

Sustainable Agricultural Practices and Agricultural Productivity in Ethiopia

Does Agroecology Matter?

Menale Kassie, Precious Zikhali, John Pender, and Gunnar Köhlin



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Abstract

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

Key Words: agricultural productivity, commercial fertilizer, Ethiopia, low and high agricultural potential, minimum tillage, propensity score matching, switching regression

JEL Classification: C21, Q12, Q15, Q16, Q24

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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 per hectare (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 program 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 the use of technologies has been reported (Kassa 2003; Tadesse and Kassa 2004). A number of factors may explain the low technology adoption rate in the face of significant efforts to promote SLM practices: 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 fertilizer prices, lack of access to

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seasonal credit, and production and consumption risks (Bonger et al. 2003; Kassa 2003; Dercon and Christiaensen 2007; Kebede and Yamoah 2009; Spielman et al. 2010, forthcoming).

The extension system in Ethiopia, the Participatory Demonstration and Training Extension System (PADETES), is mainly financed and provided by the public sector, and has emphasized the development and distribution of standard packages to farmers. These packages typically include seeds and commercial fertilizer, credit to buy inputs, soil and water conservation, livestock, and training and demonstration plots intended to facilitate adoption and use of the inputs. While the promotion of commercial fertilizers 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 there has been promotion of practices which are unprofitable, risky, or ill-suited to farmers' resource constraints (Pender et al. 2006).¹

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 percent credit guarantee scheme in 1994. For instance, under this system, about 90 percent of fertilizer is delivered on credit at below-market interest rates. In order 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. Because farmers cannot borrow from banks due to 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 fertilizer market (importation and distribution) in all regions is mainly controlled by regional holding companies that have strong ties to regional governments (NFIA 2001; Spielman et al. 2010, forthcoming). The government gave these holding companies preferential treatment with the allocation of foreign exchange for

¹The World Food Program (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 has 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 programs in Ethiopia in the past was largely a result of the “top down” approach to design and implementation.

importation and distribution of fertilizer plus government-administered credit to farmers under its large-scale extension intervention program.

Despite claims by the Plan for Accelerated and Sustained Development to End Poverty (PASDEP) that all rural development interventions should take into account the specificities of each agroecosystem and area, the package-driven extension approach offers 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 commercial fertilizers² and other natural resource management technologies, irrespective of factors that limit agricultural productivity—the availability of water, soil types, and local socioeconomic and agroecological variations, such as low- and high-agricultural potential areas³ (Kassa 2003; Croppenstedt et al. 2003; Nyssen et al. 2004; Amsalu 2006; Kassie et al. 2008; Kebede and Yamoah 2009).

To our knowledge, except for commercial fertilizer, there are no technical recommendations (packages) for other natural resource management technologies. The standardized package approach and inflexible input distribution systems, which is currently used in Ethiopia, means that farmers have had little opportunity to experiment, learn, and adapt technologies to their own needs (Spielman et al. 2010, forthcoming). This approach could make the technologies inappropriate to local conditions and eventually unacceptable to the farmers. As Keeley and Scoones (2004) noted, the conservation interventions in the country have been supported by simplistic, often unjustified, claims, and these have had potentially negative impacts on poor people’s livelihoods through their blanket application. Research has also shown that in Ethiopia the economic returns on physical soil and water conservation investments, as well as their impacts on productivity, are greater in areas with low-moisture and low-agricultural potential than in areas with high-moisture and high-agricultural potential (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).

² A blanket recommendation of 100 kg of di-ammonium phosphate (DAP) and 100 kg of urea per hectare is promoted by PADETES.

³ The Ethiopian Disaster Prevention and Preparedness Commission classified the country into drought-prone versus nondrought-prone districts. Drought-prone districts are referred to as low-agricultural potential districts and nondrought-prone districts as high-agricultural potential districts.

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 and commercial fertilizer use, is thin. Particularly, information is lacking on the relative contribution of these practices to agricultural productivity in low- versus high-agricultural-potential areas.

This paper takes a step toward filling this gap by systematically exploring the productivity gains associated with adoption of minimum tillage and commercial fertilizer in the high- and low-agricultural potential areas of the Ethiopian highlands. To do this, we used 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). By adding the dataset of the Amhara region, we can 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 pursued an estimation strategy that employed both semi-parametric and parametric econometric methods. The parametric analysis is based on matched samples of adopters and nonadopters, 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, since extrapolation or prediction can be made for regions of no common support where there are no similar adopters and nonadopters (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.

1. Literature Review

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 tended to have a bias towards soil conservation as a productivity-enhancing technology. In the case of Ethiopia, Bekele's (2005) research showed that plots with soil conservation bunds 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, soil conservation (*fanya-juu* terracing) has no productivity gains. Benin (2006) found a 42 percent increase in average yields due to stone terraces in lower-rainfall areas of the 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 percent due to stone terraces. Holden et al. (2001), on the other hand, showed that soil and water conservation measures in the form of soil bunds and *fanya-juu* terraces have no significant impact on land productivity.

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; Benin 2006; Shiferaw and Holden 2001; and 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 suffer from overlooking variations in location-specific characteristics, such as agroecosystems, soil type, and water availability, in determining the feasibility, profitability, and acceptability of different technologies. Furthermore, some studies broadly generalize 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, since it could be the case that not all types of soil conservation 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 end up being characterized by little variation across different agroecologies. Further, the estimated productivity impacts of the analyzed technologies will be biased if crucial factors, such as heterogeneity of environments, are not controlled for.

In this paper, we take into consideration the variations in the agricultural potential of different areas when determining technology performance measured in terms of land productivity. This makes it possible to craft well-informed policy recommendations that are not based on generalizations. The importance of our analysis to the adoption literature is to highlight the dangers of making blanket analyses and across-the-board policy recommendations that disregard the heterogeneity of environments. As Keeley and Scoones (2004) argued, such indiscriminate policy recommendations potentially have negative impacts on poor people's livelihoods.

2. 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 (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 used propensity score matching methods and a switching regression to overcome this and other econometric problems and ensure robust results.

2.1 *The Propensity Score Matching Methods*

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)⁴ 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 (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

⁴We took adoption of either minimum tillage or commercial fertilizer use as the treatment variable, while the net value of crop production per hectare—(net of the cost of fertilizer, labor (for plowing, incorporating residues, and weeding), and draft animal power—was the outcome of interest.

method (Caliendo and Kopeinig 2008). In this paper, nearest neighbor matching (NNM) and kernel-based matching (KBM) methods are used. The basic approach of these methods is to numerically search for “neighbors” 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 on, 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 nonadopters. 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 (Lee 2008). Although several versions of balancing tests exist in the literature, the most widely used is the standardized mean difference between treatment and control groups suggested by Rosenbaum and Rubin (1985), in which they recommended that a standardized difference of greater than 20 percent should be considered too large and thus an indicator of failure of the matching process. Additionally, Sianesi (2004) proposed 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 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 variable, a selection or hidden bias problem due to unobserved variables might arise, to which matching estimators are not robust. While we controlled for many observables, we checked the sensitivity of the estimated average adoption effects 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 hypothesized values of unobserved selection bias.

2.2 Switching Regression Analysis

To check the robustness of our findings, we also used parametric analysis. Besides the nonrandomness 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 nonadopters (via a dummy regression model, where a binary indicator is used to assess the effect of minimum tillage or commercial fertilizer on productivity) might be inappropriate, since it assumes that the set of covariates has the same impact on adopters and nonadopters (i.e., common slope coefficients for both groups). This implies that minimum tillage or commercial fertilizer adoption have only an intercept shift effect. However, for our sample, a Chow test of equality of coefficients for adopters and nonadopters of minimum tillage or commercial fertilizer 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 nonadopters.

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

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

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 summarizes 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 minimum tillage or commercial fertilizer, we needed to control for selection bias due to unobservables, which occurs if the error terms in equation (1) are correlated with whether or not the SLM practice is adopted (d_{hp}). A standard method of addressing this is to estimate an endogenous switching regression model, which is (given certain assumptions about the distributions of the error terms) 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 3⁵), thus limiting the usefulness of adding the inverse Mills' ratios from these first stage logit models to the second-stage switching regressions. This is not surprising since, in the logit regression analysis, matched samples obtained from the NNM method⁶ had no systematic differences in the distribution of covariates between adopters and nonadopters. Thus, we instead used an exogenous switching regression model, which assumes that the selection of the samples using the PSM method may reduce selection bias due to differences in unobservables.⁷

Our rich dataset of plot and household characteristics also helped reduce both household and plot (e_{hp}) unobserved effects. It is likely 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 color, soil textures, soil erosion and water-logging in plots, plot distance from homestead, altitude, and input use by plot.

Controlling for the above econometric problems, the expected net value of crop production difference between adoption and nonadoption of minimum tillage and/or commercial fertilizer becomes:

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

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

⁵ All tables and figures are located at the end of the paper.

⁶ We focused on the NNM (nearest neighbor matching) method because, compared to other weighted matching methods, such as KBM (kernel-based matching), the NNM method allowed us to identify the specific matched observations that entered the calculation of the ATT, which we then used for parametric regressions.

⁷ However, it is worth noting that using the matched sample may undermine the ability to detect and correct for selection on unobservables.

3. 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 meters above sea level) of the Tigray and Amhara regions of Ethiopia are used to explore the contribution of minimum tillage and commercial fertilizer to net value of agricultural production in low- versus high-agricultural potential areas. A stratified random sample of 99 peasant associations⁸ was selected from highland areas of the 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 was used to classify the districts according to access to an all-weather road, the 1994 rural population density (greater or less than 100 persons per km²), 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 districts' towns (greater or less than 10 km). The dataset from the Amhara region includes 435 farm households, 98 villages, and about 1,434 plots, while the Tigray dataset includes 500 farm households, 100 villages, and 1,797 plots. Due to 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. About 13.4 percent and 34.9 percent of the total sample plots in the Tigray region, and 14.6 percent and 30.3 percent in the Amhara region used minimum tillage and commercial fertilizer, respectively. Minimum tillage plots did not receive herbicides or pesticides, except for three plots in the Amhara region. A simple mean comparison test indicated that commercial fertilizer use and draft animal use per hectare are lower on minimum tillage plots than on nonreduced tillage plots (see table 2). There is, however, no statistically significant difference in labor use between the two types of plots. In order to take into account input use differences in the analysis, input costs (fertilizer; seed; labor for plowing, incorporating residues, and weeding; and draft animals) were deducted from the total value of crop production.

⁸ Known as *kebele* in Ethiopia, this is the lowest administrative unit in the government structure.

The mean plot altitude, which is closely associated with temperature and microclimates, was 2,179 and 2,350 meters above sea level for the Tigray and Amhara regions, respectively. Compared to the Tigray region and others, the Amhara region has relatively good rainfall, with an average annual rainfall of 1,981 mm, while it is 641 mm in the Tigray region. The difference in rainfall between the two regions is very large. The mean population density was 141 persons per km² in the Tigray and 144 per km² in the Amhara region.

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

4. Empirical Results

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

We conducted three comparisons to assess the impacts of minimum tillage and commercial fertilizer on productivity. These are 1) commercial fertilizer (CF) versus farmers' traditional practice (FTP), which is traditional tillage without commercial fertilizer, 2) minimum tillage without commercial fertilizer (MTWOCF) versus FTP, and 3) minimum tillage (MT) versus CF. Since our main goal is to estimate the average adoption effects, to conserve space we have not included the logit model results used to estimate propensity scores or the full switching regression model estimates, although we do present the estimated average treatment effects based on the switching regression models.⁹

⁹ The logit and full switching regression results are available from the authors upon request.

4.1 *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 overlap in the distribution of the propensity scores of both treated and nontreated groups. The bottom half of each figure shows the propensity scores distribution for the nontreated, while the upper half refers to the treated individuals. The densities of the scores are on the y-axis.

As noted above, a major objective of propensity score estimation is to balance the distribution of relevant variables between the adopters and nonadopters, 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.¹⁰ The results show that a substantial reduction in absolute standardized 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 it was never rejected before matching. The low pseudo- R^2 , low standardized 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 minimum tillage and commercial fertilizer adoption effects between adopters and nonadopters with similar observed characteristics.

4.2 *Propensity Score Matching Estimation of the Average Adoption Effects*

Table 4 reports the estimates of the average adoption effects 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 to FTP and MT, is more productive in the high-agricultural potential areas of the Amhara region (increasing net productivity in the range of ETB¹¹ 1,083 [US\$ 127] and ETB 1,377 [\$162] per hectare),¹² yet it shows no significant crop productivity impact in the low-potential agricultural areas of the Tigray and Amhara regions.

¹⁰ We reached the same conclusion using the KBM method.

¹¹ The official exchange rate averaged about ETB 8.50 (Ethiopian birr) per US\$ 1 during the survey period.

¹² In comparing MT with CF, we pooled observations of low- and high-agricultural potential areas because covariate balancing tests were not able to satisfy when observations were split into low- and high-potential areas. This may be due to the fact that there were few matched observations. For instance, the number of matched treated observations in the case of high-potential areas was reduced to 7 observations, while number of control observations in the case of low-potential areas was reduced to 13 observations.

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 fertilizer use is not very profitable in the semi-arid environments of northern Ethiopia.

On the other hand, MT—compared to CF and FTP—is more productive in the low-potential agricultural areas, increasing net productivity by about ETB 715 (\$84) and ETB 949 (\$112) per hectare in Tigray region, and ETB 277–ETB 510 (\$33–\$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, minimum tillage has no significant crop productivity impact in the high-agricultural-potential areas of the Amhara region.¹³

We believe that this is due to the greater benefits of moisture conservation associated with minimum tillage in low-potential agricultural areas because moisture conservation in high-agricultural potential areas may contribute to problems, such as water logging, weeds, and pests. Benefits of minimum tillage could have been further improved in the low-potential areas had benefits associated with the environment and its long-term impacts on plot productivity been included. The finding that SLM practices, such as minimum tillage, 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 to commercial fertilizer (Kassie et al. 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 also presented in table 5. As noted by Hujer et al. (2004), sensitivity analysis for insignificant average adoption effects estimates is not meaningful, so we omitted it here. Given that the estimated average adoption effects of minimum tillage and commercial fertilizer 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 therefore not reported in this paper. Our results

¹³ These results were consistent even when we controlled for major crops grown in the two regions. The crops included wheat, barley, teff, millet, maize, sorghum, pulses, oil crops, and vegetables. We controlled for them, in line with Di Falco and Chavas (2009), who highlighted the role of crop choice in food security and farm productivity. Results are not reported for space consideration, but are available from the authors.

are consistent with findings from other studies and are insensitive to hidden bias (e.g., Faltermeier and Abdulai 2009).

The level of hidden bias, which would make our findings of significant and positive adoption effects questionable, ranges from 1.7 to 2.0. This implies that, for the hidden bias to overturn the statistical significance adoption effects, individuals with the same x -vector should differ in their odds of adoption by a factor of 70–100 percent. These are large values, since the most important variables influencing both the adoption decision and the outcome variable have already been included. Based on these results, we can conclude that the estimates of the average adoption effects reported in table 4 are insensitive to hidden bias, and thus are a reliable indicator of the effect of commercial fertilizer and minimum tillage.

4.3 Switching Regression Estimation of the Average Adoption Effects

The switching regression results are estimated using random effects models, except for the control groups in the estimation of the impacts of MT versus FTP, and MT versus CF, in the Tigray region and low-potential agricultural areas of the Amhara region, where we used pooled OLS (ordinary least squares) due to insufficient observations to run random effects model on the matched sample.¹⁴ The dependent variable in all cases is the net value of crop production per hectare. To calculate the average adoption effects from the switching regression approach, the difference in mean predicted net value of crop production obtained by estimating equation (2) was computed. The predicted values are obtained at the mean of the covariates.

The results of the estimated average adoption effects from the parametric regression models are shown in table 6. Consistent with results from the semi-parametric analysis, the parametric results indicate that commercial fertilizer leads to significantly higher productivity gains in the high-potential areas, increasing net productivity by ETB 1,051 (\$124) per hectare. As in the semi-parametric regression results, minimum tillage has a significant impact in the low-agricultural potential areas, increasing net productivity 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.

¹⁴ We could have used fixed effects, but some of the specifications mentioned above 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.

We did not use parametric regression in comparing MT versus FTP in high-potential areas and CF versus FTP in low-potential areas of the Amhara region, since there were few matched treated and controlled observations for these cases.

5. Conclusions and Policy Implications

In this paper, we investigated the differential impacts of minimum tillage and commercial fertilizer on agricultural productivity, paying particular attention to variations in agroecology. The empirical analyses were based on plot-level data collected in the low- and high-agricultural potential areas in the Ethiopian highlands. We employed both semi-parametric and parametric econometric methods to ensure robustness of our results.

Our results provide evidence of a strong impact of minimum tillage on agricultural productivity, compared to the impact of commercial fertilizer, in the low-agricultural potential areas. In the high-agricultural potential region, however, commercial fertilizer has a very significant and positive impact on crop productivity, while minimum tillage has no significant impact. We scrutinized the estimated adoption effects to see whether they were sensitive to hidden bias, using the Rosenbaum bounds procedure. Results were 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 minimum tillage in the low-potential areas may come from its ability to conserve soil moisture in dry environments. Further, the findings suggest that commercial fertilizer is less profitable in this area due to inadequate soil moisture. In addition, the nonprofitability of commercial fertilizer in low-potential areas indicates that investing in commercial fertilizer in these environments is a financial risk, which has crucial relevance for resource-constrained areas, such as rural Ethiopia. Under these circumstances, promoting commercial fertilizer 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 nongovernmental organizations should focus more on promoting minimum tillage as a yield-augmenting technology. Relying on external inputs (such as chemicals and fertilizers) 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 minimum tillage or other moisture conservation practices and commercial fertilizer.

Tables and Figures

Table 1. Descriptive Statistics of Variables Used in the Empirical Analysis

Variables	Mean: Amhara	Mean: Tigray	Variables	Mean: Amhara	Mean: Tigray
Gross crop revenue, in ETB/hectare*	2237.845	1831.565	Net crop revenue,** in ETB/hectare	2140.853	1728.670
Household-level variables					
Gender of household head (1 = male; 0 = female)	0.924	0.826	Livestock holdings (in tropical livestock units)	2.559	9.078
Age of household head (in years)	44.939	48.367	Oxen (number owned by household)	N/A	1.224
Household size (number of household members)	6.588	5.577	Extension contact (1 = yes; 0 = otherwise)	0.583	0.132
Education level of household head (in years)	2.457	N/A	Farm size (in hectares)	1.604	1.055
Household head is illiterate (1 = yes; 0 = otherwise)	N/A	0.866	Non-farm work (1 = if farmer involved in nonfarm work; 0 = otherwise)	0.287	N/A
Household head has schooling to grades 1 and 2 (1 = yes; 0 = otherwise)	N/A	0.070	Credit (1 = if farmer has access to credit; 0 = otherwise)	0.389	0.697
Household head has schooling above grade 3 (1 = yes; 0 = otherwise)	N/A	0.064	Membership (1 = if farmer holds any organization membership; 0 = otherwise)	N/A	0.143
Plot-level variables					
Fertilizer use (1 = if plot received fertilizer; 0 = otherwise)	0.303	0.349	Silt soil in plot (1 = yes; 0 = otherwise [CF])	0.325	0.219
Minimum tillage (1 = if plot received minimum tillage; 0 = otherwise)	0.146	0.134	Clay soil in plot (1 = yes; 0 = otherwise)	0.122	0.309
Degree of plot slope	5.547	N/A	Loam soil in plot (1 = yes; 0 = otherwise)	0.431	0.307
Plot size (in hectares)	0.386	0.301	Shallow plot soil depth (1 = yes; 0 = otherwise [CF])	N/A	0.214
Red soil in plot (1 = yes; 0 = otherwise)	0.347	0.388	Moderately deep plot soil depth (1 = yes; 0 = otherwise)	N/A	0.395
Black soil in plot (1 = yes; 0 = otherwise [CF])	0.310	0.225	Deep plot soil depth (1 = yes; 0 = otherwise)	N/A	0.391
Gray soil in plot (1 = yes; 0 = otherwise)	N/A	0.244	Flat plot slope (1 = yes; 0 = steep slope [CF])	N/A	0.620
Brown soil in plot (1 = yes; 0 = otherwise)	0.274	0.143	Moderate plot slope, (1 = yes; 0 = steep slope)	N/A	0.297

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Sandy soil in plot (1 = yes; 0 = otherwise)	0.118	0105	Steep plot slope (1 = yes; 0 = steep slope)	N/A	0.083
Variables	Mean: Amhara	Mean: Tigray	Variables	Mean: Amhara	Mean: Tigray
Plot-level variables (con'd)					
Top slope position (CF)	0.139	0.114	Rented plot (1 = yes; 0 = otherwise)	0.108	0.126
Middle slope position	0.273	0.217	Distance from residence to plot (in hours walking)	0.284	0.297
Bottom slope position	0.147	0.235	Crop1 (1 = if wheat, barley and oat crops; 0 = otherwise)	0.206	0.254
Not on slope position	0.440	0.434	Crop2 (1 = if maize and sorghum crops; 0 = otherwise)	0.184	0.055
Soil bund on plot (1 = yes; 0 = otherwise)	0.066	0.019	Crop3 (1 = if teff and millet crops; 0 = otherwise)	0.268	0.670
Stone bund on plot (1 = yes; 0 = otherwise)	0.171	0.070	Crop4 (1 = if legume crops; 0 = otherwise)	0.106	N/A
Plot irrigated (1 = yes; 0 = otherwise)	0.070	0.038	Crop5 (1 = if oil crops; 0 = otherwise)	0.044	N/A
Waterlogged plot (1 = yes; 0 = otherwise)	0.109	N/A	Crop6 (1 = if vegetable crops; 0 = otherwise)	0.126	N/A
Plot not eroded (1 = yes; 0 = otherwise)	0.590	0.662	Crop7 (1 = if fruit and other crops; 0 = otherwise)	0.066	N/A
Plot moderately eroded (1 = yes; 0 = otherwise)	0.314	0.274	Crop8 (1 = if other crops; 0 = otherwise)	N/A	0.021
Plot severely eroded (1 = yes; 0 = otherwise)	0.095	0.064			
Village/district level variables					
Population density, i.e., village population (in person/km ²)	143.500	140.836	Residence distance to input market, i.e., extension office (in walking hours)	0.717	N/A
Mean rainfall (in mm)	1980.721	641.177	Residence distance to input market, i.e., input supply shop (in walking hours)	2.401	N/A
Altitude (in meters above sea level)	2350.388	2179.345	Residence distance to all weather road (in walking hours)	N/A	1.875
Residence distance to district market (in walking hours)	3.457	1.975			
Sub-regional location					

Number of plots (households)	1365 (396)	1113 (357)	
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* ETB = Ethiopian birr.

** Costs for fertilizer, labor (for plowing, incorporating residues, and weeding), and animal power for plowing deducted from value of crop production.

Note: CF = commercial fertilizer.

Source: Authors' calculations.

Table 2. Mean Input Use Difference between Minimum Tillage and Non-Reduced Tillage Plots

	Fertilizer (kg per hectare)		Oxen (oxen days per hectare)		Labor (person days per hectare)	
	<i>Mean</i>	<i>Mean difference</i>	<i>Mean</i>	<i>Mean difference</i>	<i>Mean</i>	<i>Mean difference</i>
TIGRAY						
Minimum tillage plots	21.61		17.59		70.67	
Nonreduced tillage plots	48.73	27.12 (8.62) ^{***}	30.97	13.18 (3.07) ^{***}	78.60	7.92 (11.91)
AMHARA						
Minimum tillage plots	13.13		44.03		106.51	
Nonreduced tillage plots	24.51	11.38 (3.99) ^{***}	59.01	14.98 (4.91) ^{***}	125.93	19.41 (17.30)

^{***} significant at 1%.

Note: Standard errors are in parentheses.

Source: Authors' calculations.

Table 3. Covariate Balancing Indicators before and after Matching (Commercial Fertilizer Adoption)

	AMHARA REGION					TIGRAY REGION		
	CF	CF	MTWOCF	MTWOCF	MTWOCF	MTWOCF	CF	MTWOCF
	vs. FTP	vs. FTP	vs. FTP	vs. FTP	vs. CF	vs. FTP	vs. FTP	vs. CF
	<i>High potential</i>	<i>Low potential</i>	<i>High potential</i>	<i>Low potential</i>	<i>Pooled sample</i>	<i>Entire sample</i>	<i>Entire sample</i>	<i>Entire sample</i>
Before matching								
Mean standardized difference (bias)	19.37	20.47	23.05	22.46	37.96	16.45	14.35	23.89
Pseudo R^2	0.295	0.374	0.285	0.287	0.580	0.249	0.122	0.358
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 standardized difference(bias)	6.03	11.68	12.80	9.79	11.94	10.13	2.11	10.13
Pseudo R^2	0.055	0.029	0.112	0.090	0.139	0.105	0.004	0.106
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 fertilizer; FTP = farmers' traditional practices; MTWOCF = minimum tillage without commercial fertilizer.

Source: Authors' calculations.

Table 4. Estimation of Average Adoption Effects Using Propensity Score Matching Methods

	AMHARA REGION						TIGRAY REGION					
	CF vs. FTP		MTWOCF vs. FTP		MTWOCF vs. CF		CF vs. FTP		MTWOCF vs. FTP		MTWOCF vs. CF	
	<i>High-potential areas</i>				<i>Pooled sample</i>		<i>Entire sample</i>					
	<i>NNM</i>	<i>KBM</i>	<i>NNM</i>	<i>KBM</i>	<i>NNM</i>	<i>KBM</i>	<i>NNM</i>	<i>KBM</i>	<i>NNM</i>	<i>KBM</i>	<i>NNM</i>	<i>KBM</i>
Average adoption effect (ATT)	1376.90***	1083.30***	-18.94	-253.14	-1240.05***	-935.078***	56.40	142.43	715.15***	693.67***	948.90***	302.83
Standard error	348.99	257.02	993.94	445.94	519.00	412.17	234.77	186.96	313.10	315.98	371.73	464.90
Number of observations within common support												
Number of treated	313	313	19	21	370	370	356	356	109	109	92	92
Number of control	447	447	391	391	112	112	607	607	606	606	357	357
Low potential areas												
Average adoption effect (ATT)	118.14	279.19	510.11**	276.80								
Standard error	488.10	399.36	246.04	218.76								
Number of observations within common support												
Treated	46	45	131	131								
Control	331	331	349	349								

*** significant at 1%; ** significant at 5%.

Notes: NNM = nearest neighbor matching; KBM = kernel-based matching; CF = commercial fertilizer; FTP = farmers' traditional practices; MTWOCF = minimum tillage without commercial fertilizer.

Source: Authors' calculations.

Table 5. Rosenbaum Bounds Sensitivity Analysis Results

Critical value of hidden bias (Γ)	AMHARA REGION			TIGRAY REGION	
	CF vs. FTP	MTWOCF vs. FTP	MT vs. CF	MTWOCF vs. FTP	MTWOCF vs. CF
	<i>High-potential areas</i>	<i>Low-potential areas</i>	<i>Pooled sample</i>	<i>Entire sample</i>	<i>Entire sample</i>
1	< 0.0001	< 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 fertilizer; FTP = farmers' traditional practices; MTWOCF = minimum tillage without commercial fertilizer.

Source: Authors' calculations.

Table 6. Estimation of Average Adoption Effects Using Switching Regression Framework

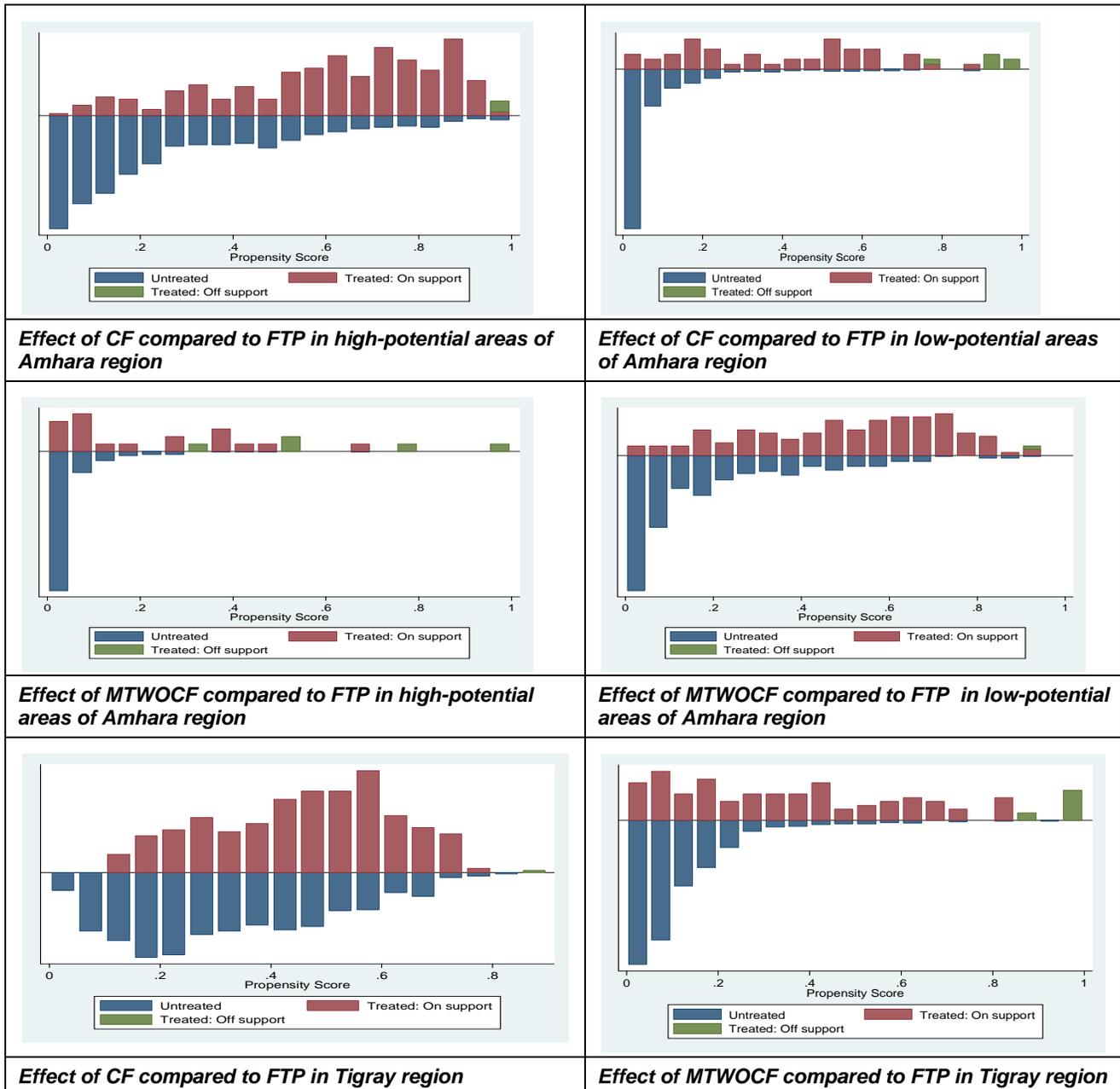
	AMHARA REGION		TIGRAY REGION		
	<i>CF</i>	<i>MTWOCF</i>	<i>CF</i>	<i>MTWOCF</i>	<i>MTWOCF</i>
	<i>vs.</i>	<i>vs.</i>	<i>vs.</i>	<i>vs.</i>	<i>vs.</i>
	<i>FTP</i>	<i>FTP</i>	<i>FTP</i>	<i>FTP</i>	<i>CF</i>
	<i>High potential areas</i>	<i>Low potential areas</i>	<i>Entire sample</i>	<i>Entire sample</i>	<i>Entire sample</i>
Average adoption effect (ATT)	1051.40***	293.34**	172.570	650.14**	784.99***
Standard error	229.20	149.03	145.35	245.29	302.26
<i>Number of matched observations</i>					
Number of treated	313	131	356	109	92
Number of control	127	74	115	73	58

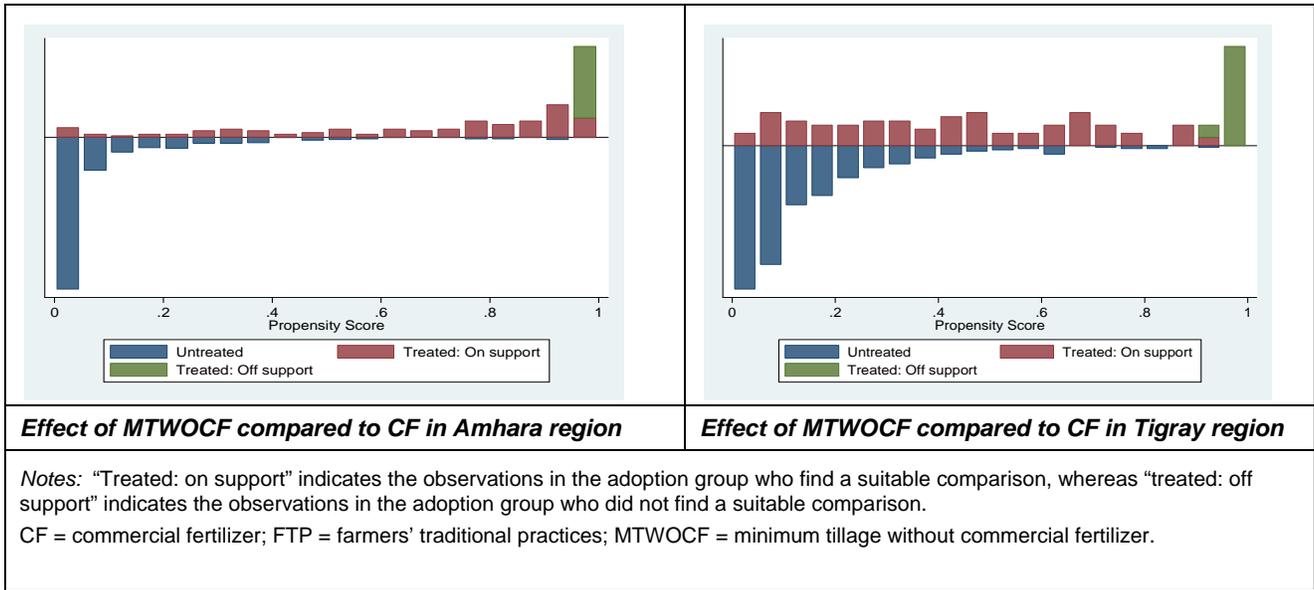
*** significant at 1%; ** significant at 5%.

Notes: CF = commercial fertilizer; FTP = farmers' traditional practices; MTWOCF = minimum tillage without commercial fertilizer.

Source: Own calculation

Figure 1. Propensity Score Distribution and Common Support for Propensity Score Estimation





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