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Beyond the field: Impact of Farmer Field Schools on food security and poverty alleviation

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Abstract

In this paper, we estimate the impact of a farmer field school intervention among small scale farmers in Northern Tanzania. Unlike previous farmer field school evaluations, we go beyond the immediate agricultural impact and estimate the impact of farmer field school participation on the pre-specified development objectives, namely poverty alleviation and food security among participating households. We exploit the implementation design of a gradual project roll-out to establish a quasi-experimental difference-in-difference setup, which can account for potential selection into the project, both at village and household level, despite the lack of baseline data. We find strong positive effects on measures of food security, but we find no effect on the poverty indicators. We investigate possible mechanisms for this and conclude that both reallocation of labor resources and improved production smoothing among participating households may, in part, lead to this finding.

Keywords: Impact assessment, farmer field schools, quasi difference-in-difference, food security, poverty, gradual roll-out, Tanzania, Africa

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*Corresponding author; hbl@rff.dk. All views are those of the authors and not necessarily reflect the views of the Rockwool Foundation. We are grateful for comments and advice from RECODA, Jens Vesterager, Mette Ejrnæs, Torben Tranæs, Cathrine Søgaard Hansen, Maria Fibæk, as well as participants in the CAM Christmas workshop 2011. All remaining errors are of course our own.

1 Introduction

The importance of food security and agriculture in promoting economic development has recently received renewed attention among multilateral donor agencies; the African Human Development Report (2012) by the United Nations Development Program focuses on food security as a means to achieve human development and the World Development Report (2008) of the World Bank is simply titled 'Agriculture for Development' and spells out how, among other things, agricultural production is important for food security and livelihoods of the rural households. Adding to this the recent African incidences of severe food crisis situations, local and small-holder agricultural production is no doubt an important means to secure national and local food security levels.

Different agricultural extension initiatives have over the last decades been promoted to increase the food and agricultural production of small-holder farmers. In particular services aiming at educating farmers in the use of new and improved agricultural technologies developed to increase yield and drought resistance have been in focus. One such popular initiative is the farmer field schools, which by 2006 had spread world wide to at least 78 countries, Braun, Jiggins, Röling, Van den Berg, and Snijders (2006). Farmer field schools were initially developed by FAO in 1989 as a way to promote integrated pest management practices among rice farmers in Indonesia. Central to the approach was a shift from pure information delivery as in traditional extension models towards participatory experiential learning with a strong focus on developing analytical skills and problem solving capacities among farmers by using highly trained facilitators, Anderson and Feder (2007). Farmer field schools are typically organized in groups of approximately 20-25 farmers, who meet frequently during one agricultural season to jointly test a new technology compared to traditional practises. Although farmer field schools originally were developed as a means to extending a new technology to small scale farmers, they are also seen as a source of empowerment and adult learning due to the educational aspect of promoting analytical decision making and thus more than just a simple agricultural extension of information services, Van den Berg and Jiggins (2007) and Friis-Hansen and Duveskog (2012).

Due to their popularity, farmer field schools have been subject to several evaluation studies of different outcomes with very mixed findings, see overview in Davis et al (2012): Table 1. The outcomes studied are either adoption and dissemination of technologies, agricultural yields or productivity, and empowerment of the participants. Many studies find positive impacts along these short term immediate outcomes, but no peer reviewed studies consider longer term development objectives such as poverty and food security.

Within this literature there has been a vivid debate about what outcomes to measure, when to assess the impact and how, e.g. Feder, Murgai, and Quizon (2008); van den Berg and Jiggins (2008); Davis and Nkonya (2008); Mancini and Jiggins (2008); Feder, Anderson, Birner, and

Deininger (2010); Braun and Duveskog (2011). First of all, Feder, Murgai, and Quizon (2004) critizises earlier farmer field school evaluations for not taking the potential positive bias of non-random program placement and selection of participants into account in their assessments of impact. This is an important point as selection into the program confounds the impact if not accounted for. Using a modified difference-in-difference method, Feder et al (2004) concluded that the Indonesian farmer field school initiative had after all *not* generated significant improvements in yields or reductions in pesticide use among farmer field school graduates. Second, the timing of the evaluation has been subject to debate: Measuring outcomes on a long time horizon would allow for an assessment of the sustainability of the intervention, but the estimated impact would potentially be confounded by spill-overs from farmer field school graduates to the control farmers in neighboring villages. The latter argument is advanced by Van den Berg and Jiggins (2007) who provides a review of several evaluation studies suggesting that there were 'substantial immediate and development benefits of participation in farmer field schools'. Accordingly, Yamazaki and Resosudarmo (2008) find that there is short term impact, but confirms the finding of Feder, Murgai, and Quizon (2004) of no medium term impact on yields and pesticide use among Indonesian farmer field school participants revealing lack of sustainability. Similarly, Rejesus et al (2012) also find no long term impact on similar outcomes among Vietnamese farmers, whereas Davis et al (2012) find positive medium term impacts on crop productivity and agricultural income (measured as the monetary value of crop and livestock production) using two-year recall data among East African farmers. In sum, most impact evaluations have focused on shorter term and/or very project specific outcomes and studies considering agricultural income do not account for substitution between agricultural and non-agricultural income to assess the overall impact on poverty.

In this paper, we contribute to this exisiting literature by presenting a rigorous impact evaluation on both short term immediate outcomes and long term development objectives of a farmer field school approach in northern Tanzania, called RIPAT (the Rockwool Initiative for Poverty Alleviation in Tanzania). The impact evaluation is part of a larger comprehensive evaluation based on both qualitative and quantitative methods summarized in Lilleør and Lund-Sørensen (2013). The RIPAT farmer field schools resemble typical farmer field schools interventions along most dimensions. They are described as slightly less participatory and more top-down than the traditional farmer field schools by Gausset, Jöhncke, Pedersen, and Whyte (2013) and Aben, Duveskog, and Friis-Hansen (2013). A key difference compared to typical farmer field schools is that they employ a 'basket of technology options' rather than just one or two technologies and therefore they are designed to run over a longer time horizon (at least three years) rather than just one agricultural season. The reason is that there has to be ample time to adopt and experiment with all the different technologies embedded in the 'basket of options' on the common group field of the participants, Maguzu, Ringo, and Vesterager (2013).

In our evaluation design of this RIPAT farmer field school intervention, we have sought to adress the main points raised in the farmer field school evaluation debate. First of all, we let the original project documentation guide us in the choice of outcome measures. Here it was stated that the overall development objectives of the intervention were to "increase food security and poverty alleviation among participating households" through sustainable improvements in the small-scale farming systems. We assess the impact on immediate project related outcome measures as well as on the originally listed development objectives, namely food security and poverty alleviation. By developing the evaluation strategy and the associated survey instrument accordingly, we have effectively tied the analysis - and our hands - to these outcome measures and thereby reduced the possibilities of 'cherry-picking' convenient results, although we did not have a full pre-analysis plan laid out, as suggested by Casey, Glennerster, and Miguel (2012).

Second, in our choice of an impact assessment methodology we have sought to adress the potential endogeneity issues raised by Feder et al (2004) stemming from non-random program placement and self-selection of participants. We exploit the fact that the intervention has gradually been rolled out at district level with the intervention starting in the Arumeru district in 2006 and in Karatu district in 2008. This allows us to construct a quasi difference-in-difference approach based on cross-section data from 2011 following Coleman (1999). We use the 2008 intervention to control for both the non-random program placement and the self-selection of participants assuming that the selection mechanisms in the two involved districts have been the same.

Third, to adress the potential problem of spill-over to control farmers diluting the impact of the intervention, as advanced by Van den Berg and Jiggins (2007), we use sufficiently distant control farmers outside the intervention villages. Qualitative and quantitative findings confirm that we do not have to worry about potential spill-over of the intervention.

For the purpose of this impact assessment, we interviewed 1947 farming households using a highly structured closed-form questionnaire from 36 villages of which 16 where intervention villages. We thus have a relatively large sample size compared to previous farmer field school impact evaluations, which typically fall in the range of 300-500 households.[1]

We find that participants in RIPAT farmer field schools employ virtually all the key technologies promoted through the basket of options to a considerably larger extent than farmers in control villages. Most notably, we find that they are more likely to be cultivating the improved banana variety, to have a larger degree of crop diversification, to have improved breeds of livestock and to enforce zero-grazing among their livestock. This substantial impact on the immediate technology adoption measures is found among participant farmers in both the 2006

[1] We only know of one study by Davis et al (op.cit.) with a similar sample size. They base their analyses of East African farmers on a total of 1126 households across 8-10 districts and 3 countries.

Arumeru farmer field schools as well as the 2008 Karatu farmer field schools. As opposed to most farmer field school evaluations, which tend to have concentrated on immediate outcomes (technology adoption, yields or agricultural income) or empowerment of the participants as well as on adoption among non-participants (see overview in Davis et al, op.cit), we go one step further and analyze the long term impact on the overall development obejctives, food security and poverty, almost five years after the first project implementation started.

We find significant impacts on one of our two main development outcome measures, namely food security. Participating households are 23 percentage points less likely to experience hunger in the lean period, their diet contains more animal proteins, and their children are more likely to have at least three meals per day. Compared to almost any previous farmer field school evaluation, the impacts on both technology adoption and on food security are substantial and likely to be sustainable given the time horizon of the analysis. We do not find any impact of the RIPAT farmer field schools on our poverty indicators.

These seemingly contradictory results led us to wonder why this is so. We therefore further investigated two possible mechanisms; reallocation of labor resources and production smoothing, as explanations for improved food consumption levels but no impact on poverty alleviation. We find indications of both. RIPAT households have significantly reduced their dependency on casual labor as an important source of income and in addition increased their own demand for hiring labor. Furthermore, we find some indications that RIPAT farmer field schools have strengthened the ability to smooth the food production over the agricultural cycle and thereby also the food consumption, reducing hunger in the lean season. However, RIPAT farmers without these specific production smoothing technologies are also more food secure than the control farmers. Thus, although the smoothing technologies are positively correlated with food security, the overall impact of RIPAT on food security is not solely driven by a shift in the agricultural production towards technologies with less seasonal variation. Other elements in the intervention must also have contributed to the increased food security. Whether or not impacts on poverty alleviation may come in the even longer time horizon, only the future can tell.

We have organized the paper as follows. In section 2, we describe the RIPAT intervention and in section 3 we explain our empirical approach, including the evaluation strategy, the data collection and our specific choices of immediate and development outcome measures. We turn to the results in section 4, where we also analyze the role of labor reallocation and production smoothing in the findings. In section 5 we conclude.

2 The intervention and its development objectives

Two RIPAT farmer field school projects are under scrutiny in this paper. They have been implemented by the local Tanzanian NGO, RECODA. Both projects target small and medium sized farmers in rural villages with at least one acre and in principle no more than five acres of land. Village leaders were asked to form two groups of 30-35 farmers in each village and assist the groups in getting access to a joint group field. Membership is voluntary. Village leaders were explained by RECODA that members must not be rich in terms of the wealth ranking of the village, must be committed to active participation (attendance records are kept and strict rules enforced), must be willing to demonstrate and share knowledge with fellow villagers and therefore on good standing with these, must come from the administrative area of the village and furthermore that each group should have an equal number of men and women and only one member per household, Maguzu, Ringo, and Vesterager (2013). The two RIPAT projects have each been implemented in eight villages, which were chosen by district officials to be the poorest villages in the given district.

There are thus two sources of endogenous selection into the project. One is endogenous village selection, since program placement was not random and if district officials followed the guidelines given to them, RIPAT villages were worse off than the other villages in the district at the outset of the project, i.e. a negative selection effect. Secondly, since participation is voluntary, households will self-select into the project given they meet the targeting criteria and hence we expect participating RIPAT households to be more motivated than other households, which will result in a positive selection effect. The *net* selection effect can therefore a priori not be signed.

The RIPAT farmer field schools draw on the bottom-up experiential and reflective approach to learning and practical demonstration of farming techniques, typical of most farmer field schools. However, there is also a strong element of more traditional technology transfer in that the farmer groups receive training in a predetermined but locally adapted 'basket of technology options'. These agricultural technology options are chosen by the implementing NGO, RECODA based on their strong agricultural expertise and in prior consultation with the villages in question. In the farmer field schools, the options are explained, demonstrated and tested on a participatory basis on the joint group field. By equipping the farmers with the necessary information, knowledge and hands-on experience in the use of different relevant and efficient technologies, each farmer is given the means to choose which technologies to adopt in his or her own agricultural production. The groups meet weekly, and the progress made with the project crops or livestock is followed and discussed throughout the agricultural cycles over the three year project period. The crops and technologies introduced in the 'basket of options' are very diverse. The standard basket entails: improved varieties of banana with new cultivation techniques, conservation agriculture, improved animal husbandry, fruit and multipurpose trees, soil and water conservation, post-harvesting technologies, and encouragement to participate in savings groups. However, the 'basket' is always adapted to suit local settings such as soil and water and climate conditions.[2]

As mentioned, our analysis is based on two RIPAT farmer field school projects implemented two years and four months apart in two districts in the Arusha Region. The implementation of one RIPAT project started in May 2006 in Arumeru District and lasted until end of 2009 (henceforth RIPAT06), the other was implemented in Karatu District starting in September 2008 and ended in August 2012 (henceforth RIPAT08). The implementation strategies of the two projects were the same except for minor adjustments based on lessons learned during the first project.[3] We can therefore exploit this gradual roll-out to account for potential self-selection of farmers into the project as well as selection of villages, see below.

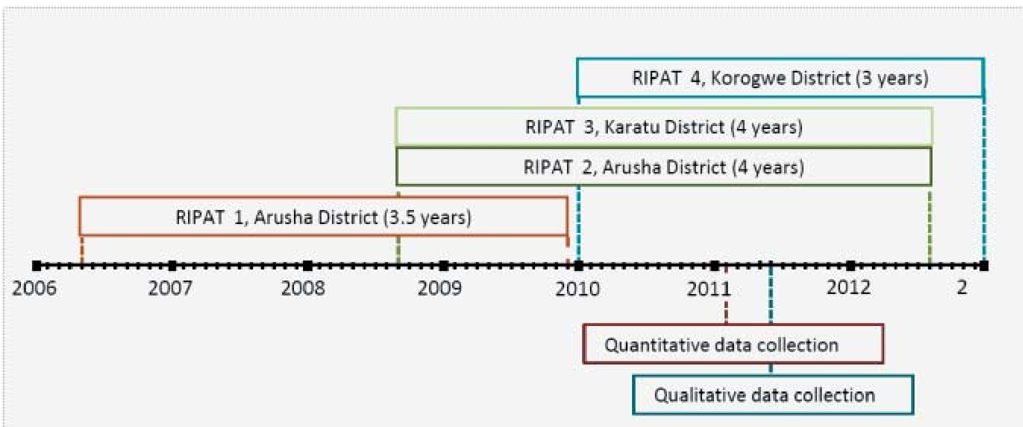

Figure 1. Timeline of RIPAT projects and data collection

3 Empirical Approach

In January 2011 we implemented a large scale quantitative household survey using a closed-form highly structured pilot-tested questionnaire to capture the impact of RIPAT on technology adoption, food security and poverty. We interviewed a total of 1947 households in 36 villages

[2] See Maguzu, Ringo, and Vesterager (2013) and Vesterager, Ringo, and Maguzu (2013) for shorter and longer detailed descriptions, respectively.

[3] Savings group participation was only encouraged, but not facilitated during the 2006 RIPAT project. Furthermore during this project it became clear that a more efficient distribution of improved goats were needed in future projects. Finally, in Karatu there was an additional demand for improved pigs, which was then also included in the basket of options.

for this analysis. Of these, there were eight RIPAT villages from each of the two districts. We aimed at interviewing all farmers which were originally signed up in the RIPAT farmer field schools, including those who later dropped out as long as they had remained in the village. In Arumeru district, 90 per cent of the original RIPAT06 farmers were interviewed while 96 per cent of the RIPAT08 farmers were interviewed in Karatu district. This resulted in 47-85 farmers being interviewed per RIPAT village. In addition, to be able to undertake comparative analyses between RIPAT and non-RIPAT villages and households, we surveyed eight control villages in Arumeru district and twelve control villages in Karatu district. In each control village, we interviewed between 38-53 farmers thus acting as control households in their respective district.

The data collection and data entry was closely supervised by us in cooperation with a survey management team from the Economic Development Initiative (a Tanzanian survey company). RECODA assisted in the hiring of a team of local interviewers and data entry clerks.

In each household, an interview was conducted with the person responsible for most agricultural decisions, often the head of the household. However, in RIPAT households, the person interviewed was always the RIPAT group member, irrespective of whether or not this person was the head of the household. Since households with female heads are overrepresented among RIPAT farmers, the same kind of overrepresentation was sought among the control households. In addition to the household interviews, we also use information from interviews with representatives of all local village governments.

3.1 Evaluation strategy

The art of a good impact evaluation lies in constructing a reasonable counterfactual. We can observe the outcomes of the RIPAT households, but in order to find the impact of participating in RIPAT we want to know the counterfactual situation; what would have happened to the RIPAT households had they *not* participated in the project. We approach the counterfactual from two different angles.

First, we compare outcomes of RIPAT06 households to outcomes of households in control villages.[4] Since we rely on cross-section data, we cannot directly account for any differences in the outcome variables prior to project implementation. This naïve assessment of the impact of the project may therefore be either upward or downward biased depending on the sign of the net selection effect. Due to the village selection described above, we may underestimate the impact as the RIPAT06 villages were possibly worse off than the control villages prior to project implementation. Due to the household selection, we may overestimate the effect if the

[4] In this exposition, a higher outcome is considered a better outcome. Obviously, the intuition is reversed when considering e.g. the Household Hunger Scale (see below) where higher values are associated with more hunger.

farmers that choose to participate and thus self-select into the project are more motivated and entrepreneurial than the average farming household in a control village.

Our second approach exploits the gradual roll-out of the project. The RIPAT08 farmer field schools in Karatu started more than two years later than in Arumeru, and we propose a Quasi-Difference-in-Difference (QDiD) method that accounts for selection by subtracting the difference between RIPAT08 and control households in Karatu from the naïve estimate of RIPAT06. This is similar to the evaluation strategy of Coleman (1999; 2006) where he uses gradual roll-out of village banks in Northeast Thailand to estimate the impact of group lending. His approach hinges on the assumption that the selection has been the same in old and new project villages. In our case, it hinges on the assumption that the selection of households and villages has been the same in the two districts.

More formally, the QDID estimator can be written using the usual notation from the treatment literature where T is an indicator variable equal to one if the household is treated and y is the outcome variable of interest. The outcome in absence of treatment is denoted y_0. Let D be a district indicator variable equal to one for the district where RIPAT was implemented early (RIPAT06, Arumeru) and zero otherwise (RIPAT08, Karatu). Then the assumption of equal net selection in the two districts can be written as

$$\begin{gathered} E[y_0|T=1,D=1,X]-E[y_0|T=0,D=1,X]= \\ E[y_0|T=1,D=0,X]-E[y_0|T=0,D=0,X] \end{gathered}$$

In words, the outcome differences due to household and village selection between treated and control households should be the same in the two districts in absence of treatment. Considering observable characteristics in section 3.3, there are indications that this has largely been the case. An estimate of the Average Treatment of the Treated (ATT) effect without any selection bias can be found as the difference in outcomes between RIPAT06 and control households subtracted the difference between RIPAT08 and their controls:[5]

$$\begin{aligned} ATT_{QDiD} = \quad & E[y|T=1,D=1,X]-E[y|T=0,D=1,X] \\ & -(E[y|T=1,D=0,X]-E[y|T=0,D=0,X]) \end{aligned}$$

We estimate the ATT_{QDiD} by applying OLS to the following parametric specification:

$$y_i = \gamma RIPAT_i + \delta D_i + \alpha RIPAT_i \cdot D_i + V_i'\lambda + D_i \cdot V_i'\eta + X_i'\beta + \varepsilon_i, \tag{1}$$

where $RIPAT_i$ is an indicator variable equal to one if household i is or has been member of a RIPAT group; D_i is a district indicator equal to one if the household is in the Arumeru

[5] We include all farmers who have ever been a member of a RIPAT group, also those who drop out just after project start. Hence, one could argue that we are estimating the intention to treat rather than the average treatment effect.

district; V_i is a vector of village characteristics, that are allowed to have a different effect in the two districts; X_i is a vector of household characteristics including a constant;[6] and ε_i is a household specific error term which we cluster at the village level.[7] The estimated coefficient to the interaction term between the RIPAT dummy and the district dummy, $\hat{\alpha}$, will be the QDiD estimate of the impact of RIPAT06. The coefficient to the RIPAT dummy, γ, will give the difference between RIPAT06 and control households in the Karatu district and hence, represent a mixture of selection and early impact of the RIPAT project in Karatu. The naïve estimate of the impact of RIPAT06 is given by $\hat{\gamma}$ when δ, α, and η are set to zero and only data from Arumeru district is applied.

Our application of the QDiD estimator differs from that of Coleman (1999, 2006) in two ways. First of all, Coleman only has data on non-participants in the same village as the intervention which implies that if positive spill-over effects are present, his impact estimates are downward biased.[8] None of the control households in our sample are located in the RIPAT villages and both qualitative and quantitative findings suggest that they are not affected by the project.[9] Conversely, Coleman's estimates are not confounded by a potential short-run impact as the late project participants have only self-selected into the project but the project implementation had not yet begun at the time of his data collection, as opposed to ours.

The relationships between the naïve estimates, the QDiD estimates and the true impact obviously depend on the degree of selection at village and household level, and the timing of the RIPAT impact. If the net selection is negative (positive), the naïve estimates will be lower than (exceed) the QDiD estimates and the true impact, ceteris paribus. With respect to selection, the QDiD estimates will provide unbiased estimates of the true impact as long as the net selection is the same for RIPAT06 and RIPAT08. With respect to the timing of impact, we expect a lag from project start to impact because participants first learn the new agricultural practises at a demonstration plot before they adopt the technologies to their own farm. In addition, we expect the impact to gradually materialize as the household learn how to benefit from the new technologies. The longer the lag between project start and full impact, the less impact we expect to detect from RIPAT08 and the closer the QDiD estimates will be to the true impact.[10] To the extent that RIPAT08 has had some impact at the time of the data collection in January 2011, the QDiD estimates provide a lower bound of the true impact.[11]

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[6] Apart from the variable *household rain,* interaction terms between household characteristics and the district dummy are not included in order to reduce dimensionality. F-tests allow joint exclusion of the interaction terms in the Household Hunger Scale specifications.

[7] As we have 36 villages and 33-74 households per village, clustering on the village level is quite conservative.

[8] This is particularly unfortunate as he finds no average impact of village bank membership (Coleman, 1999).

[9] The data shows that the improved banana cultivation introduced through the RIPAT farmer field schools has spread to 38 households in control villages.

[10] This is provided that the lag is not longer than five years which is the time from RIPAT 2006 start to data collection.

[11] The QDiD approach does not necessarily assume homogeneous impacts of RIPAT06 and RIPAT08. The

3.2 Choice of outcome measures

We evaluate RIPAT based on the development objectives stated in the original project documentation: RIPAT should improve food security and reduce poverty among the participating households. The strategy of RIPAT was to achieve these goals by upgrading the agricultural production of the participating farmers, and therefore adoption of the new technologies should be a necessary condition for RIPAT to affect the households' food security and poverty status. Hence, we also analyze whether RIPAT households have adopted key technologies in the basket of options. Although the pre-specified development objectives of improved food security and reduced poverty are broad, we chose them as our main outcomes and designed the survey instrument accordingly to add more credibility to the analysis and avoid cherry-picking of significant results. Below we explain each of our outcome measures in turn.

3.2.1 Technology adoption measures

To measure the extent to which RIPAT farmers adopted the different elements from the 'basket of technology options' which were demonstrated and implemented at the joint farmer group plot, we analyze whether RIPAT farmers are applying these on their own land to a greater extent than the control farmers. Since the basket of options entails a myriad of technologies and other elements, we have focused the analysis on six of the main components.

We analyze whether households have adopted improved banana cultivation; whether they have a larger degree of crop diversification as intercropping and crop rotation is an important element of conservation agriculture; whether they are more likely to have fruit trees; whether they are more likely to have improved varieties of small livestock; whether they are more likely to practise zero-grazing among their livestock as an element of soil conservation; and finally whether they are more likely to participate in any savings group as this was encouraged by RECODA.

3.2.2 Food security measures

In the food security literature, food security is described as consisting of three different elements, measured at different levels. *Food availability* is typically measured at the national level, while *access to food* is measured at the household level, and finally *food consumption* is measured at the individual level, see Figure 1 in Ballard, Coates, Swindale, and Deitchler (2011). Given the limited geographical coverage of RIPAT, we do not expect any impact on the national level of food availability, and we therefore focus on access to food and food consumption. We employ a household level measure capturing access to food called the 'Household Hunger Scale' which

degree of impact in RIPAT08 will determine to what extent we underestimate the impact in RIPAT06. If RIPAT08 has had an adverse impact, the QDiD method would overestimate an impact. However, qualitative studies suggest that this is not the case.

is newly developed by US Aid to ensure cross-cultural comparability and has been validated in five Sub-Saharan African countries, Ballard et al (2011).

The Household Hunger Scale is based on three questions referring to whether anyone in the household due to lack of resources 1) went to sleep at night hungry; 2) had no food to eat of any kind in the household; and 3) went a whole day and night without eating. The response codes were 0: never; 1: rarely or sometimes; 2: often. The Household Hunger Scale is simply the sum of the responses to the three questions resulting in an index from zero to six where zero corresponds to 'no hunger' and six corresponds to 'severe hunger'. Because of seasonality in the food security status of the household we consider three different time references: The self-assessed best and worst month in terms of food security during the past year, and the past four weeks. Households were interviewed in January 2011 which is neither right after harvest nor in the worst hungry period so we would expect the hunger situation in the past four weeks to be somewhere in between the best and the worst month. Since this area of Tanzania is not subject to severe and prolonged starvation, we expect to find most variation in the measure when the period of reference is the self-assessed worst month in terms of food security within the past year.

We also measure food consumption among children within the households by looking at the prevalence of households, where children had less than three meals per day. Finally, we aim to capture the nutritional quality of the diet by analyzing whether they had meat, eggs or diary products during the previous week.

3.2.3 Poverty measures

Poverty is a more complex outcome to measure. Poverty is itself a relative measure, and depends on local circumstances. There is an ongoing scientific and political discussion on how to define poverty and which standards determine poverty threshold levels in different countries. Tanzania operates with a national poverty line of TZS 492 per adult equivalent per day, representing the monetary cost of fulfilling basic needs, Schreiner (2011). This is much in line with the typical international poverty line for developing countries of USD 1 per day, after correcting for purchasing power differences.

Actual income or expenditure levels are notoriously difficult and time-consuming measures to capture acurately using a reasonably short survey instrument, partly because most rural households in developing countries rely on home production to some extent. We therefore opted for an alternative method for analysing whether the RIPAT project has had an impact on poverty levels. We use the 'Progress out of Poverty Indicator' (PPI) to capture the probability that a household falls below the national poverty line as developed by Schreiner (2011). The PPI is country specific and is based on ten simple questions, which have all proven to be good statistical predictors of whether the household's consumption level falls below the national poverty line. It is based on a large scale Household Budget Survey of 10,466 representative households from all over Tanzania in 2007, (see Annex 1 for the list of questions embedded in the PPI measure).

We have taken the Progress out of Poverty Index as our key poverty indicator because it is a widely used measure for identifying poverty levels and the only one avaible for Tanzania at the time of data collection. However, it is a composite and also somewhat static measure, meaning that it is less likely to capture temporary fluctuations in poverty and therefore less appropriate for identifying short-term changes in poverty levels.[12] We have therefore also considered the best variable predictors of poverty in isolation, namely the quality of the floor in the main dwelling and whether or not the household owns a (mobile) phone.

3.3 Data and Summary Statistics

In the data we have information on household and village level, as well as background variables at the individual farmer level. Individual, household and village level data are important for us to be able to control for background characteristics potentially correlated with the different types of selection into the project. Table 1 lists the means and standard deviations for the key background variables.

The sample includes 1706 observations after we have excluded all newcomers to the villages (40 households), all farmers with more than eight acres of land in 2006 and less than one acre of land (both RIPAT and control farmers) as these do not comply with the original target criteria for RIPAT participation (121 households)[13], and finally we have excluded households with missing observations in any of our included variables (80 households).

We have split the table into the following columns; means (and standard deviations) are listed in column (1) and (2) for households in RIPAT06 and their control villages, respectively, in Arumeru district, and (4) and (5) in Karatu district, while column (3) and (6) provide the p-values from a t-test of the difference in means between RIPAT and control households with cluster robust standard errors clustered at the village level. Finally, column (7) gives the difference between RIPAT06 and control households in Arumeru minus the corresponding difference in Karatu and (8) shows the p-values from the cluster robust t-test of this double difference being equal to zero. Thereby, the two last columns can be used to investigate whether the selection has been the same in the two districts based on observables. This will give us an indication of whether the identifying assumption of similar selection on unobservables is violated.

[12] E.g. we do not expect RIPAT to affect literacy of the main adult female.

[13] We cap the acres at eight rather than five, as it turns out in the data that 17 per cent of the RIPAT farmers did in fact have more than five acres of land while only six per cent had more than eight acres in 2006.

Table 1. Summary statistics of background characteristics

	Arumeru			Karatu			QDiD assumption	
	RIPAT	Control	p-val	RIPAT	Control	p-val	DiD	p-val
Acres 2006	3.29	3.02	0.31	3.03	2.90	0.52	0.14	0.66
	(1.78)	(1.72)		(1.61)	(1.61)		(0.32)	
Head less than 7 yrs educ.	0.30	0.32	0.71	0.28	0.41	0.01	0.11	0.11
	(0.46)	(0.47)		(0.45)	(0.49)		(0.07)	
Head more than 7 yrs educ.	0.07	0.06	0.40	0.04	0.04	0.89	0.01	0.52
	(0.26)	(0.24)		(0.20)	(0.19)		(0.02)	
Age of head	48.19	46.32	0.26	45.72	48.58	0.01	4.73	0.01
	(13.57)	(16.06)		(11.53)	(15.21)		(1.84)	
Head is female	0.19	0.19	0.87	0.07	0.16	0.00	0.09	0.03
	(0.40)	(0.39)		(0.26)	(0.37)		(0.04)	
Number of children of head	1.49	1.35	0.29	2.37	1.86	0.01	-0.36	0.09
	(1.31)	(1.33)		(1.68)	(1.70)		(0.21)	
Good in math	0.41	0.38	0.62	0.36	0.31	0.27	-0.03	0.68
	(0.49)	(0.49)		(0.48)	(0.46)		(0.07)	
Participation in other projects	0.27	0.16	0.02	0.15	0.09	0.02	0.06	0.25
	(0.45)	(0.37)		(0.35)	(0.29)		(0.05)	
Household rain	751.26	703.84	0.05	930.23	905.28	0.31	22.47	0.50
	(53.99)	(41.29)		(50.83)	(61.30)		(32.62)	
Village distance to market	9.59	5.43	0.08	8.42	8.98	0.82	4.72	0.16
	(3.68)	(4.86)		(5.96)	(3.93)		(3.26)	
Village has secondary school	0.60	0.88	0.21	0.63	0.67	0.85	-0.24	0.44
	(0.49)	(0.33)		(0.48)	(0.47)		(0.31)	
Village had devel. project	0.63	0.39	0.36	0.36	0.49	0.57	0.37	0.28
	(0.48)	(0.49)		(0.48)	(0.50)		(0.34)	
Observations	420	359		491	436		1706	

From the four sets of means on the background variables listed in table 1, it can be seen that the households included in the analysis generally have around 3 acres of land, the majority of household heads have completed 7 years of primary school, they are typically middle-aged males, and have between one and two children living at home. As the farmer's cognitive abilities could be correlated with the self-selection into the project, we tested the farmers' math skills with two simple math problems.[14] In addition, households which have participated in other development projects in the past may be more likely to self-selection into RIPAT, which appears to be the case both among RIPAT06 and RIPAT08 households. Finally, we have also included the average historical rainfall level at 1:1 km resolution based on the household's GPS coordinates,[15] since the households mainly rely on rainfed agriculture. In both districts, it seems that households receiving more precipitation self-select into RIPAT. There is also a large district difference with Karatu receiving almost 200 mm more than Arumeru. At the village level we see that RIPAT06 villages are generally more remote, less likely to have a secondary school and more likely to have had a development project than their control villages, which all suggests that RIPAT villages are worse of than controls in Arumeru. On the other hand, the village characteristics are more balanced among RIPAT08 and control villages in Karatu

[14] The farmer is considered "Good in math" if s/he answers correctly to both questions: 29-13=? and 50/10=?

[15] We used interpolated data on yearly precipitation measured in mm from the period 1950-2000 available from http://www.worldclim.org/.

district. Though this suggests that selection in RIPAT06 and RIPAT08 has not been exactly the same, the implication for our results is simply that we underestimate the true impact.

In general, there are indications that overall the selection based on observables go in the same direction in both districts as assumed in the QDiD estimation strategy. RIPAT households have slightly more land, receive more rainfall, they have more children, are a bit more educated, better in math, and they are more likely to participate in other projects in the past than controls. All these variables suggest a positive selection at the household level[16] and in particular the latter supports the idea that RIPAT households are more motivated than control households to experiment or actively change their livelihoods. The p-values in the last column of table 1 show that it cannot be rejected, at a five percent significance level, that the selection has been the same in the two districts on most of our background characteristics, except age and gender, which we control for in all regression specification below.[17]

Because standard errors are clustered at the village level we do not have enough degrees of freedom in the naive regressions to include all these household and village characteristics.[18] However, we present regression results in Annex 2 where all characteristics are included and standard errors are clustered at the subvillage level instead.[19] The inclusion of all household characteristics does not alter the results remarkedly.

In table 2, panel (A) we list the means (and standard deviations) for the key technology adoption measures. A quick glance at column (3) and (6) shows that RIPAT households in both districts are implementing virtually all the analyzed technologies provided through the 'basket of options' to a significantly larger extent than the surveyed households in control villages. The only exceptions are the cultivation of fruit trees and the use of zero grazing among livestock, which do not differ significantly across RIPAT06 and their control villages. Such significant take-up levels on almost all of the technology options in the raw data are remarkable given the very mixed findings on technology adoption in the previous farmer field school literature. In particular bananas has been in high demand with roughly two-thirds of the RIPAT farmers having adopted this technology in both districts.

Finally in panel (B) we list the summary statistics of the outcome variables for food security and poverty. Not surprisingly, the households experience more hunger in the worst month of the last year than in the best month. The raw means of the food security variables are rather similar for RIPAT and control households in both districts when we do not control for selection, household or village characteristics. Only the RIPAT08 households experience significantly less

[16] Except for number of children of head.

[17] The gender difference in Karatu is due to errors in the stratification scheme during field work, where control households in Karatu were stratified according to the share of female headed households in Arumeru district.

[18] For consistency, we control for the log of acres, education, age, age squared and gender as well as village characteristics in both the naïve and QDiD specifications.

[19] Clustering at the subvillage level leads to 52 clusters in the naïve regressions and 130 clusters in the QDiD regressions.

hunger than their controls during the past four weeks. With respect to the quality of the diet within the past week, RIPAT households in both districts are slightly more likely to have meat, eggs, and dairy products than controls, though this difference is only significant for the intake of eggs in Arumeru district.

Table 2. Summary statistics of adoption and outcome measures

	Arumeru			Karatu		
	RIPAT	Control	(p-value)	RIPAT	Control	(p-value)
	Panel A: Adoption variables					
Improved bananas	0.69	0.12	0.00	0.64	0.01	0.00
	(0.46)	(0.33)		(0.48)	(0.08)	
Number of crops in 2010	5.62	4.76	0.02	6.65	4.69	0.00
	(2.30)	(2.22)		(2.71)	(2.12)	
Fruit tree(s)	0.66	0.56	0.46	0.49	0.28	0.02
	(0.48)	(0.50)		(0.50)	(0.45)	
Improved poultry	0.27	0.02	0.00	0.25	0.01	0.00
	(0.44)	(0.14)		(0.44)	(0.10)	
Improved goats	0.40	0.15	0.00	0.19	0.05	0.00
	(0.49)	(0.36)		(0.40)	(0.22)	
Improved pigs	0.00	0.00		0.18	0.00	0.00
	(0.00)	(0.00)		(0.38)	(0.05)	
Zero grazing	0.30	0.29	0.93	0.21	0.09	0.02
	(0.46)	(0.45)		(0.41)	(0.29)	
Savings	0.23	0.03	0.00	0.30	0.11	0.01
	(0.42)	(0.18)		(0.46)	(0.31)	
	Panel B: Outcome variables					
HHS worst month	1.43	1.65	0.43	1.23	1.23	0.98
	(1.47)	(1.46)		(1.25)	(1.26)	
HHS best month	0.07	0.04	0.38	0.03	0.03	0.97
	(0.35)	(0.27)		(0.24)	(0.26)	
HHS past four weeks	0.25	0.32	0.57	0.19	0.32	0.01
	(0.66)	(0.73)		(0.53)	(0.74)	
Less than 3 meals, worst month	0.37	0.38	0.89	0.18	0.18	0.92
	(0.48)	(0.49)		(0.38)	(0.39)	
Less than 3 meals, best month	0.06	0.09	0.39	0.01	0.02	0.42
	(0.24)	(0.29)		(0.11)	(0.13)	
Less than 3 meals, past 4 weeks	0.13	0.16	0.43	0.04	0.05	0.62
	(0.34)	(0.37)		(0.19)	(0.21)	
Meat	0.74	0.69	0.48	0.40	0.39	0.70
	(0.44)	(0.46)		(0.49)	(0.49)	
Eggs	0.56	0.36	0.00	0.45	0.38	0.29
	(0.50)	(0.48)		(0.50)	(0.49)	
Dairy products	0.87	0.83	0.44	0.63	0.60	0.62
	(0.34)	(0.38)		(0.48)	(0.49)	
PPI	44.29	44.68	0.89	32.00	33.49	0.56
	(14.81)	(14.04)		(16.41)	(14.84)	
Good quality floor	0.26	0.31	0.55	0.13	0.11	0.81
	(0.44)	(0.46)		(0.33)	(0.32)	
Mobile phone	0.68	0.67	0.83	0.61	0.56	0.27
	(0.47)	(0.47)		(0.49)	(0.50)	
Casual labour	0.05	0.15	0.02	0.11	0.20	0.02
	(0.22)	(0.36)		(0.31)	(0.40)	
Hired labour	0.62	0.49	0.03	0.45	0.33	0.05
	(0.49)	(0.50)		(0.50)	(0.47)	
Observations	420	359		491	436	

Turning to measures of poverty, there are no significant differences between RIPAT and control households in PPI, but all three measures show that households in Karatu are on average poorer than households in Arumeru.[20] Finally, the raw means for use of labor resources in the households are significantly different between RIPAT and control households with RIPAT households relying less on casual labor and have been more likely than control households to hire labor.

4 Results

4.1 Adoption of technologies

At first, we look at the adoption of key technologies in the basket of options introduced by RIPAT. We regress eight different technology adoption measures on a RIPAT dummy and household and village characteristics. We do this separately for the Arumeru and Karatu samples, thus using the naïve specification described above. Standard errors are clustered at the village level. Table 3 shows the estimated coefficient (γ) to the RIPAT dummy, each row representing a different technology. Estimates for RIPAT06 are presented in column 1 and RIPAT08 estimates are shown in column 2.

RIPAT farmers are 55.8 and 61.0 percentage points more likely to be cultivating improved bananas in Arumeru and Karatu, respectively, than their respective control farmers, both significant at the one per cent level. Row 2 shows that RIPAT households also grow a larger number of different crops than controls in both districts, however the difference is smaller and less significant in Arumeru district. In addition, they are 14.0-23.3 percentage points more likely to have a fruit tree than control households as can be seen in row 3. We do not know whether households that grew many different crops and had fruit trees prior to the RIPAT project were more prone to sign up, but as improved banana cultivation was almost non-existing in the area before RIPAT we can with a reasonable degree of confidence assign the difference in banana cultivation between RIPAT and control households to the participation in RIPAT.

Row 4 to 6 show that RIPAT households are significantly more likely to have improved breeds of lifestock; both poultry, goats and pigs (the latter was only introduced in RIPAT08). They are also significantly more likely to use zero grazing. Finally, RIPAT households are significantly more prone to participate in saving groups which was also encouraged by the implemeting NGO, RECODA.

The estimates show that RIPAT has had a similar effect on adoption of technologies in both districts and therefore we cannot apply the Quasi-Difference-in-Difference (QDiD) approach to account for village and households selection when considering adoption of technologies. Nevertheless, the large and significant point estimates suggest that RIPAT has indeed affected the crop and livestock portfolio of participating farmers. The fact that we find adoption among

[20] District means for PPI, good quality floor and mobile phone are all significantly different at the one percent level.

RIPAT08 farmers and that adoption rates presented in table 2, panel (A) do not seem to differ across the two districts alludes that the adoption may already have translated into some impact on food security and poverty levels among RIPAT08 farmers in Karatu. This suggests that the QDiD estimates in the following subsections will underestimate the true impact of RIPAT.

Table 3. Impact of RIPAT on adoption measures, naïve estimates

	(1) Arumeru	(2) Karatu
Improved banana cultivation	0.614***	0.613***
	(0.09)	(0.05)
Number of crops grown, 2010	0.964**	1.640***
	(0.38)	(0.45)
Grows any fruit trees	0.235**	0.183**
	(0.09)	(0.07)
Has any improved poultry	0.277***	0.233***
	(0.06)	(0.03)
Has any improved goats	0.245**	0.137***
	(0.09)	(0.02)
Has any improved pigs	-	0.176***
		(0.03)
Uses zero-grazing	0.190**	0.105***
	(0.07)	(0.04)
Member of a savings group	0.204***	0.159***
	(0.03)	(0.05)
Observations	799	927

Notes: Each row represents a dependent variable. Both columns provide OLS regression estimates for the RIPAT dummy in a naïve specification, column (1) using Arumeru district data, column (2) using Karatu district data. Village characteristics and household characteristics as described in text are controlled for in all specifications. Standard errors in parenthesis are clustered at the village level. Significance levels are noted by * 0.1, ** 0.5 and *** 0.01. Because of missing values in the dependent variables, the number of observations in Arumeru is 773 for improved poultry and pigs; 774 for goats; and 772 for zero-grazing. In Karatu it is 921 for improved poultry, goats and pigs; and 913 for zero-grazing.

4.2 Food security

To assess the food security impact of RIPAT, we consider the Household Hunger Scale (HHS), whether the children in the household have fewer than three meals per day, and whether the households have had meat, eggs or dairy products during the past week.

Each row in table 4 presents regression coefficients of equation 1 for a different outcome variable. Column 1 shows the naïve regression coefficient (γ) for the RIPAT dummy in the Arumeru district when δ, α and η are set to zero. Column 2-4 give the regression coefficients from the QDiD regression: The RIPAT dummy (γ), the district dummy (δ) and their interaction term (α), respectively. In this regression, the coefficient to the RIPAT dummy (γ) gives the difference between RIPAT08 and control households in Karatu, ceteris paribus, and hence can be interpreted as a mixture of the selection and potential early impact among the RIPAT08 households. The coefficient to the district dummy (δ) estimates the level difference between the two districts among control households while the coefficient to the interaction term (α) estimates the difference between RIPAT06 and RIPAT08 households after district level differences are accounted for, ceteris paribus, and hence our QDiD estimate of the impact. All regressions control for village and households characteristics and standard errors are clustered at the village level.

The first three rows of panel A represents the results for the HHS for the different reference periods. The RIPAT06 households (column 1) experience significantly less hunger than their control households in the worst month, but there is no difference between RIPAT06 and control households in the best month or in the past four weeks. On the other hand, there is no significant difference between RIPAT08 and their control households (column 2) in the worst month of the last year, but the RIPAT08 households experience less hunger in the past four weeks compared to the controls. A potential explanation for this result could be found in the timing of the impact. The vast majority of the households in Karatu mention either February, March, or April as the 'worst month in the last year' (91 per cent) and as the 'past four weeks' refers to January the 'past four weeks' is almost measured a year later than the 'the worst month' leaving more time for the impact of RIPAT08 to materialize. It should be noted that the coefficient is less than a fifth of the coefficient found for RIPAT06 in the worst month.[21] Column 4 shows that a significant negative impact on the HHS in the worst month persists when correcting for selection using the QDiD approach. From this result we conclude that participation in RIPAT reduces hunger in the lean period.

The point estimates from the naïve and QDiD specifications are surprisingly similar. There are three reasons why this can happen. First of all, it can be because there is in fact a low degree of selection and the naïve estimator is thus also a good estimate of the true impact. Second, a low degree of *net* selection can also be because the negative village selection and the positive household selection cancel out. Finally, since there could be an emerging positive impact in Karatu, this can also offset a negative selection. The larger the early impact of RIPAT08 is, the closer becomes the naïve and the QDiD estimates if the net selection is negative. Most likely we are faced with a situation of both low net selection and emerging impact among the RIPAT08 households.

The magnitude of the impact on the HHS is not easily interpretable. Instead we consider the binary outcome of no hunger in the worst month, i.e. $HHS = 0$ which is the case for 29.6 per cent of the control households in Arumeru. We find a QDiD estimate of 0.232 (0.0667), significant at the one percent level and the naïve estimate for RIPAT06 is very similar.[22] This implies that participation in RIPAT reduces the probability of experiencing hunger by 23.2 percentage points, which suggests that RIPAT has contributed to a large reduction in hunger measured by the HHS.

We then turn to the number of meals among children to see if RIPAT has reduced the probability of receiving less than three meals per day. Row 4 to 6 in table 4, panel A, present

[21] This could either be because of negative net selection, because the impact of RIPAT08 has not yet fully materialized or because RIPAT06 and RIPAT08 have differential impacts - or a mixture of the three.

[22] The naïve point estimate for RIPAT08 is 0.203 (0.0572). Regression results available upon request.

the point estimates of the three time references.[23] Again, the naïve and the QDiD estimates almost coincide (column 1 and 4). Though the largest coefficient is estimated for the worst month of the year, this estimate is also very noisily estimated and not significantly different from zero. On the other hand we find that participation in RIPAT significantly reduces the likelihood for the children to have less than three meals per day both in the best month of the year and in the past four weeks. This suggests that participating in RIPAT has not only affected the food security status of the involved households in the lean period as measured by the HHS, but it has also improved the children's intake of food at other times of the year.[24]

Estimates for the household consumption of meat, eggs and dairy products within the past week can be found in the last three rows in panel A of table 4. Participation in RIPAT farmer field schools have significantly increased the probability of having meat and eggs, while dairy consumption appears unaffected. Once again, the naïve and QDiD estimates give similar results.

Since adoption of the RIPAT technologies in Karatu may already have affected the food security, we regard these results to be a lower bound estimate of the true impact. We conclude that RIPAT has had a positive impact on a central development objective: food security. The RIPAT households experience less hunger in the lean period, their children receive more meals and household members are more likely to consume meat and eggs in their weekly diets.

The next question is then whether RIPAT has also succeeded in improving the other development objective of poverty alleviation. We use the following poverty *indicators*; the Progress out of Poverty Index (PPI) as an overall indicator of poverty and two additional time variant indicators which have proven highly correlated with poverty status in Tanzania, namely whether the household has a good quality floor in the main dwelling, and whether the household owns a mobile phone.

Turning to panel B of table 4, the first row shows that we do not find any significant impact of RIPAT on poverty measured by the PPI. Estimates for the quality of the floor and ownership of a mobile phone are also insignificant. We have also checked for various degrees of heterogeneity in these results, but the conclusion remains the same, RIPAT has not had any significant impact on any of these poverty indicators and thus we expect the overall level of wealth of the participating households to have remained virtually unchanged.

[23] We loose 111 observations in the naïve specification and 191 observations in the QDiD because these households do not have any cohabitating children.

[24] We do not find any significant impact on whether the adults have less than three meals per day, which suggests that the increased access to food in the household mainly benefits the children. Results available upon request.

Table 4. Impact of RIPAT on development outcomes

	Naïve	QDiD		
	(1) RIPAT	(2) RIPAT	(3) Arumeru	(3) RIPAT*Arumeru
PANEL A: Food security outcomes				
HHS, worst month	-0.714***	0.096	1.054***	-0.809***
	(0.19)	(0.13)	(0.3)	(0.23)
HHS, best month	-0.004	0.016	0.076	-0.023
	(0.03)	(0.01)	(0.05)	(0.03)
HHS, past 4 weeks	-0.146	-0.105**	0.109	-0.046
	(0.13)	(0.05)	(0.22)	(0.13)
Less than 3 meals, worst month	-0.158*	0.016	0.291**	-0.170*
	(0.09)	(0.05)	(0.12)	(0.10)
Less than 3 meals, best month	-0.069*	-0.002	0.027	-0.065*
	(0.04)	(0.01)	(0.03)	(0.04)
Less than 3 meals, past 4 weeks	-0.106**	-0.004	0.129***	-0.101**
	(0.04)	(0.02)	(0.04)	(0.04)
Had meat past week	0.132*	-0.015	0.085	0.148*
	(0.06)	(0.04)	(0.10)	(0.08)
Had eggs past week	0.223***	0.057	0.094	0.163**
	(0.04)	(0.05)	(0.08)	(0.07)
Had dairy products past week	0.068	0.014	0.163	0.050
	(0.07)	(0.06)	(0.14)	(0.09)
PANEL B: Poverty outcomes				
PPI	3.472	-0.834	12.174***	4.047
	(2.09)	(2.31)	(4.05)	(3.10)
Has good quality floor	-0.002	0.001	0.261**	-0.006
	(0.08)	(0.04)	(0.11)	(0.08)
Has (mobile) phone	0.055	-0.013	-0.119*	0.064
	(0.03)	(0.04)	(0.06)	(0.05)
PANEL C: Labor outcomes				
Casual labor as important income	-0.107***	-0.107***	-0.161**	-0.000
	(0.03)	(0.03)	(0.06)	(0.05)
Hired labor on own farm	0.170*	0.112**	0.243**	0.058
	(0.08)	(0.05)	(0.11)	(0.10)

Notes: Each row represents a dependent variable. Column (1) provides OLS regression estimates for the RIPAT dummy in a naïve specification using data from Arumeru district only. Column (2)-(4) gives OLS regression estimates for the RIPAT dummy, the Arumeru district dummy and their interaction term, respectively. Village characteristics and household characteristics as described in text are controlled for in all specifications. Standard errors in parenthesis are clustered at the village level. Significance levels are noted by * 0.1, ** 0.5 and *** 0.01. The number of observations is 799 in the naïve specifications and 1706 in the QDiD specifications, however, for the outcomes "Less than 3 meals" the number of observations is 688 and 1515, respectively.

4.3 Possible mechanisms

Obviously, the fact that we find clear and significant improvements in food security among RIPAT households, but no improvement in their poverty status, has led us to wonder why this is so.

One explanation could be the following. RIPAT households were from the outset faced with scarce resources, when they experienced an improvement in their level of resources, they simply prioritized a more secure and improved food consumption over higher non-food consumption. We cannot empirically test this any further, but it would result in the above finding.

A second reason could be that they have reallocated their use of labor resources within the household, e.g. shifted from cash income activities towards own agricultural production thereby producing more food, but gaining less cash income, which could result in better food security (from own production) at the expense of lost income and hence a positive impact on poverty indicators are unlikely.

Finally, a third reason could be that the agricultural technologies introduced have not increased the total annual agricultural production, but has smoothed it over the agricultural cycle thereby increasing food security in what typically would have been the lean period. We analyze the two latter explanations empirically below.

4.3.1 Casual labor

During qualitative interviews it was suggested that poor households may respond to an increase in income from their agricultural produce by ceasing to supply casual labor, because casual labor is considered a 'lender of last resort'; an income source you turn to when all other options are exhausted and hence, associated with a lot of stigma. We have therefore analyzed whether the households rely on casual labor as the most or second most important income sources in the household. A reduction in the supply of casual labor can potentially result in a rather substantial decrease in income since casual labor is a remunerative income source if jobs exists, e.g. weeding one acre of land pays 2,000 Tanzanian shilling which is four times the daily national poverty line.

In panel C of table 4, the first row provides the naïve and the QDiD estimates for the impact of RIPAT on casual labor being an important income source for the household. We find that both RIPAT06 and RIPAT08 households are significantly less likely to rely on income from casual labor. This suggests that RIPAT households may have chosen to cut back on casual labor because they have experienced an increase in their agricultural income, which would dampen or maybe even offset an increase in income, but still result in a utility increase because the household avoids the stigma. We would like to stress that since we also find a significant difference for RIPAT08 households, we cannot distinguish selection from impact. It may be so that households relying on casual labor do not self-select into RIPAT, although anecdotal evidence suggests that this is not the case.

To mirror this analysis, we also consider whether the household *hired* labor on their own farm during 2010 as a measure for investment in agriculture. The second row in panel C shows a similar result. Both RIPAT06 and RIPAT08 households are significantly more likely to hire labor on their farm than control households. Again, we cannot distinguish impact from selection. Nevertheless, taken together the two results provide a suggestive explanation for why we find a profound impact on food security but no impact of RIPAT on the poverty measures employed. The RIPAT households seem to have re-optimized the allocation of labor within their households. RIPAT has not only improved food security, but has most likely also enabled the participating households to cut back on their supply of casual labor *and* increase their demand for hired labor, thus investing in the household's own agricultural production. This latter result is mainly driven by households which have adopted the improved banana variety, which is not surprising since banana cultivation is very labor intensive in the early stages.

Table 5. Smoothing mechanisms

	Adoption		HHS, worst month				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	RIPAT06	RIPAT08	RIPAT	Control	Smooth	Nonsmooth	Full
RIPAT	0.601***	0.648***			0.167	0.344***	0.365**
	(0.07)	(0.04)			(0.20)	(0.12)	(0.15)
Smooth			-0.357*	-0.369***			
			(0.18)	(0.12)			
District			0.654	0.893***	1.199**	0.745**	0.983***
			(0.56)	(0.29)	(0.55)	(0.27)	(0.31)
RIPAT*District					-0.397	-0.826**	-0.758***
					(0.32)	(0.33)	(0.26)
RIPAT*Smooth							-0.371*
							(0.19)
RIPAT*District*Smooth							-0.013
							(0.34)
N	779	927	911	795	828	878	1706

Notes: OLS estimates. The dependent variable in column (1)-(2) is an adoption dummy equal to one if the household has adopted any of the smoothing technologies, in column(3)-(7) it is HHS in worst month. Village characteristics and household characteristics as described in text are controlled for in all specifications. Standard errors in parenthesis are clustered at the village level. Significance levels are noted by * 0.1, ** 0.5 and *** 0.01.

4.3.2 Production smoothing

The agricultural technologies introduced in RIPAT farmer field schools were chosen to enhance production smoothing over the agricultural cycle. Households experience a large degree of seasonality in food security and they do not seem able to smooth consumption: In the lean period, 65 per cent of the households in control villages experience some kind of hunger while a mere two per cent experience any hunger just after harvest. Limited access to proper storage facilities and financial markets inhibits the households to smooth consumption. Several elements in the basket of options introduced by RIPAT are production smoothing technologies that provide the households with food even in the lean period. Banana plants fruit outside of the main harvest season as long as they receive some water, improved breeds of poultry lay more eggs and improved breeds of goats produce more milk than their traditional breed peers all year round. Could it be that the impact of RIPAT on food security is mainly driven by the adoption of these three production smoothing technologies, which ease the smoothing of food consumption over the year and thus increase food security in the typical lean period?

Column 1 and 2 of table 5 show that participation in RIPAT06 and RIPAT08 increases the probability of adopting at least one of the three production smoothing technologies by 57-65 percentage points, controlling for household and village characteristics. In accordance with section 4.1, participation in RIPAT is significantly correlated with adopting either banana cultivation, and improved breeds of poultry and goats. In turn, column 3 and 4 of table 5 represents regressions of the household hunger scale in the worst month on a smoothing technology dummy that equals one if the household has adopted any of the production smoothing technologies and zero otherwise. The sample is split into RIPAT households (column 3) and control households (column 4). In both groups, households using production smoothing technologies also experience significantly less hunger than households that do not use any of the three technologies. However, we do not claim that these estimates represent a causal relationship.

In column 5 we limit the sample to households that have adopted any of the production smoothing technologies and run the QDiD regression on this subsample. The estimates suggest that RIPAT households adopting the production smoothing technologies are taken to the same level of food security as the selected sample of control households that has adopted the smoothing technologies. Participation in RIPAT makes the households *as* food secure as control households using production smoothing technologies, but not more than that. However, 60-65 per cent of RIPAT households employ these, whereas this is only the case for 25 and 8 per cent of control households in Arumeru and Karatu, respectively. Column 6 presents QDiD regression results for the subsample of household not adopting any of the smoothing technologies. Among these households, we see that RIPAT households in Arumeru experience less hunger than controls at the ten percent significance level after taking the selection into account. This estimate suggests that the impact of RIPAT on food security is not purely driven by the production smoothing technologies, but that other elements of the basket of options also improve the food security status of the households in the lean period.

The last column shows a QDiD regression where the RIPAT dummy and the interaction term between RIPAT and district have been interacted with the production smoothing dummy. First, we observe that the interaction term between the RIPAT and the smoothing dummy is negative and significant implying that smoothing RIPAT households experience less hunger than RIPAT households that have not adopted smoothing technologies. Second, we note that the interaction term between the RIPAT, district and smoothing dummy is insignificant. Hence, we do not find an excess impact of RIPAT06 once smoothing technologies are adopted, which is in accordance with the conclusion from column 5. This suggests that RIPAT08 households that have adopted smoothing technologies have already experienced an increase in food security.[25] Third, the interaction term between the RIPAT and the district dummy is negative and significant. That is, RIPAT households not adopting smoothing technologies do also experience a drop in hunger in accordance with the conclusion from column 6.

Taken together the results suggest that the RIPAT households experience an impact on food security earlier if they adopt the smoothing technologies while RIPAT households that never adopt any of these technologies still are more food secure than control households after

[25] However, it cannot be distinguished from selection.

accounting for selection. It should however be kept in mind that the decision to adopt the smoothing technologies is endogenous and an alternative explanation of the results is that households that are more food secure are more likely to adopt the smoothing technologies. We can, however, still conclude that although smoothing technologies are positively correlated with food security, the overall impact of RIPAT on food security is not purely driven by these. In addition, we ascertain that the basket of technology options seems to contain other elements that are relevant for food security of the households.

5 Conclusion

This is, to the best of our knowledge, the first paper which rigorously has analyzed the impact of a locally adapted farmer field school on longer term development outcomes, food security and poverty alleviation, rather than on shorter term intermediate or project related agricultural outputs. We find strong and sustained positive effects on food security among the participating households more than one year after end of project, both in terms of access to food, food consumption and quality of diet. Participating households experience less hunger in the lean period, are more likely to have animal protein in their weekly diet, and their children are more likely to have at least three meals per day. There are indications that the positive impacts on food security measures, but lack of impact on poverty indicators could be caused by RIPAT households having prioritized food over non-food consumption, reallocated their labor resources towards improving own agricultural production, and reduced seasonal variation in food production thereby increasing food security in the lean period even more.

Taken together - and compared with earlier farmer field school evaluations - these results suggests the importance of two things. First of all, time. Although some positive impacts are found especially on technology adoption among the more recent RIPAT08 farmers, the impacts on food security are mainly found among the RIPAT06 farmers where the technology adoption has had sufficient time to raise food security levels. Timing is thus an important factor both when considering the length of the project, (a typical RIPAT farmer field school runs for at least three years as opposed to one agricultural cycle of standard farmer field schools), and when considering the timing of the impact evaluation allowing impacts from a change in agricultural systems to materialize.

Second, the importance of choice. In our analysis of technology adoption it was clear that farmers choose differently, each farmer has his or her own needs and resources to consider when choosing to adopt a new agricultural technology. By presenting the farmers with a relevant and efficient *basket* of technology options, the implementing agency left each farmer with a genuine choice, which has clearly been exercised.

This suggests that with slight modifications in terms of length of project and a relevant technology choice set, the standard farmer field schools may prove substantially more effective and with much stronger development outcomes than what has previously been the case.

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Annex 1. Progress out of Poverty Indicator (PPI)

The PPI is constructed by Schreiner (2012) based on ten simple questions listed in what he refers to as a scorecard, see the example from Tanzania below.

Entity	Name	ID	Date (DD/MM/YY)	
Member:			Joined:	
Field agent:			Today:	
Service point:			Household size:	

Indicator	Value	Points	Score
1. How many household members are 17-years-old or younger?	A. Four or more	0	
	B. Three	8	
	C. Two	15	
	D. One	23	
	E. None	30	
2. Do all children ages 6 to 17 attend school?	A. No	0	
	B. Yes, or no children ages 6 to 17	1	
3. Can the female head/spouse read and write?	A. No	0	
	B. Yes, but not in Kiswahili nor English	0	
	C. No female head/spouse	0	
	D. Yes, only in Kiswahili	5	
	E. Yes, in English (regardless of others)	12	
4. What is the main building material of the floor of the main dwelling?	A. Earth	0	
	B. Concrete, cement, tiles, timber, or other	11	
5. What is the main building material of the roof of the main dwelling?	A. Mud and grass	0	
	B. Grass, leaves, bamboo	8	
	C. Concrete, cement, metal sheets (GCI), asbestos sheets, tiles, or other	11	
6. How many bicycles, mopeds, motorcycles, tractors, or motor vehicles does your household own?	A. None	0	
	B. One	1	
	C. Two or more	11	
7. Does your household own any radios or radio cassettes?	A. No	0	
	B. Yes	5	
8. Does your household own any lanterns?	A. No	0	
	B. Yes	6	
9. Does your household own any irons (charcoal or electric)?	A. No	0	
	B. Yes	6	
10. How many tables does your household own?	A. None	0	
	B. One	2	
	C. Two	4	
	D. Three or more	7	

Microfinance Risk Management, L.L.C., `http://www.microfinance.com` **Total score:**

Annex 2. Robustness results

Table A1. Impact of RIPAT on adoption measures, naïve estimates

	(1) Arumeru	(2) Karatu
Improved banana cultivation	0.557***	0.607***
	(0.08)	(0.05)
Number of crops grown, 2010	0.628**	1.632***
	(0.28)	(0.35)
Grows any fruit trees	0.230**	0.140***
	(0.09)	(0.05)
Has any improved poultry	0.204***	0.233***
	(0.04)	(0.02)
Has any improved goats	0.250***	0.144***
	(0.05)	(0.02)
Has any improved pigs	-	0.170***
		(0.03)
Uses zero-grazing	0.183***	0.104***
	(0.07)	(0.02)
Member of a savings group	0.212***	0.158***
	(0.05)	(0.04)
Observations	799	927

Notes: Each row represents a dependent variable. Both columns provide OLS regression estimates for the RIPAT dummy in a naïve specification, column (1) using Arumeru district data, column (2) using Karatu district data. Village characteristics and household characteristics as described in text are controlled for in all specifications. Standard errors in parenthesis are clustered at the village level. Significance levels are noted by * 0.1, ** 0.5 and *** 0.01. Because of missing values in the dependent variables, the number of observations in Arumeru is 773 for improved poultry and pigs; 774 for goats; and 772 for zero-grazing. In Karatu it is 921 for improved poultry, goats and pigs; and 913 for zero-grazing.

Table A2. Impact of RIPAT on development outcomes

	Naïve	QDiD		
	(1) RIPAT	(2) RIPAT	(3) Arumeru	(3) RIPAT*Arumeru
PANEL A: Food security outcomes				
HHS, worst month	-0.590***	0.051	4.530**	-0.649***
	(0.20)	(0.13)	(1.75)	(0.23)
HHS, best month	0.012	0.016	0.286	-0.008
	(0.05)	(0.02)	(0.35)	(0.05)
HHS, past 4 weeks	-0.062	-0.104*	1.032	0.035
	(0.15)	(0.06)	(1.05)	(0.15)
Less than 3 meals, worst month	-0.137**	0.002	1.303*	-0.143*
	(0.07)	(0.04)	(0.69)	(0.08)
Less than 3 meals, best month	-0.088**	-0.002	-0.169	-0.085**
	(0.04)	(0.01)	(0.17)	(0.03)
Less than 3 meals, past 4 weeks	-0.124***	-0.003	-0.081	-0.123***
	(0.04)	(0.02)	(0.28)	(0.04)
Had meat past week	0.173**	-0.001	-0.204	0.174**
	(0.07)	(0.04)	(0.55)	(0.08)
Had eggs past week	0.212***	0.066	-0.568	0.146**
	(0.06)	(0.04)	(0.58)	(0.07)
Had dairy products past week	0.066	0.024	-0.709	0.033
	(0.07)	(0.05)	(0.49)	(0.08)
PANEL B: Poverty outcomes				
PPI	0.197	-0.490	-53.303***	0.562
	(2.47)	(1.60)	(18.09)	(2.92)
Has good quality floor	-0.098	0.005	-1.211***	-0.105
	(0.06)	(0.03)	(0.36)	(0.07)
Has (mobile) phone	0.027	-0.018	-0.476	0.039
	(0.04)	(0.03)	(0.43)	(0.05)
PANEL C: Labor outcomes				
Casual labor as important income	-0.103***	-0.103***	-0.254	-0.002
	(0.03)	(0.03)	(0.42)	(0.04)
Hired labor on own farm	0.183***	0.115***	0.176	0.071
	(0.06)	(0.04)	(0.64)	(0.07)

Notes: Each row represents a dependent variable. Column (1) provides OLS regression estimates for the RIPAT dummy in a naïve specification using data from Arumeru district only. Column (2)-(4) gives OLS regression estimates for the RIPAT dummy, the Arumeru district dummy and their interaction term, respectively. Village characteristics and household characteristics as described in text are controlled for in all specifications. Standard errors in parenthesis are clustered at the village level. Significance levels are noted by * 0.1, ** 0.5 and *** 0.01. The number of observations is 799 in the naïve specifications and 1706 in the QDiD specifications, however, for the outcomes "Less than 3 meals" the number of observations is 688 and 1515, respectively.

Table A3. Smoothing mechanisms

Outcome variable	Adoption		HHS, worst month				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample	RIPAT06	RIPAT08	RIPAT	Control	Smooth	Nonsmooth	Full
RIPAT	0.567***	0.650***			0.051	0.320***	0.338**
	(0.09)	(0.04)			(0.27)	(0.10)	(0.13)
Smooth			-0.348*	-0.313**			
			(0.18)	(0.12)			
District			6.403**	9.356*	3.244	5.194*	4.235**
			(2.45)	(5.09)	(3.35)	(2.90)	(1.96)
RIPAT*District					-0.108	-0.851**	-0.711***
					(0.40)	(0.35)	(0.25)
RIPAT*Smooth							-0.397**
							(0.18)
RIPAT*District*Smooth							0.100
							(0.37)
N	779	927	911	795	828	878	1706

Notes: OLS estimates. The dependent variable in column (1)-(2) is an adoption dummy equal to one if the household has adopted any of the smoothing technologies, in column(3)-(7) it is HHS in worst month. Village characteristics and household characteristics as described in text are controlled for in all specifications. Standard errors in parenthesis are clustered at the village level. Significance levels are noted by * 0.1, ** 0.5 and *** 0.01.