Synergies between different types of agricultural technologies: insights from the Kenyan small farm sector

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Abstract

Global demand for food and farm commodities continues to grow, while land and other natural resources are becoming increasingly scarce. Sustainable intensification is often seen as a new paradigm for increasing agricultural productivity in a socially and environmentally responsible way. Sustainable intensification requires a broad portfolio of technologies, including improved seeds, fertilizers, and various natural resource management (NRM) practices. However, possible synergies between different types of technologies are not yet sufficiently understood. Here, we address this knowledge gap. Using representative data from small farms in Kenya and a propensity score matching approach, we analyze income effects of various technologies and technology combinations. When adopted alone, some innovations produce positive effects, while others do not. Effects of certain technology combinations are larger. The largest income gains occur when improved seeds are adopted together with organic manure and zero tillage practices. This points at important synergies between input-intensive and NRM technologies. Yet, the number of farmers that have adopted such promising technology combinations is relatively small, implying that synergies are not yet fully exploited. More impact studies that explicitly account for possible synergies can add to the knowledge that is needed for designing and promoting technology combinations suitable for particular contexts.

Keywords: Agricultural technology; Sustainable intensification; Economic impact; Maize farming; Sub-Saharan Africa

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 undernutrition, 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 a 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 (Foresight, 2011). 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, 2011).

The development and use of improved seeds, chemical fertilizers, 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 and Gollin, 2003). In Africa, these input-intensive technologies have not been adopted to the same extent, due to various constraints. Wider use of improved seeds and agrochemicals will have an important role to play for increasing and stabilizing 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 et al., 2008). NRM practices can also help to reduce resource degradation and make farming more resilient to varying climatic shocks (Sanchez, 2002; Di Falco and Veronesi, 2013).

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 (Wainaina et al., 2014; Kassie et al., 2015a). 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 analyzed productivity and income effects of improved seeds, sometimes in combination with chemical inputs (Becerril and Abdulai, 2010; Asfaw et al., 2012; Kabunga et al., 2014; Mathenge et al., 2014; Shiferaw et al., 2014). Other studies have looked at the impact of organic manure, conservation agriculture, and related soil and water management practices (Pender and Gebremedhin, 2007; Kassie et al., 2010; Wollni et al., 2011; Kassie et al., 2015b). We are not aware of studies that have explicitly analyzed the impacts of adopting combinations of input-intensive and NRM technologies.

We address this research gap, using representative survey data from maize farmers in Kenya. In particular, we analyze and compare the impacts of different types of technologies – such as improved seeds, chemical fertilizers, 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, as looking at crop yields alone may be misleading. A propensity score matching approach is used to reduce problems of selection bias. 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 impact analysis, while section 3 introduces the statistical methods. Results are presented and discussed in section 4. Section 5 concludes.

2. Data and technologies considered

2.1. Farm survey

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

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

	Highland tropics	Moist tran-sitional	Moist mid-altitude	Dry tran-sitional	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 et al. (2005).

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 socioeconomic household and contextual characteristics. The reference period for all income and expenditure data was the calendar year of 2012. The average farm size in the sample is 5.6 acres. Households are relatively poor with a mean per capita annual income of 460 US dollars. Further descriptive statistics are presented in section 4.

2.2 Technologies considered

We analyze the impact of seven different technologies and selected technological combinations that have been adopted by maize farmers in Kenya to varying extents. Out of the seven technologies, two can be classified as input-intensive technologies, namely improved maize seeds and chemical fertilizers. Improved seeds, which were adopted by 85% of the farmers in our sample, 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 favorable environments. While breeders are currently also developing more stress-tolerant improved varieties of maize, such seeds are not yet commercially available in Kenya. 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 and Swinton, 2003). These two practices differ in terms of investment 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% of the farmers in the sample have actually constructed stone terraces. Soil bunds, on the other hand, are embankments made by ridging soil on the lower side of a ditch along a slope contour (Gebremedhin and Swinton, 2003). They can be constructed by hand digging or plowing and are cheaper and easier to establish than stone terraces. Soil bunds are used by 20% 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% of the farmers, whereas zero tillage was adopted by only 13%. 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% of the sample farmers, adds nutrients and organic matter to the soil.

3. Methods

3.1. Impact assessment framework

We analyze 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 labor 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 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. Therefore, adopters and non-adopters are likely different in terms of various characteristics, and 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 instrumental variable (IV) regression techniques (Heckman and Vytlacil, 2005; Imbens and Wooldridge, 2009). However, IV methods require at least one valid instrument that is correlated with technology adoption but not correlated with income. We were unable to identify suitable instruments for all seven technologies and additional technology combinations, which is why we decided to use propensity score matching (PSM) techniques, another common approach to reduce selection bias in impact assessment (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 2002; Abadie and Imbens, 2006).

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 five 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 a discrete choice model. We use a logit regression model that leads to consistent parameter estimates (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) methods. 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 (ATT). For KBM, we use a bandwidth of 0.1. RM is a variant of caliper matching (Dehejia and 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 and Kopeinig, 2008). RM as a variant of caliper matching implies that not only the nearest neighbor 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 and 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 ATT is estimated in the common support region based on the selected matching algorithm. Fifth, sensitivity analysis is undertaken to test the robustness of the results. In particular, PSM assumes that treated and untreated subjects differ only in terms of observed factors, which is referred to as the conditional independence assumption. Since with PSM it is not possible to estimate the magnitude of unobserved selection bias, Aakvix (2001) suggested the use of Rosenbaum bounds to test the null hypothesis of zero change in the ATT when different values of unobserved selection bias are introduced. This test shows how hidden bias – if relevant – might alter inferences about the ATT, but it does not indicate whether hidden bias is actually an issue.

4. Results and discussion

4.1. Descriptive statistics

Table 2 presents a summary of the key variables used in this analysis. As explained above, the outcome variable for the impact evaluation is household income. We look at total household income as well as income in per capita terms. The treatment variables are technology adoption, referring to the seven technologies described above plus selected combinations. In principle, 120 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 also shown in Table 2. They comprise a set of socioeconomic, 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 2: Summary statistics of outcome variables, technology adoption, and covariates

Variable name	*Description of the variable*	*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	45,791	70,582
Technologies			
Improved seeds	=1if seeds are improved maize varieties, 0 otherwise	0.85	0.36
Fertilizer	=1 if farmer applied chemical fertilizers, 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			
Socioeconomic 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	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
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 HH is located in the dry mid attitude, 0 otherwise.	0.16	0.37
Dry transitional	=1 if HH located in the dry transitional zone, 0 otherwise	0.15	0.36
Moist transitional	=1 if HH located in the moist transitional zone, 0 otherwise	0.26	0.44
High tropics	=1 if HH is located in the high tropics, 0 otherwise	0.18	0.38
Moist mid-altitude	=1 if HH is located in the moist mid attitude, 0 otherwise.	0.18	0.38

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] For the AEZ, the lowland tropics are defined as base category.

Figure 1 provides an overview of the structure of household incomes by agroecological zone. In spite of some regional differences, maize production accounts for 10-20% of total incomes in all zones. Other crops and livestock together account for another 30-40%, implying that off-farm activities account for 40-60% of total incomes. Among the off-farm activities, employed labor is the most important source of income, followed by self-employed trade and business activities. Table 3, compares income structures between farmers who did and did not adopt certain technologies. Various significant differences can be observed, underlining that the sub-groups are not identical and pursue different economic strategies.

Figure 1: Average structure of household income by agroecological zones

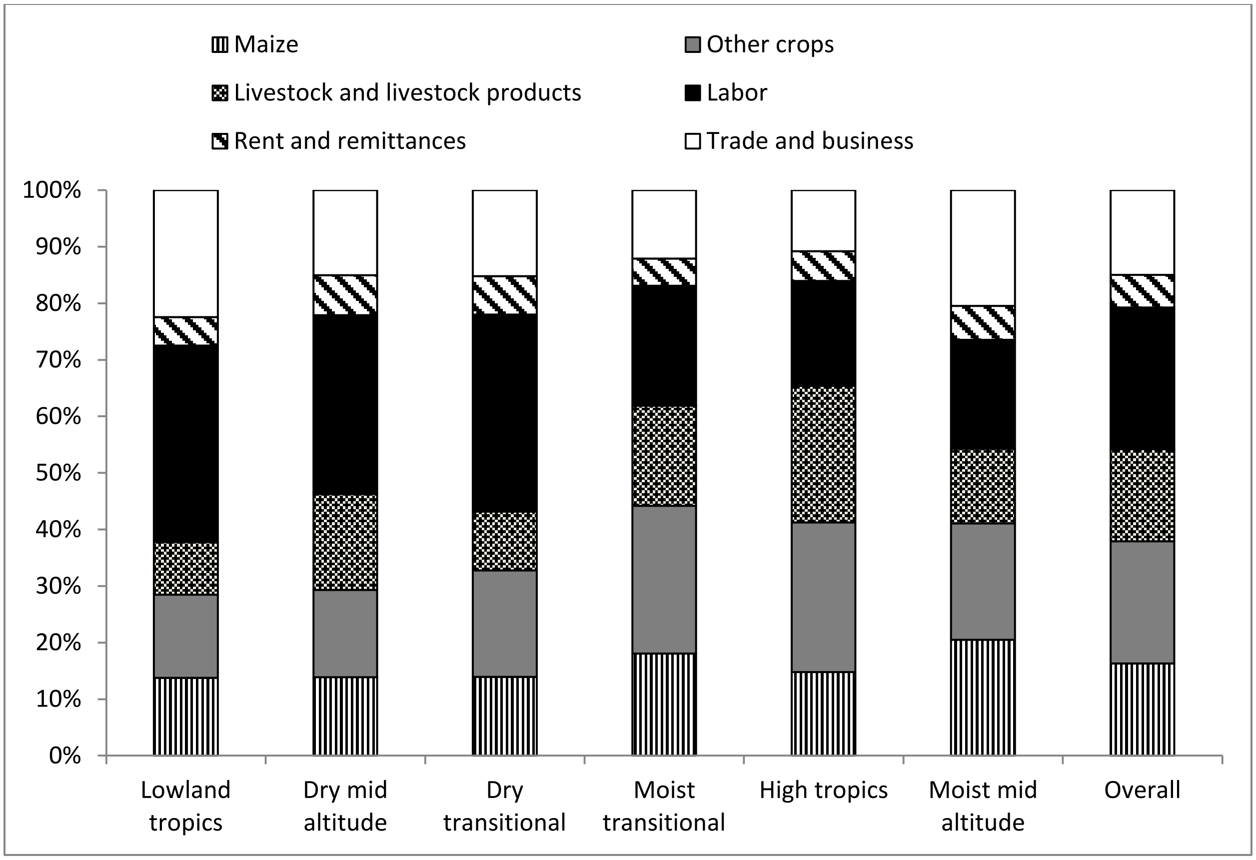

Maize
Other crops
Livestock and livestock products
Labor
Rent and remittances
Trade and business
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
Lowland tropics
Dry mid altitude
Dry transitional
Moist transitional
High tropics
Moist mid altitude
Overall

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

	Maize		Other crops		Livestock		Labor		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
Fertilizers	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	

***, **, and * indicate significant differences in income shares between adopters and non-adopters at the 1%, 5%, and 10% level, respectively (*t*-test results).

Table 4 compares mean household incomes between adopters and non-adopters of each of the seven technologies. Adopters of input-intensive technologies have significantly higher incomes than non-adopters. In comparison, income differences between adopters and non-adopters of NRM technologies are less pronounced. However, as was discussed previously, these comparisons cannot be interpreted as impacts of technology adoption because of systematic differences between adopters and non-adopters. PSM results that account for confounding factors are presented in the following section.

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)
Fertilizer	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)	(315841)	(80,556)	(68,993)
Manure	265,995	242,681	48,922**	40,183
	(352,262)	(264,715)	(80,658)	(47,024)

***, **, and * indicate significant differences in incomes between adopters and non-adopters at the 1%, 5%, and 10% level, respectively (*t*-test results). Incomes are measured in Kenyan Shilling (KES per year); 1 US dollar = 100 KES. Standard deviations are shown in parentheses.

4.2. Impact results

PSM involves estimating propensity scores for each of the technologies using logit models. The logit model results for the seven technologies considered in this study are shown in the appendix Table A.1. Using the same covariates we also estimated logit models to explain the adoption of relevant technology combinations and to calculate propensity scores. The propensity scores for adopters and non-adopters were then matched and balanced to find credible counterfactuals. Evidence of successful matching is presented in the appendix Table A.2 in terms of reduced bias, low pseudo-R^2, 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 the appendix Figure A.1). 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; it only represents 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 the appendix Table A.3. 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 robustness check, 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.

Table 5 presents the estimated ATTs for the seven technologies and relevant combinations, with total household income and per capita income as outcome variables. Also shown are the 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% in terms of unobserved characteristics in order to render the estimated ATT insignificant. We only report gamma levels for significant ATT estimates. For estimates with low gamma levels more caution is warranted. The impact magnitudes and significance levels are quite robust to the chosen matching method. In the following paragraphs we concentrate on discussing results obtained with radius matching.

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 51,527 Kenyan Shillings (KES), which is equivalent to a gain of approximately 16%. The effect of zero tillage on per capita income is positive but insignificant. Manure adopters increase their total household 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%, 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 fertilizer does not contribute to household income gains. The estimated effect for fertilizer is even negative, albeit not statistically significant. This is in spite of the fact that fertilizer adopters are significantly richer than non-adopters, as was shown above in Table 4.

What are reasons for the insignificant effect of fertilizer adoption? Average fertilizer rates used in the Kenyan small farm sector are low and many of the soils are nutrient-depleted, hence positive yield and income effects of fertilization should actually be expected. However, many of the farmers use fertilizers 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 sulfur (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 fertilizers alone may not always result in expected yield gains (Chianu et al., 2012). This could also explain the notable differences in impacts between chemical fertilizers and manure, because manure contains micronutrients as well. When we confine the group of chemical fertilizer adopters to those that used fertilizers with micronutrients, the negative ATT estimate turns positive, even though it remains insignificant due to large standard errors (Table 5). It should be mentioned that water constraints may also limit the effectiveness of chemical fertilizers. Since we only have data from 2012, which happened to be relatively dry in some parts of Kenya, the estimated effects should not be over interpreted.

We now look at the effects for technology combinations in Table 5. The adoption of improved seeds together with chemical fertilizers does not lead to a significant ATT, which is related to the disappointing fertilizer effect discussed previously. However, combining improved seeds with manure results in highly significant impacts on household (15%) and per capita incomes (18%). The combination of improved seeds with zero tillage also increases household income beyond what both technologies achieve when adopted alone. And 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 exist between input-intensive and NRM technologies. 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.

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

		Radius matching (RM)			Kernel based matching (KBM)		
	Impact on	ATT	Std error	Gamma level	ATT	Std error	Gamma level
Improved seeds (treated n=1,132)	Household income	39,885**	20,371	1.20-1.25	38,811**	20,562	1.20-1.25
	Per capita income	5,668	3,73		5,454	3,766	
Improved seeds for 3 AEZ[a] (treated n=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
Fertilizer (treated n=807)	Household income	-10,679	24,738		-13,280	24,957	
	Per capita income	98	4,477		638	4,509	
Fertilizer (incl. micronutrients) (treated n=444)	Household income	28,266	22,137		26,771	22,200	
	Per capita income	2,391	4,774		2,037	4,789	
Terraces (treated n=731)	Household income	-11,162	22,456		-9,457	22,769	
	Per capita income	2,140	4,970		2,526	5,041	
Soil bunds (treated n=270)	Household income	22,171	26,802		21,466	26,916	
	Per capita income	6,679	6,546		6,343	6,566	
Crop residue (treated n=797)	Household income	10,859	23,699		10,325	24,112	
	Per capita income	-858	5,365		-657	5,463	
Zero tillage (treated n=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 (treated n=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 + fertilizer (treated n=759)	Household income	-7,996	23,313		-10,314	23,370	
	Per capita income	991	4,449		140	4,457	
Improved seeds + manure (treated n=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 + fertilizer + manure (treated n=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 (treated n=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 (treated n=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 (treated n=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+ fertilizer (treated n=101)	Household income	63,133	41,987		61,269	42,425	
	Per capita income	9,160	8,994		9,237	9,093	

Improved seeds+ zero tillage + manure (treated n=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 (treated n=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 (treated n=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+ fertilizer (treated n=281)	Household income	16,296	25,175		18,208	25,476	
	Per capita income	6,990	5,765		7,273	5,825	

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

5. Conclusion

Sustainable intensification is seen by many as the new paradigm for increasing agricultural productivity and incomes 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, fertilizers, 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 analyze 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. Third, we could only analyze 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 a more comprehensive understanding.

References

Aakvix, A., 2001. Bounding a matching estimator; the case of a Norwegian training program. *Oxford Bulletin of Economics and Statistics* 63(1), 115-143.

Abadie, A., Imbens, G. W., 2006. Large sample properties of matching estimators for average treatment effects. *Econometrica*, 74(1), 235–267.

Altieri, M.A., 2002. Agroecology: the science of natural resource management for poor farmers in marginal environments. *Agriculture, Ecosystems and Environment* 93, 1–24.

Asfaw, S., Shiferaw, B., Simtowe, F., Lipper, L., 2012. Impact of modern agricultural technologies on small holder welfare: Evidence from Tanzania and Ethiopia. *Food Policy* 37, 283-295.

Baker, J., 2000. *Evaluating the Impact of Development Projects on Poverty. A Handbook for Practitioners*. The World Bank Washington, D.C.

Becerril, J., Abdulai, A., 2010. The impact of improved maize varieties on poverty in Mexico: A propensity score matching approach. *World Development* 38(7), 1024–1035.

Caliendo, M., Kopeinig, S., 2008. Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys* 22, 31–72.

Chianu, J. N., Chianu, J. N., Mairura, F., 2012. Mineral fertilizers in the farming systems of sub-Saharan Africa. A review. *Agronomy for Sustainable Development* 32(2), 545-566.

Dehejia, R.H., Wahba, S., 2002. Propensity score matching methods for non-experimental causal studies. *Review of Economics and Statistics* 84(1), 151–161.

Di Falco, S., Veronesi, M., 2013. How can African agriculture adapt to climate change? A counterfactual analysis from Ethiopia. *Land Economics* 89(4), 743-766.

Evenson, R.E., Gollin D., 2003. Assessing the impact of the green revolution, 1960-2000. *Science* 300, 758-762.

Foresight, 2011. *The Future of Food and Farming*. The Government Office for Science, London.

Gebremedehin, B., Swinton, S.M., 2003. Investment in soil conservation in northern Ethiopia: the role of land tenure security and public programs. *Agricultural Economics* 29, 69-84.

Godfray, H. C. J., Beddington, J. R., Crute, I. R., Haddad, L., Lawrence, D., Muir, J. F., Pretty, J., Robinson, S., Thomas, S.M., Toulmin, C., 2010. Food security: the challenge of feeding 9 billion people. *Science* 327, 812-818.

Greenpeace Africa, 2015. *Fostering Economic Resilience: The Financial Benefits of Ecological Farming in Kenya and Malawi*. Greenpeace Africa, Johannesburg.

Hassan, R.M., ed., 1998. *Maize Technology Development and Transfer: A GIS Application for Research Planning in Kenya*. CAB International, Wallingford.

Heckman, J., Vytlacil, E., 2005. Structural equations, treatment effects, and econometric policy evaluation. *Econometrica* 73, 669-738

Hertel, T., 2015. The challenges of sustainably feeding a growing planet. *Food Security* 7, 185-198.

Hobbs, P.R., Sayre, K., Gupta, R., 2008. The role of conservation agriculture in sustainable agriculture. *Philosophical Transactions of the Royal Society B* 363, 543-555.

Imbens, G.W., Woodridge, J.M., 2009 Recent developments in the econometrics of program evaluation. *Journal of Economic Literature* 47(1), 5-86.

Jaetzold, R., Schmidt, H., Hornetz, B., Shisanya, C., 2005. *Farm Management Handbook of Kenya; Second Edition*. Ministry of Agriculture, Nairobi.

Kabunga, N.S., Dubois, T., Qaim, M., 2014. Impact of tissue culture banana technology on farm household income and food security in Kenya. *Food Policy* 45, 25-34.

Kassie, M., Zikhali, P., Pender, J., Kohlin, G., 2010. The economics of sustainable land management practices in the Ethiopian highlands. *Journal of Agricultural Economics* 61, 605–627.

Kassie, M., Teklewold, H., Jaleta, M., Marenya, P., Erenstein, O., 2015a. Understanding the adoption of sustainable intensification practices in eastern and southern Africa. *Land Use Policy* 42, 400–411.

Kassie, M., Teklewold, H., Marenya, P., Jaleta, M., Erenstein, O., 2015b. Production risks and food security under alternative technology choices in Malawi: application of a multinomial endogenous switching regression. *Journal of Agricultural Economics* 66, 640-659.

KNBS, 2010. *Population Census*. Kenya National Bureau of Statistics, Nairobi.

Lunt, M., 2014. Selecting an appropriate caliper can be essential for achieving good balance with propensity score matching. *American Journal of Epidemiology* 179(2), 226-235.

Mathenge, M.K., Smale, M. Olwande, J., 2014. The impacts of hybrid maize on the welfare of farming households in Kenya. *Food Policy* 44, 262-171.

Pender, J., Gebremedhin, B., 2007. Determinants of agricultural and land management practices and impacts of crop production and household income in the highlands of Tigray Ethiopia. *Journal of African Economies* 3, 395-450.

Pretty, J., Toulmin, C., Williams, S., 2011. Sustainable intensification in African agriculture. *International Journal of Agricultural Sustainability* 9(1), 5-24.

Ravallion, M., 2001. The mystery of the vanishing benefits: an introduction to impact evaluation. *World Bank Economic Review* 15(1), 115-140.

Rosenbaum, P., Rubin, D. B., 1983. The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70, 41-55.

Ryan, J., Rashid, A., Torrent, J., Kwong Yau, S., Ibrikci, H., Sommer, R., Bulent Erenoglu, E., 2013. Micronutrient constraints to crop production in the middle East-West Asia Region: significance, research, and management. *Advances in Agronomy* 122, 1-84.

Sanchez P. A., 2002. Soil fertility and hunger in Africa. *Science* 295, 2019–2020.

Shiferaw, B., Kassie, M., Jaleta, M., Yirga, C., 2014. Adoption of improved wheat varieties and impacts on household food security in Ethiopia. *Food Policy* 44, 272-284.

Wainaina, P., Tongruksawattana, S., Qaim, M., 2014. Tradeoffs and complementarities in the adoption of improved seeds, fertilizer, and natural resource management technologies in Kenya. *GlobalFood Discussion Paper* 51, Georg-August-University of Goettingen, Goettingen.

Wollni, M., Lee, D.R., Janice L.T., 2010. Conservation agriculture, organic marketing, a collective action in the Honduran hillsides. *Agricultural Economics* 41, 373–384.

Appendix

Table A.1: Logit models for estimating propensity scores

	Improved seeds	Improved seeds (3 AEZs)	Fertilizer	Terracing	Soil bunds	Crop residue	Zero tillage	Manure
Male		-0.377	-0.085	0.288*	-0.135	-0.075	-0.035	-0.282
		(0.308)	(0.189)	(0.167)	(0.183)	(0.171)	(0.241)	(0.179)
Age	-0.002	0.001	0.003	-0.004	-0.008	-0.021***	-0.012*	0.011**
	(0.007)	(0.009)	(0.005)	(0.005)	(0.006)	(0.005)	(0.007)	(0.005)
Education	0.142***	0.180***	0.090***	-0.015	0.011	0.005	-0.052**	0.011
	(0.024)	(0.037)	(0.020)	(0.019)	(0.017)	(0.016)	(0.025)	(0.017)
Household size	0.041	0.004	-0.035	0.026	-0.026	0.105***	0.037	-0.028
	(0.036)	(0.048)	(0.028)	(0.025)	(0.028)	(0.031)	(0.037)	(0.024)
Farms size		0.019	-0.002	-8.36E-04	-0.033**	0.032***	0.024***	-0.039***
		(0.016)	(0.008)	(0.007)	(0.015)	(0.019)	(0.008)	(0.008)
TLU		0.024	-0.039**	-0.008	0.009	0.005	-0.007	0.041***
		(0.020)	(0.016)	(0.011)	(0.013)	(0.011)	(0.016)	(0.014)
Occupation		-0.352	0.051	0.231	-0.018	-0.114	0.229	0.178
		(0.283)	(0.176)	(0.161)	(0.189)	(0.164)	(0.240)	(0.162)
Productive assets	0.199***	0.109	0.184***	0.083**	-0.006	-0.101**	-0.012	0.062
	(0.067)	(0.110)	(0.050)	(0.040)	(0.048)	(0.042)	(0.056)	(0.043)
Off farm income	-1.508***	-1.795***	-0.536**	0.273	-0.399	-0.254	0.183	-0.245
	(0.328)	(0.422)	(0.249)	(0.216)	(0.255)	(0.238)	(0.334)	(0.227)
Group membership		0.052	0.056	0.307*	0.309	0.154	-0.249	0.613***
		(0.311)	(0.198)	(0.182)	(0.255)	(0.196)	(0.259)	(0.185)
Market distance	-0.107**	-0.174***	-0.005	0.027	-0.010	0.054	0.053	-0.057
	(0.048)	(0.060)	(0.040)	(0.038)	(0.042)	(0.041)	(0.055)	(0.038)
Credit		0.277	0.422**	0.024	-0.009	0.126	0.386*	-0.207
		(0.296)	(0.178)	(0.160)	(0.181)	(0.176)	(0.213)	(0.161)
Info on zero tillage							1.547***	
							(0.189)	
Info on crop residues						0.426***		
						(0.135)		
Info on soil management				0.421***	0.438**			
				(0.146)	(0.184)			
Info improved seeds	0.787***	1.383***						
	(0.241)	(0.333)						

	Improved seeds	Improved seeds (3 AEZs)	Fertilizer	Terracing	Soil bunds	Crop residue	Zero tillage	Manure
Own land		-0.905	-0.433	0.101	0.024	-0.213	-0.218	0.323
		(0.515)	(0.353)	(0.256)	(0.286)	(0.266)	(0.358)	(0.246)
Fertile land		0.260	-0.492***	-0.064	-0.441**	-0.131	0.179	-0.185
		(0.240)	(0.155)	(0.135)	(0.158)	(0.141)	(0.187)	(0.136)
Slopy land		0.413*	0.491***	0.988***	0.094	0.077	-0.041	0.212
		(0.227)	(0.154)	(0.142)	(0.165)	(0.149)	(0.194)	(0.140)
Drought	-0.045**	-0.056**	-0.099***	-0.011	-0.004	0.037*	0.009	-0.058***
	(0.018)	(0.025)	(0.019)	(0.015)	(0.018)	(0.020)	(0.021)	(0.016)
Flooding			0.059	0.033	-0.077	0.039	-0.236***	-0.017
			(0.059)	(0.043)	(0.051)	(0.062)	(0.078)	(0.042)
Dry mid-altitude	-0.291	-0.414	-0.548	1.685***	0.292	-2.508***	-0.740**	1.325***
	(0.315)	(0.342)	(0.336)	(0.299)	(0.409)	(0.381)	(0.366)	(0.290)
Dry transitional	0.659*		1.086***	2.061***	0.135	-2.391***	-1.073**	1.046***
	(0.370)		(0.329)	(0.326)	(0.419)	(0.386)	(0.418)	(0.303)
Moist transitional	1.766***		1.952***	0.673**	0.575	-0.934**	-0.233	-0.400
	(0.425)		(0.338)	(0.298)	(0.402)	(0.379)	(0.359)	(0.278)
High tropics	1.083***		2.416***	-0.131	1.254***	-1.169***	-0.149	-0.755***
	(0.381)		(0.377)	(0.313)	(0.403)	(0.384)	(0.392)	(0.288)
Moist mid-altitude	-0.884***	-1.047***	0.552*	0.402	0.194	0.0767	-0.226	0.271
	(0.313)	(0.341)	(0.332)	(0.302)	(0.417)	(0.409)	(0.376)	(0.288)
Constant	-0.787	0.480	-1.793***	-3.018***	-1.763**	2.547***	-1.410	-0.823
	(0.742)	(1.177)	(0.689)	(0.636)	(0.822)	(0.667)	(0.870)	(0.594)
Pseudo R^2	0.225	0.176	0.274	0.130	0.051	0.200	0.118	0.117

***, **, * significant at 1%, 5%, and 10% level, respectively. Figures in parentheses are standard errors.

Table A.2: Balancing tests before and after matching

Technologies	Before matching			After RM			After KBM		
	Pseudo R^2	Mean bias	LR $\chi 2$ p value	Pseudo R^2	Mean bias	LR $\chi 2$ P value	Pseudo R^2	Mean bias	LR $\chi 2$ P value
Improved seeds only	0.225	45.2	0.000	0.008	3.8	0.065	0.008	3.8	0.059
Improved seeds for the 3 AEZs	0.176	26.3	0.000	0.008	3.7	0.986	0.009	3.6	0.982
Fertilizer only	0.274	30.5	0.000	0.013	4.2	0.204	0.013	4.3	0.198
Terracing only	0.130	17.7	0.000	0.006	2.6	0.981	0.005	2.6	0.994
Soil bunds only	0.051	11.9	0.000	0.005	3.5	1.000	0.003	2.5	1.000
Crop residue only	0.200	23.5	0.000	0.014	3.9	0.185	0.012	3.6	0.303
Zero tillage only	0.118	15.3	0.000	0.006	3.1	1.000	0.003	2.1	1.000
Manure only	0.117	18.6	0.000	0.007	3.1	0.775	0.006	3.0	0.891
Improved seeds+ fertilizer	0.255	28.6	0.000	0.013	4.0	0.294	0.013	4.1	0.349
Improved seeds + manure	0.097	16.5	0.000	0.003	2.5	1.000	0.002	2.0	1.000
Improved seeds+ fertilizer+ manure	0.124	19.5	0.000	0.003	2.6	1.000	0.002	2.2	1.000
Improved seeds+ zero tillage	0.115	17.0	0.000	0.007	3.5	1.000	0.006	3.3	1.000
Zero tillage+ crop residues	0.136	18.3	0.000	0.012	3.9	1.000	0.009	3.4	1.000
Zero tillage + manure	0.119	17.5	0.000	0.008	4.0	1.000	0.008	3.9	1.000
Zero tillage + fertilizers	0.140	20.9	0.000	0.011	4.6	1.000	0.008	3.7	1.000
Improved seeds + zero tillage+ manure	0.123	18.9	0.000	0.012	4.9	1.000	0.123	4.3	1.000
Terracing + manure	0.162	20.6	0.000	0.003	2.4	1.000	0.003	2.0	1.000
Improved seeds + terracing + manure	0.157	21.1	0.000	0.003	2.3	1.000	0.002	1.9	1.000
Improved seeds + terracing + manure + fertilizer	0.157	24.3	0.000	0.004	2.7	1.000	0.004	2.5	1.000

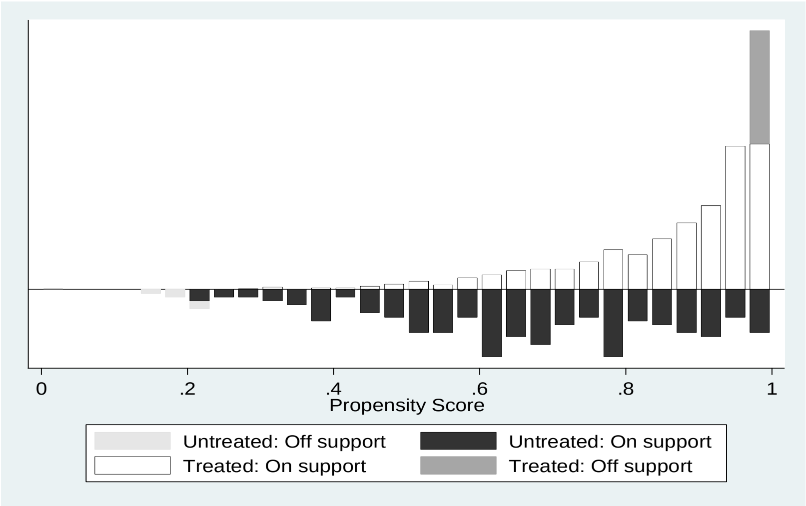
Table A.3: Differences in attributes between matched and unmatched adopters of improved seeds

Attribute	Matched adopters (n=976)		Unmatched (n=156)		P value
	Mean	Std dev	Mean	Std dev	
Household income	237,604***	273,507	504,455	616,763	0.0000
Per capita income	41,321***	48,712	96,219	154,012	0.0000
Propensity score	0.863***	0.130	0.985	0.077	0.0000
Education	7.49***	3.98	11.71	5.67	0.0000
Age	53.78	13.82	52.77	12.61	0.4141
Household size	6.50	2.53	6.28	2.33	0.3015
Productive assets	30,288***	141,507	159,452	339,407	0.0000
Off-farm income	0.483***	0.294	0.240	0.284	0.0000
Market distance	1.695***	1.646	1.247	1.239	0.0011
Drought	4.022***	4.299	2.083	2.170	0.0000
Dry mid-altitude	0.163***	0.370	0.000	0.000	0.0000
Dry transitional	0.178***	0.382	0.044	0.206	0.0000
Moist transitional	0.225***	0.418	0.776	0.419	0.0000
High tropics	0.198	0.399	0.190	0.393	0.8085
Moist mid-altitude	0.166***	0.373	0.006	0.080	0.0000

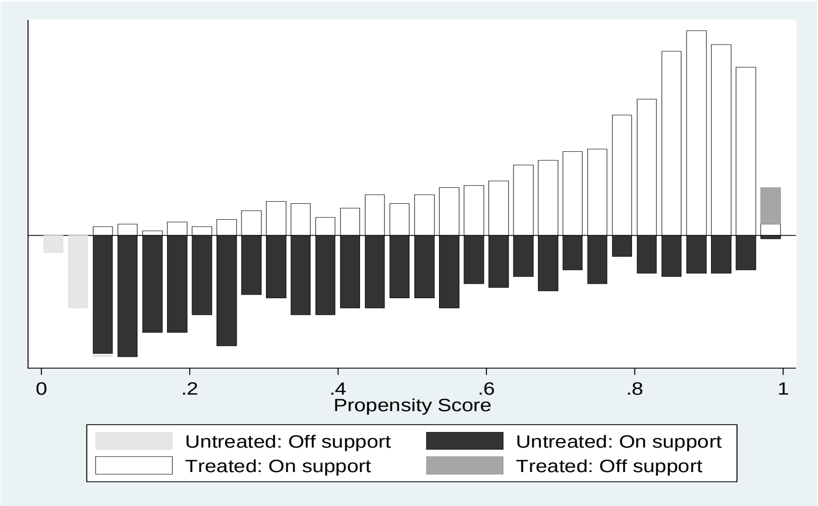
***, **, * significant at 1%, 5%, and 10% level, respectively.

Figure A.1: Propensity score histograms using radius matching showing common support between treated and untreated

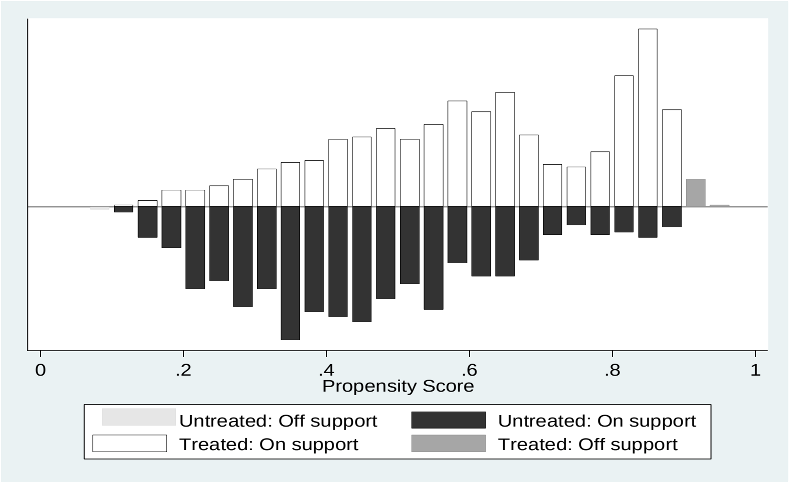
Improved seeds



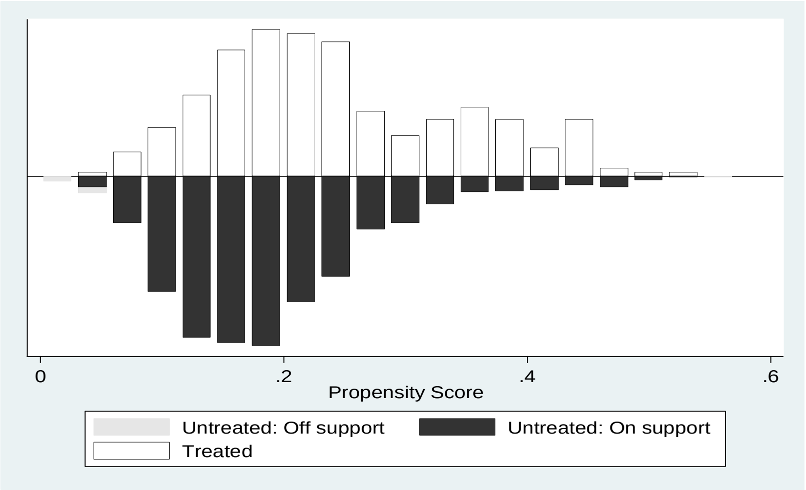
Fertilizers



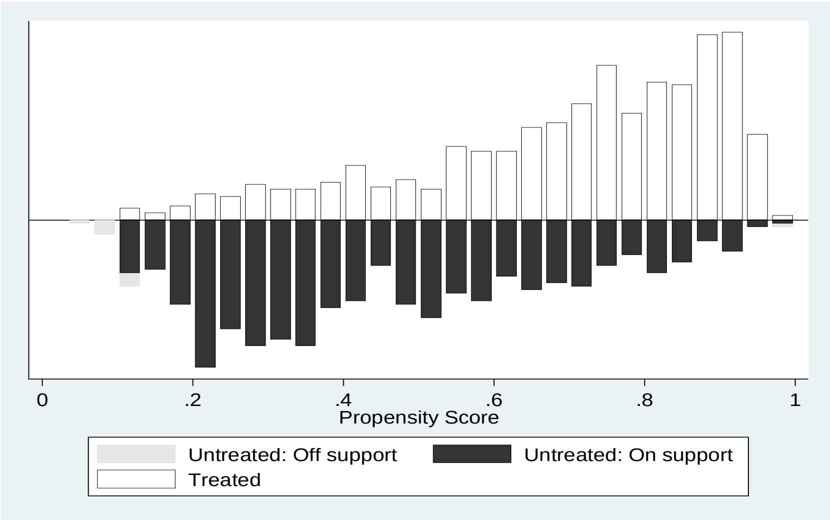
Terracing



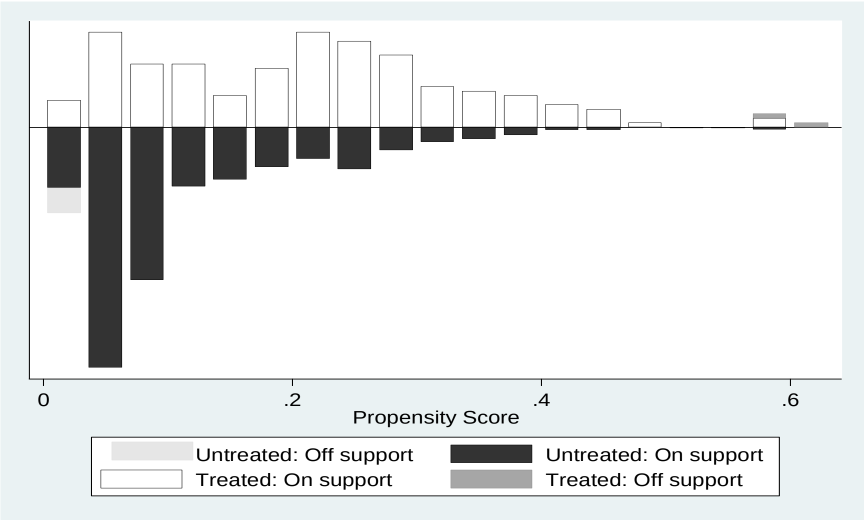
Soil bunds



Crop residues



Zero tillage



Manure