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The Impact of Farmer-Field-Schools on Knowledge and Productivity: A Study of Potato Farmers in the Peruvian Andes[1]

by

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Using survey-data from Peru, this paper evaluates the impact of a pilot farmer-field-school (FFS) program on farmers' knowledge of integrated pest management (IPM) practices related to potato cultivation. We use both regression analysis controlling for participation and a propensity score matching approach to create a comparison group similar to the FFS participants in observable characteristics. Results are robust across the two approaches as well as with different matching methods. We find that farmers who participate in the program have significantly more knowledge about IPM practices than those in the non-participant comparison group. We also find that improved knowledge about IPM practices has a significant impact on productivity in potato production.

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I. Introduction

The design of agricultural extension programs in developing countries has been the subject of heated debate. Guided by these debates, extension services have undergone several transformations in the past few decades (Byerlee, 1994). The main transformation, until recently, was a shift from the transfer-of-technology approach to the Training-and-Visit, or T&V, system. Under T&V, the extension system was reoriented from a desk-bound bureaucracy with multiple economic and social objectives to a field-based cadre of agents who focused mainly on technology diffusion (Picciotto and Anderson, 1997). T&V extension agents would meet with a small group of "contact" farmers who were expected to disseminate information to the members of their respective communities and convey farmer's opinions back to the agents, thus creating a feedback mechanism absent in the prior system (Birkhaeuser, et al, 1991). For nearly three decades, international aid donors, such as the World Bank, promoted T&V as the most cost-efficient extension system.

T&V did, however, have its critics. With continued budgetary crises of less developed countries, some argued that it was too expensive and impossible to implement over extensive regions. Highly dispersed farmers could never establish frequent contact with extension agents. And their needs varied widely and could not be addressed with a single, inflexible technology package (Picciotto and Anderson, 1997; Feder, Willett, and Zijp, 2001).[2]

In recent years, a number of development agencies have promoted farmer field schools (FFS) as a potentially more effective approach to extend knowledge to farmers. FFS programs were first introduced in East Asia, in the late eighties, as a way of diffusing knowledge-intensive integrated pest management (IPM) practices for rice.[3] FFS have since been adapted to work with other crops and diseases, and have spread rapidly across Asia, Africa, and Latin America (Nelson et al., 2001). The FFS approach represents a paradigm shift in agricultural extension: the training program utilizes participatory methods "to help farmers develop their analytical skills, critical thinking, and creativity, and help them learn to make better decisions" (Kenmore, 2002). Extension agents, who are viewed as facilitators rather than instructors, conduct learning activities in the field on relevant agricultural practices. Through interactive learning and field-experimentation, FFS programs teach farmers how to experiment and problem-solve independently, with the expectation that they will thus require fewer extension services and will be able to adapt the technologies to their own specific environmental and cultural needs (Vasquez-Caicedo et al., 2000). Participants are encouraged to share their knowledge with other farmers, and are sometimes trained to teach the courses themselves, thus reducing the need for external support.

FFS are costly undertakings, making a careful measurement of their impact important. However, empirical evidence on their effectiveness has been mixed. Results of previous impact evaluations have varied greatly according to the setting, the evaluation methods, and the yardstick used to assess impact. The few studies that

[2] An abundance of empirical research exists on the effectiveness of T&V. See Birkhaeuser et al. (1991) for a review of studies on the economic impact of these and other agricultural extension programs.
[3] IPM is knowledge-intensive because in order to effectively implement IPM – which employs natural predators to combat pests – farmers must be able to understand the origins, cycles, and natural enemies of pests.

examine the impact of FFS on farmers' knowledge generally find that FFS participants tend to have higher knowledge test scores after program participation or relative to a group of non-participants.[4] Some studies show that FFS participants use less pesticide and have higher yields compared to non-participants, while others find little evidence of impact on these outcomes. At the same time, there appears to be little evidence of diffusion of knowledge from FFS graduates to other farmers.[5]

A major drawback of most previous studies is that they do not properly control for potential differences between FFS participants and farmers in the comparison group, making it difficult to draw definitive conclusions. These differences could arise from the non-random placement of the program or from the voluntary nature of participation in FFS. For example, FFS villages might be chosen for their relative advantages in land fertility or climate. Or farmers who voluntarily participate in FFS might be more productive, on average, than those who do not participate. Selective placement (through individual choice or purposive targeting) means that data on non-participants does not reveal well the likely achievements of participants in the absence of the program. Unless proper account of non-random farmer and village selection is taken, comparison of outcomes between FFS participants and non-participants is likely to yield biased estimates of program impact.[6]

This paper uses data from a survey of potato farmers in Cajamarca, Peru, to examine the impact of a pilot FFS program on farmers' knowledge (as measured by a knowledge test score) and the impact of knowledge on productivity. To deal with selection bias, we use propensity score matching (PSM) methods to build a statistical comparison group of farmers comparable to FFS graduates. This allows us to ensure that bias in the impact estimate due to selection on observables is minimized. Any remaining bias in the matching estimator can thus be attributed to unobserved characteristics. That said, our application is well suited to PSM since the design of the program in Peru entailed considerable rationing of participation. The sample of non-participants is very likely to include people who wanted to participate but were unable to do so due to the non-availability of the program. Matching methods have been quite widely used in evaluations but there have as yet been no applications of matching to the assessment of agricultural extension programs.

Our empirical results indicate that farmers who participate in the program have significantly more knowledge about IPM practices than those in the non-participant comparison group. We also find that improved knowledge about IPM practices has a significant impact on productivity in potato production. Combining these results, we estimate that FFS participation can raise the average potato seed output/input ratio by a large amount, approximately 52% of the average value in a normal year. We should note that since the survey was conducted in the first year of program implementation, we do not attempt to assess the extent of knowledge diffusion to non-participants.

The paper proceeds as follows. Section II describes the FFS program in Peru and the data set. Section III examines how farmers obtain information on potato cultivation, and their knowledge levels. In Section IV, we

[4] See for example, Rola et al. (2002) in the Philippines, Van de Fliert et al. (1999) in Indonesia, and Preneetvatakul and Waibel (2002) in Thailand.
[5] For a summary of these studies, see Feder et al., (2003).

present the research strategy used to test the impact of FFS on knowledge. Sections V and VI apply this methodology to measure impact on knowledge. Finally, Section VII estimates how knowledge affects productivity levels in potato cultivation and Section VIII concludes.

II. The Program and Data

As the home country for the headquarters of the International Potato Center (CIP), one of the CGIAR centers, Peru has long been a focal point for the development and deployment of improved potato varieties and cultivation practices. In 1998, CIP scientists, in collaboration with CARE-Peru, launched a pilot farmer field school program for potato farmers in the department of Cajamarca. This department lies in the northern part of the Peruvian Andes, which is known as the Green Andes. Unlike the dry flatlands of the Altiplano, the Green Andes are characterized by steeply sloped, hilly terrain with relatively higher precipitation levels. The elevation of the survey region ranges from 9,000 to 12,000 feet above sea level. The economy in the survey region is dominated by small farms with potato farming as the main activity. Potatoes constitute the bulk of households' food consumption and are also their most lucrative market crop.

The main aim of the FFS program was to introduce IPM techniques to Andean potato farmers. FFS participants were expected to attend 12 training sessions (typically once a week, with each session lasting for 3 hours). As the training strategy was based on the principle of learning by discovery, during these sessions the facilitator would organize various activities and experiments that the farmers could implement themselves. The curriculum was focused on the biology of late blight, the fungus that caused the Irish Potato Famine and continues to take huge tolls on potato production in Peru. Farmers were taught its symptoms, its reproductive cycle, its contamination source, and the conditions that foster its growth. On the experimental plot (one per FFS community), they identified potato varieties that are resistant to late blight infection. They learned how to prevent and control late blight with the use of improved varieties and fungicides. The program also introduced IPM for the Andean potato weevil and the potato tuber moth in less detail.

There was a two-stage selection process that determined which farmers could participate in the program. First, CARE selected the villages in which to introduce the FFS program. These villages were chosen from a set of villages where CARE had already been implementing another rural development project named "Andino". This project worked with farmers groups to improve farm production by providing technical advice and access to credit, and by facilitating links to markets. Technical advice in Andino was imparted through conventional transfer-of-technology approaches. The Andino villages (and consequently, the FFS villages) were not a random sample of villages in the region. Rather, CARE had conducted a diagnostic survey of all communities within the watershed, and based on this survey, classified communities into three types: subsistence, middle income, and high income. The target population for the Andino program was the set of middle-income communities and, from this target group, 20 villages that were close to their respective district capitals were selected for participation. CARE planned

[6] The only study that properly controls for selection biases finds no evidence of FFS impact (Feder et al., 2003).

to introduce FFS in all the Andino villages. However, at the time of the survey, field schools were operating only in four. These four villages constitute our 'treatment villages'.

Within the FFS villages, all farmers were invited to participate in the program. The only requirement imposed on participants was that they had to attend all the training sessions. In reality, although the call for participation was open to all community members, pre-existing groups took advantage of their already-existing organization and formed an FFS group. As a result, a number of FFS participants were also participants in other farmer groups such as Andino. However, because of limits on the number of participants permitted in each school, the participation rate in FFS remained very low during the first year of implementation, with only 45 farmers out of a population of 900 (or 5% of the farmers) participating in the program. Similar low participation rates of 2.5% are observed for the Andino program in villages where it is offered.

The main objective of this paper is to analyze the impact of FFS on knowledge by contrasting FFS participants to a matched control group of non-participants in either the FFS or the Andino program. A secondary objective is to analyze the impact of Andino on knowledge by contrasting Andino participants to the same group of non-participants. Because we have a large group of non-participants, these two tests of impact can be performed. We are, however, limited by the small number of observations in testing the difference in impact on knowledge between FFS and Andino. We report information on descriptive statistics comparing the gains in knowledge achieved under the two programs, conduct statistical analysis of the impact of each program, and describe the differences in impact on knowledge, but do not have enough degrees of freedom to expect to achieve significance in comparing these two levels of impact. For this reason, we report in detail results on the impact of FFS but only secondarily on the impact of Andino.

The data for our analysis come from a 1999 survey of potato farmers in thirteen communities within the province of San Miguel located in the Department of Cajamarca. Ten of the thirteen villages included in the sample are among the CARE Andino villages, including the four villages that were selected as FFS villages at the time of the survey. The sample includes all of the FFS and Andino participants and a random sample of non-participant farmers from (a) the four villages that have FFS programs, (b) six villages which have experience with CARE through Andino but do not have farmer field schools, and (c) three control villages. The control villages were chosen to be similar to the FFS villages in observable characteristics such as agro-climatic conditions, distance to district capitals, and infrastructure. The distribution of households in the three types of villages is reported in Table 1.

Table 1. Sample of Households

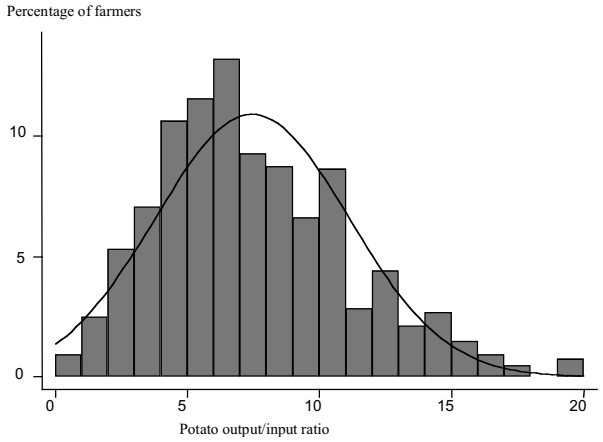
	CARE villages with FFS program	CARE villages with Andino program	Non-CARE villages	Total
FFS participants	45	0	0	45
Work with CARE, non-participants in FFS	9	62	2	73
Do not work with CARE	39	181	148	368
Total number of households in sample	93	243	150	486
Total number of households in villages	900	2337	1278	4515
Villages	4	6	3	13

The survey was carried out over two household visits. The first visit gathered detailed plot-level data, including the costs and quantities of seed, chemical, and labor inputs for each agricultural activity (from land preparation through harvest) during the year preceding the survey. It also included a knowledge test, which was based on the curriculum of the FFS. The second visit collected information on each household member's education level and marital status, off-farm activities and credit sources, and the household's experience with agricultural and other extension services. The second visit also included a full household consumption recall for the last year and an itemized account of all household and farm assets.

Examination of the potato output-seed ratio (the quantity of seed harvested divided by the quantity of seed planted per hectare) in the sample suggests that the survey was conducted in a 'normal' year (see Figure 1).[7] According to potato experts, in Cajamarca, the distribution of output-seed ratios in Figure 1 is typical for the region. A ratio of 1-3 is very bad, 4-6 is bad, 7-9 is regular, 10-15 is good, and greater than 15 is excellent. The average output ratio for the sample was 7.6 with a standard deviation of 4.2. Thirty-eight percent of the plots had productivity levels rated as bad or very bad. While 'normal', the wide dispersion in the output-seed ratios also illustrates the tremendous variation in productivity levels in the sample villages. This is the variable that we will use to measure the impact of knowledge on productivity.

[7] Tuber scientists call this measurement the multiplication ratio. It is one of the two most commonly used productivity measures, the other measure being yield estimates based on harvest sampling (Terrazas, et. al, 1998).

Figure 1. Histogram for Potato Output/Input Ratios



Part of the variation in productivity arises from production losses due to late blight, as is evident in Table 2 which shows the primary causes of production losses by plot during 1998, as reported by farmers in the sample. It illustrates the need for a curriculum with a heavy emphasis on late blight. Although this was not a wet year, 47% of the potato plots in the sample experienced losses due to late blight. 19% experienced losses from frost. The Andean potato weevil, the potato tuber moth, and hail were not critical problems in the year the survey was conducted.

Table 2. Agricultural Losses Caused by Common Pests and Weather Conditions

Source of stress	Late blight	Andean potato weevil	Potato tuber moth	Frost	Hail
% of plots affected	47.1	5.4	1.0	19.3	1.4
% of plots with 0-25% loss	31.9	3.8	1.0	7.0	1.4
% of plots with 26-50% loss	10.8	1.6	0	6.9	0
% of plots with 51-75% loss	3.0	0	0	2.8	0
% of plots with 76-100% loss	1.4	0	0	2.6	0

III. Information Channels and Knowledge Levels

Before evaluating the impact of FFS on farmers' knowledge of IPM practices, it is useful to examine how farmers in San Miguel typically obtain information on potato cultivation. The questionnaire requested farmers to name their primary sources of information on a number of tasks related to potato cultivation. Table 3 summarizes these results. The majority of farmers get information on potato farming from family members. Farmers seek information on new technologies, such as new varieties and pesticides and fungicides from other neighbors in the community. Given the traditional, rural environment, this makes sense. Using data from several surveys in India,

Foster and Rosenzweig (1995) note that information from neighbors on new technologies was as important as information from government extension services. In their study in Northern India, Feder and Slade (1986) also note the extensive role of discussions among farmers as a main source of agricultural advice. Ortiz and Valdez (1993) found a similar role for neighbors for information in other Cajamarca communities. Agricultural economists working in developed countries have also noted this phenomenon (Birkhaeuser et al., 1991). For the selection of improved varieties and the control of pests and diseases, which are more technical issues, farmers not only cite family members and neighbors as their primary sources of information, but also CARE (either FFS or conventional training) as an important source. Feder and Slade (1986) similarly found that farmers in their sample are more likely to seek information on complex agricultural practices from agricultural extension agents.

Table 3. Sources of Information on Potato Cultivation (% of farmers who use the source)

Source of information	Family member	Neighbor in the community or a nearby community	Sharecropping partner	Merchant / At the market	CARE	Other NGO	Radio	Own Experience
Agronomic practices								
Soil preparation	96	3	0.0	0	0	0	0	2
Planting	96	4	0.7	0	0	1	0	1
Fertilizing	92	8	1	0	1	1	0	3
Weeding and uphilling	94	4	5	0	0	0	0	3
Seed selection	88	8	1	0.5	1	1	0	0
Technical issues								
Improved varieties	52	34	1	6	6	1	2	2
Pesticide/fungicide use	73	24	2	3	1	2	1	5
Late blight control	71	23	2	2	2	3	0	7
Andean potato weevil control	28	9	0.7	1	1	2	0	5
Potato tuber moth control	15	3	0	2	0	1	0	2

Sources do not sum to 100% since respondents were permitted to list multiple sources

How accurate is the knowledge that farmers share with one another? The questionnaire included a test, designed by CIP extension experts, of farmers' knowledge about the control of the three major pests – late blight, the Andean potato weevil, and the potato tuber moth. Farmers were asked how to identify the pest and its cause, how it reproduces, and how to control it. For late blight, farmers were also asked what fungicides are used to control it, how to differentiate categories of pesticides in general and of fungicides in particular, and to name resistant varieties. Finally, farmers were asked how they select pesticides/fungicides, whether they could identify the meaning of different warning labels on the pesticides, and what precautions they take in applying and storing the agro-chemicals. The scores for each topic category are presented in Table 4. In general, they are very low, with average scores that do not exceed twenty-five percent of the total score.

This low level of knowledge about important agricultural problems and solutions is what motivates several NGOs to provide agricultural extension services to farmers in Cajamarca and throughout Peru. CARE-Peru works extensively in the Cajamarca region to disseminate information on new technologies through conventional transfer-

of-technology agricultural extension programs (Andino) and through experimental extension programs, such as FFS. Table 4 compares test scores of the farmers who participate in the FFS and Andino programs with farmers who do not participate in any program. Farmers who participate in the FFS have significantly higher scores on tests in every area. Farmers who worked with the Andino program also score significantly higher on the tests. Finally, FFS participants have higher scores than Andino program participants overall and in all test scores but one.

Table 4. Agricultural Knowledge Test Score Comparisons Across Groups of Farmers

	All households	FFS participants	Andino participants	Non-participants[1]	P-value difference FFS vs. Andino
Number of observations	486	45	64	329	
Test scores: % of maximum score					
Knowledge on late blight	24	35	29	24	0.06
Knowledge on Andean weevil	10	25	14	9	0.02
Knowledge on potato tuber moth	6	15	17	6	0.60
Pesticide knowledge	21	29	25	21	0.04
Knowledge on resistant varieties	17	49	33	16	0.00
Total test score	19	34	26	19	0.00

[1] All differences between FFS and non-participants and between CARE and non-participants are significantly positive at 1%.

IV. Empirical Approach

The purpose of the estimation that follows is to measure the impact of FFS on knowledge levels of those who participated in the program. This is the Average Treatment Effect on the Treated (ATE_1), where the treatment is participation in the program. The empirical problem we face is the typical one of filling in missing data on the counter-factual: what would knowledge levels of FFS participants have been if they had not participated in the program? Our challenge is to identify a suitable comparison group of non-participants whose outcomes, on average, provide an unbiased estimate of the outcomes that program participants would have had in the absence of the program. Given the non-random selection of program villages and farmer self-selection, simple comparisons of knowledge levels between participants and non-participants would yield biased estimates of program impact.

Based on program design, there are three potential sources of bias in measuring program impact. First, FFS participants are likely to differ from non-participants in the distribution of their observed characteristics, leading to a bias from "selection on observables". Such a bias is likely to arise because the criteria used for FFS village selection (e.g., distance to the district capital) and participant selection can also be expected to have a direct effect on knowledge levels even in the absence of the program. We control for selection on observables in two ways. First, in the sample design, non-FFS villages were purposively selected to be similar to the FFS villages in terms of observed characteristics such as agro-climatic conditions, prevalence of potato farming, distance to the provincial capital, etc. Table 5 reports average characteristics of households from FFS and non-FFS villages, including

demographic characteristics, assets, whether farmers are credit constrained[8], and a measure of the severity of the El Niño shock endured the year before the survey (fraction of the plots that were not harvested because of El Niño damage). It shows that the equality in means cannot be rejected for all but one characteristic. Second, as described below, we use both regression and propensity score matching (PSM) methods to control for differences in observed characteristics between FFS participants and non-participants. These approaches provide an unbiased measure of program impact under the assumption of conditional mean independence, whereby pre-program outcomes are independent of participation given the variables used as controls in the regression or for matching. The fact that the FFS were part of a small pilot program makes it more likely that this assumption would be true: the sample of non-participants very likely includes farmers who wanted to participate but were unable to do so due to the non-availability to them of the program.[9]

Table 5. Comparison of Household Characteristics in Villages With and Without FFS

	Farmers in FFS Villages Mean value	Farmers in Non-FFS Villages Mean value	P-values for equality of means between villages
Number of Observations	93	393	
Education of household head (years)	2.4	2.4	0.78
Age of household head	46.0	44.8	0.62
Number of family members	4.8	5.3	0.13
Dependency rate	1.1	1.1	0.99
Total land ownership (10 hect.)	0.12	0.11	0.66
Value of cattle assets (100 soles)	6.1	5.0	0.46
Number of inherited livestock	0.11	0.44	0.02
Value of household assets (100 soles)	1.3	0.6	0.47
Value of farm assets (100 soles)	0.43	0.47	0.45
Plots lost from El Niño the previous year	0.32	0.25	0.31
Credit Constrained	0.31	0.25	0.42

Exchange rate in 1999: 100 soles ≈ US$ 30.

A second source of bias in program impact can arise if there is diffusion of knowledge in FFS communities. In the presence of diffusion, comparing FFS participants with non-participants in the same village is likely to underestimate program impact. Because the program had been in operation for only one year at the time of the survey, the extent of diffusion is likely to have been low. In any event, to avoid all bias from potential diffusion within FFS communities, we exclude non-participants in FFS communities from the comparison group. Hence, the

[8] Farmers were categorized as credit constrained if they answered that they did not currently have a loan because they did not have access to, or did not have a guarantee for, loans from both formal banks and NGOs. There were no farmers who are currently receiving loans who responded that they could not obtain more and hence should be categorized as credit constrained.

[9] In the area that we observed, FFS was a small-scale program, with a very low participation rate (5% of the farmers in FFS villages). If it were the case that all farmers that did not participate in the program were genuine non-participants in the sense that they would not participate even in a fully developed program, then the average treatment effect of the presence of a Farmer Field School in a village could be obtained by dividing the average treatment effect on participants by the rate of participation. On the other hand, if the very low participation rate in the program was largely due to the fact that the program itself could not expand and hence was not introduced with the same level of information as a full fledged program, this calculation would lead to a large downward bias of the impact of a fully developed program.

sample that we retain $\{P(FFS) + nonFFS\}$ includes FFS participants (P) from the FFS villages and non-FFS villages farmers (excluding the participants to the Andino program).[10]

A final source of bias is that FFS participants may differ from non-participants in the distribution of unobserved characteristics (e.g., in farming ability that affects both the decision to participate in FFS and the desire to seek out new knowledge), resulting in "selection on unobservables". In the absence of a suitable instrument for program participation, we are unable to explicitly control for selection on unobservables. However, following Altonji, Elder, and Taber (2002), we use an informal way of assessing the potential bias that could result from unobservables and find that this bias is likely small compared to the estimated impact.

The assumptions underlying the above discussion can be formally expressed as follows:

Assumption 1. Stable Unit Treatment Value (SUTV) in the retained sample (*excluding non-participants from the FFS villages*)

This assumes that the treatment only affects the outcomes of those who participate, i.e., there is no diffusion of knowledge from FFS participants to control farmers in non-FFS villages.

Assumption 2. Ignorability of treatment (participation in FFS): Conditional on observed village and individual characteristics x_v, x_i, *outcomes* (y_0, y_1) *and participation w are independent.*

This assumption implies the weaker conditional mean independence:

$$\mathrm{E}(y_0|x_v, x_i, w) = \mathrm{E}(y_0|x_v, x_i) \quad \text{and} \quad \mathrm{E}(y_1|x_v, x_i, w) = \mathrm{E}(y_1|x_v, x_i), \tag{1}$$

where y_0 and y_1 are the outcomes of interest (farmers' knowledge) without and with participation in the FFS program, w is a binary indicator of participation, and x_v, u_v, x_i, and u_i denote observed and unobserved village and individual characteristics, respectively.

These two conditions allow us to build a statistical comparison group for FFS participants with similar farmers from the non-FFS villages, and to estimate the impact of the FFS program by comparing the observed outcome y_1 of FFS participants with the outcome y_0 of farmers in the comparison group. We use two different estimators.

4.1. Estimation by regression

The first method is based on assuming a parametric expression for the conditional mean independence (1):

$$\mathrm{E}(y_0|x) = \alpha_0 + (x - \bar{x})\beta_0$$

and $$\mathrm{E}(y_1|x) = \alpha_1 + (x - \bar{x})\beta_1$$

where x is the vector of covariates (x_v, x_i) with average value $\bar{x}$.

[10] Note that this assumes that there is no diffusion from FFS farmers to farmers in non-FFS villages, which seems reasonable

This gives the expected knowledge outcome y conditional on a given set of covariates as:

$$\mathrm{E}(y|x,w) = \mu_0 + \alpha w + x\beta + w(x-\bar{x})\gamma\,. \tag{2}$$

where $y = (1-w)y_0 + wy_1$ is the observed outcome (equal to y_1 for participants and y_0 for non-participants). Subtracting the average values $\bar{x}$ from the covariates x ensures that the coefficient α is the average treatment effect. Since the regression of y on $x, w, w(x-\bar{x})$ consistently estimates the parameters, we can derive an estimate of the conditional average treatment effect:

$$\widehat{ATE}^{Reg}(x) = \hat{\alpha} + (x-\bar{x})\hat{\gamma},$$

which can be averaged over the sample of participants, or any other group of farmers. In particular, $\hat{\alpha}$ is an estimation of the average treatment effect over the sample population, and the average treatment effect on the treated is estimated by:

$$\widehat{ATE}_1^{Reg} = \mathrm{E}\left(\hat{\alpha} + (x-\bar{x})\hat{\gamma}\,|\,w=1\right).$$

4.2. Estimation by matching on probability propensity scores

This method, developed by Rosenbaum and Rubin (1983), is based on modeling the probability of treatment given covariates, called the probability propensity score (PPS):

$$p(x) \equiv \mathrm{P}(w=1|x).$$

Suppose that two agents from the population have identical PPS. Then under the ignorability condition, the average treatment effect, conditional on the PPS, is equal to the expected difference in the observed outcomes between participants and matched non-participants:

$$\mathrm{E}\left(y_1 - y_0 | p(x)\right) = \mathrm{E}\left(y|w=1, p(x)\right) - \mathrm{E}\left(y|w=0, p(x)\right).$$

Averaging over the distribution of propensity scores in the treated population gives the average treatment effect on the treated:

$$ATE_1^{PSM} = \mathrm{E}\left[\mathrm{E}\left(y|w=1, p(x)\right) - \mathrm{E}\left(y|w=0, p(x)\right)\Big|\,w=1\right].$$

Implementation of this method relies on having an estimator for the PPS, which we discuss in the next section.

V. Estimation of the probability propensity score

While estimation of the average impact effect is done in the population that excludes the non-participants from the FFS villages because of the required SUTV assumption, this need not be the case for the independent estimation of the PPS. In fact, it is within the FFS villages that we have a better identification of the covariates that

given the limited time that had elapsed between training and the date of the survey.

determine FFS participation, since farmers in these villages were all, to a certain extent, given the opportunity to participate.

Using the sub-sample $\{FFS\}$ of farmers living in the FFS villages, we estimate a flexible probit model of participation, where covariates and various functions of these covariates are introduced. The estimated model can be used to predict $p(x)$ for the population $\{P(FFS) + nonFFS\}$ used for the estimation of the average treatment effect. As farmers from the non-FFS villages are not included in the estimation of the propensity score, this constitutes an out-of-sample prediction. Its validity relies on the existence of sufficient overlap of the covariates, and on the assumption that the same participation model would apply in both samples were all villages offered the FFS program. The latter is an assumption of ignorability of the choice of village for participation.

Assumption 3. Ignorability of the selection of FFS villages for participation choice: *Conditional on observed village and individual characteristics* x_v, x_i, *the choice of villages for the placement of an FFS and participation w are independent*.

This assumption implies conditional mean independence:

$$\mathrm{P}\left(w = 1 \middle| x_v, x_i, \text{presence of FFS}\right) = \mathrm{P}\left(w = 1 \middle| x_v, x_i\right).$$

The results for the probit on FFS participation are reported in Table 6. They show the importance of age, the number of family members in a household, and wealth (land and household assets) in influencing FFS participation. The correlation of FFS participation with the availability of labor in the household was corroborated by farmers during our fieldwork: many non-participants cited the lack of time and availability of labor as their main constraint in participating in the FFS program. In order to improve the prediction of treatment assignment (critical to matching methods), the model is intentionally over-parameterized, using many variables and quadratic terms.

Table 6. Farmer Field School Participation Probit
Dependent variable: participation (0/1)

	Coefficient	*p* -value
Education of household head	-0.74	0.18
Quadratic term for education	0.20	0.14
Age of household head	-0.02	0.05
Number of family members	0.21	0.02
Dependency rate	-0.27	0.32
Total land ownership (10 hect.)	0.70	0.03
Quadratic term for land ownership	1.05	0.41
Value of cattle assets (100 soles)	0.01	0.76
Number of inherited livestock	0.00	1.00
Value of household assets (100 soles)	0.22	0.00
Quadratic term for household assets	-0.01	0.00
Value of farm assets (100 soles)	0.24	0.66
Quadratic term for farm assets	-0.23	0.21
% of losses from El Niño	1.61	0.12
% of losses from El Niño squared	-2.21	0.00
Credit constraint	0.16	0.69
Constant	0.12	0.84
Number of observations	93	
Pseudo-R^2	0.18	

Prediction Table:

	Non-participant	Participant	
Predicted non-participant	40	20	60
Predicted participant	8	25	33
	48	45	93

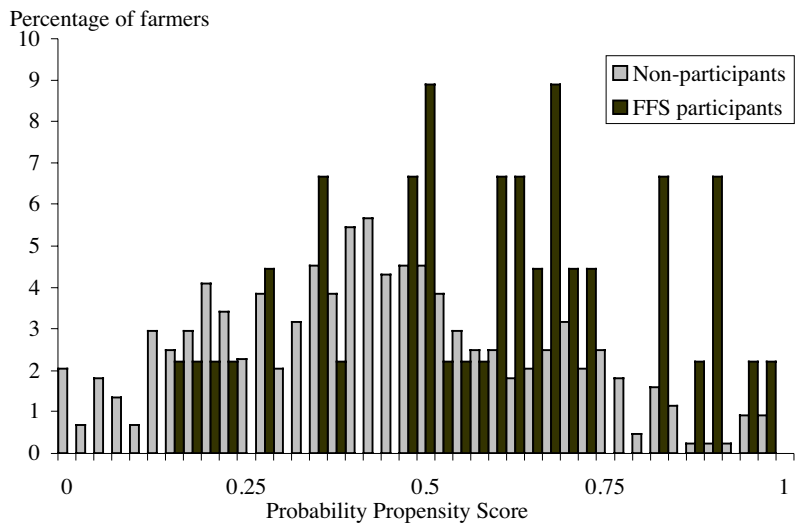
Correct prediction rate: 70%

A similar procedure (results not reported) was applied to participants of the Andino program. Prediction of participation, with 62 observed participants and 181 non-participants, has a 65% correct prediction rate. The same variables are significant in explaining participation as in the FFS prediction. The only qualitative difference is age which acts negatively in FFS participation and positively in Andino participation, which is telling of the difference between the two approaches and who might benefit most. Education is insignificant in both cases.

These parameters are used to predict the probability of participationg $p(x)$, or PPS, for the sample $\{P(FFS) + nonFFS\}$ which is then used to match FFS participants with observationally similar non-participants. Different rules of thumb could be applied to define what constitutes an observationally similar group of non-participants. Smith and Todd (2000) demonstrate that program impact estimates calculated using PPS methods are highly sensitive to which method is used, but robustness can be improved by restricting matches only to those participants and non-participants who have a common support in the distribution of propensity scores. Therefore, we derive impact estimates by applying the common support condition and further check robustness by using three different methods for selecting matched non-participants.

The distributions of propensity scores for FFS participants and non-participants are plotted in Figure 2. The distribution with the darker bars is the distribution of $p(x)$ for participants. For the purpose of matching, observations with very low or very high values of $p(x)$ are eliminated, as they may indicate a true value of 0 or 1. Observations outside the support of the two distributions of $p(x)$ for participants and non-participants were also excluded from the analysis. Fifty-one observations among the non-participants were dropped in total.

Figure 2. Histogram of Probability Propensity Scores for FFS Participants and Non-participants



The first method for constructing a matched comparison group involves choosing a propensity score cut-off point, above which all households are included in the comparison group (Revenga et. al., 1994). There are no strict rules on how to choose a cut-off point, and this is often arbitrary. We will use as a threshold the average PPS (0.60) among participants. The second method assembles a comparison group by matching each program participant with the five non-participants who have the closest $p(x)$ (Jalan and Ravallion, 2003). The crucial component of this second method is to include non-participants with scores that are close to the participants' scores. We restricted matches to those within a 0.01 PPS distance from the FFS participant. After eliminating matches that were not within this range, the mean difference between matches was 0.005, with a maximum of 0.0099.[11] Finally, the entire sample of non-participants (within the common support) can be used to construct a weighted match for each participant. We use the non-parametric kernel regression method proposed by Heckman, Ishimura, and Todd (1998) for this construction.

A "balancing test" reveals whether the comparison groups created with these techniques sufficiently resemble the treatment groups by testing whether the means of the observable variables for each group are significantly different (Smith and Todd, 2000). For the first and second methods, the balancing test was performed

by dividing each comparison and treatment group into two strata, ordered by probability propensity scores. Within each stratum, a t-test of equality of means in the two samples of participants and non-participants was conducted for each variable included in the probit on farmer participation. The results of these tests are reported in Table 7. The null was not rejected for all but two and three variables, respectively, for the two methods. For the third method, we test for the equality of means in the samples of participants and their (weighted) matches. The null was not rejected for all but two variables at the ten percent level. Overall, 7 out of the 55 test results suggest a rejection of the equality of means at less than 10%, which is about what could statistically be expected. These results can therefore be taken to indicate no systematic differences between the experiment and comparison groups in their observed characteristics. Balancing tests for the propensity score matching of Andino participants similarly show no systematic differences in observed characteristics with their comparison groups.

Table 7. FFS: Balancing Test Results for Three PPS Methods

Definition of control group	**Method 1: Cut-off point** All farmers with PPS ≥ 0.60		**Method 2: Matching** Average of five non-participants with closest PPS (within .01 PPS)		**Method 3: Weights** Entire sample (with kernel-based weights)
	p -values for equality of means of variables in the participant and control groups				
	Strata 1	Strata 2	Strata 1	Strata 2	
Education of household head	0.81	0.74	0.42	0.77	0.64
Age of household head	0.34	0.93	0.55	0.15	0.10
Number of family members	0.04	0.65	0.58	0.47	0.44
Dependency rate	0.15	0.54	0.27	0.19	0.15
Total land ownership	0.49	0.47	0.31	0.52	0.36
Value of cattle assets	0.81	0.48	0.82	0.85	0.38
Number of inherited livestock	0.98	0.36	0.85	0.63	0.75
Value of household assets	0.21	0.53	0.39	0.74	0.54
Value of farm assets	0.13	0.83	0.30	0.48	0.28
Losses from El Niño	0.13	0.55	0.76	0.73	0.18
Credit constrained	0.92	0.28	0.45	0.36	0.85
Number of observations	61	62	22	22	45

VI. Impact of FFS on knowledge

6.1. Estimation based on regression with control variables

Table 8 presents the results of a regression of knowledge test scores, controlling for FFS and Andino participation and for community and household characteristics, described in equation (2). The regression can be done with both types of participants since they have the same control group (the non-Andino participants in the non-FFS villages) and the regression has a full range of interactions. The sample of observations $\{P(FFS) + nonFFS\}$ consists of all FFS participants from FFS villages and all non-FFS villages. It shows an estimated Average Treatment Effect $\left(\widehat{ATE}^{Reg}\right)$ for FFS of 7.6 percentage points for the entire sample. Using these results, the average

[11] One FFS participant did not have a match within this range, and thus, the treatment group was reduced to 44 in this method.

of the impact over FFS participants gives an estimated value of 13.8 percentage points for the Average Treatment Effect on the Treated $\left(\widehat{ATE}_1^{Reg}\right)$.

Impact of participation on knowledge increases with land ownership, the value of household assets, and the number of family members. It is interesting that deriving greater knowledge from participation in FFS is not affected by the level of education of the household head.

The estimated Average Treatment Effect for Andino is 5.6 percentage points and the Average Treatment Effect on the treated is 7.7 percentage points. The effect on knowledge of traditional extension is thus apparently lower than that of FFS, confirming the observation made on the basis of descriptive statistics in Table 4. However, due to the very small samples of participants to the two programs, it is difficult to establish statistical significance for this difference: With an estimated value of 2.05 (standard error 3.56) for the difference between the two average treatment effects, the null hypothesis that it is equal to 0 cannot be rejected at the 5% level. On the other hand, the Inverse Power calculation proposed by Andrews (1989) indicates that the data show no evidence that the true difference is less than 5.9, at the 5% level, either.An interesting difference between the impact of the FFS and Andino programs is that in the case of Andino, knowledge is not affected by land ownership and family size and does not increase with the value of household assets. If control over land and household assets proxies for wealth, it suggests that FFS is better taken advantage of by the wealthier, while traditional transfer-of-technology approaches cater to less endowed farmers. The FFS extension method is thus better fit for younger farmers (participation) and for farmers with greater endowments.

Table 8. Impact of FFS and Andino on Agricultural Knowledge Test Scores
Dependent variable: test score[1]

	Coefficient	*p* -value
Participation in FFS	7.64	0.01
Participation in Andino	5.59	0.00
Community characteristics		
Distance from Cajamarca (kms)	-0.01	0.00
Dairy delivery station in community (0/1)	1.11	0.22
Household characteristics		
Education of household head	0.33	0.65
Age of household head	-0.03	0.47
Number of family members	0.07	0.69
Total land ownership (hectares)	6.99	0.18
Quadratic total land	-7.88	0.03
Value of cattle assets (100 soles)	-0.01	0.91
Number of inherited livestock	0.09	0.66
Value of household assets (100 soles)	0.46	0.00
Value of farm assets (100 soles)	0.42	0.67
% of losses from El Niño	1.18	0.33
Credit constrained	1.61	0.10
Interaction terms: Participation in FFS x		
de-meaned community characteristics		
Distance from Cajamarca	0.00	0.93
Dairy delivery station in community	-1.63	0.71
de-meaned household characteristics		
Education of household head	-0.66	0.75
Age of household head	-0.30	0.11
Number of family members	1.33	0.68
Total land ownership	84.0	0.08
Quadratic total land	-179	0.02
Value of cattle assets	0.18	0.65
Number of inherited livestock	-0.41	0.62
Value of household assets	3.33	0.05
Value of farm assets	-6.01	0.23
% of losses from El Niño	-10.3	0.01
Credit constrained	2.90	0.48
Interaction terms: Participation in Andino x		
de-meaned community characteristics		
Distance from Cajamarca	0.02	0.36
Dairy delivery station in community	-0.29	0.92
de-meaned household characteristics		
Education of household head	1.00	0.69
Age of household head	0.04	0.67
Number of family members	0.56	0.47
Total land ownership	23.75	0.56
Quadratic total land	-111.72	0.15
Value of cattle assets	0.20	0.52
Number of inherited livestock	0.31	0.67
Value of household assets	-1.09	0.00
Value of farm assets	5.65	0.38
% of losses from El Niño	-0.08	0.99
Credit constrained	0.20	0.96
Constant	19.72	0.00
Number of observations	438	
R-squared	0.17	

[1] For FFS, the sample consists of FFS participants and farmers from non-FFS villages.

The validity of this method is based on the assumption that there is no selection bias due to unobservables influencing both the choice of participation in FFS as well as the outcome. While we have argued that this is a reasonable assumption for a pilot program such as FFS, we also use an informal calculation proposed by Altonji, Elder, and Taber (2002) to evaluate the potential bias that would be implied by selection on the unobservables. The idea is the following. Consider a simplified model without interaction terms:

$$y = \mu_0 + \alpha w + x\beta + \varepsilon, \tag{3}$$

where y is the knowledge score, w is an indicator of FFS participation, the parameter α is the effect of FFS on knowledge, $x\beta$ captures the role of other observed factors that influence knowledge, and ε combines all unobservables. Under certain conditions, it is possible to show that selection on unobservables is comparable in magnitude to the selection on observables in terms of its influence on the outcome y, in the sense that the normalized difference between the average values of observables and of unobservables in the two groups are the same: [12]

$$\frac{\mathrm{E}(x\beta|w=1) - \mathrm{E}(x\beta|w=0)}{\mathrm{var}(x\beta)} = \frac{\mathrm{E}(\varepsilon|w=1) - \mathrm{E}(\varepsilon|w=0)}{\mathrm{var}(\varepsilon)}. \tag{4}$$

Under these conditions, by estimating equation (3), we can calculate how the index of observables in the knowledge equation varies with FFS participation, and then ask how large the normalized shift due to unobservables would have to be in order to explain away the entire FFS program effect. Applying this method we find that the bias due to unobservables on the parameter α would be 2.7 points out of the average 7.6 points for the estimated average impact. This is likely to be an upper-bound on the bias since the condition in equation (4) pessimistically assumes that the selected covariates in the impact regression are a random sample of the full set of covariates. In any event, the bias calculation suggests that selection due to unobservables is unlikely to wipe out the measured level of impact of the FFS program on knowledge.

6.2. Estimations based on PPS matching methods

Table 9 reports estimates of FFS program impact based on the Propensity Score Matching methods.The average difference in test scores between participants and their matches provides an estimate of the Average Treatment Effect on the Treated $\left(\widehat{ATE}_1^{PSM}\right)$. For all three methods, there is a significant difference between the two groups' scores in every category of knowledge. The scores are more than twice as high among FFS participants for knowledge of resistant varieties, and knowledge of the Andean potato weevil and the potato tuber moth, and these values are very similar across all three methods. Gain and knowledge attributable to the FFS are greatest for the

[12] The conditions for equality of selection on observables and unobservables are that the included regressors should be a random subset of all factors that determine the outcome, and none of the factors dominate the distribution of program participation or the outcome.

more technical issues such as identification of resistant varieties and knowledge of the most important pests (late blight and Andean potato weevil).

The impact estimates are robust to the different estimation methods: for the overall score, the three methods give a remarkably similar estimate of 14 to 15 percentage points of program impact. This is also similar to the 13.8 percentage point estimate obtained in the regression method.

Table 9. FFS: Testing Knowledge Differentials Using PPS Matching Methods

Test scores: percentage of maximum score	**FFS farmers scores**	**Control group scores**	**Difference = Average Treatment Effect on the Treated**	**Test of $ATE_1 = 0$ *p* -value**
Method 1: Cut-off point		All control farmers with PPS > .60 and under common support		
Number of observations	45	80		
Knowledge on late blight	35	24	11	0.00
Knowledge on Andean potato weevil	25	1	24	0.00
Knowledge on potato tuber moth	15	1	14	0.00
Pesticide knowledge	29	21	8	0.00
Knowledge on resistant varieties	49	17	32	0.00
Total test score	34	19	15	0.00
Method 2: Five nearest matching		Control farmers with five closest PPS (within .01 PPS) under common support		
Number of observations	44			
Knowledge on late blight	35	25	10	0.00
Knowledge on Andean potato weevil	25	9	17	0.00
Knowledge on potato tuber moth	15	4	11	0.00
Pesticide knowledge	49	16	33	0.00
Knowledge on resistant varieties	29	21	8	0.00
Total test score	34	19	15	0.00
Method 3: Kernel-weights matching		Kernel-weigted average of all control farmers under common support		
Number of observations	45			
Knowledge on late blight	35	24	11	0.00
Knowledge on Andean potato weevil	25	11	13	0.00
Knowledge on potato tuber moth	15	7	7	0.04
Pesticide knowledge	29	21	8	0.00
Knowledge on resistant varieties	49	17	32	0.00
Total test score	34	20	14	0.00

Knowledge scores are similarly significantly higher for Andino program participants relative to their control groups, with the three matching methods and for all categories of knowledge. We compare FFS and Andino estimates in Table 10, where the Average Treatment Effects on the Treated are computed as the averages of the results obtained with the three matching methods. Results show that the Average Treatment Effect on the Treated is higher for FFS than for Andino. This is particularly the case for technical issues that matter most for farmers in the region (Tables 2 and 3): knowledge of late blight, the Andean potato weevil, pesticides, and resistant varieties. For the total test score, the gain in knowledge due to treatment is 86% higher for FFS than for Andino participants.

Although there is no statistical test that can be applied to these comparisons, they confirm the suggestive results of the regression analysis.

Table 10. Differentials in Knowledge Gains: FFS vs. Andino

	Average Treatment Effect on Treated		% difference in ATE_1:
	FFS	Andino	FFS over Andino
Knowledge on late blight	10.7	6.8	56
Knowledge on Andean potato weevil	18.0	6.2	192
Knowledge on potato tuber moth	10.7	11.4	-6
Pesticide knowledge	16.3	3.6	352
Knowledge on resistant varieties	24.0	17.5	37
Total test score	14.7	7.9	86

VII. From knowledge to productivity

We can measure how score, an indicator of agricultural knowledge, is related to productivity by regressing productivity (measured by the potato output/input ratio) on knowledge score and on plot and household characteristics.

As the FFS program was only in its first year of operation, we cannot expect yields of FFS participants to yet reflect acquired knowledge from the FFS. This is because the output/input ratio is computed for the plots that were harvested during the year in which the FFS was occurring. Planting, and much of the spraying, was carried out at the very inception of the program or perhaps even before participation started. On the other hand, there is always a risk of selection bias in that farmers that choose to participate in FFS programs may be the most productive farmers anyway. For these two reasons, we choose to establish the relationship between agricultural knowledge and productivity on the 245 plots of farmers from the non-FFS communities.

We control for clustering at the household level and use an instrumental variable technique to control for endogeneity of the "knowledge score" variable. Given the cross-sectional nature of the data, it is difficult to find household variables that are correlated with knowledge and do not influence productivity. Consequently we use instruments that are statistically valid, although admittedly ad'hoc. These instruments are the average knowledge score on varieties of farmers in the same consumption category (total monthly consumption level), which is used to represent the household's welfare level, its square, and its interactions with the education of the household head and with the arable land owned by the household. The first stage regression (not shown) indicates that the instruments are strong predictors of knowledge scores (F-statistic $F(4,222) = 14.3$, p–value =0.000). The overidentification test fails to reject the null hypothesis that the instruments are statistically valid (p–value = 0.33). The results of the instrumental variable regression are presented in Table 11. The predicted knowledge score is significant and positively affects productivity. We find that a ten percent increase in the knowledge score is reflected in a 2.9 points

increase in the output/input ratio. By comparison, the sample mean (among control communities) for the output/input ratio is 7.9 with a standard deviation of 4.8.

Table 11. Impact of Score on Productivity in non-CARE Communities
Dependent variable: Plot level potato output/input ratio

	Mean	Coefficient	*p* -value
Knowledge score (0–100) (instrumented[1])	15.4	0.29	0.01
Plot characteristics			
Area of plot (hectare)	0.27	-4.96	0.00
Steep slope	0.07	1.75	0.09
Rocky soil	0.06	-1.60	0.07
Fallowed last season	0.62	0.44	0.61
Irrigated	0.32	3.26	0.00
Irrigated and fallowed last season	0.16	-2.45	0.06
Household characteristics			
Education of household head	2.4	-0.24	0.68
Age of household head	47.5	-0.04	0.27
Number of workers in family	5.4	0.10	0.64
Workers per hectare of arable land owned	1.21	-0.08	0.77
Total land ownership (10 hect.)	0.11	-3.29	0.13
Value of cattle assets (100 soles)	7.59	-0.02	0.42
Number of inherited livestock	0.57	0.14	0.37
Value of household assets (100 soles)	0.44	-0.07	0.40
Value of farm assets (100 soles)	0.57	2.43	0.02
% of losses from El Niño	0.15	-1.79	0.06
Credit constrained	0.28	-1.06	0.15
Distance from major metropolitan area (km)	244	0.01	0.24
Constant		2.27	0.58
Dependent variable: potato output/input ratio	7.9 (sd 4.8)		
Number of plots (150 households)	245		
Second stage F-statistic: F(19, 144)		2.80	0.000
Joint significance of instruments in first stage: F(4,222)		14.3	0.000
Test of overidentifying restrictions: Chi2(3)		3.42	0.33

[1] Instruments are average knowledge score on varieties among farmers of same consumption level, its square, and interactions with age of household head and owned arable land.

Using the coefficients from the regression in Table 11 and the score differentials reported in Table 9, we can calculate a rough estimate of the potential impact of FFS participation on productivity. Using the calculated score differential of 14 percentage points from FFS participation, this implies that farmer field school participation would have resulted in an increase of 4.1 points in the output/input ratio. This corresponds to a 52% increase over the average observed output/input ratio of 7.9, which corresponds to the value in a normal year. Note that non-seed inputs are not taken into consideration in the productivity measure. Therefore, although higher knowledge scores help increase productivity, we do not know if they result in higher profits.

VIII. Conclusions

The challenge of the FFS approach is whether training results in higher knowledge about complex technical issues such as IPM and whether improved knowledge in turn translates into higher productivity. Using data on a small-scale pilot FFS program targeted to Peruvian potato farmers, this paper finds that FFS participation significantly enhances knowledge on pests, fungicides, and resistant varieties – all instrumental in implementing IPM practices. The robustness of the positive results of FFS participation on knowledge is demonstrated by the fact that two separate approaches used for estimating the effect of FFS yield the same result: a fourteen-percentage point increase in knowledge score for FFS participants.

While samples of participants are too small to detect statistically significant differences, we also find suggestive evidence that the FFS approach is more effective that the traditional transfer-of-technology approach in imparting knowledge of technical issues related to IPM to farmers. Gains in knowledge are 86% higher with FFS that with the traditional approach used in the Andino program. These results will need to be confirmed with larger samples of participants to extension programs.

We show that farmers with higher levels of knowledge have significantly higher levels of productivity, and estimate that, by increasing knowledge, FFS participation can raise the average potato seed output/input ratio by 4.1, or approximately 52% of the average value in a normal year. Finally, we end with a cautionary note that because the FFS pilot in Peru was started only recently, we did not examine the extent of knowledge diffusion from FFS participants to other farmers.

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