Assessing the influence of neighborhood effects on the adoption of improved agricultural technologies in developing agriculture

AUGUSTINE S LANGYINTUO*

International Maize and Wheat Improvement Center (CIMMYT), Harare, Zimbabwe

MULUGETTA MEKURIA

International Maize and Wheat Improvement Center (CIMMYT), Harare, Zimbabwe

Abstract

Researchers generally assume spatial homogeneity when assessing the factors that influence farmers to adopt improved agricultural technologies. However, the potential for spatial heterogeneity is high due to, for example, neighborhood effects such as farmers sharing information about new technology. Ignoring spatial heterogeneity can result in biased or inefficient regression estimates and make inferences based on t and F statistics misleading. Using data collected from 300 randomly selected farmers in three districts of Mozambique during the 2003/04 crop season, a spatial Tobit model was specified to estimate which factors determined the adoption of improved maize varieties, after an initial diagnostic test rejected the null hypothesis of spatial homogeneity. On the basis of the empirical evidence, the paper makes policy recommendations to increase Mozambican farmers' adoption of improved maize varieties and concludes by emphasizing the need to test and correct for spatial heterogeneity in technology adoption modeling to improve the efficiency of the estimated results.

Keywords: Spatial Tobit model; Spatial heterogeneity; Spatial autocorrelation; Neighborhood effects, Maize farmers, Mozambique

En général les chercheurs partent du principe d'une homogénéité spatiale lorsque ces derniers évaluent les raisons qui poussent les agriculteurs à adopter des technologies agricoles améliorées. Cependant, le potentiel en faveur d'une hétérogénéité spatiale est élevé et s'explique en l'occurrence par les effets de voisinage et, à titre d'exemple, le partage de l'information des fermiers entre eux concernant les nouvelles technologies. Le fait d'ignorer l'hétérogénéité spatiale peut résulter en des estimations de régressions biaisées ou non efficaces et créer des inférences basées sur des statistiques t *et* F *trompeuses. En utilisant des données issues de 300 agriculteurs choisis au hasard dans trois districts du Mozambique pour la période 2003/04 correspondant à l'époque des récoltes, on a spécifié un modèle spatial Tobit pour évaluer les facteurs responsables de l'adoption de variétés de maïs améliorées, après qu'un test initial en matière de diagnostic a rejeté l'hypothèse nulle de l'homogénéité spatiale. En se basant sur une preuve empirique, l'article propose des recommandations politiques afin d'encourager les agriculteurs mozambicains à adopter des variétés de maïs améliorées et conclut en mettant l'accent sur la nécessité de tester et*

* Corresponding author: a.langyintuo@cgiar.org

rectifier en faveur de l'hétérogénéité spatiale dans la modélisation des adoptions technologiques pour améliorer l'efficacité des résultats estimés.

Mots-clés : *Modèle spatial Tobit ; Hétérogénéité spatiale ; Effets de voisinage ; Cultivateurs de maïs ; Mozambique*

1. Introduction

Technological change in agricultural inputs is fundamental to the transformation of rural Africa. Such change is not, however, fully embraced by smallholder farmers in the region. It has long been recognized that the continuous use of traditional, low yielding crop varieties is a major cause of low crop productivity, but correctly identifying the factors that prevent smallholder farmers from adopting improved, high yielding crop varieties remains a challenge. Drawing on three main paradigms among many, namely, the innovation-diffusion model (Feder & Slade, 1984, Feder et al., 1985), the adopters' perception paradigm (Kivlin & Fliegel, 1967), and the economic constraints model (Aikens et al., 1975), either individually or in combinations (Adesina & Zinnah, 1993; Smale et al., 1994; Morris et al., 1999; Doss et al., 2003), past adoption studies have suggested that farmers' choices of technologies are largely influenced by household characteristics. The commonly used empirical models (see for example Feder et al. 1985; Besley & Case, 1993), though rigorous, do not seem to fully account for farmers' decision-making environments, because they do not account for the neighborhood effects of farmers' interactions with other farmers in their village or in nearby villages. Such interactions have been observed by Case (1992), Ionnides and Zabel (2003) and Holloway et al. (2002) to be important when modeling the adoption of agricultural technologies. In assessing the determinants of the factors affecting the adoption of improved maize varieties by smallholder farmers in Mozambique, this paper uses a spatial Tobit model to account for neighborhood effects, after an initial diagnostic test rejected the null hypothesis of spatial homogeneity.

The potential for neighborhood effects among farmers in a community is high because, for example, those using a new technology may pass on information about it to others (Holloway et al., 2007). Spatial heterogeneity may also result from agro-ecological differences. In other words, as farmers make technological choices, they are influenced by the behavior of neighboring farmers or by agro-ecological characteristics.

The presence or absence of neighborhood effects (i.e. spatial heterogeneity or spatial dependence) has implications for policy recommendations. In the case of extreme spatial heterogeneity, every region or spatial scale (in this case each district) would be considered to be unique, and thus no general statements could be formulated, while in the case of spatial homogeneity the relationships of interest are essentially the same in all districts, and thus formulations derived for any scale can be effectively transposed to every other scale (Anselin, 1990). Yet without any diagnostic tests for spatial homogeneity, researchers commonly use, for example, the standard Tobit model (Tobin, 1958; McDonald & Moffitt, 1980), which implicitly assumes spatial homogeneity. In developing countries, adoption models that include location variables control for spatial heterogeneity due to agro-ecological differences (Doss, 2005) but neighborhood effects are largely unaccounted for. As noted by Holloway et al. (2007), neglecting information about neighborhood effects may lead the researcher to understate the influence of individual or household characteristics on economic outcomes, which will ultimately bias the parameter estimates, and this will have huge policy implications (Case, 1992).

Unlike spatial heterogeneity in continuous econometric models that have received substantial attention in the literature (e.g. Anselin, 1988, 1990; Anselin & Anil, 1998; Kelejian & Prucha, 1999), spatial heterogeneity in discrete choice models has received less attention (e.g. Case, 1992; McMillen, 1995; Pinkse & Slade, 1998). The empirical application of spatial Tobit and probit models, spurred on by the works of Case (1992), LeSage (2000) and LeSage and Smith (2004), though increasingly popular (e.g. Holloway et al., 2002; Ionnides & Zabel, 2003), has yet to be fully integrated into the modeling of agricultural technology adoption decisions in the African context, where social group dynamics are diverse (Nkonya et al., 1997; Isham, 1999).

The authors believe that, by accounting for spatial heterogeneity, this paper correctly identifies factors that prevent smallholder farmers in Mozambique from adopting improved, high yielding maize varieties, and that this identification can facilitate effective targeting of proposed interventions. In addition, the paper contributes to the limited literature on modeling the adoption of improved crop varieties among African farmers in the presence of neighborhood effects.

The rest of the paper is organized as follows. Section 2 explains spatial dependence and presents the method commonly used in testing for it. This is followed in Section 3 by an empirical exposition of how to incorporate spatial effects into a standard Tobit model. Section 4 describes the data used in this study, and the empirical results are presented in Section 5. Section 6 concludes, and offers some policy implications.

2. Testing for spatial dependence

Spatial dependence is the situation where the dependent variable (or error term) at each location is correlated with observations on the dependent variable (or values of the error term) at other locations. This may be stated mathematically as: $E[y_i y_j] \neq 0$ (or $E[\varepsilon_i \varepsilon_j] \neq 0$) for any neighboring locations *i* and *j* as opposed to the null hypothesis of homoskedastic or uncorrelated errors (i.e., $H_0 : \rho = 0$) (Anselin, 1990). By implication, two alternative hypotheses are possible when spatial dependence is present in a data set. The first alternative hypothesis relates to the dependent variable referred to as the 'spatial lag'. This is stated as: $y = \rho Wy + X\beta + \varepsilon$, where *Wy*, the spatial weights matrix, is a spatially lagged dependent variable and ρ is the spatial autoregressive coefficient. The consequence of ignoring this form of spatial dependence is that the ordinary least squares (OLS) estimates will be biased and all inferences based on the standard regression model will be incorrect. The second alternative hypothesis is the spatial error case. This is expressed as an autoregressive or a moving average form, $y = X\beta + \varepsilon$, and $\varepsilon = \lambda W\varepsilon + \xi$, where $W\varepsilon$ is a spatially lagged error term, λ the autoregressive coefficient and ξ a homoskedastic error term. The consequence of ignoring this type of spatial dependence is that, although the OLS estimator is unbiased, it is no longer efficient since it ignores the correlation between errors, and inferences based on *t* and *F* statistics will be misleading and indications of fit based on R^2 will be incorrect.

As noted by Anselin and Florax (1995), the commonly used approaches in testing for spatial dependence are the Lagrange Multiplier Error (LM_{err}) and Lagrange Multiplier Lag (LM_{lag}).

These have been shown to perform quite well in a large number of Monte Carlo simulation experiments (Anselin & Florax, 1995). The LM_{err} may be stated as follows:

$$LM_{err} = [e^{'}W_1 e / s^2 - T_1 (N\tilde{J}_{\rho.\beta})^{-1} (eW_1 y / s^2)]^2 / [T_1 - T_1^2 (N\tilde{J}_{\rho.\beta})^{-1}] \text{, with}$$

$$(N\tilde{J}_{\rho.\beta})^{-1} = [T_1 + (W_1 X\beta)' M((W_1 X\beta) / s^2]^{-1}$$

where e is a vector of regression residuals from an OLS regression of y on X, W_1 is a spatial weights matrix (in this case distance) with $T_1 = tr(W_1^{'}W_1 + W_1^{2})$ and tr as the matrix trace operator, $s^2 = e'e/N$ (with N as the number of observations) as estimate of the error variance, $W_1 X\beta$ is a spatial lag of the predicted values from an OLS regression of y on $\boldsymbol{X}$, and $M = I - X(X'X)^{-1}X'$ is the projection matrix. The LM_{err} statistic is an asymptotic test, which follows an χ^2 distribution with one degree of freedom.

Using similar notations as above, the LM_{lag}, on the other hand, may be stated as:

$$LM_{lag} = (e'W_1 y / s^2 - e'W_1 e / s^2)^2 / [N\tilde{J}_{\rho.\beta} - T_1].$$

The LM_{lag} statistic is valid under normality and asymptotic conditions and is distributed as an χ^2 variate with one degree of freedom.

Once spatial heterogeneity is detected, the empirical model should be formulated to take account of it. In technology adoption modeling, the spatial probit and spatial Tobit are two commonly used models. The former specification is suitable when the dependent variable relates to whether or not a farmer adopted an improved technology (a dichotomous choice). But if the dependent variable is defined as 'the extent of adoption or the proportion of area under the improved technology once adopted' (a continuous variable), which implicitly subsumes the first scenario, as in this study, then the latter specification is appropriate. The next section details the specification of a spatial Tobit[1] model as adopted in this study.

3. Specification of a spatial Tobit model

To stimulate the discussion of a spatial Tobit specification, consider the underlying linear regression model of the form:

[1] A full mathematical treatment of the Tobit model is not included in this paper as its usage is common in applied economics research. Thorough treatments of the model may be found in Greene (2000), chapter 20, pp. 896–951.

$$y_t = x_t\beta + e_t \quad \forall t \in N \tag{1}$$

where y is a (N x 1) vector of observations, x a known (N x K) design matrix, β a (K x 1) vector of unknown coefficients, and e a (N x 1) independently and identically distributed (*i.i.d.*) random vector with mean vector $E[e]=0$, variance $E[(e_t)^2]=\sigma^2$ and covariance $E[(e_t e_s)]=0, \forall t \neq s$. In the presence of spatial dependence, the error term violates the classical assumptions of the OLS. That is, e is no longer *i.i.d.* and thus invalidates the properties of the coefficients estimated and obscures interpretations of the statistical results (Anselin, 1988). To be able to draw appropriate inferences from empirical relationships, it is important to modify the classical statistical model to rectify the spatial dependence (whether in the spatial lag or spatial error form).

According to Anselin (1988), the spatial lag form can be accounted for in a classical linear regression model (1) by reformulating the model as a first order spatial autoregressive (AR) model of the form:

$$y = \rho_1 W_1 y + x\beta + u = (1-\rho_1 W_1)^{-1} x\beta + (1-\rho_1 W_1)^{-1} u \tag{2}$$

where y is an (N x 1) vector of observations, x a known (N x K) design matrix, β a (K x 1) vector of unknown coefficients, ρ_1 a scalar interpreted as the spatial AR correlation coefficient of the lagged dependent variable, and W_1 a (P x P) weight (or proximity) matrix. The spatially lagged endogenous variable represents the direct influence of observations on one another with the spatial structure defined by the specification of the spatial weights matrix W_1. Spatial lag is positive if $\rho_1 > 0$, negative if $\rho_1 < 0$ and there is no correlation if $\rho_1 = 0$. In the case of the spatial error form, the *u* in (2) has to be constrained to follow a first order AR process to account for any spatial structure introduced as a result of misspecifications. That is,

$$u = \rho_2 W_2 u + \varepsilon = (1-\rho_2 W_2)^{-1} \varepsilon \tag{3}$$

where ε is an (N x 1) *i.i.d.* error term, W_2 an (N x N) weight matrix structuring the spatial relationship of the residuals, and ρ_2 a scalar interpreted as a spatial residual AR correlation coefficient. Similarly, spatial error is positive if $\rho_2 > 0$, negative if $\rho_2 < 0$ and there is no correlation if $\rho_2 = 0$.

Incorporating the spatial structures of (2) and (3) into a classical linear regression model transforms the model into the standard spatial AR model:

$$y = (1-\rho_1 W_1)^{-1} x\beta + (1-\rho_1 W_1)^{-1}(1-\rho_2 W_2)^{-1}\varepsilon \tag{4}$$

Because of the error structure, $\varepsilon^* = (1-\rho_1 W_1)^{-1}(1-\rho_2 W_2)^{-1}\varepsilon$, heteroskedasticity is induced, which can be corrected by pre-multiplying (4) by the variance normalizing transformation $\Omega = [diag[E(\varepsilon^* \varepsilon^{*T})]]^{-\frac{1}{2}}$ (Case, 1992) to produce a transformed model with unit variance disturbances as:

$$y = \Omega y = \Omega(1-\rho_1 W_1)^{-1} x\beta + \Omega(1-\rho_1 W_1)^{-1}(1-\rho_2 W_2)^{-1}\varepsilon = x^*\beta + u^* \tag{5}$$

Note that the variance normalizing transformation alters the dependent variable to adjust for spatial relationship in the variables, but not the censoring point of zero or the physical interpretation of the model coefficient β.

To use a Tobit specification to model agricultural technology adoption decisions in the presence of spatial heterogeneity, the following modifications are necessary. Let the expected decision to adopt the improved technology by a farmer in location *i* be influenced by another farmer in adjacent location *j*. In the spatial Tobit model censored at zero, the relationship can be represented as:

$$E(Y_i^* | Y_j^* > 0) = x^*\beta + E(\mu_i^* | Y_j^* > 0) \tag{6}$$

The corresponding log-likelihood function of the spatial Tobit model is given as:

$$\ln L = \sum_{Y_i^*=0} \ln\left(\Phi\left(-\frac{1}{\sigma} x_i^*\beta\right)\right) + \sum_{Y_i^*>0} \ln\left(\frac{1}{\sigma}\phi\left(\frac{1}{\sigma}(Y_i^* - x_i^*\beta\right)\right) \tag{7}$$

where $\Phi(.)$ and $\phi(.)$ are the cumulative probability distribution and the standard normal density functions, respectively, and σ is the standard deviation of u*. If $\rho_1 = \rho_2 = 0$, then (7) is the log-likelihood function for the standard Tobit model.

4. Source of data

The data used in this analysis were collected from the Manica, Sussundenga and Chokwé districts of Mozambique. The Manica and Sussundenga districts, located in the Manica Province, are in sub-humid areas, while the Chokwé district is in the semi-arid region. Annual average rainfall in the former two districts ranges from 1014 to 1080 mm compared with a range of 600 to 932 mm for the latter district. The most common soil types in the Manica district are brownish loamy clay, while in the Sussundenga district they are yellowish deep clay. Soils in the Chokwé district vary from 90% sandy loams along the coast to clayish with high undecomposed organic matter deposits in the wetlands.

In each of the randomly selected districts, ten villages and ten farmers per village were randomly selected. In all, 300 farm households participated in the survey during the 2003/04 crop season as part of a region-wide farm level survey conducted by the International Maize and Wheat Improvement Center (CIMMYT). Structured questionnaires designed to capture information on a range of potential indicators related to household livelihood strategies were administered between August 2003 and July 2004 by trained enumerators directly supervised by research scientists from the Agrarian Research Institute of Mozambique and CIMMYT.

5. Results and discussion

5.1 Descriptive statistics of survey households

The descriptive statistics of the selected farm households are presented in Table 1. Farm households are comparable in size across the three districts but households in Sussundenga that have adopted improved maize varieties appear to have larger family sizes than their non-adopting counterparts. Each household is headed by a middle-aged member but household heads in Chokwé seem to be older than those in the other two districts. In the Manica and Sussundenga districts, slightly less than 15% are headed by females compared to over a quarter in the Chokwe district. Whereas over 70% of the household heads in the Manica and Sussundenga districts have formal education, less than 50% of those in the Chokwé district are literate.

Table 1: Descriptive statistics of adopters and non-adopters in selected districts in Mozambique, 2004[1]

	Manica (n=100)			**Sussundenga (n=100)**			**Chokwé (n=100)**			**Whole sample (n=300)**		
	Non-adopters	Adopters	District sample	Non-adopters	Adopters	District sample	Non-adopters	Adopters	District sample	Non-adopters	Adopters	All
Household size[2]	5.94	5.67	6.35	5.67	7.55**	6.76	7.46	8.32	7.65	6.72	7.09	6.90
	(2.82)	(3.10)	(3.12)	(3.10)	(4.10)	(3.81)	(4.16)	(3.64)	(4.05)	(3.79)	(3.64)	(3.71)
Man equivalent units	3.95	4.30	4.53	4.30	5.42*	4.95	5.28	5.85	5.41	4.82	5.08	5.04
	(1.40)	(2.01)	(2.22)	(2.01)	(3.10)	(2.74)	(2.86)	(2.71)	(2.83)	(2.53)	(2.71)	(2.63)
Total farm land (ha)	3.05	3.91	3.55	3.91	5.54*	4.86	4.93	6.68	5.32	4.38	4.73	4.57
	(1.42)	(2.71)	(2.61)	(2.71)	(4.29)	(3.78)	(6.26)	(4.37)	(5.92)	(5.01)	(3.77)	(4.38)
Cropped land (ha)	2.75	2.75	3.04	2.75	4.14**	3.55	4.02	5.11	4.26	3.48	3.74	3.62
	(1.18)	(1.71)	(2.20)	(1.71)	(3.13)	(2.71)	(3.51)	(4.12)	(3.66)	(2.90)	(3.00)	(2.95)
Total maize area (ha)	1.76	1.79	2.00	1.79	1.69	1.73	2.62*	2.00	2.48	2.26**	1.91	2.41
	(0.44)	(0.68)	(0.65)	(0.68)	(0.82)	(0.76)	(1.15)	(1.11)	(1.17)	(1.04)	(0.81)	(1.94)
Tropical livestock units	5.36	5.03	5.34	5.03	9.53	7.64	6.00	6.72	6.16	5.63	7.01	6.38
	(4.76)	(6.12)	(9.98)	(6.12)	(19.51)	(15.48)	(8.02)	(10.99)	(8.70)	(7.11)	(14.56)	(11.76)
Age of household head	43.29	49.21	46.08	49.21*	42.91	45.56	55.76	52.50	55.04	52.20**	46.11	48.93
	(7.62)	(14.16)	(14.29)	(14.16)	(13.72)	(14.19)	(14.50)	(9.13)	(13.53)	(14.36)	(14.30)	(14.62)
						%						
Association membership	0.0	13.3	11.0	16.7	24.1	21.0	18.0	40.9	23.0	15.3	20.9	18.3
Illiterate	17.6	20.5	20.0	42.9	19.0	29.0	57.7	36.4	53.0	48.2	22.1	34.0
Access to credit	23.5	20.5	20.0	9.5	15.5	13.0	3.9	13.6	6.0	8.0	17.8	13.0
Female headed households	-	-	13.0	-	-	14.0	-	-	43.0	-	-	23.0
Female adopters	-	-	84.6	-	-	44.3	-	-	11.6	-	-	35.7
Male adopters	-	-	82.8	-	-	56.0	-	-	29.8	-	-	60.0
Adoption rate (in terms of maize area)	0.0	27.6	22.9	0.0	14.4	8.3	0.0	23.3	5.1	0.0	22.3	18.1

Notes: [1]Standard deviations in parentheses

[2]Significantly different in means/proportions between adopters and non-adopters at 1% (**) and 5% (*) levels

Although land holdings are comparable across districts, Figure 1 suggests that female-headed households own relatively smaller land holdings than male-headed ones. This might be the result of the patrilineal[2] land tenure system, which precludes women from inheriting land (Meyers et al., 1993; Tique, 2002). The size of land cropped each year is often determined by available seed (49%), cash to pay for fertilizer (29%), and household labor force (17%). On average, households cultivate about 4 ha of land for maize, sorghum, millet and beans and keep 6.4 TLU[3] (made up of 3 cattle, 4 goats 0.2 sheep, 0.4 pigs, and 12 fowls) mainly as insurance against crop failure as well as for draft power and for manure for crops. Maize is the dominant crop, accounting for over 60% of the area. To spread the maize yield risk, farmers plant more than one variety. In the Manica, Sussundenga and Chokwé districts, respectively, 83%, 58% and 22% of the farmers plant improved varieties on 28%, 14% and 23% of their maize areas. In the Chokwé, Manica and Sussundenga districts, farm lands are cultivated continuously for seven to nine years before being fallowed for 0.7, 1 and 2.6 years, respectively, which indirectly reflects the pressure on land in the respective districts.

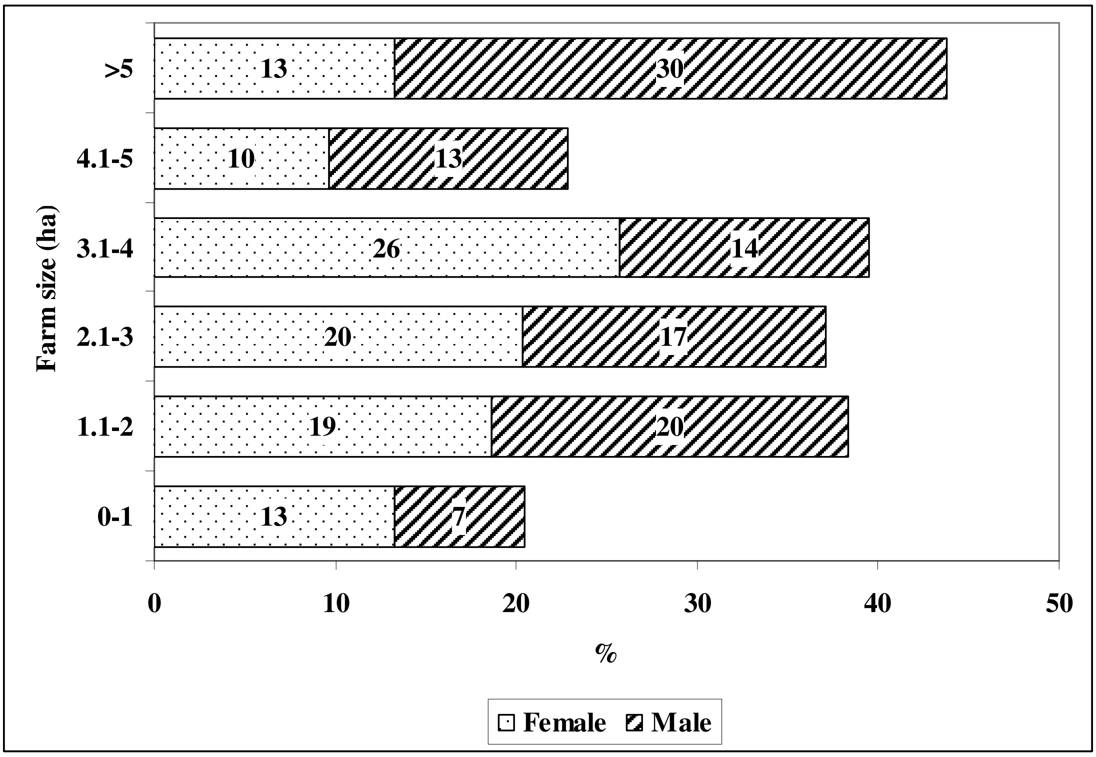

Figure 1: Distribution of farm sizes by gender of household head in Mozambique, 2004

---

[2] In a patrilineal system of inheritance, succession and/or inheritance is through the male line, i.e. a father transfers family property to his son or other descendants.

[3] A TLU (Tropical Livestock Unit) is a unit that represents an animal of 250 kg live weight. The unit is used to aggregate different species and classes of livestock as follows: bullock: 1.25; cattle: 1.0; goat, sheep and pig: 0.1; guinea fowl, chicken and duck: 0.04 and turkey: 0.05 (compiled after Janke, 1982).

With limited sources of external credit, farmers rely on earnings from agriculture (crop and livestock sales), and employment in the formal and informal (artisanal activities)[4] sectors for 38% and 50% of their household incomes estimated at Mt 8.7 million, Mt 10 million and Mt 11.7 million[5] in the Manica, Sussundenga and Chokwé districts, respectively. Of the total household expenditures of about Mt 6.1 million, Mt 5.4 million and Mt 14.2 million in the three districts, respectively, food and beverages account for 40% and farm inputs (such as seed, fertilizer and implements) 20%. Maize seeds purchases represent 7%, 3.2% and 2.7% in the three districts, respectively.

Market infrastructures, especially roads, market stalls and weights and measures, are poorly developed. Except for less than a third of the farm households that have access to animal drawn carts or bicycles for transport, farmers generally carry their farm produce on their heads to markets located between 10 and 16 km from their homesteads. These markets sometimes become inaccessible, especially during the rainy season when the roads get flooded. Whereas itinerant grain traders occasionally roam the villages to purchase grain, sometimes at low prices, input suppliers (e.g. seed companies) are often reluctant to retail their inputs (e.g. seeds) in the villages, citing high marketing costs and the limited purchasing capacity of rural farmers as the main reasons (Langyintuo et al., 2005).

5.2 Choice of variables for the empirical model

Economic theory does give guidance on the independent variables for adoption models, but does not completely dictate them. The variables in Table 2 reflecting (1) farm and farmer characteristics, (2) organizational affiliation, and (3) technology specific attributes were, therefore, selected on the basis of the adoption literature. The a priori assumptions of the selected variables are discussed below.

[4] Artisanal activities include masonry work, art and craft, fitting mechanic work, etc.
[5] The exchange rate in May 2005 was: 1US$ = Mtn 18,000 (Mozambican meticals).

Table 2: Definitions and descriptive statistics of variables used in the Tobit models

Variable	Definition	Mean
ADOPTION (Dependent)	Proportion of maize area on improved varieties	0.18 (0.19)
Exogenous variables		
A. Farm and farmer specific characteristics		
AGEHH$^{(-/+)}$	Age of household head	48.89 (14.6)
EDUCN	Years of formal education of household head	1.82 (0.71)
LABOR	Household labor-force in man equivalent units	5.04 (2.63)
GENDER$^{(-/+)}$	A binary variable with 1 if household head is male and zero otherwise	0.77 (0.42)
FARMSIZE	Total cropped area in physical units	3.62 (2.95)
B. Institutional affiliations		
ASSOCN	A binary variable with 1 if household head belongs to a farmers' association and 0 otherwise	0.18 (0.39)
EXTCON	A binary variable with 1 if household head has contact with extension services at least three times a year and 0 otherwise	0.16 (0.36)
CREDIT	A binary variable with 1 if household head had access to credit and 0 otherwise	0.13 (0.34)
DISTANCE$^{(-)}$	Distance to output markets in physical units	14.24 (17.3)
C. Technology attributes		
RKCOST$^{(-)}$	A binary variable with 1 if household head perceives that the improved maize seed is more expensive than the best local variety and 0 otherwise	0.83 (0.38)
RKAVAIL	A binary variable with 1 if household head perceives that improved seed is less readily available than local one and 0 otherwise	0.15 (0.36)
RKYIELD	A binary variable with 1 if household head perceives that the improved maize variety yields more than the best local variety and 0 otherwise	0.47 (0.50)
RKSPEST	A binary variable with 1 if household head perceives that the improved maize variety is more resistant to storage pests than the local variety and 0 otherwise	0.20 (0.40)
RKPALAT	A binary variable with 1 if household head perceives that the improved maize variety is more palatable than the local variety and 0 otherwise	0.18 (0.38)

Note: Standard deviations in parenthesis; expected signs are positive except for those indicated.

5.2.1 Farm and farmer specific characteristics

The farm and farmer specific characteristics in the model are used to evaluate whether human capital (age of household head (AGEHH), educational level (EDUCN), and household labor force (LABOR)), fixed social bias (i.e. gender of household head (GENDER)) and farm size (FARMSIZE) are important in the adoption decision process. It is generally believed that as farmers grow older they are less amenable to change and, therefore, may be unwilling to change from their old practices to new ones (Adesina & Zinnah, 1993). The model will, however, be used to test the alternative argument that age is positively related to adoption especially prior to the consolidation period in the producer's life cycle. Educated farmers are often thought to have access to literature such as research bulletins and hence to be better informed and more willing to adopt improved technologies than otherwise. An improved variety is a scale neutral technology (Hazell & Ramasamy, 1991) and would thus barely have an impact on labor use. Because extension staff are few and predominantly male, female farmers are sometimes discriminated against in extension activities. Farmers are risk averse and therefore very cautious in their willingness to devote some portions of their fields to an untried new variety. Consequently, the proportion of area devoted to the new varieties would be positively related to farm size.

5.2.2 Organizational affiliation

Organizational affiliation, such as being a member of a farmers' association (ASSOCN), or contact with extension staff (EXTCON) through attending farmer field days or demonstrations expose farmers to new technologies and stimulate communication, thereby reducing information asymmetry. These contacts are hypothesized to positively influence adoption. Farmers need cash to purchase seeds and complementary inputs such as fertilizers. Access to credit (CREDIT) is therefore postulated to be positively related to adoption decisions. Distance to grain markets (DISTANCE), on the other hand, is expected to have a negative impact on adoption because the farther farmers are from output markets the less likely they are to be willing to purchase improved, high yielding varieties that allow them to produce large quantities of grain for which they may not find markets.

5.2.3 Technology specific attributes

Regarding the technology specific attributes, each farmer compared an improved maize variety with their choice of the best local variety in terms of seed cost (RKCOST), seed availability locally (RKAVAIL), yield advantage (RKYIELD), resistance to storage pests (RKSPEST), and grain palatability (RKPALAT). Since improved seeds are often more expensive than the local ones, the cost of seed is hypothesized to have a negative impact on adoption. Seed companies are sometimes reluctant to deliver seeds to remote areas or even to use agro-dealers, so seed unavailability (locally) is expected to have a negative impact on adoption. The perceived superiority of improved maize varieties over the local ones in terms of yield and resistance to storage pests is expected to be positively related to adoption. If farmers perceive improved varieties to be more palatable than the local ones, adoption rates will increase.

5.3 Empirical results

Following Anselin and Hudak (1992), the data described in Table 2 were first tested for spatial homogeneity by the LM_{err} and LM_{lag} methods in SHAZAM. The spatial weights matrix used was an inverse distance (to agricultural research or on-farm demonstration stations). The estimated LM_{lag}

and LM_{err} values were 6.186 (ρ=0.013) and 1.87 (ρ=0.174), respectively, with corresponding standard errors of 0.065 and 0.120. These results suggest that the null hypothesis of homoskedastic or uncorrelated errors could be rejected in favor of a spatial lag as the best alternative hypothesis. To correct for the presence of spatial lag, a spatial Tobit model was specified and estimated with the proportion of maize area under improved varieties (ADOPTION) regressed on a spatial lag variable, WIMPVA, and the selected exogenous variables in Table 2. WIMPVA[6] is a product of a row-standardized spatial weights matrix ***W*** and a vector of observations on the dependent variable ADOPTION. The results are compared with those from a standard Tobit model.

The log-likelihood function value is an important statistic that can be used to compare two models. As shown in Table 3, the relatively larger log-likelihood function value of -199.712 for the spatial Tobit model compared with a value of -258.198 for the standard Tobit model suggests that the spatial Tobit model is a better fit than the standard Tobit model. In addition, the spatial Tobit model has relatively more statistically significant coefficients than the standard Tobit model. This is because the standard Tobit model specification, unlike the spatial Tobit model specification, leads to inflated variance estimates that in turn reduce the values of *t* or *z* statistics. The superiority of the spatial Tobit model over the standard Tobit model is further confirmed by the highly significant spatial lag coefficient (value = 3.640; ρ = 0.000). This statistic strongly suggests that the adoption of improved maize varieties in the selected districts is spatially correlated. That is, farmer-to-farmer interactions (or neighborhood influences) are very significant in explaining farmers' decisions to adopt improved maize varieties. This result is corroborated by the statistically significant coefficient for membership of farmers' association.

---

[6] Details on the programming of WIMPVA in SHAZAM and other software can be found in Anselin & Hudak (1992).

Table 3: Estimated coefficients from the standard and spatial Tobit models results

	Coefficient	
Variable	**Standard Tobit specification**	**Spatial Tobit specification**
WIMPVA (Spatial lag)	-	3.640**
AGEHH	-0.005	-0.023**
EDUCN	-0.063	-0.198
LABOR	0.078**	0.054
GENDER (Base = Female)	0.123	0.263
FARMSIZE	0.084**	0.188**
ASSOCN (Base = Not a member)	0.054	0.156*
EXTCON (Base = Less than three contacts per year)	0.313	0.179**
CREDIT (Base = No access to credit)	0.782**	0.784**
DISTANCE	-0.035	-0.022*
RKCOST (Base = Local variety less costly)	-0.495**	-0.595**
RKAVAIL (Base = Local variety more available)	-0.035	-0.017*
RKYIELD (Base = Local variety less yielding)	1.500**	0.944**
RKSTPEST (Base = Local variety less resistant to storage pests)	-0.204	-0.147
RKPALAT (Base = Local variety less palatable)	0.338*	0.140
CONSTANT	-0.905	-1.471**
Predicted probability of Y > limit given average X(I)	0.489	0.562
Observed frequency of Y > limit	0.544	0.544
Log-likelihood function	-258.198	-199.712
Squared correlation between observed and expected values	0.428	0.675

Note: ** Significant at 1 per cent level of error probability

* Significant at 5 per cent level of error probability

Returning to the main results, we can see that both the spatial and standard Tobit models predict, as expected, a similar relative significance of farm size, access to credit, grain yield and cost of seed but not age of household head, extension contact, distance to output market, seed availability, household labor and palatability in determining farmers' decisions to adopt improved maize varieties in Mozambique. The significant impacts of household labor force and palatability on adoption as predicted by the standard Tobit model (possibly because of its misspecification) seem debatable, further lending credence to the spatial Tobit model as the better fit. As a scale neutral technology, adoption of an improved variety is unlikely to be significantly influenced by household labor availability. Planting an improved high yielding variety may result in increased yield and consequently an increase in harvesting labor demand. But given that maize is normally harvested during the off-labor-peak period (when the marginal value product of labor is negligible or zero), labor is unlikely to be a constraint to adoption. Moreover, the great community spirit among households enjoins community members to help a member facing labor bottlenecks (Langyintuo et al., 2005). In the context of the surveyed districts where farm households are food insecure

(Langyintuo et al., 2005), grain palatability may not play a very significant role in farmers' decisions to adopt or not to adopt an improved, high yielding maize variety. In other words, until households become food secure, the taste of a staple food crop such as maize will not have a significant impact on adoption. Further discussion of the results is limited to the estimates from the spatial Tobit model.

The spatial Tobit model results show that age of farmer, farm size, access to credit, cost of seed, and grain yield significantly influence improved maize variety adoption at the 1% level of error probability, while membership of farmers' association, extension contact, distance to market and seed availability are significant at the 5% level. These results suggest that older farmers are less willing to take up improved maize varieties, implying that the alternative argument that age is positively related to adoption, especially prior to the consolidation period in the producer's life cycle can be rejected. As hypothesized, the larger the farm, the more likely it is that the farmer will be willing to experiment with new improved varieties than otherwise. A hectare increase in farm size increases the adoption and use intensity of improved maize varieties by 6%.

The empirical results emphasize the importance of access to social services such as contact with extension staff and being a member of a farmers' association in determining the adoption of improved maize varieties. Consistent with the findings of Kaliba et al. (1998), a positive relationship is observed between extension contact and adoption of improved maize varieties in Mozambique. Access to extension education through, for instance, farmer field days organized around demonstration plots, provides an effective way of showcasing the superiority of improved maize varieties over the local ones and stimulates adoption. Adoption rates will be enhanced if farmers belong to associations. The results suggest that the probability of getting a farmer to adopt an improved, high yielding maize variety will increase by 10% if he or she joins an association (Table 4). One potential benefit farmers derive from joining associations is the sharing of information. Farmers who have adopted the new varieties share their experiences with their colleagues, which allows non-adopters to better inform their decisions on whether or not to adopt.

Table 4: Decomposition of marginal effects from spatial Tobit results

Variable	Probability of adoption	Expected use intensity	Marginal change
Age of household head	-0.003	-0.001	-0.004
Association membership	0.104	0.061	0.165
Cropped land	0.039	0.021	0.060
Distance to market	-0.002	-0.002	-0.004
Extension contact	0.185	0.024	0.209
Access to credit	0.155	0.081	0.236
Seed unavailability	-0.151	-0.016	-0.167
Seed cost	-0.117	-0.062	-0.179
Grain yield	0.186	0.098	0.284

With little ability to cope with risk (due to limited financial resources), farmers are generally very sensitive to seed prices. Consequently, an increase in the price of improved seed relative to that of a local one will reduce the adoption rate drastically. The opposite impacts are expected with access to credit that can potentially relax the liquidity constraint farmers face. As also shown in the findings of Adesina and Zinnah (1993), and Doss et al. (2003), lack of access to credit (or cash) is an important constraint to the adoption of improved maize varieties among farmers. Cash is needed to purchase the improved seed and complementary inputs such as fertilizer to exploit the seed's genetic potential. Therefore, moving a farmer with no access to credit to a position of access to credit has the potential to increase the adoption rate and intensity of use of improved maize varieties by 24% (Table 4).

Distance to output market, a proxy for market inaccessibility, is found to have a negative and significant relationship with the adoption of improved maize varieties. Each kilometer decrease in distance from the farm homestead to a market center will increase the adoption rate by 0.4%. One possible explanation for this is that farmers far away from market centers tend to be less market-oriented, which means their technology use decisions would rely less on profitability considerations, and more on subsistence production. As a result, they may not be interested in investing in improved varieties so long as the traditional varieties provide a subsistence level of output for their families.

Once farmers are convinced that a given improved variety can supply a unit more yield than the local ones, adoption and use intensity of such a variety will potentially increase by 28% (Table 4). Higher yields will afford farmers the opportunity to achieve their dual objectives of producing maize for home consumption and the market, although overproduction by many farmers can depress grain prices to their disadvantage. Clearly, adoption will be enhanced if seeds are available in local retail shops. The current results suggest that the probability that a farmer will adopt an improved, high yielding maize variety will increase by 15% if the seeds are made available locally. In other words, the reluctance of seed companies to expand their retail networks is a disincentive for increased adoption rates.

6. Policy implications and concluding remarks

Researchers generally assume spatial homogeneity in their assessment of factors influencing the adoption of improved agricultural technologies by farmers. However, the potential for spatial heterogeneity is high due to, for example, neighborhood effects such as farmers sharing information about new technology. Ignoring spatial heterogeneity can result in biased or inefficient regression estimates and make inferences based on t and F statistics misleading. To improve our understanding of the factors affecting the adoption of improved maize varieties by smallholder farmers in Mozambique, this paper uses a spatial Tobit model to account for neighborhood effects, after an initial diagnostic test rejected the null hypothesis of spatial homogeneity.

The empirical evidence, similar to the observations by Case (1992), Holloway et al. (2002), and Ionnides and Zabel (2003), suggests a significant contribution of farmer-to-farmer interaction to technology adoption among Mozambican farmers in selected districts. This result draws policy makers' and development agents' attention to investing in organizing farmers to form associations.

Such associations provide opportunities for farmers to interact effectively with one another. Those who have adopted new technologies could share their experiences with non-adopters to better inform their adoption decisions. In a country like Mozambique where over 15 million farmers are serviced by an estimated 700 extension officers (Langyintuo et al., 2005), farmers' associations could also be used as conduits for extension message dissemination to ensure wider coverage. In addition, farmers' associations could evolve into marketing cooperatives that would provide an opportunity for farmers to learn how to aggregate their products, grade them and access competitive grain markets (Kelly et al., 2003). Furthermore, farmers in an association have better access to credit because most financial institutions prefer to give credit to farmer groups than to individual farmers in order to minimize administrative costs and defaulting (Lowenberg-DeBoer & Abdoulaye, 1994).

The strong neighborhood influence in the adoption decisions also highlights the need for the government and seed companies to space field demonstration days optimally to showcase the superiority of improved varieties over the local ones in terms of yield and resistance to storage pests. A frequently observed problem in rural farming communities is the limited stocking of promising varieties that farmers sometimes identify during field days. Therefore, to sustain the farmers' interest in improved seed and to expand seed sales, seed companies should be encouraged to increase their retail networks or use existing agro-dealers in strategic locations to sell their seeds.

Land size has a significant impact on improved variety adoption, yet females are discriminated against in terms of land distribution (see Figure 1). The government's attention is drawn to the need to implement land policies that allow female farmers equal access to land to improve their adoption decisions. The new Mozambican Land Law of 1997, which bequeaths all lands to the state (Tique, 2002), provides the government with an operational platform from which to effect any land reform.

In conclusion, it might be pointed out that the results of this study have wider implications since they strongly emphasize the need to test and correct for spatial homogeneity when modeling the adoption of improved technologies in developing countries, so as to increase the efficiency of the estimated results. In this way, recommendations could reflect reality for effective policy interventions to increase impact. Furthermore, the results contribute to the limited literature on modeling the adoption of improved crop varieties among African farmers in the presence of neighborhood effects.

Acknowledgements

This publication was made possible through financial support from the Rockefeller Foundation. The ideas expressed here are the authors' and do not necessarily reflect those of the Foundation. The authors are grateful to two anonymous reviewers for their constructive comments and suggestions, and to P Chaquala, and IA Buque of IIAM (Instituto de Investigação Agrária de Moçambique) for their supervisory support during field data collection.

References

Adesina, AA, & Zinnah, M, 1993. Technology characteristics, farmer perceptions, and adoption decisions: A Tobit model application in Sierra Leone. Agricultural Economics 9, 297–311.

Aikens, MT, Havens, AE & Flinn, WL, 1975. The adoption of innovations: The neglected role of institutional constraints. Mimeograph. Department of Rural Sociology, Ohio State University, Columbus, Ohio.

Anselin, L, 1988. Spatial econometrics: Methods and models. Kluwer Academic Publishers, Dordrecht.

Anselin, L, 1990. Some robust approaches to testing and estimation in spatial econometrics. Regional Science and Urban Economics 20, 141–63.

Anselin, L & Anil, KB, 1998. Spatial dependence in linear regression models with an introduction to spatial econometrics. In Ullah, A & Giles, DEA (Eds), Handbook of applied economic statistics. Dekker, New York, Basel and Hong Kong.

Anselin, L & Florax, R, 1995. Small sample properties of tests for spatial dependence in regression models: Some further results. In Anselin, L & Florax, R (Eds), New directions in spatial econometrics. Springer-Verlag, Berlin.

Anselin, L & Hudak, S, 1992. Spatial econometrics in practice: A review of software options. Regional Science and Urban Economics 22, 509–36.

Besley, T & Case, A, 1993. Modeling technology adoption in developing countries. American Economic Review Papers and Proceedings 83 (2), 396–402.

Case, A, 1992. Neighborhood influence and technological change. Regional Science and Urban Economics 22, 491–508.

Doss, CR, 2006. Analyzing technology adoption using microstudies: Limitations, challenges, and opportunities for improvement, Agricultural Economics 34, 207–19.

Doss, C, Mwangi, W, Verkuijl, H & De Groote, H, 2003. Adoption of maize and wheat technologies in East Africa: Synthesis of findings of 22 case studies. CIMMYT (International Maize and Wheat Improvement Center), Mexico.

Feder, G & Slade, R, 1984. The acquisition of information and the adoption of new technology. American Journal of Agricultural Economics 66 (2), 312–20.

Feder, G, Just, R & Zilberman, D, 1985. Adoption of agricultural innovations in developing countries: A survey. Economic Development and Cultural Change 33 (2), 119–33.

Greene, W, 2000. Econometric analysis. 4th Edition. Upper Saddle River, New Jersey.

Hazell, P & Ramasamy, C, 1991. The green revolution reconsidered: The impact of high yielding rice varieties in south India. Johns Hopkins University Press for IFPRI (International Food Policy Research Institute), Baltimore, Md.

Holloway, G, Ma Lucila, A & Lapar, MLA, 2007. How big is your neighborhood? Spatial implications of market participation among Filipino smallholders. Journal of Agricultural Economics 58 (1), 37–60.

Holloway, G, Shankar, B & Rahmanb, S, 2002. Bayesian spatial probit estimation: A primer and an application to HYV rice adoption. Agricultural Economics 27 (3), 383–402.

Ionnides, Y & Zabel, JE, 2003. Neighbourhood effects and housing demand. Journal of Applied Econometrics 18 (5), 563–84.

Isham, J, 1999. A model of technology adoption with social capital. Doctoral dissertation. University of Maryland.

Janke, HF, 1982. Livestock production systems and livestock development in tropical Africa. Kiel, Germany.

Kaliba, M, Verkujil, H, Mwangi, W, Mwilawa, T, Anandajayasekeram, P & Moshi, J, 1998. Adoption of maize production technologies in central Tanzania. CIMMYT (International Maize and Wheat Improvement Center), Mexico, the United Republic of Tanzania, and (SACCAR Southern Africa Center for Cooperation in Agricultural Research).

Kelejian, HH & Prucha, IR, 1999. A generalized moments estimator for the autoregressive parameter in a spatial model. International Economic Review 40 (2), 509–33.

Kelly, V, Adesina, AA & Gordon, A, 2003. Expanding access to agricultural inputs in Africa: A review of recent market development experience. Food Policy 28, 379–404.

Kivlin, JE & Fliegel, FC, 1967. Differential perceptions of innovations and rate of adoption. Rural Sociology 32 (1), 78–91.

Langyintuo, AS, Chaquala, P & Buque, IA, 2005. Maize production systems in Mozambique: Setting indicators for impact assessment and targeting. CIMMYT (International Maize and Wheat Improvement Center) Report, Harare, Zimbabwe. http://www.cimmyt.org/gis/rfseedsafrica/ Accessed 10 February 2007.

LeSage, JP, 2000. Bayesian estimation of limited dependent variable spatial autoregressive models. Geographical Analysis 32 (1), 19–35.

LeSage, JP & Smith, TE, 2004. A Bayesian Probit model with spatial dependencies. In LeSage, JP & Pace, RK (Eds), Advances in econometrics: Volume 18: Spatial and spatiotemporal econometrics. Elsevier, Oxford.

Lowenberg-DeBoer, J, Abdoulaye & T, Kabore, D, 1994. The opportunity cost of capital for agriculture in the Sahel: Case study evidence from Niger and Burkina Faso. Staff Paper. Department of Agricultural Economics, Purdue University, Indiana.

McDonald, JF & Moffitt, RA, 1980. The uses of Tobit analysis. Review of Economics and Statistics 62, 318–21.

McMillen, DP, 1995. Selection bias in spatial econometric models. Journal of Regional Science 35 (3), 417–36.

Meyers, G, Tanner, C & Oad, R, 1993. Land disputes and ecological degradation in an irrigation scheme: A case study of state farm divestiture in Chokwé , Mozambique. Land Tenure Center, University of Wisconsin-Madison.

Morris, ML, Trip, R & Dankyi, AA, 1999. Adoption and impact of improved maize production technologies. A case study of the Ghana Grains Development Project. Economics Program Paper 99-01. CIMMYT (International maize and Wheat Improvement Center), Mexico.

Nkonya, E, Schroeder, T & Norman, D, 1997. Factors affecting adoption of improved maize seed and fertiliser in northern Tanzania. Journal of Agricultural Economics 48 (1), 1–12.

Pinkse, J & Slade, ME, 1998. Contracting in space. An application of spatial statistics to discrete-choice models. Journal of Econometrics 85, 125–54.

Smale, M, Just, R & Leathers, HD, 1994. Land allocation in HYV adoption models: An investigation of alternative explanations. American Journal of Agricultural Economics 76 (3), 535–46.

Tique, CA, 2002. Rural land markets in Mozambique, its impact on land conflicts. http://www.sarpn.org.za/eventpapers/mozambique_april2002/tique/rural_land_markets.pdf Accessed 11 February 2007.

Tobin, J, 1958. Estimation of relationships for limited dependent variables, Econometrica 26, 24–36.