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Spatial dependence of production choice: application of Bayesian Spatial Autoregressive Probit Model on smallholder rubber producers

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Abstract: In most smallholder agricultural production activities, farmers make choices about the types of output that they sell. This choice is influenced by various market and non-market factors, including the decisions of other farmers in the neighbourhood. Taking a sample of smallholder rubber farmers from Sri Lanka, this research is conducted to study their output choice with the special interest in measuring the impact of neighbours. We estimate a Spatial Autoregressive Probit Model using recently developed Bayesian econometric techniques. Results show that while social and physical capital and transaction costs have positive impacts on the choice of sheet rubber production, education and scale of production have negative impacts. A strong spatial relationship is found, and the farmers' choice is influenced by their neighbours. There are considerable amounts of spatial spill over effects, especially with respect to physical capital. Our findings reveal the possibility of central processing to overcome resource limitations, significant reductions in extension efforts in promoting good manufacturing practices by taking stock of the 'neighbourhood' effect present in farmer choices.

Keywords: bayesian analysis, neighbourhood effect, Spatial Autoregressive Probit, sheet rubber, spatial spill-over.

Introduction

There is a lack of spatial data analysis being incorporated in applied research (Anselin and Griffith, 1988). In conventional regression, we assume that observations in a cross-section of data are independent. Making such assumptions, when, in reality, they are related, is met with erroneous statistical inferences. In the recent past, although a proliferation of studies using spatial econometrics is observed, most of them are limited to continuous dependent variable cases. One important feature is that even though, limited dependent variable models are abounded in economics, those that take spatial dependence into account are not that plentiful. Those that incorporate spatial dependence on limited dependent variable models in a Bayesian setting are infrequent.

In this study, we attempt to incorporate spatial dependence in a study of production choices, more specifically, production choices of smallholder rubber farmers in Sri Lanka. We analyse the decision on whether to produce or not to produce sheet rubber. We select this decision because it has grave implications on the household incomes of smallholders as well as implications for the country as a whole. Sheet rubber fetches higher prices in the market. If farmers opt not to produce sheet rubber and sell as direct latex, their income may be reduced. Similarly, lack of production of sheet rubber will result in importation for the vibrant tyre industry within the country resulting in a loss of valuable foreign exchange. We hypothesise that apart from market and socio-economic factors that influence such a decision, a spatial impact is at play. More specifically, we hypothesise that farmer decisions are influenced by decisions of 'neighbours', which is termed in the literature as the 'neighbourhood effect' (Holloway and Lapar, 2007; Holloway *et al.*, 2002). We relate this effect to spatial autocorrelation and measure its impact.

Methodology

Theoretical Framework for Analysis

Because of the dichotomous nature of data on production of sheet rubber (or not producing it), we use a probit model, which is the appropriate methodology in such cases. The probit model is one of the several models that falls in the general category of 'random utility models' where an underlying latent distribution (zi) of utility differences of choices is assumed. This latent distribution is related to a set of observed characteristics contained within a covariance matrix (xi) and a normally distributed error (εi) in a normal linear regression model (Koop, 2003). In general, the random utility model can be specified as below.

$$z_i = x_i\beta + \varepsilon_i \qquad (1)$$

Where, β is a vector of coefficients to be estimated. In the probit model, only two outcomes are observed. Hence, in the present context, when production of Ribbed Smoked Sheet (RSS) is not observed, the latent utility difference is assumed to be less than or equal to zero while it is more than zero when sheet rubber production is observed. Thus, the actual production (y_i) can be related to latent utility (z_i) as below.

$$\begin{aligned} y_i &= 1 \text{ if } z_i > 0 \\ y_i &= 0 \text{ if } z_i \leq 0 \end{aligned} \qquad (2)$$

Apart from observing covariates that drives production of sheet rubber, our central interest is in estimating whether neighbours influence this production choice. We hypothesise that when one farmer is deriving benefit out of a certain economic activity; others in the vicinity tend to follow him. This is difficult to measure. This motivates us to include a spatial autoregressive component in the conventional probit model. Following Lesage and Pace (2009), we define neighbours by their location and relate the production choice of one farmer to his immediate neighbours. We do this by resorting to techniques developed in spatial econometrics. More succinctly, we use a Spatial Autoregressive Probit (SARP) model in estimation, following ideas of Lesage and Pace (2009). The SARP model is specified as;

$$z = \rho W z + X\beta + \varepsilon \qquad (3)$$

This is autoregressive because latent utilities of neighbouring farmers are entered into the regression by having them at the right-hand side in the equation. Auto regression is common in time series models where a time-series variable is set to depend on its previous values (lags of the variable). Similarly, in this model, we incorporate lags of the dependent variable (z) in the right-hand side in the equation, which is termed in literature as a spatial lag. Anselin (1988) called this a spatial autoregressive model. Specifically, the weighted sum of utility derived by neighbours (spatial lag) is entered into the model as an explanatory variable. Therefore, a particular farmers' latent utility is allowed to depend on this weighted sum as below.

$$z_1 = \rho(W_{12}z_2 + W_{13}z_3 + \ldots + W_{1N}z_N) + X\beta + \varepsilon_1 \qquad (4)$$

Thus, in this equation, the latent utility of farmer 1 (z_1) is allowed to depend on utilities of his neighbouring farmers (z_2, z_3, ..., z_N). However, because it is assumed that immediate neighbours to have a 'larger' impact than distant ones, theses utilities are weighted according to a spatial weight matrix (W) that defines neighbours. This is an n×n matrix which is positive and symmetric. Each element of this matrix, w_{ij}, has weights for each pair of locations, i and j by rules set in determining neighbours. Thus, the spatial weight matrix, W_{ij} links the observation i and j. Because spill-over effects take place between neighbours in close proximity, only few of the W_{ij} are non-zero (Anselin, 1988). Therefore, this spatial lag allows the extent of a decision variable for a farmer to depend on the extents of decision variables of other farmers in the neighbourhood. The parameter ρ (the spatial correlation coefficient), which is a scalar, defines the strength of spatial dependence. If ρ is found to be zero, then the spatial dependence is unfounded. In estimating this SARP model, setting the spatial weight matrix W is crucial. We set it by using the 'location' of each farmer. The location of each farmer was captured from a GPS devise whose coordinates are read into MATLAB and the spatial weight matrix is developed by the procedure described in Lesage and Pace (2009).

Bayesian Estimation

The Spatial Autoregressive Probit Model (SAPM) described above poses challenges in estimation using classical econometric techniques. Latent variable models such as SAPM are more complicated because they often do not have a closed-form solution. To circumvent this problem, one has to be using an iterative technique in estimation. Bayesian method of analysis is one such technique. Using Bayesian methods have additional advantages. It assumes the parameters of the model to have a distribution rather than a point estimate. We can simulate these distributions of parameters of interest using techniques such as Gibbs sampling. Properties of these distributions can be used to make probabilistic statements about the parameters.

Because of foregoing reasons, we estimate the model using Bayesian techniques. In Bayesian analysis, the interest is to obtain a posterior probability distribution of regression parameters. The posterior is assumed to be proportional to the likelihood and a prior as given in equation (5).

$$\pi(\boldsymbol{\theta} \mid \mathbf{y}) \quad f(\mathbf{y} \mid \boldsymbol{\theta})\, \pi(\boldsymbol{\theta}) \qquad (5)$$

By specifying a prior probability density function (pdf) over parameters, $\pi(\theta)$, and multiplying it by the likelihood, $f(y|\boldsymbol{\theta})$, the posterior distribution $\pi(\boldsymbol{\theta}|y)$ for the parameters is obtained. These posterior distributions of parameters are examined to make probabilistic statements about the coefficients.

In the present model, the data generating density is normal. The likelihood for this model is $f^{N}(\mathbf{y}|\boldsymbol{\theta}) = \div\, {}_{i}^{N}{}_{1}\, (\Phi(-\mathbf{x}_i\beta))^{1-y_j}\, (\Phi(\mathbf{x}_i\beta))^{y_j}$ where the notation, $\Phi(.)$, denotes a cumulative distribution function of the normal distribution.

The parameters of interest in the probit model are $\boldsymbol{\Phi}(.)$, which are the regression coefficients. In estimation, we employ Gibbs sampling with data augmentation following Albert and Chib (1993). It is implemented by iteratively sampling from the following conditional distributions.

$$\beta | z, y \sim f^{N}(\hat{\beta}, \mathrm{cov}_{\hat{\beta}})$$

$$z | \beta, y \sim f^{tN}(\hat{z}, \mathrm{cov}_{\hat{z}}) \qquad (6)$$

We set the priors for regression parameters (β) to be normal with a mean of β_0, and a covariance of C_0, and we define them as, $\mathrm{cov}_{\hat{\beta}} \quad (X X + C_0)^{-1}; \; \hat{\beta} \quad \mathrm{cov}_{\hat{\beta}}(X z + C_0\beta_0)$

Because prior beliefs about regression parameters are vague or in other words because we do not have any knowledge on the β values, we use a sufficiently diffuse normally distributed prior. Therefore, the prior mean (β0) and the precision (C_0^{-1}) is set at 0 and 10^{-2}. In the Gibbs algorithm, we set the computer to sample sequentially from the distributions in (6), until convergence is achieved. We assess convergence by observing trace plots.

Study Area, Sampling and Data Collection

Primary data are used in the study. A pre-tested structured questionnaire and a Participatory Rural Appraisal (PRA) were used to collect data. The questionnaire survey covered different farmers' socio-economic and demographic characteristics that included: age and gender of the household head, production details, fertilizer application, production and sales, clean production, cost of production, social capital, marketing inefficiency, transaction cost, resource endowments, perception, knowledge, contact with extension, income and employment, and credit use. Data were collected from May to June, 2012. We limited data collection to the Kalutara district as it is the major rubber growing district in the country. Five hundred smallholder growers were interviewed with the help of Rubber Development Officers employed by the Rubber Development Department of Sri Lanka.

Within the Kalutara district, there are 14 Divisional Secretariat (DS) divisions, and they are divided into 762 Grama Niladhari (GN) Divisions, which are smallest administrative units in Sri Lanka. We used a multistage cluster sampling techniques to select GN divisions to collect data. We used a multistage cluster sampling technique, which is a form of cluster sampling where first, DS divisions are selected from the list of DS divisions available and then a sample of GN divisions is selected. Number of growers who are selected for the sample from each DS division is determined based on the weighted proportion as;

$$\text{Sample Size per DS Division} = \frac{\text{No of smallholders in DS division}}{\text{No of smallholders in district}} \times 500$$

Growers were selected purposefully from each GN division according to the concentration of the smallholders. This method of selecting clusters in stages and selecting farmers from the lowest administrative level reduced the sampling cost considerably.

Variables used in the Analysis

We used demographic, human/social, financial and physical capital, and market related variables to define the production choice (Table 1). We assume that a male farmer would be in a better position to sell sheet rubber than a female counterpart

Table 1 - Descriptions and expected signs of variables in the model.

VARIABLE	DESCRIPTION	EXPECTED SIGN
	Human Capital	
Gender	Household head is a male = 1	Positive
Education	Education in years of schooling	Positive
Experience	Years in rubber farming by the household	Positive
Member	Household head is a member of rubber society=1	Positive
Training	Household head attended training on sheet manufacture = 1	Positive
Extension	Extension visits to household in last month	Positive
	Financial Capital	
rubber only	Rubber is only income source = 1	Negative
	Physical Capital	
smoke house	Owns a smokehouse =1	Positive
Roller	Owns a roller = 1	Positive
Storage	Have storage facility = 1	Positive
	Market Related	
time to buyer	Time to closest buyer in minutes	Positive
grade correctly	Perception about grading by the buyer: Never =1, Most of the time = 2, Always = 3	Positive
price reasonable	Perception about prices paid by the buyer: Never =1, Most of the time = 2, Always = 3	Positive
Production	Production in last month	Ambiguous

and hence, the coefficient with respect to gender to be positive. One reason is the difficulty in transporting sheet rubber, which is quite cumbersome because of its weight. Some argue that variables such as gender are preference proxies (Pattanayak *et al.*, 2003). Majority of technology adoption literature show a positive impact of this variable on choice of adoption (Pattanayak *et al.*, 2003; Feder *et al.*, 1985). The education, experience, extension service and training are expected to improve human capital, which enables farmers to comprehend complex situations and make best choices. Therefore, these variables are expected to have a positive sign on the assumption that production of sheet rubber is profitable than selling it as latex. We proxy the financial capital by using a variable related to the income source. If rubber cultivation is their primary source of income, we set this variable to 1 and zero, if otherwise. We assume a farmers' income to be low if a farmer solely depends on rubber cultivation, which leads to a lack of financial capital to invest on vital fixed assets needed to produce sheet rubber, such as rollers and smokehouses. Therefore, we presume that this variable would produce a negative sign. We define physical capital by incorporating three variables: presence of a smoke house, roller and storage space. These are very important elements in producing sheet rubber, presence of which will show high probability of sheet production. However, it should be noted that, even on the absence of these, there is a possibility of producing sheet rubber, given that services from these capital items can be outsourced. We use several variables related to market, including perceptions of farmers about the market and its services. The variable, 'time to market' measures the return time taken to visit the buyer. For those farmers that sell at farm gate, this is zero. Because latex is collected mostly at farm gate and is difficult to be transported, it is expected that with the increasing time to market, the production of sheet rubber to rise. The 'price reasonable' variable records 1 if the farmer believes that his buyer always pays reasonable prices. If he thinks that this is true most of the time, it is recorded as 2 while for farmers who believe prices they get are never reasonable, it is recorded as 3. Therefore, this variable is expected to be negative.

Results and Discussion

Convergence of the Markov Chain

We iterate the Gibbs sample for 5000 times with a sample of 1500 iterations discarded as 'burn in'. This is to remove any impact of starting values given to initiate the Gibbs sample. To make inferences about the estimated parameters, the convergence of the Markov Chain Monte Carlo sequence needs to be verified. We do this by observing trace plots in Figure 1, which show super imposed trace plots of all coefficients to save space. We see that there is no increasing or decreasing pattern (or wide fluctuations) in the trace plots, and they are distributed around the mean value of each parameter estimated. Therefore, we are assured that convergence has occurred.

Posterior Means and Significance of Coefficients

The results of SARP analysis of the choice of sheet production are reported in Table 2, where we report posterior means of coefficients and their significance level.

Results show that the level of education, experience, membership to a farmer group, having a smoke house, roller and storage facility, time taken to travel to the buyer and the level of production to be significantly affecting the probability of producing rubber sheets.

Contrary to our expectation, education gave a significant negative sign. We hypothesized that with increasing education; the probability of producing rubber sheet may rise. In doing so, we assumed that because sheet production is profitable, educated would be opting to produce sheet rubber more than latex. On the other

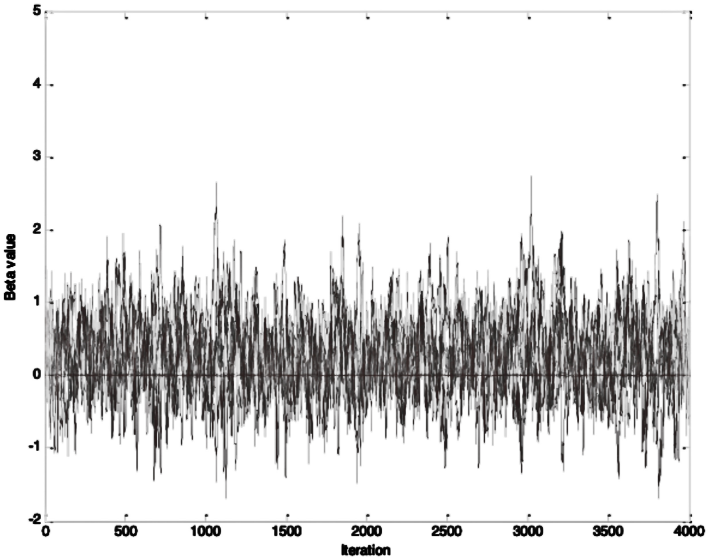

Figure 1 - Trace plot for regression parameters in SARP model.

Table 2 - Posterior Means of SARP analysis.

VARIABLE	COEFFICIENT	STD DEVIATION	P-LEVEL
Constant	0.000	0.001	0.444
Gender	0.131	0.447	0.401
Education	**-0.456**	**0.221**	**0.011**
Experience	-0.012	0.014	0.201
Member	**0.666**	**0.428**	**0.035**
Training	0.288	0.404	0.245
Extension	0.057	0.394	0.457
rubber only	-0.024	0.528	0.475
smoke house	**0.552**	**0.451**	**0.095**
Roller	**0.935**	**0.504**	**0.020**
Storage	**0.956**	**0.438**	**0.014**
time to buyer	**0.013**	**0.007**	**0.015**
grade correctly	0.865	0.862	0.147
price reasonable	0.263	0.273	0.175
Production	**-0.004**	**0.002**	**0.002**
Rho	**0.447**	**0.111**	**0.000**

Significant variables at 5% are in bold

hand, educated may find it easier for them to find employment elsewhere. This may give them less time to go through additional processing required to produce sheet rubber, making them sell their rubber directly as latex. Data reveal that majority of the farmers have formal education between 6-12 years of education (Figure 2). In Sri Lanka, having education up to 12 years (Advanced-Level Certificate) makes one very much employable. Previous research show mixed results with respect to education. For example, Matuschke et al., (2007) finds that education does not play a significant effect on adoption of hybrid wheat in India while Abdulai and Huffman, (2005) show that the levels of education of farmers have a positive impact on diffusion of agricultural technologies in Tanzania.

Our results show that the variable, 'membership of farmers' organization' has a positive impact upon the choice of sheet rubber production. Membership of farmer societies is believed to be an enhance human capital development. It is a place of interaction of farmers and therefore, they are able to learn from each other. This is the place where they get information about the profitability of various production processes and market conditions. Thus, it is a source of social capital. Similarly, Holloway *et al.* (2000) reports that farmer groups increase market participation in the case of dairy producers in East African highlands. Producer groups connect smallholders directly to markets, simplifying the longer marketing chains (Markelova and Meinzen-Dick, 2009). However, the main reason for farmers who are members of farmer groups having a higher probability of producing sheet rubber may be because that most farmer groups are specialized in collecting rubber sheets rather than direct latex. In most places, latex is directly collected by different dipped product

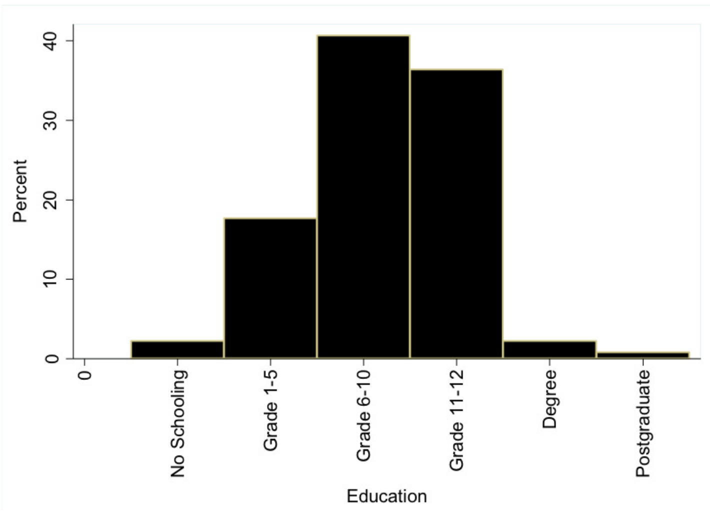

Figure 2 - Level of education of rubber farmers in the data.

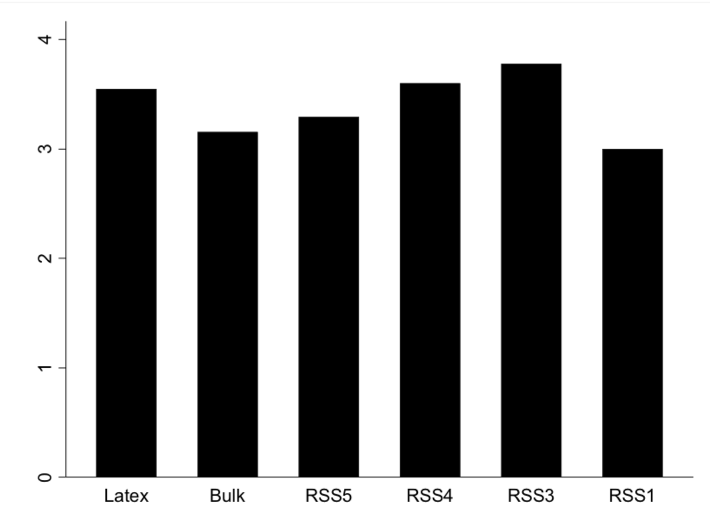

Figure 3 - Selling type by membership of farmer group.

manufacturers, who is in need of field latex rather than sheet rubber. In addition, farmers' groups do not have facilities to collect latex and hold it not letting it to coagulate until a buyer arrives. Figure 3 shows sales of different rubber output types by member farmers and non-member farmers. Although, a similar distribution of types is observed for both groups, member farmers sell less in 'bulk' form, which is selling sheet rubber without grading. Thus, membership of farmer groups may create a higher bargaining power enabling them to sell at different grades.

We further find that availability of physical capital (i.e. smoke houses, rollers and storage facilities) related to sheet rubber production is vital in the increased probability of sheet manufacture. However, availability of these resources is not a necessity for production of sheet rubber, because farmers can always outsource such activities. Results show that when such physical capital is available, the tendency to produce sheet rubber increases. This is because production of sheet rubber is a process where, raw rubber is coagulated and sent through two rollers and smoked inside a smoke house. Finally, they are stored until being sold. Descriptive statistics show that with ownership of a smoke house, production of higher-grade sheet rubber increases marginally (Figure 4).

However, the majority of farmers do not own smoke houses or rollers, but they do have storage facilities and hence the production of sheet rubber is encouraged (Table 3). They may be outsourcing the rolling and smoking activities.

When the time taken to travel to the buyer increases the probability of production of sheet rubber tends to rise. This indicates that if the transaction cost of selling is high, sheet production increases. Generally, time taken to market is incorporated as a

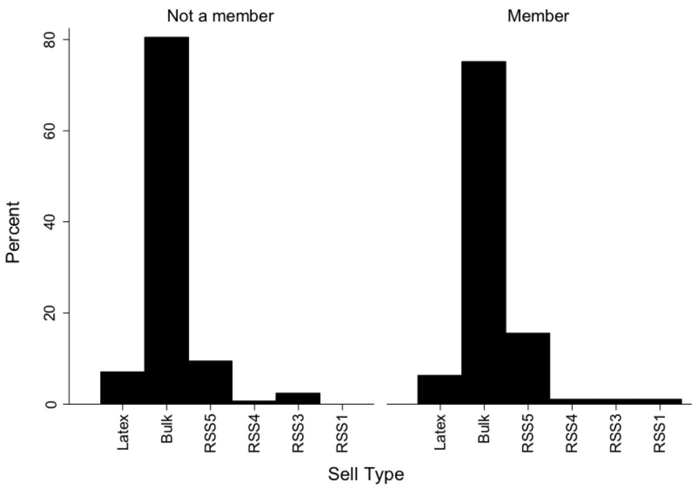

Figure 4 - Smokehouse ownership and selling type.

Table 3 - Ownership of physical capital.

	Smokehouse		Roller		Storage	
	Yes	No	Yes	No	Yes	No
Number	174	318	154	338	446	46
Percentage	35.4	64.6	31.3	68.7	90.7	9.4

measure of transaction costs. The finding of previous studies is that higher transaction costs reduce market access (Holloway *et al.*, 2004; Key *et al.*, 2000; Renkow *et al.,* 2004). From the farmer's point of view, this is prudent because, he/she can reduce unit transaction costs by collecting and selling at once. This is possible only in the case of production of sheet rubber and not in production of latex. Thus, higher the selling transaction costs, the higher the probability of producing sheet rubber.

The variable, production is incorporated to capture the size effect. It shows a negative and significant sign. Thus, larger farmers have a lesser probability of producing sheet rubber. This is as expected because latex collectors approach larger farmers (who has a large scale of operation and hence a higher output) than smaller ones to reduce their collection costs. Therefore, larger farmers may tend to sell their output as latex.

We show in our results in Table 2 and Figure 5 that the spatial correlation coefficient is positive and significant. A neighbouring farmers' production choice (production of sheet rubber) has a positive impact on the farmers' production choice. Thus, a neighbourhood effect exists. Understanding such neighbourhood effects is

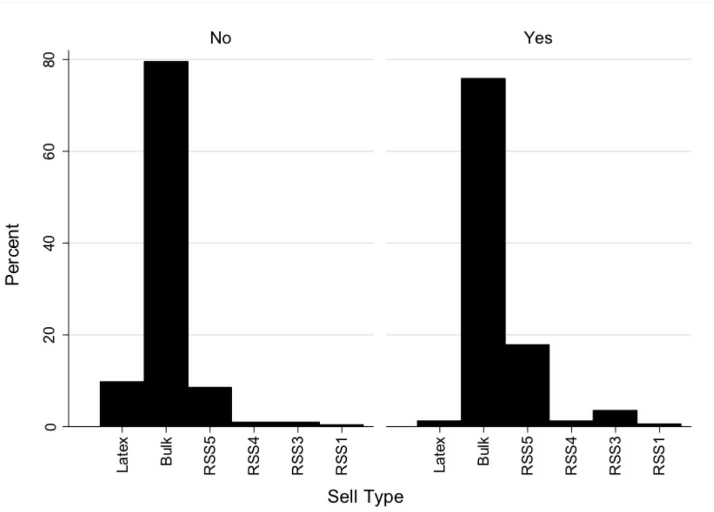

Figure 5 - Distribution of estimated spatial correlation coefficient (Rho).

important in attempting to precipitate farmers into production of sheet rubber. Once the strength of this relationship is understood, it can help extension agents to vastly reduce their extension efforts in promoting production of sheet rubber. For example, extension agents can implement demonstration farms rather than visiting all farmers. By identifying key, efficient farmers and introducing them the technology, knowhow and benefits of production of sheet rubber, farmers in the neighbourhood could be influenced into sheet rubber production. This technique is not new to extension services around the world, but if one finds the strength and how far the neighbourhood effect exists; it would definitely improve planning of where exactly such demonstration farms are to be located.

Spatial Spill-over Effects

One advantage of using Spatial Autoregressive models is its ability to predict spatial spillover effects. Spatial spill over effects are impacts of covariates relating to one farmer on the decision outcome of a neighbouring farmer.

In Table 4, we report two types of marginal effects. Direct effects show the marginal effect of a change of a unit of independent variable of farmer, i on the change of the dependent variable of the farmer *i*, $(\delta y_i^*/\delta x_i)$, while indirect effects show the change of independent variable of farmer i, on the change of the dependent variable of the farmer *j*, $(\delta y_i^*/\delta x_j)$. Therefore, the latter (indirect effects) measures the spatial spill over effect.

Table 4 - Marginal effects of the SARP model.

Variable	Direct effect			Indirect Effect			Total effect		
	lower 05	Coefficient	upper 95	lower 05	Coefficient	upper 95	lower 05	Coefficient	upper 95
Constant	0.000	**0.000**	0.000	0.000	**0.000**	0.000	0.000	**0.000**	0.000
Gender	-0.054	0.007	0.067	-0.032	0.008	0.065	-0.085	0.015	0.128
Education	-0.062	**-0.030**	-0.004	-0.062	**-0.022**	-0.002	-0.117	**-0.052**	-0.007
Experience	-0.003	-0.001	0.001	-0.003	-0.001	0.001	-0.005	-0.001	0.002
Member	-0.003	0.044	0.109	-0.002	0.032	0.106	-0.005	0.076	0.207
Training	-0.031	0.019	0.081	-0.021	0.014	0.069	-0.052	0.033	0.147
Extension	-0.047	0.004	0.065	-0.033	0.004	0.055	-0.079	0.008	0.118
rubber only	-0.074	-0.001	0.076	-0.061	-0.002	0.051	-0.129	-0.003	0.124
smoke house	-0.016	0.037	0.111	-0.012	0.025	0.082	-0.028	0.063	0.186
Roller	0.002	**0.063**	0.149	0.001	**0.044**	0.123	0.004	**0.107**	0.257
Storage	0.008	**0.064**	0.129	0.005	**0.045**	0.108	0.013	**0.108**	0.226
time to buyer	0.000	**0.001**	0.002	0.000	**0.001**	0.001	0.000	**0.001**	0.003
grade correctly	-0.047	0.058	0.195	-0.037	0.038	0.134	-0.085	0.095	0.318
price reasonable	-0.020	0.017	0.055	-0.011	0.013	0.048	-0.031	0.030	0.101
Production	-0.001	0.000	0.000	0.000	**0.000**	0.000	-0.001	0.000	0.000

We find positive and significant spill over effects with respect to ownership of rollers, storage facilities; and production. A farmer who has a roller will have a 6.4% chance (probability) over his counterpart in producing sheet rubber (direct effect). At the same time, it will have a 4.4% cumulative increase in probability of neighbouring farmers (indirect effects) and a total effect of 10.7% on the probability of sheet production. Therefore, we note that providing rollers to farmers would increase the chances of producing sheet rubber by 10.7%. With this result, the concept of 'central processing' seems prudent. In many other countries, machinery that produces sheet rubber has already been developed. Such machines are infeasible for one single farmer because their daily production is less than the full capacity of these machines. Therefore, one can employ such machinery either by selecting a base farmer of by operating one at the farmer group level. At present, the Sri Lankan government promotes farmer groups under a scheme called 'Thuru Saviya' programme. Yet, these groups work on the basis of collection of sheet rubber and selling it reducing transaction costs of individual farmers. There may be a need to re visit the mandate of such farmer groups and if necessary assistance be provided to implement group processing by these farmer organizations. However, contrary to expectation, the direct, indirect and total effect of education level of farmers on the probability of adoption is -3%, -2.2% and -5.2% respectively. This indicates that education has a negative externality on sheet production. Although, not significant, training in rubber processing, ownership of smokehouses, extension visits, and membership in rubber societies show positive externalities. Overall, there is a positive impact of one farmers' choice to produce sheet rubber on the farmers in the neighbourhood as evident by the positive and significant spatial correlation coefficient.

Conclusion

This research investigates the spatial correlation that exists in production choice by smallholder farmers by analysing the choice of production of sheet rubber. In doing so, spatial relationships are explicitly modelled in a spatial econometric framework. Specifically, a Spatial Autoregressive Probit Model (SAPM) is estimated. Findings show a strong spatial relationship in production of sheet rubber. Thus, a neighbourhood effect is evident. This has important implications for the design of extension services. Understanding the nature of this relationship can greatly reduce extension effort and thus its expenditure. Present data set reveals that neighbourhood effect spans for three neighbours. Thus, to have the full effect of extension service, visits to all farmers is unnecessary. Furthermore, a spatial spill over effect is evident with respect to ownership of fixed assets (rollers) needed to produce sheet rubber. This has important implications because it hints the ability for group processing. For example, it shows the usefulness of establishing a central processing facility for smallholders to be run either by the government or a farmer group. This is yet to be practiced in Sri Lanka. Overarching finding on how to make smallholder farmers to increase sheet production is the necessity to improve physical capital. It is evident that these not only have a marked impact on farmer choice of production of sheet rubber but also have an indirect spill over effect on others in the neighbourhood.

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