that increased labor demand associated with all ISFM packages that contain organic fertilizer mainly stems from the 'general cultivation' stage, i.e. the phase between planting and harvesting, in which inputs such as organic fertilizers are mainly applied (results available upon request). The use of improved seeds also seems to be associated with substantial increases in average labor demand, as suggested by the significant ATT between 24 and 40 labor-days/ha of the packages containing improved seeds (equivalent to average increases of 17% to 34% compared to the counterfactual). Contrary to our expectations, this does not primarily stem from the fact that improved seeds are mostly sown in lines, which should increase labor demand during the planting stage (compared to local seeds which are commonly broadcasted). By contrast, we find that much of this effect occurs during the stage of 'general cultivation' (results available upon request). This could indicate that farmers pay special attention to fields planted with improved seeds, e.g. they invest more time in weeding and pest control, since a loss of harvest would be costlier compared to produce obtained from local seeds.

Despite substantial increases in labor demand, results in Table 3.3 also show positive and significant ATT on labor productivity for all ISFM combinations, ranging between 1.5 kg/labor-day (+17%) for OF, 4 kg/labor-day for IF (+61%), 3 kg/labor-day OF + IF (+45%), 5 kg/labor-day for OF + IS (+57%), and around 8 additional kg/labor-day for IF + IS and the full ISFM package (+80 to 90%). Hence, higher requirements in terms of labor input appear to be offset by enhanced land productivity.

Ultimately, we assess ISFM effects on the profitability of unpaid labor investments. For all practices and combinations, we find positive and significant ATT for the returns to unpaid labor. The largest average effects stem from IF alone and the three packages that involve improved seeds, leading to ATT between 32 and 37 ETB/labor-day. These effects reflect increases in returns to labor between 36% and 56% compared to the counterfactuals of no ISFM on the

[43] The average application rate of manure and compost is 1,869 kg/ha, compared to inorganic fertilizer with 158 kg/ha.

same plots, and are equivalent to slightly less than half of the average daily wage rate for agricultural laborers in our study area (around 80 ETB).

3.4.2 Differential effects by agroecological zone

Due to the substantial agroecological differences in our sample, we assess heterogeneous treatment effects by type of agroecology, differentiating between the regional states of Amhara and Oromia, classified as moist or wet areas (Panel A of Table 3.4), and that of Tigray, which covers dry areas (Panel B).

Regarding the effects of fertilizers alone on land productivity of the three crops, the pattern found in the two disaggregated samples is fairly similar to the one in the full sample: Applying inorganic fertilizer alone leads to somewhat higher yield increases than organic fertilizer alone, while combining the two fertilizer types leads to a modestly stronger effect than inorganic fertilizer only. Yet, when we look into the different combinations of fertilizers and improved seeds within each subsample, the picture changes. In the moister regions, the combinations IF + IS (1,603 kg/ha) as well as OF + IF + IS (1,741 kg/ha) lead to more pronounced ATT on land productivity than OF + IS (979 kg/ha), underlining the relevance of complementing improved seeds with inorganic fertilizer. In the drier region of Tigray, by contrast, the combinations OF + IS (858 kg/ha) and OF + IF + IS (1,016 kg/ha) clearly outperform the effect of the IF + IS package (492 kg/ha). This points towards the importance of using improved seeds combined with organic fertilizer in dryer areas, probably due to its moisture-conserving effect.

In terms of net crop value, the ATT estimates for Amhara and Oromia indicate an approximately similar effect of the three packages containing improved seeds (ranging between 7,011 ETB/ha and 7,533 ETB/ha), despite the fact that OF + IS on average has a substantially smaller effect on land productivity. Again, this finding presumably reflects the reduced expenses when only organic fertilizer is used and hence, no additional costs for inorganic fertilizer are incurred. In Tigray, the combinations that include organic fertilizer and improved seeds, i.e. OF + IS (6,467 ETB/ha) and OF + IF + IS (5,582 ETB/ha), are superior to the IF + IS package (3,590 ETB/ha) in terms of net crop value (although the effect size of the OF + IS package in Tigray should not be over-interpreted due to the small sample size).

Regarding labor demand, in both subsamples the full ISFM package on average goes along with the largest increase in labor input (40 respectively 43 additional labor-days/ha). In general, magnitudes of the ATT indicate that labor requirements associated with ISFM are larger in Tigray than in the other two regions, probably because the terrain is more rugged and hence, transporting and applying inputs more cumbersome. In Amhara and Oromia, applying only one fertilizer type leads to insignificant, albeit positive ATT. Results further show that on average, labor productivity in Amhara and Oromia increases the strongest when both improved seeds and inorganic fertilizer are used together (9 to 11 kg/labor-day), while in Tigray the largest average effects come from the combinations that involve improved seeds and organic fertilizer (4 to 5 kg/labor-day). Overall, ATT magnitudes for labor productivity are substantially smaller in Tigray, since ISFM there is related to higher labor demand, yet somewhat smaller increases in land productivity. Considering returns to unpaid labor, in Tigray only the three packages including improved seeds lead to significant positive ATT, whereas packages including inorganic fertilizer but no improved seeds are even associated with negative (though insignificant) effects. This suggests that in Tigray, investments of unpaid labor only pay off when improved varieties are used, and even more when they are combined with organic fertilizer. By contrast, in Amhara and Oromia, all ISFM practices and combinations go along with substantial positive and significant ATT on labor returns.

Table 3.4. Average ISFM adoption effects on the treated plots by agroecological zone.

ISFM combination	Land productivity (kg/ha)			Net crop value (ETB/ha)			Labor demand (labor-days/ha)			Labor productivity (kg/labor-day)			Returns to unpaid labor (ETB/labor-day)			N
Panel A: Amhara & Oromia (moist/wet)																
	ATT		p	ATT		p	ATT		p	ATT		p	ATT		p	
OF	382.79	(81.06)	0.000	2282.13	(585.35)	0.000	4.30	(3.38)	0.204	2.07	(0.39)	0.000	8.72	(3.54)	0.014	225
IF	600.77	(23.46)	0.000	5552.99	(232.20)	0.000	0.95	(0.99)	0.338	5.01	(0.20)	0.000	45.13	(1.94)	0.000	1,687
OF + IF	706.18	(52.81)	0.000	5207.72	(571.62)	0.000	14.57	(3.20)	0.000	4.24	(0.33)	0.000	25.85	(4.19)	0.000	320
OF + IS	979.02	(125.86)	0.000	7010.74	(851.64)	0.000	22.66	(5.86)	0.000	5.61	(0.65)	0.000	39.15	(4.44)	0.000	110
IF + IS	1602.94	(40.47)	0.000	7533.05	(260.34)	0.000	26.57	(1.42)	0.000	10.64	(0.27)	0.000	49.22	(2.30)	0.000	996
OF + IF + IS	1741.49	(45.01)	0.000	7464.45	(279.61)	0.000	39.61	(1.79)	0.000	9.16	(0.22)	0.000	34.58	(2.11)	0.000	933
Panel B: Tigray (dry)																
	ATT		p	ATT		p	ATT		p	ATT		p	ATT		p	
OF	227.20	(108.50)	0.037	1207.41	(850.81)	0.157	18.01	(5.97)	0.003	0.73	(0.41)	0.073	3.83	(6.68)	0.567	151
IF	328.89	(43.58)	0.000	2474.13	(521.59)	0.000	26.51	(2.70)	0.000	1.33	(0.25)	0.000	-2.69	(2.84)	0.344	426
OF + IF	456.06	(59.76)	0.000	1619.93	(556.86)	0.004	37.86	(4.68)	0.000	1.88	(0.29)	0.000	-2.88	(3.83)	0.453	226
OF + IS	857.61	(302.05)	0.006	6467.05	(2197.68)	0.004	29.28	(16.52)	0.080	4.12	(1.21)	0.001	27.86	(9.88)	0.006	39
IF + IS	492.28	(44.90)	0.000	3590.02	(538.38)	0.000	27.09	(2.95)	0.000	2.54	(0.32)	0.000	5.22	(3.03)	0.085	374
OF + IF + IS	1016.23	(63.85)	0.000	5582.19	(485.57)	0.000	42.69	(4.34)	0.000	4.77	(0.29)	0.000	22.45	(2.98)	0.000	310

Note: Exchange rate during survey period: 1 US-$ ~ 27 ETB; reduced sample size stems from logarithmic transformation of outcomes during estimation procedure; standard errors in parentheses; p-values indicate statistical significance of ATT.

3.4.3 Robustness checks

Even though we control for the type of crop grown on a plot in our regression framework, we re-estimate the ATT on land productivity excluding one crop type at a time in order to check robustness of our results with regards to crop choice.[44] Since cropping patterns are somewhat different between regions, we do that for the two agroecologies separately.[45] Focusing only on the effects of the joint application of improved seeds and different types of fertilizers, Table A 3.9 in Appendix A 3 confirms that results for land productivity are largely robust to crop choice in Amhara and Oromia. Here, the combinations entailing inorganic fertilizers (IF + IS and OF + IF + IS) still lead to higher ATT than that of improved seeds and organic fertilizer alone (OF + IS) in all three cases. Similarly, in Tigray, the full ISFM package (OF + IF + IS) is associated with substantially higher yield gains than the IF + IS combination in each of the three subsamples, which is in line with results from the full Tigray sample. The same can be said for the ATT of OF + IS when either wheat or teff are excluded. Yet, when maize plots are omitted from the ATT estimations, the ATT of OF + IS for Tigray drops sharply. While this may point towards differential effects of the OF + IS combination in Tigray for different crop types, this finding relies on a fairly small sample size and should not be over-interpreted. In any case, we can safely conclude that complementing the joint use of inorganic fertilizer and improved seeds by organic fertilizer is more relevant in drier than in moister areas when it comes to increasing land productivity.

3.5 Discussion and conclusion

In recent years, ISFM is increasingly promoted as a strategy to sustainably improve soil fertility, increase returns to land and labor of rural farm households, and ultimately combat natural resource depletion. ISFM is a system technology comprising the joint application of organic and inorganic fertilizer and improved crop varieties, which are supposed to bear synergistic effects. Yet, since ISFM typically goes along with higher demand for capital and labor, it is important to assess whether these additional investments pay off for smallholders. In this study, we assessed the plot-level effects of different combinations of ISFM practices.

In line with our expectations, we find that both partial as well as full ISFM adoption is associated with significant increases in land productivity over the three major staples maize, wheat and teff. On average, the largest effect stems from adopting complete ISFM, followed by combining improved seeds only with inorganic fertilizer, and only with organic fertilizer.

[44] Very small sample sizes for some combinations of ISFM practices and crop types do not allow estimating the ATT for each crop type separately.

[45] Amhara/Oromia: 38% maize plots, 24% wheat, 37% teff; Tigray: 18% maize, 33% wheat, 49% teff.

Using either fertilizer type alone or jointly but with local instead of improved seeds, still leads to positive, yet substantially smaller yield benefits. Likewise, we find positive and significant effects of all ISFM practices and packages on net crop value, suggesting that ISFM is profitable despite additional input costs. On average, the strongest increases in net crop value stem from the adoption of either one or both fertilizer types with improved seeds. This is in spite of the lower yield effects of using only organic fertilizer with improved seeds, most likely since it does not involve costs for externally sourced inorganic fertilizer.

Further, as expected, results also show that ISFM is related to significant increases in labor demand of up to 34%. In the case of fertilizers, this most likely stems from their transportation and application, while higher labor demand for improved seeds probably originates from more weeding, pest control or other measures taken to prevent crop damage. Yet, on average, increased labor demand seems to be outweighed by enhanced crop yields and net crop value, since ISFM adoption goes along with significantly positive effects on labor productivity as well as returns to unpaid labor.

Yet, we find substantial heterogeneity regarding the effects on land productivity in different agroecological zones. In moister regions, combining inorganic fertilizer with improved seeds – whether complemented by organic fertilizer or not – clearly outperforms the combination of improved seeds and organic fertilizer only. By contrast, in drier areas, the joint uptake of organic fertilizer with improved seeds (with or without inorganic fertilizer) has a substantially larger effect on yields than the package improved seeds plus inorganic fertilizer only. This finding seems robust to the choice of crop type when the package of organic fertilizer and improved seeds is applied jointly with inorganic fertilizer. Most likely, this is because organic fertilizer increases the solubility, and thus, plant uptake of inorganic nutrients, and consequently also the potential of improved seeds to convert nutrients into biomass. The relevance of moisture-retaining technologies in drier agroecological areas is also supported by other studies (Kassie et al., 2008, 2010).

These results have important implications. Firstly, though fertilizer application is important to raise smallholders' yields, its combined uptake with improved seeds appears crucial to exploit more of the soil's productive potential. Considering that in some SSA countries improved seed adoption is still low (in Ethiopia, for instance, only around 30% of the maize area is cultivated with improved seeds), sustained efforts to promote their use appear crucial, e.g. via strengthening local seed networks, infrastructure and access to credit (Jayne et al., 2019; Sheahan & Barrett, 2017).

Secondly, despite the fact that the largest average effect on land productivity stems from the full integrated package, the difference to the package comprising only inorganic fertilizer and improved seeds is not as strong as expected. These findings are in line with Adolwa et al. (2019), who find significant effects of partial or full ISFM adoption on maize yields, but not of increasing the number of adopted components. This may question the fundamental idea of ISFM that the full synergistic potential can only be reaped by using organic and inorganic nutrients jointly, as demonstrated by numerous field trials. However, as mentioned above, while ISFM in this study is only conceptualized with a binary variable indicating adoption of each technology (combination), other factors such as the *how* and the *how much* are also crucial, especially when using data from micro-level farmer surveys instead of well-managed demonstration fields (Bationo et al., 2008; Jayne et al., 2019). In addition, the quality of applied inputs may vary, in particular when it comes to self-produced organic fertilizers. For instance, whereas around 50% of the households in our data set produce compost, a compost quality index reveals that on average, farmers do not even apply half of the best-practice recommendations for compost production, which most likely has implications for the quality of the end product. In addition, changes in soil organic matter through organic fertilizer application do usually not occur within one season, but rather build over time (Jayne et al., 2019; Marenya & Barrett, 2009). Our RCT baseline data reveals that organic fertilizer use was less prevalent among the same households in 2015, so that in 2017, some plots probably received organic fertilizer for the first or second time. Hence, mid- or long-term effects of integrated application of organic and inorganic fertilizers might be much more pronounced than those we captured with our data. In addition, our study areas have already benefitted from soil conservation through the SLMP, including physical structures, terracing or contour planting. These erosion control measures are beneficial for the accumulation of organic matter and preserving soil moisture, and hence, for the effect of inorganic fertilizer. The combination of organic and inorganic fertilizers might therefore be more crucial in other areas of Ethiopia or SSA, where soils still suffer from higher erosion levels.

Thirdly, the positive ISFM effects on land productivity, net crop value, labor productivity and returns to labor suggest that overall, ISFM is a profitable technology for smallholder farmers, at least when assessed at the plot level. Nonetheless, increased labor demand – in particular when the full ISFM package is applied – can present a prohibitive barrier to adoption, especially for labor-constrained households. In moister regions, using improved seeds solely with inorganic fertilizer may – at least in the shorter run – appear more viable. On the other hand, while combining only organic fertilizer and improved seeds leads to lower average increases in land productivity in moister zones, this combination has still substantial positive effects even in these areas, leading to an equally strong effect on net crop value. Hence, for more cash-constrained households, substituting costly inorganic fertilizers with renewable, locally available organic resources may constitute a more attractive option. In dryer areas, however, using improved seeds with organic fertilizer (either with or without inorganic fertilizer) seems vital, despite the higher labor requirements. In this context, communal labor exchange schemes might gain even more importance in order to make ISFM implementation feasible for farmers. In addition, emerging initiatives to enhance the use of labor-sparing mechanization in SSA are certainly well targeted (Jayne et al., 2019).

Lastly, despite its central role in dry regions, organic fertilizer adoption is still limited (in our sample to around 37% of plots), probably also due to its competing purposes; for instance, crop residues are often used to feed livestock, or manure as fuel. Promoting alternatives, such as planting fodder crops around plot borders and using energy-saving stoves, might lead to a higher availability of organic material to be used as fertilizer. Moreover, involving public or private sector actors to develop markets and distribution services for organic manure and compost seems important in this regard (Jayne et al., 2019).

Our study exhibits some limitations. Firstly, we apply a rather narrow definition of ISFM, only looking into the effects of the three main components, while ignoring other 'local adaptation' measures. Yet, it may be important to analyze the effects of further agricultural inputs and technologies, which might be adopted as substitutes or complements for fertilizers and improved seeds. Secondly, in the absence of plot-level panel data, we only capture farmers' plot management behavior in a cross-section, without accounting for previous input use or management decisions. In particular the application of organic resources in a previous period might have important implications for organic matter accumulation and consequently, lead to heterogeneous effects of different ISFM combinations in the season under consideration. Future studies should shed more light on these effects using longitudinal plot-level data. And finally, we only consider ISFM effects on outcomes directly related to farmers' livelihoods, while we do not capture potential positive externalities on the environment. For instance, enhanced soil organic matter levels and soil health can, in the longer run, improve the provision of vital ecosystem services, such as the storing of soil carbon and erosion control, while higher productivity may prevent further deforestation and thus, contribute to conserving natural resources (Adhikari & Hartemink, 2016). These environmental benefits can, in turn, lead to positive feedback effects on smallholders' livelihoods, as well as on society as a whole.

All in all, our evidence suggests that ISFM can contribute to overcoming the downward spiral of poor soils, poor agricultural performance and perpetuated poverty by increasing both land and labor productivity. To initiate this process, recommendations need to be carefully targeted to heterogeneous conditions, both in terms of agroecological environments as well as resources available at the farm level.

Appendix A 3

Table A 3.1. Association between instrumental variable and selection variable (adoption of ISFM practices).

	OF	IF	OF + IF	OF + IS	IF + IS	OF + IF + IS
HH lives in ISFM+ community (1 = yes)	0.259*	0.388***	0.476***	0.421**	0.397***	0.771***
	(0.147)	(0.133)	(0.153)	(0.204)	(0.134)	(0.136)
Constant	-0.288***	1.378***	-0.018	-1.290***	0.941***	0.645***
	(0.098)	(0.087)	(0.100)	(0.144)	(0.087)	(0.089)
Wald $\chi 2$ (6) = 46.96, P > $\chi 2$ = 0.000; Pseudo R^2 = 0.003						
Observations	6,247	6,247	6,247	6,247	6,247	6,247

Note: 'No ISFM' is reference category; robust standard errors in parentheses, clustered at the household level; *** p<0.01, ** p<0.05, * p<0.1.

Table A 3.2. Associations between instrumental variable and outcome variables.

	Log of land productivity (kg/ha)		Log of net crop value (ETB/ha)		Log of labor demand (labor-days/ha)		Log of labor productivity (kg/labor-day)		Log of returns to unpaid labor (ETB/labor-day)	
HH lives in ISFM+ community (1 = yes)	0.017	-0.011	-0.004	-0.016	0.003	0.014	0.015	-0.021	-0.012	-0.027
	(0.031)	(0.025)	(0.035)	(0.028)	(0.017)	(0.014)	(0.032)	(0.027)	(0.035)	(0.030)
ISFM adoption included	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Control variables included	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Constant	6.572***	2.778***	9.118***	5.986***	4.609***	3.553***	1.965***	0.469	4.584***	3.942***
	(0.044)	(0.336)	(0.042)	(0.385)	(0.023)	(0.166)	(0.043)	(0.341)	(0.046)	(0.395)
	F (7, 2030) =157.71***	F (32, 2030) = 147.02***	F (7, 2015) = 19.48***	F (32, 2015) = 54.07***	F (7, 2039) = 63.77***	F (31, 2039) = 93.31***	F (7, 2030) = 84.95***	F (31, 2030) = 74.93***	F (7, 2012) = 20.39***	F (31, 2012) = 36.33***
R-squared	0.168	0.461	0.021	0.277	0.069	0.361	0.102	0.334	0.025	0.189
Observations	6,195	6,195	6,058	6,058	6,247	6,247	6,195	6,195	6,038	6,038

Note: Reduced sample sizes because outcome variables are in logarithms. Control variables are the same as in selection and outcome models. Robust standard errors in parentheses, clustered at the household level; *** p<0.01, ** p<0.05, * p<0.1.

Table A 3.3. First stage regression estimates: multinomial selection model.

	OF	IF	OF + IF	OF + IS	IF + IS	OF + IF + IS
Gender HH head (1 = male)	0.383	0.583**	0.246	0.985**	0.538*	0.480
	(0.297)	(0.266)	(0.288)	(0.437)	(0.285)	(0.312)
Age HH head (in years)	-0.020**	-0.019***	-0.022***	-0.022**	-0.021***	-0.030***
	(0.008)	(0.007)	(0.007)	(0.009)	(0.007)	(0.008)
HH head has formal education (1 = yes)	0.082	-0.459***	-0.442**	-0.338	-0.350*	-0.449**
	(0.207)	(0.175)	(0.201)	(0.276)	(0.189)	(0.200)
No. of HH members	-0.038	-0.047	0.021	-0.060	0.023	0.024
	(0.050)	(0.043)	(0.049)	(0.069)	(0.048)	(0.050)
No. of TLU owned	0.121***	0.124***	0.155***	0.191***	0.133***	0.183***
	(0.037)	(0.033)	(0.036)	(0.043)	(0.036)	(0.037)
Log of farm size (in ha)	-0.374*	-0.364**	-0.502***	-0.924***	-0.696***	-0.834***
	(0.193)	(0.164)	(0.190)	(0.238)	(0.174)	(0.186)
HH has access to formal credit (1 = yes)	0.190	-0.150	0.159	0.573**	0.120	0.166
	(0.193)	(0.171)	(0.192)	(0.274)	(0.183)	(0.192)
No. of social organizations HH is involved	0.021	-0.041	0.014	0.060	0.069	0.131***
	(0.055)	(0.046)	(0.051)	(0.078)	(0.049)	(0.051)
Talked to extension agent (1 = yes)	0.250	-0.115	0.330*	0.784***	0.040	0.433**
	(0.194)	(0.177)	(0.194)	(0.260)	(0.185)	(0.199)
Log of walking distance to nearest FTC (in min)	0.242**	-0.040	0.228*	0.393**	-0.073	0.128
	(0.117)	(0.108)	(0.123)	(0.157)	(0.114)	(0.123)
Log of walking distance to nearest village market (in min)	-0.147	0.014	-0.073	-0.130	-0.050	-0.080
	(0.123)	(0.099)	(0.117)	(0.149)	(0.108)	(0.118)
Agri-input dealer in Kebele (1 = yes)	0.785***	0.592***	1.604***	1.120***	0.911***	1.264***
	(0.252)	(0.222)	(0.269)	(0.341)	(0.248)	(0.261)
HH lives in ISFM+ community (1 = yes)	-0.016	0.273*	0.191	0.068	0.214	0.444**
	(0.183)	(0.158)	(0.177)	(0.241)	(0.170)	(0.179)
Pest and disease stress (1 = yes)	0.004	0.111	-0.123	-0.007	-0.129	-0.062
	(0.292)	(0.270)	(0.280)	(0.355)	(0.278)	(0.284)
Weather stress (drought/flood/frost/storm) (1 = yes)	0.387*	0.162	0.463**	-0.099	0.233	0.283
	(0.216)	(0.178)	(0.197)	(0.272)	(0.189)	(0.202)

Log of av. annual rainfall (in mm)	0.706**	2.822***	2.025***	1.687***	3.714***	2.693***
	(0.311)	(0.256)	(0.297)	(0.372)	(0.286)	(0.306)
Log of walking distance to plot (in min)	-0.824***	0.097	-0.676***	-1.081***	0.165**	-0.701***
	(0.092)	(0.062)	(0.077)	(0.143)	(0.067)	(0.073)
Plot owned (1 = yes)	0.469**	-0.253	0.366*	0.703**	0.001	0.655***
	(0.206)	(0.168)	(0.197)	(0.298)	(0.180)	(0.202)
Footslope (1 = yes)	-0.439**	-0.492***	-0.293	-0.183	-0.049	-0.134
	(0.194)	(0.162)	(0.183)	(0.249)	(0.172)	(0.180)
Hillslope (1 = yes)	0.120	0.299	0.168	-0.123	0.096	0.061
	(0.305)	(0.232)	(0.274)	(0.428)	(0.254)	(0.267)
Shallow soil (1 = yes)	0.371	0.309	0.234	0.147	0.135	0.043
	(0.254)	(0.210)	(0.235)	(0.326)	(0.227)	(0.244)
Deep soil (1 = yes)	-0.023	0.170	-0.026	-0.110	0.128	0.356*
	(0.217)	(0.165)	(0.195)	(0.288)	(0.178)	(0.192)
Poor soil quality (1 = yes)	0.026	-0.268	-0.304	-0.390	-0.363*	-0.529**
	(0.226)	(0.172)	(0.198)	(0.300)	(0.189)	(0.209)
Good soil quality (1 = yes)	0.303	-0.089	0.002	0.417	0.199	0.282
	(0.221)	(0.177)	(0.199)	(0.264)	(0.187)	(0.194)
Herbicide used (1 = yes)	-0.791***	0.115	-0.079	-1.725***	-0.506**	-0.887***
	(0.278)	(0.174)	(0.219)	(0.594)	(0.201)	(0.239)
Pesticide used (1 = yes)	1.142***	0.713*	0.865**	0.989*	1.460***	1.438***
	(0.426)	(0.369)	(0.394)	(0.505)	(0.379)	(0.397)
Lime used (1 = yes)	1.780	1.279	2.853***	0.958	1.955*	3.369***
	(1.122)	(1.090)	(1.087)	(1.467)	(1.092)	(1.080)
Urea used (1 = yes)	-0.389	3.646***	3.321***	0.611**	4.645***	4.336***
	(0.259)	(0.229)	(0.241)	(0.296)	(0.246)	(0.249)
Maize plot (1 = yes)	1.635***	-3.371***	0.215	3.829***	1.302***	2.396***
	(0.272)	(0.318)	(0.284)	(0.621)	(0.270)	(0.276)
Wheat plot (1 = yes)	0.368	-0.386**	0.319	3.612***	1.481***	2.248***
	(0.287)	(0.194)	(0.221)	(0.617)	(0.216)	(0.238)
Log of total labor use (in labor-days/ha)	0.650***	0.553***	0.691***	0.915***	0.724***	0.945***
	(0.233)	(0.190)	(0.213)	(0.289)	(0.199)	(0.207)

Log of plot size (in ha)	-0.036	0.190	0.147	0.284	0.466***	0.627***
	(0.142)	(0.118)	(0.129)	(0.175)	(0.125)	(0.131)
Constant	-8.720***	-20.937***	-18.965***	-21.082***	-31.408***	-26.132***
	(2.609)	(2.163)	(2.458)	(3.252)	(2.365)	(2.492)
Wald $\chi2$ (192) = 3771.97, P > $\chi2$ = 0.000; Pseudo R^2 = 0.381						
Observations	6,247	6,247	6,247	6,247	6,247	6,247

Note: 'No ISFM' is reference category. HH stands for household; FTC stands for farmer training center; TLU stands for tropical livestock unit; Kebele is the lowest administrative unit in Ethiopia; formal credit refers to bank, microfinance institution, government or agri-input dealer; footslope/hillslope compared to midslope; shallow/deep soil compared to medium soil depth; poor soil/good soil compared to average soil quality. Robust standard errors in parentheses, clustered at the household level; *** p<0.01, ** p<0.05, * p<0.1.

Table A 3.4. Second stage regression estimates: land productivity.

	Log of land productivity (kg/ha)						
	No ISFM	OF	IF	OF + IF	OF + IS	IF + IS	OF + IF + IS
Gender HH head (1 = male)	-0.195	0.289**	0.182**	0.249**	0.310	0.098	0.041
	(0.135)	(0.135)	(0.073)	(0.121)	(0.491)	(0.075)	(0.088)
Age HH head (in years)	-0.007**	-0.004	-0.002	-0.001	0.007	-0.002	-0.007***
	(0.004)	(0.003)	(0.001)	(0.003)	(0.007)	(0.002)	(0.002)
HH head has formal education (1 = yes)	0.006	-0.133	-0.242***	-0.178**	0.176	-0.067	-0.098**
	(0.102)	(0.103)	(0.036)	(0.075)	(0.191)	(0.048)	(0.048)
No. of HH members	-0.038*	0.007	-0.039***	-0.004	0.027	-0.035***	-0.040***
	(0.021)	(0.024)	(0.008)	(0.022)	(0.065)	(0.009)	(0.013)
No. of TLU owned	0.016	0.058***	0.046***	0.035**	0.061	0.037***	0.067***
	(0.018)	(0.019)	(0.007)	(0.016)	(0.037)	(0.008)	(0.010)
Log of farm size (in ha)	0.098	-0.096	-0.070	-0.196**	-0.342	-0.069*	-0.095**
	(0.071)	(0.104)	(0.048)	(0.089)	(0.272)	(0.041)	(0.048)
No. of social organizations HH is involved	-0.113*	-0.054	-0.006	0.003	0.367	0.011	0.050
	(0.063)	(0.080)	(0.036)	(0.076)	(0.240)	(0.038)	(0.046)
Log of walking distance to nearest FTC (in min)	0.018	0.009	0.029***	0.022	0.048	0.002	0.025*
	(0.023)	(0.026)	(0.010)	(0.023)	(0.068)	(0.015)	(0.014)
Talked to extension agent (1 = yes)	0.044	-0.067	0.067*	0.018	0.140	0.026	0.052
	(0.083)	(0.097)	(0.036)	(0.087)	(0.282)	(0.042)	(0.060)
Log of walking distance to nearest village market (in min)	-0.017	-0.045	-0.055**	-0.086	-0.154	-0.056**	-0.043

	(0.047)	(0.061)	(0.022)	(0.059)	(0.147)	(0.025)	(0.035)
Agri-input dealer in Kebele (1 = yes)	-0.071	-0.037	0.027	-0.055	0.110	0.029	-0.053*
	(0.047)	(0.044)	(0.020)	(0.045)	(0.127)	(0.024)	(0.028)
HH has access to formal credit (1 = yes)	0.037	-0.194	0.253***	-0.122	0.135	-0.006	0.070
	(0.248)	(0.215)	(0.047)	(0.116)	(0.401)	(0.068)	(0.088)
Pest and disease stress (1 = yes)	0.020	0.132	-0.099*	-0.085	-0.062	-0.168***	0.058
	(0.101)	(0.103)	(0.055)	(0.135)	(0.271)	(0.057)	(0.060)
Weather stress (drought/flood/frost/storm) (1 = yes)	-0.187**	-0.088	-0.212***	-0.198**	-0.556	-0.271***	-0.180***
	(0.079)	(0.106)	(0.040)	(0.095)	(0.408)	(0.043)	(0.047)
Log of av. annual rainfall (in mm)	-0.112	0.504*	0.270***	0.331	-0.445	0.065	0.039
	(0.392)	(0.303)	(0.088)	(0.214)	(0.596)	(0.105)	(0.163)
Log of walking distance to plot (in min)	-0.028	0.144	-0.022	0.062	-0.123	0.069	-0.017
	(0.066)	(0.098)	(0.028)	(0.101)	(0.256)	(0.050)	(0.098)
Plot owned (1 = yes)	-0.006	0.048	-0.111***	-0.051	0.215	-0.067	0.036
	(0.083)	(0.132)	(0.032)	(0.106)	(0.346)	(0.048)	(0.076)
Footslope (1 = yes)	0.185**	0.006	-0.058	-0.137*	-0.002	0.017	0.019
	(0.094)	(0.084)	(0.039)	(0.075)	(0.192)	(0.043)	(0.055)
Hillslope (1 = yes)	0.044	0.146	-0.081*	0.165	0.311	0.109*	0.120
	(0.165)	(0.139)	(0.044)	(0.107)	(0.283)	(0.058)	(0.093)
Shallow soil depth (1 = yes)	-0.364***	-0.154	-0.058	-0.147	0.324	0.018	-0.140**
	(0.121)	(0.122)	(0.049)	(0.094)	(0.294)	(0.055)	(0.067)
Deep soil (1 = yes)	-0.002	0.025	0.164***	0.122	0.224	0.015	0.097
	(0.078)	(0.097)	(0.037)	(0.087)	(0.234)	(0.043)	(0.072)
Poor soil quality (1 = yes)	-0.031	-0.189**	-0.259***	-0.017	-0.314	-0.157***	-0.270***
	(0.091)	(0.096)	(0.036)	(0.075)	(0.318)	(0.054)	(0.077)
High soil quality (1 = yes)	0.117	0.228**	-0.019	0.121	0.148	0.013	0.060
	(0.081)	(0.113)	(0.037)	(0.091)	(0.336)	(0.044)	(0.055)
Applied herbicide on plot	0.214*	0.108	0.190***	0.228*	-0.420	0.310***	-0.017
	(0.130)	(0.225)	(0.045)	(0.120)	(1.045)	(0.077)	(0.098)
Pesticide used (1 = yes)	0.130	0.390***	0.053	-0.006	0.109	-0.033	-0.069
	(0.172)	(0.151)	(0.063)	(0.136)	(0.339)	(0.074)	(0.089)
Lime used (1 = yes)	0.439	-0.028	-0.183	-0.502**	0.473	-0.100	0.044

	(0.465)	(0.522)	(0.121)	(0.244)	(1.216)	(0.136)	(0.131)
Urea used (1 = yes)	-0.344	-0.161	0.179*	-0.002	-0.726	-0.052	0.149
	(0.491)	(0.818)	(0.100)	(0.230)	(1.766)	(0.156)	(0.227)
Maize plot (1 = yes)	0.413	0.904**	0.684**	0.227	1.654	0.834***	0.934***
	(0.379)	(0.376)	(0.337)	(0.426)	(2.300)	(0.321)	(0.224)
Wheat plot (1 = yes)	0.372**	0.344	0.613***	0.416	1.229	0.534***	0.629***
	(0.173)	(0.209)	(0.105)	(0.292)	(2.009)	(0.181)	(0.182)
Log of total labor use (in labor-days/ha)	0.318***	0.496***	0.297***	0.362***	0.174	0.275***	0.441***
	(0.111)	(0.116)	(0.044)	(0.090)	(0.265)	(0.044)	(0.058)
Log of plot size (in ha)	-0.319***	-0.364***	-0.217***	-0.165**	-0.130	-0.173***	-0.156***
	(0.069)	(0.091)	(0.035)	(0.084)	(0.229)	(0.041)	(0.051)
λ1		-0.910*	-0.005	0.319	-0.054	0.439	0.309
		(0.521)	(0.186)	(0.506)	(1.090)	(0.400)	(0.281)
λ2	0.113		-0.762**	-0.220	0.455	-0.254	-0.234
	(0.499)		(0.381)	(0.509)	(1.426)	(0.537)	(0.437)
λ3	0.183	0.845*		0.208	0.263	-0.048	-0.135
	(0.457)	(0.489)		(0.498)	(2.000)	(0.282)	(0.268)
λ4	0.081	-2.259**	0.175		0.098	0.237	-0.232
	(0.767)	(1.089)	(0.345)		(4.105)	(0.454)	(0.582)
λ5	-0.254	-0.346	1.280***	0.219		0.352	0.297
	(0.691)	(0.568)	(0.491)	(0.543)		(0.627)	(0.425)
λ6	-0.771	1.540***	-0.380	-0.154	-1.090		-0.113
	(0.647)	(0.507)	(0.263)	(0.621)	(1.412)		(0.480)
λ7	0.618	0.839	-0.248	-0.260	0.132	-0.669**	
	(0.871)	(0.791)	(0.254)	(0.386)	(1.762)	(0.293)	
Constant	6.211**	-0.838	2.891***	3.132*	6.107	4.995***	4.258***
	(2.949)	(2.323)	(0.750)	(1.609)	(6.274)	(1.169)	(1.201)
R-squared	0.400	0.464	0.455	0.325	0.494	0.414	0.317
Observations	436	367	2,102	537	148	1,366	1,239

Note: Standard errors in parentheses, bootstrapped with 100 replications; *** p<0.01, ** p<0.05, * p<0.1.

Table A 3.5. Second stage regression estimates: net crop value.

	Log of net crop value (ETB/ha)						
	No ISFM	OF	IF	OF + IF	OF + IS	IF + IS	OF + IF + IS
Gender HH head (1 = male)	-0.192	0.304**	0.203**	0.269*	0.237	0.189*	0.158
	(0.143)	(0.152)	(0.094)	(0.161)	(0.408)	(0.098)	(0.121)
Age HH head (in years)	-0.007*	-0.006	-0.002	-0.002	0.004	-0.005***	-0.008***
	(0.004)	(0.004)	(0.001)	(0.004)	(0.007)	(0.002)	(0.003)
HH head has formal education (1 = yes)	0.029	-0.159	-0.247***	-0.132	0.125	-0.156***	-0.171**
	(0.104)	(0.118)	(0.041)	(0.098)	(0.171)	(0.050)	(0.070)
No. of HH members	-0.033	-0.000	-0.036***	-0.012	0.036	-0.035***	-0.025*
	(0.022)	(0.027)	(0.010)	(0.023)	(0.052)	(0.012)	(0.013)
No. of TLU owned	0.009	0.061**	0.054***	0.045**	0.056	0.045***	0.061***
	(0.019)	(0.024)	(0.008)	(0.021)	(0.042)	(0.011)	(0.011)
Log of farm size (in ha)	0.083	-0.064	-0.136***	-0.234**	-0.298	-0.111*	-0.119**
	(0.067)	(0.137)	(0.051)	(0.097)	(0.252)	(0.066)	(0.050)
No. of social organizations HH is involved	-0.092	-0.071	0.045	-0.058	0.271	0.039	0.070
	(0.076)	(0.096)	(0.036)	(0.105)	(0.228)	(0.051)	(0.064)
Log of walking distance to nearest FTC (in min)	0.026	0.017	0.018	0.013	0.050	0.017	0.037*
	(0.022)	(0.034)	(0.013)	(0.029)	(0.065)	(0.017)	(0.020)
Talked to extension agent (1 = yes)	0.062	-0.060	0.067*	0.133	0.036	0.024	0.073
	(0.069)	(0.116)	(0.038)	(0.118)	(0.254)	(0.064)	(0.078)
Log of walking distance to nearest village market (in min)	-0.007	-0.024	-0.057**	-0.047	-0.133	-0.058*	-0.055
	(0.042)	(0.061)	(0.024)	(0.076)	(0.164)	(0.030)	(0.053)
Agri-input dealer in Kebele (1 = yes)	-0.081*	-0.037	0.038	-0.078	0.127	0.036	0.004
	(0.048)	(0.050)	(0.026)	(0.050)	(0.120)	(0.025)	(0.036)
HH has access to formal credit (1 = yes)	-0.028	-0.125	0.293***	-0.004	0.395	0.125	0.125
	(0.237)	(0.273)	(0.060)	(0.145)	(0.287)	(0.083)	(0.100)
Pest and disease stress (1 = yes)	-0.028	0.148	-0.061	-0.121	-0.225	-0.275***	-0.100
	(0.108)	(0.124)	(0.066)	(0.168)	(0.205)	(0.077)	(0.075)
Weather stress (drought/flood/frost/storm) (1 = yes)	-0.178**	-0.146	-0.240***	-0.304***	-0.285	-0.333***	-0.225***
	(0.090)	(0.122)	(0.051)	(0.104)	(0.336)	(0.058)	(0.072)
Log of av. annual rainfall (in mm)	-0.544*	0.163	0.156	0.275	-0.538	0.125	0.226
	(0.302)	(0.404)	(0.122)	(0.356)	(0.487)	(0.144)	(0.231)

Log of walking distance to plot (in min)	-0.069	0.036	-0.018	0.088	-0.217	0.053	0.068
	(0.070)	(0.129)	(0.034)	(0.149)	(0.298)	(0.071)	(0.137)
Plot owned (1 = yes)	0.037	0.087	-0.092**	-0.071	0.329	-0.043	0.045
	(0.097)	(0.147)	(0.044)	(0.136)	(0.359)	(0.064)	(0.109)
Footslope (1 = yes)	0.154	-0.055	-0.098**	-0.034	0.056	0.021	0.050
	(0.096)	(0.110)	(0.049)	(0.106)	(0.148)	(0.059)	(0.058)
Hillslope (1 = yes)	0.024	0.131	-0.070	0.238	0.294	0.110*	0.171*
	(0.156)	(0.152)	(0.054)	(0.162)	(0.309)	(0.065)	(0.099)
Shallow soil depth (1 = yes)	-0.312**	-0.078	-0.135**	-0.136	0.238	0.051	-0.248***
	(0.145)	(0.136)	(0.064)	(0.129)	(0.226)	(0.087)	(0.096)
Deep soil (1 = yes)	0.048	0.062	0.103**	0.148	0.352	0.043	0.048
	(0.084)	(0.110)	(0.048)	(0.097)	(0.215)	(0.060)	(0.081)
Poor soil quality (1 = yes)	-0.039	-0.128	-0.296***	-0.071	-0.148	-0.244***	-0.341***
	(0.100)	(0.154)	(0.044)	(0.100)	(0.329)	(0.076)	(0.096)
High soil quality (1 = yes)	0.088	0.296**	0.016	-0.019	0.082	-0.000	0.077
	(0.099)	(0.119)	(0.046)	(0.111)	(0.261)	(0.051)	(0.060)
Applied herbicide on plot	0.154	0.180	0.177***	0.216	-0.150	0.283***	-0.109
	(0.128)	(0.249)	(0.047)	(0.135)	(0.808)	(0.109)	(0.132)
Pesticide used (1 = yes)	0.139	0.461**	0.116	-0.045	0.070	0.015	0.063
	(0.220)	(0.191)	(0.076)	(0.145)	(0.416)	(0.096)	(0.100)
Lime used (1 = yes)	0.426	-0.264	-0.316*	-0.606*	0.299	-0.286	-0.218
	(0.571)	(0.640)	(0.183)	(0.354)	(0.959)	(0.241)	(0.202)
Urea used (1 = yes)	-0.694	-0.731	0.102	0.035	-0.569	-0.079	0.424
	(0.447)	(0.949)	(0.109)	(0.370)	(1.357)	(0.215)	(0.351)
Maize plot (1 = yes)	-0.237	0.286	-0.362	-1.082**	0.316	-0.372	-0.264
	(0.334)	(0.432)	(0.364)	(0.470)	(1.703)	(0.372)	(0.348)
Wheat plot (1 = yes)	-0.086	-0.111	0.018	-0.524	0.067	-0.129	-0.071
	(0.141)	(0.281)	(0.120)	(0.335)	(1.609)	(0.229)	(0.246)
Log of total labor use (in labor-days/ha)	0.275**	0.503***	0.321***	0.436***	0.276	0.312***	0.384***
	(0.109)	(0.134)	(0.045)	(0.122)	(0.256)	(0.060)	(0.062)
Log of plot size (in ha)	-0.372***	-0.409***	-0.245***	-0.215**	-0.199	-0.193***	-0.181***
	(0.056)	(0.099)	(0.046)	(0.106)	(0.209)	(0.059)	(0.061)
$\lambda 1$		-0.829	-0.156	0.319	-0.092	0.285	0.225
		(0.638)	(0.229)	(0.674)	(0.859)	(0.528)	(0.530)

λ2	0.576		-0.887**	-0.070	0.811	-0.925	-0.837*
	(0.530)		(0.445)	(0.678)	(1.361)	(0.600)	(0.436)
λ3	-0.201	0.832		0.403	-0.151	-0.018	0.144
	(0.387)	(0.576)		(0.602)	(1.799)	(0.350)	(0.423)
λ4	-0.334	-2.627**	0.315		0.927	0.236	-0.467
	(1.016)	(1.256)	(0.435)		(3.124)	(0.612)	(0.689)
λ5	-0.196	-0.301	1.836***	0.020		1.219	0.472
	(0.724)	(0.647)	(0.585)	(0.748)		(0.799)	(0.476)
λ6	-0.746	1.333**	-0.411	-0.087	-2.160		0.367
	(0.586)	(0.670)	(0.308)	(0.773)	(1.551)		(0.633)
λ7	0.817	1.111	-0.567*	-0.507	0.660	-0.719*	
	(0.898)	(0.902)	(0.326)	(0.480)	(1.796)	(0.384)	
Constant	11.886***	3.625	6.200***	5.717**	9.876*	6.937***	5.397***
	(2.134)	(3.067)	(0.999)	(2.316)	(5.566)	(1.535)	(1.570)
R-squared	0.269	0.385	0.335	0.337	0.506	0.255	0.252
Observations	434	366	2,054	517	146	1,342	1,199

Note: Standard errors in parentheses, bootstrapped with 100 replications; *** p<0.01, ** p<0.05, * p<0.1.

Table A 3.6. Second stage regression estimates: labor demand.

	Log of labor demand (person-days/ha)						
	No ISFM	OF	IF	OF + IF	OF + IS	IF + IS	OF + IF + IS
Gender HH head (1 = male)	0.105	0.119	-0.044	0.030	-0.327	0.021	0.050
	(0.085)	(0.087)	(0.042)	(0.053)	(0.274)	(0.044)	(0.048)
Age HH head (in years)	0.004*	0.005***	0.005***	0.004***	0.004	0.005***	0.004***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.005)	(0.001)	(0.001)
HH head has formal education (1 = yes)	0.004	0.035	0.009	-0.029	-0.061	0.015	-0.012
	(0.051)	(0.070)	(0.018)	(0.040)	(0.126)	(0.029)	(0.025)
No. of HH members	0.025**	0.010	0.028***	0.033***	0.034	0.030***	0.014**
	(0.012)	(0.014)	(0.005)	(0.012)	(0.037)	(0.007)	(0.007)
No. of TLU owned	-0.010	-0.003	-0.009***	0.005	-0.002	0.003	0.012**
	(0.010)	(0.011)	(0.003)	(0.007)	(0.028)	(0.005)	(0.005)
Log of farm size (in ha)	0.033	-0.047	0.025	-0.066*	0.079	-0.016	-0.071**
	(0.049)	(0.046)	(0.020)	(0.035)	(0.176)	(0.031)	(0.031)

No. of social organizations HH is involved	-0.015	0.060	-0.017	0.064*	0.080	-0.013	0.063**
	(0.035)	(0.046)	(0.018)	(0.038)	(0.178)	(0.026)	(0.027)
Log of walking distance to nearest FTC (in min)	-0.010	0.002	-0.004	0.011	-0.002	-0.008	0.005
	(0.011)	(0.015)	(0.006)	(0.012)	(0.037)	(0.009)	(0.008)
Talked to extension agent (1 = yes)	-0.003	0.014	0.020	0.030	0.066	0.042	0.019
	(0.051)	(0.056)	(0.015)	(0.040)	(0.193)	(0.028)	(0.034)
Log of walking distance to nearest village market (in min)	-0.020	0.032	0.018	0.054**	0.063	0.026	-0.010
	(0.024)	(0.040)	(0.012)	(0.024)	(0.098)	(0.017)	(0.021)
Agri-input dealer in Kebele (1 = yes)	0.024	-0.010	-0.022*	-0.028	-0.164**	-0.009	-0.031*
	(0.027)	(0.029)	(0.012)	(0.024)	(0.082)	(0.013)	(0.016)
HH has access to formal credit (1 = yes)	0.103	0.029	0.020	0.071	0.123	0.018	0.026
	(0.137)	(0.136)	(0.028)	(0.054)	(0.212)	(0.040)	(0.050)
Pest and disease stress (1 = yes)	-0.069	-0.030	-0.001	-0.044	0.022	0.046	-0.022
	(0.063)	(0.071)	(0.029)	(0.061)	(0.173)	(0.039)	(0.034)
Weather stress (drought/flood/frost/storm) (1 = yes)	-0.004	-0.107**	-0.017	-0.056	0.132	-0.033	0.010
	(0.047)	(0.052)	(0.021)	(0.042)	(0.210)	(0.029)	(0.032)
Log of av. annual rainfall (in mm)	0.046	-0.275*	-0.014	0.139	-0.562	-0.032	0.005
	(0.223)	(0.158)	(0.045)	(0.109)	(0.390)	(0.066)	(0.103)
Log of walking distance to plot (in min)	-0.012	-0.061	-0.000	-0.002	-0.068	0.008	0.027
	(0.036)	(0.061)	(0.015)	(0.048)	(0.200)	(0.030)	(0.056)
Plot owned (1 = yes)	0.068	0.035	-0.025	0.079*	0.230	-0.025	0.005
	(0.043)	(0.077)	(0.021)	(0.048)	(0.255)	(0.033)	(0.047)
Footslope (1 = yes)	-0.085	-0.007	-0.051***	-0.028	-0.158	-0.054*	-0.041
	(0.057)	(0.062)	(0.019)	(0.044)	(0.102)	(0.030)	(0.033)
Hillslope (1 = yes)	-0.210***	0.005	0.010	0.009	0.122	0.028	-0.035
	(0.081)	(0.084)	(0.025)	(0.058)	(0.185)	(0.034)	(0.039)
Shallow soil depth (1 = yes)	-0.067	-0.159***	-0.047**	-0.017	0.087	0.013	0.011
	(0.055)	(0.061)	(0.021)	(0.046)	(0.133)	(0.037)	(0.036)
Deep soil (1 = yes)	0.054	-0.038	0.005	-0.062	0.081	0.001	0.053
	(0.057)	(0.059)	(0.020)	(0.040)	(0.128)	(0.030)	(0.034)
Poor soil quality (1 = yes)	0.077*	0.008	-0.043*	-0.024	0.168	0.009	-0.010
	(0.044)	(0.054)	(0.023)	(0.042)	(0.139)	(0.033)	(0.034)
High soil quality (1 = yes)	0.118**	0.002	-0.023	0.057	-0.264	-0.047*	-0.020
	(0.048)	(0.062)	(0.020)	(0.047)	(0.176)	(0.027)	(0.031)

Applied herbicide on plot	-0.019	0.111	-0.065***	-0.039	0.763	0.026	-0.022
	(0.076)	(0.144)	(0.023)	(0.053)	(0.642)	(0.057)	(0.063)
Pesticide used (1 = yes)	0.109	0.032	0.065*	0.077	-0.337	0.051	0.089*
	(0.121)	(0.093)	(0.034)	(0.070)	(0.231)	(0.056)	(0.045)
Lime used (1 = yes)	-0.486*	-0.474	-0.035	-0.147	0.160	-0.120	-0.008
	(0.290)	(0.329)	(0.076)	(0.100)	(0.842)	(0.101)	(0.085)
Urea used (1 = yes)	-0.237	-0.706	0.049	0.111	-0.678	-0.049	0.112
	(0.312)	(0.480)	(0.051)	(0.136)	(1.087)	(0.108)	(0.126)
Maize plot (1 = yes)	0.241	0.171	-0.215	0.090	-1.594	-0.181	0.039
	(0.197)	(0.209)	(0.166)	(0.178)	(1.451)	(0.199)	(0.159)
Wheat plot (1 = yes)	-0.063	0.055	-0.226***	-0.116	-1.912	-0.323***	-0.210
	(0.085)	(0.133)	(0.053)	(0.122)	(1.327)	(0.117)	(0.131)
Log of plot size (in ha)	-0.244***	-0.275***	-0.289***	-0.333***	-0.534***	-0.296***	-0.318***
	(0.038)	(0.033)	(0.017)	(0.038)	(0.115)	(0.025)	(0.030)
λ1		0.515*	0.067	-0.098	-0.021	0.214	-0.294*
		(0.311)	(0.097)	(0.251)	(0.690)	(0.246)	(0.168)
λ2	0.308		-0.058	0.059	0.930	-0.117	0.172
	(0.326)		(0.182)	(0.236)	(0.746)	(0.261)	(0.230)
λ3	-0.258	-0.255		-0.151	0.075	0.262	-0.006
	(0.239)	(0.259)		(0.229)	(0.863)	(0.170)	(0.152)
λ4	-0.414	-0.139	0.059		1.977	0.002	0.077
	(0.489)	(0.675)	(0.164)		(2.051)	(0.304)	(0.343)
λ5	-0.236	0.776**	0.195	-0.036		-0.124	-0.015
	(0.365)	(0.335)	(0.223)	(0.295)		(0.332)	(0.207)
λ6	0.137	-0.253	-0.077	0.315	-1.569		0.095
	(0.349)	(0.435)	(0.121)	(0.297)	(1.086)		(0.277)
λ7	0.391	-0.708**	-0.232*	-0.117	-1.165	-0.217	
	(0.455)	(0.352)	(0.119)	(0.181)	(1.021)	(0.200)	
Constant	3.276**	5.744***	4.201***	2.551***	10.360***	4.471***	4.075***
	(1.459)	(1.126)	(0.377)	(0.797)	(3.427)	(0.712)	(0.787)
R-squared	0.338	0.351	0.337	0.450	0.517	0.322	0.361
Observations	450	376	2,113	546	149	1,370	1,243

Note: Standard errors in parentheses, bootstrapped with 100 replications; *** p<0.01, ** p<0.05, * p<0.1.

Table A 3.7. Second stage regression estimates: labor productivity.

	Log of labor productivity (kg/labor-day)						
	No ISFM	OF	IF	OF + IF	OF + IS	IF + IS	OF + IF + IS
Gender HH head (1 = male)	-0.237*	0.222	0.214***	0.219	0.671	0.082	0.020
	(0.138)	(0.164)	(0.082)	(0.137)	(0.585)	(0.076)	(0.087)
Age HH head (in years)	-0.010***	-0.007*	-0.005***	-0.003	0.003	-0.006***	-0.009***
	(0.003)	(0.004)	(0.001)	(0.003)	(0.008)	(0.002)	(0.002)
HH head has formal education (1 = yes)	-0.017	-0.146	-0.248***	-0.160*	0.240	-0.075	-0.094**
	(0.101)	(0.123)	(0.036)	(0.091)	(0.198)	(0.049)	(0.046)
No. of HH members	-0.056***	0.001	-0.058***	-0.027	-0.006	-0.057***	-0.048***
	(0.020)	(0.023)	(0.010)	(0.022)	(0.056)	(0.010)	(0.013)
No. of TLU owned	0.026	0.057***	0.052***	0.031*	0.066	0.033***	0.059***
	(0.018)	(0.021)	(0.007)	(0.018)	(0.046)	(0.009)	(0.011)
Log of farm size (in ha)	0.072	-0.049	-0.086*	-0.147*	-0.455	-0.050	-0.059
	(0.077)	(0.098)	(0.051)	(0.087)	(0.297)	(0.040)	(0.051)
No. of social organizations HH is involved	-0.102	-0.090	0.005	-0.041	0.339	0.018	0.015
	(0.072)	(0.101)	(0.039)	(0.080)	(0.304)	(0.047)	(0.050)
Log of walking distance to nearest FTC (in min)	0.021	0.002	0.033***	0.013	0.053	0.007	0.023
	(0.024)	(0.028)	(0.012)	(0.021)	(0.054)	(0.016)	(0.016)
Talked to extension agent (1 = yes)	0.047	-0.086	0.052	-0.007	0.129	-0.007	0.040
	(0.078)	(0.086)	(0.039)	(0.079)	(0.316)	(0.047)	(0.062)
Log of walking distance to nearest village market (in min)	-0.003	-0.066	-0.068***	-0.120*	-0.188	-0.077***	-0.040
	(0.048)	(0.068)	(0.021)	(0.062)	(0.174)	(0.028)	(0.036)
Agri-input dealer in Kebele (1 = yes)	-0.087	-0.033	0.042	-0.035	0.240*	0.036	-0.036
	(0.056)	(0.052)	(0.026)	(0.048)	(0.126)	(0.028)	(0.032)
HH has access to formal credit (1 = yes)	-0.004	-0.239	0.237***	-0.175	-0.025	-0.032	0.045
	(0.235)	(0.227)	(0.057)	(0.144)	(0.336)	(0.073)	(0.086)
Pest and disease stress (1 = yes)	0.072	0.149	-0.098*	-0.058	-0.068	-0.199***	0.074
	(0.105)	(0.111)	(0.059)	(0.133)	(0.260)	(0.064)	(0.059)
Weather stress (drought/flood/frost/storm) (1 = yes)	-0.178**	-0.015	-0.201***	-0.167*	-0.717	-0.249***	-0.191***
	(0.082)	(0.100)	(0.046)	(0.089)	(0.442)	(0.050)	(0.057)
Log of av. annual rainfall (in mm)	-0.051	0.623*	0.288***	0.232	-0.002	0.068	0.057
	(0.371)	(0.319)	(0.105)	(0.256)	(0.665)	(0.103)	(0.186)

Log of walking distance to plot (in min)	-0.019	0.183*	-0.021	0.074	-0.143	0.073	-0.018
	(0.076)	(0.111)	(0.032)	(0.136)	(0.315)	(0.058)	(0.109)
Plot owned (1 = yes)	-0.054	0.025	-0.094**	-0.112	0.068	-0.055	0.026
	(0.084)	(0.128)	(0.043)	(0.123)	(0.346)	(0.060)	(0.096)
Footslope (1 = yes)	0.220**	-0.008	-0.021	-0.120	0.129	0.061	0.048
	(0.104)	(0.095)	(0.047)	(0.091)	(0.209)	(0.049)	(0.050)
Hillslope (1 = yes)	0.180	0.143	-0.087*	0.163	0.144	0.091	0.140*
	(0.120)	(0.153)	(0.051)	(0.105)	(0.338)	(0.061)	(0.079)
Shallow soil depth (1 = yes)	-0.318**	-0.052	-0.026	-0.135	0.235	0.008	-0.149*
	(0.124)	(0.126)	(0.056)	(0.099)	(0.250)	(0.067)	(0.078)
Deep soil (1 = yes)	-0.044	0.046	0.161***	0.154*	0.163	0.012	0.069
	(0.082)	(0.110)	(0.042)	(0.082)	(0.251)	(0.050)	(0.076)
Poor soil quality (1 = yes)	-0.088	-0.187	-0.228***	0.003	-0.450	-0.158***	-0.266***
	(0.093)	(0.119)	(0.042)	(0.086)	(0.367)	(0.058)	(0.079)
High soil quality (1 = yes)	0.037	0.225**	-0.003	0.082	0.433	0.044	0.072
	(0.085)	(0.112)	(0.043)	(0.098)	(0.292)	(0.044)	(0.051)
Applied herbicide on plot	0.232**	0.047	0.233***	0.267**	-1.307	0.298***	-0.008
	(0.117)	(0.267)	(0.043)	(0.105)	(1.005)	(0.091)	(0.108)
Pesticide used (1 = yes)	0.086	0.376**	0.010	-0.070	0.443	-0.080	-0.113
	(0.194)	(0.161)	(0.075)	(0.122)	(0.407)	(0.069)	(0.084)
Lime used (1 = yes)	0.832*	0.158	-0.162	-0.433	0.199	-0.027	0.034
	(0.443)	(0.592)	(0.153)	(0.289)	(1.149)	(0.156)	(0.145)
Urea used (1 = yes)	-0.038	0.135	0.149	-0.086	-0.490	-0.088	0.101
	(0.523)	(0.849)	(0.108)	(0.263)	(1.572)	(0.159)	(0.229)
Maize plot (1 = yes)	0.160	0.722*	0.843**	0.105	3.462*	0.950***	0.913***
	(0.387)	(0.425)	(0.399)	(0.348)	(2.056)	(0.294)	(0.295)
Wheat plot (1 = yes)	0.390**	0.240	0.775***	0.447**	3.225	0.754***	0.758***
	(0.173)	(0.269)	(0.122)	(0.228)	(2.014)	(0.165)	(0.234)
Log of plot size (in ha)	-0.150**	-0.243***	-0.014	0.043	0.320	0.040	0.029
	(0.063)	(0.076)	(0.034)	(0.085)	(0.199)	(0.041)	(0.046)
λ1		-1.162**	-0.067	0.453	-0.103	0.526	0.517
		(0.593)	(0.214)	(0.500)	(1.240)	(0.375)	(0.358)
λ2	-0.185		-0.698**	-0.284	0.010	-0.288	-0.401
	(0.630)		(0.350)	(0.520)	(1.327)	(0.683)	(0.421)

λ3	0.442	1.156**		0.360	0.253	-0.254	-0.098
	(0.450)	(0.491)		(0.417)	(1.899)	(0.298)	(0.290)
λ4	0.447	-2.204*	0.106		-2.242	0.192	-0.370
	(1.065)	(1.173)	(0.323)		(3.580)	(0.488)	(0.573)
λ5	-0.082	-0.845	1.149**	0.202		0.436	0.346
	(0.801)	(0.656)	(0.478)	(0.557)		(0.759)	(0.419)
λ6	-0.883	1.710***	-0.313	-0.364	0.247		-0.115
	(0.654)	(0.583)	(0.299)	(0.632)	(1.862)		(0.489)
λ7	0.314	1.060	-0.087	-0.238	1.335	-0.565*	
	(0.936)	(0.793)	(0.273)	(0.438)	(1.658)	(0.319)	
Constant	3.453	-3.545	-0.121	1.644	-3.009	1.952**	1.844
	(2.471)	(2.207)	(0.840)	(1.647)	(6.666)	(0.967)	(1.293)
R-squared	0.264	0.288	0.376	0.212	0.350	0.379	0.192
Observations	436	367	2,102	537	148	1,366	1,239

Note: Standard errors in parentheses, bootstrapped with 100 replications; *** p<0.01, ** p<0.05, * p<0.1.

Table A 3.8. Second stage regression estimates: returns to unpaid labor.

	Log of returns to labor (ETB/labor-day)						
	No ISFM	OF	IF	OF + IF	OF + IS	IF + IS	OF + IF + IS
Gender HH head (1 = male)	-0.187	0.264	0.231**	0.224	0.601	0.170*	0.061
	(0.147)	(0.168)	(0.099)	(0.187)	(0.553)	(0.099)	(0.139)
Age HH head (in years)	-0.009**	-0.008*	-0.005***	-0.005	0.000	-0.007***	-0.010***
	(0.004)	(0.004)	(0.002)	(0.004)	(0.008)	(0.002)	(0.003)
HH head has formal education (1 = yes)	-0.016	-0.140	-0.248***	-0.125	0.197	-0.159***	-0.151**
	(0.121)	(0.147)	(0.037)	(0.111)	(0.158)	(0.061)	(0.060)
No. of HH members	-0.076***	-0.013	-0.056***	-0.039	0.001	-0.054***	-0.039**
	(0.023)	(0.028)	(0.011)	(0.027)	(0.062)	(0.014)	(0.016)
No. of TLU owned	0.038*	0.062**	0.064***	0.038*	0.065	0.042***	0.058***
	(0.023)	(0.026)	(0.008)	(0.021)	(0.056)	(0.011)	(0.014)
Log of farm size (in ha)	0.016	-0.033	-0.170***	-0.186*	-0.423	-0.086	-0.065
	(0.102)	(0.148)	(0.048)	(0.096)	(0.358)	(0.074)	(0.062)
No. of social organizations HH is involved	-0.099	-0.123	0.051	-0.086	0.255	0.018	0.021

	(0.078)	(0.111)	(0.047)	(0.114)	(0.264)	(0.058)	(0.059)
Log of walking distance to nearest FTC (in min)	0.022	0.012	0.031**	0.012	0.060	0.017	0.029
	(0.027)	(0.031)	(0.014)	(0.023)	(0.053)	(0.021)	(0.020)
Talked to extension agent (1 = yes)	0.053	-0.084	0.052	0.084	0.044	-0.012	0.066
	(0.094)	(0.112)	(0.043)	(0.107)	(0.384)	(0.065)	(0.074)
Log of walking distance to nearest village market (in min)	0.005	-0.039	-0.068***	-0.088	-0.138	-0.074**	-0.036
	(0.057)	(0.078)	(0.023)	(0.091)	(0.178)	(0.036)	(0.051)
Agri-input dealer in Kebele (1 = yes)	-0.140**	-0.047	0.039	-0.072	0.243**	0.038	0.020
	(0.060)	(0.065)	(0.026)	(0.060)	(0.115)	(0.029)	(0.033)
HH has access to formal credit (1 = yes)	-0.058	-0.184	0.251***	-0.098	0.262	0.079	0.110
	(0.253)	(0.310)	(0.069)	(0.201)	(0.331)	(0.095)	(0.117)
Pest and disease stress (1 = yes)	0.050	0.163	-0.039	-0.066	-0.236	-0.297***	-0.066
	(0.110)	(0.124)	(0.067)	(0.182)	(0.221)	(0.086)	(0.089)
Weather stress (drought/flood/frost/storm) (1 = yes)	-0.192*	-0.047	-0.235***	-0.248**	-0.433	-0.304***	-0.195**
	(0.100)	(0.122)	(0.053)	(0.125)	(0.402)	(0.057)	(0.078)
Log of av. annual rainfall (in mm)	-0.449	0.255	0.196	0.231	-0.138	0.117	0.126
	(0.472)	(0.466)	(0.136)	(0.337)	(0.450)	(0.151)	(0.228)
Log of walking distance to plot (in min)	-0.062	0.082	-0.002	0.102	-0.290	0.068	0.053
	(0.072)	(0.125)	(0.041)	(0.172)	(0.354)	(0.081)	(0.147)
Plot owned (1 = yes)	-0.046	0.057	-0.091*	-0.076	0.222	-0.037	0.043
	(0.092)	(0.158)	(0.049)	(0.144)	(0.349)	(0.080)	(0.110)
Footslope (1 = yes)	0.168	-0.056	-0.062	0.025	0.184	0.047	0.084
	(0.124)	(0.106)	(0.045)	(0.097)	(0.196)	(0.056)	(0.060)
Hillslope (1 = yes)	0.119	0.112	-0.078	0.282**	0.138	0.072	0.184*
	(0.131)	(0.184)	(0.056)	(0.134)	(0.317)	(0.075)	(0.096)
Shallow soil depth (1 = yes)	-0.308**	0.026	-0.118**	-0.178	0.166	0.052	-0.269***
	(0.150)	(0.148)	(0.057)	(0.118)	(0.257)	(0.082)	(0.093)
Deep soil (1 = yes)	-0.053	0.099	0.093**	0.153	0.254	0.046	0.009
	(0.112)	(0.126)	(0.044)	(0.101)	(0.197)	(0.064)	(0.079)
Poor soil quality (1 = yes)	-0.126	-0.111	-0.282***	-0.067	-0.276	-0.251***	-0.313***
	(0.104)	(0.178)	(0.055)	(0.107)	(0.326)	(0.075)	(0.103)
High soil quality (1 = yes)	-0.002	0.325**	0.018	-0.073	0.344	0.029	0.068
	(0.091)	(0.153)	(0.049)	(0.111)	(0.356)	(0.060)	(0.061)
Applied herbicide on plot	0.211	0.093	0.227***	0.311**	-1.034	0.281**	-0.012

	(0.136)	(0.288)	(0.052)	(0.155)	(1.264)	(0.127)	(0.138)
Pesticide used (1 = yes)	0.164	0.495***	0.070	-0.107	0.360	-0.046	-0.006
	(0.217)	(0.174)	(0.092)	(0.181)	(0.356)	(0.114)	(0.096)
Lime used (1 = yes)	1.197**	-0.097	-0.214	-0.621*	-0.141	-0.235	-0.223
	(0.519)	(0.650)	(0.220)	(0.351)	(1.264)	(0.239)	(0.196)
Urea used (1 = yes)	-0.228	-0.560	0.081	0.017	-0.604	-0.179	0.305
	(0.655)	(1.162)	(0.135)	(0.335)	(1.784)	(0.236)	(0.374)
Maize plot (1 = yes)	-0.763*	0.081	-0.240	-1.238***	2.097	-0.368	-0.428
	(0.438)	(0.532)	(0.387)	(0.476)	(2.538)	(0.457)	(0.343)
Wheat plot (1 = yes)	-0.169	-0.277	0.186	-0.492	2.021	0.015	-0.058
	(0.170)	(0.298)	(0.135)	(0.344)	(2.370)	(0.275)	(0.249)
Log of plot size (in ha)	-0.141**	-0.284***	-0.022	-0.007	0.206	0.014	0.014
	(0.069)	(0.084)	(0.041)	(0.090)	(0.173)	(0.053)	(0.063)
$\lambda 1$		-1.197	-0.270	0.444	-0.231	0.503	0.463
		(0.805)	(0.238)	(0.621)	(0.688)	(0.480)	(0.499)
$\lambda 2$	0.119		-0.755*	-0.189	0.450	-1.114	-1.023**
	(0.613)		(0.433)	(0.653)	(1.271)	(0.680)	(0.471)
$\lambda 3$	0.343	1.268**		0.594	-0.004	-0.188	0.089
	(0.449)	(0.618)		(0.564)	(1.694)	(0.405)	(0.439)
$\lambda 4$	0.074	-2.725*	0.116		-1.199	0.184	-0.247
	(0.999)	(1.591)	(0.513)		(4.066)	(0.634)	(0.859)
$\lambda 5$	-0.076	-0.872	1.689***	-0.057		1.405*	0.479
	(0.584)	(0.692)	(0.562)	(0.612)		(0.843)	(0.591)
$\lambda 6$	-0.956	1.689**	-0.266	-0.281	-0.988		0.169
	(0.748)	(0.721)	(0.376)	(0.943)	(1.407)		(0.716)
$\lambda 7$	0.533	1.303	-0.368	-0.422	1.608	-0.695	
	(0.936)	(0.909)	(0.330)	(0.488)	(1.980)	(0.472)	
Constant	9.335***	1.076	3.208***	4.310*	1.329	4.342***	3.877**
	(3.123)	(3.176)	(1.058)	(2.349)	(5.552)	(1.523)	(1.688)
R-squared	0.206	0.248	0.231	0.275	0.326	0.205	0.159
Observations	434	366	2,048	514	146	1,338	1,192

Note: Standard errors in parentheses, bootstrapped with 100 replications; *** p<0.01, ** p<0.05, * p<0.1.

Table A 3.9. Robustness check: crop type effects per agroecological zone.

Panel A: Amhara & Oromia (moist/wet)												
ISFM combination	Land productivity w/o maize (kg/ha)				Land productivity w/o wheat (kg/ha)				Land productivity w/o teff (kg/ha)			
	ATT		p	N	ATT		p	N	ATT		p	N
OF	156.48	(152.76)	0.309	44	405.12	(85.74)	0.000	205	409.55	(86.10)	0.000	201
IF	598.57	23.51)	0.000	1,670	371.13	(17.81)	0.000	1,253	1246.91	(49.59)	0.000	451
OF + IF	711.16	(55.84)	0.000	244	568.08	(55.46)	0.000	237	904.38	(82.14)	0.000	159
OF + IS	472.06	(277.17)	0.101	13	1046.97	(136.37)	0.000	97	979.02	(125.86)	0.000	110
IF + IS	1137.99	(48.81)	0.000	432	1740.66	(54.64)	0.000	659	1725.14	(40.66)	0.000	901
OF + IF + IS	1177.60	(70.31)	0.000	210	1843.80	(51.92)	0.000	762	1786.74	(45.77)	0.000	894
Panel B: Tigray (dry)												
ISFM combination	Land productivity w/o maize (kg/ha)				Land productivity w/o wheat (kg/ha)				Land productivity w/o teff (kg/ha)			
	ATT		p	N	ATT		p	N	ATT		p	N
OF	73.00	(74.28)	0.328	57	254.43	(113.83)	0.026	141	274.80	(139.23)	0.050	104
IF	319.39	(40.60)	0.000	409	259.95	(42.61)	0.000	335	578.67	(106.17)	0.000	108
OF + IF	465.46	(60.13)	0.000	129	389.08	(75.17)	0.000	162	515.93	(73.82)	0.000	161
OF + IS	225.71	(147.96)	0.134	23	1577.82	(458.58)	0.001	19	881.22	(319.36)	0.007	36
IF + IS	472.82	(42.61)	0.000	368	305.82	(54.11)	0.000	198	734.49	(71.58)	0.000	182
OF + IF + IS	819.04	(49.00)	0.000	243	1131.22	(126.63)	0.000	129	1149.64	(73.15)	0.000	248

Note: Reduced sample size stems from logarithmic transformation of outcomes during estimation procedure; standard errors in parentheses; p-values indicate statistical significance of ATT.

4. The effects of Integrated Soil Fertility Management on household welfare in Ethiopia[46]

Abstract

Integrated Soil Fertility Management (ISFM) is a technology package consisting of the joint use of improved seeds, organic and inorganic fertilizers. It is increasingly promoted to enhance soil fertility, crop productivity and income of smallholder farmers. While studies find positive effects of ISFM at the plot level, to date there is little evidence on its broader welfare implications. This is important since system technologies like ISFM mostly involve higher labor and capital investments, and it remains unclear whether these pay off at the household level. Using data from maize, wheat and teff growing farmers in two agroecological zones in Ethiopia, we assess the impact of ISFM on crop and household income, and households' likelihood to engage in other economic activities. We further study effects on labor demand, food security and children's education. We use the inverse probability weighting regression adjustment method, and propensity score matching as robustness check. We find that ISFM adoption for maize, wheat or teff increases income obtained from these crops in both agroecological zones. Yet, only in one subsample, it also increases household income, while in the other it is associated with a reduced likelihood to achieve income from other crops and off-farm activities. Results further show that ISFM increases labor demand. Moreover, we find positive effects of ISFM on food security and primary school enrollment in those regions where it goes along with gains in household income. We conclude that welfare effects of agricultural innovations depend on farmers income diversification strategies.

Key words: Technology adoption, household income, food security, education, labor, rural development

[46] This essay is co-authored by Meike Wollni. DH collected the data, performed the analysis, interpreted results and wrote the paper. MW contributed at various stages of the research, including interpretation of result, writing and revising the paper.

4.1 Introduction

Rising demand for agricultural commodities coupled with on-going population growth, climate change, declining soil fertility, environmental degradation and rural poverty in the developing world emphasize the urge to sustainably intensify agricultural production. Most of these conditions are particularly prevalent in Sub-Saharan Africa (SSA), where rates of undernutrition are the highest worldwide, while agricultural productivity is still far below global averages (FAO, 2020). Sustainable intensification refers to increasing agricultural production from the same area of land while reducing its negative environmental consequences (Godfray, 2010). As one strategy to sustainably intensify smallholder agriculture, 'Integrated Soil Fertility Management' (ISFM) is increasingly promoted by governments and donors in SSA. ISFM is a system technology consisting of a set of site-specific soil fertility practices which should be applied in combination. Its core is the integrated use of improved seeds with organic and inorganic fertilizers, which are supposed to bear important synergistic effects. Practices should be adapted to local conditions and, depending on the context, complemented by other technologies such as crop rotation, minimum tillage, or measures to correct soil acidity (Place et al., 2003; Vanlauwe et al., 2010). Further, ISFM includes an improvement of agronomic techniques, e.g. timely weeding or exact dosing and targeting of inputs. The general aim of ISFM is to improve soil fertility by replenishing its nutrient stocks and increasing soil organic matter levels, and thus, water-holding capacity and soil biota. On the one hand, healthier and more fertile soils can contribute to restoring and conserving natural resources by providing crucial ecosystem services, such as the storage of soil carbon, erosion control, and the prevention of further deforestation (Adhikari & Hartemink, 2016). Moreover, enhanced soil fertility is likely to improve food security, incomes, and ultimately, livelihoods of the rural population depending on small-scale agriculture (Barrett & Bevis, 2015). On the other hand, ISFM is commonly associated with increased financial costs for the purchase of inputs, as well as higher labor demand, since preparing, transporting and applying inputs – in particular bulky organic fertilizers – are time-consuming activities. Hence, despite potential positive effects on yields and the environment, farmers need to consider their farm-level costs and welfare benefits.

There is a considerable body of literature on plot-level effects of single or joint uptake of different 'sustainable' natural resource or agricultural practices (e.g. Abro et al., 2017; Arslan et al., 2014; Barrett et al., 2004; Di Falco et al., 2011; Hörner & Wollni, 2020; Jaleta et al., 2016; Kassie et al., 2008, 2010; Teklewold et al., 2013). Other studies deal, in addition or exclusively, with household-level impacts of such technologies, e.g. of improved crop varieties (Becerril &

Abdulai, 2010; Kassie et al., 2014; Khonje et al., 2015; Manda et al., 2018; Shiferaw et al., 2014), or combinations of various input- and management-intensive practices, such as improved varieties, fertilizers, conservation agriculture and crop rotation (Asfaw et al., 2012; Kassie et al., 2015; Khonje et al., 2018; Manda et al., 2016; Wainaina et al., 2018), or the system of rice intensification (Noltze et al., 2013; Takahashi & Barrett, 2014). This is important in order to determine whether potentially productivity-enhancing technologies are also welfare-enhancing for resource-constrained smallholders, who need to economize their capital, land and labor. For instance, Wainaina et al. (2018) observe no household income effects of adopting improved seeds with fertilizer, but find positive impacts when the former are combined with organic fertilizer, which is often sourced on-farm at low or no costs. For ISFM, Adolwa et al. (2019) find significant effects of the technology package on maize yields, but not on household income, which is probably related to the increased costs of production or because the contribution of maize income to total household income is not sufficiently high. Further, many farm households diversify their income sources between different crop types and potentially off-farm activities, so that investing more resources in one activity may imply reallocation effects, leaving net effects for a household uncertain. This applies even more for labor-intensive technologies in settings where mechanization levels are low, as still the case in large parts of SSA (Sheahan & Barrett, 2017). For the system of rice intensification, for example, Takahashi and Barrett (2014) as well as Noltze et al. (2013) find relatively large productivity gains, but no or small effects on total household income. In Takahashi and Barrett's (2014) study this seems to be driven by labor reallocation from off-farm to on-farm, especially among female household members. In this regard, one issue of particular concern is whether increased demand for household labor raises the work burden of children and hence, may present a threat to their educational attainment. In particular, an increase in labor productivity also increases opportunity costs of children's time and hence, may increase parents' incentives to withdraw children from school or increase at least children's absenteeism. On the other hand, positive income effects can also translate into positive impacts on child schooling. Firstly, because (unrealized) earnings from children represent a smaller share of household resources; and secondly, because higher income can enable increased spending on education as a form of long-term investment in human capital formation (Basu, 1999; Takahashi & Barrett, 2014).

Regarding food security in (semi-)subsistence settings, a conventional belief is that it is mainly driven by households' own food production. Hence, household food security should be closely related to the use of productivity-enhancing technologies for main staple crops, as evidenced by a series of studies on the relation between improved seeds and food security (Kassie et al., 2014; Khonje et al., 2015; Manda et al., 2018; Shiferaw et al., 2014). Yet, a study by Babatunde and Qaim (2010), for instance, finds that off-farm income can be equally important as farm production for household food security. Thus, both productivity and potential resource diversion effects might be at play regarding the impact of technology adoption on farm households' food security situation.

While the use of system technologies becomes increasingly important, studies on their broader welfare implications are still scarce (Jayne et al., 2019; Takahashi, Muraoka, et al., 2019). Regarding ISFM, to date evidence is largely restricted to traditional economic outcomes, like crop productivity or income, and mostly limited to maize (Takahashi, Muraoka, et al., 2019).

The objective of this study is to extend the literature by assessing household-level welfare impacts of ISFM adoption. We use primary data from 2,059 maize, wheat and teff[47] growing households from the Ethiopian highlands. We employ a doubly-robust approach to account for selection bias, which combines inverse probability weighting and regression adjustment (Wooldridge, 2010). We expand the current literature on ISFM impacts (Adolwa et al., 2019; Wainaina et al., 2018) by looking into a broader range of outcomes in order to assess welfare effects. In particular, we analyze whether the use of ISFM for at least one of three major cereal crops has effects on the income achieved from these crops as well as on household income per capita, and whether it alters the probability to engage in other farm or off-farm economic activities. In addition, we assess impacts on households' subjective food security situation. Further, we study whether labor demand increases for different groups of household members due to ISFM adoption. And lastly, we look into effects on children's education measured by children's school attendance and households' educational expenditure. With the prominent exception of Takahashi and Barrett (2014), who analyze the impact of the system of rice intensification on child schooling, we are not aware of any other studies investigating the effects of agricultural technology adoption on child education outcomes.[48] Beyond implications for individual well-being, effects on children's education may also impact human capital formation and hence, economic development of entire regions, making it particularly important to add evidence to this subject.

[47] Teff is a small cereal grain originating from the Northern Ethiopian highlands. While it is hardly grown in other parts of the world, it presents a major staple in Ethiopian and Eritrean diets (Baye, 2010).

[48] With the exception of studies that look into effects of sustainability standards on education outcomes (e.g. Gitter et al., 2012; Meemken et al., 2017), which we, however, consider another strand of literature since certification usually involves additional economic and social benefits that are not at play in our case.

This article proceeds as follows. The subsequent section describes the study context, data and econometric framework, as well as the variables used for analyses. Next, we will present results on income, food security, labor and education outcomes. The last section discusses the findings and concludes.

4.2 Materials and methods

4.2.1 Study context

With around 108 million inhabitants, Ethiopia has the second largest population in Africa, which continues to rapidly grow by around 2.6% annually (CIA, 2020). Approximately three fourths of the country's inhabitants rely on smallholder agriculture as their main source of income. Three cereal crops – maize, wheat and teff – account for over half of Ethiopia's cultivated area (CSA, 2019). They present the main staples in rural diets and thus, are particularly relevant for food security. Yet, average productivity levels of cereals remain below 2.5 tons per hectare, while rural poverty is still widespread with over one quarter of rural dwellers living below the national poverty line. In addition, over 20% of the country's population is undernourished and 38% of children under age five are affected by stunting (low height for age, reflecting sustained phases of undernutrition) (FAO, 2020).

Despite successful public programs to revert land degradation, soil erosion and reduced soil fertility are still major challenges for the Ethiopian agricultural sector. While in the past decades, the focus was more on erosion-control measures implemented via the large-scale 'Sustainable Land Management Programme' (SLMP) (Schmidt & Tadesse, 2019), recently agricultural policies began to concentrate on the intensification of smallholder agricultural practices. Since 2017, ISFM is part of the national 'Soil Health and Fertility Improvement Strategy' to sustainably enhance soil fertility, productivity and livelihoods of the rural population (MoANR, 2017).

In this context, in 2015 the German Agency for International Cooperation (GIZ) launched the 'Integrated Soil Fertility Management Project' (ISFM+ project) in 18 districts (Woredas) in the three highland regions Amhara, Oromia and Tigray. The project's main objective is the development and promotion of suitable ISFM practices for smallholders, in close cooperation with the Ethiopian Ministry of Agriculture and Natural Resources, the national extension system and farmers themselves via a decentralized and participatory learning approach (Hörner et al., 2019).

4.2.2 Sampling and data

Our study sites are located in the 18 Woredas in which the ISFM+ project was implemented, i.e. six Woredas in Amhara, Oromia and Tigray, respectively. All study sites are located in highland areas above 1,500 meters above sea level (m a.s.l.), with average elevations between 2,000 and 2,500 m a.s.l. for all three regions. In terms of precipitation, the Woredas in Amhara and Oromia can be classified as moist or wet areas (Hurni, 1998), with 1,229 mm respectively 1,426 mm average annual rainfall. By contrast, the Woredas in Tigray are much drier with 661 mm average annual rainfall. To account for these differences in agroecological potential, which might affect both technology choices and welfare outcomes, we distinguish between *wet and moist areas* (Amhara and Oromia) and *dry areas* (Tigray) in our analysis, following previous studies in similar settings (Kassie et al., 2008, 2010; Hörner & Wollni, 2020).

Within the 18 Woredas, our primary sampling units are microwatersheds, which are the implementation units of the ISFM+ project. Those are agglomerations of households (typically 200 to 300), organized in one or several villages that share a common rainwater outlet. Out of a sampling frame of 161 microwatersheds, 72 were randomly selected to benefit from the ISFM+ project, while the remaining 89 in the same Woredas are non-beneficiary (control) microwatersheds. In each of the 161 microwatersheds, we randomly draw 15 households from administrative lists to be included in the sample. We restrict our analysis to the 2,059 households that cultivated at least one of the main cereal crops teff, maize and wheat on at least one plot in the 2017 main cropping season, for which ISFM practices are primarily promoted and applied.[49]

The main data collection took place in early 2018 by means of tablet-based structured questionnaires. We collected detailed data on agricultural technology use, production, labor input, crop yields, and different income sources retrospective for the 2017 main agricultural season, as well as other socioeconomic information, inter alia. Additionally, we collected data at the Woreda and microwatershed levels, e.g. on infrastructure and climatic information. Moreover, a first, yet less detailed data collection took place in early 2016, allowing us to include some baseline characteristics in the analysis.

4.2.3 Econometric framework

The objective of our study is to assess the effect of ISFM adoption on different measures of income, food security, labor and children's education. Hence, we are interested in the average

[49] Though the ISFM+ project also advocates the use of ISFM for other crops, adoption rates for these are still low in our sample and consequently, we limit analyses to the three cereal crops.

treatment effect on the treated households (ATET), defined as the average difference in outcomes of ISFM adopters with and without the technology. Following Manda et al. (2018), the ATET is written as:

$$ATET = E\{Y_{iA} - Y_{iN} | T_i = 1\}, \qquad (4.1)$$
$$= E(Y_{iA} | T_i = 1) - E(Y_{iN} | T_i = 1)$$

in which $E\{.\}$ is the expectation operator, Y_{iA} the predicted outcome for ISFM-adopting household i under adoption, Y_{iN} the predicted outcome of the same household under non-adoption, while T_i represents the treatment status taking one for ISFM adopters and 0 for non-adopters. Yet, while the outcome for adopters under adoption $E(Y_{iA} | T_i = 1)$ can be observed in the data, the counterfactual outcome $E(Y_{iN} | T_i = 1)$ cannot. Replacing these outcomes with those of non-adopters $E(Y_{iN} | T_i = 0)$ is likely to result in biased estimates due to possible self-selection of ISFM-adopting households. To overcome this problem, we follow Manda et al. (2018) and apply the doubly-robust inverse probability weighted regression adjustment (IPWRA) method. The IPWRA estimator is obtained by combining inverse probability weighting (IPW) with regression adjustment (RA) (Wooldridge, 2010). While IPW focuses on modelling the treatment selection, RA concentrates on outcomes, which allows controlling for selection bias at both stages. This property is referred to as 'doubly-robust', since only one of the two models needs to be correctly specified in order to obtain consistent estimates of treatment effects (Wooldridge, 2010).

In a first step, the inverse probability weights need to be calculated based on the estimated probability of receiving the treatment (ISFM adoption). For this purpose, propensity scores as defined by Rosenbaum and Rubin (1983) are estimated:

$$p(X) = Pr(T_i = 1 | X) = F\{h(X)\} = E(T_i | X) \qquad (4.2)$$

where X represents a vector of exogenous variables including household and farm characteristics, infrastructure, weather, shocks, and access to information, and $F\{.\}$ is a cumulative distribution function.

Based on the estimated propensity score $\hat{p}$, inverse probability weights are calculated as $\frac{1}{\hat{p}}$ for treated households, and $\frac{1}{1-\hat{p}}$ for non-treated households. In other words, each observation is weighted by the inverse probability of receiving the treatment level it actually received (Hernán & Robins, 2019).

The RA method fits separate linear regression models for both treated and untreated observations, and then predicts the covariate-specific outcomes for each subject under each treatment status. Average treatment effects are then obtained by averaging the differences between predicted outcomes under adoption and non-adoption. The ATET for the RA model can be expressed as follows (Manda et al., 2018):

$$ATET_{RA} = n_A^{-1} \sum_{i=1}^{n} T_i[r_A(X, \delta_A) - r_N(X, \delta_N)] \tag{4.3}$$

where n_A is the number of adopters, and $r_i(X)$ describes the regression model for adopters (A) and non-adopters (N) with covariates X and estimated parameters $\delta_i(\alpha_i\beta_i)$.

The IPWRA estimator is then constructed by combining the RA method with the inverse probability weights and can be written as:

$$ATET_{IPWRA} = n_A^{-1} \sum_{i=1}^{n} T_i[r_A^*(X, \delta_A^*) - r_N^*(X, \delta_N^*)] \tag{4.4}$$

in which $\delta_A^*(\alpha_A^*\beta_A^*)$ and $\delta_N^*(\alpha_N^*\beta_N^*)$ are obtained from the weighted regression procedure.

To assess whether our sample is balanced after the inverse probability weighting procedure, we run an overidentification test, and additionally calculate normalized differences for each covariate as Imbens and Wooldridge (2009) propose:

$$norm\_diff_j: \frac{(\bar{X}_{Aj} - \bar{X}_{Nj})}{\sqrt{S_{Aj}^2 - S_{Nj}^2}} \tag{4.5}$$

where $\bar{X}_{Aj}$ and $\bar{X}_{Nj}$ represent the means for variable j for adopters and non-adopters respectively, and S_{Aj} and S_{Nj} the corresponding standard deviations.

The IPWRA method rests on two assumptions. Firstly, it assumes conditional independence or unconfoundedness. This means, conditional on observed covariates, treatment assignment can be considered random. Since selection into treatment regimes might still be based on unobservable characteristics, this is a strong assumption. Yet, conditioning on a rich set of observable covariates may help to circumvent or at least reduce selection bias due to unobservables (Imbens & Wooldridge, 2009). The second assumption postulates that, conditional on covariates, each observation has a positive probability of receiving the treatment. This is often called overlap assumption and ensures that for each adopting household, a non-adopting household with similar characteristics exists. If this assumption is violated, estimators are overly sensitive to model specification, potentially leading to imprecise estimates. Therefore, we will set a tolerance level for the estimated probability of receiving the treatment between $\hat{p}$ = 0.001 and $\hat{p}$ = 0.999.

As a robustness check for the IPWRA estimations, we use a simple propensity score matching (PSM) approach by matching the three nearest neighbors, as commonly done in the literature (e.g. Takahashi & Barrett, 2014).

4.2.4 Empirical specification

We assess the impact of adopting ISFM on at least one maize, wheat and teff plot on a set of household-level outcomes. We focus on the three ISFM core technologies – improved seeds, organic and inorganic fertilizer – in this study, leaving aside a range of other technologies one can potentially refer to as ISFM. Improved crop varieties are higher-yielding open-pollinated (wheat and teff) or hybrid (maize) varieties, which may additionally carry disease- or drought-tolerant traits. Inorganic fertilizers are locally adapted compound fertilizers, mostly NPS (and few NPK)[50] fertilizers which are often enriched with one or several locally deficient nutrients such as boron, zinc or iron (in Ethiopia referred to as 'blended fertilizers'). To account for heterogeneity of soil conditions and locally available resources, we define organic fertilizer as having applied at least one of the following practices: animal manure, compost, mulching or green manuring.

We distinguish between two treatment indicators. *Full ISFM* adoption is defined as having used improved seeds together with inorganic *and* organic fertilizers on at least one maize, wheat or teff plot. In addition, we assess the effects of *partial or full ISFM* adoption.[51] Previous research in the study area has shown that in terms of net crop value, average plot-level effects of combining improved seeds with either organic *or* inorganic fertilizer are close to the effects of combining all three practices (Hörner & Wollni, 2020). Similarly, all three combinations lead to substantial increases in labor demand. To potentially cover these effects at the household level, we define *partial or full ISFM* adoption as having used improved seeds for maize, wheat or teff in combination with at least one fertilizer type, i.e. organic or/and inorganic. This also allows to assess potential differential impacts of at least partial and complete ISFM adoption.

To measure effects on household welfare, our first outcome variable is annual *household income per capita* in Ethiopian Birr (ETB). Here we include revenues from all income-generating farm- and non-farm activities, i.e. incomes from crops, livestock sales, wage employment or business activities minus incurred costs. Following Takahashi and Barrett (2014), we focus on productive income, thus, exclude unearned income such as remittances or social transfers. Further, we do not value unpaid family labor, owned land or machinery, and hence, do not study true economic profit (Takahashi & Barrett, 2014). We also assess ISFM effects on *maize, wheat and teff income per capita* and *per hectare* by calculating the monetary value of farmers' crop

[50] N, P, S and K stand for nitrogen (N), phosphorus (P), sulfur (S) and potassium (K).

[51] Under both ISFM definitions, treatment groups are compared against the control group of non-adopters, defined as households who have not adopted at least two ISFM components, i.e. improved seeds with any fertilizer type. Yet, they might have adopted (any kind of) fertilizer without improved seeds, or improved seeds without fertilizer (which is rarely done, however).

output less all costs for inputs. To account for differences in input and output prices between districts, we use price information obtained from Woreda-level interviews. Moreover, in order to get a sense for potential resource-reallocation effects associated with ISFM use for maize, wheat or teff, we employ a binary outcome indicating whether households cultivated any other crop they consider as one of their main income sources, either for consumption or sales purposes, and hence, measure whether the *household grows other main crops*.[52] This often – but not exclusively – refers to barley, sorghum or legumes, or cash crops such as coffee or fruits. This does, however, not include cereal or vegetable crops grown on very small patches of land only for occasional self-consumption. Similarly, we use a dummy outcome indicating whether a *household has off-farm income*, taking the value of one if any household member achieves income from either wage employment or a non-farm business.[53]

Several different measures have been used in the literature to assess household food security; for instance, household calorie consumption (Babatunde & Qaim, 2010) or per capita food expenditure (Kassie et al., 2014; Manda et al., 2018; Shiferaw et al., 2014). Yet, in addition to these rather objective measures, subjective assessments of food security are increasingly used (e.g. Khonje et al., 2015; Mallick & Rafi, 2010), with a series of studies using both in a complementary manner (Kassie et al., 2014; Manda et al., 2018; Shiferaw et al., 2014). Despite several drawbacks of subjective measurements, such as a potential response bias towards overreporting food insecurity (Headey, 2013; Tadesse et al., 2020), we rely on a subjective measure due to several reasons. Firstly, self-reported indicators can be assessed in a relatively easy and low-cost way compared to capturing consumption or expenditure data. Secondly, subjective perceptions of food security status may entail psychological dimensions which matter in their own right (Headey & Ecker, 2012). And lastly, as Headey and Ecker (2012) argue, subjective indicators can be particularly suitable to assess severe forms of food insecurity, and thus, capture meaningful information in a developing-country setting.

We use an adapted version of the Household Food Insecurity and Access Scale (HFIAS) developed to measure the frequency of food deprivation in a four-week period (Coates et al., 2007). We modified this measure and asked in retrospective for the 30 days before harvest.[54]

[52] A more appropriate measure may have been to calculate income achieved from other main crops. Unfortunately, it is computationally problematic to assess effects on this outcome, since a large share of households (37%) reports not to achieve important income from other crop types, who would then be excluded in the logarithmic transformation of the variable. On average, households only grow four different crop types on their farms; while maize, wheat and teff on average make up for around 55% of both farm area and total household income.

[53] Similar to above, taking the income obtained from off-farm activities as outcome variable is difficult due to many zeros.

[54] Specifically, we asked "In the 30 days before harvest, how many times… (1) …did you or any household member go a whole day and night without eating anything at all because there was not enough food? (2) …did you or any household member go

We then calculate a binary indicator *household is food insecure*, taking one if all incidences taken together sum up to at least 30. A household could thus fall into the category of *food insecure*, because one of the conditions held true on each day of the 30 days before harvest, or alternatively, because several conditions were met on some of these days. We use several alternative specifications of this indicator as robustness checks, using thresholds for the sum of deprivation incidences of 10, 15, 20 and 25, and one specification in which the severest form of deprivation automatically defines a household as food insecure, independent of its frequency of occurrence.

In a poor rural setting, the last weeks before harvest might be particularly informative regarding the food security situation of a household. It does unarguably not capture direct effects of potentially higher yields associated with technology adoption in the season under consideration. Yet, it may well be a proxy for a households' overall vulnerability to food insecurity. This can reflect other economic activities in the season under consideration, such as off-farm employment, which has been shown to be an important determinant of household food security (Babatunde & Qaim, 2010), and is likely to be related to technology adoption via labor allocation effects. Further, it captures stocks of own food production from the preceding cropping cycle, for which technology choices are possibly correlated with those in the current season.[55] And lastly, the indicator might also gauge farmers' yield expectations for the season under consideration in retrospect, as they may have been less likely to restrict their consumption, or more likely to purchase food (e.g. on credit) in anticipation of a good harvest.

Regarding labor demand, we measure *total labor for maize, wheat and teff* (in labor-days) in the 2017 cropping season by summing up how many days[56] each household member and possible exchange or hired laborers have worked for the production of these crops during all stages of the cropping cycle: land preparation and planting, 'general cultivation' (incl. weeding, input application, inter alia) and harvesting and threshing. We further differentiate between labor input of different household members, i.e. how many days adult *male*, adult *female*, and primary-school-aged *children* (between age 6 and 15) worked for the production of these crops, as well as *exchange laborers*, i.e. unpaid laborers from outside the household.[57] We also look at *total*

to sleep at night hungry because there was not enough food? (3) … did you or any household member have to eat fewer meals in a day because there was not enough food? (4) … did you or any household member have to eat a smaller meal than you felt you needed because there was not enough food?".

[55] While we do not have data for the preceding cropping season, our baseline data confirms some degree of correlation between household-level technology adoption in 2015 and 2017.

[56] Assuming one labor-day has seven hours.

[57] It is common in rural communities in Ethiopia to work on neighbors' farms during peak times of the season, especially harvest. This often happens without remuneration, but on an exchange basis. By contrast, hiring labor is largely uncommon in

labor for maize, wheat and teff per hectare to assess whether potentially higher labor demand is not (only) driven by larger land area devoted to these crops. In addition, a binary variable indicates whether any primary-school-aged *children worked for maize, wheat and teff production* in order to measure possible impacts on child labor.

We assess potential effects on children's education with three indicators: Firstly, we measure the *enrollment rate of primary-school-aged children*, i.e. proportion of all children in primary school age who are enrolled in a school. Currently, Ethiopia is facing a considerable expansion in the provision of educational services aiming at free universal primary education of eight school years for children in both urban and rural areas, so that theoretically, all children should attend primary school between the ages of 6 or 7 and 14 (ILO & CSA, 2018). We follow Bernard et al. (2014) and define primary school age as between 6 and 15, but use an alternative specification as robustness check defining school age more narrowly between 7 and 14 years. Secondly, since enrollment not necessarily means full attendance of classes, we asked households how many days each enrolled child could not attend class due to agricultural labor, which lets us calculate the *average number of missed school days due to agricultural work*. Lastly, we examine *average education expenditure per capita*, which covers the total amount spent on uniforms, stationery, books, textbooks, school and examination fees, as well as transportation and accommodation costs for all household members who were currently enrolled in any educational institution. Hence, this indicator also covers children beyond primary school age who may be attending secondary or tertiary education.

Regarding explanatory factors, we include a comprehensive set of covariates in our treatment and outcome models, based on reviews of previous literature on technology adoption and welfare effects (e.g. Kassie et al., 2013; Knowler & Bradshaw, 2007; Manda et al., 2018; Marenya & Barrett, 2007; Teklewold et al., 2013; Wollni et al., 2010). Apart from typical socioeconomic, distance and climate-related variables, we include the share of school-aged children alongside the total number of persons living in a household, which may influence both ISFM adoption as well as income, labor, and education outcomes. Further, we account for which of the three crop types a household cultivates, and include not only total farm size, but also the share of area planted with maize, wheat or teff – potentially influencing both adoption as well as income obtained from and labor demand for these crops. Moreover, we include a binary indicator

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our study area and will therefore not be explicitly shown, but is included in the total labor variable. Likewise, costs for hired labor are accounted for in the income variables.

whether a household lives in an ISFM+ project microwatershed. We also try to capture some plot-level differences by including average plot distance from homestead as well as average plot fertility. Regarding household welfare indicators (livestock, food insecurity, basic assets, credit access), social capital (group involvement) and extension contact, we make use of our baseline data in order to prevent potential issues with reverse causality. Table 4.1 provides an overview of all outcome and explanatory variables differentiated by agroecological zone and ISFM adoption status.

Table 4.1. Descriptive statistics of all outcome and explanatory variables used in analyses.

	Amhara & Oromia (wet/moist regions)						Tigray (dry region)					
	Full Sample		Not adopted ISFM		Adopted partial or full ISFM		Full Sample		Not adopted ISFM		Adopted partial or full ISFM	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Income and food security outcomes												
Household income per capita (in ETB)	4586.27	5082.01	3313.47	3681.66	4864.51***	5300.26	4100.04	4534.01	4764.57	5636.35	3565.21***	3308.49
Maize, wheat and teff income per capita (in ETB)	2840.59	3170.44	1689.81	2127.81	3092.15***	3303.26	1174.88	1247.72	1018.49	1240.86	1300.74***	1240.44
Maize, wheat and teff income per ha (in ETB)	16547.75	10626.39	12431.26	8756.79	17447.63***	10789.00	14146.35	11790.47	12451.12	10706.40	15510.70***	610.71
Household grows other main crops (1 = yes)	0.55		0.55		0.56		0.77		0.83		0.72***	
Household has off-farm income (1 = yes)	0.43		0.37		0.44*		0.45		0.44		0.47	
Household is food insecure (1 = yes)	0.21		0.33		0.18***		0.26		0.27		0.25	
Labor outcomes												
Total labor for maize, wheat and teff per ha (in labor-days)	135.15	53.13	133.44	61.09	135.52	51.25	139.54	59.40	125.62	61.60	150.74***	55.14
Total labor for maize, wheat and teff (in labor-days)	102.28	72.86	73.45	73.85	108.58***	71.14	59.94	47.39	47.05	34.10	70.32***	53.66
Male labor	48.34	40.69	31.65	35.43	51.99***	40.86	30.08	28.46	24.42	23.12	34.64***	31.42
Female labor	22.09	19.80	15.33	14.74	23.57***	20.46	15.17	17.27	10.65	10.51	18.82***	20.50
Child labor	9.50	16.37	7.47	14.88	9.95**	16.65	3.90	7.48	3.18	6.17	4.47**	8.35
Exchange labor	17.98	24.92	16.55	27.66	18.29	24.28	6.75	10.74	5.10	8.39	8.08***	12.16
Children work for maize, wheat and teff (1 = yes)	0.53		0.46		0.55***		0.40		0.38		0.41	
Education outcomes												
Enrollment rate of primary-school-aged children	0.75	0.36	0.70	0.40	0.76**	0.35	0.82	0.29	0.79	0.31	0.84**	0.28
Av. number of missed school days due to agricultural work	3.00	5.52	2.24	3.85	3.14*	5.76	3.09	4.70	3.13	4.99	3.06	4.47
Average education expenditure per capita (in ETB)	683.98	1008.76	577.84	842.20	705.62	1038.55	386.74	720.89	410.28	809.24	369.46	649.09

Explanatory variables												
Gender HH head (1 = male)	0.89		0.81		0.91***		0.86		0.84		0.87	
Age HH head (in years)	47.23	13.73	50.42	14.71	46.53***	13.42	49.96	14.06	50.33	14.54	49.66	13.67
HH head has formal education (1 = yes)	0.42		0.44		0.41		0.37		0.28		0.44***	
No. of HH members	5.24	1.94	4.91	1.93	5.31***	1.94	5.35	1.90	5.24	2.05	5.44	1.77
Share of primary-school-aged children in HH	0.29	0.19	0.27	0.20	0.30*	0.19	0.29	0.19	0.29	0.20	0.28	0.19
Farm size (in ha)	1.54	1.10	1.63	1.31	1.52	1.05	1.08	0.76	1.20	0.84	0.98***	0.68
Share of farm area planted with maize, wheat or teff	0.59	0.27	0.42	0.28	0.62***	0.25	0.48	0.23	0.41	0.23	0.55***	0.22
No. of TLU owned [a]	3.99	3.00	3.63	3.34	4.07**	2.92	2.89	2.23	2.81	2.50	2.96	2.00
HH is food insecure (1 = yes) [a]	0.24		0.31		0.22***		0.32		0.37		0.27***	
Basic asset score (0-4) [a]	1.92	0.83	1.63	0.81	1.98***	0.82	1.79	0.94	1.71	1.00	1.85**	0.88
HH has access to credit (1 = yes) [a]	0.73		0.69		0.73		0.81		0.75		0.86***	
No. of social organizations involved [a]	4.85	1.95	4.08	1.81	5.01***	1.94	4.13	1.62	4.15	1.68	4.12	1.57
Talked to extension agent (1 = yes) [a]	0.72		0.48		0.77***		0.67		0.58		0.75***	
Walking distance to nearest FTC (in min)	30.49	24.14	37.57	33.04	28.95***	21.43	35.47	25.72	36.96	26.19	34.28	25.30
Walking distance to nearest village market (in min)	69.57	43.97	77.28	46.16	67.89***	43.32	75.01	51.85	87.08	56.99	65.29***	45.08
Walking distance to nearest all-season road (in min)	26.39	27.33	25.63	25.32	26.56	27.76	27.32	30.80	28.50	30.13	26.37	31.33
Distance to Woreda capital (in km)	10.46	6.99	9.72	6.83	10.62*	7.02	22.51	22.52	24.48	24.31	20.92**	20.86
HH grows maize (1 = yes)	0.91		0.64		0.97***		0.40		0.31		0.48***	
HH grows wheat (1 = yes)	0.53		0.48		0.54*		0.50		0.27		0.67***	
HH grows teff (1 = yes)	0.72		0.55		0.76***		0.75		0.83		0.68***	
Lives in ISFM+ community (1 = yes)	0.51		0.44		0.52**		0.43		0.32		0.51***	
HH experienced shock in the last season (1 = yes)	0.32		0.35		0.31		0.58		0.55		0.61*	
Average annual rainfall (in mm)	1337.79	326.63	1267.87	312.25	1353.07***	327.85	739.67	278.40	623.63	231.83	833.06***	277.85
Average annual temperature (in °C)	20.46	3.30	19.91	2.71	20.58***	3.41	23.55	1.64	23.18	1.81	23.84***	1.43
Average plot distance from homestead (in min)	9.71	11.74	7.61	14.42	10.17***	11.02	19.11	25.92	20.65	21.14	17.88	29.17
Average fertility of HH plots (0-5)	3.18	0.82	3.08	0.87	3.21**	0.80	3.12	0.97	2.97	1.00	3.24***	0.92
N	1,310		235		1,075		749		334		415	

Note: SD stands for standard deviation. [a] Baseline variables. HH stands for household. Basic asset score comprises the following: HH has modern roof, improved stove, modern lighting, toilet facility. TLU stands for Tropical livestock unit. FTC stands for farmer training center. Exchange rate during survey period: 1 US-$ ~ 27 ETB (Ethiopian Birr). Significance levels for differences in means: *** p<0.01, ** p<0.05, * p<0.1.

4.3 Results

4.3.1 Effects on income and food security

Table 4.2 depicts results of the IPWRA estimations regarding ISFM effects on income and food security, separately for the two agroecological zones.[58] For Amhara and Oromia we find that ISFM adoption on average is related to a statistically significant increase of around 32% (partial or full adoption) to 33% (full adoption) in total household income per capita.[59] This increase is likely to stem from higher per capita income achieved from the production of the three cereal crops, for which the ATET indicate average increases of approximately 38% and 37% due to partial or full, respectively full ISFM adoption. The ATET for income per hectare obtained from these crops is positive and significant as well, suggesting that both adopting partial or full as well as full ISFM indeed increases productivity by around 30%. Further, we cannot find any indication for effects of ISFM on the likelihood to grow other main crops in Amhara and Oromia, or to engage in off-farm income-generating activities. Yet, we find that both partial or full as well as full ISFM adoption are related to a significant reduction in the average probability of households to be food insecure of around 16 percentage points. This result is robust to all alternative specifications of the food security indicator, as shown in Table A 4.2 in Appendix A 4.

In Tigray, by contrast, the ATET for per capita household income have a negative sign, though they are not statistically significant. As in the other two regions, adopting ISFM for one of the three main cereals seems to be associated with a significant increase in income generated from these crops of about 20% to 21% when measured per capita. When measured per hectare, ATET magnitudes indicate similar effects, albeit the p-value of the ATET for full ISFM is slightly above the 10% threshold. Moreover, in Tigray, both ISFM adoption indicators are also related to a significant decrease in the likelihood to achieve income from other main crops by about 10 (partial or full adoption) respectively 13 (full adoption) percentage points. Likewise, adopting full ISFM goes along with a significant decrease in the average probability of households to generate off-farm income by 12 percentage points. As opposed to the other regions, in Tigray we find no indication for a food security enhancing effect of adopting ISFM for maize, wheat or teff. Robustness checks show that this is also true when using alternative specifications of this variable. For the lower cut-offs of the frequency of food deprivation incidences, food

[58] Estimation results of the ISFM adoption models used for the IPW procedure are shown in Appendix Table A 4.1.

[59] Since the ATET estimates represent differences between two logarithmic values, they can be interpreted as approximate relative change between the original values. Due to differences between arithmetic and geometric means, back-conversion of logarithmic outcomes would result in inaccuracies. As a robustness check, we have nevertheless performed this back-conversion, which leads to very similar effect sizes.

insecurity even seems to increase somewhat with the use of ISFM, albeit only significant at the 10% level (Table A 4.2).

Hence, even though ISFM adoption increases income from the three cereal crops in both agroecological zones, it is only related to an improvement in food security in areas where it also goes along with an increase in household income.

Table 4.2. Treatment effects of ISFM adoption on income and food security variables.

	Partial or full ISFM			Full ISFM		
	Predicted outcome under non-adoption	ATET		Predicted outcome under non-adoption	ATET	
			p-value			p-value
Amhara & Oromia						
Log of household income per capita	7.79	0.32	0.000	7.86	0.33	0.000
(in ETB)	(0.10)	(0.09)		(0.10)	(0.09)	
Log of maize, wheat and teff income	7.20	0.38	0.000	7.30	0.37	0.000
per capita (in ETB)	(0.10)	(0.07)		(0.10)	(0.07)	
Log of maize, wheat and teff income	9.25	0.30	0.000	9.31	0.29	0.000
per ha (in ETB)	(0.08)	(0.07)		(0.08)	(0.07)	
Household grows other main crops	0.51	0.04	0.370	0.55	0.00	0.960
(1 = yes)	(0.04)	(0.05)		(0.05)	(0.06)	
Household has off-farm income	0.49	-0.05	0.237	0.49	-0.04	0.305
(1 = yes)	(0.04)	(0.04)		(0.04)	(0.04)	
HH is food insecure (1 = yes)	0.35	-0.16	0.000	0.32	-0.16	0.000
	(0.04)	(0.04)		(0.04)	(0.04)	
Tigray						
Log of household income per capita	7.99	-0.12	0.143	8.00	-0.12	0.237
(in ETB)	(0.09)	(0.08)		(0.11)	(0.10)	
Log of maize, wheat and teff income	6.58	0.21	0.027	6.66	0.20	0.071
per capita (in ETB)	(0.10)	(0.10)		(0.10)	(0.11)	
Log of maize, wheat and teff income	9.17	0.19	0.041	9.28	0.18	0.103
per ha (in ETB)	(0.10)	(0.09)		(0.10)	(0.11)	
Household grows other main crops	0.82	-0.10	0.009	0.82	-0.13	0.003
(1 = yes)	(0.04)	(0.04)		(0.04)	(0.05)	
Household has off-farm income	0.55	-0.08	0.135	0.60	-0.12	0.052
(1 = yes)	(0.06)	(0.06)		(0.06)	(0.06)	
HH is food insecure (1 = yes)	0.22	0.03	0.392	0.20	0.02	0.566
	(0.03)	(0.03)		(0.03)	(0.04)	

Note: Robust standard errors in parentheses, clustered at the microwatershed level.

For our IPWRA results to be valid, we have to ensure that firstly, the overlap assumption is fulfilled. To do so, we only include observations with a probability of receiving the treatment of at least $\hat{p}$ = 0.001 and maximum $\hat{p}$ = 0.999. No observation is identified with a probability below or above these thresholds, suggesting that we have sufficient overlap in our sample. Secondly, the inverse-probability-weighted sample should be balanced between adopters and non-adopters. Therefore, we run overidentification tests testing the null hypothesis that covariates are balanced. For the Amhara and Oromia sample, test statistics are χ^2 (27) = 15.54 with p > χ^2 = 0.96 (partial or full ISFM) and χ^2 (27) = 16.16 with p > χ^2 = 0.95 (full ISFM), suggesting that the weighted samples are well balanced. For Tigray, the same can be said, based on the following test statistics: χ^2 (27) = 21.76 with p > χ^2 = 0.75 (partial or full ISFM) and χ^2 (27) = 23.91 with p > χ^2 = 0.64 (full ISFM). In addition, we calculate the normalized differences after weighting for each explanatory variable. As suggested by Imbens and Wooldridge (2009), these normalized differences should be as small as possible, but not exceed 0.25. We have 26 covariates, two subsamples and two adoption indicators, which results in a total of 104 estimates – out of these, only one estimate exceeds the threshold (Table A 4.3 in Appendix). Finally, PSM estimates are similar to our main IPWRA results, underlining the robustness of the findings (Table A 4.4).

4.3.2 Effects on labor demand

Table 4.3 shows estimation results regarding labor demand. In each of the subsamples, both ISFM adoption indicators are related to a significant increase in total labor demand, both when measured in labor-days per hectare and in absolute labor-days. The disaggregated ATET estimates suggest that in Amhara and Oromia, this additional labor demand is primarily absorbed by adult males and to some extent adult females in the household, increasing their seasonal labor input on average by around 10 to 11 respectively 3 labor-days. By contrast, in Tigray, ISFM adoption appears to increase labor input of adult females and children in the household, on average by 5 respectively 1.5 to 2 labor-days, but not for adult males. To some extent, additional labor also seems to be covered by exchange laborers, though this is not true for the full adoption indicator.

Moreover, in Tigray, partial or full as well as full ISFM adoption for maize, wheat or teff seems to significantly increase the probability of school-aged children to work for the production of these crops by 13 percentage points on average. While we cannot detect such an effect for Amhara and Oromia, the higher predicted outcome under non-adoption in these regions suggests that children are already more involved in the production of the three cereals than they are in Tigray.

The PSM robustness checks shown in Table A 4.5 qualitatively confirm most of the IPWRA results (except for the total labor demand per hectare variable in Tigray, and female labor input in Amhara and Oromia).

Table 4.3. Treatment effects of ISFM adoption on labor variables.

	Full or partial ISFM			Full ISFM		
	Predicted outcome under non-adoption	ATET		Predicted outcome under non-adoption	ATET	
			p-value			p-value
Amhara & Oromia						
Total labor for maize, wheat and teff per ha	126.04	9.48	0.035	124.65	11.47	0.023
(in labor-days)	(4.17)	(4.50)		(4.85)	(5.04)	
Total labor for maize, wheat and teff	96.18	12.40	0.019	96.43	15.03	0.005
(in labor-days)	(5.15)	(5.29)		(5.14)	(5.40)	
Male labor	42.28	9.71	0.002	42.55	11.43	0.001
	(3.24)	(3.20)		(3.26)	(3.29)	
Female labor	20.96	2.60	0.101	21.49	3.22	0.041
	(1.59)	(1.59)		(1.59)	(1.58)	
Child labor	9.41	0.54	0.692	9.51	0.15	0.917
	(1.25)	(1.36)		(1.29)	(1.48)	
Exchange labor	17.51	0.78	0.597	16.75	0.92	0.561
	(1.14)	(1.48)		(1.08)	(1.58)	
Children work for maize, wheat and teff	0.52	0.03	0.404	0.53	0.03	0.464
production (1 = yes)	(0.04)	(0.04)		(0.034)	(0.03)	
Tigray						
Total labor for maize, wheat and teff per ha	138.21	12.53	0.021	140.27	15.70	0.013
(in labor-days)	(7.52)	(5.45)		(8.17)	(6.35)	
Total labor for maize, wheat and teff	60.21	10.11	0.001	61.72	9.06	0.022
(in labor-days)	(3.26)	(3.13)		(4.01)	(3.94)	
Male labor	34.45	0.19	0.927	35.35	-0.89	0.727
	(2.85)	(2.06)		(3.31)	(2.54)	
Female labor	13.47	5.35	0.000	13.61	5.47	0.000
	(1.12)	(1.41)		(1.27)	(1.55)	
Child labor	3.00	1.47	0.018	2.69	2.20	0.002
	(0.63)	(0.62)		(0.69)	(0.70)	
Exchange labor	5.87	2.21	0.012	6.05	1.00	0.375
	(0.63)	(0.88)		(0.76)	(1.12)	
Children work for maize, wheat and teff	0.28	0.13	0.006	0.26	0.13	0.005
production (1 = yes)	(0.04)	(0.05)		(0.04)	(0.05)	

Note: Robust standard errors in parentheses, clustered at the microwatershed level.

4.3.3 Effects on children's education

In Table 4.4 we present the results regarding our measures of children's education.[60] IPWRA estimates for Amhara and Oromia suggest a positive effect of adopting partial or full as well as full ISFM on enrollment of primary-school-aged children, increasing their average likelihood

[60] We also run overidentification tests for the reduced samples of households with primary-school-aged children. For Amhara and Oromia, test statistics are $\chi2$ (27) = 17.39 with p > $\chi2$ = 0.92 (partial or full ISFM), and $\chi2$ (27) = 15.75 with p > $\chi2$ = 0.96 (full ISFM). For Tigray, test statistics are $\chi2$ (27) = 22.07 with p > $\chi2$ = 0.73 (partial or full ISFM), and $\chi2$ (27) = 20.62 with p > $\chi2$ = 0.80 (full ISFM). Thus, the null hypothesis that covariates are balanced between treatment groups in the weighted subsamples cannot be rejected.

to be enrolled by 15 and 18 percentage points. In Tigray, by contrast, we find no evidence for a significant effect of ISFM adoption on school enrollment; however, the predicted enrollment rate under non-adoption in this subsample is higher than in Amhara and Oromia. Regarding the average number of missed school days, IPWRA results do not indicate any significant effect of ISFM adoption. For both indicators, enrollment rate and missed school days, we repeat the analyses defining school age more narrowly, as between 7 and 14 years. Results are robust to these alternative specifications (available upon request). Lastly, in none of the two subsamples we find evidence for significant effects on average educational expenditure per capita.

Table 4.4. Treatment effects of ISFM adoption on education variables.

	Full or partial ISFM			Full ISFM		
	Predicted outcome under non-adoption	ATET		Predicted outcome under non-adoption	ATET	
			p-value			p-value
Amhara & Oromia						
Enrollment rate of primary-school-aged children	0.62 (0.06)	0.15 (0.06)	0.010	0.60 (0.06)	0.18 (0.09)	0.002
Average number of missed school days due to agricultural work	2.41 (0.51)	0.73 (0.56)	0.193	2.56 (0.51)	0.76 (0.59)	0.197
Log of average education expenditure per capita (in ETB)	5.64 (0.21)	0.07 (0.22)	0.755	5.75 (0.20)	0.03 (0.22)	0.885
Tigray						
Enrollment rate of primary-school-aged children	0.81 (0.05)	0.03 (0.04)	0.456	0.82 (0.06)	0.05 (0.05)	0.351
Average number of missed school days due to agricultural work	2.97 (0.68)	0.09 (0.71)	0.904	2.91 (0.66)	-0.03 (0.70)	0.967
Log of average education expenditure per capita (in ETB)	5.18 (0.17)	-0.12 (0.18)	0.510	5.27 (0.18)	-0.15 (0.20)	0.448

Note: Robust standard errors in parentheses, clustered at the microwatershed level.

Hence, IPWRA results suggest some positive effects of adopting ISFM on school enrollment in Amhara and Oromia, possibly a consequence of higher household income in these regions. PSM estimates in Table A 4.6 confirm the robustness of this finding for full ISFM adoption, albeit for the partial or full adoption indicator, the ATET is not statistically significant.

4.4 Discussion and conclusion

Agricultural system technologies such as ISFM can play an important role for the sustainable intensification of smallholder farming by making use of synergistic effects of various agricultural practices. Yet, evidence to date is mostly limited to conventional economic outcomes such as crop productivity or at best, income. By contrast, broader welfare implications for households are still understudied. This seems particularly important since many productivity-enhancing practices require higher labor and monetary investments, so that net impacts at the household level are less clear due to a potential reallocation of productive resources. For instance, effects on education as one indicator of longer-term welfare, can be ambiguous. On the one hand, increased labor demand raises the concern that children's work burden increases, with possible negative consequences for their educational attainment. On the other hand, positive income effects may also lead to higher investments in children's education. Similarly, food security is likely positively affected by higher crop productivity, while at the same time, this effect might be muted if technology adoption goes along with withdrawing labor from other productive activities.

With this study we extend the literature on the effects of technology packages by assessing the impact of ISFM on crop income, household income, food security and labor demand. In addition, we analyze ISFM effects on various measures of children's education as indicators for longer-term wellbeing, which is hardly done in the literature. We use data from Ethiopian farmers that cultivate teff, wheat or maize – three major staples in the study area – and distinguish between moist and dry areas to account for agroecological heterogeneity. We also assess whether ISFM use for these crops has implications for the likelihood to achieve income from other main crops or off-farm activities. We use the doubly-robust IPWRA method to control for selection bias, with PSM as robustness check. Further, we distinguish between households that adopt the full ISFM package – that is, improved seeds with inorganic *and* organic fertilizer – and households that adopt at least partial ISFM – that is, improved seeds with minimum one of the two fertilizer types – on at least one plot.

We find that ISFM adoption for at least one of the three crops significantly increases income achieved from these crops in the two agroecological zones, both if the full or at least the partial ISFM package is applied. Effect sizes of the two adoption indicators are very similar, suggesting that using an additional fertilizer type on a plot does not necessarily lead to higher crop income on average. However, only in Amhara and Oromia (moist agroecology) higher crop income seems to translate into significantly higher household income. In Tigray (dry agroecology), by contrast, we find no significant effect on household income, due to several possible reasons. Firstly, with and without ISFM, the income obtained from the three cereal crops on average makes up a smaller share of total household income in Tigray (61% vs. 29%), partly probably because farmers dedicate a lower share of their farm area to these crops (59% vs. 48%). Secondly, crop income gains associated with ISFM adoption are lower in Tigray than in Amhara and Oromia; either because farmers apply the technology on a smaller area of land, or because on average, ISFM has lower effects on crop productivity in the dry compared to the moister regions, as suggested by previous results in the study region (Hörner & Wollni, 2020). Thirdly, for Tigray we also find a significant negative effect of adopting partial or full as well as full ISFM for maize, wheat or teff on the probability to grow other staple crops, i.e. crops that contribute substantially to household income or consumption. In addition, adopting the full ISFM package is related to a significant reduction in the likelihood to engage in off-farm activities in Tigray. Hence, it may be that ISFM adoption for some crops absorbs (labor) resources that could otherwise be used for the production of different commodities or for generating off-farm income and thus, does not lead to gains in total household income. This is in line with findings by Takahashi and Barrett (2014), who draw similar conclusions for the system of rice intensification. In Amhara and Oromia, neither the negative effect on other main staple crops nor on off-farm activities is observed, suggesting that in this subsample no resource diversion effects are present.

We also find that partial or full as well as full ISFM adoption reduce households' probability to be food insecure in Amhara and Oromia, but not in Tigray, even though ISFM increases income obtained from the three staple crops in both subsamples. Hence, improvements in food security only occur in those areas where we do not observe negative effects on other crop or off-farm income, but gains in overall household income. This points towards the importance of not only considering farm production of staple crops, but all household income sources in order to derive more comprehensive conclusions regarding the relationship between technology adoption and food security.

Results further show that ISFM adoption is associated with increased demand for household labor, both in absolute terms and when measured per hectare. This holds true for both adoption variables, though effects sizes are somewhat larger for full ISFM adoption. Households in Amhara and Oromia seem to largely cover this additional demand with labor input from adult males and to some extent adult females, while in Tigray, most of the additional labor is borne by females and children in the household and partly exchange laborers from outside the household. One explanation might be that households in Tigray are generally more likely to grow main crops other than maize, wheat and teff, for which male adults possibly dedicate more of their time.

Ultimately, we find some evidence for positive impacts of ISFM adoption on child schooling. For Amhara and Oromia, IPWRA estimates suggest a positive effect of ISFM on school enrollment for children in primary school age, both if we consider partial or full and full ISFM adoption; PSM robustness checks support this finding for the full ISFM indicator. This result might be interpreted as a form of enhanced investment in children's education due to income gains associated with ISFM. By contrast, in Tigray, where we observe no increase in household income related to ISFM, there is no indication for child schooling impacts. Moreover, in none of the two subsamples, we find evidence for effects on per capita educational expenditure. On the positive side, we find no indication that ISFM adoption induces school absenteeism or even drop-outs among children, despite the finding that their involvement in agricultural production of major cereal crops increases with ISFM in Tigray. Recent evidence from a long-term study in rural Ethiopia shows that moderate involvement of children in household economic activities is not harmful if combined with school attendance, and can even have positive effects on long-term educational attainment, probably due to cross-fertilizing between skills obtained by working with schooling (Mussa et al., 2019). However, it is important to emphasize that we cannot make any statement on the overall work burden for children, as we only assess labor input for maize, wheat and teff production. In general, many children in our study area participate to some extent in cereal crop production. Yet, they are oftentimes also considerably involved in other (economic) activities of the household, such as livestock keeping (especially boys), household chores (especially girls) or resource collection (e.g. fetching water or collecting firewood) (ILO & CSA, 2018). Hence, we do not know whether increased labor demand for major cereal crops, which is not or only partly borne by children directly, may affect their overall work load due to reallocation effects of adult labor, possibly at the expense of children's leisure time. Unfortunately, such analysis is not possible with our data.

All in all, our results suggest that broader welfare effects of agricultural innovations have to be evaluated within the complex system of income diversification strategies of households. While we find robust evidence that adopting ISFM practices for certain crops on average goes along with income gains achieved from these crops, it is context-specific whether these effects translate into higher household income, food security or school attendance. This seems to depend on the contribution different crop types make to farmers' overall income; and whether higher resource needs associated with an innovation for some crops crowd out other crops or economic activities. In this regard, our findings fit well into a strand of literature drawing similar conclusions (Adolwa et al., 2019; Noltze et al., 2013; Takahashi & Barrett, 2014). However, unlike other innovations such as the system of rice intensification, ISFM is not tied to just the three crop types studied here. On the contrary, using improved seeds and a well-adapted fertilization strategy is generally recommended and has proven positive yield effects for a large variety of crops, including barley, sorghum and legumes (Agegnehu et al., 2016; Bationo et al., 2008, 2012), which present other staple products grown in our study area and beyond. While to date, the use of improved varieties and fertilizers is relatively low for these crops, it will be important to look into household welfare impacts once adoption levels have increased for other crops as well.

Several policy implications emerge from our findings. Firstly, it is key for agricultural policies to consider the full range of heterogeneous farm types, agroecological conditions and resource levels. As the adoption of technologies can provide different welfare returns for different types of smallholders, it seems paramount to adjust principles to local needs and conditions. This supports the rationale of large nationwide, but decentralized programs of agricultural extension, which involve farmers as active stakeholders to facilitate bi-directional learning between research and farmers (Hörner et al., 2019; Jayne et al., 2019). Secondly, much remains to be done to improve rural infrastructure and institutions. In particular, instable supply and restricted access to capital and input markets prevent many smallholders from purchasing seeds or fertilizer (Jayne et al., 2019; Suri, 2011). For example, Sheahan and Barrett (2017) show for several SSA countries that maximum 5% of farmers use credit to purchase improved seeds and fertilizer. Minten et al. (2013) find that underdeveloped rural road networks in remote areas of Ethiopia can make the transaction costs of acquiring fertilizer prohibitively high, in particular when traded quantities per farmer are small. Improving rural feeder roads might lower transportation costs, while expanding distribution services to remote areas can help to reap economies of scale. Moreover, creating and strengthening local seed distribution networks for a larger variety of crop types should be encouraged. And thirdly, policies should focus on developing suitable sharing and rental arrangements for labor-saving mechanization equipment, in order to enhance the use of ISFM technologies without diverting family labor from other activities.

Ultimately, we hardly find differential effects between a rather lax definition of ISFM that also comprises partial adoption – improved seeds with at least either organic *or* inorganic fertilizer –, and a stricter definition – improved seeds with organic *and* inorganic fertilizer – which constitutes the actual core concept of ISFM. One reason for that can be the additional costs associated with applying two compared to only one fertilizer type. Thus, even if productivity gains of the complete compared to the partial ISFM package are larger, this may not be mirrored in net crop income due to higher input costs. Further, there is evidence that the synergistic effects of the joint use of organic and inorganic fertilizers do not immediately materialize to the full extent, in particular when the soil is heavily degraded, so that soil organic matter and nutrient levels need to be replenished over time (Marenya & Barrett, 2009). This result is in line with Adolwa et al. (2019), who find that partial or complete adoption of ISFM improves maize yields, but increasing the number of adopted components does not. Moreover, ISFM is a knowledge-intensive technology in terms of input quantities, dosage or timing, and also depends on the quality of materials (Jayne et al., 2019; Vanlauwe et al., 2015), which might be particularly variable for self-produced organic fertilizers. Consequently, productivity and related income effects of the full ISFM package may be more pronounced after some time – with growing experience on the farmers' side, and higher soil organic matter levels and nutrient stocks on the soil's side. In this respect, it seems interesting to revisit longer-term welfare effects in other domains – be it in consumption, education, nutrition or health – once the technology is more mature and income gains more stable.

Appendix A 4

Table A 4.1. Logit estimation results of ISFM adoption, used for calculation of IPW.

	Amhara & Oromia (wet/moist regions)		Tigray (dry region)	
	Adopted partial or full ISFM	Adopted full ISFM	Adopted partial or full ISFM	Adopted full ISFM
Gender HH head (1 = male)	0.305	0.301	-0.051	0.101
	(0.291)	(0.292)	(0.336)	(0.444)
Age HH head (in years)	-0.017**	-0.015**	0.010	0.008
	(0.007)	(0.007)	(0.009)	(0.010)
HH head has formal education (1 = yes)	-0.661***	-0.543**	0.708***	0.833***
	(0.246)	(0.255)	(0.221)	(0.259)
No. of HH members	-0.002	-0.027	0.120	0.105
	(0.055)	(0.065)	(0.075)	(0.093)
Share of primary-school-aged children in HH	0.403	0.626	-0.099	-0.464
	(0.591)	(0.671)	(0.555)	(0.684)
Farm size (in ha)	0.055	0.003	-0.181	-0.085
	(0.169)	(0.174)	(0.263)	(0.312)
Share of farm area planted with maize, wheat or teff	1.614***	1.522**	1.351**	2.139***
	(0.540)	(0.599)	(0.597)	(0.772)
No. of TLU owned [a]	-0.003	0.009	0.046	0.070
	(0.044)	(0.054)	(0.056)	(0.065)
HH is food insecure (1 = yes) [a]	-0.265	-0.378	-0.283	-0.344
	(0.211)	(0.234)	(0.210)	(0.276)
Basic asset score (0-4) [a]	0.493***	0.352*	0.066	0.153
	(0.152)	(0.181)	(0.119)	(0.126)
HH has access to credit (1 = yes) [a]	-0.005	0.076	0.290	0.260
	(0.217)	(0.231)	(0.256)	(0.304)
No. of social organizations involved [a]	0.202***	0.253***	0.067	0.048
	(0.054)	(0.068)	(0.057)	(0.074)
Talked to extension agent (1 = yes) [a]	1.102***	1.303***	0.605**	0.915***
	(0.205)	(0.220)	(0.301)	(0.280)
Log of walking distance to nearest FTC (in min)	-0.160	-0.072	-0.240*	-0.482***
	(0.173)	(0.173)	(0.140)	(0.161)
Log of walking distance to nearest village market (in min)	-0.201	-0.236	-0.130	0.021
	(0.171)	(0.171)	(0.151)	(0.195)
Log of walking distance to nearest road (in min)	0.079	0.023	-0.051	-0.054
	(0.094)	(0.108)	(0.112)	(0.112)
Log of distance to Woreda capital (in km)	0.247	0.208	0.267*	0.086
	(0.192)	(0.202)	(0.156)	(0.161)
HH grows maize (1 = yes)	3.241***	3.912***	1.168***	0.880***
	(0.291)	(0.360)	(0.266)	(0.321)
HH grows wheat (1 = yes)	0.125	0.172	2.851***	2.897***
	(0.217)	(0.236)	(0.448)	(0.478)
HH grows teff (1 = yes)	-0.047	0.148	-0.013	-0.256
	(0.286)	(0.315)	(0.389)	(0.435)
HH experienced shock in the last season (1 = yes)	0.209	0.268	0.259	0.061
	(0.201)	(0.230)	(0.283)	(0.285)
Log of average annual rainfall (in mm)	1.747**	1.285*	3.346***	3.432***

	(0.743)	(0.704)	(0.592)	(0.605)
Log of average annual temperature (in °C)	1.629*	0.972	-11.481***	-10.175***
	(0.932)	(0.955)	(2.227)	(3.008)
Log of average plot distance from homestead (in min)	0.304***	0.263**	0.010	-0.092
	(0.098)	(0.103)	(0.092)	(0.107)
Average fertility of HH plots (0-5)	0.114	0.267*	0.296***	0.368***
	(0.117)	(0.139)	(0.114)	(0.122)
Lives in ISFM+ community (1 = yes)	0.308	0.406	0.381	0.515*
	(0.284)	(0.305)	(0.300)	(0.294)
Constant	-21.592***	-18.148***	9.079	4.164
	(6.345)	(6.122)	(5.958)	(9.044)
Observations	1,300	935	738	575

Note: [a] Baseline variables. HH stands for household. Basic asset score comprises the following: HH has modern roof, improved stove, modern lighting, toilet facility. TLU stands for Tropical livestock unit. FTC stands for farmer training center. Robust standard errors in parentheses, clustered at the microwatershed level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table A 4.2. Treatment effects on alternative specifications of food security indicator.

	Partial or full ISFM			Full ISFM		
	Predicted outcome under non-adoption	ATET		Predicted outcome under non-adoption	ATET	
			p-value			p-value
Amhara & Oromia						
HH is food insecure (1 = yes),	0.35	-0.15	0.000	0.32	-0.15	0.000
cut-off 30, plus severest form[a]	(0.04)	(0.04)		(0.04)	(0.04)	
HH is food insecure (1 = yes),	0.35	-0.14	0.000	0.33	-0.15	0.000
cut-off 25	(0.04)	(0.04)		(0.04)	(0.04)	
HH is food insecure (1 = yes),	0.35	-0.11	0.005	0.32	-0.11	0.007
cut-off 20	(0.04)	(0.04)		(0.04)	(0.04)	
HH is food insecure (1 = yes),	0.39	-0.12	0.003	0.36	-0.11	0.010
cut-off 15	(0.04)	(0.04)		(0.04)	(0.04)	
HH is food insecure (1 = yes),	0.40	-0.10	0.016	0.37	-0.09	0.033
cut-off 10	(0.04)	(0.04)		(0.04)	(0.04)	
Tigray						
HH is food insecure (1 = yes),	0.22	0.03	0.392	0.20	0.02	0.566
cut-off 30, plus severest form[a]	(0.03)	(0.03)		(0.03)	(0.04)	
HH is food insecure (1 = yes),	0.23	0.03	0.379	0.22	0.01	0.697
cut-off 25	(0.03)	(0.03)		(0.04)	(0.04)	
HH is food insecure (1 = yes),	0.22	0.07	0.074	0.20	0.06	0.158
cut-off 20	(0.04)	(0.04)		(0.04)	(0.04)	
HH is food insecure (1 = yes),	0.23	0.08	0.060	0.21	0.09	0.061
cut-off 15	(0.04)	(0.04)		(0.04)	(0.05)	
HH is food insecure (1 = yes),	0.28	0.08	0.053	0.25	0.09	0.051
cut-off 10	(0.04)	(0.04)		(0.04)	(0.05)	

Note: Cut-offs refer to sum of frequencies of food deprivation incidences a household experienced within the 30 days before harvest, in order to be classified as food insecure. [a] In this indicator, households that have experienced the severest form of food deprivation (going a whole day and night without food) are automatically classified as food insecure, independent of the frequency of occurrence. Robust standard errors in parentheses, clustered at the micro-watershed level.

Table A 4.3. Normalized differences of covariates between treatment and control groups after IPW.

	Amhara & Oromia (wet/moist regions)		Tigray (dry region)	
	Partial or full ISFM	Full ISM	Partial or full ISFM	Full ISM
Gender HH head (1 = male)	0.17	0.08	0.04	0.02
Age HH head (in years)	-0.20	0.22	-0.15	-0.18
HH head has formal education (1 = yes)	-0.02	0.01	-0.13	-0.21
No. of HH members	0.21	0.15	-0.01	0.05
Share of primary-school-aged children in HH	0.00	0.02	0.03	0.03
Farm size (in ha)	-0.02	0.05	0.05	0.09
Share of farm area planted with maize, wheat or teff	0.15	0.09	0.00	-0.05
No. of TLU owned[a]	0.02	0.03	-0.07	-0.15
HH is food insecure (1 = yes) [a]	0.09	0.11	-0.03	-0.10
Basic asset score (0-4) [a]	-0.20	0.22	-0.12	-0.21
HH has access to credit (1 = yes) [a]	-0.04	0.05	-0.01	-0.09
No. of social organizations involved[a]	-0.03	0.11	0.04	-0.04
Talked to extension agent (1 = yes) [a]	-0.06	0.05	0.00	-0.03
Walking distance to nearest FTC (in min)	-0.17	0.16	0.00	-0.08
Walking distance to nearest village market (in min)	0.14	0.16	0.13	0.13
Walking distance to nearest all-season road (in min)	0.16	0.23	-0.04	-0.08
Distance to Woreda capital (in km)	0.07	0.14	-0.14	-0.09
HH grows maize (1 = yes)	0.03	0.01	-0.14	-0.15
HH grows wheat (1 = yes)	-0.07	0.04	0.00	-0.04
HH grows teff (1 = yes)	0.02	0.04	-0.05	-0.04
Lives in ISFM+ community (1 = yes)	-0.16	0.18	0.02	0.02
HH experienced shock in the last season (1 = yes)	0.18	0.20	-0.01	0.08
Average annual rainfall (in mm)	-0.22	0.21	-0.05	-0.04
Average annual temperature (in °C)	0.24	**0.30**	-0.14	-0.17
Average plot distance from homestead (in min)	0.18	0.18	0.07	0.06
Average fertility of HH plots (0-5)	-0.10	0.17	0.02	0.04

Note: [a] Baseline variables. HH stands for household. Basic asset score comprises the following: HH has modern roof, improved stove, modern lighting, toilet facility. TLU stands for Tropical livestock unit. FTC stands for farmer training center.

Table A 4.4. Treatment effects of ISFM adoption on income and food security variables using PSM.

	Partial or full ISFM		Full ISFM	
	ATET		ATET	
		p-value		p-value
Amhara & Oromia				
Log of household income per capita (in ETB)	0.26 (0.11)	0.019	0.32 (0.10)	0.001
Log of maize, wheat and teff income per capita (in ETB)	0.41 (0.11)	0.000	0.48 (0.09)	0.000
Log of maize, wheat and teff income per ha (in ETB)	0.37 (0.09)	0.000	0.35 (0.06)	0.000
Household grows other main crops (1 = yes)	0.04 (0.08)	0.622	0.01 (0.06)	0.873
Household has off-farm income (1 = yes)	0.06 (0.08)	0.459	0.00 (0.09)	0.979
HH is food insecure (1 = yes)	-0.12 (0.07)	0.104	-0.18 (0.04)	0.000
Tigray				
Log of household income per capita (in ETB)	-0.08 (0.08)	0.272	-0.14 (0.12)	0.264
Log of maize, wheat and teff income per capita (in ETB)	0.20 (0.07)	0.003	0.28 (0.09)	0.002
Log of maize, wheat and teff income per ha (in ETB)	0.14 (0.06)	0.013	0.23 (0.08)	0.004
Household grows other main crops (1 = yes)	-0.11 (0.04)	0.002	-0.11 (0.05)	0.044
Household has off-farm income (1 = yes)	-0.08 (0.06)	0.198	-0.13 (0.05)	0.014
HH is food insecure (1 = yes)	0.00 (0.05)	0.938	-0.06 (0.07)	0.436

Note: Robust Abadie-Imbens standard errors in parentheses, clustered at the microwatershed level.

Table A 4.5. Treatment effects of ISFM adoption on labor variables using PSM.

	Partial or full ISFM		Full ISFM	
	ATET		ATET	
		p-value		p-value
Amhara & Oromia				
Total labor for maize, wheat and teff per ha (in labor-days)	9.07 (3.59)	0.011	5.16 (1.23)	0.000
Total labor for maize, wheat and teff (in labor-days)	15.93 (6.77)	0.019	22.75 (6.33)	0.000
Male labor	14.20 (3.48)	0.000	18.47 (3.09)	0.000
Female labor	1.48 (2.40)	0.537	3.31 (2.61)	0.204
Child labor	1.40 (1.82)	0.441	0.87 (2.22)	0.695
Exchange labor	-0.19 (1.37)	0.893	0.51 (1.49)	0.730
Children work for maize, wheat and teff production (1 = yes)	0.04 (0.02)	0.078	-0.01 (0.07)	0.919
Tigray				
Total labor for maize, wheat and teff per ha (in labor-days)	2.04 (6.74)	0.761	7.85 (6.86)	0.252
Total labor for maize, wheat and teff (in labor-days)	9.72 (2.43)	0.000	11.97 (6.38)	0.061
Male labor	-0.24 (2.62)	0.927	-1.20 (5.41)	0.824
Female labor	4.13 (1.31)	0.002	6.41 (0.84)	0.000
Child labor	1.61 (0.35)	0.000	2.28 (0.73)	0.002
Exchange labor	2.54 (0.60)	0.000	1.46 (0.81)	0.072
Children work for maize, wheat and teff production (1 = yes)	0.13 (0.03)	0.000	0.11 (0.03)	0.001

Note: Robust Abadie-Imbens standard errors in parentheses, clustered at the microwatershed level.

Table A 4.6. Treatment effects of ISFM adoption on education variables using PSM.

	Partial or full ISFM		Full ISFM	
	ATET		ATET	
		p-value		p-value
Amhara & Oromia				
Enrollment rate of primary-school-aged children	0.12 (0.10)	0.193	0.15 (0.03)	0.000
Average number of missed school days due to agricultural work	-0.25 (0.49)	0.616	-0.02 (0.61)	0.977
Log of average education expenditure per capita (in ETB)	0.08 (0.26)	0.757	0.11 (0.24)	0.652
Tigray				
Enrollment rate of primary-school-aged children	0.04 (0.04)	0.317	0.02 (0.07)	0.791
Average number of missed school days due to agricultural work	-0.04 (0.41)	0.915	-0.28 (0.58)	0.623
Log of average education expenditure per capita (in ETB)	0.01 (0.18)	0.934	0.12 (0.15)	0.403

Note: Robust Abadie-Imbens standard errors in parentheses, clustered at the microwatershed level.

5. General Conclusion

Growing global demand for food and farm products and high levels of environmental degradation call for strategies to sustainably intensify agricultural production; this means, increasing the agricultural production on the same land area while reducing its adverse effects on the environment. Hence, instead of further expanding the agricultural frontier, yields on underperforming lands need to be boosted. Agricultural productivity is particularly low in SSA, to a large extent due to long-term nutrient mining, land degradation, lagged adoption of agricultural innovations and low input use intensities. At the same time, SSA has the worldwide highest rates of undernutrition and rural poverty, while large parts of the population depend on small-scale agriculture for their livelihoods. Even more in the light of on-going population growth and the adverse impacts of climate change, it is of great importance to replenish soil nutrients and restore degraded lands, in order to sustainably raise agricultural yields.

As one means towards sustainable intensification, governments in SSA increasingly encourage the use of ISFM. ISFM is a technology package consisting of improved seeds, organic and inorganic fertilizers, which needs to be adapted and further complemented according to local needs. Practices are thought to bear important synergies that help to raise yields and restore soil health, and hence, may improve livelihoods while helping to preserve natural resources and ecosystem services. Yet, ISFM is generally considered knowledge-, resource- and management-intensive, which prevents many farmers from adopting it.

In order to induce technology adoption, effective knowledge creation and dissemination systems are crucial, of which agricultural extension presents a main pillar. Nowadays, extension in many SSA countries follows a more participatory approach, with a strong focus on peer-to-peer learning induced through model farmers and farmer extension groups. Yet, little is known on how effectively farmer-to-farmer extension encourages adoption among extension group members as well as their neighbors when it comes to system technologies, i.e. sets of practices that should be applied jointly. Moreover, since incomplete information transmission is more likely in the case of more complex (system) technologies, it is important to study whether information failures can be counterbalanced by providing additional information via other extension tools.

Ultimately, the profitability and benefits of a technology are crucial for farmers' decision to adopt. Since ISFM typically involves more capital and labor input, comprehensive evidence is needed on whether these additional investments pay off for farmers. In spite of the high policy relevance, micro-level evidence on ISFM beyond yield and income effects is scarce to date.

Against this background, the dissertation addresses two main research objectives: Firstly, to assess the role of farmer-to-farmer and non-traditional forms of extension to enhance knowledge and adoption of ISFM. And secondly, to assess the productivity and welfare implications of adopting ISFM practices at the plot and household level.

5.1 Main findings

The first essay shows that farmer-to-farmer extension leads to increased adoption of ISFM, both of its individual components and the full package, i.e. the integrated adoption of all practices on the same plot. Effects are particularly strong for farmers who are involved in group-based extension activities, but exist to a weaker extent also for farmers in treatment communities who are not involved in extension groups. This suggests the presence of information spillovers from extension group members to non-members. Yet, regarding the integrated adoption of the full ISFM package, the extension treatment alone seems to hardly be effective for not involved farmers. Complementing farmer-to-farmer extension with a video intervention explaining why the ISFM package is important does not have a significant additional effect *on average*. However, for farmers in treatment mws who are not members of an extension group we do find an additional positive effect of the video. Further, while both farmer-to-farmer extension alone and in combination with the video induce gains in ISFM knowledge, effects are significantly stronger for the combined treatment, in particular when it comes to understanding *why* ISFM is important. A causal mediation analysis reveals that treatment effects on adoption can partly be explained by gains in knowledge; both by knowledge of the underlying principles of ISFM, and of how the practices should be implemented.

All in all, these results suggest that farmer-based extension can indeed disseminate technologies, among both extension group members and non-members in the same communities. Yet, farmers who only learn via spillovers appear more likely to pick up less or incomplete information, and are less likely to adopt the complete technology package on a plot. For this group of farmers, an additional information intervention seems particularly beneficial to increase knowledge, and ultimately foster the adoption of complex system technologies such as ISFM.

The second essay shows that partial as well as complete ISFM adoption on average increase land productivity and net crop value of the three cereals maize, wheat and teff at the plot level. The gains are particularly high when improved seeds are used. The largest average effect on land productivity stems from adopting the full package, i.e. improved seeds with organic *and* inorganic fertilizer, followed by the combinations comprising only one fertilizer type.

Regarding agroecological heterogeneity, findings underline the importance of complementing improved seeds with inorganic fertilizer to raise land productivity in moister regions, whereas in drier regions, organic fertilizer is crucial, most likely due to its water-conserving effect. Concerning net crop value, average effects of combining improved seeds with either one of the two or both fertilizer types are similar, despite the larger effect of the complete package on land productivity; probably due to reduced input costs when only one of the two fertilizers is used. Results further show that ISFM adoption goes along with increased labor demand, but also with higher labor productivity and higher financial returns to (unpaid) labor input. Hence, it seems that both increased input costs and labor demand are outweighed by enhanced crop yields, suggesting that ISFM is a profitable technology at the plot level.

The third essay complements the first two by analyzing ISFM effects at the household level. In accordance with findings from the second essay, results show that ISFM adoption for maize, wheat or teff is associated with increased income per capita obtained from these crops in both the moist and the dry agroecological zone. We hardly find differential effects between a rather lax definition of ISFM – having used improved seeds in combination with at least one fertilizer type – and a stricter definition that necessarily comprises both organic and inorganic fertilizer. This might be due to the additional costs associated with using two instead of only one fertilizer type; or because the full synergistic potential of their joint use does not materialize immediately, yet only after some seasons. However, we find that household income per capita only goes up in the moister regions. In the dry region, by contrast, ISFM adoption for the three cereals is related to a significantly lower probability of achieving income from other crops as well as off-farm activities; probably an effect of resource reallocation, in particular labor. Further, ISFM adoption is related to a significant decrease in the likelihood to be food insecure in the moist agroecology, but not in the dry region. In both subsamples, ISFM adoption requires more household labor, which is primarily covered by adult male and female labor in the moister regions, but by adult female and child labor in the dry region. Yet, despite this effect on children's workload, there is no evidence for increased school absenteeism or even reduced enrollment rates. On the contrary, in the moist agroecological zone, ISFM adoption is related to higher enrollment rates of children in primary school age.

Hence, for areas where ISFM adoption goes along with increased household income, we also find positive effects on other welfare indicators such as food security and education. Overall, these results imply that broader welfare impacts of agricultural innovations decisively depend on households' income diversification strategies.

5.2 Discussion

In line with the overall research objectives, two main conclusions can be drawn from the results of this thesis. Firstly, our findings confirm that farmer-to-farmer and other, not traditional forms of agricultural education have the potential to increase knowledge and catalyze adoption of system technologies such as ISFM, even among farmers who are not members of extension groups. This partly contradicts research, for instance by Kondylis et al. (2017), finding that training lead farmers does not increase adoption among other farmers in their communities. Taking into account results from other studies which conclude that model farmers may be more important to increase awareness rather than broad-scale adoption (Fisher et al., 2018), and that farmers need to learn from multiple sources (Beaman et al., 2018), our set-up – the combination of model farmers and extension groups – might be a promising way forward: while progressive model farmers may be important as entry points for new information, participatory extension groups, composed of farmers who are potentially more similar to 'ordinary' farmers, might be crucial to spread information more broadly. Yet, more studies in different settings are needed regarding this hypothesis. In any case, the emerging literature on network-targeting suggests that it is crucial to identify the 'right' communicators (Beaman et al., 2018), and to provide them the right incentives to disseminate information (BenYishay and Mobarak, 2019; Shikuku et al., 2019), which certainly provides much scope for future research.

Yet, in line with previous studies (Niu & Ragasa, 2018), our findings suggest that knowledge is not transmitted perfectly through farmer-to farmer extension, probably since both communicators and recipients fail to focus on all relevant pieces of information. Additional interventions, which convey all important dimensions of information regarding a technology package in a farmer-friendly way, can help to counterbalance information failures and foster more widespread adoption. Our study suggests that video can be an effective tool to complement other extension activities. High compliance rates, feedback from farmers and results from other studies (Bernard et al., 2014; Van Campenhout et al., 2017; Van Mele, 2006; Vasilaky et al., 2018; Zossou et al., 2010) support that farmers respond positively to this form of audiovisual information provision and value its entertaining character. Against this background, an initiative started in 2014 by the Ethiopian government and the NGO Digital Green to extend the use of video for agricultural extension seems well targeted. First analyses of the project show that the approach is useful to complement decentralized extension in a cost-effective way, and increases adoption of agricultural technologies. Findings indicate that video extension helps to reach out to a broader population of smallholders, in particular female farmers, who have otherwise limited access to agricultural information (Bernard et al., 2016). All in all, a creative and innovative mix of participatory, low-cost and easy-to-implement extension interventions seems necessary to reach different kinds of farmers.

The second broad conclusion of this thesis is that ISFM can indeed enhance agricultural productivity and income of major cereals, and welfare among smallholder farmers, though agroecological heterogeneity needs to be addressed properly. Albeit household-level effects are context-dependent, at the plot level ISFM appears to be a profitable technology, as additional demand for capital and labor seems to be outweighed by higher productivity. While our evidence is restricted to teff, maize and wheat, the latter two present main staples across many countries within and outside of SSA, and hence, boosting their productivity can have important implications for food security. Whether farmers face economic incentives to adoption at the household level depends on the composition of their economic activities, mainly their crop choices and off-farm income sources. It is worth mentioning again that to date, the use of improved seeds and fertilizers in our setting is mostly restricted to the three main cereals, and still largely concentrated on maize in SSA as a whole (Sheahan & Barrett, 2017), while ISFM as a management concept is recommended for a large variety of crop types. Hence, extending its use to other cereals, legumes or vegetable crops may increase household income for different types of farm households in different settings.

5.3 Broader policy implications

All of this taken together, enhancing knowledge and awareness for the benefits of ISFM via extension appears essential, but relaxing information constraints is unlikely to suffice. Some countries have tried input subsidy programs to catalyze modern input use, albeit their viability in the long run is still subject to debate. While studies have shown success in stimulating input use and raising production levels, others conclude that their overall impact is smaller than expected, because programs are badly targeted, crowd out private sector initiatives or farmers fail to graduate out of subsidies (Jayne et al., 2018).

In any case, policies need to address a number of important obstacles which hinder farmers from adopting ISFM. For instance, weak land tenure security – due to customary systems, short rental periods or the risk of elite capture – restrains many farmers in SSA and beyond from investing resources, when they cannot be sure to reap future profits (Holden & Otsuka, 2014; Jayne et al., 2019).

Further, it is largely agreed on that improving access to financial and input markets is crucial to enhance modern input use in SSA. For instance, Sheahan and Barrett (2017) find for a number of SSA countries that only between 1% and 5% of farmers use credit to purchase fertilizer or improved seeds, while the unavailability of these inputs at the right point in time is a common obstacle to adoption (Suri, 2011). Another important impediment in this regard are underdeveloped rural road networks, which can make transportation and transaction costs for the 'last mile(s)' between distribution hubs and farm gates prohibitively high in remote areas. For instance, Minten et al. (2013) show for Ethiopia that farmers living some 35km away from the distribution point incur costs that are 50% higher than the cash price on-site, and leads to a 75% decrease in the use of improved seeds and fertilizer. Spatial models for Tanzania show that farmers behave as if each kilometer of distance to a sales hub added travel costs of 5.7% ad-valorem to the price of fertilizer (Aggarwal et al., 2018). These costs arise from explicit transportation and administrative costs (especially if distribution is government-led), but also implicit opportunity costs of time, and might be particularly unviable if traded quantities per farmer are very small. In the case of Ethiopia, where input distribution is mainly organized by the state, allowing private actors to some extent might lead to greater spatial dispersion of input suppliers also in remoter areas (Minten et al., 2013; Suri, 2011). Moreover, initiatives to facilitate bulk purchases and distribution services could help to reap economies of scale in the case of fertilizer. In addition, the formation and expansion of local seed distribution networks should be further supported.

Moreover, very low prevalence of irrigation presents an obstacle not only for agricultural productivity growth by itself, but also for modern input adoption, since mineral fertilizer and improved seeds require certain levels of soil moisture (Mueller et al., 2012; Van Ittersum et al., 2016). For instance, Rosegrant et al. (2009) claim that not even 3.5% of all agricultural area in SSA is irrigated, while Sheahan and Barrett (2017) find only around 2% of smallholder land is under irrigation in six SSA countries. Hence, public investment in irrigation infrastructure appears vital, even more in the light of expected increases in climate variability and drought incidence.

Another important question is how organic fertilizer use can further be encouraged. In particular, since our plot-level findings suggest average financial returns of using improved seeds with organic fertilizer in about the same range as using them with inorganic fertilizer, and the latter is often physically or financially inaccessible for farmers. While on-farm availability of organic resources may be limited as well, competing purposes might further explain their underutilization to fertilize soils; for instance, manure is often used as fuel, or crop residues as animal feed. Hence, recommendations of alternatives, such as using energy-saving stoves or planting multipurpose and fodder crops around plot borders, should go hand in hand with the promotion of organic fertilizer. In addition, governments should consider increased private sector involvement in developing commercial production and distribution services of manure and compost (Jayne et al., 2019).

In our setting, additional labor demand for ISFM adoption is largely borne by family labor, and results suggest that these investments can pay off for households. Nevertheless, whether this holds in other contexts largely depends on the opportunity costs of agricultural labor. Where labor is abundant and off-farm economic opportunities are scarce, applying labor-intensive ISFM practices is probably more viable (Jayne et al., 2019). By contrast, in economically more vivid and rather sparsely populated areas, mechanization can present a means to substitute capital for labor. In general, using labor-sparing mechanization is still uncommon among smallholders in SSA. For instance, Ashburner and Kienzle (2011) show that on around 80% of SSA's agricultural area, land preparation is done by hand tools, on 15% by draft animals and only on 5% tractors are used. Yet, other data from Tanzania shows large spatial heterogeneity: while in economically dynamic areas around 20% of farmers rented mechanization equipment in the 2014/15 cropping season, less than 4% did so in remote areas (Jayne et al., 2019). Considering farmers' lack of capital, small farm sizes and scattered plots, a further development of suitable sharing and rental arrangements is probably vital to raise mechanization levels in SSA.

Summing up, improving institutions as well as rural markets and infrastructure are indispensable to enhance the adoption of ISFM practices. And lastly, weaving together findings from all three essays supports the rationale for creating strong nationwide, but location-specific programs of agricultural research and extension, which actively involve farmers in the innovation process. Better collaborations and higher investments in agricultural research to further advance plant genetic improvement, large-scale soil mappings (as laudably done in Ethiopia to date) and the development of well-adapted fertilizers should be top-priorities on African government agendas. Creating knowledge regarding local best practices based on agroclimatic conditions and different resource levels requires mutual learning between researchers and farmers, in order to ultimately foster sustainable productivity growth in smallholder agriculture.

5.4 Limitations and scope for future research

As developed in the introductory part, this thesis assumes that the ISFM technology package is a 'sustainable' soil management concept to intensify smallholder agriculture, and then evaluates approaches for its dissemination as well as productivity and welfare implications for farmers.

Although this assumption is derived from a sound base of literature, we do not address environmental effects in this dissertation. For instance, the longer-term effects of organic fertilizer for soil health can have important implications for the provision of ecosystem services. Positive environmental externalities might in turn entail important effects for society as a whole.[61] Hence, future studies on effects beyond the plot and household level should provide a more holistic view on the potential of ISFM as a sustainable intensification strategy.

It should also be mentioned again that ISFM effects in the second and third essay are captured within a cross-section, while long-term effects might differ, in particular in the light of organic matter accumulation. In addition, positive effects of ISFM might reinforce themselves in the long run via indirect linkages. For instance, more fertile soils that are richer in micronutrients may over time produce crops that are richer in micronutrients, and ultimately also improve the nutritional and health status of humans consuming these crops (Barrett & Bevis, 2015). In turn, a healthier rural work force (farming more fertile soils) is likely to be more productive and hence, more likely to break the negative link between poor soil status and poverty.

Further, both environmental implications as well as impacts for farmers also depend on farmers' technical efficiency, conventionally described as the ratio of observed output to the maximum output farmers could theoretically attain, given their choice of inputs (Reinhard et al., 1999).[62] Hence, effects of ISFM depend not only on which and how much of inputs are used, but also on how farmers apply these – e.g. whether they sow in lines and target inputs precisely – and on accompanying management strategies. Apart from implications for yields and income, well-dosed and -targeted use of agrochemicals is important to avoid contamination of water bodies or other harmful environmental impacts. The question of smallholders' technical efficiency in the context of ISFM should be addressed in future research.

Furthermore, the second and third essay do not provide full cost-benefit analyses. For instance, owned land, equipment and household labor input are not accounted for in the income measures and hence, we do not study true economic profit, but rather 'quasi profit'. In particular the imputation of unpaid family labor (e.g. by the prevailing wage rate) results problematic in many studies in smallholder contexts, as estimated net income then often becomes negative (Takahashi, Muraoka, et al., 2019). Though, unlike most other studies, we include a measure

[61] In this regard, it is worth mentioning the lively debate and growing body of literature on 'payments for ecosystem services' as means to reward and incentivize farmers (Schomers & Matzdorf, 2013).

[62] This definition describes the output-oriented version of efficiency, as opposed to the input-oriented variant (Reinhard et al., 1999).

for the financial returns to unpaid (household) labor, implications regarding income and profitability still need to be interpreted with these limitations in mind.

Regarding the RCT in the first essay, some of the limitations common to experimental studies apply. We do not expect distorting effects of the evaluation itself, e.g. that treated farmers act differently because they are aware of being observed (*Hawthorne effect*), or that control farmers change their behavior due to anticipation of future treatment or competition with treatment individuals (*John Henry effect*) (Duflo et al., 2008). However, some degree of 'contamination' of the control group might exist, since few, yet some control farmers indicate to have participated in treatment activities. Likewise, information spillovers from treated farmers or extension staff to control households might have occurred. Though this should certainly be appreciated from a policy point of view, our results might suffer from a slight downward bias.

Despite identifying ISFM 'how-to' and 'principles' knowledge as drivers of adoption, their overall contribution to explaining adoption is not overly large. Investigating other cognitive impact channels, e.g. psychological factors or subjective yield expectations, would certainly be beneficial for designing future information treatments in the most effective way.

Furthermore, video interventions for agricultural education are often considered a low-cost tool (Bernard et al., 2016), but no cost-benefit analyses of the video nor the farmer-to-farmer extension intervention are provided in the scope of this thesis. Inducing high compliance and outreach at low cost outside of an experimental setting is a key factor for efficient public budget allocation and thus, should be addressed by research and practitioners.

And lastly, studying the sustainability of gains in knowledge and adoption, and thus, the longer-term impacts of the experimental interventions, as well as of adoption itself, provides interesting scope for future research. In particular, effects of ISFM adoption on other welfare measures – such as nutrition, health or assets – should be addressed in further studies.

All in all, this thesis adds an important piece of evidence towards approaching the much-needed sustainable intensification of smallholder agriculture, and the global community's vision of sustainable development as manifested in the SDGs.

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