Does sending farmers back to school have an impact? a spatial econometric approach

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Abstract

The Farmer Field School (FFS) is an intensive training program providing farmers with science-based knowledge and practices, including integrated pest management (IPM). Recently there has been intensive debate as to whether or not this kind of training has any significant impact. Most case studies argue that the impact, in terms of a farmer's ability to reduce the use of pesticides while increasing yields, is significant. However, studies conducted by Feder et al., using a household panel data set for Indonesia, could not confirm that this is the case. This paper utilizes Feder et al.'s data set and applies a modified model specification and a spatial econometric technique to re-evaluate whether or not the FFS induces better performances among farmers enrolled in the program and also among their neighbors, who are expected to receive some spillover knowledge from the FFS alumna.

Key words: agricultural economics, spatial econometrics, economic development

JEL Classification: Q12, C59, O13

1. Introduction

The Food Intensification Program in Indonesia in the 70s and 80s resulted in a significant expansion in agricultural production, especially in rice yield. However, this caused serious environmental problems due to an excessive use of pesticides (Oka, 1991). In 1989, the Indonesian government recognized the negative side effects of pesticides, and proposed integrated pest management (IPM) techniques as an alternative national pest control strategy to sustain environmentally friendly agricultural production while minimizing the risks associated with pesticide use (Röling et al., 1994 and van den Berg, 2004). To implement IPM techniques, the Indonesian government established the Farmer Field School (FFS) — a farmer participatory intensive training program to provide science-based knowledge and cultivation practices especially tailored to IPM (Rola et al., 2002).

Indonesian IPM program monitoring and evaluation teams concluded that the immediate impact of the program up to 1993 was a 60% reduction in total pesticide expenditure after the training program was implemented (MET, 1993). The FAO technical assistance team also showed from several case studies in 1997–98 that there was a 70–99% reduction in insecticide sales by outlets in IPM sub-districts, and a 24% increase in yield (van den Berg, 2004).

The works by Feder et al. (2004a and b) opposed the conclusions drawn from these case studies. They utilized a two-period household panel data set to test the direct impact of the FFS on participating farmers' performances (rice yield and pesticide cost) and also to test the presence of knowledge diffusion.[1] The analysis, employing a modified difference-in-differences model, indicates no significant evidence of improvements in the farmers' performance, and knowledge spillovers were also not confirmed.

However, the importance of spatial interactions between farmers, which could be substantial in determining their performance, has been ignored in previous literature. Ignoring neighborhood effects could bias the evaluation of the impact of the FFS program. To overcome this problem, a spatial econometric approach is employed in this paper. This paper will re-evaluate the impact of the Indonesian FFS, and test whether or not the performance of a farmer who has graduated from this training scheme is improved, and also whether or not farmer-to-farmer knowledge diffusion occurs.

2. The model

2-1. Basic model: Feder et al.'s specification

In this model farmers are categorized into three groups: 1) 'graduate' farmers who participated in an FFS; 2) 'exposed' farmers who live in the same village as graduates; and 3) 'control' farmers whose villages were not exposed to FFS. Hence, there are two types of village; a village where the FFS is introduced; and a village not exposed to the FFS. The FFS approach is expected to induce performance improvements not only for graduates, but also for exposed farmers, due to indirect knowledge acquisition from graduates. Since the graduates obtain new knowledge directly from the FFS, their performance improvement is

[1] The impact of FFS on farmers' knowledge is tested in various countries. For example, see Godtland et al. (2004) for Peru, Praneetvatakul et al. (2006) for Thailand, Rola et al. (2002) for The Philippines, and Tripp et al. (2005) for Sri Lanka.

expected to be the highest among farmers. Due to the farmer-to-farmer knowledge diffusion process, the exposed farmers' performance is also expected to be higher than the control group, but not as high as that of graduates. Performance progress is modeled as an exponential growth process.

$$Y_{99} = Y_{91}\ Exp\{\alpha(T^p - T_{91}) + \beta_1\ D_E(T_{99}\text{-}T^p) + \beta_2\ D_G(T_{99}\text{-}T^*) + \gamma\Delta\boldsymbol{X} + \delta\Delta\boldsymbol{Z}\} + e \qquad (1)$$

Y denotes the farmer's performance indicators, yield and pesticide cost. D_E and D_G represent dummy variables for a graduate and exposed farmer, respectively. $\boldsymbol{X}$ and $\boldsymbol{Z}$ are vectors of household and village characteristics. $\Delta\boldsymbol{X} = \boldsymbol{X}_{99} - \boldsymbol{X}_{91}$ and so for $\Delta\boldsymbol{Z}$. γ and δ are corresponding vectors of household and village parameters. The variable e is the error term. The first survey was conducted in 1991 and the second in 1999. T^p denotes when the first farmer in a village participates in an FFS. Hence, from this time onwards, knowledge diffusion is expected to occur. T^* is when farmer i participates in the program. Therefore, α represents the pre-program growth rate, β_1 is the growth rate while knowledge diffusion occurs, and β_2 is the post-program growth rate.

The model allows us to capture different timing across different villages for the effects of exposure to the FFS, and different timing across different farmers for a farmer's participation in the program. The underlying logic is that those farmers who participate in the FFS early on may perform better, because they have had the opportunity to employ the new knowledge for a longer period.

This model contains the following two major weaknesses; 1) model specification; and

2) the absence of revealing instances of spatial interactions. Concerning the first weakness, suppose the FFS was conducted twice in village A (Figure 1). The first FFS was introduced in the village at time T^p and the second one at time T^*. There are three farmers (e.g., farmers G1, G2 and E) in village A. Farmer G1 participated in the first FFS program and so has been a graduate since T^p. Farmer G2 participated in the second FFS program, hence G2 was an exposed farmer from T^p to T^* then was a graduate after T^*. Farmer E never attended the FSS, but has been an exposed farmer since T^p. It is important to note that the equation (1) can only exactly capture the situation of farmers G1 and E. It is unclear, however, how the equation captures the exact situation of farmer G2. In particular, equation (1) does not capture the period during which G2 was an exposed farmer; i.e. during the T^p to T^* period. Note that around 57% of graduates in the data set actually fall into the G2 category. Hence, we believe that it is critical to develop a model that can precisely capture the situation of G2.

[Figure 1 about here]

Concerning the second point, as Winarto (2004) observed during her fieldwork in Java, it seems a common for adjoining farmers to work together to overcome various issues in their fields. If this is the case and such spatial interaction is ignored in the regression analysis, the estimators will be inefficient or biased.

Feder et al. (2004b) obtained efficient estimators by controlling the correlation between farmers within a cluster (village). However, this method cannot handle the omitted biasness problem which would be caused by ignoring the spatial correlation in observed variables such as a farmer's performance. It is hence important to utilize a spatial econometric approach to handle this.

2-2. Extension of the basic model

The first step to extend Feder et al.'s specification is by developing a model that can also fully capture the situation of farmer G2 discussed above. The paper hence adopts the following model specification:

$$Y_{99} = Y_{91}\, Exp\{\theta + b_1 D_E + b_2 D_G + \beta_1 (T^* - T^p) + \beta_2 (T_{99} - T^*) + \gamma \Delta \mathbf{X} + \delta \Delta \mathbf{Z}\} + e \quad (2)$$

The interpretation of this model is the following. θ represents a common growth rate of output experienced by all farmers (including the controls). The b_1 is an 'additional' growth rate over the 'total' sample period experienced by farmers who have been exposed but have never attended an FSS and b_2 is an 'additional' growth rate over the 'total' sample period for farmers who are graduates of an FFS, regardless of how long they have been graduates or have been exposed. β_1 is the average extra growth rate per cropping season for exposed farmers and β_2 for graduates. This new specification can explicitly assess the two types of impact. b_1 and b_1 capture the overall impact of the program during the total sample period, and β_1 and β_1 capture the impact durability per cropping season.[2] The growth rate of output experienced by an exposed farmer who has never participated in the program (farmer E) is $\theta + b_1 + \beta_1 (T^* - T^p)$, in which T^* equals T_{99}. The growth rate of a graduate farmer who participates in the first FFS program in his/her village (farmer G1) is $\theta + b_2 + \beta_2 (T_{99} - T^*)$

[2] On the other hand the specification in Feder, et al. (2004b) only captures the long-run impact and compares the performance level before/after the FFS was implemented.

in which $T^p = T^*$. Finally, the growth rate experienced by a graduate farmer who participates in a later FFS program (farmer G2) is $\theta + b_2 + \beta_1 (T^* - T^p) + \beta_2 (T_{99}-T^*)$. To investigate the impact of the FFS, we test the statistical significance and sign for each of these estimated parameters, θ, b_1, b_2, β_1, and β_2. Therefore, if the FFS program has the expected impact, then $b_1 > b_2 > 0$ and $\beta_1 > \beta_2 > 0$ for yield of rice, and the opposite inequalities are held for pesticide cost. This indicates that graduate and exposed farmers successfully adopted the IPM and continued to improve the practice in their fields.

2-3. Empirical specifications

To be able to implement the specification in equation (2), this paper employs a first differencing method (FD) and adds additional district dummies. The model hence becomes as follows:

$$Y = \theta + b_1 D_E + b_2 D_G + \beta_1 (T^* - T^p) + \beta_2 (T_{99}-T^*) + \gamma\Delta\boldsymbol{X} + \delta\Delta\boldsymbol{Z} + \varphi\, \boldsymbol{D} + e \qquad (3)$$

where $Y = ln\ Y_{99} - ln\ Y_{91}$ for rice yield and $Y = Y_{99} - Y_{91}$ for pesticide costs, $e = e_{99} - e_{91}$ is the idiosyncratic error, and $\boldsymbol{D}$ is a matrix for district dummies. The paper then estimates the equation (3) using an OLS estimation. It is important to note that the fixed effect is unobserved, so it is not in the estimation. Consequently, if the fixed effect is correlated with any of the explanatory variables, this pooled OLS estimation causes a heterogeneity bias.

2-4. Spatial specifications[3]

The final step in extending Feder et al.'s model is to capture the spatial effect or neighborhood influence by employing spatial error and spatial lag models. The argument is that if there are spatial correlations in unobserved factors or in a farmer's performance, and if those correlations are ignored in the estimation, the estimators will be either inefficient or biased.

The spatial error model (SEM) is based on the assumption that any unobserved differences, such as weather and soil fertility, differ from village to village, but are shared by farmers in the same village. Hence, now the error term is spatially correlated. The model takes the following form with a spatially parameterized error term:

$$Y = \theta + b_1 D_E + b_2 D_G + \beta_1 (T^* - T^p) + \beta_2 (T_{99}\text{-}T^*) + \gamma \Delta \boldsymbol{X} + \delta \Delta \boldsymbol{Z} + \varphi \, \boldsymbol{D} + e^* \qquad (4)$$

where: $e^* = \lambda \, W \, e + u$. λ is the spatial error parameter, u is white noise, and W is an $n \times n$ standardized binominal spatial weight matrix. A weight matrix is a matrix in which each element of the weight matrix, w_{ij}, represents a relationship between farmers; i.e. if both farmers, i and j, live in the same village, $w_{ij} = 1$ and 0 otherwise. The diagonal elements of the matrix are 0. The standardized weight matrix implies that every row of the weight matrix summed to 1 (i.e. $\sum_j w_{ij} = 1$).

Meanwhile, in a spatial lag model (SLM), it is assumed that spatial interactions occurred between farmers' performances in the same village. The formula for a spatial lag

[3] Case (1991) is the first study employing a spatial econometric approach in the Indonesian agricultural context.

model is:

$$Y = \rho\, W\, Y + \theta + b_1\, D_E + b_2\, D_G + \beta_1\, (T^* - T^p) + \beta_2\, (T_{99} - T^*) + \gamma\, \Delta \boldsymbol{X} + \delta\, \Delta \boldsymbol{Z} + \varphi\, \boldsymbol{D} + e \qquad (5)$$

The OLS estimation in the spatial specifications will render either inconsistent or inefficient results. Thus, the spatial models are estimated using the maximum likelihood estimation (MLE) (Anselin 1988). The estimated parameters derived by the MLE are consistent, asymptotically efficient and normal. The spatial specifications are superior to the OLS specification, particularly if the OLS residuals present any spatial autocorrelation.

3. Data description

The data was randomly taken from a panel survey of Javanese farm households, conducted by the Indonesian Center for Agro-Socioeconomic Research (CASER) in April/May 1991 and again in June 1999.[4] Although the Indonesian FFS was initially established in 1989, this data set focuses only on those villages that had not yet been exposed to the program when the survey commenced. Hence, none of the villages in the data set were exposed to the FFS when the first survey was conducted.

The total number of households is 320, of which 112 of them are graduates, 156 are exposed farmers, and 52 constitute the control group. The descriptive statistics for the key variables among categorized farmers are summarized in table 1. While average Javanese farmers decreased yields of rice with increasing pesticide costs over the sample period, we

[4] See Feder, et al. (2004b) for the details of this survey.

still can test the hypotheses as if graduate and exposed farmers could more effectively control the negative trends than could the control group.

[Table 1 about here]

4. Results and discussions

Prior to estimating our models, the presence of global spatial autocorrelations in performance variables are tested by Moran's I and Geary's C statistics. This test is important, especially with respect to judging whether or not any diffusion processes can occur between neighboring farmers. We reject the null hypothesis of the absence of the correlations at a 5% level of significance for both variables, and hence the presence of the spatial autocorrelations is confirmed (Table 2). Moran's I and Geary's C positive statistics indicate that adjoining farmers are similar (e.g. a highly productive farmer's neighbors tend to be highly productive as well). Since the similarity of neighboring farmers is a necessary condition for the existence of a diffusion process, this result partly but positively confirm the presence of knowledge spillovers.

[Table 2 about here]

The results from regression analyses are reported in Table 3 and Table 4.[5] In order to decide which specifications are more appropriate, first of all, the presence of spatial autocorrelations in the FD residuals is tested (see the lower part of Table 3 and 4) by

[5] F and Likelihood ratio statistics suggest that the explanatory variables of household and village characteristics and district dummy variables are jointly significant at a 5% level of significance in all specifications. Hence, the estimated parameters for key variables should not be biased due to the other factors such as input of labor or education.

applying three test statistics (Wald, likelihood ratio (LR), and Lagrange multiplier (LM)).[6] The significance of the test statistics indicates the presence of spatial autocorrelation in the FD residuals. Moreover, with regard to the estimated spatial parameters, the asymptotic t-statistics are greater than the critical value at the 5% level of testing. The rejections of the null hypotheses $\lambda = 0$ and $\rho = 0$ indicate spatial dependences between neighboring farmers. From this evidence, it is fair to judge that spatial specifications (SEM and SLM) are a more appropriate model.

To then choose whether SEM or SLM is better is a rather ambivalent task.[7] One way to deal with this issue is to test for the presence of spatial autocorrelation in the SLM residuals; if present, the estimators are inefficient. Utilizing the SLM test which has chi-squared distribution with degree of freedom one, the test result (see the lower part of Table 3 and 4) indicates that it would probably be better to use the SEM than the SLM specification.

[Table 3 about here]

[Table 4 about here]

The interpretations of the results are as follows. Where the growth rate of the rice yield is concerned (Table 3), the significant positive estimated parameters for dummy variables for graduate and exposed farmers indicate that overall the FFS enhanced the rice yield by 48-66% for graduate farmers and by 35-52% for exposed farmers compared to the control

[6] See Anselin (1988) for the difference between these test statistics.
[7] Regarding this, see Anselin (2002) for a discussion from both theory and data driven perspectives.

group of farmers on average.[8] Also note that the extra growth rate for exposed farmers is not as high as that of graduates. Therefore, these results are consistent so far with our hypothesis that those who attended the FFS and the exposed farmers would perform better than the control group.

However, it is important to notice that while the estimated parameters for the number of post-program and exposure seasons are significant, they have negative signs. This result indicates farmers' performances declining progressively with every cropping season, and hence the positive impact of the FFS on the rice yield phasing out over time.

One potential reason for this is that over time graduate farmers might forget or due to some economic constraints might not be able to apply the best planting practices as they initially did just after attending the FSS. This is contrary to our intuition, which is that the longer the farmer has been a graduate of the program, the more opportunity he has had to improve his planting practices, and hence growth rates should increase.

Where a change in pesticide cost is concerned (Table 4), while none of the key variables are significant in FD and SEM, the estimated parameters for dummy variables in SLM are significantly negative, and the value of the graduate is less that that of the exposed farmer. Moreover, the estimated parameters for post-program and exposure seasons are not significant. Hence, the result in SLM indicates that graduate and exposed farmers significantly reduced their costs for pesticide consumption and continue this practice over time.[9]

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[8] These numbers should not be interpreted directly as a short-run impact, since what we estimated are the extra growth rates over the 'total' sample period.

[9] The long-run persistence of the IPM for graduates is also confirmed in Feder et al.

5. Conclusion

This paper evaluated the impact of the FFS by utilizing the same data set as Feder et al. (2004b) but by employing different model specifications and a different econometric technique. The empirical results of this paper turn out to be different to those of Feder et al. (2004b). There are several important policy implications of the results. We confirmed substantial positive impacts on agricultural productivities by the FFS for both farmers who participated in the FFS and those who indirectly obtained the new knowledge. However, the impact of the FFS on rice yields is declining over time. Where pesticide management is concerned, some empirical results reveal evidence that farmers who participated in the FFS and those who indirectly obtained the new knowledge reduced their spending on pesticides and conducted this practice over time.

In terms of spatial analysis, we find that the farmers' performance is positively-spatially correlated between neighbors in the same village. With our empirical result, this positively supports the existence of farmer-to-farmer knowledge diffusion. However, further studies are required to investigate farmers' spatial interactions, such as how the new knowledge is shared and adopted by farmers, and which elements will support long-run learning environments and which factors will obstruct them.

(2004a), Praneetvatakul et al. (2006), and Rola et al. (2002).

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Table 1
Descriptive statistics for dependent variables

		Category of farmer			
Variables	**Total**	**Controls**	**Graduates**		**Exposed**
			G1	**G2**	
sample no.	320	52	48	64	156
Performance variables					
Growth rate of yield of rice (kg/ha)	-0.12	-0.19	-0.099	-0.15	-0.096
	(0.33)	(0.30)	(0.29)	(0.30)	(0.36)
Change in pesticide cost ('000s of 1998 Rp/ha)	102.94	110.90	87.94	94.31	109.14
	(222.90)	(275.07)	(172.62)	(181.20)	(233.83)

Note: Standard deviations are in parentheses.

Table 2
Tests of spatial autocorrelation in dependent variables

	Growth rate of yield of rice		Change in pesticide cost	
Moran's I	0.161	**	0.134	**
	(Prob = 0.000)		(Prob = 0.000)	
Geary's C	0.836	**	0.864	**
	(Prob = 0.000)		(Prob = 0.000)	

Note : ** represents statistical significance at the 5% level.

Table 3
Impact of FFS on rice yield (Dependent variable: Growth rate of yield of rice)

	FD		SEM		SLM	
Key variables						
# of seasons for exposure	-0.0061		-0.0059		-0.0080	
	(-1.32)		(-1.67)	*	(-1.83)	*
# of seasons for post-graduate	-0.015		-0.015		-0.017	
	(-2.76)	**	(-3.30)	**	(-3.26)	**
Dummy for exposed	0.36		0.35		0.52	
	(2.71)	**	(3.46)	**	(3.68)	**
Dummy for graduate	0.51		0.48		0.66	
	(3.53)	**	(4.31)	**	(4.41)	**
Household characteristics: change between 1991 and						
Un-irrigated area (ha)	0.080		0.048		0.063	
	(1.70)	*	(1.13)		(1.44)	
logarithm of area for main plot (ha)	-0.049		-0.052		-0.049	
	(-2.12)	**	(-2.35)	**	(-2.25)	**
Total sawah area owned (ha)	-0.0013		-0.000055		-0.00074	
	(-0.099)		(-0.0046)		(-0.063)	
Number of household members	-0.015		-0.010		-0.012	
	(-1.13)		(-0.83)		(-1.02)	
Number of adult males (15 - 49yrs)	-0.0078		-0.012		-0.0093	
	(-0.47)		(-0.75)		(-0.60)	
Number of adult females (15 - 49yrs)	0.017		0.013		0.015	
	(0.87)		(0.69)		(0.79)	
Number of old males (over 50yrs)	-0.0040		-0.0039		-0.0046	
	(-0.12)		(-0.13)		(-0.15)	
Number of old females (over 50yrs)	0.013		0.014		0.013	
	(0.38)		(0.43)		(0.42)	
Village characteristics: change between 1991 and 1999						
Presence of pest observer (0 1)	0.19		0.18		0.26	
	(3.04)	**	(3.90)	**	(3.93)	**
Distance to Kecamatan centre (time)	0.0011		0.0013		-0.00067	
	(0.22)		(0.38)		(-0.15)	
% sawah land that is rainfed	-0.15		-0.13		-0.18	
	(-1.57)		(-1.86)	*	(-2.0)	**
Length of asphalted road (km)	-0.011		-0.017		-0.036	
	(-0.11)		(-0.24)		(-0.40)	
Number of kiosk	0.087		0.087		0.10	
	(1.89)	*	(2.56)	**	(2.24)	**
Initial conditions						
logarithm of yield of rice in 1991	-0.71		-0.69		-0.68	
	(-9.05)	**	(-9.24)	**	(-9.26)	**
Highest # years of education in 1991	0.0021		-0.0014		0.0006	
	(0.34)		(-0.23)		(0.11)	
Whether there is elementary school in village (0 1)	0.04		0.02		-0.07	
	(0.11)		(0.06)		(-0.19)	
# KUD in village in 1991(0 1)	-0.01		-0.01		0.005	
	(-0.091)		(-0.21)		(0.06)	
Constant	5.18		5.02		4.27	
	(3.38)	**	(4.15)	**	(2.91)	**
ρ					-0.38	
					(-2.41)	**
λ			-0.32			
			(-2.04)	**		
R^2	0.42					
Log likelihood			99.42		100.49	
Observations	320		320		320	
Tests of spatial autocorrelation in FS residuals — Wald	Prob = 0.000	**				
Tests of spatial autocorrelation in FS residuals — LR	Prob = 0.108					
Tests of spatial autocorrelation in FS residuals — LM	Prob = 0.249					
Test of spatial autocorrelation in SLM residuals — LM					Prob = 0.000	**

Note : t statistics are in parentheses. * significant at 10%; ** significant at 5%;
All specifications control district dummies.

Table 4
Impact of FFS on pesticide cost (Dependent variable: Change in pesticide cost)

	FD		SEM		SLM	
Key ariables						
# of seasons for exposure	-1.38		-1.88		-0.020	
	(-0.41)		(-0.97)		(-0.0070)	
# of seasons for post-graduate	0.47		0.52		1.90	
	(0.12)		(0.18)		(0.54)	
Dummy for exposed	-36.84		-33.64		-159.45	
	(-0.38)		(-0.61)		(-1.87)	*
Dummy for graduate	-89.20		-70.49		-204.69	
	(-0.85)		(-1.081)		(-2.23)	**
Household characteristics: change between 1991 and						
Un-irrigated area (ha)	22.95		15.31		19.06	
	(0.67)		(0.56)		(0.63)	
logarithm of area for main plot (ha)	-42.05		-26.48		-33.94	
	(-2.48)	**	(-1.68)	*	(-2.30)	**
Total sawah area owned (ha)	-13.97		-15.76		-13.53	
	(-1.52)		(-1.83)	*	(-1.69)	*
Number of household members	7.50		3.17		4.00	
	(0.78)		(0.36)		(0.48)	
Number of adult males (15 - 49yrs)	-3.40		-4.30		-2.86	
	(-0.28)		(-0.38)		(-0.27)	
Number of adult females (15 - 49yrs)	-0.27		3.68		2.38	
	(-0.019)		(0.27)		(0.19)	
Number of old males (over 50yrs)	-36.67		-38.25		-34.37	
	(-1.56)		(-1.76)	*	(-1.68)	*
Number of old females (over 50yrs)	-0.56		0.94		1.28	
	(-0.023)		(0.040)		(0.060)	
Village characteristics: change between 1991 and 1999						
Presence of pest observer (0 1)	-1.65		2.40		-53.18	
	(-0.035)		(0.093)		(-1.29)	
Distance to Kecamatan centre (time)	0.86		0.68		4.71	
	(0.25)		(0.38)		(1.54)	
% sawah land that is rainfed	37.87		31.57		71.05	
	(0.56)		(0.93)		(1.21)	
Length of asphalted road (km)	265.61		259.10		449.58	
	(3.77)	**	(7.00)	**	(7.09)	**
Number of kiosk	16.01		15.95		50.80	
	(0.48)		(0.91)		(1.72)	*
Initial conditions						
Pesticide cost in 1991	-0.74		-0.73		-0.68	
	(-5.075)	**	(-5.30)	**	(-5.35)	**
Highest # years of education in 1991	-3.33		-3.03		-3.08	
	(-0.76)		(-0.76)		(-0.80)	
Whether there is elementary school in village (0 1)	998.34		955.74		1613.57	
	(3.30)	**	(5.81)	**	(6.00)	**
# KUD in village in 1991(0 1)	34.65		31.53		40.40	
	(0.59)		(1.06)		(0.79)	
Constant	4125.59		4046.51		7089.73	
	(4.18)	**	(7.94)	**	(7.91)	**
ρ					-0.88	
					(-11.81)	**
λ			-0.88			
			(-11.12)	**		
R^2	0.32					
Log likelihood			-1995.83		-1994.04	
Observations	320		320		320	
Tests of spatial autocorrelation in FS residuals: Wald	Prob = 0.000	**				
Tests of spatial autocorrelation in FS residuals: LR	Prob = 0.000	**				
Tests of spatial autocorrelation in FS residuals: LM	Prob = 0.000	**				
Test of spatial autocorrelation in SLM residuals: LM					Prob = 0.000	**

Note : t statistics are in parentheses. * significant at 10%; ** significant at 5%;
All specifications control district dummies.

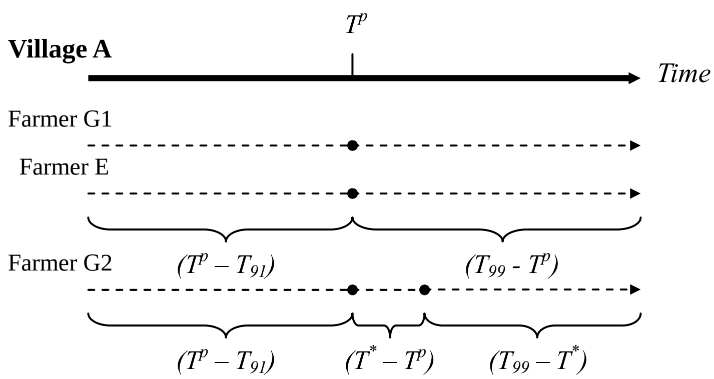

Fig. 1. Time Path of Different Farmers