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The effects of Integrated Soil Fertility Management on household welfare in Ethiopia

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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, inverse probability weighting regression adjustment

JEL codes: J23, O13, O33, Q12, Q16

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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 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 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[1] 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 (Imbens & Wooldridge, 2009; Manda et al., 2018; Wooldridge, 2003). 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.[2] Beyond implications for individual wellbeing, 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.

[1] 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).

[2] 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.

2. Materials and methods

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).

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.[3]

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.

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

[3] 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:

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

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) (Imbens & Wooldridge, 2009; Wooldridge, 2003). While IPW focuses on modelling the treatment selection, RA concentrates on outcomes, which allows controlling for selection bias at both stages (Manda et al., 2018). 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 (Cattaneo, 2010; Manda et al., 2018; Wooldridge, 2003).

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:

$$p(X) = Pr(T_i = 1|X) = F\{h(X)\} = E(T_i|X) \quad (2)$$

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):

$$ATET_{RA} = n_A^{-1} \sum_{i=1}^{n} T_i [r_A(X, \delta_A) - r_N(X, \delta_N)] \quad (3)$$

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:

$$ATET_{IPWRA} = n_A^{-1} \sum_{i=1}^{n} T_i [r_A^*(X, \delta_A^*) - r_N^*(X, \delta_N^*)] \quad (4)$$

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:

$$norm\_diff_j\text{:}\ \frac{(\bar{X}_{Aj} - \bar{X}_{Nj})}{\sqrt{S_{Aj}^2 - S_{Nj}^2}} \quad (5)$$

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).

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)[4] 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.[5] 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

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

[5] 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).

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 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*.[6] 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.[7]

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.

[6] 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.

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

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.[8] 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.[9] 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[10] 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

[8] 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 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?".

[9] 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.

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

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.[11] We also look at *total 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

[11] 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 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.

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 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 1 provides an overview of all outcome and explanatory variables differentiated by agroecological zone and ISFM adoption status.

Table 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.

3. Results

3.1 Effects on income and food security

Table 2 depicts results of the IPWRA estimations regarding ISFM effects on income and food security, separately for the two agroecological zones.[12] 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.[13] 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 A2 in the Appendix.

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

[12] Estimation results of the ISFM adoption models used for the IPW procedure are shown in Appendix Table A1.

[13] 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 A2).

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 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 $\chi^2(27) = 15.54$ with $p > \chi^2 = 0.96$ (partial or full ISFM) and $\chi^2(27) = 16.16$ with $p > \chi^2 = 0.95$ (full ISFM), suggesting that the weighted samples are well balanced. For Tigray, the same can be said, based on the following test statistics: $\chi^2(27) = 21.76$ with $p > \chi^2 = 0.75$ (partial or full ISFM) and $\chi^2(27) = 23.91$ with $p > \chi^2 = 0.64$ (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 A3 in the Appendix). Finally, PSM estimates are similar to our main IPWRA results, underlining the robustness of the findings (Table A4).

3.2 Effects on labor demand

Table 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 A5 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 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 production (1 = yes)	0.52	0.03	0.404	0.53	0.03	0.464
	(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 production (1 = yes)	0.28	0.13	0.006	0.26	0.13	0.005
	(0.04)	(0.05)		(0.04)	(0.05)	

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

3.3 Effects on children's education

In Table 4 we present the results regarding our measures of children's education.[14] 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

[14] 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. 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	0.15	0.010	0.60	0.18	0.002
	(0.06)	(0.06)		(0.06)	(0.09)	
Average number of missed school days due to agricultural work	2.41	0.73	0.193	2.56	0.76	0.197
	(0.51)	(0.56)		(0.51)	(0.59)	
Log of average education expenditure per capita (in ETB)	5.64	0.07	0.755	5.75	0.03	0.885
	(0.21)	(0.22)		(0.20)	(0.22)	
Tigray						
Enrollment rate of primary-school-aged children	0.81	0.03	0.456	0.82	0.05	0.351
	(0.05)	(0.04)		(0.06)	(0.05)	
Average number of missed school days due to agricultural work	2.97	0.09	0.904	2.91	-0.03	0.967
	(0.68)	(0.71)		(0.66)	(0.70)	
Log of average education expenditure per capita (in ETB)	5.18	-0.12	0.510	5.27	-0.15	0.448
	(0.17)	(0.18)		(0.18)	(0.20)	

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 A6 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. 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

Table A1. 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 A2. 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 A3. 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 A4. 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 A5. 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 A6. 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.

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