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THE SUSTAINABILITY OF PROJECT OUTCOMES FROM FARMER-LED DISSEMINATION OF HIGH-YIELDING GROUNDNUT ROSETTE DISEASE RESISTANT GROUNDNUT VARIETIES

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THE SUSTAINABILITY OF PROJECT OUTCOMES FROM FARMER-LED DISSEMINATION OF HIGH-YIELDING GROUNDNUT ROSETTE DISEASE RESISTANT GROUNDNUT VARIETIES

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Abstract

The major objective of this study is to evaluate the adoption of groundnut varieties that are high yielding, drought tolerant, and groundnut rosette disease (GRD) resistant in eastern Uganda. In particular, this study examines differences in adoption and farm-level productivity associated with participation in the Appropriate Technology Uganda (ATU) seed dissemination project during the early 2000s. We are particularly interested in the sustainability of the project outcomes 10-years after the end of the original intervention. The impact of the ATU intervention is examined with respect to increased productivity (higher expected yields) and risk-reduction (improved disease resistance and drought tolerance).

We find that participating farmers allocated 21% more of their available land to improved groundnut varieties. The results also show that, for improved varieties, beneficiaries produce 32% higher yields than their non-participating neighbors, and 55% higher yields relative to non-neighbor controls. This implies that the project led to significant increases in profitability for participating farmers.

In addition, we observe significant spillover effects from the project, which is clearly revealed by the yield difference between non-participating neighboring households and non-neighbor controls. These results imply that project beneficiaries transferred some benefits to the neighbor control group over the course of the 10-year period following the project. This is an important result suggesting that farmer-led programs offer additional advantages to developing communities and may provide a cost-effective means of information and technology dissemination.

Background and Motivation

A prominent feature of rural households (HHs) in developing countries is the reliance on subsistence-level farming as a primary source of food and fiber (World Bank, 2007). This feature reveals the inherent risk faced by poor communities as these populations cope with nutritional and financial challenges stemming from crop failures, famine, and a lack of access to well developed markets. These risks are expected to be exacerbated by global climate change; consequently, food insecurity in many parts of the world is likely to worsen (Field and Van Aalst, 2014). Research that evaluates the causes and degree of food insecurity suggests that this threat is particularly significant in sub-Saharan Africa (Smith et al., 2006, 2000). In response to these concerns, the greatest food security gains need to come from productivity growth and increased off-farm employment (Barrett, 2010; World Bank, 2007). Thus, it is critical for researchers to continue to study potential mechanisms that can improve agricultural productivity, specifically for highly nutritious crops.

The research presented herein focuses on the role of agricultural technology adoption in leading to increases in HH productivity. In particular, it looks at groundnut farming in eastern Uganda and the response by farmers to a program that sought to provide access to high-yielding GRD resistant groundnut varieties (RGVs). Groundnuts provide significant nutritional benefits and are an important staple in the diet of eastern Uganda. Moreover, groundnuts are a nitrogen fixing legume and are used in crop rotations as an effective means of improving soil quality (Okello et al., 2015, 2014, 2010). Yet, disease (GRD) historically has been an major constraint to production for farmers in the region growing groundnuts (Naidu et al., 1999).

Bonabana-Wabbi et al. (2006) provide evidence that yield losses from pests and disease exceeded losses from poor soil, drought, and inferior planting material for groundnut producers in eastern Uganda. Major declines in domestic groundnut production during the 1970s have given way to steady growth in more recent years (Okello et al., 2013). From 2005 to 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 1970s (Tanellari et al., 2014). These large increases in domestic production are largely attributed to the uptake of improved production practices and RGVs (Shiferaw et al., 2010). Kassie et al. (2011) suggest that groundnut producers in Uganda benefit significantly from improved varieties exhibiting average yield gains of 35% and average per unit cost reductions around 40%. Improved seed varieties are thus a cost-effective approach to improving yields and returns to farmers.

The National Semi Arid Resources Research Institute (NaSARRI) in Serere, which is part of Uganda’s National Agricultural Research Organization (NARO), has released a number of new groundnut varieties including Igola and Serenut 1 though 6 (Okello et al., 2016). These varieties offer a less risky alternative to groundnut producers when compared to the land race varieties that are widely cultivated (Wilber et al., 2015). At the time of the project, in 2002, it is estimated that 90% of all crops in Uganda were planted in home-saved seed, i.e., land race varieties, and by 2014 10-15% of Ugandan farmers planted improved seed (Joughin, 2014a; Mwebaze, 2002). Researchers have identified improved seed through breeding programs and selection of introduced and locally adapted varieties observed to be disease and drought resistant (Okello et al., 2015; Shiferaw et al., 2010). At the same time, experts have cited the relatively high cost of purchased seed to poor farmers as well as the limited profitability associated with seed multiplication and production as the two major hurdles to seed adoption (Joughin, 2014a). Furthermore, concerns have been raised over the increased prevalence of counterfeit or fake seeds in the market, which is both exploitive and likely to become a disincentive to adoption by small farmers (Joughin, 2014b). Yet, the associated productivity gains from improved seed contribute to poverty reduction and food security among adopters. Correspondingly, a significant body of literature, demonstrates the importance of technology adoption to development, with particular attention given to the uptake of high yielding seeds in India (Foster and Rosenzweig, 2010, 1995). Notable studies in Africa by Conley and Udry (2001, 2010) highlight the role of networks in the dissemination of agricultural technologies. More recently, work in Uganda by Shiferaw et al. (2010), Kassie et al. (2011), (Thuo et al., 2014, 2013) focuses directly on groundnut producers.

An earlier survey of farmers located in eastern Uganda was conducted during the Appropriate Technology Uganda (ATU) LIFE project beginning in 1999, revealed that groundnuts were not being grown by poor farmers because of the high risk associated with production, even though groundnuts were highly profitable compared to other regional crops (Tino et al., 2004). One important source of risk stems from the high seeding rate in groundnuts, relative to production, and another is the threat of crop failure from diseases (Okello et al., 2015). 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 (Mugisa et al., 2015). The use of disease resistant seed varieties offers a cost-effective and sustainable alternative to combating disease related crop failure and is thereby likely to provide significant benefit to poor farmers (Moyo et al., 2007). The diagnostic results from the LIFE Project provided the basis and justification for the farmer-led groundnut seed multiplication and dissemination program carried out from 2001 to 2004 (Tino et al., 2004). The goal of this project was to increase the availability of RGVs and in turn generate significant benefits to regional groundnut farmers.

Our research provides a novel contribution to the existing literature on technology adoption by focusing on the sustainability and lasting impact of an intervention implemented 10-years before the most recent data collection event. Specifically, our primary research question is: did the ATU seed dissemination program result in increased adoption of RGVs by participating HHs over the last 10 years? The overall findings illustrate the importance and effectiveness of continued farmer-led extension efforts in sub-Saharan Africa, particularly in Uganda, with respect to the adoption of new and improved technologies.

Theoretical Framework & Methodology

An effective means of mitigating the risks associated with HH crop production is through the use of improved technologies in order to promote higher productivity (Bravo-Ureta et al., 2012, 2007). These technologies may include the adoption of new or improved inputs, such as machinery, chemical inputs, irrigation, and high-yielding, disease and drought resistant seed varieties. Yet, the availability of new technologies does not directly translate into adoption; education and outreach are necessary components to facilitate this process (Conley and Udry, 2001; Foster and Rosenzweig, 1995). Economic feasibility is also critical to adoption, i.e. the expected returns associated with adoption must be higher than those obtained from the current technology (Kassie et al., 2011). For these reasons, inter-governmental and non-governmental organizations facilitate adoption by making new technologies readily available and lowering the overall cost of adoption for poor HHs (Cromwell et al., 1993; Langyintuo et al., 2008). Further consideration is given to targeting specific crops expected to have a significant regional impact on increasing food security among the rural poor, which is necessitated by concerns over population growth and pressures associated with global climate change (Godfray et al., 2010; Lobell et al., 2008).

The theoretical framework for technology adoption is based on the notion of utility maximization. Thus, HH i adopts if the expected utility from adoption (U_{iA}) is higher than non-adoption (U_{i0}); stated differently, $U_{iA} - U_{i0} > 0$ (Ali and Abdulai, 2010; Becerril and Abdulai, 2010; Kassie et al., 2011). Since utility itself is not observable, empirical models typically rely on a binary or fractional dependent variable (set between 0 and 1), where 0 represents non-adoption, values between 0 and 1 represent partial adoption, and 1 represents full adoption (Asfaw et al., 2012; Kassie et al., 2011). The classic version of the model relies on a purely binary dependent variable, where individuals are considered either adopters or non-adopters (Comin and Mestieri, 2010). The appropriate model is technology dependent, because adoption may be (1) an all-in condition, (2) assume a cutoff level for adoption (e.g., 50% or more of the area is devoted to the new technology), or (3) measured as a continuous fractional variable. Options (1) and (2) are used to capture the extent of technology diffusion within a given population by considering all individuals using the new technology as adopters. Case (3) utilizes HH data on the proportion of total production under the new technology (i.e., RGVs) to measure adoption, which can take any value from 0 to 1. This fractional data can provide a richer insight into the adoption process. Ultimately, the question is not simply whether or not a new technology is adopted, but also how much so, since farmers must balance their own taste for specific varieties and risk preference when making production decisions and allocating their limited resources. Further constraints to the adoption decision for poor HHs include limited access to credit and market demand for specific variety characteristics (Foster and Rosenzweig, 2010).

Methodologically the identification of causal effects associated with the ATU program is the primary task of this research, namely: did the dissemination efforts lead to greater uptake of RGVs? Given the variables included in the 2004 survey, analysis using the panel dataset over the 10-year period from 2004 to 2014 is restricted to a binary measure, which captures the proportion of adoption. This indicator of adoption designates HHs that planted *any* RGVs as adopters ($y = 1$) and HHs that did not plant RGVs as non-adopters ($y = 0$). As indicated, the more detailed micro-level data collected in 2014 allows for additional insight into the nature of adoption at the HH level. In this case, the indicator of adoption is specified as the proportion of area planted in RGVs out of the total area planted in groundnuts, and can therefore take a fractional value from 0 to 1, as opposed to *only* 0 or 1 in the former case. This fractional measure requires a more intense recall from growers so the data should be collected close to the end of the production period to insure reliability.

Alternative models are constructed to evaluate the adoption characteristics and the sustainability of the program benefits 10 years after its conclusion. Controlling for various exogenous factors, we assume that the association between adoption and program participation provides a good estimate of the impact of training. First, the effect of the program is evaluated by estimating equation (1) via a linear model using ordinary least squares (OLS). The model can be written as:

$$y = \alpha + \gamma p + \beta x + \mu \tag{1}$$

where y is the indicator for adoption measured as the proportion of groundnut area planted in RGVs; α is the intercept term; γ is the coefficient that measures impact where ($p = 1$) for beneficiary HHs and ($p = 0$) for non-participants; β is a vector of parameters for the covariates (x), which includes information about the household head (age, sex, marital status, and education), the sex of the respondent, location (sub-district), family size, and total HH acres cultivated; and μ is the error term (Greene, 2011). Recent developments have allowed for fractional outcome variables to be modeled according to their unique non-linear structure (Murteira and Ramalho, 2014; Papke and Wooldridge, 1996). Though linear models have historically been used to estimate non-linear data, such as binary or fractional variables, sufficient theoretical and empirical evidence demonstrates regular incidence of bias from linear estimation models (Papke and Wooldridge, 1996; Maddala, 1986; Tobin, 1958). Fractional regression models differ structurally from OLS, and are estimated via QML (quasi maximum likelihood). First, a functional form is imposed for the conditional mean of the fractional dependent variable (y) such that:

$$E(y|x) = G(x\theta) \tag{2}$$

where x is a set of explanatory variables, θ are the associated parameters to be estimated, and G is a nonlinear function that satisfies the following condition as a fractional estimator: $0 \leq G(\cdot) \leq 1$ (Papke and Wooldridge, 1996). In this case $G(\cdot)$ is specified as a probit, which has a normal cumulative distribution function (Φ) shown in equation (3). The Bernoulli log-likelihood function and QML estimator used for estimation are given by equations (4) and (5) respectively.

$$G(x\theta) = \Phi(x\theta) \tag{3}$$

$$LL(\theta) = y \log[G(x\theta)] + (1 - y) \log[1 - G(x\theta)] \tag{4}$$

$$\hat{\theta} \equiv \arg\max_{\theta} \sum_{i=1}^{N} LL(\theta) \tag{5}$$

Next, we consider the potential endogeneity that would arise if participation in the project (p) is correlated with the error term μ, illustrated in equation (1), and utilize instrumental variable regression (IV) as well as propensity score matching (PSM) to control for this (Cavatassi et al., 2011; Kassie et al., 2011). IV regression is used to evaluate the impact attributable to an intervention via two-step estimation (Angrist et al., 1996; Angrist and Krueger, 2001; Stock and Trebbi, 2003). Estimation with IV requires a suitable instrument (z) that must satisfy two important conditions: 1) it must be correlated with the regressor (p); and 2) it must be independent of the error term (μ) and uncorrelated with the dependent variable (y) (Duflo, 2001). A particular instrument that has been applied in this context is the intent to treat (ITT), which is adopted from the experimental medical literature (Duflo et al., 2008). Thus $z = 1$ for eligible members of the population and $z = 0$ for non-eligible ones, regardless of program participation (p). In the first step, p is predicted ($\hat{p}_i$) as a function of ITT (z) as shown in equation (6), where $z = 1$ for all HHs in program villages (Cavatassi et al., 2011). In the second step, the model includes the predicted value ($\hat{p}$) generated in the first step, equation (7). The same set of covariates (x) included in the initial model are included in both (6) and (7). The OLS version of the model is utilized here to illustrate the two-step estimation process with the following equations (Papke and Wooldridge (2008) provides a detailed exposition of fractional IV regression in a follow up to their seminal paper from 1996):

$$\hat{p} = \alpha + \delta z + \varphi x + \epsilon \tag{6}$$

$$y = \alpha + \gamma \hat{p} + \beta x + \mu \tag{7}$$

While IV can mitigate biases from unobservables when only cross sectional data is available, the use of PSM makes it possible to correct biases from observables (Dehejia and Wahba, 2002; Khandker et al., 2009). In order to avoid biases, the ideal would be to observe a group at a given point in time in both the treated and untreated states. Clearly this is not possible; thus, it is necessary to create a counterfactual in order to be able to attribute any changes on the indicator of interest to the intervention (Gertler et al., 2011).

Randomization is the primary means to generate a robust counterfactual where, in principle, the researcher simply allocates individuals from the study population into treated and control groups. However, if randomization is not incorporated into the study then other methods must be used to construct a suitable counterfactual. One such method is PSM, which is used to generate a control group that is as similar to the treated group as possible in terms of observables (Caliendo and Kopeinig, 2008; Dehejia and Wahba, 2002; Ravallion, 2007). The average treatment effect (ATE) is then calculated based on the mean differences between the two matched groups. The ATE can be expressed as:

$$ATE = E[y^T - y^C] \tag{8}$$

where y^T is the value of the outcome indicator for the treated HHs and y^C is the value for the control HHs (Winters et al., 2010). A Probit model (equation 3) is used to generate estimates of the probability of being treated, referred to as a propensity score, given a vector of observable characteristics (Greene, 2011). We then use the nearest neighbor criterion without replacement to match beneficiaries with non-beneficiary HHs and estimate the ATE (Caliendo and Kopeinig, 2008; Dehejia and Wahba, 2002; Leuven et al., 2015).

Given the 10-year gap between the program completion and the follow up survey, bias from external contamination is another source of concern. External contamination comes from other programs and activities that are likely to produce similar outcomes to the project under evaluation (Baker, 2000; Gertler et al., 2011). In this case, we assume local authorities and NGOs are responsible for such activities in similar fashion to ATU. We therefore examine the presence of sources of external contamination based on the response to questions in the 2014 survey concerning the involvement of HHs in any other programs or farm groups over last decade. The preliminary analysis of these data revealed that contamination is not an issue in this sample.

ATU Project Scope & Data

In an effort to promote adoption of improved groundnut varieties, the AT Uganda project promoted farmer-led multiplication of high-yielding, drought tolerant, and groundnut rosette disease resistant material by poor households under the supervision of local authorities. AT Uganda facilitated the access to new varieties through the following set of outputs:

(i) Extension staff, local authorities, and farmers trained in groundnut production and storage.

(ii) Foundation seed for new groundnut rosette disease resistant varieties obtained and multiplied by farmer group members.

(iii) Farmers that multiply seeds return double the amount of planting materials received, for redistribution and further multiplication.

The process of collection, redistribution, and monitoring of multiplied seed is effectively handed over to local leadership for management (Tino et al., 2004). Thus, the project was designed to be an efficient and practical means for the dissemination of RGV seeds. Lessons from previous projects indicate that farmer-led seed multiplication is an effective means of promoting access to and utilization of RGVs and best practices, resulting in increased productivity among resource poor HHs. The project expected to achieve the following targets, each of which are assessed and documented in the December 2004 AT Uganda Final Technical Report:

(i) Production of groundnuts by 9000 poor participating farmers.

(ii) 16 Extension staff, 300 community leaders (160 contact farmers and 140 local leaders), and 2000 households trained in groundnut seed production, storage and multiplication.

(iii) Sufficient foundation seed to plant 400 acres (161.9 Ha) of new varieties obtained and multiplied by the end of project (EOP).

(iv) Redistribution and further multiplication of sufficient improved groundnut varieties to plant at least 2500 Ha by EOP.

The ATU farmer-led seed multiplication and dissemination program was conducted from 2001 to 2004. The end goal of the project was to increase the adoption of RGVs by making seeds readily available to farmers. In order to evaluate project outcomes, a survey was completed close to the end of the project in 2004, and an additional survey of the same HHs was completed in 2014 to assess the lasting impacts of the project. The 2014 survey contained additional outcome indicators to assess the nature of RGV adoption in greater detail. A major advantage of the data (2004 and 2014) is that it contains both participants (*Beneficiaries*) and their non-participant counterparts (*Controls*). We employ a cross-sectional approach to estimation in order to exploit the greater detail of the 2014 data. Panel data (combining 2004 and 2014 surveys) is also used to assess attrition and demographic consistency, which is important given the long time period between data collection and analysis (Schultz and Strauss, 2008).

Uganda is divided into 112 districts and each district is subdivided into 1 to 5 counties for a total of 181 counties, which are then split into a total of 1,382 sub-counties. Sub-counties are divided into parishes that are made up of a group of villages with many HHs (Rwabwogo, 2007). For the purpose of the seed dissemination project, participating HHs were grouped into local farmer associations within selected parishes. Non-participating HHs were therefore not members of the farmer associations included in the dissemination project, but may be neighbors of participating HHs, i.e. residents of the same village or of a village that did not include any participating HHs.

At the outset of the project in the early 2000's, randomization was used to determine project locations. First, half of the sub-counties in a given district were randomly selected to participate in the project. A single parish was then chosen at random within each of the selected sub-counties. Then, three farmer associations were selected from each parish and finally 10 members from each participating farmer association were randomly selected as respondents. Non-participating HHs were selected at random from project and non-project parishes. The following explicitly describes the composition of the survey sample:

Beneficiaries: The final sample of program beneficiaries consists of 8 sub-counties, 8 parishes, and 24 farmer associations (10 members from each), for a total of 240 HHs.

Control: A two-part control group was also sampled to provide a suitable counterfactual. The first part of the total control group was made up of five HHs neighboring beneficiaries from each of the beneficiary farmer associations. The neighbors were randomly selected, so that 15 were sampled in each sub-county for a total of 120 non-beneficiary neighbors. The second part of the control is made up of non-participating parishes in randomly selected sub-counties. Then, a total of 15 HHs were randomly picked from each parish. Thus, a total of 120 non-neighboring non-beneficiary parish respondents were surveyed as the second part of the control group. The total control group is composed of 240 HHs.

Survey Implementation. The first survey for which we have data was conducted in late 2004 at the end of the ATU Project. A follow-up survey was conducted in early 2014 for all 240 treatment and 240 control HHs. The 2014 survey was done by ATU and consisted of a questionnaire that recorded HH demographic and agricultural production data. The general characteristics of the 2004 data followed by adjustments introduced in the 2014 survey are as follows:

(i) Household: demographic and socioeconomic characteristics;

(ii) Agricultural Production: total acres planted, crop and groundnut varieties grown, farmer association membership, seed multiplication participation, farming experience (years), and marketing. In addition, the 2014 survey included: acreage and quantity of seed planted by groundnut variety, recall questions for 2004 total groundnut area, and inputs use – labor, fertilizer, and supplies.

Results and Discussion

Trends for adoption over the last 10 years indicate significant differences between groups. Figure 1 illustrates the proportion of the sample that grows *any* RGVs by group (note the Retrospective Baseline illustrates a key assumption that on average all HHs in the survey region faced the same level of adoption prior to the project). Because beneficiaries were required to grow RGVs during the project period it is not surprising that some HHs reverted to former production practices (land race varieties) over the 10-year period. Nevertheless, the proportion of adopting HHs remains significantly higher for the beneficiary group (BEN) than the controls. The results show that the number of adopters in the beneficiary group decreased over the 10-year period from 78% to 71%, whereas both control groups show a positive trend for adoption from 56% to 63% (C_ALL). The proportion of adopters in the neighbor control group (C_IN) increased significantly more over the 10-year period when compared the non-neighbor control group (C_OUT), which reflects spillover of project benefits to the neighbor HHs. From 2004 to 2013 the adoption rates for the controls are 60% to 67% (C_IN) and 53% to 59% (C_OUT), respectively.

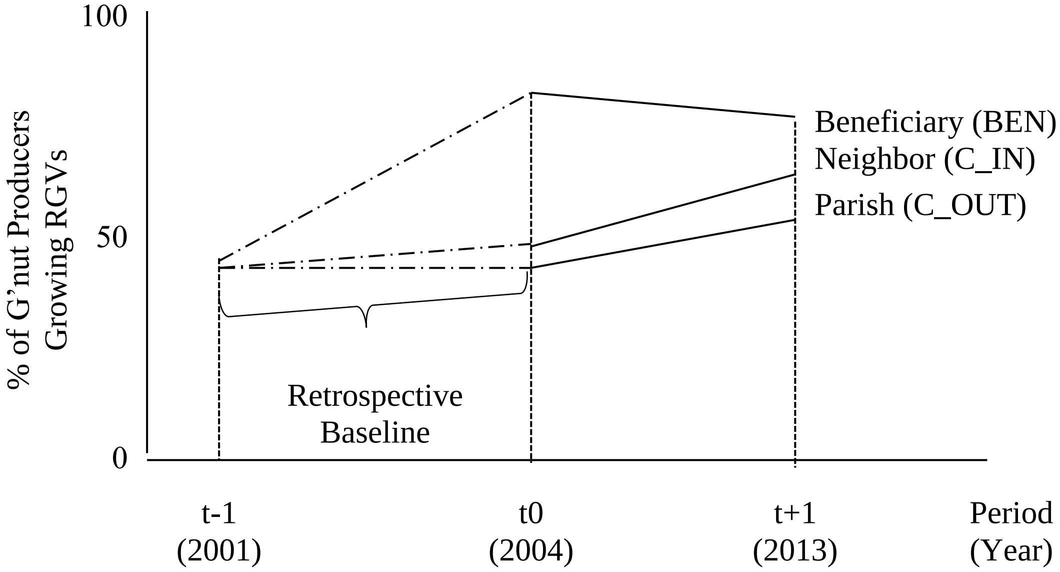

Figure 1. RGV Adoption Trends by Subgroup: Proportion of Groundnut Producers that Grow RGVs (2001-2014)

Given the properties of the adoption data our analysis and discussion relies on the results from the fractional regression model and the corresponding average marginal effects estimates. These results along with the ones for the OLS model are included in Table 1. We also find that the fractional regression and OLS models are consistent across all estimates. The results for the first model indicates +13.8% for beneficiary HHs (BEN) and +13.5% for the neighboring (C_IN) in comparison to the non-neighboring control HHs (C_OUT), the second model combines all HHs in project villages (PV) into one group (i.e., BEN + C_IN) and results in an estimated +13.7% adoption compared to the non-neighboring controls (C_OUT). These estimates are all observed to be significant at the 1% level. The coefficient estimate for C_IN from the first model is primarily attributed to project spillover; accordingly, to account for this the second model includes all members of the project villages as treated (i.e., project beneficiaries). In order to correct for spillover and selection bias we implement IV regression as well as several PSM specifications.

Given the cross sectional data structure, the presence of significant spillover, and the likelihood of selection bias among program village HHs, an IV regression model is estimated. Results from the first stage provide evidence that the ITT is a strong instrument by having an F-test value of 13.4 (Stock et al., 2012). The second stage IV estimate for the effect of the program is 21.4%, which is highly significant at the 1% level. Next, we specify a PSM model for each of the possible comparisons between groups. The initial PSM estimates for the ATE compare program beneficiaries (BEN) with the combined control group (C_ALL), this is followed by the comparison of BEN and the neighboring control group (C_IN). Given the prevalence of spillover, these results support the intuition that findings for the beneficiary group are not significant when their neighbors are included in the control group specification. Thus, the estimate for the ATE between the BEN and C_IN groups is not statistically significant 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. Furthermore, these results are consistent with the IV regression when compared with the PSM specification where beneficiaries are matched with non-neighbor control HHs, with an estimated difference of 21.4% vs. 21.5% respectively. Demonstrated consistency across results bolsters 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 to illustrate the sustainability and extension of program outcomes well after completion.

Table 1. Estimation of the Proportion of Groundnut Production Area in RGVs: Base Models (1) and (2), (3) Instrumental Variables, and Propensity Score Matching

Model	OLS	Fractional Regression^
(1) Beneficiaries (BEN)	0.142*** (0.046)	0.138*** (0.044)
(1) Neighbors (C_IN)	0.133** (0.053)	0.135*** (0.051)
(2) Project Village (PV)	0.139*** (0.043)	0.137*** (0.041)
(3) IV: Intent-to-treat	0.212*** (0.067)	0.214*** (0.065)
PSM: BEN vs. C_ALL		0.072 (0.046)
PSM: BEN vs. C_IN		0.028 (0.057)
PSM: C_IN vs. C_OUT		0.115** (0.054)
PSM: PV vs. C_OUT		0.135*** (0.053)
PSM: BEN vs. C_OUT		0.215*** (0.052)

Note: *, *P* < 0.10; **, *P* < 0.05; ***, *P* < 0.01; ^results provided as average marginal effect.

In all other cases, where the C_OUT group is used as the basis of comparison, we observe statistically significant results. This further illustrates the high level of spillover to HHs within the project villages. We examine the difference between C_IN and C_OUT once more using PSM. 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. These results are directly comparable to the estimates from the second model (13.5% at the 1% level), where the small difference is likely attributed to program selection. The PSM results that included the entire project village (PV) as beneficiaries are ever more similar in magnitude to those from the base estimation model (2), 13.5% vs. 13.7%, both of which are highly significant at the 1% level. The largest estimated ATE 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.

HH productivity levels are also evaluated as an important component of our analysis. Differences in productivity between varieties and groups may be of particular interest in this case. For instance, typically the promotion of RGVs includes the promise of higher yields in addition to drought tolerance and disease resistance. In this case, the opposite is observed, where on average land race varieties produce higher yields than the RGVs (Table 2). However, this finding is consistent with some of the literature on technology adoption, and several studies have provided evidence that producers face lower productivity levels as they adapt to a new technology (Schultz and Strauss, 2008). In this case, it is also important to note productivity differences between land race and RGVs are much less pronounced for the beneficiaries than for the neighbor or parish groups. This again is in line with the literature as the beneficiaries have both more experience with RGVs as well as specific training 10-years prior, and presumably greater capital accumulation, or deepening, compared to the counterpart groups (Kumar and Russell, 2002).

A key hypothesis of the original project was that beneficiaries obtain a higher average productivity than controls, given the training provided 10-years prior. We observe significant statistical differences in productivity levels between the beneficiaries and control groups, leading us to reject the null hypotheses that no such differences exist. Upon further inspection, these differences are shown to be consistent across all major groundnut varieties, where beneficiaries obtain the highest yields on average. In the case of RGVs, the difference is highly significant between beneficiaries and both neighbors and parish groups, at the 5% and 1% levels, with a yield of 265 kg/acre compared to 200 kg/acre and 171 kg/acre, respectively (Table 2).

It is important to consider the long period of time since the program was implemented and the likelihood of diffusion of any such benefits to the other groups. Coupled with the relatively small sample, these results are particularly striking. For the overall sample the mean HH-level productivity is 172 kg harvested for a yield of 249 kg/acre. Productivity for land race varieties and RGVs are 161 kg and 307 kg/acre and 101 kg and 228 kg/acre respectively. In the cases of the two most widely grown varieties Serenut 2 and Red Beauty mean productivity are 105 kg and 223 kg/acre and 179 kg and 346 kg/acre respectively.

Our results for groundnut productivity levels are not consistent with those recently published by Okello et al. (2015). In the case of Red beauty the average yield in our sample is greater than the maximum yield listed in their recent report. Furthermore, in no case are average yields for RGVs in Okello et al. (2015) less than land race varieties, whereas the opposite is observed in our sample. This finding is likely due to the following three factors: 1) greater marketability for red varieties, 2) genetic contamination as a result of seed saving beyond the recommended 3-year period, and 3) increased prevalence of counterfeit seeds (Joughin, 2014a; Okello et al., 2015).

Table 2. Quantity Harvested and Yield for Groundnuts by Variety in 2013 (Season A)

	Beneficiary		Neighbor		Parish		Total	
Quantity Harvested (kg)	Count	Mean	Count	Mean	Count	Mean	Count	Mean
Land Race	**105**	**172**	**44**	**178**	**66**	**164**	**215**	**171**
Red beauty	62	175	31	193	32	174	125	179
Igola 1	2	37	1	40	3	196	6	117
Erudurudu red	33	142	11	153	27	160	71	151
Etesot	22	127	3	36	7	117	32	115
Magwere	1	42	1	14	2	28	4	28
Kitambi	0	0	0	0	1	42	1	42
RGV	**128**	**112**	**55**	**113**	**49**	**98**	**232**	**109**
Serenut 1R	1	17	0	0	0	0	1	17
Serenut 2	112	107	49	103	45	103	206	105
Serenut 3R	8	85	4	281	2	23	14	133
Serenut 4 T	14	115	1	70	1	100	16	112
Serenut 5R	1	60	0	0	0	0	1	60
TOTAL	**184**	**176**	**82**	**172**	**95**	**165**	**361**	**172**

Mean Yield (kg/acre)								
Land Race	**105**	**313**	**44**	**311**	**66**	**269**	**215**	**299**
Red beauty	62	350	31	374	32	311	125	346
Igola 1	2	69	1	160	3	221	6	160
Erudurudu red	33	302	11	185**	27	231	71	257
Etesot	22	245	3	110**	7	318	32	248
Magwere	1	168	1	112	2	112	4	126
Kitambi	0	0	0	0	1	168	1	168
RGV	**128**	**265**	**55**	**200****	**49**	**171*****	**232**	**229**
Serenut 1R	1	68	0	0	0	0	1	68
Serenut 2	112	257	49	183**	45	182**	206	223
Serenut 3R	8	557	4	707	2	86**	14	533
Serenut 4T	14	380	1	280	1	80	16	355
Serenut 5R	1	240	0	0	0	0	1	240
TOTAL	**184**	**263**	**82**	**237**	**95**	**233**	**361**	**249**

Note: Significance level is given for the difference in mean yield by category compared to beneficiary, based on a 1-tailed t-test, *, $P < 0.10$; **, $P < 0.05$; ***, $P < 0.01$.

Production costs for groundnut farmers in the study area are estimated as labor inputs and the amount paid for purchased inputs (Table 3). This is a critical distinction because most growers rely on family labor to limit cash expenses. Labor input is found to be consistent across the three groups of farmers, with weeding, harvesting, and land preparation requiring the greatest amount of worker-days, respectively. The apparent variation in costs between the three groups is due in part to the use of hired labor. Other inputs that are widely used by growers include the purchase of seed and bags for storage. The only chemical input worth noting is insecticide, which is used by a moderate subset of growers (~40%). The overall average cost of producing groundnuts for the farms in the sample is 1,941 USh/kg (Ugandan shilling per kilogram). Across groups the average cost of production (COP) is as follows: beneficiaries 2,034 USh/kg, neighbors 2,066 USh/kg, and parish 1,664 USh/kg. These figures are consistent with recent findings from Okello et al. (2015) who report a range in average COP between 1,541 USh/kg and 4,074 USh/kg. As expected, the COP for beneficiaries and their neighbors is very similar. On the other hand, the apparent difference between beneficiaries and the parish group is not statistically significant because of considerable variability in COP across HHs.

Table 3. Average Groundnut Production Costs: Labor by Activity and Other Inputs

	Beneficiary		Neighbor		Parish		Total	
Labor Input	Days	Cost	Days	Cost	Days	Cost	Days	Cost
Land Prep	21.6	66630	21.3	83671	25.0	29832	22.4	60800
Planting	3.5	33020	3.7	28256	3.5	33131	3.5	31887
Watering	0.0	0	0.0	0	0.0	0	0.0	0
Fertilization	0.0	0	0.0	0	0.0	0	0.0	0
Herbicide*	0.0	261	0.0	0	0.0	0	0.0	134
Spraying	1.2	2893	0.6	1236	0.8	3136	1.0	2584
Weeding 1	37.0	77170	32.7	55885	37.4	43846	36.1	63622
Weeding 2	28.5	52542	31.4	39631	31.8	37574	30.0	45702
Harvest	29.1	51787	29.6	44445	32.1	40080	30.0	47058
Threshing	17.2	24729	11.6	1780	11.5	2708	14.5	13775
Drying	21.9	219.9	20.9	589	21.3	0	21.5	245
Transport	10.9	10561	7.9	1853	11.9	3735	10.5	6807
Other Inputs	N	Cost	N	Cost	N	Cost	N	Cost
Seed (USh/kg)	114	3486	51	3363	64	3419	229	3440
Land Race	*70*	*3511*	*28*	*3323*	*44*	*3461*	*142*	*3459*
RGV	*62*	*3468*	*30*	*3320*	*29*	*3504*	*121*	*3440*
Insecticide	56	12487	20	11819	38	11565	114	12088
Herbicide	1	24300	0	0	0	0	1	24300
Fertilizer	1	1166	1	650	0	0	2	958
Sprayer	22	5488	10	6347	8	9844	40	6536
Bags	130	26807	53	48297	60	21688	243	29551

*Note: *1 HH in Tororo.*

On average, HHs sell 3,474 kg of groundnuts at a price of USh 2,187/kg (Table 4). Beneficiaries sell more on average than their neighbors or parish counterparts, with average sales of 3,781 kg, 3,212 kg, and 3,077 kg respectively; Mean prices for unshelled groundnuts are observed to be more consistent across the three groups at USh 2,171/kg, USh 2,067/kg, and USh 2,325/kg, respectively. The value-addition from shelling results in a greater mean value of output equal to USh 3,440/kg averaged across the full sample. This is comparable to the results from Okello et al. (2015), with a range in price from USh 2,400/kg to USh 7,000/kg, where the upper limit of this range is associated with the most recently released RGVs. Given limited access to cash, these higher prices are prohibitive to the adoption of newly released RGVs, which explains the prevalence of Serenut 2 and home saved seed.

Table 4. Mean Quantity and Price of Groundnuts Sold in 2013 (Season A)

	Beneficiary		Neighbor		Parish		Total	
	Mean	N	Mean	N	Mean	N	Mean	N
Quantity (Kg)	3781	128	3212	56	3077	62	3474	246
Price (USh/Kg)	2171	128	2067	57	2325	64	2187	249

Further examination of the relative price difference between groundnut purchased seed and the selling price for unshelled groundnuts indicates additional processing costs for threshing, which is listed as an input in Table 3. The mean cost associated with threshing is 17.2 man-days and 24,729 USh to process a significant portion of the entire crop. This process of value-addition results in the premium price for shelled groundnuts or seed, versus unshelled. Given the mean selling price for unshelled groundnuts at 2,187 USh/kg, in comparison to shelled groundnut seed at 3,440 USh/kg (Tables 3 and 4), we find a clear rational for the use of home saved seed rather than purchased seed as a cost-saving measure. These figures are once more in line with the recent work by Okello et al. (2015). Ultimately, producers rely heavily on family labor and threshing is done simply to prepare their own saved seed for the following season.

Concluding Remarks

After a thorough review of the lasting impacts of the ATU seed dissemination project it is clear that significant benefits were received by participating producers during the project period and continued through the following decade. Furthermore, The results of our analysis support existing theory regarding the returns to technology adoption in a development context, and are in line with the empirical findings from other recent studies in Uganda (Kassie et al., 2011; Okello et al., 2015; Shiferaw et al., 2010; Thuo et al., 2014, 2013). 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 ended. Although some beneficiary HHs ceased to grow groundnuts, and for that matter RGVs, we find a 21% difference in adoption levels of RGVs between HHs that received program benefits and those that did not when we control for spillover and selection bias. Beneficiaries are also observed to be more productive and achieve greater returns than their respective neighbor and non-neighbor controls. 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 ATU. The sustainability of development interventions is often considered an important objective, but is rarely documented because the data required are simply not available. Our overall findings provide a unique perspective and illustrate the importance and effectiveness of farmer-led extension efforts in Uganda with respect to the adoption of new and improved technologies. As a final note, it is important to further examine and address concerns over counterfeit seeds in the marketplace as well as the need for continued support to local farmers through extension services. Increased affordability of seeds, quality assurance and monitoring efforts for seed producers, and extension services to farmers are each important tools to promote the sustainability of groundnut farming in Uganda.

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