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Synergies between Different Types of Agricultural Technologies in the Kenyan Small Farm Sector

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ABSTRACT *Sustainable intensification of agriculture will have to build on various innovations, but synergies between different types of technologies are not yet sufficiently understood. We use representative data from small farms in Kenya and propensity score matching to compare effects of input-intensive technologies and natural resource management practices on household income. When adopted in combination, positive income effects tend to be larger than when individual technologies are adopted alone. The largest gains occur when improved seeds are adopted together with organic manure and zero tillage. These results point at important synergies between plant breeding technologies and natural resource management practices.*

1. Introduction

Global demand for food and farm commodities continues to grow, while land and other natural resources required for agricultural production are becoming increasingly scarce (Godfray et al., 2010; Hertel, 2015). In sub-Saharan Africa, population growth is particularly strong and will likely remain so over the coming decades. Sub-Saharan Africa is also the region with the highest rates of poverty and under-nutrition, and the lowest rates of productivity growth in agriculture. Many of the poor and undernourished people live in rural areas and depend on smallholder agriculture as the main source of income and employment. To reduce poverty and increase food security in sub-Saharan Africa will require substantial productivity and income growth in the small farm sector (Carletto, Ruel, Winters, & Zezza, 2015; Christiaensen, 2017). There is an urgent need for sustainable agricultural intensification, defined as producing more from the same area of land while reducing negative environmental impacts and increasing contributions to environmental services (Godfray et al., 2010; Pretty, Toulmin, & Williams, 2011).

The development and use of improved seeds, chemical fertilisers, pesticides, and irrigation has contributed to large productivity gains in Asia and Latin America over the last few decades. These developments became widely known as the green revolution (Evenson & Gollin, 2003). While more recently the use of external inputs has also increased in Africa, input intensities are still much lower than

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in most other parts of the world, due to various constraints (Binswanger-Mkhize & Savastano, 2017). Wider use of improved seeds and agrochemicals will have an important role to play for increasing and stabilising yields in the African small farm sector. However, in addition to the use of external inputs, sustainable intensification will also require improved agronomy to conserve natural resources. Natural resource management (NRM) technologies build on integrated agronomic principles and include practices such as conservation tillage, intercropping, terracing of sloped land, and use of locally available organic inputs. NRM technologies can reduce farmers' reliance on external inputs and thus reduce the environmental footprint of agricultural production (Altieri, 2002; Hobbs, Sayre, & Gupta, 2008). NRM practices can also help to reduce resource degradation and make farming more resilient to varying climatic shocks (Di Falco & Veronesi, 2013; Sanchez, 2002).

While in the wider public debate, input-intensive technologies and NRM practices are often depicted as two conflicting approaches (Greenpeace Africa, 2015), recent evidence shows that farmers sometimes adopt combinations of both types of technologies (Kassie, Teklewold, Jaleta, Marenya, & Erenstein, 2015; Wainaina, Tongruksawattana, & Qaim, 2016). Synergistic relationships may contribute positively to agricultural production and incomes. For instance, Sanchez (2002) argued that green revolution varieties could have been more successful in Africa if they had been adopted together with improved soil management practices. While this is plausible, there is little concrete evidence about synergistic relationships in smallholder environments. This is mainly due to the fact that available impact studies primarily focus on single technologies or compare effects of similar types of technologies. For instance, recent studies have analysed productivity and income effects of improved seeds, sometimes in combination with chemical inputs (Asfaw, Shiferaw, Simtowe, & Lipper, 2012; Becerril & Abdulai, 2010; Kabunga, Dubois, & Qaim, 2014; Mathenge, Smale, & Olwande, 2014; Shiferaw, Kassie, Jaleta, & Yirga, 2014). Other studies have looked at the impact of organic manure, conservation agriculture, and related soil and water management practices (Kassie, Zikhali, Pender, & Köhlin, 2010; Pender & Gebremedhin, 2008; Wollni, Lee, & Thies, 2010). A few recent studies have started to take a broader approach, analysing the impact of selected technology combinations in Zambia, Malawi, and Ethiopia (Kassie, Erenstein, Jaleta, Marenya, & Mekuria, 2015: Kassie, Teklewold, Marenya, Jaleta, & Erenstein, 2015; Manda, Alene, Gardebroek, Kassie, & Tembo, 2016; Teklewold, Kassie, Bekele, & Köhlin, 2013). This is an emerging and important body of literature. More evidence from various settings is needed, in order to guide future agricultural technology strategies. We contribute to this literature by using representative survey data from maize farmers in Kenya. In particular, we analyse and compare the impacts of different types of technologies – such as improved seeds, chemical fertilisers, organic manure, zero tillage, and crop residue management – as well as various technology combinations on farm household income. Household income is chosen as a comprehensive welfare measure, because looking at crop yields or revenues alone might be misleading from a broader development perspective. A propensity score matching approach is used to reduce problems of selection bias. Estimates with instrumental variables are also conducted as a robustness check. As the analysis builds on data collected in one single year and the number of adopters for certain technology combinations is relatively small, our intention is not to provide conclusive evidence about impacts and synergies. Rather, we want to highlight that important synergistic relationships exist, which should be accounted for more explicitly in future technology adoption and impact studies.

The rest of this article is structured as follows. Section 2 provides an overview of the survey data and the technologies considered in the analysis, while Section 3 introduces the statistical methods. Estimation results are presented and discussed in Section 4. Section 5 concludes.

2. Data, technologies considered, and descriptive statistics

2.1. Farm survey

A representative survey of maize-producing farm households was conducted in Kenya in 2012/13, covering all of the country's six agroecological zones (AEZs) as defined by Hassan (1998). Maize is

Table 1. Agroecological zones in Kenya and regional distribution of sampled households

	Highland tropics	Moist transitional	Moist mid-altitude	Dry transitional	Dry mid-altitude	Lowland tropics
Elevation (meters)	1600–2900	1200–2000	1100–1500	1100–1700	700–1400	<700
Annual rainfall(mm)	>1800	1000–1800	800–1200	<800	400–800	400–1400
Average temperature (°C)	15.2	19.7	22.1	19.7	22	25.5
Maize area (‘000 ha)	307	461	118	118	118	33
Share of national maize production (%)	35	20	20	10	10	5
Potential maize yield (t/ha)	6.7	5.2	5.2	4.5	2.7	3.3
Actual maize yield (t/ha)	2.0	0.7	1.1	1.1	0.5	1.0
Share of households surveyed (%)	18	26	18	15	16	7

Source: Adapted from Hassan (1998) and Jaetzold, Schmidt, Hornetz, and Shisanya (2005).

the main staple food crop in Kenya and is produced by almost all farm households for home consumption; surplus quantities are sold in local markets. To select households, we used a multi-stage random sampling technique, building on official statistics and census data (Kenya National Bureau of Statistics [KNBS], 2010). In each AEZ, we randomly selected sub-locations (Kenya’s smallest administrative units). The appropriate number of sub-locations was determined proportional to the maize area in each AEZ. In total, 120 sub-locations were sampled. In each sub-location, 12 households were randomly selected, except for the coastal lowlands where only six households were selected per sub-location due to budgetary constraints. The total sample includes 1344 farm household observations. Table 1 shows a few general characteristics of the six AEZ and the regional distribution of the sampled households.

The survey was implemented between December 2012 and February 2013. Face-to-face interviews were conducted by a local team of enumerators who were supervised by the researchers. The structured questionnaire focused on maize production aspects at the individual plot level, technology adoption, other farm and non-farm economic activities of the household, as well as broader socio-economic household and contextual characteristics. The reference period for all income and expenditure data was the calendar year 2012. The average farm size in the sample is 5.6 acres. Households are relatively poor with a mean per capita annual income of around 46 thousand Kenya shillings (KES), equivalent to 460 US dollars (Table 2). Other sample descriptive statistics are described in the following.

2.2 Technologies considered

In this analysis, we consider seven different technologies. These seven technologies include the most widely used technologies by maize farmers in Kenya, as well as NRM practices that have recently been promoted by local and international development programmes (Wainaina et al., 2016). Out of the seven technologies, two can be classified as input-intensive technologies, namely improved maize seeds and chemical fertilisers. Improved seeds, which were adopted by 85 per cent of the farmers in our sample (Table 2), include both hybrids and open-pollinated varieties (OPVs). Improved hybrids and OPVs that are available in Kenya have higher yield potentials than traditional landraces under favourable environments. While breeders are also developing and disseminating more stress-tolerant improved varieties of maize (including drought-tolerant seeds), their uptake was still relatively low in Kenya during the time of our survey in 2012/13 (Fisher et al., 2015). The other five technologies considered can be classified as NRM technologies, namely terracing, soil bunds, crop residue management, zero tillage, and use of organic manure.

Terraces and soil bunds are both practices intended to reduce the problem of soil erosion, especially on sloped land (Gebremedhin & Swinton, 2003). These two practices differ in terms of investment

Table 2. Summary statistics of outcome variables, technology adoption, and covariates

Variable name	*Variable description*	*Mean*	*Std. Dev.*
Outcome variables			
Household income	Total annual income generated by the household in KES [a]	257,643	323,721
Per capita income	Total household income per person in KES [a]	45,791	70,582
Technologies			
Improved seeds	=1if seeds are improved maize varieties, 0 otherwise	0.85	0.36
Fertiliser	=1 if farmer applied chemical fertilisers, 0 otherwise	0.60	0.49
Terraces	=1if farmer has constructed terraces, 0 otherwise	0.55	0.50
Soil bunds	=1 if farmer had soil bunds on the plot, 0 otherwise	0.20	0.40
Crop residues	=1if farmer left any crop residues on the plot, 0 otherwise	0.60	0.49
Zero tillage	=1if farmer practiced zero tillage, 0 otherwise	0.13	0.33
Manure	=1 if farmer used animal manure, 0 otherwise	0.65	0.48
Covariates			
Socio-economic characteristics			
Age	Age of the household head in years	53.96	13.86
Male	= 1 if the household head is male, 0 otherwise	0.81	0.39
Education	Years of formal education of the household head	7.71	4.48
Household size	Number of household members.	6.46	2.56
Farm size	Total land owned by the household in acres.	5.59	9.12
TLU	Total livestock units	5.57	7.46
Occupation	= 1 if farming is the main occupation of the household head, 0 otherwise	0.76	0.42
Productive assets	Total value of non-land productive assets in KES [a]	42,552	173,962
Off-farm income	Proportion of off-farm income in total income	0.47	0.31
Institutional variables			
Credit	=1if household took any credit in the previous year, 0 if not	0.20	0.40
Group membership	=1 if household participates in any group and 0 otherwise.	0.87	0.33
Market distance	Distance in walking hours to the nearest main market	1.62	1.57
Info improved seeds	=1 if household got extension information on improved maize varieties, 0 otherwise	0.65	0.48
Info on zero tillage	=1 if household got extension information on zero tillage, 0 otherwise	0.14	0.34
Info on crop residue	=1 if household got extension information on crop residues, 0 otherwise	0.33	0.47
Info on soil management	=1 if household got extension information on soil and water conservation practices, 0 otherwise	0.47	0.50
Farm characteristics			
Slopy land	Proportion of slopy land	0.69	0.44
Fertile land	Proportion of fertile land	0.38	0.46
Own land	Proportion of owned land out of all land under cultivation	0.88	0.25

(*continued*)

Table 2. (*Continued*)

Variable name	*Variable description*	*Mean*	*Std. Dev.*
Climatic shocks			
Drought	Frequency of drought experienced between 2003–2012	4.06	4.35
Flooding	Frequency of flooding experienced between 2003–2012	1.10	1.60
AEZ dummies [b]			
Dry mid-altitude	=1 if household is located in the dry mid attitude, 0 otherwise.	0.16	0.37
Dry transitional	=1 if household is located in the dry transitional, 0 otherwise	0.15	0.36
Moist transitional	=1 if household is located in the moist transitional, 0 otherwise	0.26	0.44
High tropics	=1 if household is located in the high tropics, 0 otherwise	0.18	0.38
Moist mid-altitude	=1 if household is located in the moist mid attitude, 0 otherwise.	0.18	0.38

Notes: The number of observations is n = 1337 (seven observations had to be dropped due to missing values). [a] KES, Kenyan Shilling; 1 US dollar = 100 KES. [b] AEZ, agroecological zone; the lowland tropics are defined as the base category.

costs, durability, and effectiveness of erosion abatement. Stone terraces are constructed walls that retain embankments of soil. Their construction involves preparing a base for the wall, transporting construction rocks, and carefully layering the stones. Stone terraces are more effective than soil bunds in preventing soil erosion on steep slopes prone to heavy runoff. More than 50 per cent of the farmers in the sample have actually constructed stone terraces (Table 2). Soil bunds, on the other hand, are embankments made by ridging soil on the lower side of a ditch along a slope contour (Gebremedhin & Swinton, 2003). They can be constructed by hand digging or ploughing and are cheaper and easier to establish than stone terraces. Soil bunds are used by 20 per cent of the sample farms.

Crop residue management and zero tillage are both important elements of conservation agriculture (Hobbs et al., 2008), which, however are not always adopted together. In our sample, crop residue management is practiced by 60 per cent of the farmers, whereas zero tillage was adopted by only 13 per cent. Both practices help to conserve the structure of the uppermost soil layers, thus reducing erosion and water evaporation. Crop residue management (mulching) also improves water infiltration and reduces maximum temperatures in the soil surface layers. Finally, livestock manure, which is used by 65 per cent of the sample farmers, adds nutrients and organic matter to the soil.

2.3. Socio-economic characteristics

Table 2 presents summary statistics of the key socio-economic variables used in this analysis. As explained, the outcome variable for the impact evaluation is household income. We look at total household income as well as income in per capita terms. Household income is defined as the net income (revenue minus production costs) from all economic activities of the different household members, including maize and other farm enterprises, as well as off-farm income sources. Looking at revenues alone would not be sufficient, because technology adoption can also affect production costs. While technologies adopted in maize may be expected to have the largest effects on income from maize production, spillover effects to other farm and non-farm activities may occur. The use of certain inputs or practices in one crop may affect productivity also in other crops, and constraints in household endowments with land, labour, and financial capital can imply important spillover effects to other farm and non-farm activities (Babatunde & Qaim, 2010; Lee, 2005; Noltze, Schwarze, & Qaim, 2013). Such spillovers between the different economic activities of the household are captured when looking at total household income as the outcome variable in the impact evaluation. Net income is considered a comprehensive measure of household living standard.

Figure 1 provides an overview of the structure of household income by agroecological zone. In spite of some regional differences, maize production accounts for 10–20 per cent of total income in all zones. Other crops and livestock together account for another 30–40 per cent, implying that off-farm activities account for 40–60 per cent of total incomes. Among the off-farm activities, employed labour is the most important source of income, followed by self-employed trade and business activities.[1]

The treatment variables for the impact evaluation are technology adoption, referring to the seven technologies described above plus selected technology combinations. In principle, 128 different combinations are possible, but many of these combinations are not observed in reality. We focus on those that are more common so that a sufficient number of adopters is available for the statistical analysis. It should be mentioned that data on technology adoption were collected at plot level, even though the impact evaluation is done at household level. We define a household as adopter if it adopted the particular technology on at least one of the plots. The covariates used to explain adoption are shown in the lower part of Table 2. They comprise a set of socio-economic, institutional, farm, and agroecological characteristics. We also use two variables related to climatic shocks, namely drought and flooding events experienced by farmers during a period of 10 years prior to the survey.

Table A1 (Supplementary Materials) compares mean values for different socio-economic variables between adopters and non-adopters of the various technologies. Adopters of input-intensive technologies are significantly more educated and have better access to markets and credit than non-adopters of these technologies. For NRM technologies, while certain differences can be observed, there is no uniform pattern when comparing adopters and non-adopters. Table 3 compares income structures

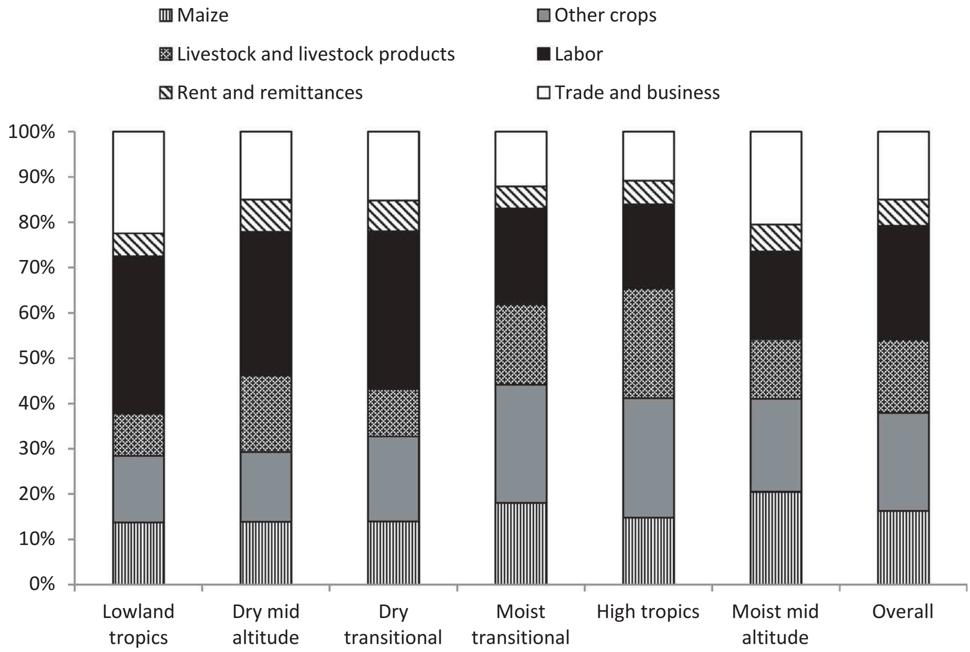

Figure 1. Average structure of household income by agroecological zone.

between technology adopters and non-adopters. Various significant differences can be observed, underlining that the sub-groups are not identical and pursue different economic strategies.

Table 4 compares mean household income between adopters and non-adopters of each of the seven technologies. Adopters of input-intensive technologies have significantly higher income than non-adopters. In comparison, income differences between adopters and non-adopters of NRM technologies are less pronounced. However, these comparisons cannot be interpreted as impacts of technology adoption because of systematic differences between adopters and non-adopters. Such differences are controlled for in the subsequent statistical analysis.

3. Statistical methods

3.1. Impact assessment framework

We analyse the impact of technology adoption on farm household income. Income does not only refer to cash income but also includes the value of subsistence production. Agricultural technologies can affect income through various pathways, such as higher yields, lower production costs, or changes in household labour requirements that may entail time reallocation and higher or lower incomes from alternative economic activities. As different technologies can involve different pathways, we use income as a comprehensive indicator of household living standard.

The analysis is based on observational data, that is, the technologies considered were not assigned randomly. Instead, farmers chose themselves which particular innovations to adopt. As shown above, adopters and non-adopters are different in terms of various socio-economic characteristics. Hence, we cannot simply interpret observed income disparities as impacts of the technology without controlling for confounding factors. One common approach to deal with possible selection bias in impact assessment is to use propensity score matching (PSM) (Abadie & Imbens, 2006; Dehejia & Wahba, 2002; Rosenbaum & Rubin, 1983). We use PSM techniques, as explained in more detail below.

Table 3. Average structure of household income by status of technology adoption (income shares in %)

	Maize		Other crops		Livestock		Labour		Rent and remittances		Trade and businesses	
	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters	Adopters	Non-adopters
Improved seeds	16.64*	14.51	22.51***	16.61	17.09***	11.64	23.82***	31.84	5.22***	8.80	14.71	16.59
Fertilisers	17.63***	14.32	23.49***	18.73	16.99	15.13	21.85***	29.92	5.09**	6.82	14.96	15.07
Terracing	15.84	16.89	21.71	21.48	14.70***	18.13	25.89	24.03	6.06	5.43	15.79	14.05
Soil bunds	16.03	16.39	24.46**	20.88	18.38**	15.71	21.49**	25.95	6.32	5.63	13.32	15.43
Crop residues	18.63***	12.91	21.92	21.14	15.16**	17.88	23.84*	26.84	4.82***	7.20	15.65	14.05
Zero tillage	15.61	16.42	23.89	21.27	15.44	16.37	23.20	25.32	6.57	5.66	15.29	14.96
Manure	15.29***	18.15	21.87	21.13	16.67	15.50	25.02	25.10	5.97	5.43	15.17	14.69
Overall	16.32		21.60		16.25		25.05		5.77		15.00	

Notes: ***, **, and *indicate significant differences in income shares between adopters and non-adopters at the 1 per cent, 5 per cent, and 10 per cent level, respectively.

Table 4. Average household income levels by technology adoption status

	Household income		Per capita income	
	Adopters	Non-adopters	Adopters	Non-adopters
Improved seeds	274,379***	165,227	48,886***	28,700
	(341,817)	(168,528)	(75,198)	(30,484)
Fertiliser	281,019***	229,049	52,461***	35,635
	(343,532)	(287,662)	(81,977)	(46,600)
Terracing	254,066	261,958	45,765	45,823
	(297,444)	(353,028)	(63,737)	(78,100)
Soil bunds	272,661	253,843	52,026	44,213
	(409,995)	(298,074)	(102,419)	(59,870)
Crop residues	257,391	258,015	41,900**	51,533
	(341,788)	(295,352)	(71,763)	(68,466)
Zero tillage	316,030**	249,195	53,214	44,717
	(369,461)	(315,841)	(80,556)	(68,993)
Manure	265,995	242,681	48,922**	40,183
	(352,262)	(264,715)	(80,658)	(47,024)

Notes: Mean values are shown with standard deviations in parentheses. Incomes are measured in Kenyan shillings (KES) per year; 1 US dollar = 100 KES. *** and ** indicate significant differences between adopters and non-adopters at the 1 per cent and 5 per cent level, respectively.

One drawback of PSM is that it relies on the conditional independence assumption, meaning that adopters and non-adopters are assumed to differ only in terms of observed characteristics. In other words, possible bias due to unobserved heterogeneity is not controlled for. We use two approaches to deal with this potential issue. First, we calculate Rosenbaum bounds to test the null hypothesis of zero change in the estimated effect when different values of unobserved selection bias are introduced (Aakvik, 2001). This test shows how unobserved heterogeneity (or hidden bias) – if relevant – might alter inferences about the estimated treatment effect, but it does not indicate whether unobserved heterogeneity is actually an issue. Second, we use instrumental variable (IV) techniques to test for unobserved heterogeneity (Heckman & Vytlacil, 2005; Imbens & Wooldridge, 2009).[2]

3.2. Propensity score matching

PSM reduces selection bias by only comparing groups of adopters and non-adopters ('treated and 'untreated' subjects in the terminology of the impact evaluation literature) that are sufficiently similar based on observable characteristics. We follow four steps involved in applying PSM, as outlined by Baker (2000) and Caliendo and Kopeinig (2008).

First, propensity scores are estimated for each farm household using discrete choice models. For each technology and technology combination, we estimate a regression model with the binary adoption decision as dependent variable.[3] We use logit regression models that lead to consistent parameter estimates in PSM analysis (Baker, 2000; Ravallion, 2001). Propensity scores describe the likelihood of adopting a certain technology based on a set of covariates.

Second, the matching algorithm is selected. Matching is the technique to select treated and untreated subjects that are similar in terms of their propensity score. We use kernel based matching (KBM) and radius matching (RM). KBM is a non-parametric matching method that uses the weighted average of the outcome variable (household income) for all non-adopters to construct the counterfactual outcome, attributing a higher weight to those observations that provide a better match. This weighted average is then compared with the outcome variable for the group of adopters. The difference in mean outcomes provides an estimate of the average treatment effect on the treated. For KBM, we use a bandwidth of 0.1. RM is a variant of caliper matching (Dehejia & Wahba, 2002). Applying caliper matching means that an individual from the group of non-adopters is chosen as a matching partner for an adopter that lies within the caliper (propensity range) and is closest in terms of propensity score (Caliendo & Kopeinig, 2008). RM as a variant of caliper matching implies that not only the nearest neighbour within each caliper is used as a match, but all of the comparison members within the caliper. A benefit of this approach is that it uses only as many comparison units as are available within the caliper and therefore allows for usage of extra (fewer) units when good matches are (not) available. For RM we use a radius caliper of 0.1. A balancing test is then conducted after matching to ascertain that the differences in covariates between adopters and non-adopters have been eliminated, such that the matched comparison group can be considered as a credible counterfactual (Caliendo & Kopeinig, 2008).

Third, the common support (overlap) condition is identified. Common support is the area where the balancing score has positive density for both treated and untreated units. No matches can be made to estimate average treatment effects when there is no overlap.

Fourth, the average treatment effect on the treated (ATT) is estimated in the common support region based on the selected matching algorithm.

4. Estimation results

4.1. Covariate balancing and common support

As explained, logit models were estimated to calculate propensity scores. Results of the logit estimates for the seven technologies considered in this study are shown in Table A2 (Supplementary Materials).[4] Using the same covariates we also estimated logit models to explain the adoption of relevant technology combinations. The propensity scores for adopters and non-adopters were then matched and balanced to find credible counterfactuals. Evidence of successful matching is presented in Table A5 (Supplementary Materials) in terms of reduced bias, low pseudo-R2, and insignificant log-likelihood values after matching. Successful bias reduction was achieved for all technologies except for improved seeds. To achieve successful matching, the number of available untreated controls should be greater than the number of treated subjects (Lunt, 2014). Due to the high share of adopters of improved seeds in our sample, this condition could not be fulfilled for this particular technology. To enable balancing, we had to reduce the number of covariates in the logit model for improved seeds. Also, we used a tighter caliper and kernel bandwidth of 0.05 for improved seeds (as compared to 0.1 for the other technologies) to reduce bias as much as possible.

Similarly, the common support condition was fulfilled for all technologies except for improved seeds (propensity score histograms are shown in Figure A1, Supplementary Materials). For improved seeds, we could not find suitable matches for 156 adopters and therefore the ATT estimates for this technology should be interpreted with caution; the estimates only represent the impact on the income of those adopters for whom suitable matches were found. We present differences in important covariates between matched and unmatched adopters in Table A6 (Supplementary Materials). Matched adopters are less wealthy and have lower propensity scores than unmatched adopters, meaning that the ATT results are more relevant for the lower part of the income distribution. Problems with successful matching and common support relate to the high adoption rates of improved seeds in three of the AEZs, namely the moist transitional zone (97%), the highland tropics (94%), and the dry transitional zone (87%). As an additional test, we exclude these three AEZs and estimate the impact of improved seeds in the remaining three AEZs (moist mid-altitude, dry mid-altitude, and lowland tropics), where adoption rates were lower and matching was successful.

4.2. Impact of technology adoption on household income

Table 5 presents the estimated ATTs for the seven technologies and relevant combinations, with total household income and per capita income as outcome variables. The impact magnitudes and significance levels are quite robust to the chosen matching method. We concentrate on discussing results obtained with radius matching.

Table 5. Impact of the adoption of technologies and technology combinations on household income using PSM

			Radius matching (RM)			Kernel based matching (KBM)		
	Treated (N)	Impact on	ATT	Std. error	Gamma level	ATT	Std. error	Gamma level
Improved seeds	1132	Household income	39,885**	20,371	1.20–1.25	38,811**	20,562	1.20–1.25
		Per capita income	5,668	3,733		5,454	3,766	
Improved seeds for 3 AEZ [a]	388	Household income	65,184***	22,635	1.20–1.25	64,445***	22,976	1.20–1.25
		Per capita income	10,813***	3,449	1.20–1.25	10,737***	3,496	1.20–1.25
Fertiliser	807	Household income	−10,679	24,738		−13,280	24,957	
		Per capita income	98	4,477		638	4,509	
Fertiliser (incl. micronutrients)	444	Household income	28,266	22,137		26,771	22,200	
		Per capita income	2,391	4,774		2,037	4,789	
Terraces	731	Household income	−11,162	22,456		−9,457	22,769	
		Per capita income	2,140	4,970		2,526	5,041	
Soil bunds	270	Household income	22,171	26,802		21,466	26,916	
		Per capita income	6,679	6,546		6,343	6,566	
Crop residue	797	Household income	10,859	23,699		10,325	24,112	
		Per capita income	−858	5,365		−657	5,463	
Zero tillage	169	Household income	51,257*	31,093	1.70–1.75	52,821*	31,265	1.70–1.75
		Per capita income	8,080	6,799		8,765	6,838	
Manure	858	Household income	36,644*	19,234	1.55–1.60	35,595*	19,422	1.55–1.60
		Per capita income	10,000***	3,854	1.45–1.50	9,704**	3,883	1.45–1.50
Improved seeds + fertiliser	759	Household income	−7,996	23,313		−10,314	23,370	
		Per capita income	991	4,449		140	4,457	
Improved seeds + manure	711	Household income	41,947**	17,366	1.50–1.55	41,026**	17,494	1.50–1.55
		Per capita income	9,576***	3,343	1.45–1.50	9,423***	3,364	1.45–1.50
Improved seeds + fertiliser + manure	449	Household income	7,514	20,089		4,141	20,249	
		Per capita income	3,817	4,121		3,203	4,144	
Improved seeds + zero tillage	146	Household income	57,308*	34,530	1.85–1.90	57,001*	34,562	1.80–1.85
		Per capita income	8,900	7,578		8,858	7,585	
Zero tillage + crop residues	121	Household income	31,721	36,449		30,739	36,600	
		Per capita income	1,704	6,940		1,816	6,980	
Zero tillage + manure	99	Household income	129,188***	45,518	1.10–1.15	128,618***	45,515	1.10–1.15
		Per capita income	22,514**	10,375	1.40–1.45	22,192**	10,374	1.45–1.50
Zero tillage + fertiliser	101	Household income	63,133	41,987		61,269	42,425	
		Per capita income	9,160	8,994		9,237	9,093	

(*continued*)

Table 5. (*Continued*)

			Radius matching (RM)			Kernel based matching (KBM)		
	Treated (N)	Impact on	ATT	Std. error	Gamma level	ATT	Std. error	Gamma level
Improved seeds + zero tillage + manure	81	Household income	150,150***	53,851	1.15–1.20	148,858***	53,941	1.15–1.20
		Per capita income	25,669**	12,356	1.35–1.40	25,697**	53,941	1.35–1.40
Terracing + manure	510	Household income	10,138	22,163		6,566	22,488	
		Per capita income	5,945	4,867		5,684	4,936	
Improved seeds + terracing + manure	429	Household income	22,169	22,238		20,244	22,476	
		Per capita income	7,574	4,930		7,391	4,969	
Improved seeds + terracing + manure + fertiliser	281	Household income	16,296	25,175		18,208	25,476	
		Per capita income	6,990	5,765		7,273	5,825	

Notes: ***, **, and *significant at 1 per cent, 5 per cent, and 10 per cent level, respectively. PSM, propensity score matching; ATT, average treatment effect on the treated. Results are reported in Kenyan Shillings (KES) per year; 1 US dollar = 100 KES. [a] This refers to the three agroecological zones (AEZ) moist mid-altitude, dry mid-altitude, and lowland tropics, where a sufficient number of non-adopters was found for robust impact assessment.

For terracing, crop residue management, and soil bunds we do not observe any significant impact on household income. In comparison, for the other two NRM technologies, zero tillage and use of manure, significantly positive income effects are observed. Adoption of zero tillage increases household income by KES 51,527 which is equivalent to a gain of approximately 16 per cent. The effect of zero tillage on per capita income is positive but insignificant. Manure adopters increase their total income by KES 36,444 (14%) and their per capita income by KES 10,000 (20%).

Turning to the input-intensive technologies, adoption of improved maize seeds contributes to an increase in household income by almost 15 per cent, when observations from all six AEZ are included. When only looking at the three AEZ with somewhat lower adoption rates, the ATT gets even larger, indicating that improved seeds help to raise household living standards. Somewhat strikingly, however, the use of chemical fertiliser does not contribute to household income gains. The estimated effect for fertiliser is even negative, albeit not statistically significant. This is in spite of the fact that fertiliser adopters are significantly richer than non-adopters, as was shown above in Table 4.

What are reasons for the insignificant effect of fertiliser adoption? Average fertiliser rates used in the Kenyan small farm sector are still lower than recommended levels. Many of the soils are nutrient-depleted, hence positive yield and income effects of fertilisation should actually be expected. However, many of the farmers use fertilisers that only contain nitrogen (N), phosphorus (P), and potassium (K). While these are the key macronutrients that plants need for healthy growth, several micronutrients – such as sulphur (S), boron (B), zinc (Zn), copper (Cu), or manganese (Mn) – are also required (Ryan et al., 2013). Many of the African soils are micronutrient depleted, so that using NPK fertilisers alone may not always result in expected yield gains (Chianu, Chianu, & Mairura, 2012). Furthermore, Marenya and Barrett (2009) showed that constraints in biophysical soil conditions, such as low carbon content, may also reduce the effectiveness of chemical fertilisers. These factors could also explain the notable differences in impacts between chemical fertilisers and manure, because manure contains a broader set of nutrients (including micronutrients) and also improves biophysical soil conditions. When we confine the group of chemical fertiliser adopters to those that used fertilisers with micronutrients, the negative ATT estimate turns positive, even though it remains insignificant due to large standard errors (Table 5).

We now look at the effects for technology combinations in Table 5. The adoption of improved seeds together with chemical fertilisers does not lead to a significant ATT, which is related to the disappointing fertiliser effect discussed previously. However, combining improved seeds with manure results in highly significant impacts on household income (15%) and per capita income (18%). The combination of improved seeds with zero tillage also increases household income beyond what both technologies achieve when adopted alone. The largest positive income effects are observed when improved seeds are combined with manure and zero tillage. On average, this combination of three technologies produces household income gains of KES 150,150 (35%) and per capita income gains of KES 25,669 (35%). These results clearly underline that important synergies between input-intensive and NRM technologies exist. On the other hand, we also see in Table 5 that the number of adopters of such promising technology combinations is relatively low, suggesting that the synergies are not yet fully exploited.

4.3. Robustness checks

As mentioned, PSM relies on the conditional independence assumption, meaning that there no unobserved heterogeneity (hidden bias) between adopters and non-adopters. We calculate Rosenbaum bounds (critical gamma levels) that indicate how hidden bias – if present – might affect the estimated impact. The gamma level is defined as the odds ratio of differential treatment assignment due to an unobserved covariate. For instance, a gamma level of 1.50 would imply that matched subjects would have to differ by a factor of 50 per cent in terms of unobserved characteristics in order to render the estimated ATT insignificant. In Table 5, we report gamma levels for the significant ATT estimates. In most cases, the values are larger than 1.3, especially for the per capita income estimates that account for household size. Hence, most of the general inferences seem to be fairly robust to unobserved heterogeneity. However, the gamma levels for the effects of improved seeds are smaller (1.20–1.25), meaning that more caution is warranted.

In another robustness check, we test for selection bias due to unobserved heterogeneity using IV treatment effect models. Finding valid instruments that are correlated with technology adoption but uncorrelated with household income is difficult. We were unable to find one single instrument that passed the identification tests for all the different technologies. Hence, we had to use different instruments. One instrument that worked well for several technologies is the adoption rate for that particular technology at sub-location level. Studies in different contexts showed that individual technology adoption behaviour is often influenced by adoption rates in the local network through learning and imitation effects (Bandiera & Rasul, 2006; Matuschke & Qaim, 2009). Another instrument that we use for some of the NRM technologies is the proportion of land with slopes at the farm level. Previous research showed that slope of the land is an important factor in explaining the adoption of practices to reduce soil erosion, such as terracing (Wainaina et al., 2016). While steep slopes can also affect household income through other pathways, most of the land with slopes in our sample is moderately sloped so that there is no direct correlation with income. Finally, we use farmers' exposure to technologies through extension services or other channels as additional instruments. NRM technologies are often knowledge-intensive, so that good access to agricultural extension is an important adoption determinant (Lee, 2005; Noltze et al., 2013).

Table A7 (Supplementary Materials) shows in more detail which instruments were used for which technologies together with IV estimates of the treatment effects on income and tests of the null hypothesis of no unobserved heterogeneity (hidden bias). For most technologies, this null hypothesis cannot be rejected. We conclude that unobserved heterogeneity does not bias our estimation results with PSM. The only exception is manure, where hidden bias seems to be an issue. Interestingly, however, the treatment effects for the adoption of manure estimated with the IV models are larger than those estimated with PSM, meaning that we rather underestimate the true effect with PSM due to negative selection bias. While the exact magnitude of the estimates should not be over-interpreted, the general findings do not seem to be undermined by hidden bias. Nevertheless, as some of the instruments used could be challenged, some caution is warranted. Follow-up research with different identification strategies will be useful to re-examine the magnitude of the treatment effects.

5. Conclusion

Sustainable intensification is seen by many as the new paradigm for increasing agricultural productivity and income in the African small farm sector while conserving natural resources and reducing negative environmental externalities. Sustainable intensification requires a broad portfolio of innovations and technologies, including improved seeds, fertilisers, as well as various natural resource management (NRM) practices. While in the public debate technologies that rely on external inputs are sometimes depicted as being incompatible with NRM technologies, in reality there may be interesting synergistic relationships when elements of both types of technologies are combined. Possible synergies in smallholder environments are not yet sufficiently understood. Most impact studies focus on the effects of single technologies. In this article, we have used representative data from smallholder farmers in Kenya to compare the effects of various input-intensive technologies, NRM technologies, and selected combinations.

In particular, we have used propensity score matching methods to analyse impacts of technology adoption on household income. The estimation results show that – when adopted alone – some technologies produce positive income effects, while other technologies do not. At the same time, some of the technology combinations lead to higher positive impacts. The largest positive income effects are observed when improved seeds are adopted together with organic manure and zero tillage practices. This clearly underlines that there are important synergies between input-intensive and NRM technologies. On the other hand, the number of farmers adopting such promising technology combinations is relatively low, suggesting that the synergies are not yet fully exploited. More impact studies that explicitly account for possible synergies can help to improve the knowledge that is needed for designing and promoting suitable technology combinations in particular settings.

Our analysis has a few limitations. First, we used cross-section data from only one year, even though impacts of technologies may vary over time due to climatic variability and other factors. Second, while propensity score matching helps to control selection bias due to observable factors, unobserved heterogeneity may still lead to hidden bias. We tested for hidden bias by using instrumental variables, but identifying valid instruments for all technologies is challenging with cross-section data. Third, we could only analyse a few technology combinations, because for other combinations we did not have sufficient adoption observations for meaningful impact assessment. Against this background the exact numerical results should be interpreted with caution. However, our intention was not to provide conclusive evidence. Rather, we wanted to show that important synergies between different types of technologies exist, which were often neglected in previous impact studies. Follow-up research is needed for more comprehensive understanding.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1. In principle, it is possible to evaluate the impact of maize technology adoption on all the different components of farm and off-farm income and thus analyse possible spillovers between household economic activities more explicitly. However, using multiple outcome variables in the impact analysis and presenting the effects of seven technologies and various technology combinations would have been beyond the scope of this article.
2. IV techniques require the use of valid instruments for the potentially endogenous treatment variables. Finding valid instruments is challenging, especially when using multiple treatment variables, as in our case. We discuss the instruments used below.
3. We use separate regression models for each technology and technology combination. It is possible that the different adoption decisions are not independent, which would lead to correlation between the error terms. To test whether such correlation has an influence on the estimated coefficients, which are used for the propensity score calculations, we also run a multivariate probit model that accounts for error term correlation.
4. To test whether error term correlation could lead to possible bias, we run a multivariate probit model for the seven technologies and compare with results from separately estimated probit models. Results of these models are shown in Tables A3 and A4 (Supplementary Materials). The estimated coefficients do not differ significantly, so we conclude that error term correlation does not bias the propensity score calculations.

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