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Neighbours' Influence on Farmer Adoption of Fertiliser Recommendations in Rubber Cultivation

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Farmers' individual choices relating to agronomic practices are influenced by socio economic factors related to the farmer and his family as well as physical factors relating to the farm. Many studies that investigate these choices fail to recognise the importance of neighbours' influence on decision making. This research attempted to determine whether there exists a relationship between one farmer's choice and the choices of the neighbouring farmers in adoption of fertiliser recommendations in rubber cultivation of a sample of 393 smallholder farmers in one of the non-traditional rubber growing districts in Sri Lanka. Major aims of the research were to explicitly model spatial relationships in adoption of fertiliser application in rubber cultivation and to identify the factors that influence them. Bayesian Spatial Autoregressive Probit (SARP) model was used in the study. The neighbours' influence was measured in terms of a spatial correlation coefficient. Results revealed that the spatial correlation coefficient was positive and statistically significant, implying a strong influence by neighbours on a decision by a particular farmer. The results also highlighted the importance of socio economic factors and soil characteristics in adopting these practices.

Keywords: Bayesian Econometrics; neighbourhood effect; Spatial Autoregressive Probit

Rubber is a crop that provides a major source of income to more than twenty million farmers worldwide[1]. This provides an extremely important source of income for the poor as it can prevent those who are hovering on the poverty line from falling below it[2]. In most of the rubber producing nations, the majority belong to the smallholder sector although the definitions of a smallholder may vary among the nations. One common feature is the existence of productivity gaps between experimental figures and what farmers produce[3]. This is very often attributed to farmers' inability or unwillingness to adopt correct agronomic practices. Therefore, improving productivity is associated with the use of proper cultivation practices. Some of these practices are directly related to productivity while others are related to soil and moisture conservation that help the environment apart from increasing productivity. This research seeks to investigate the factors that motivate farmers to adopt one such practice, fertiliser application.

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Studies on technology adoption typically measure the impact of variables relating to preferences, resource endowments, market incentives, biophysical factors and risk[4]. However, empirical observations reveal that the impact on adoption is likely to depend not only on these but also decisions made by neighbouring farmers. This unique factor is referred to as 'neighbourhood' effect[5]. The neighbourhood effect is a social interaction that influences the behaviour or socio economic outcome of an individual. Individual choices are often influenced by the choices and opinion of others in their immediate environment[6]. This is difficult to measure. Therefore, neighbourhood effect is modelled as a spatial relationship using a sample of smallholder rubber producers from Sri Lanka. Spatial analysis uses formal techniques which study persons or an entity using their topological geometric or geographic properties. Such studies are increasingly becoming common due to the availability of low cost Geographic Information System (GIS) with user friendly interfaces.

In this research, we attempted to explicitly model the spatial relationships in the adoption of fertiliser recommendations in rubber cultivation, taking a sample of smallholder farmers from Sri Lanka. Our objectives were twofold. One was to measure the impact of traditional variables on adoption and the second was to assess the neighbourhood effect on adoption.

METHODOLOGY

Study Site and Data

This study used a data set of 393 smallholder rubber farmers in Moneragala district which is one of the districts where rubber was introduced recently. The sample covered 62 Grama Niladhari (GN) divisions which are the units at the lowest administrative level in Sri Lanka. As Moneragala is not a traditional rubber growing area, most farmers are relatively new to rubber cultivation. Data were collected by the Rubber Research Institute of Sri Lanka in 2007/2008.

Econometric Model

The questionnaire used for data collection recorded the farmers who have adopted fertiliser application as a 'yes' or 'no'. Therefore, the variable related to adoption was dichotomous. For this reason, the analysis used here is a probit model, which relates a latent distribution to a set of covariates as:

$$y^* = X\beta + e \qquad e \sim f^N(0, I_N) \qquad \ldots 1$$

Where y* = latent/unobservable utility from adoption, X = covariates related to adoption, β = coefficients to be estimated, e = random error. The observed dichotomous variable relating to adoption is related to an unobserved latent utility from adoption (y*) as

$$y = 1 \text{ } if \text{ } y^* > 0$$

$$y = 0 \text{ } if \text{ } y^* \leq 0$$

This assumes that we observe adoption of fertiliser application when a farmer derives a positive utility and we do not observe fertiliser application when the utility is zero or negative. The aim of this study was to assess the influence of neighbours on adoption decisions of farmers in the neighbourhood. Spatial autoregressive component in the latent regression was used to capture this issue. Thus, the Spatial Autoregressive Probit (SARP) model estimated is as follows[4]:

$$y^* = \rho W y^* + X\beta + e \qquad \ldots 2$$

This model assumes that the spatially weighted sum of utility derived by neighbours (spatial lag) enters as an explanatory in the specification of latent utility formation of a farmer. That is,

$$y^*_1 = \rho\,(W_{12}y^*_2 + \ldots + W_{1N}y^*_N) + X\beta + e_1 \qquad \ldots 3$$

The spatial weight matrix, W_{ij} links the observation i and j and only few of the W_{ij} are non zero because spill over effects take place between neighbours in close proximity. Therefore, by having an autoregressive component (a spatial lag) in the SARP model, the magnitude of a decision variable for an economic agent is allowed to depend on the magnitudes of the decision variables set by other economic agents in the neighbourhood defined by W[7]. The scalar parameter ρ measures the strength of this dependence. Hence, if $\rho = 0$, then there is no dependence. Defining neighbours in the sample was carried out by setting the matrix W using the 'location' of each farmer. Because this data set was not collected for spatial analysis, the 'location' of each farmer is not recorded by GPS coordinates. However, the data set recorded the name of the GN division of the farm. GPS coordinates of these GN divisions were therefore taken to build the 'neighbourhood' matrix, W.

Estimation

A Bayesian method was used to estimate the SARP model because of the difficulty in modelling spatial auto regression in a maximum likelihood framework[8]. Bayesian econometrics is based on a few simple rules of probability[9].

$$P(B|A) = \frac{P(A|B)P(B)}{P(A)} \qquad \ldots 4$$

Where $P(B|A)$ = conditional probability of B given A, $(PA|B)$ = conditional probability of A given B, $P(B)$ = marginal probability of B, $P(A)$ = marginal probability of A. The Bayesian would replace B by θ (coefficients) and A by y (data). Then,

$$P(\theta|y) = \frac{P(y|\theta)\,P(\theta)}{P(y)} \qquad \ldots 5$$

For Bayesian analysis, $p(y)$ can be omitted and the expression above can be stated as $\pi(\theta|y) \propto f\,(y|\theta)\pi(\theta)$, which states that the posterior (distribution of the coefficients given data, $\pi(\theta|y)$) is proportional to likelihood of observing data, y, given the parameters; $f\,(y|\theta)$ times a prior assumption of distribution of parameters before analysis; $\pi(\theta)$. The objective of Bayesian analysis is then to model the distribution of the posterior, given the likelihood and the prior. Parameter vector, θ include the unknown coefficients β and the latent variable, y^* is estimated alongside regression coefficients using Gibbs sampling with data augmentation following Albert and Chib[10]. Due to lack of information on the distribution of the prior (how the regression coefficients are distributed), it was assumed that it is diffused. Thus, the posterior has the form:

$$\pi(\theta/y,y^*) \propto \prod_{i=1}^{N} f^{TN} + (y^*_i/\beta_i)^{yi} \times f^{TN} - (z^*_i/\beta_i)^{(1-yi)} \times \pi(\rho|\rho_0,\sigma_0) \times \pi(\beta|\beta_0,C_0) \qquad \ldots 6$$

We used the posterior to derive the conditional distributions from which Gibbs sampling draws are made. The conditionals had the form:

$$\boldsymbol{\beta|\rho, y, y^* \sim f^{MN}(\hat{\beta}, Cov_{\hat{\beta}})} \qquad \ldots 7$$

$$y^*|\rho, y, \beta \sim f^{TN}(\hat{y}^*, Cov_{\hat{z}}) \qquad \dots 8$$

Where $\hat{\beta} = (X'X + C_0^{-1})^{-1} (X'(I_N - \rho W)y^* + C_0^{-1}\beta)$, $Cov_{\hat{\beta}}$ $(X'X + C_0^{-1})^{-1}$, $Cov_{\hat{z}} = [(I_N - \rho W)' (I_N - \rho W)]^{-1}$ and $\hat{y}$ $[(I_N - \rho W)' (I_N - \rho W)] (I_N - \rho W)'X\beta$. Because it is difficult to find a suitable conditional for ρ, the draw for ρ followed a Random Walk Metropolis Hastings Algorithm. Data were sampled from the conditional for 25,000 iterations keeping aside 5,000 iterations as 'burn in' sample. Draws were checked for stationarity by observing trace plots. Analysis was carried out using the Matlab R2009a software.

Two types of variables were used as covariates in the X matrix, *viz*. socio economic and physical factors. Age, gender, education, distance from home, family size, occupation, ownership and fertiliser subsidy were used as the socio economic factors and soil type, topography, extent and maturity of rubber stand were used as physical factors (*Table 1*).

RESULTS AND DISCUSSION

Descriptive Statistics of the Sample

Summary statistics of the sample of households studied are given in *Table 1*. Mean, standard deviations, minimum value and maximum values are reported. Out of the 393 samples, there were only 64 females and all others were male. Two hundred and fifty nine rubber cultivators did intercropping while only 72 were adding fertiliser to their fields. Ten cultivators planted cover crops in their rubber fields. Most of the cultivators were middle aged and their mean land extent was 1.645 acres (0.67 ha). The majority of them were engaged with farming while a few of them stated farming as another way of generating income.

Results of SARP Analysis

The results of the SARP estimation are reported in *Table 2*. Direct effects show the marginal effect of change of a unit of independent variable of farmer *i*, on the change of the dependent variable of the farmer *i* ($\partial y^*/\partial x_i$), while indirect effects show the change of independent variable of farmer i, on the change of the dependent variable of the farmer *j* ($\partial y^*/\partial x_i$). These indirect estimates are known as 'spatial spill over effects'. The sum of the two effects (direct and indirect) represent the (cumulative) total effect associated with a change in an observation for that explanatory variable[5].

Results show a positive and significant spatial correlation coefficient of 0.4 for fertiliser application indicating that the 'neighbourhood' effect is an important element in farmer choices. *Figure 1* shows the distribution of the estimated spatial correlation coefficient. One point to note is that the coefficient associated with the spatial lag of the dependent variable *Wy*, is more than five standard deviations away from zero. Therefore, one farmer's decision is influenced by the decision of the neighbouring farmers. It was also found that this neighbourhood effect runs across 7 GN divisions.

Posterior means (coefficients) of most of the variables are significant (*Table 2*). *Table 3* shows that the variables, maturity, extent, distance from home, dummy for soil texture, intercrops and subsidies have a significant direct and indirect effect on fertiliser application. As expected, highest direct and indirect effects are observed in the case of availability of a fertiliser subsidy. Farmers who obtained a subsidy have a probability of 54% of applying fertiliser than those who do not get fertiliser subsidy (direct effect). Similarly, a farmer having a subsidy has an indirect

TABLE 1. SUMMARY STATISTICS OF THE SAMPLE

Variable	Description	Mean	Min	Max	% yes(=1)	% no(=0)
Family size	Number of family members	4.47	1	10	-	-
Age	Age of farmer in years	47.43	23	80	-	-
Education	Primary =0	0.54	0	3	-	-
	Up to Ordinary level =1					
	Up to Advance level =2					
	Higher =3					
Extent	Rubber extent in acres	1.64	0.5	27	-	-
Dis-home	Distance from home to rubber land in km	0.69	0	16	-	-
Topography	Flat =0					
	Mid slope =1					
	Steep slope =2	0.77	0	2	-	-
Ownership	Single ownership = 0					
	Group ownership =1					
	Licence = 2					
	Other = 3	0.48	0	3	-	-
Maturity	Mature stand =1					
	Immature stand = 0	-	-	-	36.89	63.1
Gender	Male = 1					
	Female =0	-	-	-	83.71	16.28
Sandy	If soil texture is sandy =1, otherwise 0	-	-	-	6.36	93.63
Clay	If soil texture is clay =1, otherwise 0	-	-	-	12.97	87.02
Gravel	If soil texture is gravel =1, otherwise 0	-	-	-	14.24	85.75
Intercrop	Intercrops present = 1, otherwise, 0	-	-	-	65.90	34.09
Cover crop	Cover crop present =1, otherwise, 0	-	-	-	10.94	85.05
Subsidy	Obtained fertiliser subsidy=1, otherwise, 0	-	-	-	54.19	45.80

spill over effect of 36.6%, on the probability of adoption on a neighbouring farmer. Thus, the total effect of increase in probability of adoption for a farmer who gets a subsidy than those who do not, is around 90.6%, holding all others constant. Hence, providing fertiliser subsidy is important as it carries the highest marginal effects directly on the farmers and a spill over effect on other farmers. Contrary to the belief that farmers are reluctant to apply fertiliser to mature stands, the present findings reveal that there is a significant difference in application of fertiliser in mature stands than immature stands. This observation may be due to two reasons. First, because this is a non traditional rubber growing area, what we see here can be different from the traditional rubber growing areas. Second, rubber prices have increased considerably in the past few years. Therefore, farmers may apply fertiliser to reap the benefits of price hikes. Results further revealed that male farmers are more probable in adoption of fertiliser recommendations than females. One other finding that is contrary to expectations is the negative sign with respect to education level. It is expected that with the increase in education level, probability of adoption of recommended practices increase. However, it is not the case for adoption of fertiliser application in the present sample. Extent is positive and significant as expected in all three technologies, implying that larger

TABLE 2. POSTERIOR ESTIMATES OF THE SARP MODEL

Variables	Fertiliser			Marginal effects		
	Coeff.	SD	p value	Direct	Indirect	Total
Constant	-4.51**	1.231	0.000	-	-	-
Maturity	2.34**	0.551	0.000	0.199	0.136	0.336
Family size	-0.81	1.243	0.255	-0.068	-0.047	-0.115
Gender	0.92**	0.526	0.035	0.079	0.053	0.132
Age	-0.25	1.262	0.423	-0.021	-0.015	-0.037
Education	-1.31**	0.710	0.030	-0.112	-0.077	-0.188
Extent	2.59**	1.302	0.019	0.220	0.150	0.371
Dis-home	3.94**	1.927	0.005	0.338	0.228	0.566
Topography	0.82*	0.612	0.090	0.071	0.048	0.119
Sandy	2.15**	0.782	0.001	0.184	0.126	0.309
Clay	0.70*	0.479	0.072	0.061	0.041	0.102
Gravel	0.21	0.438	0.313	0.019	0.012	0.031
Ownership	0.14	0.504	0.390	0.013	0.008	0.021
Intercrop	0.70**	0.338	0.016	0.060	0.041	0.101
Cover crop	-0.74**	0.459	0.047	-0.063	-0.044	-0.107
Subsidy	6.32**	0.958	0.000	0.540	0.366	0.906
Rho(ρ)	0.43**	0.057	0.000			

**significant at 5% level; *significant at 10% level.
Note: Coeff = Coefficient, SD= Standard Deviation, Dis-home = Distance from home

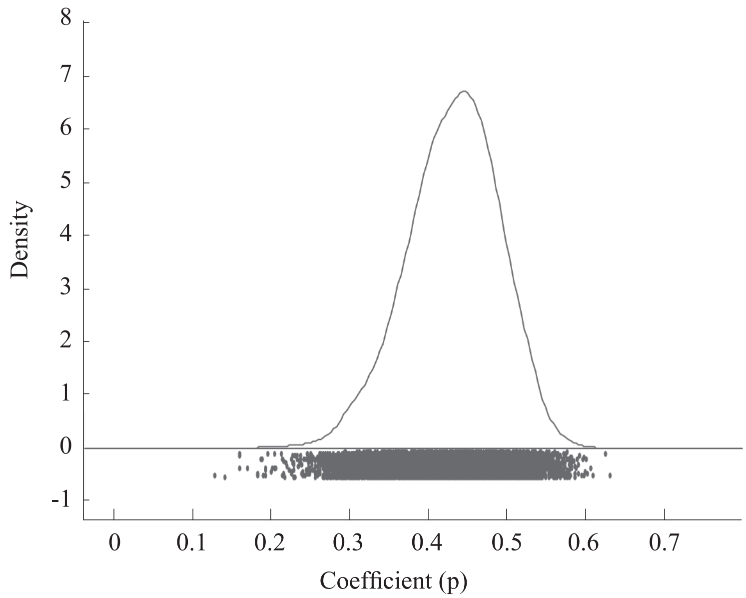

Figure 1. Distribution of the estimated spatial correlation coefficients for fertiliser.

farmers tend to adopt more compared to smaller farmers. Distance from home was included to identify any transaction costs hindering adoption. There is evidence that the greater the distance between the homestead and land, use of cultivation inputs is less intensive[3]. It may be due to the fact that most farmers who live in a distance from the land are employed elsewhere and may have the financial capability of applying fertiliser than those poor farmers whose main income is rubber. The dummies related to soil types are significant and imply that probability of adopting these three practices vary according to the soil type. This finding is as expected. Further, having an intercrop improves the probability of applying fertiliser. This is expected because farmers may apply fertiliser to get a higher output from the intercrop as well as from rubber.

CONCLUSIONS

The research is specially focused on interpretation of estimates arising from use of a spatial autoregressive probit model, where spatial lags of the dependent variable allow for interdependence in choices. Significant spatial auto regression parameter (ρ) implies that farmers' decision is influenced by neighbours. Nearby farmers are likely to make similar decisions because of their common location which leads to similar options regarding adoption of agronomic practices in rubber cultivation. This is important in designing extension activities to increase adoption of recommendations. Extension is usually a public good provided by the state. However, the state incurs considerable costs in providing this service. The finding that the spatial relationship runs across 7 GN divisions provides insights into how target oriented extension programmes can be planned in a cost effective manner. Research in different areas will provide different magnitudes as well as extents to which the spatial effect expands. Proliferation of such research is important in other rubber growing regions/countries to plan cost effective ways of diffusing important technologies.

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