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Yield Effects of Tissue Culture Bananas in Kenya: Accounting for Selection Bias and the Role of Complementary Inputs

Nassul S. Kabunga [a*], Thomas Dubois [b], Matin Qaim [a]

Abstract

We analyze yield effects of tissue culture (TC) banana technology in the Kenyan small farm sector, using recent survey data and an endogenous switching regression approach. TC banana plantlets, which are free from pests and diseases, have been introduced in East Africa since the late-1990s. While field experiments show significant yield advantages over traditional banana suckers, a rigorous assessment of impacts in farmers' fields is still outstanding. A comparison of mean yield levels between TC adopters and non-adopters in our sample shows no significant difference. However, we find a negative selection bias, indicating that farmers with lower than average yields are more likely to adopt TC. Controlling for this bias results in a positive and significant TC net yield gain of 7%. We also find that TC technology is more knowledge-intensive and more responsive to irrigation than traditional bananas. Simulations show that improving access to irrigation could lift TC productivity gains to above 20%. The analytical approach developed and applied here may also be useful for the evaluation of other knowledge-intensive package technologies and innovations in perennial crops.

Keywords: Biotechnology, adoption, productivity, impact, endogenous switching regression, Kenya

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1. INTRODUCTION

Tissue culture (TC) banana technology has been introduced in Kenya and other East African countries since the late-1990s (Qaim, 1999; Mbogoh et al., 2003; Dubois et al., 2006; Smale and Tushemereirwe, 2007). TC plantlets are propagated in the laboratory, and thus they are free from most pests and diseases that are easily spread through traditional sucker propagation (Eckstein and Robinson, 1995). Using clean and healthy TC plants for the establishment of new banana orchards can contribute to more vigorous growth and higher crop productivity. Field trials, carried out in Kenya and elsewhere, confirm that TC bananas have significantly higher yields than sucker-propagated bananas under favourable conditions and with high input regimes (Robinson et al., 1993; Wambugu and Kiome, 2001). This is in line with observations from commercial banana plantations in Latin America and South Africa, where TC technology has already been used for much longer (Vuylsteke, 1998).

However, the situation may potentially look different in East Africa, where banana is largely produced by smallholder farmers with low input regimes and less than optimal conditions. An ex ante study for Kenya, which was conducted before significant adoption had occurred, suggested that TC impacts would depend on proper management practices and use of complementary inputs such as irrigation water and fertilizer (Qaim, 1999). More recently, Njuguna et al. (2010) carried out focus group discussions and case studies with selected TC banana adopters; they reported higher yields and other socioeconomic benefits, but their results may not be representative of all adopters. Muyanga (2009) used a random sample of adopters and non-adopters and found no significant differences in yield; yet he did not control for other influencing factors and possible non-random selection bias.

We contribute to the literature by analyzing yield effects of TC bananas in Kenya with representative survey data and a more sophisticated econometric approach. In particular, we build on a sample of 385 banana growers and use endogenous switching regression (ESR) (e.g., Fuglie and Bosch, 1995; Alene and Manyong, 2007; Kassie et al., 2010). The ESR approach does not only allow estimation of unbiased treatment effects on yield, but also takes into account that TC adoption may systematically change production elasticities of farm inputs and other relevant factors. Since TC requires changes in traditional crop management practices, it is a relatively knowledge-intensive technology package. Against this background, we also analyze the role of information constraints. And finally, we predict how treatment effects might look like under improved conditions.

The empirical results will be useful for better understanding the adoption and impact of TC technology in Kenya and other countries. Solid impact assessment is important also for policy-making purposes (Winters et al., 2011), for instance to develop and implement appropriate support measures. In addition to banana, TC technology is gaining in importance in a number of other vegetatively propagated crops in Africa (Obembe, 2010). More generally, the analytical approach developed and applied here may also be useful for the evaluation of other knowledge-intensive package technologies and innovations in perennial crops. While the literature on the adoption and impact of crop technologies is large, most studies refer to annual crops and high-yielding seed cultivars that are relatively easy to use (e.g., Feder et al., 1985; Doss, 2006; Matuschke and Qaim, 2008). Much less is known about how to disentangle the effects of different components of a technological package and achieve desirable adoption outcomes of knowledge-intensive innovations in the small farm sector (Morris and Heisey, 2003; Barrett et al., 2004; Tripp, 2006; Cavatassi et al., 2011).

The remainder of this article proceeds as follows: Section 2 presents the analytical approach and describes how unbiased treatment effects are estimated within the ESR framework. Section 3 describes the situation of banana cultivation in Kenya and presents the survey data. Section 4 provides some descriptive analyses, before the regression results are presented and discussed in section 5. Section 6 concludes.

2. ANALYTICAL FRAMEWORK

2.1 Statistical Approach for Impact Assessment

For banana farmers who adopt TC technology, higher yields are expected. However, just comparing yield levels between adopters and non-adopters may be misleading, because there may also be differences in the use of other inputs, which may lead to spurious conclusions, because not all of the observed differences can be attributed to TC technology alone. A regression model of a production function, which contains TC adoption as a treatment variable and controls for the use of other inputs can help in this respect. However, unless a randomized experiment is carried out, farmers decide themselves whether or not to adopt the technology. Therefore, adopters and non-adopters may differ systematically, which can lead to non-random selection bias (e.g., Barrett et al., 2004; Winters et al., 2011). When panel data exist, fixed-effects estimators can be used to control for farm and household level heterogeneity, but very often only cross-section data are available for impact assessment. This is true also in our case.

Statistical methods to deal with selection bias in cross-section data include propensity score matching (PSM) and instrumental variable (IV) approaches (Rosenbaum and Rubin, 1983; Smith and Todd, 2001; Deaton, 2010). PSM can only control for observed heterogeneity, while technology adoption may also be determined by unobserved factors such as farmers' ability and motivation. IV approaches can control for unobserved heterogeneity, but they mostly build on the assumption that the treatment effect can be represented as a simple parallel shift with respect to the outcome variable. This is not appropriate to assume for TC banana technology, which is hypothesized to not only impact yield but also the output responsiveness of other inputs. Such interactions between the technology regime and other explanatory variables can be better captured through endogenous switching regression (ESR). ESR estimates two separate but related outcome equations, one for each regime, in combination with a selection equation (e.g., Alene and Manyong, 2007; Rao and Qaim, 2011).

2.2 The ESR Model

Building on a random utility framework, the selection equation in our case is a binary adoption model, where farmers choose whether or not to adopt TC technology based on farm, household, and contextual characteristics:

$$A = Z\gamma + \mu \tag{1}$$

where A is a dummy variable for TC adoption, Z is a vector of explanatory variables, γ is a vector of parameters to be estimated, and μ is an error term with mean zero and variance σ_μ^2. The two outcome equations are banana production functions:

$$y_1 = X\beta_1 + \varepsilon_1, \qquad \text{if } A = 1\text{, and} \tag{2a}$$

$$y_0 = X\beta_0 + \varepsilon_0, \qquad \text{if } A = 0. \tag{2b}$$

where y_1 and y_0 are continuous variables, representing banana yield for adopters and non-adopters, respectively. X is a vector of explanatory variables, and β_1 and β_0 are parameters to be estimated for the adopter and non-adopter regimes. ε_1 and ε_0 are the respective error terms. Estimating β_1 and β_0 by ordinary least squares would produce inconsistent estimates, because the expected values of these error terms, conditional on the sample selection criterion, are non-zero (Maddala, 1986). The error terms μ, ε_1 , and ε_0 are assumed to have a trivariate normal distribution with zero mean and non-singular covariance matrix specified as:

$$\mathrm{cov}(\varepsilon_1, \varepsilon_0, \mu) = \begin{bmatrix} \sigma_1^2 & \sigma_{10} & \sigma_{1\mu} \\ \sigma_{10} & \sigma_0^2 & \sigma_{0\mu} \\ \sigma_{1\mu} & \sigma_{0\mu} & \sigma_\mu^2 \end{bmatrix} \tag{3}$$

where $\sigma_1^2 = \mathrm{var}(\varepsilon_1)$, $\sigma_0^2 = \mathrm{var}(\varepsilon_0)$, $\sigma_{10} = \mathrm{cov}(\varepsilon_1, \varepsilon_0)$, $\sigma_{1\mu} = \mathrm{cov}(\varepsilon_1, \mu)$, and $\sigma_{0\mu} = \mathrm{cov}(\varepsilon_0, \mu)$. It can be assumed that σ_μ^2=1 since γ in equation (1) is estimable only up to a scale factor (Greene, 2003); the expected values of the truncated error terms are:

$$E(\varepsilon_1 | A = 1) = \sigma_{1\mu}\lambda_1 \tag{4a}$$

$$E(\varepsilon_0|A=0)=\sigma_{0\mu}\lambda_0 \quad (4b)$$

where λ_1 and λ_0 are the inverse mills ratios (IMR) evaluated at $Z\gamma$ (Greene, 2003). λ_1 and λ_0 can be included in equations (2a) and (2b) to correct for selection bias in a two-step estimation procedure (Maddala, 1983; Wooldridge, 2002).

One problem with this two-step estimation procedure is that it generates heteroscedastic residuals that cannot be used to derive consistent standard errors without cumbersome adjustments (Maddala, 1986). A more efficient and consistent way to estimate the ESR model is the full information maximum likelihood (FIML) method (Greene, 2003; Lokshin and Sajaia, 2004). Apart from estimates for β_1 and β_0, FIML also generates $\rho_{1\mu}$ and $\rho_{0\mu}$, which are estimates of the correlation coefficients between the error terms in the outcome and selection equations. The signs and significance levels of these estimated correlation coefficients have economic interpretations (Fuglie and Bosch, 1995; Lokshin and Sajaia, 2004). If either $\rho_{1\mu}$ or $\rho_{0\mu}$ is non-zero, there is endogenous switching, which would lead to selection bias if not controlled for. $\rho_{1\mu}<0$ implies a positive selection bias, meaning that farmers with above average yields are more likely to choose TC technology. By contrast, $\rho_{1\mu}>0$ would imply a negative selection bias.

2.3 Estimating Treatment Effects on Yield

The ESR model estimates the marginal effects of inputs and other explanatory variables on banana yield in the TC and non-TC technology regimes, but to estimate the technology's net effect on yield, some further calculations are required. Essentially, we want to compare the yield of adopters with and without adoption to derive the average treatment effect on the treated (ATT). Likewise, the average treatment effect on the untreated (ATU) is of interest, which is a comparison of yield of the non-adopters with and without adoption. Some of these scenarios are real, while others are hypothetical. The coefficient estimates from the ESR model help to calculate the following expected banana yields in the real and hypothetical scenarios:

adopters with adoption *(real);*

$$E[y_1|A = 1] = X\beta_1 + \sigma_{1\mu}\lambda_1 \tag{5a}$$

adopters had they decided not to adopt *(hypothetical);*

$$E[y_0|A = 1] = X\beta_0 + \sigma_{0\mu}\lambda_1 \tag{5b}$$

non-adopters had they decided to adopt *(hypothetical);*

$$E[y_1|A = 0] = X\beta_1 + \sigma_{1\mu}\lambda_0 \tag{5c}$$

non-adopters without adoption *(real);*

$$E[y_0|A = 0] = X\beta_0 + \sigma_{0\mu}\lambda_0. \tag{5d}$$

These expected outcomes can be used to derive unbiased treatment effects ATT and ATU that control for observed and unobserved heterogeneity (Maddala, 1983; Wooldridge, 2002):

$$ATT = E[y_1|A = 1] - E[y_0|A = 1] = X(\beta_1 - \beta_0) + \lambda_1(\sigma_{1\mu} - \sigma_{0\mu}) \tag{6a}$$

$$ATU = E[y_1|A = 0] - E[y_0|A = 0] = X(\beta_1 - \beta_0) + \lambda_0(\sigma_{1\mu} - \sigma_{0\mu}). \tag{6b}$$

3. THE KENYAN BANANA SECTOR AND FARM SURVEY

3.1 Banana and TC Technology in Kenya

In Kenya, banana is almost exclusively grown by smallholder farmers for home consumption and local markets. The crop's perennial nature, the possibility of year-round harvest, and the fact that some yield can also be obtained without purchased inputs make banana a typical security crop in the local context (Qaim, 1999; Smale and Tushemereirwe, 2007). Recently, with strong fluctuations in coffee and tea prices, banana has also gained popularity as a cash crop in some regions. However, banana yields have decreased in Kenya and other countries of East Africa since the 1970s, partly due to pests and diseases and poor crop management (Dubois et al., 2006; Njuguna et al., 2010).

The development and dissemination of pest- and disease-resistant cultivars would be an interesting approach, but unfortunately bananas are genetically *triploid* and can hardly be improved through conventional breeding (Ortiz et al., 1995; Tripathi et al., 2008). Traditionally, bananas are vegetatively propagated using suckers. However, this practice fosters the transfer of pests (especially weevils and nematodes) and diseases (especially fungi and bacteria), consequently reducing potential yield from the beginning in newly established banana orchards. Tissue culture is an alternative form of plant propagation using in-vitro techniques in the laboratory. This results in pathogen-free plantlets, which have to be hardened before they can be transplanted into the field (Vuylsteke, 1998). TC plantlets are not resistant to pests and diseases, however, so they can be infested at a later stage (Dubois et al., 2006).

The potential of TC technology to contribute to productivity growth in banana stimulated different organizations to promote this technology in an East African context (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 Biotech Foundation International (Africa Harvest) has promoted more widespread TC adoption, using innovative models of technology delivery and a whole value chain approach. Considering Kenya as a whole, less than 10% of all banana farmers have adopted TC so far, although in the Central and Eastern Provinces, where most of the dissemination programs started, adoption rates are already higher (Njuguna et al., 2010). The TC adoption process is relatively slow for two reasons. First, TC plantlets are fairly expensive. Second, they 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 orchards (Qaim, 1999).

3.2 Farm Survey

We carried out a survey of banana farmers in late 2009, 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 many years. Agro-ecological factors were also taken into account, as these can matter much for banana yield potentials, problems with pests and diseases, and the expected advantages of TC technology (Frison et al., 1998). Based on climate data, altitude, and information about soil conditions, we differentiate between high-potential and low-potential areas. High-potential areas include the districts of Embu, Meru and the northern half of Kirinyaga (Ndia and Gichugu Divisions), which are mainly located on the slopes of Mount Kenya. They receive relatively high rainfall and have fertile volcanic soils. Low-potential areas are Thika, Murang'a, Maragua and the southern half of Kirinyaga District dominated by the undulating Mwea plains.

Kiambu is outside of this classification. Although agro-ecological production conditions are favorable, Kiambu District was chosen because of its closeness to Nairobi and the peri-urban nature of farming. Furthermore, banana farmers in Kiambu have received particularly strong institutional support through Africa Harvest. In addition to intensive training and technical backstopping, Africa Harvest has promoted a banana ripening facility there and has linked farmers to high-value markets in the city.

Within each district, banana-growing villages, specifically those where TC activities took place in the past, were purposively selected. Within the villages, farm households were sampled randomly. Separate village lists of adopters and non-adopters were prepared, and adopters were oversampled to have a sufficient number of observations for robust impact assessment. In total, 385 banana farmers, composed of 223 adopters and 162 non-adopters, were sampled. Using appropriate weights to take account of the multi-stage sampling procedure, the sample is considered representative for banana farmers in Central and Eastern Provinces of Kenya.

In each sample household, the household head was interviewed using a structured questionnaire specifically designed for this purpose. Data on farm and household characteristics were collected, including input and output details for the banana crop. Likewise, institutional aspects, such as access to information, credit, roads, and market infrastructure were covered in the questionnaire. A particular challenge was assessing banana yields. Farmers routinely sell banana bunches based on visual characteristics of size and quality, but without weighing them. Therefore, many farmers had difficulties to report harvested quantities in exact weight terms. To ensure reliable estimates, we carried out own weight and yield assessments in farmers' orchards using a non-destructive allometric method as suggested by Wairegi et al. (2009). This method uses pseudo stem girth at the base and 1 m above ground and the number of hands and fingers to estimate bunch weight. For each farmer in the sample, we randomly sampled 10-20 typical bunch-bearing plants in the orchard for this purpose.

Table 1 describes key farm, household, and contextual characteristics for the whole sample and for TC adopters and non-adopters separately. The average farm size of 3.3 acres confirms that banana farmers are predominantly small scale. TC adopters have slightly larger farm sizes, and they are also somewhat older and better educated than non-adopters. Adopters are also less credit and information constrained. These variables are based on farmers' responses to the question whether they can always obtain the credit and information that they would like to have for their farm business, including both formal and informal sources.

[TABLE 1]

Membership in farmer or other social groups can be used as an indicator of information networks. Finally, farmers were asked to name their three closest social network contacts and specify who of them had adopted TC technology ahead of them. Similar variables were used previously in research on technology adoption and social interactions (Manski, 2000; Matuschke and Qaim, 2009). In terms of location characteristics, there are no significant differences observed between adopters and non-adopters. This should not surprise, because both groups were sampled in the same villages.

4. YIELDS AND INPUT USE: DESCRIPTIVE ANALYSIS

Average banana yields for farmers in our sample are shown in Figure 1. Mean yields for farmers without TC are 9.1 tons/acre, which is higher than the 8.1 tons/acre achieved by TC adopters. While this difference is not statistically significant, the comparison is somewhat surprising, because TC is expected to increase effective yield. However, this comparison neglects plantation age. While most traditional banana orchards are at least several years old, TC orchards were only established more recently. Yield curves in banana usually follow a certain pattern over time, first increasing, then reaching a peak, and finally declining again in older plantations (Qaim, 1999; Kagoda et al., 2005). Gold et al. (2004) showed that the peak is reached after 4-5 years under typical conditions in East Africa, although this may vary depending on pest pressure and orchard management.

In our sample, of all 223 TC plantations, 56% are young orchards (<4 years old), 26% are medium-aged orchards (4-5 years old), and 18% are old orchards (>5 years old). Figure 1 also shows a disaggregation of mean yield levels by these age categories. Medium-aged TC plantations yield more than traditional plantations, and this difference is statistically significant. On the other hand, young TC plantations yield significantly less than traditional plantations.[1] The difference for old TC plantations is insignificant. With optimal input regimes, TC yield advantages can be

[1] Unfortunately, we do not know the exact age of traditional banana plantations, so that we cannot disaggregate this subsample by age categories.

maintained also in the medium and long run, but such optimal conditions are not always found in smallholder environments (Vuylsteke, 1998).

[FIGURE 1]

Table 2 shows that average input use is very low. Around 70% of all farmers in our sample do not use any inputs on a regular basis, which is consistent with other studies from East Africa (e.g., van Asten et al., 2011). Water in particular is crucial for proper plant growth, especially in young TC plantations. Nonetheless, only 10% of the TC adopters reported to irrigate their crop. While this share is somewhat higher than among the non-adopters, no significant difference can be observed for the overall cost of irrigation. For chemical fertilizers and pesticides, higher application rates are observed among TC adopters, although use intensities are still very low when compared to banana plantations elsewhere (e.g., Eckstein and Robinson, 1995; Frison et al., 1998). Because of diverse units of measurement used by farmers, we converted all inputs into monetary values, with the exception of labour, which is measured in labour days.

[TABLE 2]

Even though TC bananas are considered to be more labour-intensive than traditional bananas, Table 2 shows that adopters actually use less labour. In addition to applications of purchased inputs, the labour variables capture operations such as weeding, harrowing, pruning, and de-suckering, among others. The relatively low use of inputs and insufficient orchard maintenance may be reasons why the yield potential of TC technology is not yet fully realized among small-scale banana farmers in Kenya.

5. ECONOMETRIC ESTIMATES

5.1 Selection Equation: Determinants of Adoption

As described in section 2, we analyze TC net impacts on banana yield with an ESR approach. At first, we take a closer look at the selection equation, which models the determinants of TC technology adoption. In the FIML procedure, this selection equation is estimated jointly with the outcome equations for the adopter and non-adopter regimes, but for analytical purposes it is useful to discuss the results sequentially. Table 3 shows the factors that influence the farmers' decision and their marginal effects on the probability of adoption. Explanatory variables were chosen based on previous technology adoption research in smallholder settings (e.g., Feder et al. 1985; Doss, 2006; Matuschke and Qaim, 2009). Sample mean values of these variables were shown above in Table 1. The estimates in Table 3 are based on a probit specification.

[TABLE 3]

Educated farmers are more likely to adopt, which is a common finding in the technology adoption literature. The farmer's age has no significant effect on the TC adoption decision, nor does farm size seem to matter. The latter is interesting, because comparisons above showed that adopters tend to have larger farm sizes than non-adopters. The results here suggest that TC technology is scale-neutral as such, but there are other factors that reduce the probability of adoption, which are correlated with farm size. A case in point is access to credit, which is often easier for farmers with larger land sizes. The results in Table 3 show that a credit constraint reduces the probability of TC adoption by 13 percentage points. Even more important is an information constraint, which reduces the probability of adoption by almost 21 percentage points.

Farmers who are organized in groups are also much more likely to adopt. This is not surprising, because many of the dissemination efforts for TC bananas by various organizations build on farmer groups. Africa Harvest in particular uses a group approach for its training and market linkage activities. Strikingly, however, the variable measuring TC adoption by the farmer's social network shows a negative effect, which is small but still significant. This indicates that farmers with friends who have adopted TC ahead of them are less likely to adopt the technology themselves. This is contrary to adoption studies in other contexts (e.g., Matuschke and Qaim, 2009) and may be explained by two possible reasons. First, not all farmers may be fully satisfied with their TC experience, so that mixed opinions may spread through informal social networks. Second, farmers with friends who already have established TC orchards, may find it attractive to receive suckers from these orchards, which reduces their own incentive to buy original TC plantlets. While using suckers from TC orchards is discouraged by agronomists, some farmers do so nonetheless, because of the relatively high price of original TC plantlets.

Unsurprisingly, farmers who know the location of a TC nursery are much more likely to adopt the technology. Many of the nurseries are operated by fellow farmers. The distance to the closest market has a positive and significant effect on the probability to adopt. This is unexpected, because market distance is usually negatively correlated with access to information and farm-gate output prices. However, in our specification we already control for information. Moreover, the different organizations involved in TC dissemination deliberately also target locations with poorer market access, in order to reduce existing social disparities. And finally, farmers further away from the market often focus more on bananas, which are perishable but less so than many other fruits and vegetables commonly produced in the region.

Table 3 also shows that farmers located in high-potential areas are less likely to adopt TC. In high-potential areas, bananas grow relatively well even under poor management conditions, so that the need for a new technology may not be felt to the same extent as in low-potential areas. This was also observed by Edmeades and Smale (2006), who analyzed the demand for new banana cultivars in Uganda.

5.2 *Outcome Equations: Determinants of Yield*

To estimate the ESR outcome equations for the TC and non-TC regimes, we use production functions of the Cobb-Douglas type, yet without imposing a constant-returns-to-scale constraint. We use the natural logarithm of banana yield per acre as dependent variable, which is a function of input use, also expressed in natural log-terms, and other relevant household and contextual variables. Since many banana farmers use zero inputs, the log-transformation would produce many missing values, so that we employ the method suggested by Battese (1997) to correct for zero input observations. Empirical tests showed that not all the variables that influence adoption are also determinants of yield, so that the simultaneous equations model is properly identified.

Results for the outcome equations are shown in Table 4. We first concentrate on model (1). The coefficient estimates for the adopter and non-adopter regimes differ notably with respect to some of the variables, indicating that the switching regression approach is preferred over a simple treatment effects model. Particularly noteworthy is the difference in the coefficient estimate for irrigation cost, which is much higher for TC bananas. Increasing irrigation in TC orchards by 1% would increase yields by 0.41%, while the estimate for non-adopters is insignificant. This is plausible. Young TC plants are known to be more susceptible to drought stress (Qaim, 1999). Furthermore, while water critically determines banana yield in general (Carr, 2009; van Asten et al., 2011), traditional bananas usually suffer more than TC plants from pest and disease stress, so that their yields are less responsive to changes in only one input such as water.

[TABLE 4]

Differences in yield responsiveness are also observed for the high-potential area dummy, whose coefficient is positive and large for TC bananas, but small and insignificant for traditional bananas. High-potential areas receive more rainfall and have more fertile soils than low-potential areas, which are used as the reference category in our model. In this connection it should also be noted that 2009, when the survey data were collected, was a particularly dry year in Kenya. The estimation results imply that TC bananas were probably more negatively affected by the drought than traditional bananas. This should be kept in mind for the interpretation of yield effects.

Another interesting difference between the two regimes is the role of farmer age. In TC bananas, age contributes significantly to higher yields (albeit at a diminishing rate), while this is not the case in traditional bananas. Age can be seen as a proxy for farmers' experience and managerial ability. As mentioned, TC bananas require changes in traditional crop management practices, and they are also more sensitive to the implementation and timing of certain maintenance operations (Vuylsteke, 1998). More experienced farmers seem to have an advantage in this respect.

Proper crop management also requires access to good information. This is underlined by the information constraint coefficient, which is negative and highly significant for TC adopters, but not for non-adopters. TC farmers who feel information constrained have more than 30% lower yields than their colleagues with good access to relevant information. Hence, extension and training is critical for the successful adoption of TC banana. Without sufficient technical support, the adoption experience may turn out to be negative. In this respect, location in Kiambu is also of particular interest. As mentioned, Kiambu is a peri-urban area, where Africa Harvest has provided particularly intensive technical and marketing support to farmers adopting TC bananas. This is reflected in the positive coefficient of the Kiambu dummy in the adopter regime.

Model (2) in Table 4 is similar to model (1), but additionally includes dummy variables for the age of TC plantations. Again, this model was estimated within the ESR framework using the FIML procedure; but since the results for the non-adopter regime hardly differ from those in model (1), only the adopter regime is shown. The coefficients for the plantation age dummies are positive and significant, indicating that old and medium-aged TC plantations have higher yields than young plantations, which are used as the reference category. Especially the medium-age coefficient is large, which confirms and further strengthens the results from the descriptive analysis. The other coefficient estimates in model (2) are very similar to those in model (1). Only the Kiambu coefficient is now somewhat smaller and insignificant, which is due to correlation with plantation age. Many of the TC farmers in Kiambu had adopted the technology between 2004 and 2006. These results suggest that yield impacts in perennial crops crucially depend on the time of data collection.

In the lower part of Table 4, we present estimates of the covariance terms and model diagnostics. Of particular interest here is the positive and significant coefficient $\rho_{1\mu}$, which measures the correlation between the error terms of the selection equation and the outcome equation for the TC regime. It clearly indicates a negative selection bias, implying that farmers with lower than average yields are more likely to adopt TC. This is unlike many other impacts studies, which have found a positive selection bias, because more progressive and productive farmers are usually the first adopters of technical and institutional innovations (e.g., Fuglie and Bosch, 1995; Barrett et al., 2004; Alene and Manyong, 2007; Rao and Qaim, 2011).

The negative selection bias in our example is not implausible, however. Especially in perennial crops like banana the adoption of new planting material is a decision with long-term implications; it is also associated with a considerable setup cost. Given that yield curves in banana – after reaching a peak – tend to decline with plantations age, farmers who own old, lower-yielding plantations have a higher incentive to adopt TC. Likewise, farmers who have experienced severe problems with pests and diseases may be more willing to adopt, whereas banana growers with healthy and high-yielding traditional plantations may be less interested in TC or may decide to postpone adoption. A negative selection bias may also be expected for other technologies in perennial crops, especially when adoption involves the use of new planting material.

5.3 Estimating Treatment Effects

We now use coefficient estimates from model (1) in combination with equations (5) and (6) (see section 2) to predict mean yield levels for adopters and non-adopters with and without adoption, and to derive the net effect of TC technology. Both the ATT and the ATU are calculated. This differentiation is of particular importance, as it controls for the selection bias identified above. Results are shown in Table 5.

[TABLE 5]

The upper part of Table 5 shows calculations based on observed sample mean values for adopters and non-adopters. The ATT, which is the actual effect that adopters have through adoption, is a yield gain of 7.1%, which is highly significant. This is the net effect of TC, assuming that the use of other inputs is held constant. Accordingly, the overall yield effect of the innovation package is higher, because TC adoption is also associated with higher input use. In contrast, the ATU effect is insignificant, implying that current non-adopters would not realize higher yields with TC, so that their non-adoption decision seems rational.

Yet the analysis so far has revealed that the intensity of irrigation and input use is still very low among TC adopters, even though TC yields are input responsive, especially with respect to water. Therefore, it can be expected that more irrigation could further improve the TC productivity gains. This is confirmed in the lower part of Table 5, which shows additional treatment effects for hypothetical scenarios with improved conditions. In a first scenario, we assume that all farmers would irrigate their banana crop at an irrigation cost level of 1,500 K.shs/acre, which is equivalent to the average cost incurred by those 10% TC adopters that actually irrigate. As can be seen in the Table, this would triple the ATT to 21%. Again, this is a net TC effect, as the same increase in irrigation is assumed with and without adoption. With more irrigation, also the current non-adopters would realize significant yield gains through TC, as is indicated by the ATU of

12.7%. Yield gains could still be higher with more intensive irrigation. As mentioned above, even among those farmers who irrigate the observed irrigation intensity is relatively low.

Similar simulations were also made by assuming that all farmers have good access to technical information (nobody is information constrained). As can be seen, this would also increase the TC treatment effects, because farmers could adjust crop management practices more competently to the new technology. In comparison to the initially predicted effects, the changes are relatively small however. This is due to the fact that the majority of the adopting households are already relatively well informed about TC. Without the training and extension efforts of the TC-promoting organizations, the productivity effects would look much worse. Therefore, while access to information is crucial for successful TC use, the bigger constraint for fully tapping the technology's potential in the Kenyan situation seems to be limited access to irrigation facilities.

6. CONCLUSION

In this article, we have analyzed the yield effects of TC banana technology among smallholder farmers in Kenya, using primary survey data. Simple mean value comparisons revealed no significant difference in banana yields between adopters and non-adopters of this technology. However, econometric estimations with an endogenous switching regression approach revealed a negative selection bias, implying that farmers with lower than average yields are more likely to adopt TC. This is plausible, because the adoption of new planting material in a perennial crop involves a longer-term investment and a high setup cost, which farmers in older and lower-yielding plantations are more willing to undertake. Controlling for this bias results in a significant net yield gain of 7% for TC adopters. On the other hand, the average treatment effect on the untreated was found to be insignificant, suggesting that current non-adopters would not benefit from switching to TC under the given conditions.

But the regression results and related simulations have also demonstrated that the potential of TC technology has not yet been fully tapped in Kenya. In other words, the productivity effects could be higher with improved conditions. TC technology is knowledge-intensive, and it requires a change in traditional crop management practices, including higher levels of inputs, especially water. While TC adopters in Kenya use more inputs than traditional banana growers, input intensities are still very low in an international comparison, which is largely due to limited access to credit and irrigation. Our results clearly show that higher irrigation intensities would lead to much higher net yield gains of TC technology. This holds true for both current adopters and non-adopters of this technology.

Our results also underline the importance of access to information. Some organizations in Kenya are already implementing innovative models of technology delivery, training, and institutional support, but these efforts need to be intensified, expanded, and complemented with investments in irrigation infrastructure. Promoting TC banana as a stand-alone technology, without extension and access to the necessary package of inputs, should be avoided, as this may contribute to frustrating experiences among farmers. This general conclusion also holds for TC technologies in other crops.

While the literature on the adoption and impact of crop technologies is large, most studies refer to annual crops and high-yielding seed cultivars that are relatively easy to use. Much less is known about how to disentangle the effects of different components of a technological package and achieve desirable adoption outcomes of knowledge-intensive innovations in the small farm sector. Against this background, the analytical approach developed and applied here may also be useful for the evaluation of other knowledge-intensive package technologies and innovations in perennial crops.

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FIGURES:

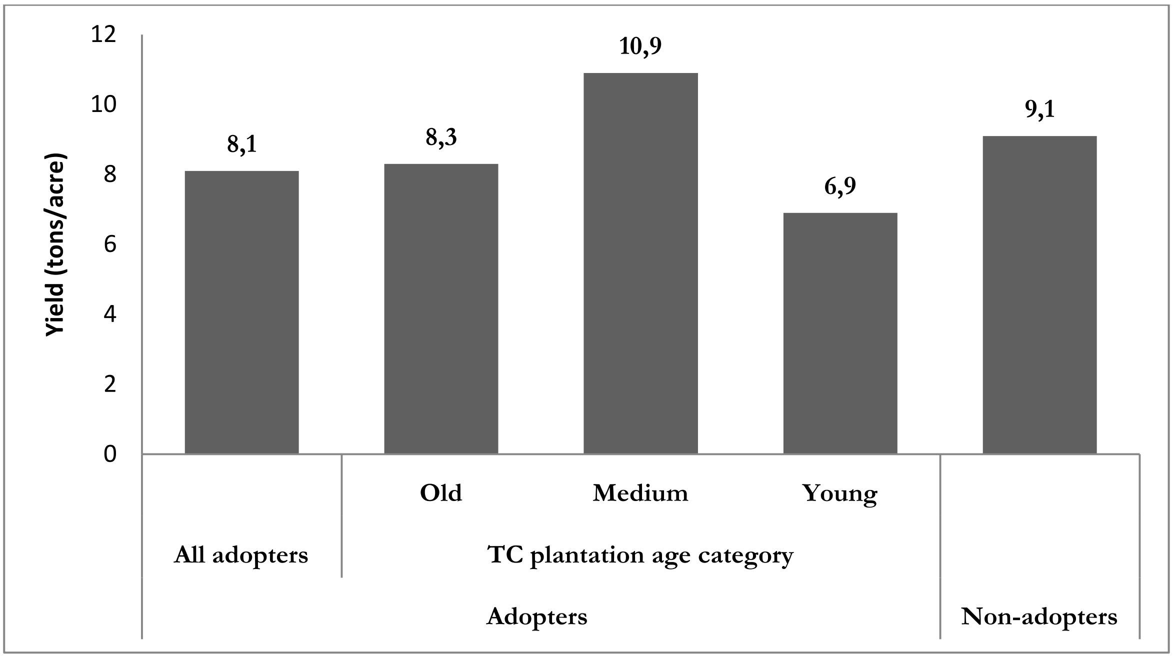

Figure 1: Average banana yields for TC adopters and non-adopters

TABLES:

Table 1: Descriptive statistics of sampled farm households

	Full sample (N=385)		Adopters (N=223)		Non-adopters (N=162)	
	Mean	SD	Mean	SD	Mean	SD
Human capital						
Education of household head (years)	8.5	4.0	9.1***	4.1	7.7	3.8
Age of household head (years)	58.2	13.6	59.8***	13.2	56.0	13.8
Time spent on farm (days per month)	23.3	4.6	23.4	4.5	23.1	4.7
Female headed (% of households)	17.7	38.2	17.0	37.7	18.5	39.0
Household size (members)	4.6	2.0	4.6	2.0	4.6	2.0
Proportion of crops sold to market [a] (%)	44.4	29.0	44.8	29.2	43.7	28.9
Assets and financial capital						
Farm size (acres)	3.30	3.01	3.83***	3.36	2.57	2.27
Value of non-land productive assets	178.8	224.2	216.0***	248.9	127.2	172.3
Agricultural wage payments [a] ('000 K.shs per year)	14.8	22.9	18.4***	25.3	9.9	17.8
Off-farm income share [a] (%)	35.8	100.0	32.1	132.2	40.9	34.3
Credit constrained (% of households)	40.1	49.1	33.6***	47.4	49.1	50.1
Social capital and access to information						
Information constrained (% of households)	29.4	45.5	19.7***	39.9	42.6	49.6
Group membership (% of households)	90.9	28.8	96.9***	17.4	82.7	37.9
TC adoption by social network (% of netw. contacts)	17.2	28.8	15.2	27.9	20.0	29.8
Location characteristics						
Distance to closest all-weather road (km)	3.4	3.8	3.6	4.0	3.3	3.5
Distance to closest market (km)	5.0	15.5	5.5	20.1	4.4	3.7
Distance to closest water source (m)	169	658	142	550	207	784
Located in high-potential area (% of households)	53.0	50.0	52.5	50.0	53.7	50.5
Located in Kiambu (% of households)	13.3	33.9	13.9	34.7	12.3	33.0

Notes: ***, ** and * means that mean values for TC adopters are significantly different from those of non-adopters at the 1%, 5%, and 10% level, respectively. The exchange rate in December 2009 was: US $1 = K.shs 76.
[a] These variables exclude the banana enterprise, in order to avoid possible endogeneity problems in the adoption model.

Table 2: Banana input use by adoption status

	Adopters (N=223)		Non-adopters (N=162)	
	Mean	SD	Mean	SD
	Percentage of farmers using (%)			
Irrigation	10.3**	30.5	3.7	18.9
Chemical fertilizer	20.2***	40.2	1.2	11.1
Organic manure	11.7	32.2	9.3	29.1
Pesticides	11.7***	32.2	1.9	13.5
Hired labour	47.5***	16.2	22.8	20.4
	Average cost of ('000 K.shs/acre)			
Irrigation [a]	1.5	6.7	1.3	9.2
Chemical fertilizer	1.4***	5.7	0.1	0.9
Manure application [a]	2.0	11.7	1.3	5.3
Pesticide	0.4**	1.6	0.1	0.5
	Labour use (labour days/acre)			
Total labour [b]	218.4**	210.7	291.8	357.1
Family labour [b]	190.4***	204.3	273.3	344.4
Hired labour [b]	28.7	62.6	19.2	89.2

Notes: ***, ** and * means that mean values for TC adopters are significantly different from those of non-adopters at the 1%, 5%, and 10% level, respectively. The exchange rate in December 2009 was: US $1 = K.shs 76.
[a] Costs for these operations include the cost of labour.
[b] These values exclude the labour used for irrigation and manure application to avoid double counting.

Table 3: Determinants of TC adoption

	Marginal effects	z-value
Education of household head (years)	0.020**	2.02
Age of household head (years)	-0.023	-1.37
Age squared	2.83E-04*	1.88
Female headed (dummy)	0.130	1.46
Time spent on farm (days per month)	0.005	0.90
Proportion of crops sold to market [a] (%)	-8.40E-04	-0.68
Farm size (acres)	0.014	0.78
Value of non-land productive assets ('000 K.shs)	2.08E-04	0.98
Agricultural wage payments [a] ('000 K.shs)	-1.07E-03	-0.68
Household size (members)	0.010	0.59
Off-farm income share [a] (%)	-0.001	-1.63
Credit constrained (dummy)	-0.133**	-2.10
Information constrained (dummy)	-0.207***	-2.92
Group membership (dummy)	0.549***	8.38
TC adoption by social network (%)	-0.002**	-2.11
Farmer knows TC nursery location (dummy)	0.673***	13.95
Distance to closest all-weather road (km)	0.009	1.08
Distance to closest market (km)	0.021**	1.99
Distance to closest water source (m)	2.19E-06	0.05
Located in high-potential area (dummy)	-0.118*	-1.70
Located in Kiambu (dummy)	-0.031	-0.30
N	*383*	
Log likelihood	*-163.23*	
LRchi2	*139.52****	
Pseudo R2	*0.37*	

Notes: ***, ** and * denotes statistical significance at the 1%, 5%, and 10% level, respectively. Z-values are estimated based on robust standard errors. This selection equation was estimated simultaneously with the outcome equations shown in Table 4.

[a] These variables exclude the banana enterprise, in order to avoid possible endogeneity problems.

Table 4: Determinants of banana yield

	(1) Without plantation age dummies				(2) Adopters with plantation age dummies	
	Adopters		Non-adopters			
	Coefficient	z-value	Coefficient	z-value	Coefficient	z-value
Ln of fertilizer cost	-0.039	-0.39	-1.197	-0.66	-0.011	-0.12
Ln of manure application cost	0.189	1.46	0.220	0.84	0.108	0.87
Ln of irrigation cost	0.410***	3.36	0.200	1.04	0.390***	3.35
Ln of pesticide cost	-0.152	-1.17	1.052	0.69	-0.117	-0.93
Ln of family labour	0.132***	2.79	0.205***	3.97	0.135***	2.94
Ln of hired labour	0.187***	2.89	0.185*	1.91	0.158**	2.51
Education of household head (years)	-0.003	-0.17	-0.022	-1.09	-0.015	-0.96
Age of household head (years)	0.058**	2.09	-0.018	-0.56	0.063**	2.36
Age squared	-4.70E-04**	-2.05	6.83E-05	0.24	-0.001**	-2.51
Female headed (dummy)	0.093	0.66	0.274	1.57	0.103	0.77
Share of off-farm income (%)	-0.001*	-1.91	-0.004*	-1.92	-0.001	-1.52
Credit constrained (dummy)	-0.235**	-2.03	-0.266**	-2.00	-0.207*	-1.85
Information constrained (dummy)	-0.314**	-2.29	-0.056	-0.41	-0.195	-1.48
Value of non-land productive assets ('000 K.shs)	7.09E-05	0.31	-3.32E-05	-0.09	7.64E-05	0.35
Distance to closest all-weather road (km)	0.047***	3.42	0.016	0.94	0.036***	2.71
Distance to closest market (km)	0.002	0.62	-0.038**	-2.28	0.001	0.57
Located in high-potential area (dummy)	0.378***	3.16	0.091	0.68	0.384***	3.31
Located in Kiambu (dummy)	0.392**	2.30	-0.053	-0.24	0.194	1.13
Old TC plantations (dummy)					0.276*	1.73
Medium-aged TC plantations (dummy)					0.557***	3.82
Constant	1.386	0.69	6.179	0.76	1.826	0.96
No fertilizer use (dummy)	-0.597	-0.73	-10.861	-0.65	-0.266	-0.34
No manure use (dummy)	1.533	1.31	1.574	0.64	0.773	0.69
No irrigation (dummy)	3.767***	3.44	2.354	1.22	3.623***	3.46
No pesticide use (dummy)	-0.948	-0.97	8.597	0.68	-0.716	-0.76
No family labour use (dummy)	0.197	0.52	1.081**	2.46	0.054	0.15
No hired labour use (dummy)	0.565**	2.31	0.957***	2.64	0.482**	2.02
Ln σ_1	-0.288***	-4.68			-0.345***	-6.58
$\rho_{1\mu}$	0.780***	2.79			0.585**	2.22
Ln σ_0			-0.349***	-6.21		
$\rho_{0\mu}$			-0.076	-0.39		
N	*380*				*380*	
Wald χ^2	*86.71****				*107.81****	
Log likelihood	*-545.05*				*-512.17*	
LR test of indep. eqns.: χ^2 *(1)*	*9.98****				*8.67****	

Notes: ***, ** and * denotes statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5: Average TC treatment effects on banana yield

Farmer subsample	Adoption decision: Adopting Mean yield [a]	SD	Not-adopting Mean yield [a]	SD	Treatment effect [a]		Treatment effect in %
	Calculations based on actual sample mean values						
Adopters	8.62	0.49	8.05	0.48	ATT:	0.57***	7.1***
Non-adopters	8.69	1.37	8.81	0.48	ATU:	-0.13	-1.4
	Calculations based on assumed changes in irrigation and information						
Adopters all with irrigation	11.33	1.06	9.37	1.51	ATT:	1.97***	21.0***
Non-adopters all with irrigation	11.52	0.73	10.23	0.61	ATU:	1.30	12.7***
Adopters all without info constraint	8.70	0.46	8.06	1.36	ATT:	0.64***	7.9***
Non-adopters all w/o info constraint	8.77	0.49	8.84	0.51	ATU:	-0-07**	-0.8**

Notes: ***, ** denotes that the treatment effects are significant at the 1% and 5% level, respectively.

[a] The yields shown are predictions based on the coefficients estimated with the ESR model. Since the dependent variables in the ESR outcome equations are the logs of yield in kg per acre, the predictions are also given in log form.