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Impact of Tissue Culture Banana Technology on Farm Household Income and Food Security in Kenya

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Abstract:

While tissue culture (TC) technology for vegetative plant propagation is gradually gaining in importance in Africa, rigorous ex post assessments of welfare effects for smallholder farm households is lacking. Using recent survey data and accounting for self-selection in technology adoption, we analyze the impacts of TC banana technology on household income and food security in Kenya. To assess food security outcomes, we employ the Household Food Insecurity Access Scale (HFIAS) – a tool that has not been used for impact assessment before. Estimates of treatment-effects models show that TC banana adoption increases farm and household income by 153% and 50%, respectively. The technology also reduces relative food insecurity in a significant way. These results indicate that TC technology can be welfare enhancing for adopting farm households; its use should be further promoted through upscaling appropriate technology delivery systems.

Keywords: Technology adoption; tissue culture; impact assessment; household income; food security

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1. Introduction

While there is widespread consensus that agricultural technologies can play an important role for the reduction of food insecurity and poverty, there is less consensus on what are appropriate technologies for the small farm sector (Renkow and Byerlee, 2010). Moreover, especially in Africa, many available technologies are not, or only slowly, adopted, which may be due to unsuitable technological characteristics or unfavorable framework conditions (Barrett et al., 2004; Smale and Tushemereirwe, 2007). Rigorous adoption and impact studies are required to better understand what type of technologies work under what conditions. Recent research has analyzed productivity, income, and poverty effects of different agricultural technologies (Christiaensen et al., 2010; Cunguara and Darnhofer, 2011; Subramanian and Qaim, 2010; Thirtle et al., 2003). But there is relatively little empirical evidence directly linking technologies to household food security outcomes. This may partly be due to data problems, because agricultural surveys often do not include variables that are suitable for food security assessment.

Here, we analyze the impacts of tissue culture (TC) banana technology on household income and food security in Kenya, contributing to the existing literature both methodologically and empirically. The methodological contribution is the use of the Household Food Insecurity Access Scale (HFIAS), a recently developed tool to measure household access to food (Coates et al., 2006a). To our knowledge this tool has not previously been used for impact assessment. One advantage of the HFIAS is that data collection is relatively easy and cheaper than for other approaches to measure food security or nutrition, such as dietary recalls or anthropometric indicators. The empirical contribution relates to the concrete example of TC banana technology. TC technology in bananas and other vegetatively propagated crops has recently gained in importance in Sub-Saharan Africa (Obembe, 2010). While there is some debate about the potential and actual effects for farmers (Mbogoh et al., 2003; Muyanga, 2009; Njuguna et al., 2010), a rigorous assessment of broader welfare impacts has not yet been carried out. Our analysis builds on a survey of banana-growing households in Kenya, including adopters and non-adopters of TC technology. We use treatment-effects models to account for possible non-random selection bias.

The remainder of this article is organized as follows: in the next section, we present a brief background to TC banana cultivation in Kenya and describe the household survey. Then, we discuss descriptive statistics, followed by the analysis of food security aspects using the HFIAS tool. Subsequently, we develop the treatment-effects models and estimate the net impacts of TC technology adoption. The last section concludes.

2. Background

2.1 Banana production and TC technology in Kenya

In Kenya, banana is almost exclusively grown by smallholder farmers for home consumption and for 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, diseases, and poor crop management (Dubois et al., 2006; Kahangi, 2010; 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 (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 (Dubois et al., 2006). TC bananas were shown to result in higher yields than traditional bananas under favorable conditions. They may also result in more uniform fruit production and higher quality, thus fetching higher market prices. This could positively impact farm income and food availability at the household level (Mbogoh et al., 2003).

The potential of TC technology to contribute to productivity growth and food security in the small farm sector 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 (Qaim, 1999). 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 International has promoted more widespread TC adoption, using innovative models of technology delivery.

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 smallholders, who often tend to neglect their banana crop (Qaim, 1999).

2.2 Household survey

A survey of banana farm households was carried out in the major banana-growing areas of Central and Eastern Provinces of Kenya in the second half of 2009. The districts of Meru, Embu, Kirinyaga, Kiambu, Murang'a, and Thika were purposely selected based on information on the distribution of TC plantlets provided by different organizations. Furthermore, agro-ecological factors were taken into account, as these can matter much for banana yield potentials and problems with pests and diseases. Based on climate data, altitude, and information about soil conditions, we differentiate between high-potential and low-potential areas. High-potential areas are mainly located on the slopes of Mount Kenya; they receive relatively more rainfall and are at higher altitudes, with terrain dominated by ridges and fairly fertile volcanic soils (Oginosako, 2006). High-potential areas include the districts of Embu, Meru and the northern half of Kirinyaga. 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 there, Kiambu District was chosen because of its closeness to Nairobi and the peri-urban nature of farming. All sampled districts were classified as moderately or severely food-insecure in 2009 (KFSSG, 2009).

Within each district, banana-growing villages, specifically those where TC dissemination activities took place in the past, were purposely selected. Within the villages, farm households were sampled randomly. However, due to relatively low TC adoption rates, 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. Household heads were interviewed using a structured questionnaire specifically designed for this purpose. The questionnaire was pretested prior to formal data collection to ensure content validity and clarity. Interviews were carried out in the local language by trained enumerators, who were supervised by the researchers.

We collected both qualitative and quantitative data on household human capital and demographic characteristics, banana cultivation practices, details for other farm enterprises as well as off-farm economic activities. Sample descriptive statistics are provided in the next section. The questionnaire also included a HFIAS module to explore household food insecurity (Coates et al., 2006b), which is described and analyzed thereafter.

3. Descriptive analysis

3.1 Farm and household characteristics

Table 1 presents descriptive statistics of key farm, household, and contextual variables from the sample of banana-growing households. Disaggregation by adoption status reveals that TC adopters are significantly older and better educated than non-adopters. Adopting and non-adopting households are both predominantly male headed. A gender perspective is particularly interesting, because banana in Kenya has traditionally been a woman's crop. Yet with increasing levels of commercialization and technology adoption, traditional gender roles within households may potentially change (von Braun, 1995).

[TABLE 1]

TC adopters are wealthier than non-adopters in terms of farm size (land owned) and non-land productive assets. Further, adopters face fewer constraints in accessing credit and agricultural information. In the survey, we captured formal and informal credit sources, both of which can play an important role for innovation adoption (Fafchamps and Lund, 2003). To capture aspects of information, we asked farmers whether they have access to any reliable formal or informal source of agricultural information for their farm business. Failure to adopt technologies may also emanate from seed access constraints and inadequate local supply of planting material (Shiferaw et al., 2008; Tripp and Rohrbach, 2001). We capture this in our study through a variable measuring whether or not a household knows the location of a nursery for obtaining TC planting material. Table 1 shows that adopters are significantly more likely than non-adopters to know the location of a TC nursery. In terms of geography, there are no significant differences, which should not surprise, because we used stratified random sampling in the same villages.

3.2 Gross margin and household income

The lower part of Table 1 shows economic indicators of banana production. There are no significant differences between TC adopters and non-adopters in terms of the value of banana output and gross margins per acre. However, adopters use higher amounts of purchased inputs. We also used the survey data to calculate total farm, off-farm, and household income. Farm income covers all product sales and subsistence production valued at local market prices, to reflect approximate opportunity costs of own consumption. From this, production costs were subtracted. Respondents were asked to specify input costs for all crop and livestock enterprises over the 12-months period prior to the survey. Off-farm income includes agricultural and non-agricultural wages, profits from self-employed activities, transfers, food aid, and other sources. Total household income is the sum of farm and off-farm income. We express all incomes in annual per capita terms.

Table 1 shows no significant differences in any of the income sources between TC adopters and non-adopters. This may surprise, because adopters are expected to benefit economically from TC technology. However, it needs to be stressed that these comparisons are merely descriptive, so that a conclusion of limited technological impacts would be premature. As TC technology was not randomly assigned to farmers, a possible self-selection bias needs to be accounted for. We do so in the econometric analysis further below.

4. Measuring food security

4.1 The Household Food Insecurity Access Scale (HFIAS)

While food insecurity is still a very widespread phenomenon, and thus ranking high on the development policy agenda, the issue does not receive sufficient direct attention in quantitative policy analysis and impact assessment research. This is partly related to complexities in terms of measuring food insecurity (Barrett, 2010; Webb et al., 2006). The most common measurement approaches at the micro level build on dietary recalls, anthropometric indicators, or health data, which have also been used for impact assessment in a few studies (Babatunde and Qaim, 2010; Ecker and Qaim, 2010; Haddad et al., 1998; Rusike et al., 2010). There are also studies that try to measure food insecurity through data on household coping strategies (Maxwell et al., 1999; Maxwell et al., 2008). However, all these approaches have their methodological and empirical problems, and they are data-intensive and relatively costly to implement (de Haen et al., 2011).

A more recently developed approach is the Household Food Insecurity Access Scale (HFIAS), which does not measure food intake or nutritional outcomes, but household's own perception of food insecurity. HFIAS is relatively easy and less cost-intensive to implement than most other measurement approaches. Originally developed to monitor food insecurity in the United States (Wolfe and Frongillo, 2001), the HFIAS tool has been further refined for developing country contexts (Coates et al., 2006a; Coates et al., 2006b). It has recently been validated in Bangladesh (Coates et al., 2006c), Brazil (Hackett et al., 2008; Melgar-Quinonez et al., 2007), Costa Rica (Gonzélez et al., 2008), Tanzania (Knueppel et al., 2010), Ethiopia (Maes et al., 2009) and Burkina Faso (Becquey et al., 2010; Frongillo and Nanama, 2006), among others. In all cases, measures constructed were strongly correlated with common indicators of poverty and food consumption. While HFIAS seems to gain in importance in the nutrition literature, to our knowledge it has not been used previously for impact assessment studies, as we propose here.

Following guidelines by Coates et al (2006b) and Frongillo and Nanama (2006), we developed 9 questions related to food insecurity access, which were included in the questionnaire for the survey of banana-growing households. These 9 questions constitute the so-called sub-domains, which are clustered in three domains, as shown in Table 2. Domain I, with only one sub-domain, represents anxiety and uncertainty about household food supply. Domain II, with 3 sub-domains represents food quality, while domain III, composed of 5 sub-domains, represents food quantity intakes related to the physical availability at the household level. Respondents answered each question using a score from 0 to 3, depending on whether the particular problem described occurred never, rarely (1-2 times), sometimes (3-10 times), or often over the last 30 days. Hence, the higher the score the greater the perceived food insecurity. For each household, the HFIAS score corresponds to the sum of the individual scores and ranges between 0 (maximum food security) and 27 (maximum food insecurity).

[TABLE 2]

Interpreting sample statistics of the HFIAS is founded on observing the proportion of households that responded 'never' to all sub-domains (Coates et al., 2006b). Table 2 shows that in our case the proportion of 'never' responses in the first sub-domain is about 40%, implying that about 60% of the sampled households are worried about fulfilling their food needs. Similarly, 69% have insufficient food quality (unweighted mean of 3 sub-domains in domain II), and about 21% have insufficient food quantity intake due to physical unavailability (domain III). The last column of Table 2 shows that the correlation coefficients between sub-domains and per capita household income are negative; almost all are highly significant, which we use as an indication of the tool's general suitability in the local context.

4.2 *Principal factor analysis*

Using 9 different indicators, which all measure slightly different aspects of food insecurity, would not be very practicable in impact analysis. However, high correlation among them could produce a lower number of latent variables that fit common patterns in the data. We employ principal factor analysis (PFA) to look for sub-domains that 'factor' well together and have notable loading magnitudes in absolute terms. Initially, Bartlett's test and the Kaiser-Meyer-Olkin (KMO) criterion were used to verify whether sub-domains share a common core (Worthington and Whittaker, 2006). The Bartlett's test estimates the probability that the correlation matrix is zero, while the KMO indicates the extent to which variables have common features to warrant factor analysis. Generally, KMO scores above 0.60 are acceptable, above 0.90 are exceptional. Our analysis yielded a KMO value of 0.90, while the Bartlett test yielded χ^2 = 3446.38 (*p=0.00*), signifying the data's adequacy for factor analysis.

We implemented rotating factor loadings to obtain a clear pattern that tries to maximize variance, aiming to find the best suitable pattern that describes the data. Rotation is possible because of the indeterminate nature of the factor model, for which rotations seek to create a set of variables that much look like the original variables but more isolated and meaningful. We used oblique (non-orthogonal) rotations, which yield are more accurate and reproducible solutions than orthogonal rotations (Fabrigar et al., 1999). We tried several oblique rotation criteria and finally settled for the quartimin, which minimizes the sum of inner products of squared loadings (Sass and Schmitt, 2010).

For the actual PFA, we first determined the number of factors to retain based on the eigenvalue criteria, the screeplot and parallel analysis (Velicer and Jackson, 1990), results of which are shown in Appendix 1. All criteria indicate a two-factor solution with extracted variance of up to 103%. The cumulative proportion slightly exceeds 100% because of the negative eigenvalues observed. Table 3 shows a clear factor structure. All 9 sub-domains (FIQ1-FIQ9) loaded heavily on the two extracted factors, signifying high correlations. However, even after rotation, sub-domain 6 (FIQ6) persistently exhibited cross-loadings along the two factors and was therefore dropped from the analysis; this does not affect the Cronbach's alpha index of internal consistency, which has a value of a=0.92.

[TABLE 3]

The HFIAS questions represent perceptions of food insecurity with increasing levels of severity as one moves from FIQ1 to FIQ9. With this in mind, we observe that sub-domains FIQ1-FIQ5 have high loadings on 'Factor 1', while sub-domains FIQ7-FIQ9 have high loadings on 'Factor 2'. Moreover, all the loadings that matter (shown in bold in Table 3) have positive signs, confirming that food insecurity severity increases with higher reported sub-domain values. Against this background, we refer to 'Factor 1' as a general 'food insecurity' measure, whereas 'Factor 2' is a measure of 'severe food insecurity'.

4.3 Identifying the food-insecure

PFA can be used to score and construct household-specific indices for the indentified factors within the sample. Such aggregated indices are normally distributed across the sample with mean zero and standard deviation of 1. Accordingly, for the two factors extracted above, we constructed the food insecurity index (FII) and the severe food insecurity index (SFII), using regression-based methods (Thomson, 1951). The FII and SFII are arrays of generated values centered at zero. Like the HFIAS score, higher positive index values indicate higher levels of food insecurity. Noteworthy is that these indices represent relative food insecurity within the sample and are best used when comparing the extent to which one household differs from the other, a key principle in impact assessment.

Mean values for the two indices in our sample are shown in Figure 1, disaggregated by adopters and non-adopters of TC banana technology. Adopters have lower values than non-adopters, suggesting that they are more food-secure. Another way of looking at this is shown in Figure 2, where households are categorized into quartiles using the FII, rendering food-secure, mildly food-insecure, moderately food-insecure, and severely food-insecure households. The proportion of food-secure and mildly food-insecure households is higher among TC adopters, while the proportion of severely food-insecure households is higher among the non-adopters. However, based on these comparisons alone, we cannot yet conclude that TC adoption causally improves food security. This will be analyzed econometrically in the next section, using the FII and SFII indices as dependent variables.

[FIGURE 1]

[FIGURE 2]

5. Econometric analysis

5.1 Model specification

We want to analyze net impacts of TC banana adoption on household welfare. First, we concentrate on income effects. As TC is supposed to lead to higher banana yields and better fruit quality, the main expected effect will be on farm income. However, farm income is an imperfect measure of household welfare, as technology adoption may result in resource reallocation. Hence, we also estimate adoption impacts on total household income, which is a more comprehensive indicator of living standard. Second, we estimate potential effects of TC adoption on household food security, using the FII and SFII indicators, as described above.

We estimate different econometric models with these welfare indicators as dependent variables. On the right-hand side, we include TC adoption as treatment variable next to a number of farm, household, and contextual controls. Yet, a major challenge associated with isolating unbiased treatment effects is the likely endogeneity of the treatment variable. TC adoption is not random;

it may be influenced by various characteristics, potentially leading to selection bias in impact assessment (see e.g. Greene, 2003; Heckman, 1979; Imbens and Wooldridge, 2009; Maddala, 1983; Rosenbaum and Rubin, 1983). One option with cross-section data is to use propensity score matching, which can control for a bias due to observable characteristics (Heckman and Vytlacil, 2007). However, TC adoption may also be influenced by unobserved factors, such as farmers' ability or agroecological conditions at the micro level. Hence, we use treatment-effects models (Greene, 2003), which account for both observed and unobserved heterogeneity through the use of instrumental variables (IVs).

For treatment-effects model estimation, we implement a full information maximum likelihood (FIML) approach (Greene, 2003; Nawata and Nagase, 1996), which is more efficient than the Heckman two-step estimator. We use agricultural information constraint and knowledge of a TC nursery as instruments, which are correlated with TC adoption but uncorrelated with all outcome variables. Sample mean values of the explanatory variables were shown in Table 1. Results of the selection equation are displayed in Appendix 2. The outcome equations are shown and discussed below. For each model, the treatment-effects estimation is compared with results from ordinary least squares (OLS) estimation, which is preferred when no selection bias is detected.

5.2 Impacts on income

The results of the income models are shown in Table 4. For the treatment-effects models, the parameter ath$(\boldsymbol{\rho})$ represents the inverse hyperbolic tangent of the correlation between the error terms in the selection and outcome equations. If ath$(\boldsymbol{\rho})$ is significant, a selection bias exists. As can be seen from Table 4, in both models this parameter is highly significant, indicating that the OLS model leads to biased estimates. Hence, the treatment models are preferred. Moreover, the sign of ath$(\boldsymbol{\rho})$ has important implications. Unlike many other impact studies, where ath$(\boldsymbol{\rho})$ has a positive value, the parameter is negative here, indicating a negative selection bias. Accordingly, there is a bias in favor of farmers at the lower end of the income distribution. While this may surprise, there is a plausible explanation. Farmers who have experienced severe problems with pests and diseases are more willing to adopt TC, whereas banana growers with healthy and high-yielding traditional plantations may be less interested in this technology (Kabunga et al., 2011). Pest and disease problems are often negatively correlated with yields and incomes.

[TABLE 4]

Results of the treatment-effects models show that TC adoption positively affects income. Adoption increases annual farm and household income by K.shs 50,192 (US$660) and 28,221 (US$370), respectively. This translates into an increase of 153% in farm income and of 50% in household income, using sample mean values as the reference. These substantial results are mainly due to positive productivity and revenue effects caused by TC, which could not be observed when only comparing descriptive statistics of adopters and non-adopters, due to the mentioned selection bias.[3] The farm income effect is bigger than the total income effect; this is because TC adopters tend to specialize more on bananas, partly reducing the allocation of scarce household resources to other economic activities. Overall, the income effects estimated here are in line with previous ex ante and pilot phase studies (Mbogoh et al., 2003; Qaim, 1999). In contrast, Muyanga (2009) did not find any positive income effects of TC bananas in Kenya, but he did not control for selection bias.

The coefficient estimates in Table 4 show that other variables also affect income. An extra year of formal education increases household income by K.shs 1,665. Likewise, female-headed households have significantly higher household incomes. This gender dimension is particularly interesting; it underlines that women earn higher incomes than men when they are fully in control of household resources. Household size has a negative effect on per capita incomes, whereas

[3] Indeed, Kabunga et al. (2011) showed that TC adoption causes a significant positive yield effect when controlling for this bias.

non-land assets have a positive effect, at least on total household income. Finally, farmers with higher shares of off-farm income and those living in Kiambu have lower farm incomes.

5.3 Impacts on food (in)security

Table 5 shows the estimation results of the FII and SFII models. Unlike the income estimations, the parameter ath($\boldsymbol{\rho}$) is insignificant here, suggesting that there is no selection bias. Also, results from the likelihood ratio (LR) tests, shown in the last row of Table 5, indicate that the null hypothesis of independent selection and outcome equations cannot be rejected. Even though we showed that food security, as measured by the HFIAS in Table 2, is significantly correlated with income, the correlation coefficients are relatively small, so that divergent results should not surprise. Against this background, the OLS estimates in Table 5 are considered unbiased and are therefore preferred.

[TABLE 5]

For interpreting the coefficient estimates, we remind that higher values for both FII and SFII indicate higher levels of food insecurity. Thus, negative coefficient estimates connote improvements (reductions in relative food insecurity) and vice versa. The results in Table 5 suggest that TC bananas contribute to significant net improvements in household food security. TC adoption reduces food insecurity and severe food insecurity by 0.21 and 0.26 index points, respectively.

These encouraging findings can partly be explained by the positive net income effects, which were demonstrated above. Yet, in addition to the mere magnitude of annual incomes, several other factors may play a role. First, banana is grown as a semi-subsistence crop; on average, in our sample 42% of the harvest is kept for household consumption. Hence, productivity growth through TC technology directly contributes to better food availability at the household level.

Second, in the local context, banana is considered a security crop, which – in contrast to crops with seasonal production peaks – provides food and income more or less continuously throughout the year. TC technology further contributes to this security function and reduces actual and perceived household vulnerability to consumption shortfalls.[4] Third, banana has traditionally been a woman's crop, so that – compared to typical cash crops – women have more control over production and income. This may contribute to positive food security impacts, as women's income is known to have a particularly positive effect for household nutrition and welfare (Katz, 1995; Quisumbing et al., 1995). We have no evidence that TC adoption changed gender roles within households significantly, although we have not analyzed this aspect in greater detail.

The other results in Table 5 indicate that education also improves food security: one additional year of schooling reduces relative food insecurity by 0.04 index points, while the effect for severe food insecurity is not significant. Non-land assets reduce food insecurity with respect to both indicators. Conversely, larger household sizes and credit constraints are associated with higher food insecurity. Credit constraints in particular have a large impact, which should not surprise. In addition to facilitating investments, being able to obtain credit when needed can also insure against consumption shortfalls, so that credit constrained households are more vulnerable to food insecurity.

6. Conclusion

We have analyzed the impacts of TC banana technology on household income and food security in Kenya. While there is a relatively broad literature looking at impacts of different agricultural technologies, surprisingly little previous research has directly analyzed food security or nutrition

[4] One advantage of using the HFIAS for impact assessment is that perceived food security risks are also captured, which is not possible with most other approaches, such as dietary recalls or anthropometric measurements.

effects. This is partly due to conceptual difficulties in measuring food security and relatively costly data collection approaches. Our methodological contribution was to use the Household Food Insecurity Access Scale (HFIAS), a tool composed of relatively simple survey questions to capture food security at the household level. HFIAS has been tested and validated in different developing country settings, but to our knowledge it has not been used previously for impact assessment.

While HFIAS is not a perfect measure of nutritional outcomes, it includes many facets of food security. One advantage is that it also captures subjectively perceived risks of food insecurity, which is not the case for alternative approaches, such as dietary recalls or anthropometric indicators. We obtain robust results with the HFIAS tool, so that we see scope for its wider use in impact assessment. Integrating food security more explicitly in technology adoption and impact studies is important for research priority setting and the design of broader food and agricultural policies.

Our empirical contribution relates to the concrete example of TC bananas. While TC technology for vegetative plant propagation is gradually gaining in importance in Africa, rigorous ex post assessments of welfare effects for smallholder farm households is lacking. Using a sample of Kenyan banana farmers, we have shown that there is no significant difference when one simply compares gross margins and incomes between TC adopters and non-adopters. However, we find a negative selection bias, implying that poorer households are more likely to adopt TC technology. Controlling for this bias through estimation of treatment-effects models reveals large and significant net income effects. TC adoption increases farm income by 153% and total household income by 50%. This is mainly the result of higher net yields and revenues.

TC technology also contributes significantly to food security. Building on our derived HFIAS indices, adoption reduces relative food insecurity by 0.21 and severe food insecurity by 0.26 index points. On the one hand, this can be explained by the positive income effects, allowing better economic access to food. On the other hand, banana is a semi-subsistence crop, so that a productivity-increasing technology also directly improves food availability at the household level. As bananas can be harvested throughout the year, seasonal fluctuations in consumption are mitigated. Moreover, the fact that banana is a typical woman's crop in Kenya may contribute to the positive food security effects, although more research is needed to better understand the gender implications of technology adoption in semi-subsistence crops.

Our results suggest that TC technology can be clearly welfare enhancing for adopting farm households. Therefore, its use should be further promoted. Since successful TC adoption is relatively knowledge-intensive and requires proper access to input and output markets, a conducive institutional setup is an important precondition. Appropriate technology delivery systems need to be developed and implemented on a broader scale.

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Table 1: Descriptive statistics of TC adopters and non-adopters

Variable	**Description**	**Full sample** *N=385*	**Adopters** *N=223*	**Non-adopters** *N=162*
Farm and household characteristics				
Education	Education of household head (years)	8.54	9.13***	7.72
		(4.04)	(4.09)	(3.85)
Age	Age of household head (years)	58.20	59.79***	56.01
		(13.57)	(13.17)	(13.84)
Female head	Female headed households (dummy)	0.18	0.17	0.19
		(0.38)	(0.38)	(0.39)
Household size	Number of household members	4.61	4.63	4.59
		(1.99)	(1.98)	(2.01)
Area owned	Total arable land owned by farmer (acres)	3.30	3.83***	2.57
		(3.01)	(3.36)	(2.27)
Assets	Value of non-land productive assets (000 K.shs)	178.77	216.02***	127.17
		(224.17)	(248.97)	(172.25)
Credit constrained	Household faces credit constraints (dummy)	0.40	0.34***	0.49
		(0.49)	(0.47)	(0.50)
Information constrained	Household faces agricultural information constraints (dummy)	0.29	0.20***	0.43
		(0.46)	(0.40)	(0.50)
TC nursery	Household knows TC nursery location (dummy)	0.76	0.95***	0.49
		(0.43)	(0.22)	(0.50)
High-potential area	Household is located in high potential banana growing areas (dummy)	0.53	0.52	0.54
		(0.50)	(0.50)	(0.50)
Kiambu	Household is located in Kiambu District (dummy)	0.13	0.14	0.12
		(0.34)	(0.35)	(0.33)
Banana enterprise				
Value of output	Value of banana production per acre (000 K.shs)	100.28	98.01	103.39
		(91.77)	(92.46)	(90.99)
Value of input costs	Value of purchased inputs per acre (000 K.shs)	7.57	9.91***	4.36
		(15.79)	(17.69)	(12.07)
Gross margin	Gross margin per acre (000 K.shs)	92.70	88.11	99.03
		(90.88)	(91.05)	(90.54)
Household income				
Household income	Total household income per capita (000 K.shs)	56.32	57.19	55.11
		(62.79)	(53.92)	(73.50)
Farm income	Total farm income per capita (000 K.shs)	32.77	33.78	31.39
		(47.68)	(37.44)	(59.04)
Off-farm income	Total off-farm income per capita (000 K.shs)	23.35	23.41	23.26
		(36.32)	(36.59)	(36.04)
Off-farm income share	Off-farm income to total income (%)	35.77	32.08	40.89
		(103.13)	(132.17)	(34.29)

Notes: *** denotes that mean values for adopters are significantly different from those of non-adopters at the 1% level. Figures in parentheses are standard deviations.

Table 2: Domains and sub-domains of the HFIAS with sample statistics

	Percentage response on occurrences over last 30 days				Pearson correlation with household income	
	'never' (0 times)	*'rarely'* (1-2 times)	*'sometimes'* (3-10 times)	*'often'* (> 10 times)	Coefficient	*p-value*
I. Anxiety and uncertainty about household food supply						
1. Did you worry that your household would not have enough food? (FIQ1)	39.6	23.2	26.0	11.2	-0.217	0.000
II. Insufficient quality (includes food variety and preferences)						
2. Were you or any household member not able to eat the kind of foods you preferred because of lack of resources? (FIQ2)	29.4	29.7	30.2	10.7	-0.223	0.000
3. Did you or any household member eat just a few kinds of food day after day due to lack of resources? (FIQ3)	32.3	27.0	28.9	11.7	-0.217	0.000
4. Did you or any household member eat food that you preferred not to eat because of a lack of resources to obtain other types of food? (FIQ4)	32.0	28.7	28.4	10.9	-0.200	0.000
III. Insufficient food intake and physical consequences						
5. Did you or any household member eat a smaller meal than you felt you needed because there was not enough food? (FIQ5)	58.1	22.1	15.6	4.2	-0.162	0.002
6. Did you or any household member eat fewer meals in a day because there was not enough food? (FIQ6)	65.6	20.6	11.7	2.1	-0.174	0.001
7. Did you or any household member go to sleep at night hungry because there was not enough food? (FIQ7)	86.2	9.4	3.7	0.8	-0.145	0.004
8. Did you or any household member go a whole day without eating anything because there was not enough food? (FIQ8)	93.5	4.4	1.8	0.3	-0.075	0.142
9. Was there ever no food at all in your household because there were no resources to get more? (FIQ9)	93.8	3.9	2.1	0.3	-0.127	0.013

Table 3: Summary of the PFA results (N=384)

Variable (sub-domains)	Factor 1 **'Food Insecurity'**	Factor 2 **'Severe Food Insecurity'**	Uniqueness (1-communaltiy)
FIQ1	**0.790**	0.067	0.311
FIQ2	**0.946**	-0.033	0.139
FIQ3	**0.952**	-0.030	0.126
FIQ4	**0.951**	-0.043	0.141
FIQ5	**0.681**	0.285	0.236
FIQ7	0.133	**0.764**	0.283
FIQ8	-0.075	**0.902**	0.258
FIQ9	0.057	**0.627**	0.563
Eigen values	*4.969*	*0.974*	
Percent variance explained (1.035)	*0.866*	*0.170*	

Note: bolded loadings are greater than 0.60.

Table 4: Estimated impacts of TC adoption on income

	Farm income (000 K.shs/capita)		Household income (000 K.shs/capita)	
	Treatment model	OLS	Treatment model	OLS
TC adoption (IV)	50.192***	-5.805	28.221*	-15.098**
	(6.628)	(4.779)	(16.793)	(5.877)
Education	-0.317	1.041	1.665*	2.716***
	(0.807)	(0.697)	(0.978)	(0.857)
Age	0.220	0.493	-0.235	-0.025
	(1.366)	(1.187)	(1.538)	(1.460)
Age *squared*	-0.004	-0.004	0.002	0.003
	(0.012)	(0.010)	(0.013)	(0.013)
Female head	9.890	11.159*	15.502*	16.484**
	(7.102)	(6.172)	(7.997)	(7.591)
Household size	-6.638***	-6.738***	-9.803***	-9.881***
	(1.371)	(1.192)	(1.542)	(1.465)
Area owned	1.578	2.711***	0.839	1.715*
	(0.971)	(0.841)	(1.134)	(1.035)
Assets	0.020	0.029**	0.090***	0.097***
	(0.013)	(0.011)	(0.015)	(0.014)
Off-farm income share	-0.079**	-0.081**	0.041	0.040
	(0.037)	(0.032)	(0.041)	(0.039)
Credit constrained	-2.070	-6.288	-10.253	-13.516**
	(5.574)	(4.838)	(6.372)	(5.950)
Kiambu	-16.418*	-15.464**	-12.829	-12.091
	(8.783)	(7.633)	(9.883)	(9.387)
High-potential area	-4.674	-4.774	-5.460	-5.537
	(5.696)	(4.951)	(6.408)	(6.089)
Constant	27.768	25.793	46.569	45.041
	(39.306)	(34.163)	(44.221)	(42.014)
ath(ρ)	-1.205***		-0.692***	
	(0.135)		(0.264)	
$\ln \sigma$	3.916***		4.034***	
	(0.048)		(0.061)	
N	*384*	*384*	*384*	*384*
Wald χ^2/F-statistic	*121.04****	*7.15****	*135.26****	*12.77****
Log likelihood	*-2,160.22*		*-2,247.61*	
Adjusted R-square		*0.16*		*0.27*
LR test of independent equations (Prob> χ^2)	*0.000*		*0.028*	

Notes: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. Figures in parenthesis are standard errors.

Table 5: Estimated impacts of TC adoption on food insecurity

	Food insecurity index (FII)		Severe food insecurity index (SFII)	
	Treatment model	OLS	Treatment model	OLS
TC adoption (IV)	-0.084	-0.209**	-0.266*	-0.261***
	(0.167)	(0.089)	(0.157)	(0.094)
Education	-0.042***	-0.039***	-0.016	-0.016
	(0.013)	(0.013)	(0.014)	(0.014)
Age	0.023	0.023	0.010	0.009
	(0.022)	(0.022)	(0.023)	(0.023)
Age *squared*	-2.03E-04	-2.02E-04	-2.44E-05	-2.44E-05
	(1.89E-04)	(1.91E-04)	(1.97E-04)	(2.01E-04)
Female head	-0.007	-0.004	-0.043	-0.043
	(0.114)	(0.115)	(0.119)	(0.121)
Household size	0.073***	0.073***	0.046**	0.046*
	(0.022)	(0.022)	(0.023)	(0.023)
Area owned	0.004	0.006	-0.019	-0.019
	(0.016)	(0.016)	(0.016)	(0.016)
Assets	-1.11E-03***	-1.09E-03***	-4.37E-04**	-4.38E-04*
	(2.11E-04)	(2.13E-04)	(2.21E-04)	(2.23E-04)
Off-farm income share	-1.30E-04	-1.34E-04	1.68E-04	1.68E-04
	(5.88E-04)	(5.97E-04)	(6.16E-04)	(6.26E-04)
Credit constrained	0.682***	0.673***	0.473***	0.473***
	(0.090)	(0.090)	(0.094)	(0.095)
Kiambu	0.263*	0.266*	0.145	0.145
	(0.141)	(0.143)	(0.147)	(0.150)
High-potential area	-0.127	-0.128	-0.102	-0.102
	(0.091)	(0.092)	(0.095)	(0.097)
Constant	-0.574	-0.578	-0.356	-0.356
	(0.629)	(0.638)	(0.658)	(0.669)
ath($\boldsymbol{\rho}$)	-0.128		0.005	
	(0.146)		(0.124)	
$\ln \sigma$	-0.219***		-0.174*	
	(0.037)		(0.036)	
N	*384*	*384*	*384*	*384*
Wald χ^2*/F-statistic*	*181.65****	*15.14****	*74.31****	*6.40****
Log likelihood	*-641.71*		*-660.40*	
Adjusted R-squared		*0.31*		*0.14*
LR test of independent equations (Prob> χ^2*)*	*0.386*		*0.969*	

Notes: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. Figures in parenthesis are standard errors.

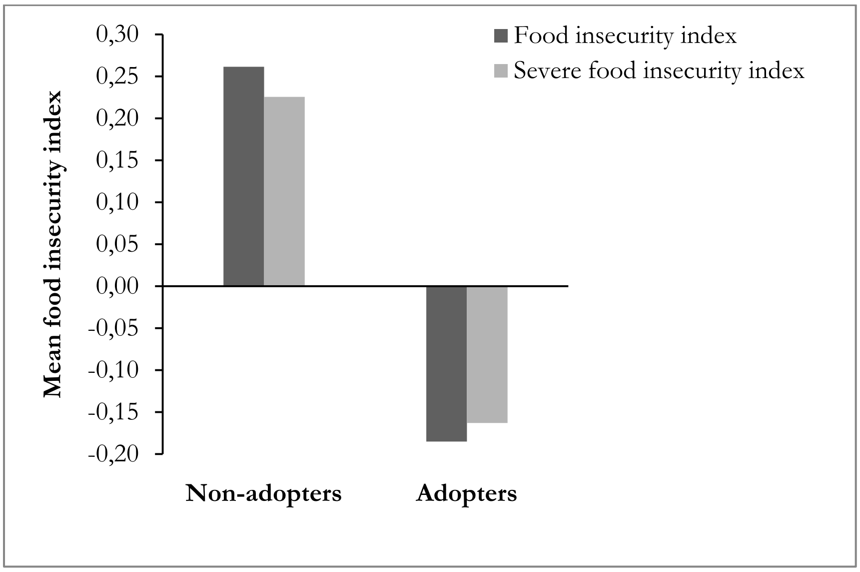


Figure 1: Mean relative food insecurity scores by adoption status

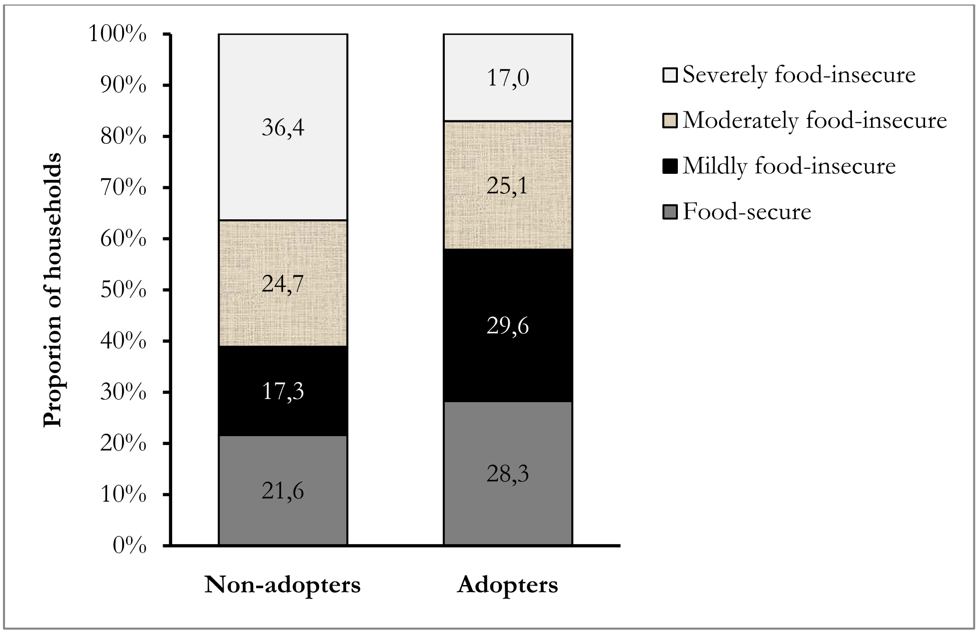
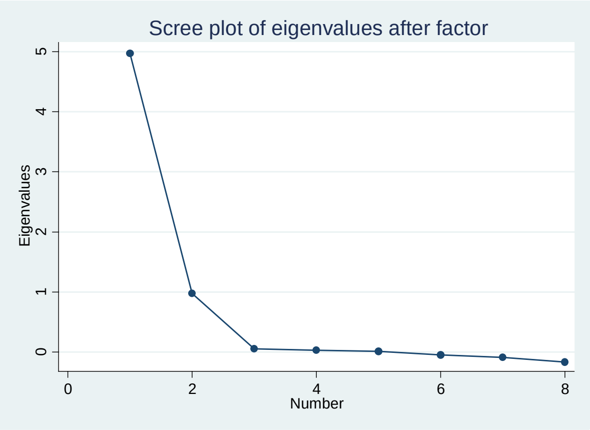
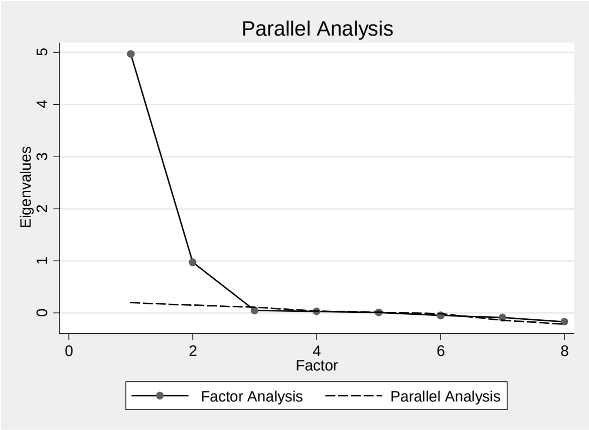


Figure 2: Proportion of food-insecure households by adopter status

Appendix 1: Screeplot and parallel analysis for utmost factor solutions





Appendix 2: First stage (selection) equation

Dependent variable: *Adoption (1/0)*	Coefficients
Education	0.035*
	(0.021)
Age	-0.005
	(0.038)
Age *squared*	1.79E-04
	(3.39E-04)
Female head	0.123
	(0.191)
Household size	-0.010
	(0.037)
Area owned	0.054**
	(0.026)
Assets	1.25E-04
	(3.80E-04)
Off-farm income share	7.80E-05
	(8.33E-04)
Credit constrained	-0.207
	(0.148)
Kiambu	0.019
	(0.240)
High-potential area	0.002
	(0.155)
Information constrained	-0.248**
	(0.126)
TC nursery	1.040***
	(0.183)
Constant	-1.426
	(1.064)

***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.
Figures in parenthesis are standard errors.