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The Economics of Sustainable Land Management Practices in the Ethiopian Highlands

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Abstract

This article uses data from household- and plot-level surveys conducted in the highlands of the Tigray and Amhara regions of Ethiopia. We examine the contribution of sustainable land management (SLM) practices to net value of agricultural production in areas with low vs. high agricultural potential. A combination of parametric and non-parametric estimation techniques is used to check result robustness. Both techniques consistently predict that minimum tillage (MT) is superior to commercial fertilisers (CFs), as are farmers' traditional practices (FTPs) without CFs, in enhancing crop productivity in the low agricultural potential areas. In the high agricultural potential areas, in contrast, use of CFs is superior to both MT and FTPs without CFs. The results are found to be insensitive to hidden bias. Our findings imply a need for careful agro-ecological targeting when developing, promoting and scaling up SLM practices.

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JEL classifications: *C21, Q12, Q15, Q16, Q24.*

1. Introduction

The Ethiopian economy is supported by its agricultural sector, which is also a fundamental instrument for poverty alleviation, food security and economic growth. However, the sector continues to be undermined by land degradation – depletion of soil organic matter, soil erosion and lack of adequate plant nutrient supply (Grepperud, 1996; Pender *et al*., 2006). There is, unfortunately, plenty of evidence that these problems are getting worse in many parts of the country, particularly in the highlands (Pender *et al*., 2001). Furthermore, climate change is anticipated to accelerate the land degradation in Ethiopia. As a cumulative effect of land degradation, increasing population pressure and low agricultural productivity, Ethiopia has become increasingly dependent on food aid. In most parts of the densely populated highlands, cereal yields average less than 1 metric ton/ha (Pender and Gebremedhin, 2007). Such low agricultural productivity, compounded by recurrent famine, contributes to extreme poverty and food insecurity.

Over the last three decades, the government of Ethiopia and a consortium of donors have undertaken a massive programme of natural resource conservation to reduce environmental degradation, poverty and increase agricultural productivity and food security. However, the adoption and adaptation rate of sustainable land management (SLM) practices is low. In some cases, giving up or reducing use of technologies has been reported (Kassa, 2003; Tadesse and Kassa, 2004). Several factors may explain the low technology adoption rate in the face of significant efforts to promote SLM practices. These include a poor extension service system, blanket promotion of technology to very diverse environments, top–down approach to technology promotion, late delivery of inputs, low return on investments, escalation of fertiliser prices, lack of access to seasonal credit and production and consumption risks (Kassa, 2003; Bonger *et al*., 2004; Dercon and Christiaensen, 2007; Kebede and Yamoah, 2009; Spielman *et al*., 2010).

The extension system in Ethiopia, the Participatory Demonstration and Training Extension System, is mainly financed and provided by the public sector, and has emphasised the development and distribution of standard packages to farmers. These packages typically include seeds and commercial fertiliser (CF), credit needed to buy inputs, soil and water conservation, livestock and training and demonstration plots intended to facilitate adoption and use of the inputs. Although the promotion of CFs and improved seeds often includes extension workers demonstrating their use to farmers, this is not the case with natural resource management technologies, such as soil and water conservation technologies. Additionally, efforts promoting other SLM practices have tended to focus on arresting soil erosion without considering the underlying socioeconomic causes of low soil productivity. As a result practices have been promoted which are unprofitable, risky or ill-suited to farmers' resource constraints (Amsalu, 2006; Pender *et al*., 2006).[2]

The rural credit market has also been subject to extensive state intervention. To stimulate the uptake of agricultural technology packages, all regional governments in Ethiopia initiated a 100% credit guarantee scheme in 1994. For instance, under this system, about 90% of fertiliser is delivered on credit at below-market interest rates. To finance the technology packages, credit is extended to farmers by the Commercial Bank of Ethiopia (a state-owned bank) through cooperatives, local government offices, and – more recently –microfinance institutions. As farmers cannot borrow from banks as a result of collateral security problems, agricultural credit is guaranteed by the regional governments (Kassa, 2003; Spielman *et al*., 2010, forthcoming).

Although there are a few private-sector suppliers, the fertiliser market (imports and distribution) in all regions is mainly controlled by regional holding companies with strong ties to regional governments [NFIA (National Fertilizer Industry Agency), 2001; Spielman *et al*., 2010, forthcoming]. The government provides these holding companies with preferential treatment for the allocation of foreign exchange for imports and in the distribution of fertiliser, using government-administered credit to farmers under its large-scale extension intervention programme.

Despite claims by the Plan for Accelerated and Sustained Development to End Poverty that all rural development interventions should take into account the specificities of each agro-ecosystem and area, the package-driven extension approach is based on recommendations that show little variation across different environments (i.e. blanket recommendations). The packages are not site- or household-specific and are introduced through a 'quota' system. To date, a blanket recipe is the traditional approach for applying CFs[3] and other natural resource management technologies, irrespective of factors that limit agricultural productivity, such as the availability of water, soil types and local socioeconomic and agro-ecological variations, for example, between low and high agricultural potential areas[4] (Hundie *et al*., 2000; Croppenstedt *et al*., 2003; Kassa, 2003; Nyssen *et al*., 2004; Amsalu, 2006; Kassie *et al*., 2008; Kebede and Yamoah, 2009).

Except for CF and improved seeds, there are no technical recommendations (packages) for other natural resource management technologies. The standardised package approach and inflexible input distribution systems, which is used in Ethiopia to date, means that farmers have had little opportunity to experiment, learn and

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[2] The World Food Programme (2005) also noted that there is a growing agreement in the area of land rehabilitation and soil and water conservation that profitability and cost effectiveness have in the past been largely neglected. For many years, technical soundness and environmental factors have provided the only guiding principles for government and donors. The limited success of soil conservation programmes in Ethiopia in the past was largely a result of the 'top–down' approach to design and implementation.

[3] A blanket recommendation of 100 kg of diammonium phosphate and 100 kg of urea per hectare is promoted both in moisture stress and adequate areas (Hundie *et al*., 2000; Croppenstedt *et al*., 2003; Kassa, 2003).

[4] The Ethiopian Disaster Prevention and Preparedness Commission classified the country into drought-prone vs. non-drought-prone districts. Drought-prone districts are referred to as low agricultural potential districts and non-drought-prone districts as high agricultural potential districts.

adapt technologies to their own needs (Spielman *et al.*, 2010, forthcoming). Under this, it is probable that technologies are inappropriate to local conditions and unacceptable to farmers. As Keeley and Scoones (2004) note, the conservation interventions in the country have been supported by simplistic, often unjustified, claims, and these have had potentially negative impacts on poor peoples' livelihoods through their blanket application. Research has shown that in Ethiopia the economic returns on physical soil and water conservation investments, as well as their impacts on productivity, are greater in low moisture and low agricultural potential areas than in high moisture and high agricultural potential areas (Gebremedhin *et al.*, 1999; Benin, 2006; Kassie *et al.*, 2008). In wet areas, investment in soil and water conservation may not be profitable at the farm level, although there are positive social benefits from controlling runoff and soil erosion (Nyssen *et al.*, 2004).

To ensure sustainable adoption of technologies (including SLM practices) and beneficial impacts on productivity and other outcomes, rigorous empirical research is needed on what determines adoption and where particular SLM interventions are likely to be successful. Although there is substantial evidence on the adoption and productivity impacts of soil and water conservation measures in Ethiopia (Gebremedhin *et al.*, 1999; Shiferaw and Holden, 2001; Benin, 2006; Pender and Gebremedhin, 2007; Kassie *et al.*, 2008), the evidence of adoption and productivity impacts of other land management practices, including minimum tillage (MT) and CF use, is thin. Particularly, information is lacking on the relative contribution of these practices to agricultural productivity in low vs. high agricultural potential areas.

This article fills this gap by systematically exploring the productivity gains associated with adoption of MT and CF use in the high and low agricultural potential areas of the Ethiopian highlands. To do this, we use household- and plot-level data from the Tigray and Amhara administrative regions. The Tigray region is typical of the low moisture and generally low agricultural potential areas (Benin, 2006). The dataset of the Amhara region allows us to make an intraregional comparison of the performance of SLM practices because the dataset covers both low and high agricultural potential areas. This controls for the influence of public policy interventions, such as credit, extension services and input distribution systems on adoption and productivity, even though these interventions are similar across the two regions.

To achieve our objectives, and at the same time ensure robustness, we pursue an estimation strategy that employs both semi-parametric and parametric methods. The parametric analysis is based on matched samples of adopters and non-adopters, obtained from the Propensity Score Matching (PSM) process. This analysis is useful because impact estimates based on full (unmatched) samples are generally more biased than those based on matched samples, as comparison and prediction can be made based on incomparable samples and for regions of no common support (incomparable samples) where there are no similar adopters and non-adopters (Rubin and Thomas, 2000). Our results indicate that technology adoption and performance vary by agricultural potential, suggesting that technology development and promotion need targeted approaches.

2. Previous Research

A number of empirical studies have examined the productivity impacts of different land management practices, especially in Ethiopia and in developing countries in general. Most of these studies, however, have a bias towards soil conservation as a productivity-enhancing technology. In moisture-stressed area of eastern Ethiopia, Bekele's (2005) research showed that plots with soil bunds[5] produce higher yields than those without. Kassie and Holden (2006) used cross-sectional farm-level data to demonstrate that in high rainfall areas, such as those in northwestern Ethiopia, *fanya-juu* terracing has no productivity gains. Benin (2006) found a 42% increase in average yields owing to stone terraces in lower rainfall areas of Amhara region. Consistent with this, Pender and Gebremedhin (2006) used a sample from the semi-arid highlands of Tigray and found an average increase of 23% owing to stone terraces. Holden *et al.* (2001), in contrast, showed that soil and water conservation measures in the form of soil bunds and *fanya-juu* terraces have no significant impact on land productivity in high rainfall areas.

These mixed results suggest the need for careful, location-specific analyses. In particular, these studies indicate that the economic returns on physical soil and water conservation investments, as well as their impacts on productivity, vary by rainfall availability. Specifically, it indicates that these returns are greater in low moisture and low agricultural potential areas than in high moisture and high agricultural potential areas (see also Gebremedhin *et al.*, 1999; Shiferaw and Holden, 2001; Benin, 2006; Kassie *et al.*, 2008).

Results from other countries also support the importance of land management practices and specifically soil conservation measures in enhancing land productivity. Zikhali (2008) found that contour ridges have a positive impact on land productivity in Zimbabwe. Shively (1998, 1999) reported a positive and statistically significant impact from contour hedgerows on yield in the Philippines. Results by Kaliba and Rabele (2004) also supported a positive and statistically significant association between wheat yield and short- and long-term soil conservation measures in Lesotho.

Yet, as argued in the preceding section, most existing analyses on technology adoption ignore variations in location-specific characteristics, such as agro-ecosystems, soil type and water availability, in determining the feasibility, profitability and acceptability of different technologies. Furthermore, some studies broadly generalise technologies without being specific about their types. For instance, although Byiringiro and Reardon (1996) demonstrated a positive impact of soil conservation on farm-level productivity in Rwanda, the authors did not control for the type of conservation. This weakens the policy relevance of their work, as it could be the case that not all types of soil conversation enhance farm productivity; in other words, effective policy formulation needs information about individual technologies and their specific impacts on productivity. Policy recommendations resulting from such studies result in little variation across different agro-ecologies. Further, the estimated productivity impacts of the analysed technologies will be biased if crucial factors, such as heterogeneity of environments, are not controlled.

3. Econometric Framework and Estimation Strategy

Farmers are likely to select SLM practices for their plots, based on the endowments and abilities of the farm household and the quality and attributes of their plots

[5] Soil bunds are soil conservation structures that involve the construction of an earthen bund by excavating a channel and creating a small ridge on the downhill side.

(both observable and unobservable). Given this, simple comparisons of mean differences in productivity on plots with and without use of particular SLM practices are likely to give biased estimates of the impacts of these practices on productivity when observational data is used. Estimation of the effects of these practices on productivity of plots requires a solution to the counterfactual question of how plots would have performed had they not been subjected to these practices. We use PSM methods and a switching regression to overcome this and other econometric problems and ensure robust results.

3.1. The PSM method

We adopt the semi-parametric matching methods as one estimation technique to construct the counterfactual and reduce problems arising from selection biases. The main purpose of using matching is to find a group of non-treated plots (non-adopters) similar to the treated plots (adopters)[6] in all relevant observable characteristics; the only difference is that one group adopts SLM practices and the other does not.

After estimating the propensity scores, the average treatment effect for the treated plots (ATT) can then be estimated. Several matching methods have been developed to match adopters with non-adopters of similar propensity scores. Asymptotically, all matching methods should yield the same results. However, in practice, there are tradeoffs in terms of bias and efficiency with each method (Caliendo and Kopeinig, 2008). Here, we use nearest neighbour matching (NNM) and kernel-based matching (KBM) methods. The basic approach is to numerically search for 'neighbours' of non-treated plots that have a propensity score that is very close to the propensity score of treated plots. The seminal explanation of the PSM method is available in Rosenbaum and Rubin (1983), and its strengths and weaknesses are elaborated, for example, by Dehejia and Wahba (2002), Heckman *et al.* (1998), Caliendo and Kopeinig (2008) and Smith and Todd (2005).

The main purpose of the propensity score estimation is to balance the observed distribution of covariates across the groups of adopters and non-adopters. The balancing test is normally required after matching to ascertain whether the differences in covariates in the two groups in the matched sample have been eliminated, in which case the matched comparison group can be considered as a plausible counterfactual (Ali and Abdulai, 2010). Although several versions of balancing tests exist in the literature, the most widely used is the standardised mean difference (bias) between treatment and control groups suggested by Rosenbaum and Rubin (1985), in which they recommend that a standardised difference of greater than 20% should be considered too large and thus an indicator of failure of the matching process. Additionally, Sianesi (2004) propose a comparison of the pseudo R^2 and the P-values of the likelihood ratio tests obtained from the logit analysis before and after matching the samples. After matching, there should be no systematic differences in the distribution of covariates between the groups. As a result, the pseudo R^2 should be lower and the joint significance of

[6] We took adoption of either MT or CF as the treatment variable, whereas the net value of crop production per hectare – (net of the cost of fertiliser, seed, labor (for plowing, incorporating residues, and weeding), and draft animal power – were the outcomes of interest.

covariates should be rejected (or the *P*-values of the likelihood ratio should be insignificant).

If there are unobserved variables that simultaneously affect the adoption decision and the outcome variables, a selection or hidden bias problem might arise, to which matching estimators are not robust. Although we controlled for many observables, we checked the sensitivity of the estimated average adoption effects (ATT) to hidden bias, using the Rosenbaum (2002) bounds sensitivity approach. The purpose of the sensitivity analysis is to investigate whether inferences about adoption effects may be changed by unobserved variables. It is not possible to estimate the magnitude of such selection bias using observational data. Instead, the sensitivity analysis involves calculating upper and lower bounds with a Wilcoxon sign-rank test to test the null hypothesis of no adoption effect for different hypothesised values of unobserved selection bias.

3.2. Switching regression analysis

To check the robustness of our findings, we also used parametric analysis. Besides the non-randomness of selection in technology adoption, another important econometric issue is heterogeneity of the impacts of SLM practices. The standard econometric method of using a pooled sample of adopters and non-adopters (*via* a dummy regression model, where a binary indicator is used to assess the effect of MT or CF on productivity) might be inappropriate, as it assumes that the set of covariates has the same impact on adopters and non-adopters (i.e. common slope coefficients for both groups). This implies that MT and CF adoption have only an intercept shift effect. However, for our sample, a Chow test of equality of coefficients for adopters and non-adopters of MT and CF rejected the equality of the non-intercept coefficients. This supports the idea that it may be helpful to use techniques that capture the interaction of technology adoption and covariates and that differentiate each coefficient for adopters and non-adopters.

To deal with this problem, we employ a switching regression framework, such that the parametric regression equation to be estimated using multiple plots per household is:

$$\begin{cases} y_{hp1} = x_{hp}\beta_1 + u_{h1} + e_{hp1} & \text{if } d_{hp} = 1 \\ y_{hp0} = x_{h0}\beta_0 + u_{h0} + e_{hp0} & \text{if } d_{hp} = 0 \end{cases} \tag{1}$$

where y_{hp} is the net value of crop production per hectare obtained by household h on plot p, depending on its technology adoption status (d_{hp}); u_h captures unobserved household characteristics that affect crop production, such as farm management ability and average land fertility; e_{hp} is a random variable that summarises the effects of plot-specific unobserved components on productivity, such as unobserved variation in plot quality and plot-specific production shocks (e.g. microclimate variations in rainfall, frost, floods, weeds and pest and disease infestations); x_{hp} includes plot, household and village observed factors; and β is a vector of parameters to be estimated.

To obtain consistent estimates of the effects of MT and CF, we need to control for selection bias owing to unobservables, which occurs if the error terms in equation (1) are correlated with SLM adoption (d_{hp}). A standard method of addressing this is to estimate an endogenous switching regression model, which (given certain assumptions about the distributions of the error terms) is equivalent to adding the inverse Mills' ratio to each equation (Maddala, 1983). However, using the matched dataset from the PSM process in the parametric analysis results in insignificant first-stage logit models in an endogenous switching regression (i.e. the likelihood ratio test of the joint significance of all covariates is insignificant; see Table 3). This limits the usefulness of adding the inverse Mills' ratios from these first-stage logit models to the second-stage switching regressions. This is not surprising because, in the logit regression analysis, matched samples obtained from the NNM method[7] had no systematic differences in the distribution of covariates between adopters and non-adopters. Thus, we use instead an exogenous switching regression model, which assumes that the selection of the samples using the PSM method may reduce selection bias as a result of differences in unobservables.[8]

Our rich dataset of plot and household characteristics also helped reduce both household and plot (e_{hp}) unobserved effects. It is probable that observed plot quality is positively correlated with unobserved plot quality (Fafchamps, 1993; Levinsohn and Petrin, 2003). In terms of plot characteristics, the dataset includes plot slope, plot size, soil fertility, soil depth, soil colour, soil textures, soil erosion and water-logging in plots, plot distance from homestead, altitude and input use by plot.

Controlling for these econometric problems, the expected net value of crop production difference between adoption and non-adoption of MT and/or CF becomes:

$$E\left(y_{hp1}\middle|x_{hp}, u_{h1}, d_{hp} = 1\right) - E\left(y_{yp0}\middle|x_{hp}, u_{h0}, d_{hp} = 0\right) = x_{hp}(\beta_1 - \beta_0) + u_{h1} - u_{h0}. \tag{2}$$

The second term on the left-hand side of equation (2) is the expected value of y_{hp}, if the plot had not received MT or CF treatment. The difference between the expected outcome with and without the treatment, conditional on x_{hp}, is our parameter of interest in the parametric regression analysis. It is important to note that the parametric analysis is based on matched samples of adopters and non-adopters obtained from the PSM process to ensure comparable observations.

4. Data and Descriptive Statistics

Data from household- and plot-level surveys conducted in 1998 and 2001 in the highlands (above an altitude of 1,500 m above sea level) of the Tigray and Amhara regions of Ethiopia are used to explore the contribution of MT and CF to net value of agricultural production in low vs. high agricultural potential areas. A stratified random sample of 99 peasant associations[9] was selected from highland areas of the

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[7] We focus on the NNM method because, compared with other weighted matching methods, such as KBM, the NNM method allows us to identify the specific matched observations that enter the calculation of the ATT, which we then use for parametric regressions.

[8] However, it is worth noting that using the matched sample may undermine the ability to detect and correct for selection on unobservables.

[9] Known as *kebele* in Ethiopia, this is the lowest administrative unit in the government structure.

two regions. Strata were defined according to variables associated with moisture availability (one major factor affecting agricultural productivity), market access and population density.

In the Amhara region, secondary data were used to classify the districts according to access to an all-weather road, the 1994 rural population density (greater or less than 100 persons/km^2), and whether the area is drought-prone (following the definition of the Ethiopian Disaster Prevention and Preparedness Commission). The Tigray region is typically a low moisture and generally low agricultural potential region (Benin, 2006). The peasant associations in this region were stratified by whether an irrigation project was present or not, and for those without irrigation, by distance to the district's towns (greater or less than 10 km). The dataset from the Amhara region includes 435 farm households, 98 villages and 1,434 plots, whereas the Tigray dataset includes 500 farm households, 100 villages and 1,797 plots. As a result of missing values for some of the explanatory variables, the numbers of observations used in the final sample are 1,365 (396) and 1,113 (357) plots (households) in the Amhara and Tigray regions, respectively.

Table 1 presents the descriptive statistics of variables used in the analysis; 13.4% and 34.9% of the total sample plots in the Tigray region, and 14.6% and 30.3% in the Amhara region used MT and CF, respectively. MT plots did not receive herbicides or pesticides, except for three plots in the Amhara region. A simple mean comparison test indicated that CF use and draft animal use per hectare are lower on MT plots than on non-MT plots (see Table 2). There is, however, no statistically significant difference in labour use between the two types of plots. To take into account input use differences in the analysis, input costs (fertiliser; seed; labour for plowing, incorporating residues and weeding; draft animals) were deducted from the total value of crop production.

The mean plot altitude, which is closely associated with temperature and microclimates, are 2,179 and 2,350 m above sea level for the Tigray and Amhara regions, respectively. Compared with the Tigray region, the Amhara region has relatively good rainfall, with an average annual rainfall of 1,981 mm, whereas it is 641 mm in the Tigray region. The mean population density was 141 persons/km^2 in the Tigray and 144/km^2 in the Amhara region.

In addition to these variables, several plot characteristics, household characteristics and endowments and village-/district-level variables are included in the empirical model. Farmer technologies and production decisions may also be inhibited by limited access to input and output markets, lack of sufficient credit to acquire inputs and make necessary investments, and inadequate information about, and unfamiliarity with technologies. To capture such constraints, access to credit, extension services and market variables are included in the regression models. The choice of these variables is guided by economic theory and previous empirical research. Given missing and/or imperfect markets in Ethiopia, the households' initial resource endowments and characteristics are expected to play a role in investment and production decisions and are thus included in the analysis. Including the observed plot characteristics also helps address selection bias as a result of plot heterogeneity, as observable plot characteristics are likely to be correlated with the unobservable, as noted before.

Table 1

Descriptive statistics of variables used in the empirical analysis

Variables	Mean Amhara	Mean Tigray	Variables	Mean Amhara	Mean Tigray
Gross crop revenue* (ETB/ha)	2,237.85	1,831.57	Net crop revenue** (ETB/ha)	2,140.85	1,728.67
Household-level variables					
Gender of household head (1 = male; 0 = female)	0.92	0.83	Oxen (number owned by household)	N/A	1.22
Age of household head (years)	44.94	48.37	Extension contact (1 = yes; 0 = otherwise)	0.58	0.13
Household size (number of household members)	6.59	5.58	Farm size (ha)	1.60	1.06
Education level of household head (years)	2.46	N/A	Non-farm work (1 = if farmer involved in nonfarm work; 0 = otherwise)	0.29	N/A
Household head is illiterate (1 = yes; 0 = otherwise)	N/A	0.87	Credit (1 = if farmer has access to credit; 0 = otherwise)	0.39	0.70
Household head has schooling to grades 1 and 2 (1 = yes; 0 = otherwise)	N/A	0.07	Membership (1 = if farmer holds any organisation membership; 0 = otherwise)	N/A	0.14
Household head has schooling above grade 3 (1 = yes; 0 = otherwise)	N/A	0.06	Silt soil in plot [1 = yes; 0 = otherwise (CF)]	0.33	0.22
Plot-level variables					
Fertiliser use (1 = if plot received fertiliser; 0 = otherwise)	0.30	0.35	Clay soil in plot (1 = yes; 0 = otherwise)	0.12	0.31
Minimum tillage (1 = if plot received minimum tillage; 0 = otherwise)	0.15	0.13	Loam soil in plot (1 = yes; 0 = otherwise)	0.43	0.3
Degree of plot slope	5.55	N/A	Shallow plot soil depth [1 = yes; 0 = otherwise (CF)]	N/A	0.21

Table 1 (*Continued*)

Variables	Mean		Variables	Mean	
	Amhara	Tigray		Amhara	Tigray
Plot size (ha)	0.39	0.30	Moderately deep plot soil depth (1 = yes; 0 = otherwise)	N/A	0.40
Red soil in plot (1 = yes; 0 = otherwise)	0.35	0.39	Deep plot soil depth (1 = yes; 0 = otherwise)	N/A	0.39
Black soil in plot [1 = yes; 0 = otherwise (CF)]	0.31	0.23	Flat plot slope [1 = yes; 0 = steep slope (CF)]	N/A	0.62
Gray soil in plot (1 = yes; 0 = otherwise)	N/A	0.24	Moderate plot slope, (1 = yes; 0 = steep slope)	N/A	0.30
Brown soil in plot (1 = yes; 0 = otherwise)	0.27	0.14	Steep plot slope (1 = yes; 0 = steep slope)	N/A	0.08
Sandy soil in plot (1 = yes; 0 = otherwise)	0.12	0.11	Top slope position (CF)	0.14	0.11
Livestock holdings (tropical livestock units)	2.56	9.08	Middle slope position	0.27	0.22
Bottom slope position	0.15	0.24	Distance from residence to plot (walking hours)	0.28	0.30
Not on slope position	0.44	0.43	Crop 1 (1 = if wheat, barley and oat crops; 0 = otherwise)	0.21	0.25
Soil bund on plot (1 = yes; 0 = otherwise)	0.07	0.02	Crop 2 (1 = if maize and sorghum crops; 0 = otherwise)	0.18	0.06
Stone bund on plot (1 = yes; 0 = otherwise)	0.17	0.07	Crop 3 (1 = if teff and millet crops; 0 = otherwise)	0.27	0.67
Plot irrigated (1 = yes; 0 = otherwise)	0.07	0.04	Crop 4 (1 = if legume crops; 0 = otherwise)	0.11	N/A
Waterlogged plot (1 = yes; 0 = otherwise)	0.11	N/A	Crop 5 (1 = if oil crops; 0 = otherwise)	0.04	N/A

Table 1 (*Continued*)

	Mean			Mean	
Variables	Amhara	Tigray	Variables	Amhara	Tigray
Plot not eroded (1 = yes; 0 = otherwise)	0.59	0.66	Crop 6 (1 = if vegetable crops; 0 = otherwise)	0.13	N/A
Plot moderately eroded (1 = yes; 0 = otherwise)	0.31	0.27	Crop 7 (1 = if fruit and other crops; 0 = otherwise)	0.07	N/A
Plot severely eroded (1 = yes; 0 = otherwise)	0.10	0.06	Crop 8 (1 = if other crops; 0 = otherwise)	N/A	0.02
Rented plot (1 = yes; 0 = otherwise)	0.11	0.13			
Village-/district-level variables					
Population density, i.e. village population (person/km^2)	143.50	140.84	Residence distance to extension office (walking hours)	0.72	N/A
Mean rainfall (mm)	1,980.72	641.18	Residence distance to input market (walking hours)	2.40	N/A
Altitude (m.a.s.l.)	2,350.39	2,179.35	Residence distance to all-weather road (walking hours)	N/A	1.88
Residence distance to district market (walking hours)	3.46	1.98			
Sub-regional location					
Number of plots (households)	1,365 (396)	1,113 (357)			

Notes: *ETB, Ethiopian birr; **Costs for fertilizer, labour (for ploughing, incorporating residues, and weeding) and animal power for ploughing deducted from value of crop production. CF, commercial fertiliser; N/A, not applicable; m.a.s.l., metres above sea level.

Table 2
Mean input use difference between minimum tillage and non-minimum tillage plots

	Fertiliser (kg/ha)		Oxen (oxen days/ha)		Labour (person days/ha)	
	Mean	Mean difference	Mean	Mean difference	Mean	Mean difference
Tigray region						
Minimum tillage plots	21.61	27.12 (8.62)***	17.59	13.18 (3.07)***	70.67	7.92 (11.91)
Non-minimum tillage plots	48.73		30.97		78.60	
Amhara region						
Minimum tillage plots	13.13	11.38 (3.99)***	44.03	14.98 (4.91)***	106.51	19.41 (17.30)
Non-minimum tillage plots	24.51		59.01		125.93	

Notes: Standard errors are in parentheses; ***indicates significance at the 1% level.
Source: Own calculation.

5. Empirical Results

In this section, we present and discuss the results from the semi-parametric analysis, followed by results from the parametric estimations.

We conduct three comparisons to assess the impacts of MT and CF on productivity. These are: (i) CF vs. traditional tillage without CF, which is the farmers' traditional practice (FTP); (ii) MT without CF (MTWOCF) vs. FTP; (iii) MT vs. CF. In the article, we only present and discuss the estimates of the ATT. For the full logit model results used to estimate propensity scores and switching regression model estimates the reader is referred to Tables S1–S4.

5.1. Estimation of the propensity scores

Although we do not look at the logit model estimates here, we do discuss the quality of the matching process. The common support condition is imposed in the estimation by matching in the region of common support. A visual inspection of the density distributions of the propensity scores (Figure 1) indicates that the common support condition is satisfied, as there is substantial overlap in the distribution of the propensity scores of both treated and non-treated groups. The bottom half of each figure shows the propensity scores distribution for the non-treated, whereas the upper half refers to the treated individuals. The densities of the scores are on the y-axis.

As noted before, a major objective of propensity score estimation is to balance the distribution of relevant variables between the adopters and non-adopters, rather than obtaining precise prediction of selection into treatment. Table 3 presents results from covariate balancing tests before and after matching, using the NNM method. The results show that a substantial reduction in absolute standardised bias was obtained through matching. The P-values of the likelihood ratio test indicate that the joint significance of covariates was always rejected after matching, whereas

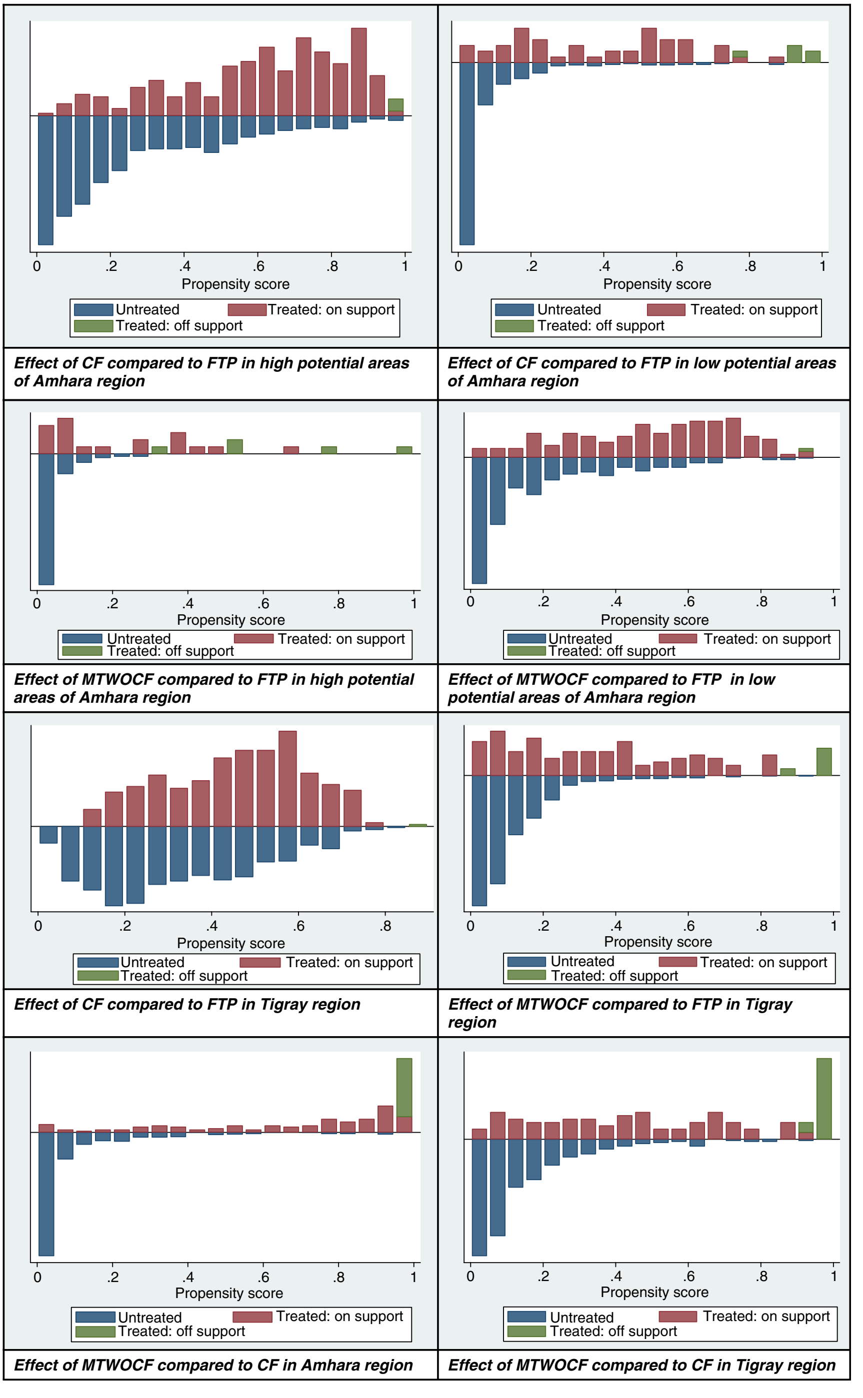

Figure 1. Propensity score distribution and common support for propensity score estimation

Notes: 'Treated: on support' indicates the observations in the adoption group who find a suitable comparison, whereas 'treated: off support' indicates the observations in the adoption group who did not find a suitable comparison. CF, commercial fertiliser; FTP, farmers' traditional practices; MTWOCF, minimum tillage without CF.

Table 3

Covariate balancing indictors before and after matching (CF adoption)

	Amhara region					Tigray region (entire sample)		
	CF vs. FTP		MTWOCF vs. FTP		MTWOCF vs. CF			
	High potential	Low potential	High potential	Low potential	Pooled sample	MTWOCF vs. FTP	CF vs. FTP	MTWOCF vs. CF
Before matching								
Mean standardised difference (bias)	19.37	20.47	23.05	22.46	37.96	16.45	14.35	23.89
Pseudo R^2	0.30	0.37	0.29	0.29	0.58	0.25	0.12	0.36
P-value of LR (χ^2)	0.000	0.000	0.031	0.000	0.000	0.000	0.000	0.000
After matching								
Mean standardised difference (bias)	6.03	11.68	12.80	9.79	11.94	10.13	2.11	10.13
PseudoR^2	0.06	0.03	0.11	0.09	0.14	0.11	0.00	0.11
P-value of LR (χ^2)	0.111	0.815	1.000	0.650	0.208	0.583	1.000	0.995

Notes: CF, commercial fertiliser; FTP, farmers' traditional practices; MTWOCF, minimum tillage without CF; likelihood ratio, LR.
Source: Own calculation.

it was never rejected before matching. The low pseudo R^2, low standardised bias and the insignificant P-values of the likelihood ratio tests suggest that there is no systematic difference in the distribution of covariates between both groups after matching. Thus, in the next section, we evaluate MT and CF adoption effects between adopters and non-adopters with similar observed characteristics.

5.2. PSM estimation of the ATTs

Table 4 reports the estimates of the ATTs estimated by NNM and KBM methods. The results are reported in terms of net value of crop production per hectare. The results reveal that using CF, compared with FTP and MT, is more productive in the high agricultural potential areas of the Amhara region (increasing net value of crop production in the range of ETB[10] 1,083 (US$127) and ETB 1,377 ($162) per hectare,[11] yet it shows no significant crop productivity impact in the low-potential agricultural areas of the Tigray and Amhara regions. These estimated impacts are large, relative to the average net value of crop production in the Amhara highlands, which averaged ETB 2,141 ($252) per hectare in the survey sample (see Table 1). This result is consistent with Pender and Gebremedhin (2007), who found that fertiliser use is not very profitable in the semi-arid environments of northern Ethiopia.

On the other hand, MT compared with CF and FTP is more productive in the low-potential agricultural areas, increasing net value of crop production by about ETB 715 ($84) and ETB 949 ($112) per hectare in Tigray region, and ETB 277 ($33) to ETB 510 ($60) per hectare in the Amhara region. These estimated impacts are also large relative to the average net value of crop production in the Tigray highlands, which averaged ETB 1,729 ($203) per hectare in the survey sample (see Table 1). However, MT has no significant crop productivity impact in the high agricultural potential areas of the Amhara region.[12]

It is likely that there are greater benefits of moisture conservation associated with MT in low-potential agricultural areas because moisture conservation in high agricultural potential areas contributes to problems such as water logging, weeds and pests. Benefits of MT could be greater in the low-potential areas if the benefits associated with the environment and its long-term impacts on plot productivity were included. The finding that SLM practices, such as MT, enhance crop productivity is consistent with findings of previous research based on data from Tigray. For example, empirical results in the Tigray region demonstrate the superiority, in terms of the impact on productivity, of using compost compared with CF (Kassie *et al.*,

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[10] The official exchange rate averaged about ETB 8.50 (Ethiopian birr) per US$1 during the survey period.

[11] In comparing MT with CF, we pool observations of low and high agricultural potential areas because covariate balancing tests were not satisfied when observations were split into low- and high-potential areas. This may be owing to the fact that there were few matched observations. For instance, the number of matched treated observations in the case of high-potential areas is reduced to 7, whereas the number of control observations in the case of low-potential areas is reduced to 13.

[12] These results are consistent even when we control for the major crops grown in the two regions. The crops included wheat, barley, teff, millet, maize, sorghum, pulses, oil crops and vegetables. We control for them following Di Falco and Chavas (2009), who highlight the role of crop choice in food security and farm productivity.

Table 4

Estimation of average adoption effects (ATT) using Propensity Score Matching methods

	Amhara region									
	High-potential areas				Low-potential areas				Pooled sample	
	CF vs. FTP		MTWOCF vs. FTP		CF vs. FTP		MTWOCF vs. FTP		MTWOCF vs. CF	
	NNM	KBM	NNM	KBM	NNM	KBM	NNM	KBM	NNM	KBM
ATT	1376.90***	1083.30***	−18.94	−253.14	118.14	279.19	510.11**	276.80	−1240.05***	−935.078***
Standard error	348.99	257.02	993.94	445.94	488.10	399.36	246.04	218.76	519.00	412.17
Number of observations within common support										
Number of treated	313	313	19	21	46	45	131	131	370	370
Number of control	447	447	391	391	331	331	349	349	112	112

	Tigray region					
	CF vs. FTP		MTWOCF vs. FTP		MTWOCF vs. CF	
	NNM	KBM	NNM	KBM	NNM	KBM
ATT	56.40	142.43	715.15***	693.67***	948.90***	302.83
Standard error	234.77	186.96	313.10	315.98	371.73	464.90
Number of observations within common support						
Number of treated	356	356	109	109	92	92
Number of control	607	607	606	606	357	**357**

Notes: ***indicates significance at the 1% level and **indicates significance at the 5% level.
NNM, nearest neighbour matching; KBM, kernel-based matching; CF, commercial fertiliser; FTP, farmers' traditional practices; MTWOCF, minimum tillage without CF.
Source: Own calculation.

2009). Previous research in Ethiopia (Gebremedhin *et al*., 1999; Benin, 2006; Kassie *et al*., 2008) has also shown that stone bunds are more productive in drier areas than in wetter areas.

Results from the sensitivity analysis for the presence of hidden bias are presented in Table 5. As noted by Hujer *et al*. (2004), the sensitivity analysis for insignificant ATT estimates is not meaningful, so we omit it here. Given that the estimated ATTs of CF and MT are positive, the lower bounds – under the assumption that the true adoption effects have been underestimated – are less interesting (Becker and Caliendo, 2007) and are also not reported here. Our results are consistent with findings from other studies and are insensitive to hidden bias (e.g. Faltermeier and Abdulai, 2009).

The hidden bias will need to increase by more than a factor of $\Gamma = 1.7$–2 to overturn the findings obtained under an assumption of no hidden bias ($\Gamma = 1$). These values imply that the significance of the adoption effects on the value of crop production may be questionable, if plots that have same x-vector differ in their odds of adoption by more than a factor of 70–100%. It is difficult to think of a variable that causes a 1.7–2-fold difference in the odds of adoption, as most of the relevant variables that influence adoption decision have already been controlled for with matching. Based on these results, we conclude that the estimates of the ATTs reported in Table 4 are insensitive to hidden bias and thus are a reliable indicator of the effect of CF and MT.

5.3. Switching regression estimation of the ATTs

The switching regression results are estimated using random effects models, except for the control groups in the estimation of MT vs. FTP, and MT vs. CF, impacts

Table 5

Rosenbaum bounds sensitivity analysis results

Critical value of hidden bias (Γ)	Amhara region			Tigray region (entire sample)	
	High-potential areas	Low-potential areas	Pooled sample		
	CF vs. FTP	MTWOCF vs. FTP	MTWOCF vs. CF	MTWOCF vs. FTP	MTWOCF vs. CF
1	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
1.10	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001
1.20	< 0.001	0.001	< 0.001	< 0.001	0.001
1.30	< 0.001	0.004	< 0.001	< 0.001	0.003
1.40	< 0.001	0.026	< 0.001	0.001	0.007
1.50	< 0.001	0.026	< 0.001	0.002	0.014
1.60	< 0.001	0.050	< 0.001	0.005	0.025
1.70	< 0.001	0.085	< 0.001	0.012	0.042
1.80	< 0.001	0.135	< 0.001	0.021	0.065
1.90	0.002	0.196	< 0.001	0.034	0.096
2.00	0.006	0.267	< 0.001	0.053	0.132

Notes: CF, commercial fertiliser; FTP, farmers' traditional practices; MTWOCF, minimum tillage without CF.
Source: Own calculation.

Table 6
Estimation of average adoption effects (ATT) using switching regression framework

	Amhara region				
	High-potential areas	Low-potential areas	Tigray region (entire sample)		
	CF vs. FTP	MTWOCF vs. FTP	CF vs. FTP	MTWOCF vs. FTP	MTWOCF vs. CF
ATT	1,051.40***	293.34**	172.570	650.14 **	784.99***
Standard error	229.20	149.03	145.35	245.29	302.26
Number of matched observations					
Number of treated	313	131	356	109	92
Number of control	127	74	115	73	58

Notes: *** indicates significance at the 1% level and ** indicates significance at the 5% level. CF, commercial fertiliser; FTP, farmers' traditional practices; MTWOCF, minimum tillage without CF.
Source: Own calculation.

in the Tigray region and low-potential agricultural areas of the Amhara region. In these cases, we use pooled ordinary least squares owing to insufficient observations in the matched sample for the random effects model.[13] The dependent variable in all cases is the net value of crop production per hectare. To calculate the ATTs from the switching regression approach, the difference in mean-predicted net value of crop production obtained by estimating equation (2) is computed. The predicted values are obtained at the mean of the covariates.

The results of the estimated ATTs from the parametric regression models are shown in Table 6. Consistent with the results from the semi-parametric analysis, the parametric results indicate that CF leads to significantly higher productivity gains in the high-potential areas, increasing net value of crop production by ETB 1,051 (US$124) per hectare. As in the semi-parametric regression results, MT has a significant impact in the low agricultural potential areas, increasing net value of crop production by ETB 630 ($74) per hectare in the Tigray region and ETB 293 ($34) per hectare in the low agricultural potential areas of the Amhara region.

6. Conclusions and Policy Implications

We investigate the differential impacts of MT and CF on agricultural productivity, paying particular attention to variations in agro-ecology. The empirical analyses are

[13] We could have used fixed effects, but some of the specifications mentioned before had insufficient observations to run fixed effects. Some samples also had one plot per household, which made it difficult to apply fixed effects unless we dropped these observations, where dropping observations may lead to biased estimates. Also, we did not use parametric regression in comparing MT vs. FTP in high-potential areas and CF vs. FTP in low-potential areas of Amhara region, because there were few matched treated and controlled observations for these cases.

based on plot-level data collected in the low and high agricultural potential areas in the Ethiopian highlands. We employ both semi-parametric and parametric econometric methods to ensure robustness of our results.

Our results provide evidence of a strong impact of MT on agricultural productivity, compared with the impact of VF, in the low agricultural potential areas. In the high agricultural potential region, however, CF has a very significant and positive impact on crop productivity, whereas MT has no significant impact. We scrutinise the estimated adoption effects for sensitivity to hidden bias, using the Rosenbaum bounds procedure. Our results are shown to be insensitive to hidden bias.

These findings highlight the need for moisture-conserving technologies in semi-arid environments. In particular, the productivity advantages of MT in the low-potential areas may come from its ability to conserve soil moisture in dry environments. Further, the findings suggest that CF is less profitable in this area owing to inadequate soil moisture. In addition, the non-profitability of CF in low-potential areas indicates that investing in CF in these environments is a financial risk, which has crucial relevance for resource-constrained areas, such as rural Ethiopia. Under these circumstances, promoting CF only puts poor farmers in debt without tangible productivity gains.

More importantly, our results suggest that a one-size-fits-all approach is not an advisable approach for developing and promoting technologies. Rather, different strategies are needed for different environments. For instance, in the low agricultural potential areas, government and non-governmental organisations should focus more on promoting MT as a yield-augmenting technology. Relying on external inputs (such as chemicals and fertilisers) in low-potential areas, which has been the strategy in the past, is not likely to be beneficial unless moisture availability issues are addressed. Future research should investigate the combined effects of MT or other moisture conservation practices and CF.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Table S1. Adoption of commercial fertiliser and minimum tillage, Amhara region.

Table S2. Adoption of commercial fertiliser and minimum tillage, Tigray region.

Table S3. Commercial fertiliser and minimum tillage productivity analysis using a switching regression, Amhara region.

Table S4. Commercial fertiliser and minimum tillage productivity analysis using a switching regression, Tigray region.

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