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

Abstract: While tissue culture (TC) technology for vegetative plant propagation is gradually gaining in importance in Africa, rigorous assessment of broader welfare effects for adopting smallholder farm households is lacking. Using survey data and accounting for selection bias in technology adoption, we analyze the impact 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, combined with improved crop management, causes considerable increases in farm and household income. Technology adoption also reduces relative food insecurity in a significant way. These results indicate that TC technology can be welfare enhancing for adopting farm households. Adoption should be further promoted through upscaling appropriate technology delivery systems.

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 the type of technologies that may be appropriate for the small farm sector (Renkow and Byerlee, 2010). Moreover, especially in Africa, many available technologies are not adopted, or only very slowly, which may be due to unsuitable technological characteristics or unfavorable framework conditions (Suri, 2011; 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 (Kathage and Qaim, 2012; Christiaensen et al., 2011; Cunguara and Darnhofer, 2011; Subramanian and Qaim, 2010). 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 impact of tissue culture (TC) banana technology on household income and food security in Kenya, contributing to the existing literature 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 been used previously 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 banana 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 (Njuguna et al., 2010; Muyanga, 2009; Mbogoh et al., 2003), a rigorous assessment of broader welfare impacts has not 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 of 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 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 (Smale and Tushemereirwe, 2007; Qaim, 1999). Recently, with strong fluctuations in coffee and tea prices, banana has also gained popularity as a cash crop in some regions, although this potential has not yet been fully tapped.

Due to pests, diseases, and poor crop management, banana yields have decreased in Kenya and other countries of East Africa over the last 30 years (Kahangi, 2010). The development and dissemination of pest- and disease-resistant cultivars would be an interesting approach, but edible bananas are seedless clones, which makes conventional breeding very difficult. Attempts to combine resistance traits with desirable quality characteristics based on conventional breeding techniques were so far not very successful (Tripathi et al., 2008). Traditionally, bananas are vegetatively propagated using suckers. 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 plantations. 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 (Kahangi, 2010). 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, a Kenya-based international non-governmental organization (NGO), 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 recent dissemination programs took place, adoption rates are already higher (Njuguna et al., 2010). The TC adoption process has been 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 local farmers, who often tend to neglect their banana crop (Qaim, 1999). Hence, wealthier farmers and those with better access to credit and input markets were among the first to adopt TC bananas in the early dissemination phase. Not all of these early adopters were satisfied, especially not when they had adopted the technology spontaneously without proper information and training (Kabunga et al., 2012a). In the absence of specific extension, problems were sometimes associated with low-quality planting material or insufficient crop management. Such problems were explicitly addressed by NGOs during the last 10 years. Africa Harvest, in particular, promotes the formation of farmer groups to which it provides technical training. These smallholder groups are also linked to input and output markets and to certified TC laboratories and nurseries. Fischer and Qaim (2012a) showed that smallholder farmers who are organized in groups nowadays have significantly higher TC adoption rates and better access to markets.

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 purposively 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. 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, 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 had taken place, were purposively 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. All sample households are diversified smallholders, most of them with farm sizes of less than 5 acres. In addition to banana, sample farms grow maize for home consumption and different horticultural crops. Many also have some livestock activities such as raising chicken and small ruminants, and some grow cash crops such as coffee on a small scale.[1]

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

[1] In other regions of Central and Eastern Kenya, there are also more specialized commercial farms focusing on dairy or horticultural products for the export sector. Such specialized commercial farming was not observed in the banana-growing villages sampled here.

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, details of which are described further below.

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 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 (Fischer and Qaim, 2012b).

[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. 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). Social networks may also play an important role. Recent studies have shown that individuals often learn from their peers and share information with friends and other farmers about their experience with innovations (Maertens and Barrett, 2013; Matuschke and Qaim, 2009). To capture such effects, we asked farmers to name their three closest social network contacts and specify who among these contacts had adopted TC technology ahead of them. Based on this information, we constructed the variable 'TC adoption by social network', which measures the share of earlier adopters in an individual's social network. We deliberately focused on earlier adopters among the network members to reduce possible problems of simultaneity.[2]

3.2 Gross margin and household income

The lower part of Table 1 shows economic indicators of banana production. On average, TC adopters have larger banana areas than non-adopters. But there are no significant differences in terms of the value of banana output and gross margins per acre, although 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 about technological impacts would be premature. As TC technology was not

[2] The group of network members influences the behavior of the individual, but the individual also influences the group. This issue of simultaneity has been termed the 'reflection problem' by Manski (1993). One approach to reduce this problem in econometric analysis is to assume a dynamic adoption framework (Manski, 2000), where an individual farmer is influenced by the behavior of the network but with a lag. By focusing on those network members that had adopted TC technology ahead of the farmer we can be more certain about the direction of causality.

randomly assigned to farmers, a possible self-selection bias needs to be accounted for. We do so in the econometric analysis further below. In any case, the descriptive analysis underlines that TC adoption in Kenya now also occurs among relatively poor smallholder farmers.

4. Measuring food security

4.1 The Household Food Insecurity Access Scale (HFIAS)

While food insecurity is still a widespread phenomenon, and is thus ranking high on the development policy agenda, the issue does not receive sufficient 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 (Qaim and Kouser, 2013; Ecker and Qaim, 2011; Rusike et al., 2010; Haddad et al., 1998;). There are also studies that have tried to measure food insecurity through data on household coping strategies (Maxwell et al., 2008). However, all these approaches have their methodological and empirical drawbacks, 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 their access to food (Swindale and Bilinsky, 2006). HFIAS is relatively easy and less costly 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), Costa Rica (Gonzélez et al., 2008), Tanzania (Knueppel et al., 2010), Ethiopia (Maes et al., 2009), and Burkina Faso (Becquey et al., 2010), among others. 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.

It should be emphasized that HFIAS is not an all-encompassing measure of food insecurity. According to the common FAO definition, food security has four dimensions, namely food availability, access, utilization, and stability. HFIAS focuses primarily on a household's access to food and thus also captures local food availability. HFIAS questionnaires usually refer to the household's experience over a 30-day period, so that longer-term stability and seasonality aspects cannot be analyzed, unless the survey is repeated. The same problem also applies to dietary recall data. Nor does the HFIAS tool capture utilization, involving aspects of food preparation, intra-household distribution, and feeding practices, among others (Swindale and Bilinsky, 2006; Webb et al., 2006). A very comprehensive assessment of food security at household and individual levels requires more research and the combination of both quantitative and qualitative approaches. Nevertheless, HFIAS measures were shown to be correlated closely with other indicators of poverty and food consumption in multiple contexts (e.g., Knueppel et al., 2010; Becquey et al., 2010; Maes et al., 2009; Coates et al., 2006c). Hence, HFIAS seems to be a cost-effective tool to capture important aspects of food security in impact assessment studies.

4.2 HFIAS survey module

Following guidelines by Coates et al. (2006b), 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 three sub-domains represents food quality, while domain III, composed of five 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 is 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 60% of the sampled households are worried about fulfilling their food needs. Similarly, 69% have insufficient food quality (unweighted mean of three sub-domains in domain II), and 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.

4.3 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 these indicators can help to 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 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, scores 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 more accurate and reproducible solutions than orthogonal rotations. 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 Figure A1. 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 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'.

4.4 Identifying the food-insecure

PFA can be used to score and construct household-specific indices for the identified factors within the sample. Accordingly, for the two factors extracted above, we calculated the food insecurity index (FII) and the severe food insecurity index (SFII) for each household through linear combinations between observed variable values and factor loadings. These indices are normally distributed across the sample with mean zero and standard deviation of one. 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 non-adopters. However, based on these comparisons alone we cannot conclude that TC adoption causally improves food security. This will be analyzed in the next section where we use the FII and SFII indices as dependent variables in econometric models.

[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 an increase in 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 (Greene, 2011; Imbens and Wooldridge, 2009). One option with cross-section data is to use propensity score matching, which can control for bias due to observable characteristics (Heckman and Vytlacil, 2007). However, TC adoption may also be influenced by unobserved factors, such as farmers' ability, agroecological conditions, or problems with pests and diseases at the micro level. Hence, we use treatment-effects models (Greene, 2011), which account for both observed and unobserved heterogeneity through the use of instrumental variables.

For model identification, an appropriate instrument needs to be identified. Instrument validity in our case requires that the instrument is correlated with TC adoption but has no influence on the outcome variables other than through the adoption pathway. This is not easy to find, because typical variables that are expected to influence technology adoption (such as education, market distance, risk perceptions, or credit constraints) may also affect household income and food security through other pathways. The share of technology adoption at the village level, which has been used as an instrument in some studies related to other technologies, is also not suitable in our case because of the existing TC dissemination programs. As described above, especially in more recent years, groups of farmers in banana-growing villages received technical and market support from NGOs to facilitate TC adoption. Villages with a higher share of TC adopters are probably those that received particularly intensive NGO support, which may affect household income and food security through multiple pathways.

We are in the fortunate situation to have TC adoption data from farmers' individual social networks, which differs from village level adoption rates. First, individual social networks are not confined to village boundaries. Second, as explained above, to avoid the reflection problem the variable 'TC adoption by social network' only refers to network members who had adopted earlier than the farmer. It turns out that this social network variable is closely correlated with adoption. Interestingly, the correlation coefficient is negative, implying that farmers who know early TC adopters are less likely to adopt themselves. This is related to the fact that some of these early adopters, especially those that did not benefit from the NGO support programs, were dissatisfied with their TC adoption experience (see explanations above). It appears that negative attitudes towards this technology were spread through social networks, a fact that we exploit for identification. On the other hand, 'TC adoption by social network' does not influence household income or food security directly, which we tested through correlating with the outcome variables (see Appendix Table A1). None of the correlation coefficients is statistically significant, so that 'TC adoption by social network' is a valid instrument for all impact models to be estimated. The first-stage estimation results (selection equation) are shown in Table A2 in the Appendix. Results for the different outcome equations are presented and discussed below.

5.2 Impacts of TC adoption on income

The results of the income models are shown in Table 4. For comparison, the treatment-effects results are shown next to estimates from ordinary least squares (OLS) models. For the treatment 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. In both models in Table 4 this parameter is highly significant, indicating that the OLS models lead to biased estimates. Moreover, results from the likelihood ratio (LR) tests, shown in the last row of Table 4, point to the rejection of the null hypothesis of independent selection and outcome equations. Hence, the treatment models are preferred. The sign of ath($\boldsymbol{\rho}$) has important implications. Unlike many other impact studies, where ath($\boldsymbol{\rho}$) has a positive value showing positive selection bias, the parameter is negative here, indicating negative selection bias.[3] Hence, the OLS models underestimate the impacts of TC technology. Negative selection bias means that poorer farmers are more likely to adopt this technology, which is plausible: as TC provides pathogen-free planting material, farmers who have experienced severe problems with pests and diseases and thus have lower banana productivity and income may be more willing to adopt TC.[4] This was also pointed out by Kabunga et al. (2012b). Any bias through observed and unobserved factors is effectively controlled through the instrumental variable approach in the treatment models.

[TABLE 4]

Results of the treatment models show that TC adoption positively affects income. Adoption increases annual farm and household income by K.shs 38,051 (US$500) and 50,286 (US$662),

[3] While positive selection bias is more common in impact studies for new agricultural technologies in the small farm sector, there are also a few studies that found negative selection bias. Examples of negative selection bias include Suri (2011) in her analysis of hybrid maize adoption in Kenya and Noltze et al. (2013) in their research on the system of rice intensification in Timor Leste.

[4] It should be stressed that TC adoption rates are further increasing in Kenya and have not yet reached their saturation point. In later adoption phases, some of the current non-adopters may potentially also decide to adopt, which could alter statements on determinants of adoption.

respectively. This translates into an increase of 116% in farm income and 89% in household income, using sample mean values as the reference. Such effects could not be observed when only comparing descriptive statistics between adopters and non-adopters, due to the mentioned negative selection bias. The income effects estimated here are in line with ex ante studies carried out during the early phases of TC adoption (Mbogoh et al., 2003; Qaim, 1999). In contrast, Muyanga (2009) did not find any positive income effects of TC bananas, but he did not control for selection bias. A recent study analyzed the yield effects of TC bananas in Kenya, building on the same sample of farmers as we use here (Kabunga et al., 2012b). That study, which controlled for selection bias, found a net TC yield gain of 7% when holding the quantity of other inputs constant. But the same study also showed that the yield gains can be much larger when the input mix is adjusted, as recommended for TC bananas (Kabunga et al., 2012b). Our estimates of income effects comprise the impact of TC planting material together with the associated adjustment of the input mix.

In fact, improved crop management and higher input intensities are important conditions for successful TC adoption and related productivity increases (Qaim, 1999). Without changes in traditional banana cultivation practices, the adoption experience can be frustrating, as was observed in Kenya among some of the early TC adopters. As explained above, this issue was addressed by NGOs through innovative approaches of technology delivery, including technical training and institutional support for farmers to reduce market access constraints. The innovation package around the TC planting material seems to cause more profound changes in household behavior. It contributes to larger areas under banana among TC adopters (see Table 1), higher input intensities, and a higher degree of commercialization. There also seem to be positive spillovers to other farm and non-farm economic activities, as indicated by the total household income effect that is even larger in absolute terms than the farm income effect.

The other coefficient estimates in Table 4 show that income is also affected by several other factors. Household size has a negative effect on per capita farm and household income, which is related to more children in larger households. Land area has a positive and significant effect on farm income, while non-land assets show a positive and significant effect on household income. Households with higher off-farm income shares have lower farm incomes but higher household incomes, a result that underlines the important role of off-farm income for household welfare. Finally, credit constrained households have significantly lower household incomes.

5.3 Impacts of TC adoption on food (in)security

Table 5 shows the estimation results of the FII and SFII models. Similar to the income estimations above, the significant ath($\boldsymbol{\rho}$) parameter and the LR tests indicate negative selection bias, which is effectively controlled in the treatment models. The OLS models, which are shown for comparison, underestimate the treatment effects. For correct interpretation, 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 the adoption of TC bananas significantly improves household food security. TC adoption reduces food insecurity and severe food insecurity by 0.44 and 0.32 index points, respectively. Percentage interpretations relative to sample mean values are not possible, because the sample mean for both indices is zero by construction. However, given that the indices have a standard deviation of one, the estimated impacts are relatively large. This should not surprise against the background of the sizeable income effects of TC adoption discussed above.

[TABLE 5]

Beyond the income gains measured in monetary terms there are other factors that contribute to positive food security effects of TC bananas. 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.[5] 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 (Quisumbing et al., 1995). We have no evidence that TC adoption has changed gender roles within households, although the data available do not allow us to analyze 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 0.03 index points; the effect of education 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.

[5] 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.

6. Conclusion

We have analyzed the impact 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 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 previously been used 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 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 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 116% and total household income by 89%. This is mainly the result of higher net yields and net revenues resulting from using TC technology and associated adjustments in the input mix. In addition, the broader innovation package seems to have positive spillovers also to other farm and non-farm economic activities of adopting households.

TC technology also contributes significantly to food security. Building on indices derived from the HFIAS tool, adoption reduces relative food insecurity by 0.44 and severe food insecurity by 0.32 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, such as those developed by NGOs in Kenya, should be further refined 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 household (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 (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)
TC adoption by social network	Share of network contacts that have adopted TC ahead of the farmer (%)	17.19	15.17	19.96
		(28.81)	(27.95)	(29.83)
Kiambu	Household is located in Kiambu District (dummy)	0.13	0.14	0.12
		(0.34)	(0.35)	(0.33)
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)
Banana enterprise				
Banana area	Area cultivated with banana (acres)	0.37	0.44***	0.26
		(0.48)	(0.55)	(0.34)
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 factor analysis 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
Eigenvalues	*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.sh/capita)		Household income (000 K.sh/capita)	
	Treatment model	OLS	Treatment model	OLS
TC adoption	38.051***	0.394	50.286***	-6.023
	(11.955)	(3.471)	(12.132)	(5.117)
Education	-0.180	0.820*	0.220	1.715**
	(0.536)	(0.442)	(0.792)	(0.755)
Age	-0.144	0.088	-0.074	0.272
	(0.161)	(0.114)	(0.225)	(0.187)
Female head	5.469	7.025	7.373	9.699
	(5.435)	(5.016)	(7.399)	(6.823)
Household size	-6.322***	-6.338***	-9.763***	-9.787***
	(0.984)	(0.869)	(1.344)	(1.145)
Area owned	1.869**	2.487***	1.703	2.628**
	(0.866)	(0.777)	(1.144)	(1.087)
Assets	0.002	0.011	0.047**	0.061***
	(0.012)	(0.011)	(0.019)	(0.018)
Off-farm income share	-0.223***	-0.273***	0.416***	0.342***
	(0.061)	(0.058)	(0.097)	(0.086)
Credit constrained	-5.311	-8.187**	-9.540*	-13.841***
	(3.487)	(3.263)	(5.000)	(4.650)
Kiambu	-4.789	-4.959	-1.855	-2.109
	(6.411)	(5.388)	(10.223)	(9.132)
High-potential area	2.406	1.662	2.871	1.758
	(3.923)	(3.520)	(5.568)	(4.742)
Constant	45.042***	43.079***	35.502*	32.566**
	(12.942)	(11.245)	(18.637)	(15.663)
ath(ρ)	-0.830***		-0.861***	
	(0.314)		(0.238)	
$\ln \sigma$	3.537***		3.914***	
	(0.149)		(0.104)	
N	382	382	382	382
Wald $\chi 2$/F-statistic	100***	8.49***	125.74***	12.59***
Log likelihood	-2065.87		-2206.74	
Adjusted R-*square*		0.30		0.34
LR *test of independent equations (Prob> $\chi 2$)*	0.008		0.000	

Notes: ***, ** and * denote significance at 1%, 5% and 10% level, respectively. Figures in parenthesis are robust 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	-0.437***	-0.203**	-0.316***	-0.245***
	(0.127)	(0.090)	(0.102)	(0.092)
Education	-0.032**	-0.039***	-0.019	-0.021
	(0.013)	(0.012)	(0.013)	(0.013)
Age	0.002	0.000	0.007*	0.006
	(0.004)	(0.004)	(0.004)	(0.004)
Female head	0.010	-0.001	-0.056	-0.060
	(0.117)	(0.115)	(0.135)	(0.133)
Household size	0.072***	0.072***	0.040	0.040
	(0.024)	(0.024)	(0.028)	(0.028)
Area owned	0.013	0.009	-0.010	-0.011
	(0.013)	(0.013)	(0.011)	(0.011)
Assets	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Off-farm income share	0.001	0.002	0.004**	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Credit constrained	0.675***	0.693***	0.487***	0.492***
	(0.093)	(0.093)	(0.099)	(0.100)
Kiambu	0.269*	0.273*	0.147	0.146
	(0.154)	(0.155)	(0.149)	(0.150)
High-potential area	-0.127	-0.121	-0.089	-0.088
	(0.093)	(0.092)	(0.100)	(0.100)
Constant	-0.044	-0.033	-0.354	-0.347
	(0.362)	(0.359)	(0.356)	(0.358)
ath(ρ)	0.304***		0.090*	
	(0.118)		(0.052)	
$\ln\sigma$	-0.210***		-0.180*	
	(0.035)		(0.097)	
N	382	384	382	384
Wald $\chi2$/F-statistic	240.6***	21.14	59.03***	5.17***
Log likelihood	-596.43		-613.93	
Adjusted R-square		0.33		0.19
LR *test of independent equations (Prob> $\chi2$)*	0.009		0.084	

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

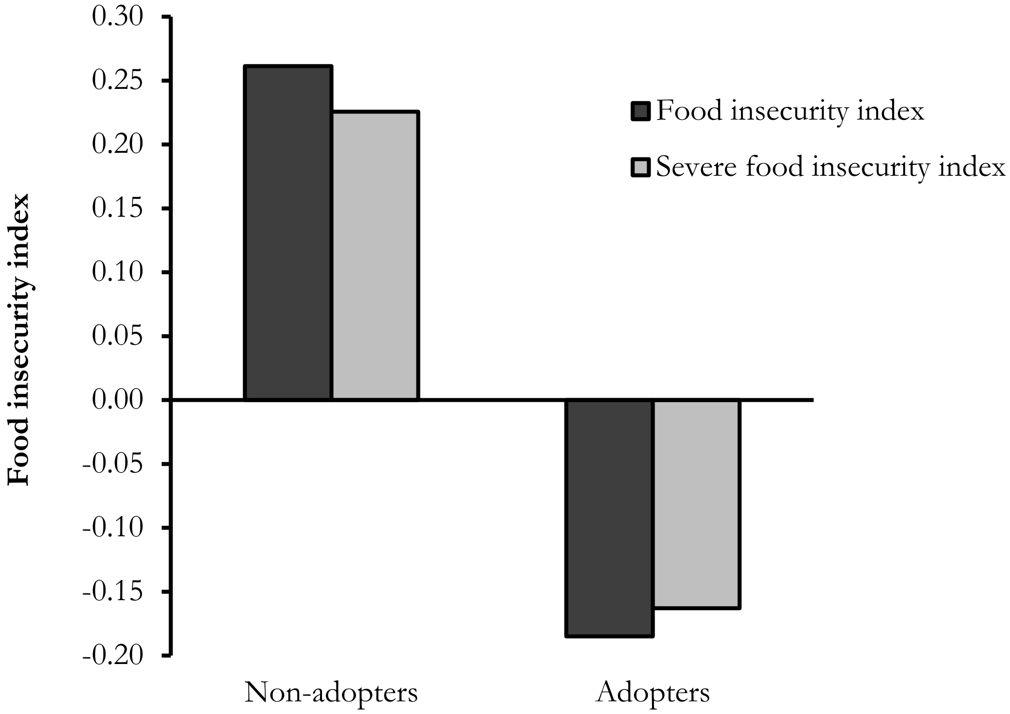


Figure 1: Mean relative food insecurity scores by adoption status

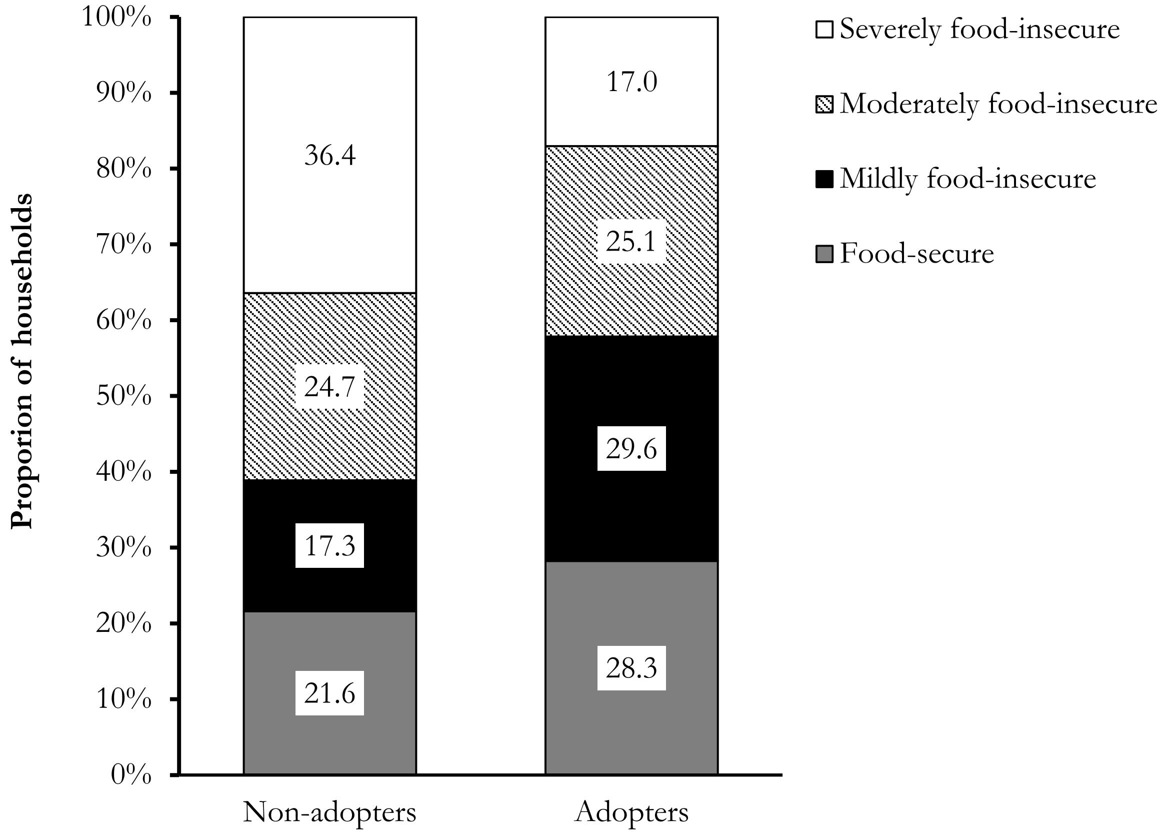
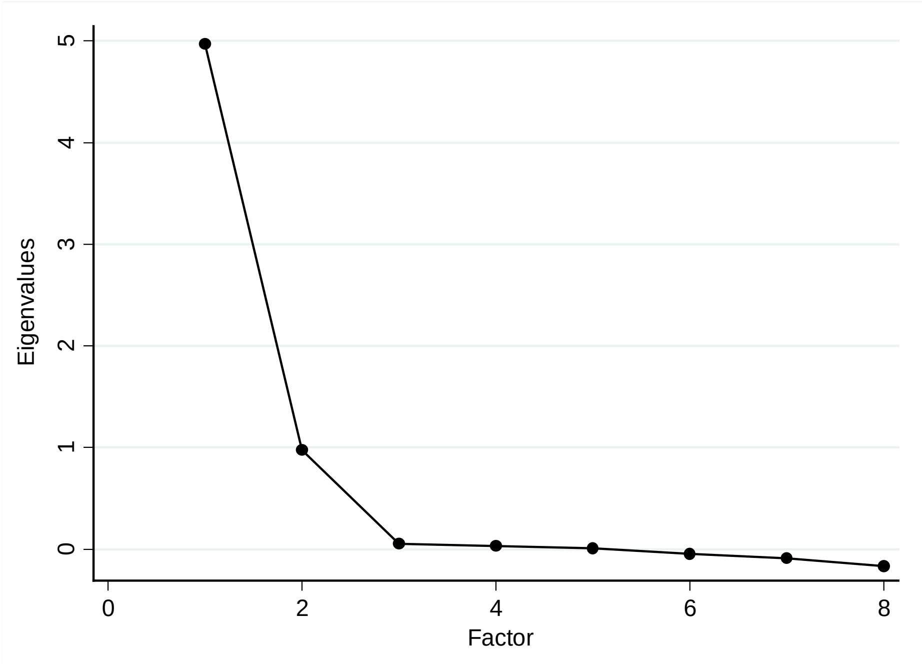


Figure 2: Proportion of food-insecure households by adoption status

Appendix

(a) Screeplot of eigenvalues



(b) Parallel analysis

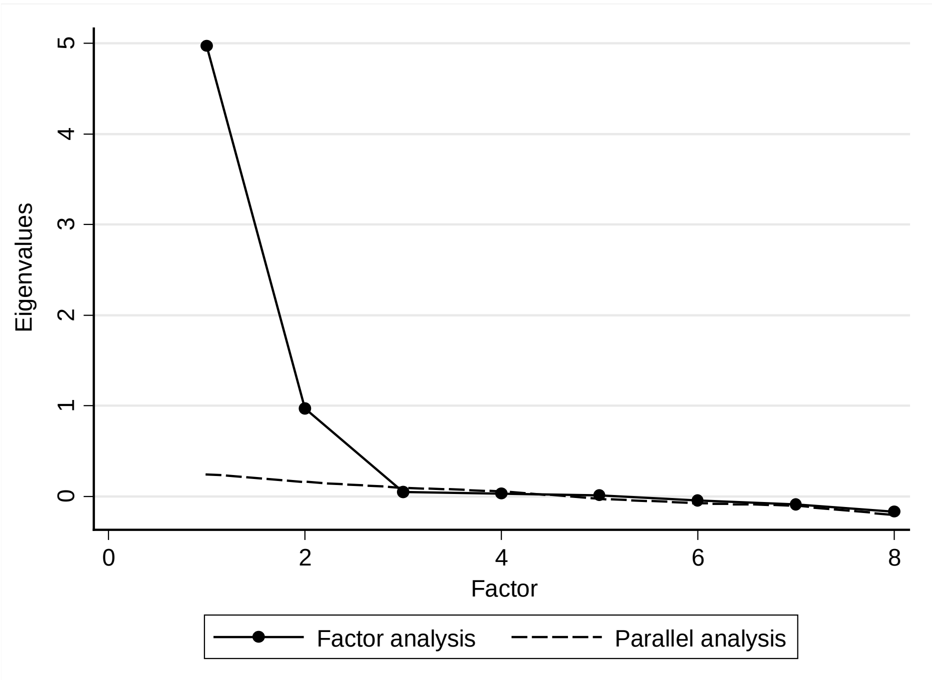


Figure A1: Screeplot and parallel analysis for utmost factor solutions

Table A1: Correlation of 'TC adoption by social network' with outcome variables

	Farm income	Household income	Food insecurity index	Severe food insecurity index
Correlation	-0.035	-0.019	0.041	0.033
P-value	*0.499*	*0.705*	*0.428*	*0.514*

Table A2: First stage (selection) equation

Dependent variable: TC adoption 1/0	Coefficients
Education	0.046*
	(0.027)
Age	0.008
	(0.007)
Female head	0.066
	(0.222)
Household size	-0.030
	(0.038)
Area owned	0.108**
	(0.048)
Assets	0.0003
	(0.001)
Off-farm income share	0.0002
	(0.003)
Credit constrained	-0.274
	(0.184)
Kiambu	0.275
	(0.280)
High-potential area	-0.262
	(0.187)
TC adoption by social network	-0.048***
	(0.013)
Constant	3.476**
	(1.475)
N	*384*
Wald $\chi 2$	*41.59****
Pseudo R-square	*0.46*

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