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Impact of tissue culture banana technology in Kenya: A difference-in-difference estimation approach

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Abstract: Most micro-level studies on the impact of agricultural technologies build on cross-section data, which can lead to unreliable impact estimates. Here, we use panel data covering two time periods to estimate the impact of tissue culture (TC) banana technology in the Kenyan small farm sector. TC banana is an interesting case, because previous impact studies showed mixed results. We combine propensity score matching with a difference-in-difference estimator to control for selection bias and account for temporal impact variability. TC adoption has positive impacts on banana productivity and profits. The technology increases yields by 40-50% and gross margins by around 100%. These large effects represent the impact of TC technology in combination with improved management practices and higher input use, which is recommended. Looking at the isolated TC effect may underestimate impact because of synergistic relationships. The results suggest that extension efforts to deliver the technological package to smallholder farmers should be scaled up.

Key words: Agricultural technology; Difference-in-difference; Selection bias; Temporal impact variability; Impact; Kenya.

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1. Introduction

There is a large body of literature on agricultural technology adoption and impacts, underlining the important role that suitable innovations can play for rural growth and poverty reduction in developing countries (Feder et al., 1985; Doss, 2006; Mendola, 2007; Minten and Barrett, 2008; Becerril and Abdulai, 2010; Maredia and Raitzer, 2012). Most of this research builds on cross-section observational data. For impact assessment, such data can be associated with two types of problems, namely non-random selection bias and the inability to analyze temporal impact variability. Selection bias can occur when technology adopters differ systematically from non-adopters due to observed or unobserved factors (Heckman et al., 1998; Duflo et al., 2007; Winters et al., 2011). Temporal impact variability may occur in particular when the performance of the technology is influenced by weather or pest infestation conditions, which tend to vary over time. Use of panel data is a suitable approach to reduce these problems, but panel data are rarely available for impact assessment. In this study, we use panel data and suitable statistical techniques for more robust and reliable impact assessment. In particular, we combine propensity score matching with a difference-in-difference estimator to analyze the impact of tissue culture (TC) banana technology in Kenya.

Traditionally, bananas are propagated by using suckers from old plantations. While this method is cheap for farmers, it contributes to spreading pests and diseases, thus hampering crop development and productivity. TC is an in-vitro technique of plant propagation, resulting in pathogen-free plantlets. Experience from Latin America and South Africa suggests that TC technology can contribute to significant yield gains in well managed, commercial banana plantations (Vuylsteke, 1998). However, it is unclear whether these results can be transferred to the small farm sector, where crop management is often influenced by institutional and human capital constraints. TC banana technology has been available in Kenya since the late-1990s (Wambugu and Kiome, 2001); adoption rates are still relatively low (Njuguna et al., 2010). A few studies have analyzed the impact of TC bananas in Kenya, yet with mixed results. While Njuguna et al. (2010) reported large productivity gains, Muyanga et al. (2009) did not find significant yield differences between TC and conventional bananas. Both studies did not control for possible selection bias. Kabunga et al. (2012a) collected cross-section data and showed that there is selection bias, using an instrumental variable approach. When controlling for this bias, they found a moderate productivity gain associated with TC adoption. But they also pointed out that impacts depend on water availability, as TC plants seem to convert water input more effectively into banana output than conventional plants (Kabunga et al., 2012a). Hence, temporal impact variability may be expected. This makes TC bananas an interesting technology for impact assessment with panel data and improved econometric techniques.

The remainder of this article is organized as follows. The next section describes some further background on TC banana in Kenya. Section 3 presents the statistical approach and describes the panel data. Section 4 presents and discusses the results. Conclusions are drawn in section 5.

2. Background on TC banana in Kenya

Banana in Kenya was traditionally grown by smallholder farmers mostly for home consumption, with some surplus sold to the local market. More recently, with growing banana demand in urban areas, degrees of commercialization have increased (Qaim, 1999). However, banana yields in Kenya are low and stagnating, largely due to problems with pests, diseases, drought, and poor agronomic practices (Dubois et al., 2006; Njuguna et al., 2010). Most small-scale banana growers establish new plantations with suckers from old plantations, thus exacerbating pest and disease problems. The potential of TC technology to contribute to productivity growth stimulated different organizations to promote this technology in East Africa (Smale and Tushemereirwe, 2007). In Kenya, the International Service for the Acquisition of Agri-biotech Applications (ISAAA) had started a project in the late-1990s, producing and disseminating TC plantlets to local banana farmers (Wambugu and Kiome, 2001). Later on, the Kenya Agricultural Research Institute (KARI) and Jomo Kenyatta University of Agriculture and Technology (JKUAT) also became involved in TC bananas. Since 2003, Africa Harvest, an international nongovernmental organization, has promoted more widespread TC adoption, using innovative models of technology delivery with a whole value chain approach. Whereas KARI and JKUAT have spun off laboratories and set up farmer group-managed TC nurseries in several parts of the country, Africa Harvest collaborates with private companies to provide TC plantlets to farmers who are organized in groups.

Considering Kenya as a whole, less than 10% of all banana farmers have adopted TC so far (Njuguna et al., 2010). In Central and Eastern Provinces, where most of the dissemination programs started, adoption rates are around 15% (Kabunga et al., 2012b). The TC adoption process is relatively slow for two reasons. First, TC plantlets are fairly expensive. Whereas traditional suckers can be dug out from old plantations, the average price of a TC plantlet is around 80 Kenyan shillings (KES), equivalent to about 1 US dollar. Second, TC plantlets require proper plantation management and more inputs in order to yield successfully, implying a mentality change for the smallholders, who tend to neglect their banana crop (Qaim, 1999).

3. Materials and methods

3.1 Statistical approach

We want to establish the impact of TC banana adoption on smallholder yields and profits in Kenya. The general idea of impact assessment is to evaluate the mean effect of adopting the technology or any other kind of treatment. This requires comparison of the outcome variable for the same group of farmers with and without treatment. For example, if the outcome is banana yield (Y) the impact of TC technology could be measured by comparing the mean yield of all TC adopting banana growers with the mean yield they would obtain had they not adopted the technology. The difference between these two mean yields is referred to as the average treatment effect on the treated (ATT):

$$ATT = E(Y^1 \mid A = 1) - E(Y^0 \mid A = 1) \tag{1}$$

where Y^1 is the banana yield of an adopting farm household with TC, and Y^0 is the yield of the same adopting farm household without TC. A = 1 indicates that we are looking at the same group of adopters in both cases. Unfortunately, the difference between $Y^1 \mid A = 1$ and $Y^0 \mid A = 1$ cannot be observed for the same farm household, because adopters have adopted and we do not know what their yield would have been had they not adopted.

A common approach to get out of this dilemma is to find a control group of non-adopters, whose outcomes are compared with those of adopters. However, adoption of TC banana in Kenya is non-random; that is, subjects self-select into treatment. In that case, a fundamental problem in calculating the treatment effect is that the yield difference between adopters and non-adopters may also be due to systematic differences other than TC. This would result in selection bias, and the TC treatment effects would be overestimated or underestimated, depending on the type of bias.

The problem of selection bias can be reduced through different statistical methods. A popular method is propensity score matching (PSM), which can control for bias due to observed differences between treatment and control groups, but not for unobserved heterogeneity (Rosenbaum and Rubin, 1983; Mendola, 2007; Becerril and Abdulai, 2010). Another method is instrumental variable (IV) regressions (Greene, 2008). IV regressions can deal with unobserved heterogeneity, but the problem is that good instruments are often difficult to find, especially in cross-section data. When panel data are available, fixed-effects models can be used (Krishna and Qaim, 2012). However, impact analysis with fixed-effects estimators requires sufficient within-group variability with respect to the treatment variable. Michalopoulos et al. (2004) showed that propensity score methods may be preferable in some cases. The advantage of PSM is that it can be combined with other estimators to also deal with unobserved heterogeneity, when panel data are available. We build on two years of panel data and combine PSM with a difference-in-difference (DID) estimator. In the following, we first describe the PSM method as such, before we introduce the DID estimator.

The idea of PSM is that TC adopters and non-adopters with similar observable characteristics are matched (Rosenbaum and Rubin, 1983; Smith and Todd, 2001, 2005). The propensity score is defined as the conditional probability that a farm household i adopts TC given a set of farm household characteristics X:

$$p(X) = \text{Prob}(A = 1 \mid X_i), \tag{2}$$

where $A = (0,1)$ is an adoption dummy, and X_i is a vector of pre-treatment covariates, including variables that can affect both TC adoption and yield (or other outcomes). Propensity scores can be estimated using logit or probit models (Maddala, 1983). We use a probit model in this study.

Two conditions are imposed when executing PSM, the balancing property and common support. The balancing property is achieved when households with the same (or similar) propensity scores have the same distribution of *X*, irrespective of the technological status. This is important to reduce the influence of possible confounding factors (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 2002). The common support, or overlap, condition assures that households with the same (or similar) *X* values have a positive probability ($0 < p(X) < 1$) of both adopting and non-adopting TC technology (Heckman et al., 1997). That is, the calculation of the treatment effect is only performed for treated and control households that share a common support in their estimated propensity scores, excluding the tails of the distribution of $p(X)$.

When using cross-section data, selection bias is addressed based on a single difference matching estimator. Adopters and non-adopters with similar observable characteristics are matched (Dehejia and Wahba, 2002). After estimating the propensity score, the ATT is estimated as:

$$ATT = E\{Y^1 \mid A = 1, p(X)\} - E\{Y^0 \mid A = 0, p(X) \mid A = 0\} \tag{3}$$

With this estimator, possible differences between adopters and non-adopters that are due to unobserved factors cannot be controlled. This is different when panel data are available, as in our case. With panel data, PSM can be combined with a DID estimator, so that time-invariant unobserved factors cancel out (Smith and Todd, 2005). Thus, a combination of PSM and DID can improve the quality of non-experimental evaluation significantly (Blundell and Costa Dias, 2000; Benin et al., 2011).

The DID estimator exploits the fact that observations from two time periods are available for each individual, in our case 2009 and 2010. The ATT of TC adoption is then calculated by comparing the changes in individual outcomes among adopters ($Y_{2010}^{1} - Y_{2009}^{1}$) with the changes among their non-adopting matches ($Y_{2010}^{0} - Y_{2009}^{0}$):

$$ATT = E\left\{Y_{2010}^{1} - Y_{2009}^{1} \mid A = 1, p(X)\right\} - E\left\{Y_{2010}^{0} - Y_{2009}^{0} \mid A = 0, p(X) \mid A = 0\right\}$$

$$= \frac{1}{N_1}\left\{\sum_{i=1}^{N_1}\left(Y_{2010}^{1} - Y_{2009}^{1}\right) - \sum_{i=1}^{N_1}\left(Y_{2010}^{0} - Y_{2009}^{0}\right)\right\}, \qquad (4)$$

where N_1 is the number of matches.

Different matching algorithms are available for PSM (Caliendo and Kopeinig, 2008). The most common ones are kernel matching and nearest neighbor (NN) matching. Kernel matching computes treatment effects by deducting from each outcome observation in the treatment group a weighted average of outcomes in the control group. NN matches adopters with non-adopters with the nearest propensity score, while controlling for differences between adopters and non-adopters (Abadie and Imbens, 2006). We use kernel matching with two band widths (BW=0.03 and BW=0.06) and NN matching one and five (NN=1 and NN=5). Analyses are based on common support and caliper, reflecting that the distributions of TC adopters and non-adopters were closely alike in terms of observable characteristics. As a balancing test, we test for significant differences in terms of independent variables between TC adopters and non-adopters before and after matching (Dehejia and Wahba, 2002).

In estimating the ATT, we use bootstrapping methods for robust standard errors, because we match adopting to non-adopting households with replacement, as explained further by Dehejia and Wahba (2002). The outcome variables considered are banana yield (annual production per acre) and profit (annual gross margin per acre).

3.2. Data and descriptive statistics

The empirical analysis is based on two rounds of a survey of banana farmers, covering Central and Eastern Provinces of Kenya. In these two provinces, the districts of Meru, Embu, Kirinyaga, Kiambu, Murang'a, and Thika were purposively selected; these are the main banana-growing districts where TC dissemination efforts have been ongoing for several years. In each district, banana-growing villages were purposively selected. At the village level, farm households were sampled with a stratified random procedure. Separate village listings of TC adopters and non-adopters were prepared, and adopters were oversampled to have a sufficient number of observations for robust impact assessment. The first round of data was collected between September and December of 2009, referring to banana production in 2009, which was a drought year in large parts of Kenya. The second round of data was collected in December 2010 and January 2011, referring to production in 2010 with more rainfall.

Table 1 shows the distribution of adopters and non-adopters during the two survey rounds. In 2009, a total of 385 banana farmers were sampled, comprising 223 TC adopters and 162 non-adopters. In 2010, 320 of these farmers were interviewed again: 193 were adopters and 127 non-adopters. The sample attrition rate of approximately 17% is within the bounds of attrition commonly found in longitudinal surveys from developing countries (Alderman et al., 2001). An analysis of observable characteristics for 2009 showed that the dropouts in 2010 did not differ systematically from those who remained in the sample. Our analysis is based on a balanced sample, that is, we use 320 farm households for which two rounds of data are available. Out of these, around 60% are TC adopters, and 40% are non-adopters.

Using appropriate weights to take account of the multi-stage and stratified sampling procedure, the sample is considered representative for banana farmers in Central and Eastern Provinces of Kenya. In each farm household, the household head was interviewed using a structured questionnaire. Data on farm and household characteristics were collected, including input and output details for the banana crop. Additionally, data on institutional aspects, such as access to information, credit, roads, and market infrastructure were covered in the questionnaire.

Table 2 shows descriptive sample statistics. TC adopters and non-adopters are similar with regard to gender of the household head, household size, and income from off-farm activities. Significant differences are observed for a number of other characteristics, such as education, age, farm size, and other productive assets. There are also differences in terms of membership in social groups and access to information, factors which were shown in other studies to influence technology adoption behavior (Bandiera and Rasul, 2006; Matuschke and Qaim, 2009; Murshed-E-Jahan and Pemsl, 2011).

Mean values for the two outcome variables of interest, banana yield and gross margin, are shown in Table 3 for 2009 and 2010. Both adopters and non-adopters had significantly higher yields in 2010 than in 2009. This is in line with the better rainfall conditions in 2010. Gross margins, expressed as total value of banana production less total variable costs per acre, were also higher in 2010 than in 2009, albeit the difference is statistically significant only for the adopters. Strikingly, yields and gross margins in both years were lower for adopters than for non-adopters. Yet, this comparison should not be overinterpreted as it may be misleading. Kabunga et al. (2012a) showed that there is negative selection bias, meaning that farmers with lower than average yields are more likely to adopt TC technology in Kenya. This is plausible. As pathogen-free TC plants help reduce pest and disease problems, farmers suffering more from such problems have a higher incentive to adopt this technology. In the next section, we derive TC treatment effects that control for such selection bias.

4. Results and discussions

4.1. Propensity scores and matching

Table 4 shows the results of the probit model, which we estimated in order to derive the propensity scores. The estimates suggest that farm size, the value of other productive assets, off-farm income, education, group activities, and access to agricultural information are important determinants of TC banana adoption in Kenya. This is in line with earlier adoption research for TC bananas and other technologies in the small farm sector (Feder et al, 1985; Doss, 2006; Kabunga et al., 2012b). The estimated model with common support imposed and the balancing property condition satisfied is statistically significant and has a reasonable goodness-of-fit.

Figure 1 shows the distributions of propensity scores before and after matching.[1] The balancing test results are shown in Table 5. These results are based on kernel matching (BW=0.06). Before matching, TC adopters were significantly different from non-adopters with respect to most characteristics. Of the 193 TC adopters, 21 did not match any of the non-adopters and were thus excluded from the subsequent analyses. The test results show that all significant differences between adopters and non-adopters in the unmatched sample were eliminated after matching[2]

4.2. Average treatment effects on the treated

The ATT, calculated with the DID estimator and different matching algorithms, are shown in Table 6. We use log values for the two outcome variables, banana yield and gross margin, so that the results can be interpreted in terms of percentage changes. Adoption of TC has large positive

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[1] Matching estimates were obtained using the Psmatch2 command in Stata 11 developed by Leuven and Sianesi (2003).

[2] Other balance indicators were computed for kernel and nearest neighbor matching, as proposed by Sianesi (2004). These additional specifications passed the balancing tests; they are not reported here to save space.

effects. During the period of investigation this technology increased banana yields by 40-50% and banana gross margins by 90-120%. These results are quite different from the simple comparison of TC yields and gross margins in Table 3, confirming that there is significant negative selection bias. Farmers with lower than average yields and gross margins are more likely to adopt TC. Hence, a simple comparison between adopters and non-adopters underestimates the technology's treatment effect. This selection bias is controlled for by the PSM and DID methodology. Most of the estimates in Table 6 are significant, underlining the robustness of the results.

Kabunga et al. (2012a) had analyzed yield effects of TC bananas in Kenya based on cross-section data from 2009. Using an IV regression approach, they also found negative selection bias and identified an average net yield effect of TC technology of 7%. This is much lower than the yield effect found here, which is due to three reasons. First, 2009 was a drought year, which dampened the TC yield effect. Here, we use data from 2009 with below average rainfalls and from 2010 with more rainfalls, thus taking better account of temporal fluctuations. Second, results from IV regressions depend on the strength of the instruments; good instruments are often not easy to find in cross-section data. The panel approach employed here is expected to lead to more robust and reliable results. Third, the interpretation of the results in the two studies is different. Kabunga et al. (2012a) estimated a production function where they controlled for differences in input use. Thus, the TC yield effect in their study has a ceteris paribus interpretation: when adopting TC and holding all other inputs constant, yield levels would increase by 7%. But for TC adopters it is recommended to use more inputs such as fertilizer and water and also change crop management practices. Hence, TC can be considered as a technological package, the impact of which is bigger than that of just adopting TC alone. Here, we consider the impact of the whole package. As the differences input use and crop management are induced by TC technology (rather than other factors that we control for through PSM), this is justified. Kabunga et al. (2012a) also noted that the yield effects of TC technology can be much higher when the use of complementary inputs is adjusted as recommended.

5. Conclusion

We have analyzed the impact of TC banana technology adoption in Kenya. Unlike previous impact studies for TC and other agricultural technologies, most of which build on cross-section data, we have used panel data covering two time periods. This allowed us to combine propensity score matching with a difference-in-difference estimator to control for selection bias and account for temporal impact variability. The estimation results show that TC adoption has positive impacts on banana productivity and profits. The technology increases yields by 40-50% and gross margins by around 100%. Thus, TC banana technology can contribute significantly to rural development in the Kenyan small farm sector.

The estimated effects are very large. They represent the impact of TC technology in combination with improved management practices and higher input use. One might argue that improved management practices and higher input use could also increase banana yields without TC technology. While this is true, smallholder banana growers tend to use very low amounts of inputs in their conventional crop. Thus, TC adoption can be seen as a trigger to intensify banana production systems. Against this background, it is useful to look at the impact of the complete technology package. Even among the TC adopters, labor use and the application of inputs such as fertilizer and water are still quite low (Kabunga et al., 2012a). Stronger intensification could further improve the outcomes.

This discussion underlines that technology adoption is not easy to define when the technology consists of various components. This holds true for many natural resource management technologies that largely build on agronomic innovation (Lee, 2005; Noltze et al., 2012). In the case analyzed here, switching to TC combined with better crop management and higher input use produces positive synergistic effects. In contrast, adopting only TC without any other changes in traditional practices can lead to frustrating experience. Hence, TC is a knowledge-intensive technology, and successful uptake requires proper extension. This is also one of the reasons why TC adoption is still relatively low in Kenya. Our results suggest that extension efforts to deliver the technological package to smallholder farmers should be scaled up.

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Tables

Table 1: Number of sampled farm households in two survey rounds

	Year of survey		
	2009	2010	Attrition rate (%)
TC adopters	223	193	13.4
Non-adopters	162	127	20.9
All banana growers	385	320	16.9

Table 2. Descriptive statistics for TC adopters and non-adopters (2009)

	Mean (SD)			
Variables	All	Adopters	Non-adopters	Difference
Household characteristics				
Male hh head (dummy)	0.18(0.38)	0.16(0.36)	0.20 (0.41)	-0.26
HH size (members)	4.56(2.02)	4.60 (2.02)	4.51(2.01)	0.09
Education of hh head (years)	8.44(4.05)	9.03(4.09)	7.55(3.83)	1.48***
Age of hh head (years)	58.85(13.65)	60.21(13.35)	56.79(13.90)	3.41***
Asset and financial capital				
Off-farm income (‘000 KES)	92.24(151.09)	90.94(144.92)	94.22(160.57)	-3.28
Farm size (acres owned)	3.34 (3.00)	3.83 (3.27)	2.60 (2.35)	1.24***
Other productive assets (‘000 KES)	165.82(203.50)	193.30(220.41)	124.06(167.06)	69.24***
Social capital and information access				
Group membership (dummy)	0.91(0.28)	0.97(0.20)	0.83(0.38)	0.14***
Information constrained (dummy)	0.28(0.45)	0.19(0.39)	0.42(0.49)	-0.23***
Knows TC nursery location (dummy)	0.78(0.43)	0.96(0.20)	0.50(0.50)	0.45***
Drought experience				
Affected by drought in 2009 (dummy)	0.47(0.50)	0.48 (0.50)	0.44(0.49)	0.47
Affected by drought in 2010 (dummy)	0.21(0.41)	0.24 (0.43)	0.17 (0.37)	0.07
Number of observations	*320*	*193*	*127*	

Note: hh means household.
* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

Table 3. Descriptive statistics for outcome variables

		2009		2010		Difference
Variable		Mean	SD	Mean	SD	
Banana yields (‘000 kg/acre)	All	8.40	7.47	13.09	11.66	4.69***
	Adopters	7.65	7.59	11.72	10.16	4.07***
	Non-adopters	9.54	7.18	15.15	13.41	5.63***
Banana gross margins (‘000 KES/acre)	All	91.66	8.62	111.17	112.03	19.71***
	Adopters	87.29	9.15	107.46	106.54	20.17**
	Non-adopters	98.31	7.74	117.33	120.09	19.02

** Significant at 5% level.
*** Significant at 1% level.

Table 4. Probit estimates for propensity to adopt TC banana (2009)

Variables	Coefficients
Farm size	0.148**(0.064)
Farm size squared	-0.008**(0.003)
Other productive assets	2.20E-06* (1.28E-06)
Other productive assets squared	-1.41E-12(1.22E-12)
Information constrained	-0.351*(0.198)
Education of hh head	0.070**(0.028)
Male hh head	0.282(0.244)
Age of hh head	-0.078(0.052)
Age squared	0.001*(0.000)
Household size	0.046(0.046)
Group membership	1.468***(0.390)
Knows TC nursery location	1.754***(0.064)
Off-farm income	-1.92E-06***(1.28E-06)
Affected by drought in 2009	0.108(0.175)
Constant	-2.530*(1.363)
Regression statistics	
Pseudo R-squared	0.35
LR chi-square	149.49***
Number of observations	320

Notes: hh means household. Standard errors in parentheses.
* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

Table 5. Balancing test for differences between TC adopters (treated) and non-adopters (control)

	Before matching			After matching		
Variable	Treated	Control	t-value	Treated	Control	t-value
Propensity score	0.777	0.350	15.57***	0.747	0.747	0.03
Farm size	3.834	2.597	3.68***	3.495	3.796	-0.83
Farm size squared	25.334	12.232	2.26**	22.093	26.962	-0.70
Other productive assets	$1.9x10^5$	$1.2x10^5$	3.02***	$1.7x10^5$	$1.6\ x10^5$	0.81
Assets squared	$8.6\ x10^{10}$	$4.3\ x10^{10}$	1.91*	$7.4\ x10^{10}$	$6.0\ x10^{10}$	0.69
Information constrained	0.192	0.417	-4.52***	0.2093	0.170	0.94
Education of hh head	9.034	7.552	3.25***	8.881	8.386	1.20
Male hh head	1.155	1.204	-1.13	1.145	1.187	-1.05
Age of hh head	60.207	56.795	2..20**	58.581	60.363	-1.36
Age squared	3802.2	3417.3	2.10**	3589.4	3778.0	-1.26
Household size	4.601	4.512	0.39	4.581	4.520	0.29
Group membership	0.969	0.827	4.53***	0.971	0.961	0.50
Knows TC nursery	0.959	0.504	11.30***	0.953	0.940	0.55
Off-farm income	90937	94215	-0.19	85196	76541	0.64
Affected by drought 2009	0.482	0.441	0.72	0.494	0.535	-0.30

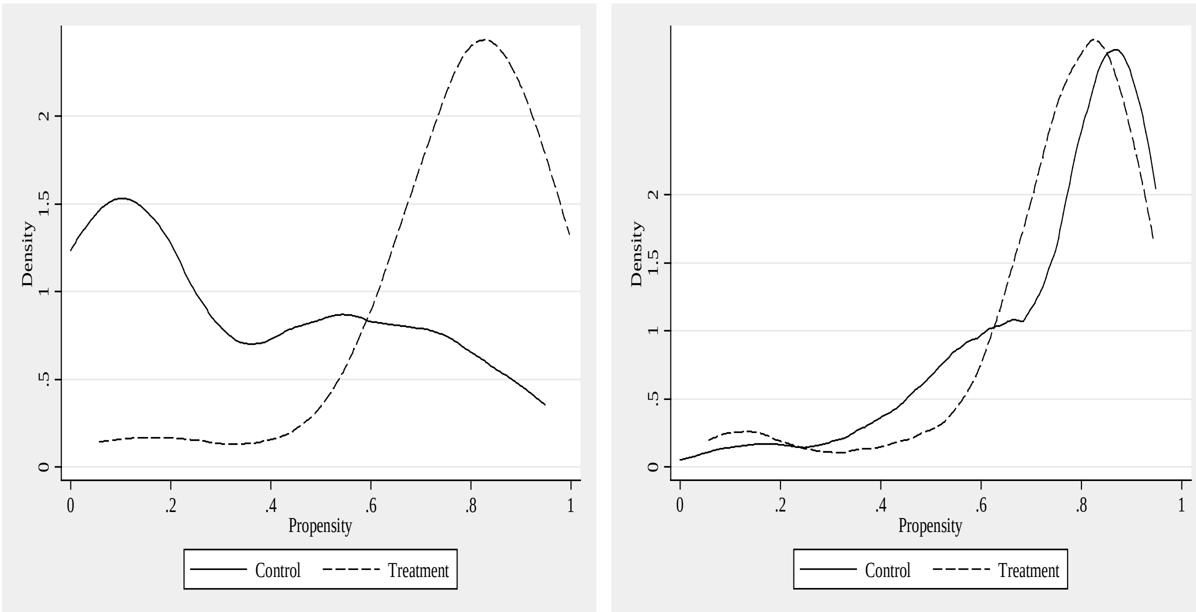
* Significant at 10% level.
** Significant at 5% level.
*** Significant at 1% level.

Table 6. Average treatment effect on the treated (ATT) of TC banana (2009-2010)

	Matching algorithm			
	Kernel (BW=0.03)	Kernel (BW=0.06)	Nearest-neighbor (NN=1)	Nearest-neighbor (NN=5)
Outcome	ATT	ATT	ATT	ATT
Yields	0.457**(0.225)	0.502**(0.234)	0.414(0.263)	0.428*(0.232)
Gross margins	0.987*(0.567)	1.142*(0.593)	1.247*(0.702)	0.869(0.592)

Notes: 0.03 and 0.06 band widths (BW) and Epanechnikov kernel used for kernel and 1 and 5 nearest neighbor (NN) matching. Bootstrapped standard errors, based on 1000 replications, are reported in parentheses. Log differences are reported for the outcome variables. Multiplied by 100 these can be interpreted as percentage effects.
* Significant at 10% level.
** Significant at 5% level.

Figures



(a) Before matching (b) After matching

Fig. 1. Propensity score distributions