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Assessing the impact of improved agricultural technologies in rural Mozambique

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Abstract

This paper analyzes the use of improved agricultural technologies, and implications for food security and poverty reduction in rural Mozambique. The results are drawn from a nationally representative household survey covering the agricultural season of 2004/05. As a robustness check, the paper uses three econometric approaches: the doubly robust estimator, regression and matching, and sub-classification and regression. The results show that the impact of improved technologies is positive, conditional on irrigation use. Additionally, the results attest to the importance of increasing agricultural productivity in tandem with improvements on farmers' ability to store food.

Keywords: improved agricultural technologies; poverty; impact assessment; Mozambique.

JEL Classification: Q16, R13, I30.

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1 Introduction

While 80 percent of the population is engaged in agriculture, and the agricultural sector contributes with about a quarter of the country's gross domestic product, agricultural productivity in Mozambique fares among the lowest in the world [1]. Multiple intertwined factors have a bearing on the current productivity levels. The agricultural technology used, market failures, and farmer's health and nutritional status during the dry season figure prominently among these reasons.

The adoption of improved technologies is often recognized as a critical aspect in addressing food insecurity and poverty. A myriad of research exists on the determinants of adoption [2,3,4,5,6]. Most of the adoption studies, however, tacitly assume that improved technologies have a positive and significant effect on household welfare, while failing to properly assess the impact of such technologies. Accordingly, there has been a longstanding interest in evaluating the impact of improved technologies on food security and poverty.

Empirical evidence on this crucial matter is thin and flawed. Previous studies have focused on rate of return and net present value criteria [7]. These methods, however, have some limitations, especially when the conditions of the investment require substantial commitment under uncertainty arising from prices, yields, technology, and weather [8]. Using a nationally representative household survey from rural Mozambique, this paper aims to fill that void in the literature, by assessing the economic impact of tractor mechanization, animal traction, improved maize seeds, and improved granaries.

As a robustness check, the results are drawn from three econometric approaches: the doubly robust estimator, sub-classification and regression, and matching and regression. In general, the use of improved technologies has a positive and significant impact on household incomes, conditional on irrigation use. Scope exists for enhancing the impact of improved technologies, in view of low use of other inputs (e.g. fertilizers) and irrigation. In addition, efforts to increase agricultural production and productivity should be in tandem with improvements in farmer's ability to store food.

The remainder of the paper is structured as follows. Section 2 discusses the need for improved technologies in rural Mozambique. Section 3 delves into the econometric approaches used, followed by a description of data sources, presented in section 4. Results and discussion are covered in section 5. Section 6 presents the conclusion, while providing some tentative leads for agricultural policy, as well as an agenda for future research.

2 The need for improved agricultural technologies

The importance of agriculture in Mozambique stems both from a high percentage of the population engaged in agricultural activities, and from its economic contribution to the gross national product. Agricultural productivity, however, remains very low, even by African standards. Zavale, Mabaya, and Christy [9] report that maize yields are estimated at 1.4 tons/ha, far below the potential yields of 5 – 6.5 tons/ha. They also found that with the current technology, scope exists for fostering cost efficiency by 70 percent without any loss of the output.

Besides cost inefficiency, a number of equally important factors are associated with low agricultural productivity in Mozambique. First, the use of improved agricultural technologies is very limited and unequal. Most of the production is rainfed, with extremely low use of external inputs, particularly among the poorest households, who also depend more on agricultural income. Additionally, of the 2 percent of farmers that used tractor mechanization in 2005, 49 percent were located in Maputo province, a region of relatively lower agricultural potential, but of better infrastructure, including roads.

Second, associated with a lower use of improved agricultural technologies are credit and insurance market failures. Asset ownership, particularly liquid assets (e.g. livestock flocks), and access to nonfarm income activities have been shown to play an important role in overcoming credit constraints [10,11,12]. Furthermore, agricultural productivity rises significantly with increases in household income in parallel with the diminishing reliance on agriculture of wealthier households [13].

Third, in Mozambique the beginning of the rainy season coincides with the highest rates of malaria incidence [14]. Delays in some agricultural operations (e.g. plowing, sowing, and weeding) due to malaria or any other reasons usually translate into lower production per unit area. Farmer's health status has been systematically ignored in adoption or impact assessment studies, much less malaria. Notwithstanding its importance, HIV/AIDS pandemic is given far more attention, one of the arguments being its potential effect on labor availability.

Fourth, farmer's nutritional status also plays a crucial role in enhancing agricultural productivity levels. Post-harvest losses significantly reduce household access to food during the dry season. When faced with prospects of high food storage losses, farmers are compelled to forego opportunities for inter-temporal price arbitrage through storage and are observed to sell their produce right after the harvesting season at prices lower than observed prices for purchases in the subsequent lean season. This has been dubbed "sell low, buy high" puzzle [15]. As a result, many farmers are unable to purchase food during the dry season, debilitating their nutritional statuses, which deteriorate their ability to undertake some agricultural operations.

To make matters worse, agricultural productivity and land availability appear to be shrinking for many Sub-Saharan African countries (SSA), including the apparently land-abundant countries like Mozambique. Jayne et al. [16] found that the average per capita cultivated area has been declining over the last 40 years in SSA. The implication is that increases in agricultural production have to be met through increases in agricultural productivity, and less through expansion of cultivated area.

Another worsening factor is the climate change and global warming. Some studies predict that global warming will significantly and negatively affect African agriculture [17,18]. They also indicate that the use of irrigation reduces the harmful impact of global warming. In addition, irrigation use is a catalyst of improved technology adoption [19], which will have a substantial impact on food security.

The author’s understanding of food security is informed by Sen’s entitlement theory [20]. Farmer’s access to food can be seized either through the output markets or through increases in productivity levels and improvements in food storage. As elicited by the “sell low, buy high” puzzle, the mark-up is usually very high and a significant number of households in rural Mozambique may not afford to purchase food during the lean season. Therefore, it becomes crucial to enhance both agricultural productivity and farmer’s ability to store food.

Selective mechanization, improved storage, and other improved agricultural technologies play an essential role in ensuring farmers’ food entitlements. Previous attempts to mechanize the agricultural sector in the post-colonial period have failed, one of the reasons being the 16-year civil war that started a year after the independence in 1975. Moreover, the government established tractor-hire schemes had serious planning, management, and training problems, denting the image of agricultural mechanization in general.

Agricultural mechanization is also mistakenly perceived as tractor mechanization. Agricultural mechanization is the use of any mechanical technology and increased power to agriculture. This includes the use of tractors, animal-powered and human-powered implements and tools (e.g. jab planters), as well as irrigation systems, food processing and related technologies and equipment [19]. Although not addressed in this paper, the use of jab planters has been shown to significantly reduce labor requirements [21].

Information on the economic impact of selected improved agricultural technologies is needed to target interventions efficiently and equitably, and to justify investment in such technologies.

This paper assesses the impact of improved agricultural technologies by constructing a counterfactual comparison group. In this setting, a comparison of the outcome variable (total household income) is made between farmers using a given technology (henceforth treated farmers) and their counterparts with similar observable covariates (henceforth untreated farmers).

3 The empirical model

The literature on causal inference contains numerous approaches that can be used to evaluate the effect of a farmer's exposure to a treatment (agricultural technology) on some outcome (household income). The econometric approaches often encountered in the literature include: instrumental variable approach [22,23,24,25,26]; regression discontinuity design [27,28,29,30,31]; bounds approach [32,33,34]; difference-in-differences [35,36]. In addition, Imbens and Wooldridge [37] recommend the use of the doubly robust estimator, matching and regression, and sub-classification and regression. As a robustness check, this paper uses all three approaches.

One of the challenges in causal inference is to find a suitable comparison group of which, given the outcome of a treated farmer, one is able to identify what the outcome would look like had the same farmer been untreated. In such an endeavor, researchers often rely on propensity score estimation.

3.1 Propensity score estimation

The propensity score is defined as the conditional probability of receiving treatment, and can be expressed as [38]:

$$e(x) = \Pr(W_i^k = 1 \mid X_i = x) = E[W_i^k \mid X_i = x] \qquad (1)$$

where W_i is a binary indicator: $W_i = 1$ for treated farmers, and $W_i = 0$ for untreated farmers; k is the improved agricultural technology; and X_i is the vector of pre-treatment covariates. The conditional probability model is usually estimated using flexible binary response models such as logit or probit. For ease of estimation, most applications have used the logit model [39], although nowadays it has been made easier with modern computers. The author takes the conservative approach and uses a stepwise logit regression.

The propensity score allows the identification of farmers of similar covariates. The main purpose of propensity score is, given a treated farmer, to find an untreated farmer with similar characteristics. Accordingly, the difference in the outcome variable will be attributed to the treatment, and is denoted the average treatment effect. There are obviously some contentious issues, mainly the overlap and the unconfoundedness assumptions.

3.1.1 Assessing the overlap assumption

The overlap assumption postulates that the conditional distributions of the covariates of treated and untreated individuals overlap completely. There are two formal methods of testing the overlap assumption. The first is to plot the distribution of the propensity scores of treated and untreated individuals and visually assess whether the overlap assumption holds. The second method is to calculate normalized differences between treated and untreated individuals.

Formally, the normalized difference is given by [37]:

$$\Delta x = \frac{\bar{x}_1 - \bar{x}_0}{\sqrt{\sigma_1^2 + \sigma_0^2}} \tag{2}$$

where $\bar{x}_i$ is the mean and σ_i^2 is the sample variance. Imbens and Wooldridge [37] consider a normalized difference greater than 0.25 (in absolute value) to be substantial. One resort to high normalized differences is to trim some of the observations and get a more balanced sub-sample of treated and untreated individuals.

3.1.2 Assessing the unconfoundedness assumption

The unconfoundedness assumption implies that beyond the observed covariates, there are no unobserved characteristics of the individual associated both with the potential outcome and the treatment. Although the unconfoundedness assumption is not directly testable, this paper assesses its plausibility in the spirit of Heckman, Ichimura, and Todd [35], by estimating a pseudo causal effect that is known to be zero.

Within untreated farmers, the author distinguishes two potential untreated groups, the ineligible and the eligible untreated. The first control group includes widow female headed households. The other control group, the eligible untreated, includes non-widow female headed households and all male headed households who did not use agricultural technology k. Non-rejection of the test makes it more plausible that the unconfoundedness assumption holds. By setting widow female headed households as ineligible untreated, the purpose is obviously not to negatively influence future outcomes for this disadvantaged group. To a certain extent, this paper also aims to demonstrate that this is indeed the case, as consistently reported elsewhere [40,41,42,43].

3.2 Doubly robust estimator

The use of single approaches to estimate average treatment effects is less appealing than mixed methods. Although one method alone is sufficient to obtain consistent or even efficient estimates, incorporating regression may eliminate remaining bias and improve precision [37]. The interesting feature of the doubly robust estimator is that, as long as the parametric model for either the propensity score or the regression function is correctly specified, the resulting estimator for the average treatment effect is consistent [37,44]. Specifically, the doubly robust estimator can be represented as:

$$\hat{\Delta}_{DR} = n^{-1}\sum_{i=1}^{n}\left[\frac{W_i Y_i}{e(X_i,\beta)} - \frac{\{W_i - e(X_i,\beta)\}}{e(X_i,\beta)} m_1(X_i,\hat{\alpha}_1)\right] - n^{-1}\sum_{i=1}^{n}\left[\frac{(1-W_i)Y_i}{1-e(X_i,\beta)} + \frac{\{W_i - e(X_i,\beta)\}}{1-e(X_i,\beta)} m_0(X_i,\hat{\alpha}_0)\right] \quad (3)$$

where $e(X_i,\beta)$ is the postulated model for the propensity score, n is the number of treated and untreated farmers, and $m_i(X_i,\hat{\alpha}_i)$ is the postulated regression model. The parametric model for the propensity score was specified as in section 3.1. In turn, the regression function is a linear (regression) model where the dependent variable is the outcome variable Y_i, the total household income.

Independent variables in the regression model include demographic characteristics (household head's gender and years of schooling, and household size), asset endowments (total landholding size and tropical livestock units), access to public services (measured by membership to farmers' association), participation in off-farm activities, and district dummies. The author considered using agroecology zone dummies, but district dummies are relatively more disaggregated. District dummies are subsets of agroecology zone dummies.

3.3 Sub-classification and regression

The motivation for using sub-classification and regression is to contrast the average treatment effect in different blocks. The observations were grouped into quintiles of propensity scores. For each quintile q (or block), the following model was estimated:

$$Y_i = \alpha_q + \tau_q W_i + \beta_q X_i + \varepsilon_i \qquad (4)$$

The average treatment effect is then calculated as the average of the five treatment effects τ from each block q, weighted by the number of observations contained in each block. The vector X_i of exogenous variables is the same as the one used in the regression part of the doubly robust estimator.

3.4 Matching and regression

The motivation for using matching and regression is twofold. The first goal is to improve the model results by correcting for possible remaining bias. The second goal is to compare the robustness of the estimation results given the econometric approach used. The model is similar to the sub-classification and regression model, except for the fact that the estimation is carried out for the whole sub-sample of matches, as opposed to estimating one model for each of the 5 blocks.

4 Data sources

This paper uses data from the National Agricultural Survey of 2005, commonly known as TIA05. The survey was implemented by the Department of Statistics within the Directorate of Economics of the Ministry of Agriculture in 2005, for the agricultural season of 2004/2005, covering the period from September 2004 to August 2005. The sample was designed to be representative both at the province level and the agro-ecological zone. A total of 6149 households were interviewed.

The TIA05 covered 94 out of 128 districts. Smallholders were asked whether they used selected agricultural technologies (k). The author's interest lies in the use of animal traction, improved seeds (maize), tractor mechanization, and whether the household owns an improved granary. Thus, there are four observable variables W_i^k, indicating the cause to which a given household is exposed to.

Animal traction is practically inexistent in northern provinces due to the occurrence of tsetse fly disease in cattle. Northern provinces include Niassa, Cabo Delgado, Nampula, and Zambézia. The analysis of the impact of animal traction is restricted to the central provinces of Tete, Manica, and Sofala, and the southern provinces of Inhambane, Gaza, and Maputo. The analyses of the remaining technologies use national data.

The outcome variable is the total household income in 2004/05 agricultural season. Household incomes are calculated from TIA data as the value of own production and off-farm earnings, less any paid-out costs [40]. Income sources include (i) net crop income, (ii) livestock sales, (iii) off-farm self-employment, net small-business income, (iv) off-farm self employment, resource-extraction income, (v) off-farm agricultural wage income, (vi) off-farm non-agricultural wage income, and (vii) remittance income.

5 Results

5.1 Descriptive analysis

Table 1 presents descriptive statistics. With regard to demographic characteristics, two patterns are worth mentioning. First, farmers using all four improved technologies belong to households whose heads are significantly more educated than their counterparts. Second, household size is significantly larger among treated farmers. One possible explanation is the fact that larger households are more likely to have members engaged in nonfarm income generating activities, and hence are able to bear the costs and the risk of adopting improved technologies.

TABLE 1 AROUND HERE

The use of tractor mechanization is significantly correlated with road infrastructure. The distance to the nearest tarred road is three times higher among households who did not use tractors, relative to their counterparts. Remarkably, among the 2 percent of the population that used a tractor, 49 percent accrues to Maputo province, and 32 percent to Gaza province, both located in the south, a region of relatively lower agricultural potential, but of better road infrastructure. The remaining 19 percent are distributed across the other 8 provinces, which includes agro-ecological zones of higher agricultural potential, but relatively poorer road infrastructure.

Unsurprisingly, adoption rates rise with increases in both landholding size and livestock flocks for all four improved technologies. Households with larger landholdings will potentially have higher production and thus feel compelled to invest in improved granaries. The use of animal traction or tractor mechanization is also cost-effective in larger fields. Additionally, the adoption of animal traction and tractor mechanization require some initial investment, and asset endowment is positively and significantly correlated with household welfare.

With regard to access to credit, the difference between treated and untreated households was only significant for the adoption of tractor mechanization, and marginally significant for the use of animal traction. This result, however, is an artifact of a low data variation as not many households could access the emerging rural credit market. Furthermore, a tractor can be used as collateral, a bottleneck for many rural households in accessing to the credit market.

Membership to farmers' association is also significantly correlated with the use of improved agricultural technologies. The number of farmers using tractor mechanization is three times higher among members of an association. Similarly, there are twice as many farmers using improved seeds among members of a farmers' association.

5.2 The plausibility of the overlap and unconfoundedness assumptions

Figures 1A through 4A (Appendix) show the distribution of propensity scores for all four technologies. Treated and untreated households overlap very well, suggesting that the overlap assumption is plausible. Additionally, the assessment of the overlap assumption was complemented by the analysis of normalized differences. The results are presented in Table 2, and they show that normalized differences are in general smaller than 0.25 (in absolute value). Exceptions are the variables on head's age and tropical livestock units. However, this outcome did not affect the estimation results because these two variables were dropped from the stepwise logit model due to their low explanatory power. The results on the stepwise logit model are not reported to save space, but are available from the author upon request.

TABLE 2 AROUND HERE

The results on the plausibility of the unconfoundedness assumption are presented in Table B1 (Appendix). The pseudo causal impact of all four technologies considered in this paper is not significantly different from zero, supporting the unconfoundedness assumption. The results implicitly attest to the hypothesis that widow female headed households are among the disadvantaged ones.

5.3 Estimation results

As the 2004/05 agricultural season was a year of widespread drought, the impact of some of the improved technologies analyzed here will likely be affected by whether the household used irrigation. Table 3 provides the correlation matrix of selected agricultural technologies, including irrigation use. The use of tractor mechanization and improved seeds are positively and significantly correlated with irrigation use. While farmers using animal traction would have incurred relatively higher losses in 2004/05 agricultural season due to widespread drought, those using tractors and improved seeds may have had the negative impact of drought reduced through irrigation use. The reader is also reminded that animal traction is more predominant in southern provinces, a region where drought was more severe [43].

TABLE 3 AROUND HERE

Table 4 presents the estimation results of the impact of selected improved agricultural technologies, contrasting the results obtained through three econometric approaches. With the exception of animal traction, the impact of improved agricultural technologies is consistently positive and significantly different zero. The impact is greater for tractor mechanization, followed by the use of improved seeds, and finally the use of improved granaries.

Farmers that used animal traction and experienced losses in 2004/05 agricultural season may be enticed to abandon such technology, especially if they rented the animals and the implements. This is probably one of the reasons why “adoption rates” of improved agricultural technologies are usually very low: some farmers abandon the technology after some unsuccessful adoption attempts. Policies to sustain adoption of improved agricultural technologies should be put in place. Irrigation investments fall in that category.

TABLE 4 AROUND HERE

The significance of improved granaries underscores the relevance of post-harvest losses, and reducing these losses potentially results in (i) higher household income in light of opportunities for inter-temporal price arbitrage; and (ii) improved food entitlements and farmer’s nutritional status. The author speculates that the benefits from an improved granary might outstrip by far its construction costs, considering that it will be used for more than a year.

The impact of improved seeds on maize is about 2 000 Meticais/ha, and 5 180 Meticais/ha for tractor mechanization (roughly $80/ha and $212/ha, respectively). The estimates of the impact can also be regarded as shadow prices. Specifically, during the 2004/05 agricultural season, the use of tractor mechanization would be profitable for the farmer whenever the market cost of hiring a tractor (including gas expenses, driver, etc.) was below $212/ha. Likewise, the market price of improved maize seeds required to sow 1 hectare of maize should be lower than $80.

Taking into account that mean household income in 2004/05 was about $137 per adult equivalent (and the median was about $70/adult equivalent), and that less than 5 percent had access to credit, understanding why adoption of improved technologies is extremely low becomes trivial. Even if improved agricultural technologies were riskless, a bulk of farmers would not be financially capable of investing in such technologies, much less irrigation.

There is certainly an ample scope to enhance the impact of improved seeds and tractor mechanization, considering that less than 5 percent use irrigation or inorganic fertilizers, and about half of the tractors used in Mozambique are located in Maputo province, and more than 3/4 of all tractors are located in the south. If the Mozambican government wants to achieve the much talked-about green revolution, then huge investments on basic infrastructure and irrigation may pave the way for higher adoption rates and profitability of improved agricultural technologies.

The bad news is that climate change and global warming is a translucent reality, potentially with severe implications to African agriculture. In the Mozambican agriculture context, the implication is that any effort to foster adoption of animal traction, improved seeds, tractors, and other improved technologies should be accompanied by investments on irrigation or water conservation technologies. Furthermore, drought-tolerant improved seeds will also significantly increase both agricultural production and productivity amidst low irrigation use and recurrent drought spells across the country.

6 Conclusion

Using a nationally representative household survey from 2005, this paper analyzes the economic impact of improved agricultural technologies in rural Mozambique. The use of improved technologies is significantly correlated with household characteristics, road infrastructure, asset endowments, membership to a farmers' association, and access to credit. In general, the use of improved technologies had a positive and significant impact on household incomes, with the exception of animal traction.

The results underscore the need to combine efforts to increase agricultural productivity with those tailored to enhance farmers' ability to store food, a result marked by the significant impact of improved granary technology. The use of improved granaries translates into higher household incomes, and potentially improved food entitlements, and farmer's health and nutritional status.

Additionally, there is also a need to sustain adoption of improved technologies over time by means of ensuring a positive and significant impact of improved technologies. Measures to sustain adoption of improved technologies include investments on irrigation use, water conservation technologies, and drought-tolerant crop varieties, which raises the need for further research on these three subjects.

Scope certainly exists to enhance the impact of improved technologies, in view of the unequal adoption of such technologies, and a low use of other inputs (e.g. fertilizers). Besides significant investments on irrigation systems, creating a favorable environment to achieve the so much talked-about green revolution requires substantial investments in infrastructure and credit markets, particularly in central and northern Mozambique, in light of the agricultural potential in these two regions. Such investments would foster and sustain the adoption of improved agricultural technologies, with a significant impact on poverty reduction due to the importance of the agricultural sector in Mozambique, by a large amount the main source of employment and government revenues.

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Table 1
Descriptive statistics (means)

Improved technology	Total	Animal traction[a]			Tractor mechanization			Improved maize seeds			Improved granary		
		Treated	Control	P-value[b]	Treated	Control	P-value	Treated	Control	P-value	Treated	Control	P-value
Head's years of schooling	2.559	3.066	2.481	0.005	3.890	2.539	0.000	3.446	2.515	0.000	2.868	2.510	0.007
Widow female headed	0.085	0.122	0.153	0.003	0.120	0.084	0.023	0.061	0.086	0.224	0.045	0.090	0.000
Non-widow female headed	0.168	0.125	0.175	0.000	0.137	0.169	0.039	0.118	0.171	0.031	0.120	0.175	0.000
HH size[c] (# of members)	6.004	7.760	6.375	0.000	8.301	5.969	0.000	6.495	5.981	0.000	6.514	5.930	0.000
Head's age in years	43.997	49.104	46.490	0.000	48.565	43.928	0.000	42.498	44.064	0.233	45.616	43.760	0.000
Head is engaged in off-farm	0.602	0.555	0.595	0.000	0.692	0.601	0.099	0.658	0.599	0.135	0.609	0.601	0.713
HH used animal traction	0.092	1.000	0.000	NA	0.230	0.090	0.000	0.126	0.091	0.000	0.105	0.091	0.000
HH used inorganic fertilizers	0.037	0.049	0.054	0.224	0.130	0.035	0.000	0.091	0.034	0.000	0.066	0.032	0.000
Distance to the nearest tarred road (Km)	61.632	50.854	53.180	0.000	19.698	62.268	0.000	70.123	61.174	0.000	69.105	60.473	0.000
Tropical livestock units	0.976	4.237	1.195	0.000	2.455	0.954	0.000	1.711	0.943	0.000	1.646	0.879	0.000
Total landholding size (ha)	1.806	2.687	1.884	0.000	2.185	1.800	0.000	2.254	1.785	0.000	2.369	1.722	0.000
Membership to association	0.064	0.084	0.061	0.000	0.197	0.062	0.000	0.147	0.060	0.000	0.078	0.062	0.069
HH grows cash crops[d]	0.231	0.161	0.210	0.000	0.212	0.231	0.166	0.344	0.226	0.000	0.322	0.218	0.000
Household received credit	0.035	0.028	0.033	0.105	0.134	0.033	0.000	0.048	0.034	0.266	0.033	0.035	0.980
Number of observations	6,087	1,210	2,390		205	5,882		351	5,727		1,004	5,074	

Source: Author's own calculations based on TIA05 data

Notes: [a] Standard deviation not reported to save space;
[b] Ha: The difference in means is not equal to zero;
[c] HH stands for household;
[d] cash crops include cotton, tobacco, tea, sunflower, sesame, sisal, soybeans, paprika, ginger, and sugar cane.

Table 3
Correlation matrix of the selected improved agricultural technologies and irrigation use

	Tractor		Animal traction		Improved seeds		Improved granary	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Tractor	1.000							
Animal traction	0.058	0.000	1.000					
Improved seeds	0.007	0.612	0.025	0.050	1.000			
Improved granary	0.017	0.198	0.016	0.217	-0.010	0.457	1.000	
Irrigation[a]	0.096	0.000	0.018	0.154	0.029	0.026	0.013	0.322

Source: Author's own calculation based on TIA05 data
Notes: [a] Irrigation refers to water pump irrigation

Table 4
The impact (in Meticais) of selected improved agricultural technologies

Technology	Econometric approach	Coefficient	Std. Error	P-value
Tractor	Doubly robust	13 549.86	3 131.15	0.000
	Sub-classification and regression	11 332.82	608.06	0.000
	Matching and regression	8 148.71	2 767.16	0.003
Animal traction	Doubly robust	-613.29	997.08	0.538
	Sub-classification and regression	-1 599.53	1 758.23	0.486
	Matching and regression	407.96	1 220.54	0.738
Improved maize seeds	Doubly robust	4 596.61	1 649.63	0.005
	Sub-classification and regression	4 687.87	157.54	0.000
	Matching and regression	3 324.68	1 466.34	0.024
Improved granaries	Doubly robust	2 762.14	870.85	0.002
	Sub-classification and regression	2 782.54	21.56	0.000
	Matching and regression	2 603.29	772.09	0.001

Sources: Author's own calculations based on TIA05 data
Notes: Exchange rates in 2005 ($1.00=24.5 Meticais)

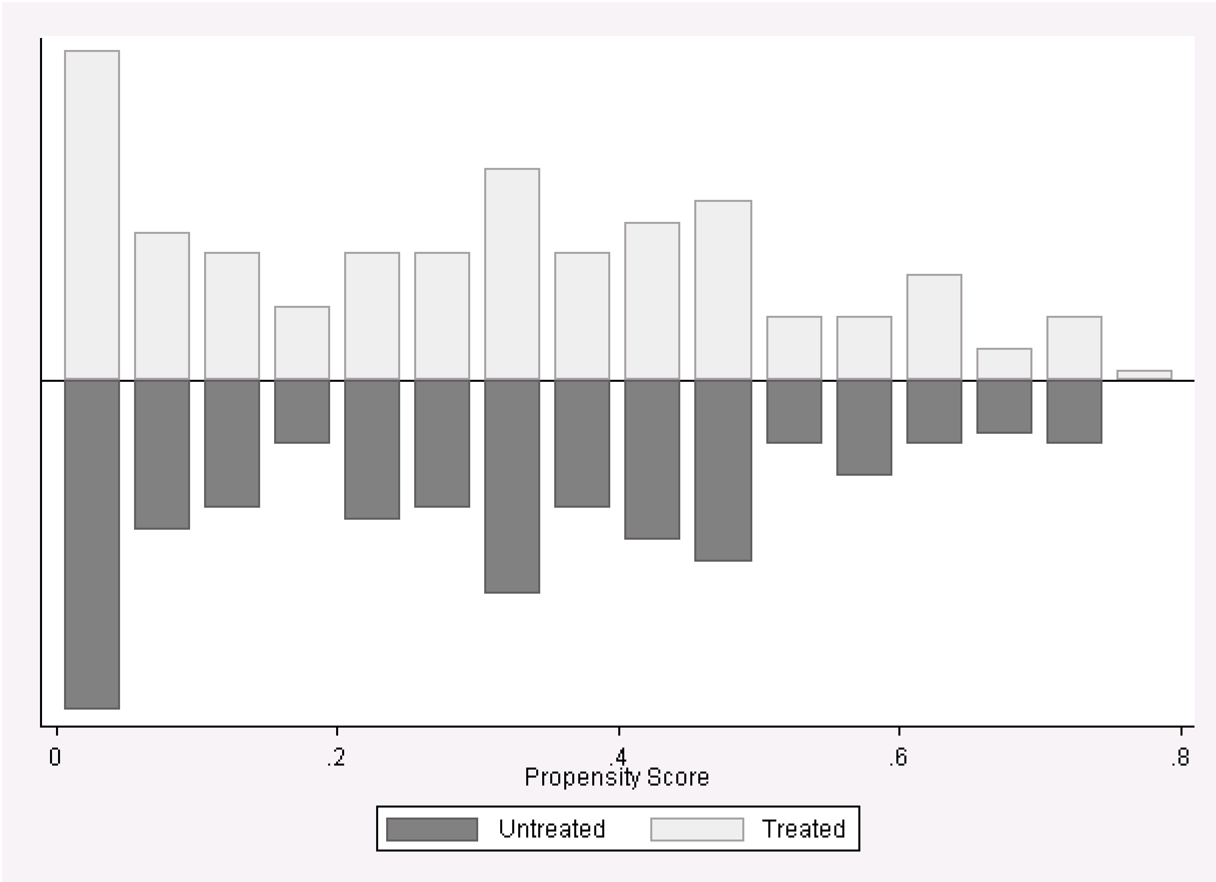

Figure 1A Propensity score distribution of treated and untreated farmers – tractor mechanization

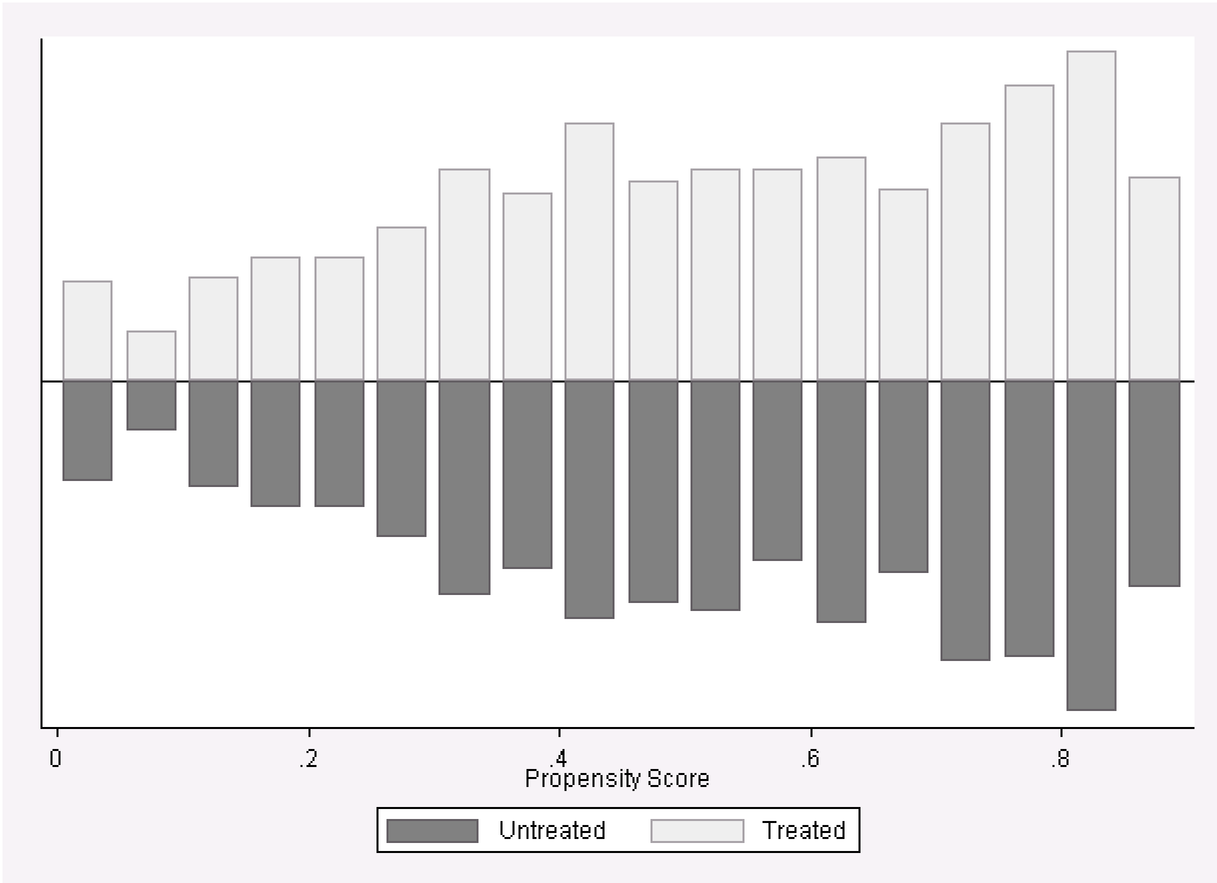

Figure 2A Propensity score distribution of treated and untreated farmers – animal traction

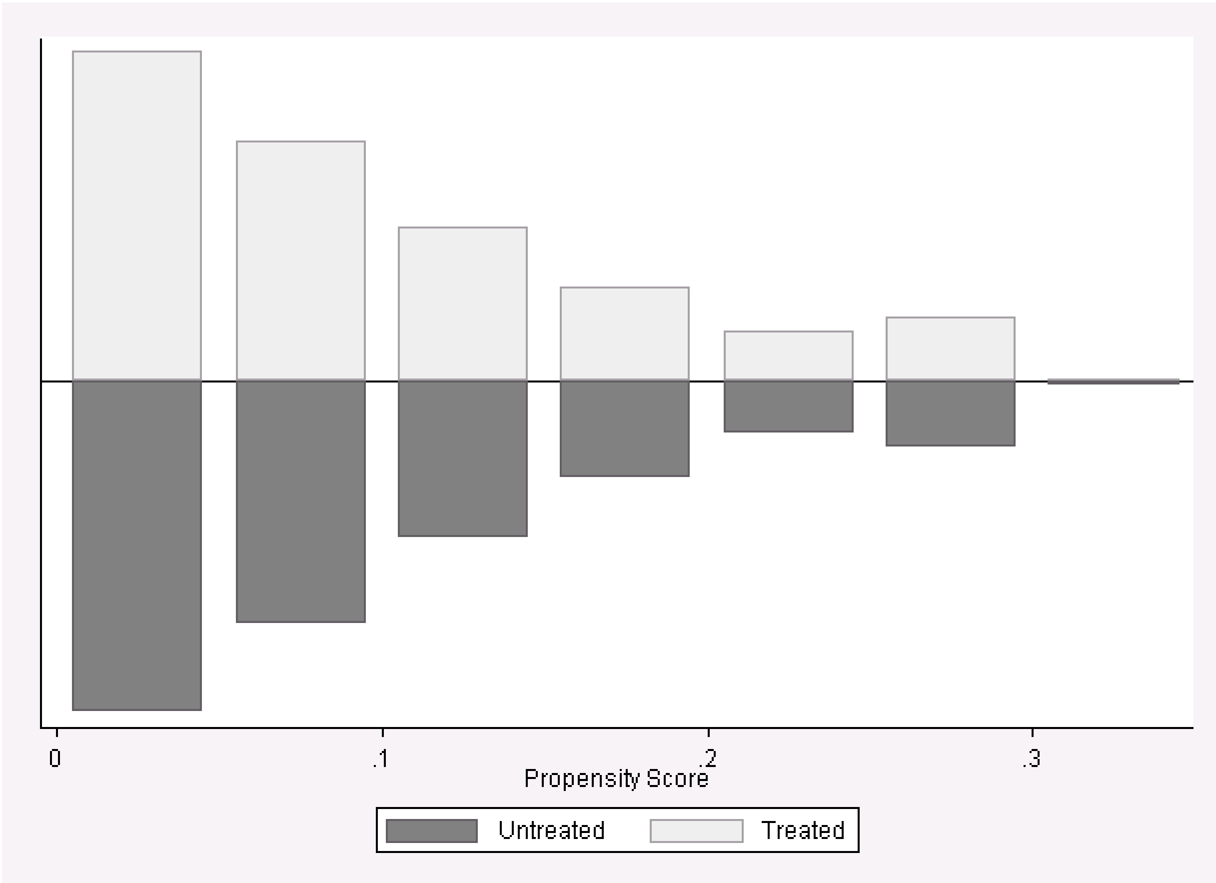

Figure 3A Propensity score distribution of treated and untreated farmers – Improved maize seeds

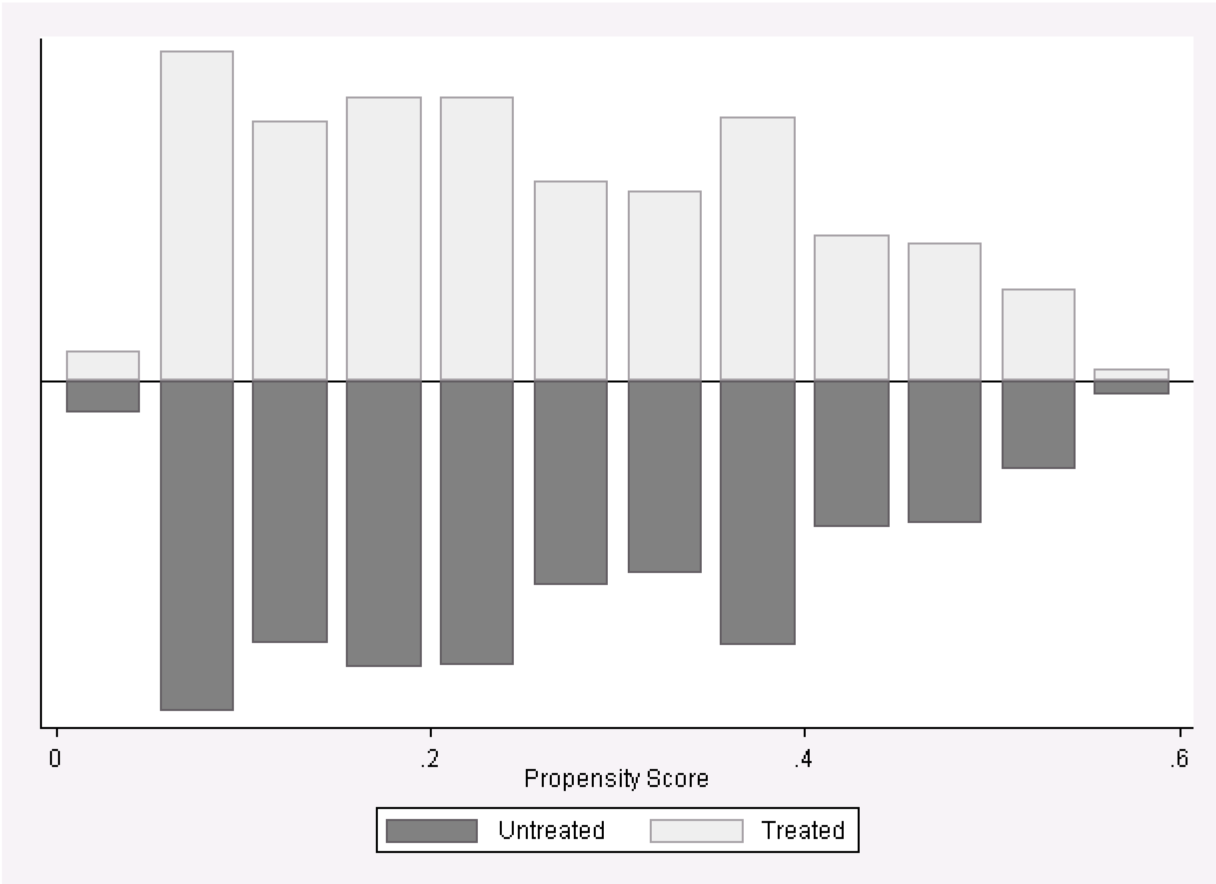

Figure 4A Propensity score distribution of treated and untreated farmers – Improved granary

Table B1
Pseudo impact (in Meticais) of selected improved agricultural technologies: assessing the unconfoundedness assumption

Technology	Econometric approach	Coefficient	Std. Error	P-value
Tractor	Doubly robust	-1 541.76	1 099.93	0.161
	Sub-classification and regression	-596.69	709.99	0.584
	Matching and regression	-886.18	939.75	0.346
Animal traction	Doubly robust	-2 073.73	1 765.71	0.240
	Sub-classification and regression	-2 213.78	1 610.73	0.221
	Matching and regression	-1 697.12	1 231.07	0.168
Improved maize seeds	Doubly robust	-411.08	1 283.01	0.749
	Sub-classification and regression	1 160.83	1 505.20	0.694
	Matching and regression	58.39	1 003.00	0.951
Improved granaries	Doubly robust	-826.41	1 034.73	0.424
	Sub-classification and regression	1 575.84	845.04	0.170
	Matching and regression	-28.92	970.37	0.976

Notes: Exchange rates in 2005 ($1.00=24.5 Meticais)
Sources: Author’s own calculations based on TIA05 data