Spatial Dependence in the Adoption of the Urea Deep Placement for Rice Production in Niger State, Nigeria: A Bayesian Spatial Autoregressive Probit Estimation Approach

Serge, Adjognon,
Michigan State University

Lenis Saweda O. Liverpool-Tasie
Michigan State University

Contact information: adjognon@msu.edu

Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.

1. INTRODUCTION

Sustainable input intensification is now a subject of keen interest in many developing countries. With growing populations and limited supply of inputs like land, water and energy, increasing food supply in a sustainable manner is critical (IFPRI, 2013). This includes the use of improved technologies (like improved seeds and fertilizers) and management strategies. Despite the agronomic advantages of many of these input intensification strategies, a long-standing puzzle is why farmers do not adopt such technologies. Numerous questions still remain about the real drivers (or constraints) to farmers' adoption of new agricultural technologies particularly those with the potential to increase farmer productivity and incomes.

In addition to the commonly cited constraints to adoption (like transactions costs and profitability issues due to poor input and output markets) another key challenge is limited farmer knowledge about new and potentially profitable agricultural technologies. Even after farmers hear about some technology, their decision to adopt it or not depends on many interrelated factors, and may very well be influenced by neighbors' attitudes towards the technology (Case 1992). Faced with limited access to and poorly functioning extension systems, farmers in developing countries often rely on other informal sources of information. It is thus important for government and development practitioners to understand and successfully leverage these alternative sources of information for broader impact.

Increasingly, spatial econometric methods are being used by applied researchers in agricultural, environmental and development economics, to analyze situations in which decision or outcomes if individual are spatially correlated. Also, theoretical motivations for the inclusion of spatial dependence in regression models have also been discussed by many authors (Anselin 2002, Pace and LeSage 2009). However, applications to situations of adoption of agricultural technology are very rare. Moreover, the number of applications in discrete-choice settings remains very limited, and despite its appeal, applications of the Spatial Bayesian method are even fewer. Amongst the few empirical studies that incorporate or control for neighborhood effect in farmers' decision to adopt new agricultural technologies, Holloway, Shankar et al. (2002) found evidence of spatial dependence in binary choices regarding high-yielding variety (HYV) adoption among Bangladeshi rice producers. Such results have important policy implications for technology diffusion and also the design of cost effective extension programs. When farmers interact with each other in a way that the adoption decision of each farmer is positively correlated with the adoption decision of their neighbors, there is great potential for reducing extension cost by taking this into account. Within Sub Saharan Africa generally and Nigeria particularly, there is a dearth of information on the existence of spatial dependence in technology adoption decisions. Furthermore, a major problem related to ignoring the existence of spatial dependence when it exists is the omitted variable problem, leading to biased and inconsistent estimates of the determinants of adoption. Consequently, this paper adds to both the literature on spatial dependence in technology adoption and Bayesian estimation of spatial dependence in discrete choice. The paper analyzes the role of spatial interactions in the spread (of information) and adoption of an innovative technique for the application of fertilizer (Urea) for rice production in Niger State, Nigeria.

The rest of this paper is organized as follows. Section 2 provides a brief background on the Urea Deep Placement technology and its promotion in Nigeria. Section 3 describes the study's theoretical and empirical framework while section 4 presents the Bayesian spatial estimation method used. In section 5 we discuss our data source and describe our sample. Section 6 presents our results and section 7 concludes.

2. BACKGROUND ON UREA DEEP PLACEMENT TECHNOLOGY

Urea super granules for deep placement (Urea Deep Placement (UDP)) is one among several current innovations for sustainable input intensification currently being encouraged in developing countries (including Nigeria). The UDP technology involves the use of compacted urea super granules usually 1-3 grams each placed at a depth of between 7-10 cm by hand at the center of every four rice seedling hills in rice soils during or after rice transplanting. The urea super granules are said to increase nitrogen use efficiency because more urea nitrogen stays in the soil, close to the plant roots where it is absorbed more effectively. Urea deep placement is said to potentially increase crop yields by 25 percent while reducing nitrogen losses by 40 percent. Compared to the traditional application of urea by broadcasting, done two or three times in a planting cycle, the urea super granules are only applied once. Because it is deep placed, the fertilizer nutrients are beyond the reach of weeds thus reducing weed incidence. UDP is potentially profitable for farmers because it increases crops yield, reduces the number of fertilizer applications necessary as well as lowers weeding costs, while being competitively priced relative to other fertilizers. Field demonstrations in several sites across Africa and Asia have indicated significant potential benefits of the Urea deep placement approximating 45 percent advantage over traditional practices (IFDC, 2012). While USG has not yet been widely adopted in Nigeria, field tests have shown very promising results that have been stable across different locations. In Niger State, irrigated rice crop yields are found to increase 20-30 percent over traditional farmer’s practice (IFDC, 2013). Nitrogen use efficiency was also found to increase by 40 percent. While 2 out of 3 bags of urea were lost by the traditional method of fertilizer application (broadcasting), only one out of three bags of USG was lost when deep placed (IFDC, 2013). Increased Nitrogen use efficiency was found to lead to increase productivity in several locations: For instance, rice output increased to an average of 7 tonnes per hectare in the dry season with best practices and USG application, compared to an average of 4.4 tonnes per hectare based on farmer's traditional practices (this is average ouput from Gombe, Kebbi and Niger States) (IFDC 2013). As a result of productivity increases, USG also increased gross revenues and ultimately profits by a very healthy margin (IFDC, 2013).

The use of USG is actively being promoted across Nigeria (and other African countries) by various development partners. In Nigeria, a development agency, International center for soil fertility and development (IFDC) and Notore (a private fertilizer supply company in Nigeria) have used several approaches to encourage the adoption of USG. In the two study villages in Niger State; Washe and Sheshi villages, a key component of the promotion of UDP was the use of a village promoter. The concept of the village promoter is a mix of commerce and extension developed by Notore to sell fertilizer. The village promoter is a farmer based in the village who has sufficient social capital to be able to teach other farmers improved farming practices while simultaneously serving as the local supplier of the technology. Notore village promoters are trained in the best practices in the use of USG, and then serve as a source of information and fertilizer to other villagers. In addition to the use of the village promoter, IFDC and Notore also jointly set up demonstration plots (in the vicinity of the two villages) in conjunction with local farmers. On these plots, USG was utilized with recommended best practices, These best practices included the establishment of nurseries which are then transplanted to a well-watered and levelled plot. The USG is deep placed on the plot (with a recommendation that 1 USG serve 4 rice plants) a week after transplanting at a depth of about 7-10cm. Fields are recommended to be well watered during and after application of the USG.

The demonstration plots were placed directly beside plots where only traditional farmers' practices were used. Villagers were able to see the clear difference between the two plots in terms of plant development and ultimately yield. In the two study villages, the village promoter was also one of the demo plot farmers, adding to his credibility in the village.

Village field days were held with officials of Notore and IFDC. During the field days, all farmers from both villages were told more about the technology and able to view the progress of the rice fields.

3. THEORETICAL AND EMPIRICAL FRAMEWORK

The spatial reaction function

The theoretical basis for the spatial autoregressive model is a spatial reaction function that expresses how the magnitude of a decision variable for an economic agent depends on the magnitudes of the decision variables set by other economic agents (Anselin 2002). Brueckner (2003) developed two theoretical frameworks for strategic interaction that yield a reaction function as the equilibrium solution: the spillover model and the resource flow model. While the resource flow model can also be made relevant, the spillover model seems more relevant to the case of neighborhood effect in technology adoption.

According to the spillover model, an agent i's objective function is affected not only by his choice of a decision variable, y_i , but also the values of the y chosen by other agents (say,y_{-i} , where the $-i$ subscripts refers to all agents other than i).

$$U_i = U(y_i, y_{-i})$$

Choosing the decision variable to maximize this objective functions yields the following reaction function:

$$y_i = R(y_{-i})$$

When the other agents are neighbors, this reaction function coincides with a spatial lag model where agent i decision is a function of the decision made by his neighbors. Models of social learning, learning from others, technological externalities (Foster and Rosenzweig 1995, Conley and Udry 2001, Foster and Rosenzweig 2010) are all consistent with this spillover model.

The model of learning from others developed by Foster and Rosenzweig (1995) established that farmer's decisions about technology use, depend not only on a farmer's evaluation of its profitability, but also the nature of a farmer's interactions with the other farmers in her neighborhood. This is because if one farmer experiments with a new technology, this generates information for all neighbors and increases their expected profits. However this learning externality can have both a positive and negative effect on farmers' adoption decision. The more experimentation a farmer expects her neighbors to conduct, the higher the profit she expects. At the same time, a farmer who expects that many neighbors will adopt the new technology may delay adoption (Bardhan and Udry 1999, Bandiera and Rasul 2006, Liverpool-Tasie and Winter-Nelson 2012).

A spatial latent variable model

We develop here a spatial latent variable model (Anselin 2002, Pace and LeSage 2009) based on the utility maximization approach for modeling individuals' decision choice. We treat the observed choice of each individual i=1,..,N as the realization of a random choice variable Y_i, where Y_i =1 if individual i adopts the UDP technology, and Y_i =0 otherwise. It is postulated that choices are based on utility maximizing behavior, where individual i's net utility from adoption is:

$$\boldsymbol{y_i^* = U_{i1} - U_{i0} = X_i\beta + \varepsilon_i} \qquad \textbf{(1)}$$

Where U_{is} is the utility of individual i from choosing alternatives=1,2. We do not observe y*, but only the choice made, which are reflected in the random variable y:

$$\boldsymbol{y_i = \begin{cases} 1, & if\ y_i^* \geq 0 \\ 0, & if\ y_i^* < 0 \end{cases}} \qquad \textbf{(2)}$$

Therefore our observed dependant variable is Y. Consider X is an (N x K) matrix of K explanatory variables that are assumed to affect individual farmers utilities and therefore decision to adopt UDP technology. Our interest lies primarily in the response probability:

$P(X) = E[y|X] = \Pr(y_i = 1|X) = \Pr(y_i^* \geq 0|X)$ (Wooldridge 2002).

The assumption made on the distribution of the random component ε determines whether we have a Probit or a Logit model. If normal distribution is assumed the model is probit. If a logistic distribution is assumed, the model is logit (Wooldridge 2002). Moreover, when spatial interdependence exists within the data, standard models will not only result in biased and inconsistent estimates, but also sacrifice important policy relevant information (Case 1992, Holloway, Shankar et al. 2002, Pace and LeSage 2009, Loomis, Mueller et al. 2013). The model used in this paper allows for neighbors to influence one another in their decision choice. Therefore the model for the latent variable takes the following Spatial Autoregressive form:

$$\boldsymbol{y}^* = \boldsymbol{\rho W y}^* + \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \qquad \textbf{(3)}$$

$$\boldsymbol{y}^* = (\boldsymbol{I_n} - \boldsymbol{\rho W})^{-\mathbf{1}}(\boldsymbol{X\beta} + \boldsymbol{\varepsilon}) = (\boldsymbol{I_n} - \boldsymbol{\rho W})^{-\mathbf{1}}\boldsymbol{X\beta} + \boldsymbol{\epsilon} \qquad \textbf{(4)}$$

where

$$\boldsymbol{\epsilon} = (\boldsymbol{I_n} - \boldsymbol{\rho W})^{-\mathbf{1}}\boldsymbol{\varepsilon} \sim \boldsymbol{N}(\mathbf{0}, \boldsymbol{\sigma_\varepsilon}\,[(\boldsymbol{I_n} - \boldsymbol{\rho W})'(\boldsymbol{I_n} - \boldsymbol{\rho W})]^{-\mathbf{1}}) \qquad \textbf{(5)}$$

X is a (N x K) matrix of K explanatory variables that are assumed to affect the dependant variable. ε is the (N x 1) vector of random error component assumed to be iid $N(0,\sigma_\varepsilon)$.

The parameter ρ is the parameter of interest. It reflects the spatial correlation between a given farmer's probability of adopting the UDP technology, and his neighbors' probability. A significant ρ implies that farmers' decision to adopt UDP technology is influenced by their neighbors' behavior.

W is the (N x N) spatial weighting matrix that summarizes the spatial relationship between individuals. The matrix W is a square matrix of order n, defined by:

$$w_{ij} = \begin{cases} 1 & \text{if individuals i and j are neighbors} \\ 0 & \text{otherwise} \end{cases}$$

By convention we set the diagonal elements are set to w_{ii} =0. (Case 1992, Pace and LeSage 2009). The rows of W are normalized using $\sum_j w_{ij} = 1$ so that each observation receives the same influence from each of its neighbors. This is called a row-stochastic matrix (Pace and LeSage 2009). $Wy = \sum_j w_{ij} y_j$ is called the spatial lag, and represents a linear combination of values of the variable y constructed from individuals that neighbor individual i. Given the row normalization, the spatial lag variable results in a scalar that represent, for each individual, the average of y_j over his neighbors. Who is considered a neighbor defines the weighting matrix. In this paper we conduct the main analysis using three different weighting matrices: the 3-nearest neighbor, the 4-nearest neighbor, and the 6-nearest neighbor weighting. Sensitivity of the results to the alternative weighting matrices is discussed in our results.

The approach discussed above is almost equivalent to some previous studies that have looked into the effect of social network on technology adoption by including the number of adopters in the network, or in the village of the farmer, as explanatory variable (Conley and Udry 2001, Munshi 2004, Liverpool-Tasie and Winter-Nelson 2012). One main critic to the approach used in those paper is the reflection problem pointed out by (Manski 1993). While our approach does not fully solve the reflection problem, the related endogeneity issue is mitigated here by the specification of w_{ii} =0 in the spatial weighting matrix (Pinkse and Slade 2010). Also, in our model, the definition of neighbor is purely based on geographical location assumed to be random, whereas in other studies, neighbor is defined based on social network or residence in the same village, which are more likely to be endogenous.

Apart from the Spatial Autoregressive (SAR) model mentioned above, there are many other ways in which spatial dependence may enter a process. The SAR model developed above assumes that a given household's predisposition toward adoption of UDP technology is due to the direct influence the neighbors have through their own predispositions toward adoption. We could expand this model by allowing individual farmer's probability of adoption to be influenced by neighbors' probabilities as well as neighbors' characteristics. This gives rise to the Spatial Durbin Model (SDM) that includes spatial lags of the explanatory variables as well as the dependant variables (Pace and LeSage 2009):

$$\boldsymbol{y} = \boldsymbol{\rho W y} + \boldsymbol{X\beta} + \boldsymbol{WX\theta} + \boldsymbol{\varepsilon} \quad \textbf{(6)}$$

$$\boldsymbol{y} = (\boldsymbol{I_n} - \boldsymbol{\rho W})^{-1}(\boldsymbol{X\beta} + \boldsymbol{WX\theta} + \boldsymbol{\varepsilon}) \quad \textbf{(7)}$$

$\varepsilon \sim N(0, \sigma_\varepsilon \, I_n)$

Spatial correlation can also appear in the disturbance term, leading to the following Data Generation Process (DGP) called Spatial Error Model (SEM) (Pace and LeSage 2009).:

$$\boldsymbol{y} = \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \quad \textbf{(8)}$$

$\varepsilon = \rho W\varepsilon + u$

$u \sim N(0, \sigma_u \, I_n)$

Finally there is a spatial model that incorporates both a spatial lag and spatial residuals, called SAC or Spatial General Model, where the matrix W_1 may be set equal to W_2:

$$\boldsymbol{y} = \boldsymbol{\rho W_1 y} + \boldsymbol{X\beta} + \boldsymbol{\varepsilon} \quad \textbf{(9)}$$

$\varepsilon = \theta W_2 \varepsilon + u$

$u \sim N(0, \sigma_u \, I_n)$

$$\boldsymbol{y} = (\boldsymbol{I_n} - \boldsymbol{\rho W_1})^{-1}\boldsymbol{X\beta} + (\boldsymbol{I_n} - \boldsymbol{\rho W_1})^{-1}(\boldsymbol{I_n} - \boldsymbol{\theta W_2})^{-1}\boldsymbol{\varepsilon} \quad \textbf{(10)}$$

Since our main interest is the estimation of diffusion effects, we will focus on correlation across the dependent variable using the SAR model.

4. SPATIAL BAYESIAN ESTIMATION METHOD

Calabrese and Elkink (2013) discussed five main algorithms commonly used in the literature for estimating binary spatial autoregressive models: the Expectation Maximization algorithm (McMillan 1992); the Bayesian Gibb sampler approach (LeSage 2000); the Recursive Importance Sampling (Beron and Vijverberg 2004); the Generalized Method of Moment (Pinske and Slade 1998); and the Linearized version of the Generalized Method of Moment (Klier and McMillen 2008).

The spatial model presented in equation 3 above is estimated using a probit Bayesian methodology in conjunction with Markov Chain Monte Carlo (MCMC) estimation and the Gibbs sampler approach. The Bayesian approach, proposed by LeSage (2000), is a popular and powerful estimation method used to model binary choices model with spatial dependence. The benefit of using Bayesian approach is that it is robust with respect to small sample sizes, and allows detailed analysis of parameter distributions obtained by simulating from the posterior distribution of the model. Basically, the latent continuous variable is replaced with its expected value, solving thereafter a spatial continuous model using the Gibbs sampling approach. In the Gibbs sampling approach, one begins by postulating suitable prior distributions for all parameters, and then derives the corresponding conditional posterior distributions given the observed data (Smith and LeSage 2004). More details about the Bayesian estimation of spatial regression models can be found in Pace and LeSage (2009).

The software used for estimation of the spatial probit model is MATLAB for which LeSage (1999) has developed a ready-for-use spatial econometrics library.

5. DATA AND VARIABLE DESCRIPTION

Plot level data were used for this study to evaluate the neighbourhood effects in the use of UDP technology. The data were collected from a census survey conducted in two villages in

Niger State, Nigeria, and include information about the characteristics of the plot, the agricultural practices used on the plot, the characteristics of the plot manager, and also the geographical location of the plots captured by GPS coordinates.

The spatial probit model developed in equation 3 is estimated using farmers' use of UDP technology in 2012 as observed dependant variable. Then the GPS coordinates of the plots were used to generate the spatial weighting matrices used in the estimation. As mentioned earlier, we use 3 different weighting matrices and compared the results: the 3-nearest neighbor, the 4-nearest neighbor, and the 6-nearest neighbor weighting.

The other explanatory variables included to control for other factors that may influence adoption of the UDP technology include the plot characteristics and the socio-economic characteristics of the plot manager (like age, gender, marital status), as well as plot manager's previous exposure to or experience with UDP.

In particular, to account for farmers' diverse experience in farming, information was gathered on farmers' previous yields and their exposure to UDP. Farmers who participated in the Notore demonstration are likely to have seen and heard of the benefits of UDP while others have not. To capture farmers unobserved but differential ability, motivation and/or likely strength, independent of exposure to UDP, we collected information on farmers' prior yields in 2011.

Table 1 describes the socio-economic characteristics of the managers of the plots included in our analysis.

Table 1: Descriptive statistics

		Mean/percentage			
Variables		UDP plots	Non UDP plots	Total	T test
Have heard of UDP		100%	90.64%	93.79%	-5.8299***
Use UDP		100%	0%	52.32%	
Gender	Male	91.30%	94.16%	91.55%	
	Female	8.70%	5.84%	8.45%	-1.3938
Age		37.95 (14.43)	36.59 (13.28)	37.17 (14.01)	-1.2373
Number of years of residence in the village (years)		37.83 (14.57)	35.99 (13.73)	36.84 (14.34)	-1.6581*
Experience in agriculture (years)		27.60 (14.16)	25.79 (13.74)	26.67 (14.16)	-1.6423
marital status	Married	80.86%	80.56%	80.31 %	-0.0958
	Single	19.14%	19.44%	19.69%	
Schooled		88.29%	83.70%	85.63%	-1.7139
size of plots cultivated (ha)		4.42 (14.28)	7.30 (97.48)	14.44 (206.65)	0.6082
Asset index		.055 (1.21)	-.014 (1.19)	-.0065 (1.24)	-0.7406
Member of farmer association		83.58%	74.92%	78.79%	-2.7092***
Attended the Notore training		96.86%	93.90%	96.10%	-1.5408
Ownership of cultivated plot		98.22%	91.80%	95.39%	-3.8330***
Irrigation practice		14.37%	12.94%	13.40%	-0.5169
Only rice on the plot		92.01%	89.74%	89.95%	-0.8743
Use of hired labor		97.92%	94.41%	95.73%	-2.3395**
Yield in 2011 (kg/ha)		177.48 (1470.39)	1904.87 (9065.67)	705.48 (5194.6)	3.1314***
Use of improved seeds in 2011		73.03%	46.81%	59.14%	-6.5590***
Distance from plot to home (km)		1.89 (5.52)	2.30 (5.13)	1.97 (4.91)	0.9433
Area of rice plots (ha)		4.41 (14.85)	1.23 (1.56)	2.849 (10.89)	-2.7530***

Overall, UDP plots, which are plots on which UDP technology was used, represent 52.32% of the total number of plots. We present the descriptive stats by UDP and NON-UDP plots. The table reveals that the majority (91.55%) of the plots are managed by male famers. This is also the case amongst UDP and NON-UDP plots.

The overall average age of plot manager is 37.17 years with an average of 26.67 years of experience in farming activities, and 36.84 years of residence in the village on average. These do not differ significantly between UDP and NON-UDP plots. This result is not surprising knowing that most farmers are native of the area and have started participating in farming activities from a young age. Also most plot managers are married (80.31 %) and have received some formal education (85.63%) irrespectively of adoption status.

Adopters and non adopters are similar in terms of wealth status. The asset index computed to capture wealth status indicates that there is not a significant difference between the 2 groups.

Overall about 78% of the plots are managed by farmers that are members of farmer's organization. This number is higher for UDP plots than non-UDP plots. Most plots managers (96% overall) participated to the training organized by NOTORE.

As far as ownership of the plot is concerned, most plots are owned by their managers but a significantly higher proportion of the UDP plots (98%) are owned by their manager, compared to the NON-UDP plots where 91% of them are owned by the plot manager.

Irrigation practices are not very common in the study area. Only 13.40% of the plots analyzed were irrigated. This percentage is similar amongst UDP and NON –UDP plots.

On the majority of the plots, whether they are UDP or non UDP plots, rice is not cultivated in association with any other crop.

Hired labor is used on 97% of the UDP plots and on 94% of the non-UDP plots. This may indicate that the use of UDP requires some additional tasks that increase the need for hired labor.

6. RESULTS

Table 2 presents the estimation results for our Bayesian probit model for UDP technology adoption. The results indicate overall the presence of a positive and significant spatial dependence in the adoption of UDP technology in Niger State, Nigeria. The values of the spatial lag coefficient rho are all positive and significant at 1% for the 3 weighting matrices used in our estimations. This suggests that adoption rate in the neighborhood circle of some farmer increases the farmers' probability of adoption of UDP technology. This result is consistent with the findings of Holloway, Shankar et al. (2002) about the adoption of HYV of rice in Bangladesh.

In general, the regression results obtained using the 3 different weighting matrices are fairly similar. In addition to the similarity in observed neighborhood effect, the other variables that affect adoption decision significantly are the same across all the 3 weighting matrices. In particular, female farmers, older farmers, and farmers who have heard of the USG before are more likely to adopt the UDP technology. Also plots with rice cultivated in pure culture are more likely to be treated with the UDP technology. But the use of hired labor on the plot, the area of the plot, and the education of the plot manager, have negative and significant impact on the probability of UDP technology being used on the plot.

Table2: Bayesian Probit Estimation Results

	W3 model estimates		W4 model estimates		W6 model estimates	
Explanatory variables	**Coef**	**P values**	**Coef**	**P values**	**Coef**	**P values**
Rho	0.144	0.001***	0.213	0.002***	0.169	0.007***
Have Heard of usg	8.454	0.061*	11.860	0.031**	14.546	0.014**
Age plot manager	0.177	0.028**	0.176	0.042**	0.138	0.080*
Squared age	-0.001	0.060*	-0.001	0.064*	-0.001	0.131
Seniority plot manager	-0.044	0.308	-0.043	0.337	-0.032	0.366
Farming experience	-0.006	0.433	-0.007	0.420	-0.010	0.372
Membership association	0.071	0.417	0.197	0.330	0.283	0.211
Notore training	0.535	0.241	0.374	0.301	0.303	0.324
Asset index	0.127	0.177	0.095	0.251	0.113	0.210
Tenure	-0.071	0.516	0.142	0.437	0.138	0.427
Distance to home	0.014	0.453	-0.006	0.469	-0.017	0.431
Used improved seeds in 2001	-0.360	0.153	-0.431	0.126	-0.327	0.180
Used hired labor	-35.461	0.000***	-36.202	0.000***	-28.273	0.057*
Area rice plot	-0.543	0.007***	-0.310	0.088*	-0.215	0.098*
Square area rice plot	0.081	0.000***	0.049	0.017**	0.034	0.001***
Irrigation	-0.035	0.456	0.045	0.444	0.020	0.047*
Rice only	0.881	0.020**	0.817	0.036**	0.735	0.048*
Female plot manager	17.695	0.000***	25.017	0.002***	35.059	0.000***
Married plot manager	0.506	0.183	0.441	0.226	0.326	0.280
Schooled plot manager	-6.956	0.000***	-4.171	0.000***	-2.707	0.001***
Constant	30.919	0.014	25.193	0.003	13.77	0.361

Source: Estimated by the authors using STATA

Note: *= significant at 10%, **= significant at 5%, and ***= significant at 1%.

These results have important implications for the design of appropriate and cost effective extension program in Nigeria. They indicate that strategies that focusing training for a new technology like UDP on particular farmers or groups of farmers within a village is likely to enhance the spread of information about the technology and its consequent adoption. This is an important contribution to the understanding of the diffusion process of agricultural technologies in a developing countries context. More similar studies might be needed to improve our understanding of the phenomenon.

Besides, table 3 presents the results of the non-spatial probit model. The comparison of the spatial and non spatial results reveals some significant differences in the determinants of adoption. This suggests that the estimation of the determinants of UDP adoption without accounting for spatial dependence leads to biased results. Indeed, as mentioned before, not controlling for spatial dependence when it does exit, leads to an omitted variable situation in which estimates results can be proved to be biased and not consistent.

Table3: Non spatial Probit Estimation Results

Explanatory variables	**Coef**	**P values**
Have Heard of usg	6.566	0.910
Age plot manager	0.133	0.215
Squared age	-0.001	0.300
Seniority plot manager	-0.030	0.715
Farming experience	-0.007	0.798
Membership association	0.220	0.563
Notore training	0.367	0.600
Asset index	0.132	0.282
Tenure	0.380	0.684
Distance to home	0.021	0.856
Used improved seeds in 2001	-0.104	0.754
Used hired labor	-0.584	0.910
Area rice plot	-0.444	0.170
Square area rice plot	0.079	0.193
Irrigation	-0.110	0.760
Rice only	0.934	0.034**
Female plot manager	5.177	0.910
Married plot manager	0.075	0.888
Schooled plot manager	-5.779	0.999
Constant	-2.846	0.910

Source: Estimated by the authors using STATA

Note: *= significant at 10%, **= significant at 5%, and ***= significant at 1%.

7. CONCLUSION

This paper examines neighborhood effect in the adoption of Urea Deep Placement technology for rice production in Niger state, Nigeria. We estimated a spatial autoregressive model of UDP adoption using Bayesian estimation approach in conjunction with Markov Chain Monte Carlo (MCMC) estimation and the Gibbs sampler approach. The results indicate that there is significant spatial correlation in rice farmers' adoption of UDP in the study area, and have important implications for the design of appropriate and cost effective extension program in Nigeria. The results, which are robust to the changes in the spatial weighting matrix used for estimation, suggest that training focused on a new technology to a specific group is likely to increase the spread of information and adoption. This is an important contribution to the understanding of the diffusion process of agricultural technologies in a developing countries context. Moreover, the spatial probit estimates were compared to the non-spatial probit estimates and revealed significant differences. This confirms the importance of controlling for spatial correlations while estimating the determinants of technology adoption, in order to get unbiased and more consistent estimates.

REFERENCES

Anselin, L. (2002). "Under the hood issues in the specification and interpretation of spatial regression models." Agricultural Economics **27**(3): 247-267.

Bandiera, O. and I. Rasul (2006). "Social networks and technology adoption in northern mozambique*." The Economic Journal **116**(514): 869-902.

Bardhan, P. and C. Udry (1999). Development microeconomics, Oxford University Press.

Brueckner, J. K. (2003). "Strategic interaction among governments: An overview of empirical studies." International regional science review **26**(2): 175-188.

Calabrese, R. and J. A. Elkink (2013). "Estimators of Binary Spatial Autoregressive Models: A Monte Carlo Study." arXiv preprint arXiv:1302.3414.

Case, A. (1992). "Neighborhood influence and technological change." Regional Science and Urban Economics **22**(3): 491-508.

Conley, T. and C. Udry (2001). "Social learning through networks: The adoption of new agricultural technologies in Ghana." American Journal of Agricultural Economics: 668-673.

Foster, A. D. and M. R. Rosenzweig (1995). "Learning by doing and learning from others: Human capital and technical change in agriculture." Journal of political Economy: 1176-1209.

Foster, A. D. and M. R. Rosenzweig (2010). "Microeconomics of technology adoption." Annual Review of Economics **2**.

Holloway, G., et al. (2002). "Bayesian spatial probit estimation: a primer and an application to HYV rice adoption." Agricultural Economics **27**(3): 383-402.

LeSage, J. P. (1999). "The theory and practice of spatial econometrics." University of Toledo. Toledo, Ohio **28**: 33.

LeSage, J. P. (2000). "Bayesian estimation of limited dependent variable spatial autoregressive models." Geographical Analysis **32**(1): 19-35.

Liverpool-Tasie, L. S. O. and A. Winter-Nelson (2012). "Social Learning and Farm Technology in Ethiopia: Impacts by Technology, Network Type, and Poverty Status." The Journal of Development Studies **48**(10): 1505-1521.

Loomis, J. B., et al. (2013). "A Spatial Probit Modeling Approach to Account for Spatial Spillover Effects in Dicotomous Choice Contingent Valuation Surveys." Journal of Agricultural and Applied Economics **45**(01).

Manski, C. F. (1993). "Identification of endogenous social effects: The reflection problem." The review of economic studies **60**(3): 531-542.

Munshi, K. (2004). "Social learning in a heterogeneous population: technology diffusion in the Indian Green Revolution." Journal of Development Economics **73**(1): 185-213.

Pace, R. K. and J. LeSage (2009). "Introduction to spatial econometrics." Boca Raton, FL: Chapman &Hall/CRC.

Pinkse, J. and M. E. Slade (2010). "THE FUTURE OF SPATIAL ECONOMETRICS*." Journal of Regional Science **50**(1): 103-117.

Wooldridge, J. M. (2002). Econometric analysis of cross section and panel data, The MIT press.