Neighborhood Effects in Pesticide Use: Evidence from the Rural Philippines
(Preliminary Draft)

Takeshi Aida[a]

Abstract

This study investigates how pesticide use in neighboring farm plots affects one's own use. Although it is taken for granted that there are externalities in pesticide use, very few empirical economic studies directly analyze this issue. Applying spatial panel econometric model to the plot level panel data in Bohol, the Philippines, this study shows that the pesticide use, especially for herbicide, is spatially correlated though there is no statistically significant spatial correlation in unobserved shocks. This implies that farmers apply pesticides by mimicking neighboring farmers' behavior, rather than rationally responding to the intensity of infestation.

Keywords: Pesticide, neighborhood effects, externality, spatial econometrics, Philippines
JEL classification: Q56, Q12, O13

[a] JSPS Research Fellow, National Graduate Institute for Policy Studies
Address: 7-22-1 Roppongi, Minato-ku, Tokyo 106-8677, Japan.
E-mail: aidatakeshi@gmail.com

1. Introduction

Pesticides, if properly used, can enhance agricultural productivity by reducing crop damage. However, its inappropriate use can be a serious problem for environment, farmers' health, and food safety. In addition, especially in developing countries, farmers often do not know the proper use of pesticides, which leads to acute and chronic poisoning and environmental degradation (e.g., Rola and Pingali 1993; Shetty 2004). Thus, better understanding of farmers' decision on pesticide use is very important not only for academic purpose but also for policy makers' perspectives to reduce improper pesticide use.

In the economic analysis of pesticide use, farmers are assumed to optimize their application amount by equalizing marginal benefit and marginal cost (e.g., Headley 1972; Sexton et al. 2007). However, this optimization often does not incorporate spatial externalities of pesticide use, and the results might not be socially optimal.

In the case of pesticide use, spatial externalities, i.e., neighborhood effects (e.g., Durlauf 2004; Ioannides and Topa 2010), can matter in several ways. First, pesticide use in surrounding plots can affect the use in his/her own plot because it directly reduces the insect and weed population ("endogenous effect"). In contrast, it is also possible that neighbors' insecticide use increase one's own use because it can kill beneficial insects (Grogan and Goodhue 2012). Thus the expected spatial correlation can be both positive and negative. Second, insect and weed infestation, which are difficult for econometricians to observe accurately, can be spatially correlated ("correlated effect"). In this case, positive spatial correlation in usage is expected to respond to correlated intensity of infestation. In addition to these effects, it is possible to observe positive neighborhood effect because of farmers' irrational pesticide use. If the usage pattern is spatially correlated without significant spatial correlation in the degree of infestation, it indicates that farmers simply mimic neighboring farmers' pesticide application pattern. In this case, there is room for policy interventions to reduce the usage.

However, very few empirical studies examine spatial externalities of pesticide use directly. An interesting exception is Grogan and Goodhue (2012), who analyze the effect of landscape-level use of pesticide on individual growers' use in the California citrus industry. However, in the case of Asian countries, where small-scale farming is dominant, the distribution of each farm plot is very complex. Thus, it is necessary to analyze plot-level data by explicitly incorporating geographical information to discuss externalities of pesticide use.

One of the straightforward ways to incorporate these spatial effects is to employ spatial econometric approach (e.g., Anselin 1988). Spatial econometrics is effective for agricultural and environmental studies, where spatial effects can be important. However, to the best of my knowledge, none of the studies apply this approach to the analysis of pesticide use.

The aim of this study is to analyze neighborhood effects of pesticide use by employing spatial panel econometric approach. The advantage of the dataset is that plot-level panel data of agricultural input and GPS data are available. Thus, by including individual fixed effects, we can control for time-invariant preference parameters, which are important determinants of pesticide use (e.g., Pannell 1991; Liu and Huang 2013).

2. Data

The study site is the northeastern part of Bohol Island in the Philippines. In this area, the Bayongan irrigation system started operation in 2008. In order to assess its socio-economic impact, the International Rice Research Institute (IRRI) conducted a series of household survey over four cropping seasons from 2009-2010[1]. Original sampling target was randomly-selected 847 rice farmers covering both irrigated and rainfed areas. In this survey, they collected data on agricultural input and output in each farmer's main plot with its GPS coordinates as well as other household characteristics. After dropping missing values, household-plot level balanced panel data is available for 665 households.

3. Empirical Strategy

In order to test neighborhood effects in pesticide use, this study employs spatial econometric models. Spatial econometric models incorporate spatial dependence and heterogeneity (e.g., Anselin 1988; LeSage and Pace 2008). Among these models, combined spatial lag and error (SAC) model with individual fixed effects (e.g., Elhorst 2014) is used for the purpose of this study[2]. The model to be estimated is:

$$y_t = \rho W y_t + X_t \beta + \tau_t + \eta + u_t$$
$$u_t = \lambda W u_t + \epsilon_t,$$

where y_t is a vector of the amount of herbicide or insecticide use, W is an n x n inverse distance weight matrix (row-standardized) to capture spatial effects, X_t is a set of control variables, τ_t is period fixed effects to control for period-specific aggregate shocks, η represents household-plot fixed effects, and ϵ_t is a vector of well-behaved error term. The coefficient on the spatial lag term, ρ, captures spatial correlation in pesticide use.

After controlling for observed and unobserved characteristics, the residual u_t captures the intensity of infestation, which can also be spatially correlated. If unobserved insect or weed infestation correlates spatially, λ should be positive. If λ is not significantly different from zero, (1) shocks are actually not spatially correlated or (2) farmers' pesticide application is not based on pest infestation, which can result from using pesticides as a preventive measure.

---

1 See JICA and IRRI (2012) and Tsusaka et al. (2013) for detail.

2 The transformation approach by Lee and Yu (2010) is used for bias correction. Because of this approach, the sample size reduces from NT to $N(T\text{-}1)$.

The main parameters of interest are ρ and λ, which captures spatial dependence (endogenous effect) and heterogeneity (correlated effect), respectively. As mentioned above, ρ captures the mixture of the spillover effect of neighboring farmers' pesticide usage and the response to spatially correlated pest damage. Thus the sign of this term is an empirical question. Note that, if there is no spatial correlation in the error term, i.e., $\lambda = 0$, there is no reason for the usage to be spatially correlated. Thus, if $\rho > 0$ and $\lambda = 0$, farmers do not respond to the intensity of infestation, implying that they mimic neighboring farmers behavior.

4. Empirical Results

The first 4 columns of Table 1 show the results when the dependent variable is the amount of herbicide used. The spatial lag term is significantly positive with and without fixed effects. In contrast, the spatial error term is not significant in both cases. This finding suggests that the farmers' usage pattern is correlated regardless of spatially correlated shocks, implying they are mimicking their neighbors. The distance to the agricultural supplier in the nearest town is negatively associated with the usage, suggesting that the cost of buying pesticide is hindrance for application. Though the irrigation dummy itself is significantly positive, irrigation water usage is significantly negative and its magnitude is not affected very much even after controlling for fixed effects. This implies that irrigation water generally prevents the growth of weed population, but insufficient irrigation water use may rather foster it. The sign of the size of surveyed plot is negative, which could represent economy of scale (Liu and Huang 2013). Larger household size is associated with lower herbicide use, suggesting that herbicide can be substituted for weeding by family member.

The last 4 columns show the results when the dependent variable is the amount of insecticide used. In contrast to herbicide use, both spatial lag and error are insignificant. This is reasonable because the insignificant spatial lag term can result from the lack of spatially correlated insect infestation. Similar to herbicide case, the size of the surveyed plot has negative impact on the insecticide use. Interestingly, though the irrigated dummy is significantly negative, irrigation water use is insignificant and robust to the inclusion of fixed effects. The coefficient on household size is negative but insignificant, which contrasts with herbicide case. This is because insect infestation is more difficult to monitor or predict than weed infestation.

5. Concluding Remarks

This study investigates the neighborhood effects in pesticide use employing spatial econometric approach. The estimation results show that though there is no significant spatial correlation in unobserved degree of pest infestation, the usage is spatially correlated especially for herbicide use. This finding indicates that when farmers apply pesticide, they do not respond to the degree of infestation, rather mimic the neighboring farmers application. Thus, the current usage amount may not be optimal, and there is room for pesticide reduction.

Reference

Anselin, Luc (1988) *Spatial Econometrics: Methods and Models*. Dordrecht, The Netherlands: Kluwer Academic Publishers.

Antle, John M., and Prabhu L. Pingali (1994) "Pesticides, Productivity, and Farmer Health: A Philippine Case Study," *American Journal of Agricultural Economics* 56, pp.418-30.

Durlauf, Steven N. (2004) "Neighborhood Effects," in *Handbook of Regional and Urban Economics*, vol. 4, J. V. Henderson and J.-F. Thisse, eds., Amsterdam: North Holland, 2004.

Elhorst, J. Paul (2014) *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels*, New York: Springer.

Grogan, Kelly A. and Rachael E. Goodhue (2012) "Spatial Externalities of Pest Control Decisions in the California Citrus Industry," *Journal of Agricultural and Resource Economics* 37(1), pp.156–179.

Headley, J. C. (1972) "Defining the Economic Threshold," In: *Pest Control Strategies for the Future,* Agricultural Board, Washington, DC: National Academy of Sciences.

Ioannides, Y.M. and Topa, G. (2010). Neighbourhood Effects: Accomplishments and Looking Beyond them. *Journal of Regional Science* vol. 50 (1), pp. 343–62.

Japan International Cooperation Agency and International Rice Research Institute (2012) "Impact Evaluation of the Bohol Irrigation Project (Phase 2) in the Republic of the Philippines"

Liu, Elaine M. and JiKun Huang (2013) "Risk preferences and pesticide use by cotton farmers in China," *Journal of Development Economics* 103, pp.202–215.

Pannell, David J. (1992) "Pests and pesticides, risk and risk aversion," *Agricultural Economics* 5, pp.61-383

Rola, A. C., & Pingali, P. L. (1993) *Pesticide, Rice Productivity and Farmer's Health: An Economic Assessment*. Washington, DC: World Resources Institute and Los Banos, Philippines: IRRI.

Sexton, Steven E., Zhen Lei, and David Zilberman (2007) "The Economics of Pesticides and Pest Control," *International Review of Environmental and Resource Economics*, 1: 271–326.

Shetty, P. K. (2004) "Socio-ecological Implications of Pesticide Use in India," *Economic and Political Weekly* 39(49), pp.5261-5267.

Tsusaka, Takuji W., Kei Kajisa, Valerien O. Pede, and Keitaro Aoyagi (2013) "Neighbourhood effects and social behaviour: the case of irrigated and rainfed farmers in Bohol, the Philippines," *MPRA Paper* No. 50162.

Table 1: Results for Herbicide Use

MODEL VARIABLES	(1) OLS Herbicide kg/ha	(2) SAC Herbicide kg/ha	(3) FE Herbicide kg/ha	(4) SAC FE Herbicide kg/ha	(1) OLS Insecticide kg/ha	(2) SAC Insecticide kg/ha	(3) FE Insecticide kg/ha	(4) SAC FE Insecticide kg/ha
Irrigated dummy	0.0183	0.0209			-0.0263***	-0.0284**		
	(0.0167)	(0.0137)			(0.00990)	(0.0114)		
Size of surveyed plot	-0.0185**	-0.0178**	-0.0359**	-0.0352**	-0.0112**	-0.0115**	-0.0280*	-0.0279*
	(0.00758)	(0.00758)	(0.0155)	(0.0154)	(0.00544)	(0.00553)	(0.0152)	(0.0151)
Log (irrigation water use +1)	-0.0103**	-0.00949**	-0.0120**	-0.0103**	0.00343	0.00295	0.00285	0.00246
	(0.00433)	(0.00430)	(0.00492)	(0.00497)	(0.00256)	(0.00325)	(0.00310)	(0.00320)
Hybrid dummy	-0.00232	-0.00258	0.0141	0.0122	0.0179	0.0179	0.0235	0.0234
	(0.0166)	(0.0207)	(0.0150)	(0.0147)	(0.0200)	(0.0152)	(0.0205)	(0.0206)
Credit constrained	-0.0234***	-0.0234**	-0.00507	-0.00634	-0.00676	-0.00645	-0.000997	-0.000484
	(0.00897)	(0.0106)	(0.00894)	(0.00892)	(0.00905)	(0.00775)	(0.0116)	(0.0118)
Distance to the nearest agricultural supplier	-0.00844***	-0.00603***			-0.00125	-0.00148		
	(0.00137)	(0.00126)			(0.000953)	(0.00109)		
Age of household head	0.00303	0.00291			0.00500***	0.00505***		
	(0.00265)	(0.00217)			(0.00156)	(0.00157)		
Age squared (divided by 100)	-0.00280	-0.00271			-0.00509***	-0.00513***		
	(0.00250)	(0.00201)			(0.00141)	(0.00145)		
Education level of household head	0.000408	0.000357			-0.00146	-0.00141		
	(0.00148)	(0.00121)			(0.000991)	(0.000884)		
Female household head dummy	-0.0166	-0.0161			0.00764	0.00811		
	(0.0214)	(0.0162)			(0.0187)	(0.0117)		
Household size	-0.00680***	-0.00679***			-0.00123	-0.00131		
	(0.00200)	(0.00154)			(0.00126)	(0.00111)		
2009 dry season dummy	-0.0231***	-0.0142	-0.0192**	-0.0139*	0.0118*	0.0163	0.0131*	0.0108

	(0.00827)	(0.00886)	(0.00822)	(0.00833)	(0.00715)	(0.0156)	(0.00754)	(0.0102)
2010 wet season dummy	-0.0100	-0.00971	-0.00756	-0.00781	0.0228***	0.0294*	0.0236***	0.0185*
	(0.00904)	(0.00846)	(0.00905)	(0.00915)	(0.00636)	(0.0167)	(0.00666)	(0.0111)
2010 dry season dummy	-0.00953	-0.0108	-0.00785	-0.00839	0.0680***	0.0882***	0.0684***	0.0534**
	(0.0107)	(0.00901)	(0.0108)	(0.0110)	(0.00898)	(0.0282)	(0.00929)	(0.0254)
Spatial lag (ρ)		0.619***		0.396**		-0.346		0.213
		(0.189)		(0.163)		(0.410)		(0.325)
Spatial error (λ)		-0.317		0.0249		0.485		0.0628
		(0.287)		(0.166)		(0.321)		(0.328)
Constant	0.201***	0.115*	0.120***	NA	-0.0382	-0.0246	0.0378***	NA
	(0.0685)	(0.0648)	(0.0136)	NA	(0.0438)	(0.0487)	(0.0125)	NA
Observations	2,660	2,660	2,660	1,995	2,660	2,660	2,660	1,995
Log likelihood	650.4261	655.69448	1411.859	1366.1933	1522.141	1523.25	2070.159	2021.8134

Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1