Adaptation and Adoption of Improved Seeds through Extension: Evidence from Farmer-Led Groundnut Multiplication in Uganda

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(Abstract)

In sub-Saharan Africa, reliance on subsistence-level farming is a significant source of risk since farmers face protracted periods of drought and the frequent incidence and expanding reach of diseases and pests. It is likely that such occurrences will be exacerbated by global climate change, given recent forecasts and scientific findings. One strategy to mitigate these effects is through the adoption of new technologies. Following the established literature on technology adoption and productivity, this work is a reassessment of a 2004 AT Uganda farmer-led seed multiplication and dissemination project for groundnut growers. The major objective of this research is to determine the lasting impact of the project with respect to the adoption of rosette resistant varieties of groundnuts (RRVs). Panel data for the 2004 and 2013 growing seasons are used and include a set of participating farm households (HHs) and non-participating (control) HHs. The control sample is composed of both a neighboring and a non-neighboring farm group, which makes it possible to account for spillover effects and selection bias. In order to further control for possible biases, our identification strategy employs propensity score matching and instrumental variables methods. In this way, we examine the sustainability and lasting impact of the original intervention a decade after the fact.

<u>Background</u>

Literature on global climate change indicates developing nations are expected to bear the brunt of the associated damages and costs over the next century. Given the lack of infrastructure, both physical and institutional, these nations face much greater risk than the world's more developed regions (Field and Van Aalst 2014). In particular, the agricultural sector in developing countries needs many improvements in order to adapt to, and thus mitigate, the impending effects of global and regional climate change. The preponderance of subsistence-level farming and the use of low-level technologies is a significant source of risk as farmers face protracted periods of drought and the frequent incidence and expanding reach of diseases and pests, factors that are particularly significant to the sub-Saharan region of Africa (Smith, Alderman, and Aduayom 2006; Smith, El Obeid, and Jensen 2000). It is for these reasons that a critical field of study for agricultural economists is the nexus of international development, productivity, climate change, and food security. Therefore, the research presented in this paper addresses these issues by highlighting the key results from a project that focused on improving agricultural productivity in Uganda.

The AT Uganda organization's farmer-led dissemination program in eastern Uganda was implemented in order to increase the supply and adoption of high yielding rosette resistant groundnut varieties (RRVs) in the program region. The justification of these efforts included the significant nutritional benefits from groundnuts and their importance in the regional cuisine of eastern Uganda, where they are commonly used to make sauces. As a member of the legume family, groundnuts fix nitrogen and are used in crop rotation as an inexpensive means for improving soil quality. Yet, major crop losses from the rosette virus have historically discouraged farmers in the region from producing groundnuts, which is clearly seen in the nearly 75% reduction in output during the decade following peak domestic groundnut production levels in the early 1970's. The LIFE project, an earlier survey of farmers in eastern Uganda conducted in the same region as this study, indicated that groundnuts were not being grown by poor farmers due to the high risk associated with production, even though groundnuts are highly profitable compared to other regional crops (as described in the 2004 AT Uganda, Report to stakeholders). The risk stems from the high seed rate associated with groundnuts and the chance of crop failure from disease. Although diseases can be controlled using chemicals, availability is limited,

especially to poor farmers, and diseases are observed to become more resistant to these methods over time, requiring greater inputs at an even higher cost. The use of disease resistant seed varieties, on the other hand, offers a highly cost-effective and sustainable alternative to combating disease related crop failure, and is thereby likely to benefit all groundnut farmers.

As of 2002, Uganda's National Agricultural Research Organization's (NARO) Serere Agricultural and Animal Research Institute (SAARI) has released 5 RRVs (Igola and Serenut 1-4), which offer a less risky alternative to regional groundnut producers. Breeders identified these RRVs through research and selection of locally adapted varieties observed to be disease and drought resistant (Shiferaw et al. 2010). Since the major declines in domestic groundnut production during the 1970's, overall production has increased steadily (Okello, Biruma, and Deom 2013). Most recently, between 2005 and 2012, domestic groundnut production increased by 31% to 295,000 metric tons with 421,000 hectares harvested, surpassing the previous production highs of the early 1970's (Tanellari et al. 2014). These large increases in domestic production are largely attributed to the uptake of improved production practices and RRVs. The 2011 study by Kassie et al. suggests that groundnut producers in Uganda benefit significantly from improved varieties with a 35% average yield increase and a 41% average cost reduction. Improved seed varieties are thus a particularly cost-effective approach to improving yields and returns to farmers in the region of interest.

The associated productivity gains from such technologies lead to more general welfare effects and poverty reduction among those who adopt them. This process is in line with a significant body of literature, notably research in India by Foster and Rosenzweig (1995) and their later theoretically focused paper (2010), which provides much of the basis for the importance of technology adoption in development. More recent studies in Africa by Conley and Udry (2010 and 2001) provide evidence of the importance of networks of farmers in the dissemination of new and improved technologies. Even more recently, work in Uganda, by Shiferaw et al. (2010) and Kassie, Shiferaw, and Muricho (2011), focuses directly on groundnut producers. However, the sustainability of development interventions is often considered to be an important objective, but is rarely documented because the data required are simply not available. As far as we can

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tell, no such studies have been done with respect to the adoption of improved seed varieties in sub-Saharan Africa, and, more importantly, we are confident that this is certainly the case for groundnut production.

Objective

Following the established literature on technology adoption and productivity, this paper reassesses the 2001 AT Uganda farmer-led seed multiplication and dissemination project for groundnut growers. The major objective of this research is to determine the lasting impacts of the project with respect to the adoption of RRVs. Using panel data over a considerable time gap between the end of project (2004) and the 2014 follow-up survey with minor attrition, we assess changes in the proportion of HHs growing RRVs. Cross sectional data from the follow up survey are used to examine the intensity of adoption in the study region, i.e. the proportion of production (area) in RRVs for HHs that grow groundnuts. By exploiting the structure of the sampling we are also able to evaluate spillover of program benefits to neighboring HHs during the years following the project. This result is of particular interest as it provides evidence of a potentially cost-effective means of information and technology dissemination, which occurs during the project and may continue well after its conclusion. Unfortunately, evidence for changes in yield, cost, and farm-level productivity associated with the adoption of RRVs is constrained by the limited sample size, which is unlikely to provide statistical significance for the difference in means between groups unless these differences are very large.

Data

The AT Uganda farmer-led seed multiplication and dissemination program was not initially designed with research in mind. In other words, our study faces challenges to identification because of the nature of the project design. Furthermore, the survey instrument used in 2004 to evaluate the program impacts did not include certain economic variables and measures of relative welfare. Such variables were added to the 2014 follow-up survey. Both of the surveys were carried out to evaluate the achievement of the project outputs and purpose. Also, because only some survey questions were repeated in both rounds, the panel is limited in terms of

analysis. Based on a multi-stage sample from the entire project, the data are structured as follows for project participants: *Beneficiaries*, and their non-participant counterparts, or *Control*.

Beneficiaries. The sampling of sub-counties, parishes, farmer groups, and respondents was randomized. Half of the sub-counties in a given district were selected to receive the program benefits. One parish was sampled in each sub-county and three groups in each parish. The final sample of program beneficiaries consisted of 8 sub-counties, 8 parishes, and 24 groups (10 members per group), for a total of 240 group members.

Control. A two-part control group was also sampled to provide a counterfactual to program results. The first part of the control group was made up of five HHs neighboring beneficiaries. These neighbor controls were selected at random for each of the beneficiary farmer groups so that 15 were sampled in each sub-county, with a total of 120 non-beneficiary neighbors surveyed. The second part of the control is made up of HHs from non-neighboring parishes, 15 households were selected from each village, randomization was used in each stage of sampling; a total of 120 non-neighboring non-beneficiary 'parish' respondents were thus surveyed as the second part of the control group. Like the beneficiary group, the two-part control groups is composed of 240 HHs in total.

Survey Implementation. The initial program evaluation surveys were conducted in September 2004 for each of the 240 treated and control HHs (480 total). Field work was done by the AT Uganda organization and consisted of a questionnaire that recorded HH demographic and agricultural production data, defined as:

 (i) Household: demographic and socioeconomic characteristics (age, sex, and education of HHH, total HH members – age, sex, HH expenditures, etc.). The 2014 survey included an additional set of questions to evaluate HH welfare between 2004 and 2014.

 (ii) Agricultural Production (additional variables included in 2014 follow up survey listed separately): total acres planted, crop and groundnut varieties grown, farmer association membership, seed multiplication participation, farming experience (years), and marketing.

2014: acreage and quantity of seed planted by groundnut variety, recall questions for 2004 groundnut area, and production inputs – labor, fertilizer, supplies.

The 2014 follow-up surveys were conducted from January to March. The 2014 surveys were then enumerated and compiled with the 2004 data into a final dataset, which was completed in October 2014.

Theoretical Framework and Methodology

An effective means of mitigating the risk associated with HH crop production is through the use of technology, which is often referred to as technological progress (Bravo-Ureta et al. 2007). This may include the use of additional inputs, such as machinery, chemicals, and irrigation, or, in this case, improved seed varieties. Yet the availability of new technologies does not directly translate into adoption, and a key component to technology adoption is education and outreach (T. Conley and Udry 2001; Foster and Rosenzweig 1995). Furthermore, economic feasibility is critical to adoption, i.e. expected returns must be sufficiently high (Kassie, Shiferaw, and Muricho 2011). For these reasons, efforts by inter-governmental and non-governmental organizations have been made to facilitate adoption by making new technologies readily available and lowering the overall cost of adoption to poor HHs. Further consideration is given to targeting the specific crops expected to have a significant regional impact on reducing food insecurity among the rural poor, and groundnuts are a good example of such a crop for eastern Uganda.

The theoretical basis for technology adoption is such that adoption by HH i occurs if and only if it increases their level of utility U_i. In this way the difference in utility given adoption (U_i^a) and non-adoption (U_i^o) must be positive for adoption to take place, such that U_i^a - U_i^o > 0 (Ali and Abdulai 2010; Becerril and Abdulai 2010; Kassie, Shiferaw, and Muricho 2011). Of course, this difference in utilities cannot be observed directly and instead may be estimated based on the observed adoption among farmers. Estimation therefore relies on the assumption of utility maximization and the corresponding set of first order conditions, which are well described and derived in detail in Shiferaw et al. (2010).

By utilizing the panel dataset over the 10-year period from 2004 to 2014, we are able to look at RRV adoption levels as they relate to program participation. A binary variable is included to identify HHs growing RRVs by period. This allows for the proportion of adopting HHs to be easily identified by taking a simple average of this variable across groundnut growing HHs. It is also possible to evaluate the trends in adoption from the end of the program in 2004 to 2014. This initial approach to evaluating adoption is extensive because it is focused on the extent to which the population is RRV adopting. Data for the extensive margin tend to be very reliable and in our case is available for both survey rounds. On the other hand, results from this sort of analysis can be difficult to interpret since many factors may contribute to these trends. In the case of this project, because participating HHs were required to grow RRVs during the project time period, it is expected that the proportion of beneficiary farmers growing them would at most remain constant if not decrease. However, the amount of RRVs grown by beneficiaries in terms of the proportion of total production was not specified by the project. This measure of the intensive margin of adoption may therefore be estimated to better capture the impact of the project in terms of the level of RRV adoption by adopters

Estimation of the intensive margin of adoption requires additional HH information, which is most reliable when collected during or close to the end of the production period around harvest time. This information was only collected in 2014 for the most recent growing season and is used to examine the differences in adoption levels between groups in more detail than the more general extensive measure of adoption. The indicator used in this case is the proportion of total groundnut production area in RRVs. Unfortunately, since this information was not collected in 2004, and because of concerns over the lack of reliability for recall data, only data for overall groundnut production area in 2004 are available. Yet, the advantages of estimation on the intensive margin are clear as they allow us to gain a closer look into the adoption practices of regional farmers. Therefore, the majority of our analysis focuses on the examination of cross sectional data from the 2014 survey.

Multiple models are constructed to evaluate the adoption characteristics and the sustainability of program benefits 10 years later. Controlling for various exogenous factors, we assume that the

correlation between adoption and program participation provides a good estimate of the impact of training. In the first model, the effect of the program is estimated using ordinary least squares (OLS) regression. The OLS model is given as:

$$Y_i = \alpha + \gamma P_i + \beta X_i + \mu_i \tag{1}$$

where, Y_i is the indicator for adoption measured as the proportion of groundnut area planted in RRVs; α is the constant y-intercept term to be estimated; γ is the coefficient of program participation to be estimated, where P is a dummy variable for program participation taking the value $P=1$ for beneficiary HHs and $P=0$ for non-participants; β is a vector of parameters to be estimated for X, a set of exogenous variables; and μ is the error term.

A third specification of the adoption model is a sort of hybrid where data on the intensive margin of adoption are used to construct a binary variable for adoption where HHs with a certain proportion of area planted in RRVs are considered adopters. The basic extensive model simply sets this criterion as any amount of RRVs planted. One concern is that such an approach requires the arbitrary selection of a cutoff level, e.g. Y=1, if the proportion of the total area of groundnut production in RRVs is greater than 50%. Typically, a probit specification is used for this estimation and has been implemented in other recent studies of Ugandan groundnut farmers (Shiferaw et al. 2010; Tanellari et al. 2014). This approach is likely to generate alternative coefficient estimates to the OLS specification. Others have estimated the intensive model using a Tobit specification where adoption rates in terms of relative frequencies are bounded, ranging from 0 to 1 (Kassie, Shiferaw, and Muricho 2011; Oladele 2006). Because it is expected that farmers will adopt in such a way that they maximize HH utility over the long run, they will diversify the mix of varieties grown based on risk management and taste preferences. Models of proportion of adoption can therefore better capture this utility maximizing behavior by not treating adoption as an all-or-nothing condition. Upon further examination of our data, we have found that the tobit model does not provide us with any additional benefits when compared to the simple OLS case and the additional models we incorporate to account for spillover and selection biases.

Because HHs were selected into the program, it is likely that there is associated bias (Heckman et al. 1998). Methods that have been proposed to estimate and correct such bias include propensity score matching and instrumental variables (Bravo-Ureta, Greene, and Solís 2012). Their purpose is to correct for endogeneity bias between the adoption variable and program involvement. Propensity score matching (PSM) is implemented in the estimation to correct for these biases based on observable characteristics. In this case, nearest-neighbor matching is used, whereby propensity scores are generated in the first step from probit estimation and in the second step each treated HH is matched with an untreated one with the propensity score that is closest in value to its own. Ultimately, the average treatment effect (ATE) is estimated based on the mean differences between the treated and matched control groups, which can be expressed as:

$$ATE = E[Y_i^T - Y_i^C] \tag{2}$$

where Y_i^T is the value of the outcome indicator for the treated HHs and Y_i^C is the counterfactual or value for the control HHs (Winters, Salazar, and Maffioli 2010). The probability of a HH being treated is estimated with a vector of exogenous time-invariant observable characteristics X_i. In this case we use a probit model to generate the estimates, which are referred to as propensity scores. The probit model that is provided in equation (3) assumes a normal distribution represented by Φ. The nearest neighbor matching procedure minimizes the overall residual difference in propensity scores between the treated and untreated groups. This may be done on a 1-to-1 basis where each beneficiary HH is matched with a non-beneficiary HH with propensity scores most similar in value.

$$\Pr(Y_i^T = 1 | X_i) = \Phi(\beta X_i) \tag{3}$$

Instrumental variables regression is another technique that is implemented to correct for potential bias from spillover effects. In particular, two stage least squares (2SLS) estimation is used to reduce bias from potentially endogenous variables. In our case, we utilize the intent-to-treat (ITT) in the first stage regression as an instrumental variable. This is a common approach used to capture spillover by considering all HHs in eligible villages as treated since they are likely to have been fully exposed to the program benefits given sufficient time (Cavatassi et al. 2011). In the first step of our 2SLS estimation, participation is predicted as a function of the ITT variable,

which is represented as the vector Z_i in equation (4). In the second step, the OLS model (1) is estimated using the predicted value of P (p_hat) generated in the first step, illustrated in equation (5). The results from the IV should therefore be directly comparable to the PSM results where the ATE is estimated between beneficiary and control HHs from the non-project villages.

$$P_i = \alpha + \delta Z_i + \epsilon_i \qquad\qquad (4)$$

$$Y_i = \alpha + \gamma \hat{p}_i + \beta X_i + \mu_i \qquad\qquad (5)$$

Additional checks for the effect of program participation on adoption and the sustainability of program benefits to HHs are addressed using simple differences in means. This approach compares the sample of beneficiary HHs to the control group in order to examine the mean differences. For indicators with significant variance, it is not possible to generate meaningful estimates when sample size is limited. In this case, the sample size is further decreased when additional measures, such as productivity, cost of production, and relative profitability, are assessed. We therefore rely on the associated literature that provides significant evidence and support for the benefits of adoption. Albeit these features are included in the discussion of summary statistics and results, the major impact indicator we are concerned with is adoption. Given the long 10-year gap between the program completion and follow up survey, bias from external contamination is another source of concern. We control for this by including survey questions that address the involvement of HHs in any other programs or farm groups over recent years. This covers observable sources of contamination but will not capture the full effect of information drift and macro-trends in the region, which are not readily captured with micro-level survey data. Information on HH access to markets is collected and may serve as a proxy for access to networks and information.

Results and Discussion

To begin with, a key observation from the recent 2014 survey is that the mean trend for HH welfare is increasing for the entire sample. Figure 1 illustrates the average trend in perceived HH welfare across program groups, where the left-hand axis represents a relative measure or 'ladder' of HH welfare. In this way, respondents were provided a simple ladder diagram and asked to

indicate their current welfare and their welfare in 2004. Upon inspection, the beneficiary HHs group increased in welfare at a greater rate compared to the other two groups, which do not appear to be statistically different from one another. The interpretation of this result is that the general sense among respondents is an improvement in HH welfare conditions over recent years. Interestingly, perception of such improvements is greater for those who participated in the program than their non-participant counterparts.

Figure 1. Changes in Mean Perceived Level of HH Welfare by Group from 2004 to 2014.
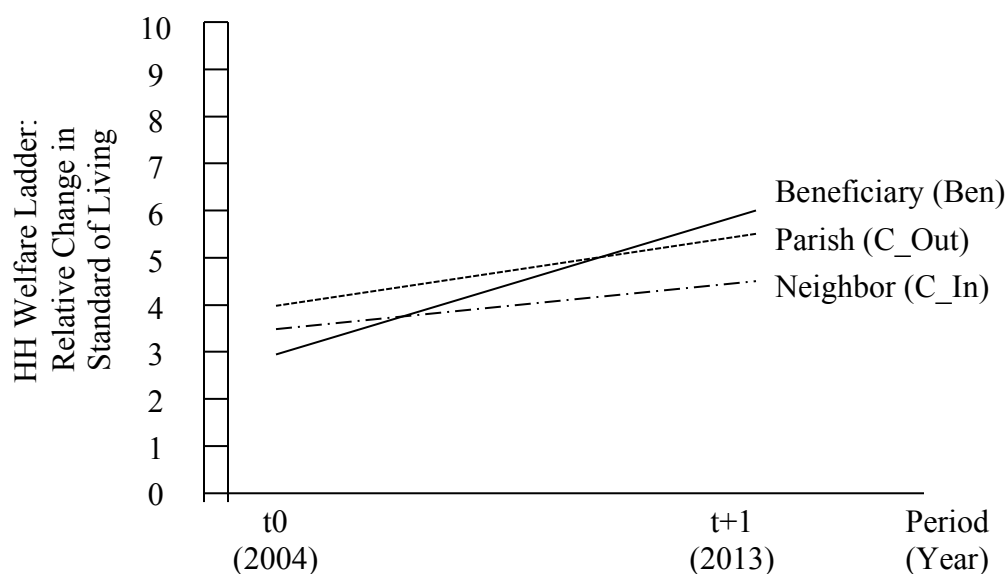
Trends for adoption over the last 10 years indicate significant differences between groups. These estimates are given for the proportion of total HHs that grow RRVs, or the extensive margin of adoption. As expected, the results show that the number of adopters in the beneficiary group decreased over the 10-year period from 78.4% to 71.0%, whereas both of the control groups show a positive trend for adoption from 55.9% to 62.6% (C_Full). The proportion of adopters in the neighbor control group (C_In) increased more than the non-neighbor control group (C_Out), which is also an expected result due to program spillover. Respectively, the rates for the control are 59.8% to 67.4% and 53.0% to 58.8%. Figure 2 provides a graphical depiction of the trend in the proportion of HHs that adopted RRVs during the 10-year period.

Figure 2. Changes in Rosette Resistant Groundnut Variety Adoption, measured as the proportion of HHs that grow improved varieties.
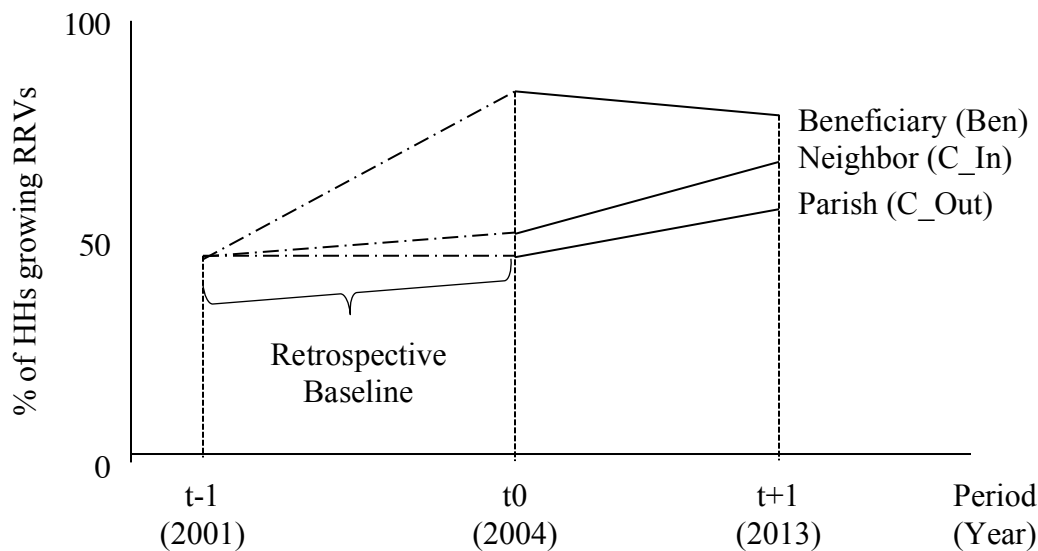
The results indicate that there were significant effects from the program in terms of adoption. Furthermore, there is evidence of high levels of spillover to the neighbors of beneficiary HHs. This is consistent with the expectation that over the 10-year period since the project implementation there has been information-sharing between neighboring farmers. OLS results provided in Table 1 indicate a difference in the proportion of total area planted in RRVs between beneficiary HHs and non-neighboring control HHs of 14.2% and 13.3% between neighboring and non-neighboring control HHs. Comparison between HHs in the project villages (PV) and the non-neighboring controls (C_Out) are observed to be directly in between at 13.9% when weighted according to their respective sample sizes (i.e. 1/3 neighbors and 2/3 beneficiaries). The findings from these initial linear models are all observed to be highly significant at the 5% and 1% levels. The results from the initial OLS model also indicate significant levels of spillover and potential selection bias associated with the treatment group. To account for these factors, additional estimations using several PSM specifications and an IV are included.

The PSM results are based on the comparison of each of the groups to one another in an exhaustive set of combinations. The initial PSM estimates for the ATE are done with the

program beneficiaries (Ben) and the combined control group (C_Full), followed by the comparison of the Ben and neighboring control group (C_In). These are the two cases where spillover is prevalent because of the use of the neighbors for comparison. Since spillover is an important component of this analysis, we expect that the beneficiary group would not be significantly different from the control groups that contain their neighbors. The estimate for the ATE between the Ben and C_In groups is thus statistically insignificant with a magnitude of 0.028 and a standard error of 0.057. By including the non-neighbor controls (C_Out), the magnitude of the ATE estimate increases in size but not enough so as to be significantly different from the beneficiary group. In all other cases, where the C_Out group is used as the basis of comparison, we observe statistically significant results that suggest a near complete level of spillover to HHs in the project villages. Another measure of spillover is to examine the difference between C_In and C_Out. If the benefits have accrued to the C_In group, then the associated ATE should be statistically significant, which is indeed the case with an estimated difference of 11.5% and a 5% significance level. The PSM results that included the entire project village (PV) as the beneficiary group are very similar in magnitude to those from OLS estimation (13.5% vs 13.8%), both of which are highly significant at the 1% level. The largest estimated ATE for all of the models is the matched comparison between the Ben and C_Out groups. Under this specification, we estimate a difference in adoption of 21.5% at the 1% significance level.

Table 1. Average Treatment Effect (ATE) Estimation Results for Proportion of Groundnut Production Area in RRVs: Ordinary Least Squares (OLS), Propensity Score Matching (PSM), and Instrumental Variables (IV)

Model Specification	Coefficient Estimate	Standard Error
OLS: Beneficiaries (Ben)	0.1420***	0.0456
OLS: Neighbors (C_In)	0.1330**	0.0525
OLS: Project Village (PV)	0.1389***	0.0427
PSM: Ben vs. C_Full	0.0724	0.0462
PSM: Ben vs. C_In	0.0280	0.0570
PSM: C_In vs. C_Out	0.1154**	0.0540
PSM: PV vs. C_Out	0.1353***	0.0528
PSM: Ben vs. C_Out	0.2151***	0.0520
IV: intent-to-treat (ITT)	0.2115***	0.0667

Note: *, $P < 0.10$; **, $P < 0.05$; ***, $P < 0.01$.

Given the presence of significant spillover and the likelihood of selection bias among program village HHs, we instrument for program participation. Each of the HHs in the program villages is considered treated and takes a value of 1 for intent to treat (ITT). The program impact is estimated using two-stage least squares (2SLS). Results from the first stage results provide evidence that the ITT is a strong instrument because it fulfills the general criteria for goodness of fit by having an F-test value of 10 or greater (13.39). The second stage IV estimate for the effect of the program is 21.2%, which is highly significant at the 1% level. This is consistent with the results using PSM, where beneficiaries are matched with non-neighbor control HHs, with an estimated difference of 21.5%. The similarity in outcomes helps to bolster the robustness of our impact estimates 10 years after the project. Furthermore, the results for spillover effects in program villages are equally, if not more, important and illustrate the sustainability of program outcomes well after completion.

Concluding Remarks

The results of our analysis support existing theory and are in line with the empirical findings from other recent studies in the region (Shiferaw et al. 2010; Kassie, Shiferaw, and Muricho 2011). In addition, we provide a novel contribution to the existing literature on technology adoption insofar as the sustainability and lasting impact of the original intervention is examined using data collected nearly a decade after the intervention. Although some beneficiary HHs ceased to grow groundnuts, and for that matter RRVs, on the intensive margin we find a 20% difference in the levels of adoption of RRVs between HHs that received program benefits and the ones that did not when we control for spillover and selection bias. Given the long period of time since the conclusion of the project, this finding is important because it illustrates the lasting impact of the efforts by AT Uganda. The sustainability of development interventions is often considered an important objective, but is rarely documented because the data required are simply not available. Once again, our overall findings illustrate the importance and effectiveness of farmer-led extension efforts in sub-Saharan Africa and Uganda with respect to the adoption of new and improved technologies.

It is also important to mention certain limitations to our study that stem from the fact that the purpose of the AT Uganda project was extension, the dissemination of RRV seeds and training to regional farmers in groundnut production and seed multiplication. The program did not have an explicit research focus from the outset, and limited attention and resources were devoted to the potential research questions and identification strategies for the evaluation of the project impacts. This is clearly seen in the initial survey, which contained gaps and did not allow for a panel-data analysis of certain key variables. The 2014 follow up survey allowed us to capture some of the lasting program effects several years later; however, the availability of panel data between the two periods would have likely increased the statistical power given the sample size.

Moving forward, an additional avenue for inquiry is to examine the risk mitigation behavior of farmers, who balance preference for the taste characteristics of risky groundnut varieties with the reliability of improved varieties. In this case, a model may be estimated to evaluate the extent of risk-modifying portfolio structures, along with portfolio characteristics on the intensive margin, associated with optimal risk-reward incentive and utility maximization. Further research to estimate the risk preferences of rural farmers associated with technology adoption is needed. Finally, our results suggest that another promising line of research is the detailed analysis and quantification of spillover effects from extension projects and the overall benefits to treated and neighboring communities.

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