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Farm Level and Environmental Impacts of Farmer Field Schools in Thailand

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Abstract

This paper presents an application of a difference in difference model to measure environmental and economic impacts of Farmer Field School in Thailand. Panel data of 241 farm households were collected three times over a period of four years in five rice-producing provinces of Thailand. Data included socio-economic data describing household and farm characteristics, rice input and output data including detailed accounts of pesticide use and other pest management practices and farmers' knowledge of crop management and agro ecosystem factors. Using the concept of environmental impact quotient parameters on the health and environmental consequences of a change in pesticide use was computed. Data analysis was performed in two steps. First, statistical analysis using t-test was applied to detect differences in performance indicators, which we assume are influenced by the training. These included farmer knowledge, yield, pesticide use, gross margin, pesticide health costs and environmental consequences of pesticides. In the next step, changes in farm performance, which were found to be significant in the linear statistical test were further analysed using a two and a three periods growth model. Results showed that trained farmers significantly reduced pesticide use on the short term. It was also found that they retain their reduced pesticide use practices several years after the training. However no significant change in rice gross margin could be detected.

Keywords: Farmer Field School, Impact Assessment, Multi-Period Panel Data Model, Pesticide Use

1. Introduction

Projects on farmer training in Integrated Pest Management (IPM) in developing countries using the Farmer Field School (FFS) approach are still widely implemented by donor organizations including for example the World Bank. This is in spite of criticism that such projects are fiscally unsustainable (Quizon et al 2001) and are not always effective in changing pest management practices or in improving farm performance (Feder et al 2003) and have only limited diffusion effects (Rola et al 2002, Feder et al 2004, Tripp et al 2005). On the other hand it was shown that FFS can improve farmer knowledge in pest identification and improve their ecosystems understanding (Godtland et al 2004, van den Berg 2004, Tripp et al 2005). Also it was found that public investments in integrated pest management programs on cotton in several Asia countries showed good rates of return (Erickson 2003, Ooi et al 2005) Moreover, in China, where bollworm-resistant transgenic cotton varieties have been widely introduced, FFS was found to be effective in helping to realize the potential of pesticide reduction that Bt varieties offer (Yang et al 2005).

A common facet of past impact analyses of Farmer Field School projects is that data were being used that did not allow the definition of good counterfactual scenarios because no control area was available or only insufficient baseline data existed. Also comparisons were based on only two observation points before and after the training. In addition, most of these studies concentrated on simple performance parameters like knowledge, pesticide use and yield but did not include for example impact on the environment. In this paper we use a set of panel data that were collected over a period of four years covering at maximum of 10 rice-growing seasons from three groups of farmers. The analysis presented here is an advancement of an earlier study that looked at the short-term impact of FFS in Thailand (Praneetvatakul and Waibel 2003).

2. Data and impact indicators

Data were collected in five pilot sites on Farmer Field Schools of the Department of Agricultural Extension (DOAE) in Thailand. The sample included 241 farmers and was composed of three groups of farmers: (1) training participants (FFS farmers), on average 20 farmers per FFS; (2) 15 exposed farmers, per FFS village (non FFS) ; (3) 15 unexposed farmers, randomly selected from a control village located near-by a FFS village (control farmers). The control villages had similar socio-economic and natural production conditions but only a minimal possibility of information exchange with the respective FFS village existed[1]. The farmers were interviewed at three different points of time: (1) in February 2000 at the end of the wet rice-cropping season, which was before the training had started (2) in February 2001, in the rice growing the season after the training, i.e. where farmers could apply their new knowledge for the first time and (3) in February 2003, two years after the second survey. Thus, trained farmers had the opportunity to apply their new knowledge in four to eight rice growing seasons after the training, depending on the intensity of rice production, which varied in the five pilot villages. Unfortunately for the third survey the sample size had to be reduced because of heavy flooding in two FFS villages..

The questionnaire included information on farm household characteristics, farmer knowledge on rice pest management, data on rice production inputs and outputs, and questions on health issues related to pesticide use. Particular emphasis was given to a detailed account of pesticide use regarding quantity, common and brand name, active ingredients and formulation.

To assess impact of FFS we defined several impact indicators. First, we measured farmers' knowledge of rice and pest management. A score was constructed from a set of knowledge questions developed in cooperation with national IPM experts. Second, total rice yields per farm including sales and home consumption were based on farmers' estimates and divided by the respective area planted to rice. Third, the amount spent on pesticides including insecticides, molluscisides (chemicals used to kill snails), fungicides and herbicides were calculated in $ per ha. Fourth, the gross margin of rice production in $ per ha, measured as total revenue above total variable costs excluding the value of family labor. Fifth, as a measure of net farm benefit we deducted health costs from chemical pesticide use from the gross margin. . For health costs were accounted for by using a ratio of pesticide costs to health costs of 1:1 based on the results of study of Rola and Pingali (1993). Finally, the Environmental Impact Quotient (EIQ) was calculated to quantify the environmental and health impacts of pesticides by means of an index (Kovach, et al 1992). The EIQ index provides a measure of the side effects of pesticides by differentiates according to crop type, pesticide type, quantity and toxicity to pesticide applicators, toxicity to consumer and toxicity to the ecological environment. The index sums up all pesticides used by a farmer hence a higher EIQ number indicates a higher risk to health and environment.

[1] The control villages had for example different market places than the FFS villages

3. The Model

The analysis applies a difference in difference (DD) model (Greene, 2000). DD models can be used to analyse changes in farm performance such as pesticide use, yield and profit. In our analysis we proceeded in two steps. First we investigated linear shifts in performance and second we measured change as a growth process. The linear shift implies a one-off performance change at the observation point relative to the baseline period. The change in the growth rate takes account of the fact that the development process influences performance and thus assumes an exponential path in the rate of change for trained and untrained farmers. Hence the model accounts for the fact that change is taking place even without the FFS training. The linear shift was measured by applying a paired t-test (Anderson, Sweeney and Williams, 2002), to test for the differences between before and after training for FFS, non-FFS and control farmers. For those performance indicators where we find a significant linear shift we proceed with the two and three periods growth model. The rationale for this procedure is that we do not expect significant results as we increase the degree of rigor in the testing procedure, i.e. if we do not get a significant difference in the t-test, we cannot expect a significant coefficient in an econometric growth model. Since we have three observation points over time we can apply two alternative models: a two period and a three period panel data model. With the three period model a simultaneous estimation of the time period effects is achieved using a larger sample.

In applying this model we draw upon and expand the procedure developed by Feder et al (2003) used to measuring impact of IPM in Indonesia. Accordingly the change in farmers' performance (e.g. yield) through training can be modeled as an exponential growth process. This is displayed in equation 1:

$$Y_1 = Y_0 \cdot \mathbf{e}^{\{\alpha + \beta D_{nffs} + \mu D_{ffs} + \gamma \Delta X + \delta \Delta Z\}} \qquad (1)$$

where:

Y_1	rice yield after the training,
Y_0	rice yield before the training,
α	coefficient for yield growth before the training,
μ	rate of yield growth of FFS farmers after the training,
β	rate of yield growth rate for the non-FFS farmers after training,
D_{ffs}	dummy variable for FFS farmers, for FFS = 1 and zero = otherwise,
D_{nffs}	dummy variable for non-FFS farmers, for non FFS = 1 and zero = FFS and control,

X vector of farmer characteristics,

Z vector of village characteristics,

γ and δ corresponding coefficients of these vectors,

Δ the differencing operator between before and after the training,

e the exponential operator.

The specification for an empirical estimation of the model can be obtained by taking the natural log of equation (1) and rearranging it accordingly:

$$\Delta(\ln Y) = \alpha + \beta D_{nffs} + \mu D_{ffs} + \gamma \Delta X + \delta \Delta Z \tag{2}$$

where: $\Delta(\ln Y) = (\ln Y_1 - \ln Y_0)$

Unlike in models that are based on cross sectional data, panel data allow for the unobserved effects, a_i, to be correlated with the explanatory variables (Wooldridge, 2000) This is because a_i is assumed to be constant over time, hence one can compute the difference in the observed parameters over the two years.

The equations for period 2 (eq 3) and period 1 (eq 4) are as follows:

$$Y_{i2} = (\delta_0 + \alpha) + \gamma_2 X_{i2} + a_i + u_{i2} \tag{3}$$

$$Y_{i1} = \delta_0 + \gamma_1 X_{i1} + a_i + u_{i1} \tag{4}$$

Subtracting the equation (4) from equation (3) results:

$$\Delta Y_i = \alpha + \gamma \Delta X_i + \Delta u_i \tag{5}$$

where:

Δ denotes the change from period 1 (t=1) to period 2 (t=2), Y_i is the dependent variable, X_i are independent variables and U_i is the error term. The unobserved effect, a_i, does not appear since it has been differenced away. The resulting intercept (α) denotes the change in the intercept between the two periods.

Extending the analysis to three periods (t= 1,2, and 3), the procedure is analogous as shown in equation (6):

$$Y_{it} = \delta_1 + \delta_2 d2_t + \delta_3 d3_t + \gamma_1 X_{it1} + ... + \gamma_k X_{itk} + a_i + u_{it} \tag{6}$$

Equation (6) includes dummies for two periods, d2 and d3. The intercept for the first period is δ_1 for the second period it is $\delta_1 + \delta_2$. For period three the definition of intercept is analogous. In the t=3 case, time period one is subtracted from time period two and time period two from time period three resulting in Eq 7:

$$\Delta Y_{it} = \delta_2 \Delta d2_t + \delta_3 \Delta d3_t + \gamma_1 \Delta X_{it1} + ... + \gamma_k \Delta X_{itk} + \Delta u_{it} \tag{7}$$

for t=2 and t=3. Equation (7) contains the differences in the time period dummies, $d2_t$ and $d3_t$; i.e. for t=2, $\Delta d2_t = 1$ and $\Delta d3_t = 0$; for t=3, $\Delta d2_t = -1$ and $\Delta d3_t = 1$. Re-writing equation (7) displays the intercept of the equation, which is a measure of the growth in performance of the control group:

$$\Delta Y_{it} = \alpha_0 + \alpha_3 d3_t + \gamma_1 D_G + \gamma_2 D_N + \gamma_3 \Delta X_{it3} + ... + \gamma_k \Delta X_{itk} + \Delta u_{it} \quad (8)$$

for t=2 and t=3, the estimates of the γ_j are identical in both equation (7) and (8).

Applying these growth models to those performance parameters, which have passed the test of the linear model, introduces a more rigorous test on the impact of FFS training.

4. Results

4.1. Linear shift effects from the FFS training

Table 1 summarizes the results of the t-test comparing before and after differences for the three groups of farmers. For the FFS farmers significant shifts were observed in all parameters except the gross margin from rice production. FFS farmers significantly reduced their pesticide use in gram active ingredient by 41.7 % after the training while no significant reduction was observed between the two other groups. Due to the pesticide reduction the two other parameters linked to pesticide use, i.e. farmer net benefit and EIQ also showed significant differences. The difference in the EIQ however is also influenced by a change in the type of pesticide used, i.e. FFS farmers after the training opted for less toxic pesticides. Results for rice yields were less conclusive as they increased among all three groups of farmers. It must be recognized however that FFS training gives emphasis on the pest management aspects of rice production so that yield effects are difficult to attribute as several confounding factors such as promotion of new varieties can come into play. This problem is compounded in gross margin differences where changes in the use of other inputs can take place.

Table 1: Summary of short-term linear shift effects from FFS training

Farmer group	Total knowledge in rice & pest management [score]	Yield [kg/ha]	Pesticide use (gr a.i./ha) [$/ha]	Gross margin [$/ha]	Farmer net benefit [$/ha]	Environment impact [score]
FFS	**	*	***	n.s.	**	***
Exposed	ns	*	n.s.	n.s.	n.s.	n.s.
Control	ns	**	n.s.	n.s.	n.s.	n.s.

Note: *, **, *** indicates the difference of before and after training at 0.10, 0.05 and 0.01

4.2. Two periods growth model

Based on the methodology outlined above the analysis was proceeded by testing for change in performance in the growth rates of impact parameters. Here we included just two impact measures, namely quantity of pesticide use and EIQ. We discarded the gross margin because t-test results were non significant. Likewise we did not include yield because the somewhat ambiguous t-test results. We also ignored the net benefits because the results strongly depend on pesticide reduction, which was included.

The results of the two period growth model using the change in pesticide expenditures as the dependent variable show that FFS training has a significant effect on reducing farmers' pesticide use (see table 2). This result is supported by the significant coefficient for rice and pest management knowledge. The positive sign of the constant term indicates that pesticide use is likely to continue to grow without FFS. Since the dummy variable for non-FFS is non-significant there is no change in the trend of pesticide use among exposed farmers. The results questions whether FFS training has indeed a diffusion effect and thus confirms the results found by Feder et al (2004) from Indonesia. Summarizing the hypotheses tests in the lower panel of the table show that a change in the positive trend in pesticide use is attributable to FFS. FFS farmers have significantly lower pesticide expenditures when compared to the non-FFS and control farmers on the short term (Table 2).

Using the environmental impact quotient as a dependent variable in the two period model also confirms the results of the t-test. FFS participation reduces the trend in the negative consequences of pesticides on environment in the short term (Table 2). As measured through the FFS participation dummy, the growth rate in EIQ of the FFS farmers shows a significant decline. It is also interesting to note that the counterfactual scenario (no FFS training) shows growing negative environmental impact from pesticides. This can be concluded from the intercepts of the models, which were significant at the 0.01 % level in the short term. Again, within villages diffusion towards more environmentally benign pesticide use practices does not seem to be sustained as shown by the non-significant variable for Non-FFS.

Table 2: Impact of FFS on pesticide expenditures and environmental impact quotient in the short term, two period growth model

Two periods growth model	Δ in Pesticide costs	Δ in EIQ
Constant (α)	0.248	2.340
	(1.576)	(3.096)***
Dummy for FFS (μ)	-0.485	-1.685
	(-2.368)**	(-1.715)*
Dummy for Non-FFS (β)	-0.220	-1.008
	(-0.937)	(-0.895)
Knowledge on rice and pest managements (ln ΔK)	-0.030	-0.133
	(-2.593)**	(-2.421)**
Total labor use (ln ΔL)	0.052	0.160
	(3.911)***	(2.498)**
R^2	0.109	0.064
F-statistics	7.236***	4.005***
Durbin-Watson statistic	1.853	1.883
N	241	241

Note: data in parenthesis are the t-value. Pesticide expenditures are converted to real value.

4.3. Three periods growth model

To test for the long-term effects of FFS training a three period growth model (see Wooldridge, 2000) was used. Two time period dummies are included as explanatory variables.

The long-term effects of FFS on farmer's pesticide use confirm the results of the short-term effect. Hence, FFS farmers retain their improved judicious pesticide use practices and continue to reduce pesticide use over time. By contrast, no significant change can be observed for the non-FFS farmers and the control farmers in either period. Again change for both on the short and the long term knowledge had a significant effect on pesticide reduction.

For the EIQ parameter the long-term change followed the results of pesticide use expenditures. On the log term FFS farmers not only reduce pesticide use levels but also continue to adopt safer products and knowledge seems to be a major driver for this process. On the other hand, no significant change can be observed for non-FFS farmers. The counterfactual scenario however indicates that there may indeed be an overall trend towards less harmful pesticides as indicated in the time period dummies.

Table 3: Impact of FFS on pesticide expenditures and environmental impact quotient in the short term, three period panel data growth model

Three periods panel data growth model	Δ in Pesticide costs	Δ in EIQ
Period 2 Dummy	-0.001	1.365
	(-0.006)	(2.798)***
Period 3 Dummy	0.077	-1.894
	(0.730)	(-4.063)***
Dummy for FFS	-0.254	-1.869
	(-2.167)**	(-3.616)***
Dummy for Non-FFS	0.137	0.041
	(1.219)	(0.068)
Knowledge on rice and pest management (ln ΔK)	-0.229	-0.073
	(-2.517)**	(-0.181)
Total labor use (man-day) (lnΔL)	0.445	1.060
	(10.561)***	(5.698)***
R^2	0.448	0.294
F-statistics	28.183***	11.505***
Durbin-Watson statistic	1.817	1.467
N	188	188

Note: data in parenthesis are the t-value. Pesticide expenditures are converted to real value.

5. Conclusion

Results show that farmers who participated in the Farmer Field School retain their knowledge and continue to practice improved IPM practices. Growth rates of pesticide expenditures and environmental impact are significantly reduced by the FFS training both in the short and long term. On the other hand farmers not trained in FFS tend to continue non-judicious ways of using chemical pesticides. Thus for rice production in Thailand, the Farmer Field School is an effective method to reduce uneconomical use of chemical pesticides and make farmers to adopt more environmentally benign pesticide use practices. Thus this study confirms the finding of other studies on Farmer Field Schools (e.g. Tripp 2005). Changing farmer's pesticide use practices thus generates environmental benefits that not only accrue to the farmers but to society at large. However, the direct economic benefits of farmers expressed in terms of gross margins are difficult to detect and may be small. One reason could be that in technologically advanced rice production systems possible yield gains are small and hardly measurable by means of recall surveys. Also pesticide use does not account for a high share of the variable costs and therefore gross margin differences can be confounded by other factors. Besides increased productivity effects of chemical pesticides through better timing are small unless there are pest outbreaks, which however did not occur during the years that the surveys were conducted.

Using difference in difference growth models to panel data reveals the factors that cause a change in pest management technologies. At the same time new questions arise. For example what is the driving force for farmers to adopt IPM in a crop like rice if the effects on profit are insignificant?

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