Impact Assessment with Multiple Interventions:

Evidence from a rural development project in Nicaragua

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ABSTRACT

In this paper we conduct impact evaluation of a pro-poor rural development project in Central America that promoted multiple interventions with opt-in. We identify changed behavior – measure as adoption of technologies and practices promoted – as the first step toward long-term impacts on incomes and sustainable production. In order to control for purposive program placement and project participant self selection to project interventions, we use several quasi-experimental panel data techniques – first difference, propensity score matching difference-in-differences estimation, and propensity score weighted regression – to correct for selection bias. We find increases in adoption of agricultural conservation practices, construction of agricultural conservation structures, use of improve storage technologies, and household savings. These are likely to translate into stabilization of annual crop yields and cash flows, further reduction of stored grain losses, and reduction of risk of asset liquidation. Analysis of project impacts by area of cultivated land revealed that adoption of different practices is related to the farm size, suggesting that targeting project interventions by asset level can enhance impacts.

1. Introduction

In spite of efforts to reduce poverty worldwide rural areas still lag behind. Of the 1.4 billion people living with less than $1.25 a day in 2005, around 70% lived in rural areas (International Fund for Agricultural Development, 2010). Adoption of improved agricultural technologies has the potential to reduce poverty, either directly by increasing production for home consumption, raising revenues from sales, or reducing production costs for the adopters of the technology, and/or indirectly by reducing prices of food, increasing wages in agricultural production, or through linkages with other economic sectors (de Janvry & Sadoulet, 2002; Minten & Barrett, 2008).

Questions on how effective are the strategies promoted by development projects in achieving the goal of poverty reduction is of particular interest for governments, project implementers and donors. Impact evaluations of projects promoting improved agricultural technologies have been conducted with the goal of answering these questions. Several studies find that improved seed varieties increases household consumption and expenditures (Becerril & Abdulai, 2010; Mendola, 2007); technological changes brought by agricultural conservation projects increase technological efficiency (Cavatassi, Salazar, González-Flores, & Winters, 2011; Solis, Bravo-Ureta, & Quiroga, 2008); and the use of improved storage technologies reduces stored grain losses (Gitonga, De Groote, Kassie, & Tefera, 2013).

Sometimes rural development projects promote multiple interventions to achieve the goal of poverty reduction. Techniques for evaluating projects with this design are available to determine the impact of each intervention and some combinations (Cuong, 2009; Lechner, 2001; Wooldridge, J., 2010). Data collection requires a sample size that allows for meaningful inferences about these effects. Yet when project participants self-select into different program interventions, it is difficult *ex ante* to forecast levels of participation. These challenges make difficult to conduct evaluations of rural development projects with multiple interventions, and may explain why the literature on impact evaluation of these projects is scant.

When two or more agricultural technologies are promoted as a package and the elements of the package are divisible, project participants may adopt elements of this package instead of the package as a whole (Byerlee & Hesse de Polanco, 1986; Feder, Just, & Zilberman, 1985). To achieve project goals, such as increase in agricultural productivity and agricultural income, increases in adoption rates of improved technologies is required (Teklewold, Kassie, & Shiferaw, 2013). But adoption is not automatic upon exposure to a project treatment. Learning about the benefits of different technologies does not imply that project beneficiaries will adopt them. This is because of costs associated with adoption (Feder et al., 1985). Resource constraints also affect adoption, so farm households may be willing but unable to adopt the recommended technologies (Nowak, 1992).

Different project interventions are also likely to vary in the time horizons for achieving impacts (King & Behrman, 2009; Tjernström, Toledo, & Carter, 2013). For instance, agricultural conservation practices and structures will take a long time before stabilizing soils can stabilize crop yields. In contrast, interventions such as improved storage can lead to fairly rapid reduction of storage losses. These different periods of elapsed time from project start date to moment of project impact mean that consideration must be given to two issues: 1) what outcomes to evaluate at different stages of project implementation, and 2) how to identify early indicators of project effectiveness.

Our objective with this research is to conduct an impact evaluation of a rural development project with multiple interventions after two years of project implementation, and identify early outcomes to answer an empirical question: whether the project strategy – promoting multiple interventions for all beneficiaries – changed behaviors as measure by impacts on adoption of improved agricultural technologies. We test for heterogeneity of project impacts according to relative wealth, as measured by the area of cultivated land. With this study we contribute to the literature on impact evaluation of rural development projects with multiple, opt-in interventions.

The project to be evaluated, called Agriculture for Basic Needs (A4N), promoted agricultural conservation practices and structures, post-harvest management, nutritious crops in kitchen gardens, and saving and lending groups, among other interventions. Farm households in participating villages had the opportunity to opt in to a set of A4N interventions. We focus on the evaluation of A4N in Nicaragua, a country characterized by high concentration of the poor in rural areas, and by low levels of agricultural productivity(World Bank, 2008), which is the case for many developing countries(International Fund for Agricultural Development, 2010).

Project beneficiaries were not randomly assigned. Instead, they self-selected into project interventions, so selection bias was a concern for impact evaluation. Since experimental design was not feasible, the program evaluation uses quasi-experimental methods. First difference (FD), propensity score matching difference in difference (PSM-DID) and propensity score weighting (PSW) are quasi-experimental methods that can be used to control for time invariant, unobservable characteristics and to correct for selection bias on observables (Smith & Todd, 2005).

Our results suggest that the project increased the adoption of agricultural practices that are likely to translate into longer-term impacts of increase in farm productivity and agricultural income. The results also suggest that project interventions should be targeted according to the resource constraints that households face, instead of being promoted to all households.

This paper is organized as follows: section 2 presents the project to be evaluated; section 3 describes a conceptual framework for the analysis of project impacts; section 4 describes the survey data used of analysis; section 5 addresses the problem of impact evaluation and presents the methods we use for evaluating project impacts; section 6 presents results and finally section 7 concludes.

2. The Agriculture for Basic Needs (A4N) Project

The Agriculture for Basic Needs (A4N) project was three year integrated rural development project implemented in four Central American countries during 2009-2012. It was managed by Catholic Relief Services (CRS) and implemented in the field by its partners Caritas and the Foundation for Research and Rural Development (FIDER).

The A4N project aimed to provide farmers with a set of skills for achieving sustainable farm production and increased agricultural income, training farmers on farmer field schools, producer groups, and saving and lending groups, as well as providing technical assistance at the farm. The project promoted agricultural conservation practices and construction of agricultural conservation structures, training in post harvest management, storage practices, use of metallic silos for storage of grains, and training in small livestock management (husbandry, feed production, vaccination regimes, manure collection). Participation in farmer innovation groups, implementation of trial plots with improved varieties of maize and beans, improved farming practices, nutritious vegetable crops in kitchen gardens (cabbage, carrots, onion, tomatoes and green leafy vegetables). The project also addressed market failure by promoting saving and lending groups to establish the habit of saving and to increase access to credit.

The project provided beneficiaries with agricultural assets, such as metallic silos, construction material for animal enclosures, water harvesting structures, plastic water tanks and water filters, and small animals, such as poultry, pigs and goats. Project interventions were available for all project participants, the project encouraged participants in different project activities to participate on other project interventions; for instance, producer groups were encourage to form saving groups. The project also encouraged members of the same household to participate in multiple project interventions.

The A4N project first targeted villages considered poor, in terms of limited access to basic services such as water and sanitation, predominance of small land holdings and reliance on production of staple grains (maize and beans). These villages are located in areas of natural resource degradation with relatively high vulnerability to natural disasters. Within these villages, in order to be eligible to participate in the A4N project, households were expected to be characterized by most of the following official eligibility criteria:

- Cultivated land area less than two *manzanas* (1 Mz = 1.73 acres).
- Cultivated land on steep slopes.
- Lack of access to any of the following public services: piped water, sanitation, and electricity.

- Materials for house walls not brick or concrete; roof not concrete, zinc or brick; floor not concrete, ceramic or tile.
- Household experiences hunger during some period of the year.
- Household head is female.
- Household includes children younger than five years old.

In spite of these formal eligibility criteria, the A4N's village-level managers found it difficult to exclude participation of village members. So the program allowed some technically ineligible individuals to participate, in the hope that they would help to spread A4N interventions during and after program implementation.

Two different processes led to nonrandom participation in specific A4N interventions. First, official eligibility criteria that were not evenly enforced, so households permitted to participate in the A4N project vary on observable traits. Second, the self-selection of individuals into specific A4N interventions means that unobservable traits may also affect participation assignments.

3. Conceptual framework.

Development projects with multiple interventions like A4N provide treatment in the form of exposure to training and provision of inputs. As beneficiaries, farmer households learn about new technologies and practices, they update the information used for solving the inter-temporal maximization process, to make decisions on input allocation in each period (Besley & Case, 1993; Feder et al., 1985). These decisions are made in a process of learning by doing and learning by using (Feder et al., 1985). Moreover, adoption of new technologies and practices implies different costs. These costs could take the form of labor (e.g. building agricultural conservation structures), purchased inputs (e.g. high yield seed varieties, fertilizer), or acquiring information about the new technology, both on its use and its benefits (Sunding & Zilberman, 2001).

Farmer households that are both willing and able to adopt a given technology will do so. But timing for adopters to realized project impacts will differ for different technologies. Figure 1, panel I, illustrates the impact of a technology with benefits that happen in the long term after adoption. Whereas Figure 1, panel II, shows a technology that leads to impacts in short term, close to adoption. Practices such as the construction of terraces and stone barriers, which are agricultural conservation structures, imply significant up-front investments by project beneficiaries for construction and maintenance. Benefits in the form of averted yield decline and reduced yield variability are realized only gradually and unevenly, with the greatest benefits occurring under rare, extreme rainfall conditions. The contrary will occur with the adoption of the use of metallic silos for storage. Once the silos have been provided by the project and farmers trained in their use, the costs are the time that needed to prepare the grain for storage. Reduced storage losses can be realized in less than a year.

Figure 1. Here.

If the project is evaluated at an early stage, say time 1 (t1) in Figure 1, we are able to observe adoption of the technologies and practices promoted by the project and their early benefits. For a conservation technology like the one in Panel I, early impacts will be small, regardless of the degree of adoption; for a storage technology like the one in Panel II, early impacts tend to be relatively much larger. With this difference in mind, we evaluate project impacts on the adoption of a range behaviors promoted, including agricultural conservation structures and practices, improved storage technologies, vegetable kitchen gardens, and membership in savings and credit associations. We also evaluate early outcomes from these practices, specifically the number of households that experiencing stored grain losses or food scarcity.

4. Evaluating project impacts

We approach program evaluation though Rubin's potential outcome framework (Rubin, 1974). The objective of program evaluation is to determine how the intervention or applied treatment affects a desired outcome, evaluating the treatment effect against a counterfactual. Participation of individual *i* in the project is referred to as a "treatment" given by $w_i=1$, so $w_i=0$ if the individual has not been exposed to treatment. The observed outcome for individual *i* is:

$$y_i = w_i y_{1i} + (1 + w_i) y_{0i} \tag{1}$$

which means that the outcome for an individual who participates is y_{1i} and if she does not participate the outcome is y_{0i}. The treatment effect of the program intervention is:

$$\tau_i = \Delta y_i = y_{1i} - y_{0i} \tag{2}$$

But the resulting outcome attributable to a program cannot be observed in an individual participating and not participating in the program at the same time. Therefore, the problem of program evaluation is a problem of missing data, and the program effect cannot be calculated for the same individual, but instead requires constructing a counterfactual to calculate average treatment effects across individuals in a sample from the population.

The average treatment effect on the treated, ATT, is the expected value of the outcome for those who participated in the program, conditional on the individual characteristics that determine program participation, **x**:

$$ATT = E(\tau(\mathbf{x}) \mid w = 1) = E(y_1 \mid \mathbf{x}, w = 1) - E(y_0 \mid \mathbf{x}, w = 1) \qquad (3)$$

As already mentioned, $E(y_0|\mathbf{x}, w=1)$, the expected outcome of the treated if they were not exposed to the treatment, cannot be observed directly. However, we can observe $E(y_0|\mathbf{x}, w=0)$, the expected outcome of the untreated, given that they were not exposed to the treatment. Subject to the assumption of no selection bias, in the absence of the program, those who participated in the program would have had equal outcomes to those who did not:

$$E(y_0 \mid \mathbf{x}, w = 1) - E(y_0 \mid \mathbf{x}, w = 0) = 0 \qquad (4)$$

However, if program selection has not been made randomly selection bias occurs, and individuals exposed to the treatment will systematically differ from those not exposed to the treatment. Hence, program impact appears as a consequence of these differences, distorting the measure of the benefits from the program.

Selection bias can be a consequence of difference in characteristics between participants and non-participants: Some differences can be observed by the researcher, such as housing characteristics, land allocated to agricultural production, and topographical location of fields. These characteristics are by the program, and they determined eligibility for program participation. Other differences are not observed by the researcher and can be assumed not to change over time, including such individual characteristics as motivation, cognitive learning ability, and attitudes towards innovation.

In this paper we use first difference (FD) estimation and compare its results with propensity score matching difference-in-difference (PSM-DID) and propensity score weighted regression (PSW) (Heckman, Ichimura, & Todd, 1997; Smith & Todd, 2005), to estimate program impacts. As detailed below, these methods are based on different assumptions to control for different sources of selection bias.

4.1. Propensity score based methods:

Propensity score matching (PSM) consists of choosing the comparison group according to the probability of being selected for a treatment, given a set of observable pre-treatment characteristics and outcome values that do not change with program intervention but that affect program placement. The main assumptions for propensity score matching are:

1) Unconfoundedness:

$$y_0, y_1 \perp w \mid \mathbf{x} \qquad (5)$$

where y_0 is the outcome for non-participants and y_1 is the outcome for participants, w is participation and $\mathbf{x}$ represents a set of variables that may influence participation. Program outcomes are independent of program participation, conditional on $\mathbf{x}$.

2) Mathematically, there is common support (overlap) between the probability distributions of program participants and non-participants (Caliendo & Kopeinig, 2008; Imbens & Wooldridge, 2008; Ravallion, 2008) (Eq. 6):

$$0 < \Pr(w = 1 \mid w) < 1 \qquad (6)$$

To estimate the propensity score (PS), we include a rich set of variables that determine both participation in the project and pretreatment outcomes to reduce bias in estimates (Heckman, Ichimura, Smith, & Todd, 1998).

Propensity score matching assumes that after controlling for observable characteristics, outcomes are mean independent of participation in the program. But it is likely that there are systematic differences in outcomes for participants and non-participants due to unobservable characteristics, known as bias on unobservables.

Assuming that unobserved heterogeneity is time invariant and uncorrelated with treatment assignment, we can control for this source of bias using the PSM-DID estimator defined by Smith and Todd (2005). By using the PSM-DID estimator we control for observable sources of bias by building our comparison group using PSM as well as time invariant characteristics, by taking the difference of outcomes before and after treatment. The PSM-DID estimator, defined by Smith and Todd (2005), is as follows

$$\hat{\tau}_{ATT,PSM-DID} = \frac{1}{N_1} \sum_{i \in I_1 \cap S_p} \left\{ (y_{1it} - y_{1it-1}) - \sum_{j \in I_0 \cap S_p} \varphi(i,,j)(y_{0jt} - y_{1jt-1}) \right\} \tag{7}$$

As an additional robustness check, we compare the matching estimates with the propensity score weighted (PSW) regression (Wooldridge, 2010), in the panel data context we take the difference between outcomes before and after treatment:

$$\hat{\tau}_{ATT,PSW} = \frac{1}{N} \sum_{i=1}^{N} \frac{(w_i - \hat{\Pr}(\mathbf{x}_i))(y_{it} - y_{it-1})}{\hat{\rho}(1 - \hat{\Pr}(\mathbf{x}_i))} \tag{8}$$

For equations (8) and (9) the subscripts *1* and *0* refer to treated and untreated respectively, S_p refers to the common support, *t* refers to the time period, N to the total number of observations, $\varphi(.)$ is a weight that depends on the matching method used, $\Pr(x_i)$ is the propensity score and ρ refers to the proportion of treated observations in the sample (N_1/N).

4.2. Regression based methods.

The main assumption of FD is that the unobserved differences between participants and non-participants are invariant in time. Examples would be particular individual characteristics like motivation and cognitive ability. By taking the first difference we removed time invariant unobservable characteristics. Then obtaining the first difference between periods t and t-1, the unobservable characteristics, assumed invariant in time are eliminated, correcting for this source of bias in the program impact estimation (Wooldridge, J., 2010):

$$\Delta y_{it} = \alpha_0 + \tau w_{it} + \beta \Delta \mathbf{x}_{it} + \Delta u_{it} \tag{9}$$

where $\Delta y_{it}=y_{it}-y_{it-1}$, $\Delta \mathbf{x}_{it}=\mathbf{x}_{it}-\mathbf{x}_{it-1}$ and $\Delta u_{it}=u_{it}-u_{it-1}$. We obtain the program impact by the regression of the change in the outcome variable *y* the project participation variable *w,* and the change in a set of time varying covariates *x*. The first difference equation will be consistent if $E(\Delta \mathbf{x}_{it}'\Delta u_{it})=0$. The parameter of interest is τ, when we omit Δx_{it} we obtain the difference in difference (DID) estimator.

The difference in difference estimator assumes parallel trends for both treatment and control in the absence of the treatment (Abadie, 2005). Therefore, correcting for differences between the two groups requires controlling for covariates related to household characteristics (Abadie, 2005). To take care of possible differences of covariates between treatment and control, we include some time varying household characteristics as in equation (9) for estimating program impacts.

4.3. *Heterogeneity of program impacts.*

Our study focuses on the ATT, the mean effect of a program on the treated. Yet as an overall average, the ATT can miss program impacts that vary among subsets of individuals or households. Even if our results on the program ATT for some outcomes are not statistically significant, given the wide range of interventions within A4N, households with certain characteristics might have benefited differentially. For example, the poorest groups might have benefited from most of the project interventions, or to the contrary, the better off beneficiaries might have gotten the most from the project. This analysis is conducted for different groups identified in the sample, according to a pretreatment indicator of wealth or income generating capacity. We estimate project impact on outcome y for each of group g.

5. Survey data use for evaluation of impacts.

The dataset was based on two-stage sampling of treatment and non-treatment villages, where "treatment" refers to being offered the package of interventions under the A4N project. We randomly selected villages from the list of beneficiary villages, and chose similar non-participant villages using the population and agricultural census data from Nicaragua. The sampled villages were selected according to the population weights of each of the municipalities where the project intervened. Non-participant villages were identified according to national census data on poverty levels, as measured by the index of unmet basic needs, the importance of staple crops, small landholdings (Instituto Nacional de Información de Desarrollo, 2008a, 2008b, 2008c, 2008d, 2008e, 2008f, 2008g, 2008h), and location in the same agrarian zones (Nitlapan, 2001). From each village we randomly selected 10 households in the participant villages and 10 to 15 households in the non-participant villages, depending on village size. In A4N participant villages, CRS provided lists of participating households. In non-participant villages, sample lists were developed in consultation with village leaders, who were requested to identify households that would meet the eligibility criteria of the A4N program.

A baseline survey measured livelihoods and income for the agricultural year 2008-09, before project implementation, and a follow up survey did the same for the agricultural year 2010-11, the second year after project implementation. The survey also collected information on the different technologies and practices implemented by farmers in their plots. The survey was conducted in the departments of Estelí, Jinotega and Matagalpa, located in the northeast of Nicaragua. The final balanced panel includes 578 households, 284 in participant villages and 294 in non-participant villages. The abandonment rate between the two rounds of the survey was 6%, and we did found no evidence of systematic attrition. More non-participant households were interviewed intentionally, in order to permit the trimming of observations when applying propensity score matching. A survey of village characteristics was conducted among village leaders in each of the 63 villages.

The data set was reduced from the original set of 578 observations due to dropping two outliers, for a total of 576 observations. For the PSM-DID and PSW analysis, missing data for the estimation of the PS (11 observations) and the trimming of observations with PS above 0.90 and below 0.10 (11 observations) was conducted (Imbens & Wooldridge, 2008; Wooldridge, J., 2010). The total number of observations used for the PSM-DID and PSW analysis is 554.

6. Results: A4N project impacts.

The estimation of project impacts starts with estimating the probability of participation in the project using a logit model. These estimated probabilities will later be used for propensity score matching. Balancing tests after matching are presented to measure the degree of differences between treatment and control households. Then we show the estimated impacts for intermediate outcomes related to the adoption of the technologies and practices promoted by the project. Finally, we estimate project impacts by terciles of area of cultivated land.

Project treatment effects were estimated using FD, PSM-DID and PSW. The point estimates are very similar for most of the outcomes across the methods used. We present these results showing first the regression approach with FD and compare these results with PSM-DID and PSW in order to compare regression-based method results with PS based methods results.

The FD estimation includes as control variables household size, average of years of education of household members and cultivated land[1]. Then we estimate program impacts using PSM-DID kernel Epanechnikov (kernel(epan)), nearest neighbor with replacement, using five neighbors (NN(5)), and local linear regression with the tricube kernel (LLR), to conduct sensitivity analysis of the matching results. We estimated program impact using the difference in the outcome variables before and after the project as dependent variable, for both continuous and binary

[1] We also conducted fixed effects estimation, and the results did not differ from the FD ones. Therefore we consider that violation of the strict exogeneity assumption is not a concern (Wooldridge, J., 2010).

outcomes. Treatment refers to whether the household was exposed to the package of interventions promoted by the project[2]. Before presenting the results for the average treatment effects, we present the estimation for the propensity score of probability of participating in the A4N project.

6.1. Propensity score estimation

The probability of program participation or propensity score was estimated using a logit model with the data from 272 treated and 282 non-treated households. Upon application of Dehejia and Wahba's (2002) algorithm for estimating the propensity scores, it was determined that no interaction terms and higher level terms were justified to improve the estimation, so the logit model was estimated with all covariates entering linearly.

The logit model estimates the probability of program participation (Table 1). Focusing on variables that are statistically significant (p-value less than 0.10), the A4N households were more likely to be female-headed and to have lower value of farm infrastructure but also less inadequate services as defined by the basic needs index (housing lacking piped water and where a toilet is missing). A4N households tended to be situated in villages closer to markets but with fewer large farms and less likely to have a health facility. These variables reflect some pretreatment differences between treatment and comparison households.

[2] Information on participation in other projects was collected in one of the household survey questions. To test for attribution to the A4N project of impacts that are due to other projects, we estimated the correlation of participation in A4N and participation in other development projects. We found no correlation (ρ=-0.03), so misattribution is not a concern. We also estimated DID including a dummy variable for participation in other projects and did not find this variable statistically significant.

Table 1 Here

The predicted probabilities of selection into the A4N participant and non-participant groups are presented in Figure 2. The non-participant distribution contains more observations with propensity scores below 0.6, and a disproportionate number of observations with propensity scores below 0.4. In spite of this, overlap does not seem to be a problem, and we have comparison observations to match treatment ones.

Figure 2 Here

Matching of participant and non-participant observations using according to the values of the propensity score, was conducted using STATA's psmatch2 (Leuven & Sianesi, 2012). The results for the balancing tests (Caliendo & Kopeinig, 2008; Wooldridge, J., 2010) after matching with replacement are provided in Table 2. Matching improved overlap between the marginal distributions of the covariates. As evidence, the percentage bias decreases for the covariates below the benchmark of 25% for covariate balance (Imbens & Wooldridge, 2008).

Table 2 Here

6.2. Project impacts on outcomes related to adoption of technologies and practices.

With the goal of determining whether there was a project impact in the adoption of promoted practices, the evaluation of intermediate outcomes focuses on six groups of outcomes: (1) agricultural conservation structures, (2) agricultural conservation practices, (3) post-harvest grain storage, (4) kitchen gardens, (5) saving and credit, and (6) food scarcity[3]. Table 3 presents detailed definitions of the outcomes to be evaluated. Tables 4 and 5 present the results for the average treatment effect on the treated (ATT) for the different methods use for estimating program impacts, FD, PSM-DID for kernel(epan), NN(5) and LLR matching to compare the sensitivity of estimates to different matching methods (Abadie & Imbens, 2008), and PSW regression.

Table 3. Here.

The results are robust to different estimation methods, as can be seen by the similar point estimates and levels of significance obtained for project treatment effects. Overall, our results using FD, PSM-DID and PS weighting were almost identical. This was expected because the sampling frame explicitly included a set of control villages and households for comparison with similar characteristics to the A4N ones according to poverty and population indicators. The comparison group was similar by construction to the treatment group according to observable characteristics.

[3] We did not conduct impact evaluation on the use of improved maize and beans varieties due to unreliable data on the names of the varieties planted by farmers collected in the survey.

The construction of agricultural conservation structures and the use of agricultural conservation practices for soil and water conservation increased thanks to the project, as shown in Table 4. Agricultural conservation structures represent significant investments of capital and labor with a gradual payoff. The adoption of their construction under the A4N project was measured by the change in length of rows built structures per unit of cultivated land (meters/manzana). The information was obtained with a recall question in 2011 on the length of agricultural conservation structures built over the past two years. This question was asked for each of the plots under the management of the household. On average the increase in agricultural conservation structures was 77m/Mz, measured by first differences (Table 4); the estimates for PSM-DID and PSW are similar, and all are highly statistically significant. This increase was explained mostly by the increase in area under stone barriers and terraces (24m/Mz), live barriers (16m/Mz), and ditches (7m/Mz) (Table 4).

Table 4. Here

Agricultural conservation practices included reduced tillage, vermiculture and cover crops, all three of which are much less demanding than the construction of terraces, barriers, or ditches. The adoption of practices was measured by changes in whether the household was implementing one or more of the practices promoted by A4N on at least one of the plots managed by the household. On average there was not an overall impact in the use of these practices, but there was significant substitution of minimum tillage for zero tillage. The percentage of households using minimum tillage in at least one of their plots decreased by 14%, whereas this percentage increased by 19% for zero tillage (Table 4). In addition, there was an increase in households implementing vermiculture and cover crops in at least one of their plots.

The project had a significant, positive effect on adoption of metallic silos for grain storage. On average there was an increase of 11% in the share of households using metallic silos for storage (Table 5). Presumably associated with this, the number of households that experienced stored grain losses fell by 11% to 16%, based the four estimates with p-values below 0.15. The increased use of metallic silos translated into a reduction on stored grain losses within the first two years of the A4N project, and it is possible that project beneficiaries were still in the process of learning how to best apply postharvest management practices to avoid losses. The successful adoption of these practice can lead to further reduction of losses of grain stored for consumption (Gitonga, De Groote, Kassie, & Tefera, 2013).

Table 5. Here

The project had a significant impact in the percentage of households with savings, which increased by 14% (Table 5). This is not an agricultural technology intervention, but this was a very successful intervention of the project that aimed to stabilize income flow over the year and to provide funds in times of household food scarcity. This outcome is mostly a result of the formation of saving and lending groups promoted by the project. Savings gains are likely to reduce vulnerability to asset liquidation in times of food scarcity, and consumption smoothing (Kaboski & Townsend, 2005). Savings accumulation can also be used for productive investments (e.g., in agricultural assets) (Chowa & Elliott III, 2011).

6.3. Heterogeneity if project impacts by area of cultivated land.

Continuing with the analysis of project impacts, we look at the distribution of project effects across households of varying asset levels. It is possible that even if average treatment effects for the agricultural income and household wealth related outcomes were not statistically significant, some groups benefited more (or less) than others (Khandker, Koolwal, & Samad, 2010). The sample was divided into approximate terciles using the information on the pretreatment area of cultivated land. Farmland, an important asset, is the key input for agricultural production. The first group is composed of households with less than 1.5 Mz (small area) of cultivated land, the second one with households with between 1.5 Mz and 3 Mz of land (medium area) and the third one with households with more than 3 Mz of cultivated land (large area).

Table 6 presents the estimated coefficients of average treatment effects for each of the three groups formed using the area of cultivated land in 2009. The FD, PSM-DID and PSW estimates of average treatment effects are all very similar, so for this analysis we simply report FD, for each tercile of area of cultivated land. The FD estimation uses the same explanatory variables as those included in the estimation of overall program effects: household size, average of years of education of household members and cultivated land.

Table 6. Here.

The results pointed to notable differences in impact by asset level. Households with large and medium area of cultivated land built higher densities of agricultural conservation structures, whereas households with small area were more likely to increase their use of agricultural conservation practices. On average, households with medium and large cultivated area built 41m/Mz and 74m/Mz of agricultural conservation structures (see Table 6). The implementation of agricultural conservation practices in at least one of the plots under the management of the household increased by 20% among the households with small area, and 20% of these households also increased the use of zero tillage. In contrast, 30% of households with larger area decreased their use of minimum tillage, and 19% increased the use of zero tillage (Table 6). These results are consistent with results of studies about decisions of carrying out agricultural conservation investments, which depend on access to land and labor, as well as land tenure security (Gebremedhin & Swinton, 2003), indicating that differences in household characteristics matter for household decisions of take up of project interventions.

The households with medium cultivated area are the ones most likely to increase adoption of improved grain storage practices and to experience decreased stored grain losses. A total of 30% more of medium area households experienced reduced losses of stored grain, and 16% more of these households stored grain in metallic silos (Table 6).

Households with small cultivated area were the ones to add kitchen gardens and to gain savings. The ATT for households with kitchen gardens was not statistically significant for the whole sample, but 12% more households with small land area have kitchen gardens thanks to the project (Table 6), which in turn helps to improve food security. Also these households are the ones that take advantage of the creation of savings and lending groups, with a 22% increase in households with savings.

These results suggest that household resource constraints may limit adoption of certain practices. Capital is required to undertake the investments in construction of agricultural structures, including the hiring of labor. For households with small cultivated area, practices that do not require this level of investment, such as participation in savings groups or growing small vegetable gardens, constitute practices that they are more likely to adopt.

7. Conclusion

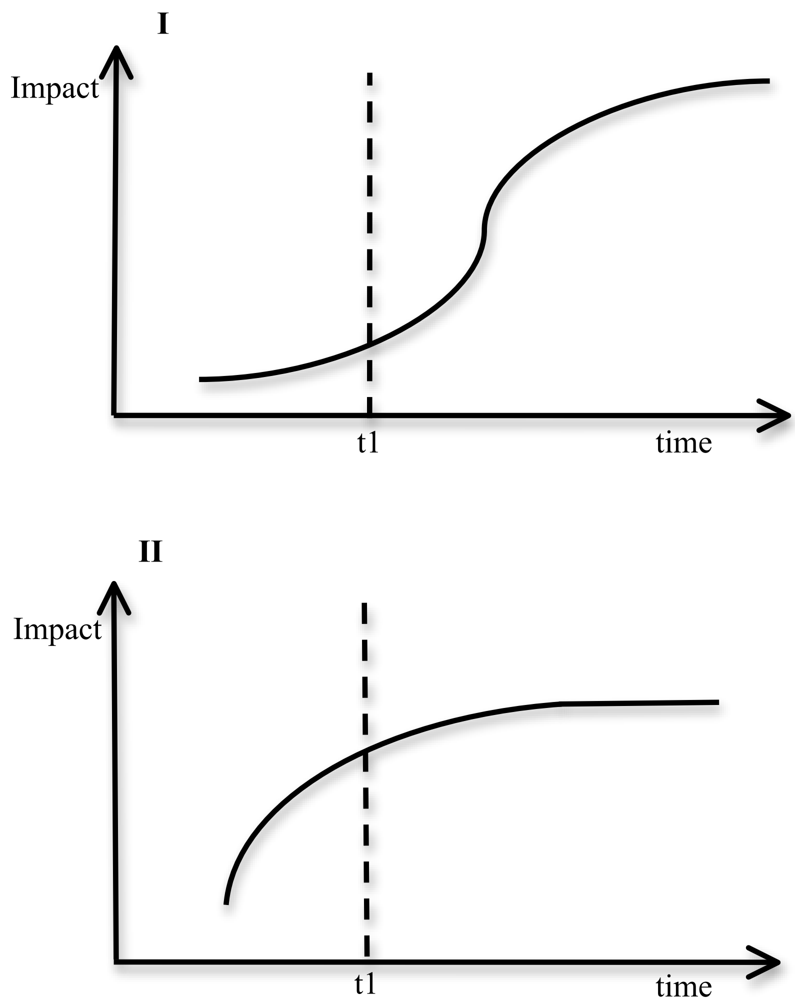
Using different methods, FD, PSM-DID and PSW, we find identical results. Stability of project impact estimates across the methods used was expected. Due to careful design of the impact evaluation with data collected of comparison households to construct a valid counterfactual for analysis.

We focused on the adoption of improved agricultural technologies to measure changes in behavior, as early indicators of project impact. We found that adoption did increase for many of the technologies promoted. If these behavioral changes are maintained over time, they are likely to translate into increases in agricultural productivity and agricultural income by several mechanisms: Investments in agricultural conservation structures and adoption of agricultural conservation practices are both likely to lead to long-term stabilization of yields. Adoption of improved storage technologies, the associated reduction in the number of households experiencing stored grain losses, and increases in households with savings should all lead to more stable, rising cash flows and reduced of risks of food scarcity and asset liquidation.

However, rates of adoption of project technologies were not the same across households of different asset levels. The analysis of project impacts by farm size reveals that they vary according to the household's area of cultivated land. Hence, the targeting of project interventions by participant asset level can increase rates of adoption of practices by tailoring interventions to household resources. Such an approach could increase project impacts for different groups of beneficiaries, instead of promoting all the interventions for all the beneficiaries—a more cost-effective strategy.

An important recommendation from this impact assessment is that the heterogeneity across project interventions of the expected time lapse before participants experience benefits should be considered both for project design and for impact evaluation. As shown here, the realization of gains for some interventions (e.g. construction of stone barriers and terraces) takes much longer than others (e.g. storage in metallic silos). Therefore, development projects that promote multiple interventions may want to set poverty relief objectives that explicitly incorporate the timing of expected benefits from adoption of specific practices. In an environment of donor impatience to see rapid impacts, such an approach would calibrate donor expectations to a realistic sequence of intermediate impacts that culminate in long-term desired outcomes.

Figure 1. Impact trajectories of different type of project interventions.



Adapted from King and Behrman (2009)

Figure 1. Estimated propensity score or probability of program participation.

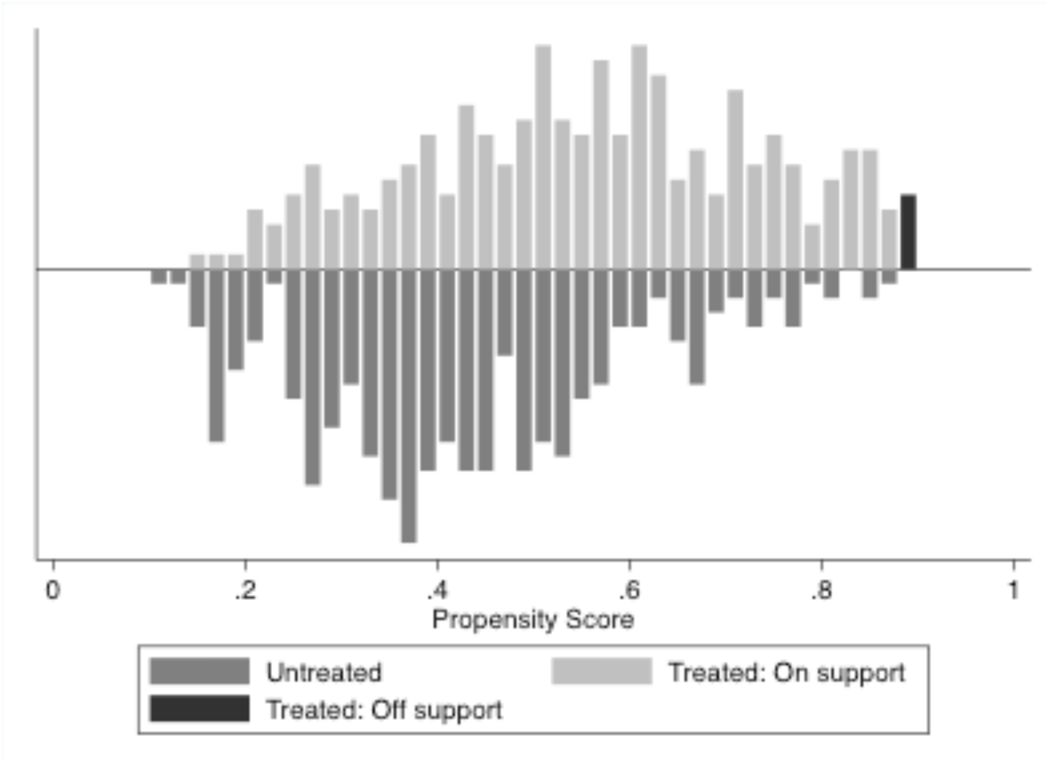


Table 1. Logit model for estimating the propensity score or probability of participation in A4N.

Explanatory variables	Coefficient	Standard errors
Farm characteristics		
Cultivated land Mz	0.03	(0.03)
Steep slope=1	0.18	(0.20)
hh characteristics		
Inadequate services=1	-0.51**	(0.22)
Inadequate housing=1	0.11	(0.29)
Electricity=1	-0.05	(0.22)
Hunger=1	0.34*	(0.20)
head female=1	1.19***	(0.31)
#children<5	0.06	(0.15)
head age	0.00	(0.01)
head education	-0.01	(0.04)
household size	-0.05	(0.06)
people per room	-0.02	(0.06)
Value of productive assets		
Infraestructure C$/1000	-0.09*	(0.06)
Livestock C$/1000	-0.02*	(0.01)
Equipment C$/1000	0.00	(0.02)
Village charcteristics		
Population 2009	0.00	(0.00)
Dist. Market Km/10	-0.05***	(0.01)
Dist. Paved road Km/10	0.02	(0.01)
Health facility=1	-0.82***	(0.26)
% basic grains 2003	-0.18	(0.63)
% lanholdings<10Mz 2003	2.25***	(0.50)
Constant	-0.20	(0.84)
Log likelihood	-345	
n	554	

Levels of significance ***1%, **5%, *10%
Standard error in parenthesis
1 Mz = 1.73 acres
U$1=C$22.42 in 2011

Table 2. Balancing tests of pretreatment covariates used for estimation of the propensity score.

	Before matching			After matching		
	Mean			Mean		
Variable	A4N	Non-A4N	%bias	A4N	Non-A4N	%bias
Cultivated land Mz	3.29	3.50	-2.68	3.32	3.37	-1.6
Steep slope=1	0.32	0.32	-25.87	0.32	0.37	-9.7
Inadequate services=1	0.66	0.79	21.39	0.67	0.66	3.6
Inadequate housing=1	0.88	0.85	60.10	0.88	0.86	4.4
Electricity=1	0.61	0.63	15.32	0.60	0.58	4.9
Hunger=1	0.39	0.32	-17.89	0.38	0.40	-4.2
head female=1	0.20	0.07	-73.06	0.18	0.22	-12.8
#children<5	0.51	0.51	-24.23	0.51	0.41	14.1
head age	49	48	68	49	49	-1.2
head education	2.83	3.04	3.13	2.84	2.79	1.7
household size	5.20	5.36	49.55	5.20	4.99	9.3
people per room	3.82	3.86	40.94	3.84	3.85	-0.6
Infraestructure C$/1000	0.52	1.48	-11.12	0.53	0.47	3.3
Livestock C$/1000	6.71	9.07	-17.33	6.80	6.08	5.7
Equipment C$/1000	1.76	2.08	-49.91	1.80	2.09	-6.2
Population 2009	637	640	16.68	645	678	-5.9
Dist. Market Km/10	14.09	16.29	38.19	14.34	14.46	-1.5
Dist. Paved road Km/10	9.53	8.95	-0.99	9.56	8.63	10
Health facility=1	0.21	0.28	-37.29	0.21	0.21	0.7
% basic grains 2003	0.86	0.88	71.93	0.86	0.87	-4.9
% lanholdings<10Mz 2003	0.59	0.52	64.34	0.58	0.54	18

1 Mz = 1.73 Acres
U$1=C$22.42

$$\%bias = \frac{(\bar{x}_{1j} - \bar{x}_{0j})}{\sqrt{s_{1j}^2 + s_{0j}^2}}$$

Table 3. Definition of intermediate outcome variables and units of measurement.

Outcome Variables	Unit	Definition
Agricultural Conservation Structures (Length built in meters between 2009 and 2011)		
All structures	m/Mz	Difference length built in agricultural conservation structures 2011-2009
Stone barriers/terraces	m/Mz	Difference length built in stone barriers and terraces 2011-2009
Live barriers	m/Mz	Difference length built in live barriers 2011-2009
Ditches	m/Mz	Difference length built in ditches 2011-2009
Agricultural Conservation Practices		
All practices	1=yes, 0=no	The household has implemented at least one cons ag practice in one of the plots under its management
Minimum tillage	1=yes, 0=no	The household has implemented minimum tillage at least in one plot
Zero tillage	1=yes, 0=no	The household has implemented zero tillage at least in one of its plots
Vermiculture	1=yes, 0=no	The household has implemented vermiculture at least in one of its plots
Cover crops	1=yes, 0=no	The household has implemented cover crops at leas in one of its plots
Storage Practices		
Household experienced stored grain losses	1=yes, 0=no	The household has experienced stored grain losses. Only for households that stored grain.
Household stored grain in metallic silos	1=yes, 0=no	The household uses metallic silos for grain storage. Only for households that stored grain
Number of metallic silos	number	Number of metallic silos owned by the household
Kitchen Garden		
hh had a kitchen garden	1=yes, 0=no	Household has a kitchen garden
Savings and Credit		
hh has savings	1=yes, 0=no	Household had savings on January 1st
hh has credit	1=yes, 0=no	Household had credit on January 1st
Food Scarcity		
hh experience food scarcity	1=yes, 0=no	Household experienced a period of the year when they could not cook one of the daily meals

hh means household
1 Mz = 1.73 acres

Table 4. Project impacts on construction of agricultural conservation structures and on agricultural conservation practices.

Difference outcome variables	FD	PSM-DID kernel (epan)	PSM-DID NN(5)	PSM-DID llr (tricube)	PSW
Agricultural Conservation Structures					
All structures m/Mz	77***	76***	75***	73***	72***
	(25)	(25)	(27)	(27)	(27)
Stone barriers/terraces m/Mz	24***	24***	23**	22**	24**
	(10)	(10)	(10)	(11)	(10)
Live barriers m/Mz	16***	17***	17***	17***	17***
	(5)	(5)	(6)	(5)	(5)
Ditches m/Mz	7***	7***	8***	7***	7***
	(3)	(3)	(3)	(3)	(3)
Agricultural Conservation Practices					
All practices[1]	0.04	-0.02	-0.03	-0.02	0.00
	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)
Minimum tillage[1]	-0.14***	-0.17***	-0.16**	-0.17**	-0.15***
	(0.05)	(0.07)	(0.08)	(0.07)	(0.05)
Zero tillage[1]	0.19***	0.19***	0.20***	0.18***	0.18***
	(0.0	(0.07)	(0.07)	(0.07)	(0.07)
Vermiculture[1]	0.05***	0.05**	0.05**	0.05**	0.04***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Cover crops[1]	0.03***	0.04*	0.04*	0.04*	0.04*
	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)

Levels of significance ***1%, **5%, *10%
NN refers to nearest neighbor, LLR to local linear regression
untrimmed sample n=567, trimmed sample n=546
A total of 265 pairs formed with PSM-DID
1 Mz = 1.73 acres
[1] For binary outcomes the difference takes values -1, 0 and 1.

Table 5. Project impacts on storage practices, kitchen gardens, savings and credit and food scarcity.

Difference outcome variables	FD	PSM-DID kernel (epan)	NN(5)	llr (tricube)	PSW
Storage Practices					
Experienced stored grain losses[1,2]	-0.16*** (0.06)	-0.11~ (0.08)	-0.07 (0.08)	-0.13~ (0.09)	-0.11~ (0.08)
hh stored grain in metalic silos[1,2]	0.11*** (0.04)	0.10** (0.05)	0.11** (0.05)	0.10* (0.05)	0.09~ (0.06)
Number of metalic silos owned	0.14*** (0.05)	0.13*** (0.05)	0.12** (0.06)	0.13*** (0.05)	0.13*** (0.05)
Kitchen garden					
hh had a kitchen garden[1]	0.04 (0.03)	0.04 (0.04)	0.04 (0.03)	0.04 (0.03)	0.04 (0.03)
Savings and credit					
hh has savings[1]	0.14*** (0.04)	0.13*** (0.04)	0.13*** (0.05)	0.12*** (0.05)	0.13*** (0.04)
hh has credit[1]	-0.01 (0.04)	-0.01 (0.05)	-0.03 (0.06)	-0.03 (0.05)	0.00 (0.05)
Food scarcity					
hh experienced food scarcity[1]	-0.06 (0.05)	0.04 (0.05)	0.05 (0.06)	0.05 (0.05)	0.04 (0.04)

[2] Correspond only to the households that stored grain, non trimmed sample n=476, trimmed sample n=460

[1] For binary outcomes the difference takes values -1, 0 and 1

Levels of significance ***1%, **5%, *10%, ~ 15%.

NN refers to nearest neighbor, LLR to local linear regression

hh means household

untrimmed sample n=575, trimmed sample n=554

A total of 265 pairs formed with PSM-DID

Table 6. Project impacts by area of cultivated land on outcomes related to adoption of practices and technologies.

	<=1.5Mz n=191		1.5<land<=3Mz n=199		>3Mz n=186	
Outcomes	**Coef**	**se**	**Coef**	**se**	**Coef**	**se**
Agricultural Conservation structures						
All structures m/Mz	111	(73)	41***	(16)	74***	(27)
Stone barriers m/Mz	3	(27)	27**	(12)	31***	(11)
Live barriers m/Mz	16	(15)	13***	(5)	18***	(7)
Ditches m/Mz	11**	(5)	4**	(2)	8	(8)
Agricultural conservation practices						
All practices[1]	0.20**	(0.09)	-0.03	(0.08)	-0.06	(0.06)
Minimum tillage[1]	-0.08	(0.09)	-0.05	(0.09)	-0.30**	(0.09)
Zero tillage[1]	0.20**	(0.08)	0.15	(0.08)	0.19*	(0.08)
Vermiculture[1]	0.05**	(0.03)	0.02	(0.02)	0.08*	(0.04)
Cover crops[1]	0.03	(0.02)	0.02	(0.02)	0.03	(0.02)
Storage Practices						
Stored grain losses[1]	-0.06	(0.12)	-0.28***	(0.09)	-0.12	(0.09)
Stored in metallic silos[1]	0.06	(0.06)	0.15**	(0.06)	0.10	(0.08)
Number of metallic silos owned	0.07	(0.07)	0.16**	(0.07)	0.21*	(0.10)
Kitchen garden						
hh has a kitchen garden[1]	0.12**	(0.05)	-0.02	(0.04)	0.02	(0.05)
Saving and credit						
Saving[1]	0.22***	(0.07)	0.08	(0.06)	0.09	(0.08)
Credit[1]	0.10	(0.07)	-0.03	(0.07)	-0.13	(0.09)
Food scarcity						
Experienced period of hunger[1]	-0.03	(0.08)	-0.06	(0.08)	-0.08	(0.08)

[1] For binary outcomes the difference takes values -1, 0 and 1

1 Mz = 1.73 acres

hh means household

Note: the total sample of 576 observations was divided in terciles, and for each tercile there was an approximate equal share of treatment and comparison observations.

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