Accounting for neighborhood influence in estimating factors determining the adoption of improved agricultural technologies

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Abstract

Researchers have traditionally applied censored regression models to estimate factors influencing farmers' decisions to adopt improved technologies for the design of appropriate intervention strategies. The standard Tobit model, commonly used, assumes spatial homogeneity implicitly but the potential for the presence of spatial heterogeneity (spatial autocorrelation or dependence) is high due to neighborhood influence among farmers. Ignoring spatial autocorrelation (if it exists) would result in biased estimates and all inferences based on the model will be incorrect. On the other hand, if spatial dependence is ignored the regression estimates would be inefficient and inferences based on *t* and *F* statistics misleading. To account for neighborhood influence, this study applied a spatial Tobit model to assess the factors determining the adoption of improved maize varieties in southern Africa using data collected from 300 randomly selected farm households in the Manica, Sussundenga and Chokwe districts of Mozambique during the 2003/04 crop season. Model diagnosis confirmed the spatial Tobit model as a better fit than the standard Tobit model.

The estimated results suggest that farm size, access to credit, yield and cost of seed significantly influence maize variety adoption at less than 1% error probability while age of household head and distance to market influence adoption decisions at 5% error probability. The marginal effect analysis showed that convincing farmers that a given improved maize variety would give a unit more yield than the local one would increase adoption rate by 18% and intensity of use by 10%. Given that improved maize seeds are relatively more expensive than local ones, making credit accessible to farmers would increase adoption and intensity of use of improved maize varieties by 24% (15% being the probability of adoption and 8% the intensity of

use of the varieties). On the other hand, increasing seed price by a unit over the local variety would decrease the adoption rate by 12% and area under the improved variety by 6%. Targeting younger farmers with extension messages or making markets accessible to farmers would marginally increase the adoption and use intensity of improved maize varieties by only 0.4%.

These results suggest that increasing field demonstrations to show farmers the yield advantage of improved varieties over local ones in Mozambique are essential in improving the uptake of improved varieties, which may be enhanced by making credit available to farmers to address the high improved seed costs. Alternatively, assuring farmers of competitive output markets through marketing innovations would enhance improved maize variety adoptions decisions. It may be concluded that the significance of the paper is its demonstration of the need to include spatial dependency in technology adoption models where neighborhood influences are suspected. Such an approach would give more credence to the results and limit the errors in suggesting areas to emphasize in individual or group targeting. The results thus have implications beyond the study area. Furthermore, the paper contributes to the scanty literature on the application of spatial econometrics in agricultural technology adoption modeling.

Introduction

The dream of improving the livelihoods of rural farm households in developing countries through increased agricultural productivity would remain an illusion if the adoption rates of proven technologies remain low (Morris et al., 1999; Gemeda et al., 2001; Ajayi et al., 2003). The challenge to social scientists has been to accurately identify factors limiting the uptake of improved technologies for the design of appropriate intervention strategies. To achieve that goal they have relied on three main paradigms to explain technology adoption decisions, namely the innovation-diffusion, the adopters' perception, and the economic constraints models, The underlying assumption of the innovation-diffusion model, which was the focus of the majority of past adoption studies is that the technology is technically and culturally appropriate but the problem of adoption is one of asymmetric information of very high search cost (Feder and Slade, 1984; Shampine, 1998; Smale *et al.,* 1994). By emphasizing the use of extension, experiment station visits, on-farm trials and other vehicles to transmit technical information, the search costs of the information could be reduced.

The adopters' perception paradigm, on the other hand, suggests that the perceived attributes of the technology condition adoption behavior of farmers. Thus even with full technical information, farmers may subjectively evaluate the technology differently than scientists (Kivlin and Fliegel 1967; Norris and Batie, 1987; Gould et al., 1989; Ashby et al., 1989; Ashby and Sperling, 1992). As farmers are the penultimate decision makers in the adoption process, understanding whether or not their perceptions of a given technology are important in the adoption process is critical to designing information dissemination programs.

The economic constraint model contends that input fixity in the short run, such as access to credit, land, labor or other critical inputs limit production flexibility and condition technology adoption decisions (Aikens et al., 1975; Smale et al., 1994; Shampine, 1998). In the short-run, production patterns are less flexible than in the long-run as resources cannot be diverted to new activities without compensating effects on existing production patterns.

Recent studies have shown that neither hypothesis can fully explain the adoption decision independently (Adesina and Zinnah, 1993; Morris et al., 1999; Gemeda et al., 2001; Langyintuo et al., 2003). Emphasizing the three paradigms in modeling technology adoption by farmers would undoubtedly improve the explanatory power of the model but not necessarily the efficiency of the results. The standard Tobit[1] model, a censored regression model commonly used in technology adoption modeling, maximizes a two-part log-likelihood function, which is continuous for adopters and discrete for non-adopters. The model, however, implicitly assumes spatial homogeneity but the potential for the presence of spatial heterogeneity (spatial autocorrelation or dependence[2]) is high due to, for example, interaction among farmers of nearby villages, or if farmers nearer to research stations or on-farm demonstration plots adopt a technology faster than those far away. Ignoring spatial autocorrelation would result in biased estimates and all inferences based on the model will be incorrect. On the other hand, if spatial dependence is ignored the regression estimates would be inefficient and inferences based on t and F statistics misleading. Therefore, it is critical to test and correct for any spatial heterogeneity (or neighborhood influence) in the modeling process to improve the efficiency of the results.

[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.

[2] Spatial autocorrelation or 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 for the error term at other locations. (More in the section “Testing for Spatial Dependence”).

To account for neighborhood influence, this study applied a spatial Tobit model to assess the factors determining the adoption of improved maize varieties in Mozambique, southern Africa. During the 2003/04 crop season, a total of 300 farm households (100 per district) were randomly selected from Manica and Sussundenga districts in the Manica Province and Chokwe district in the Gaza Province and interviewed as part of a region-wide farm level survey undertaken by the International Maize and Wheat Improvement Center (CIMMYT). [Details of the selection procedure and number of farmers selected per village and district are contained in Langyintuo et al. (2005).] Structured questionnaires were used to collect data on socio-economic and institutional variables such as farmer's age, household size, farming experience, access to credit, distance to market, and extension contact, as well as technology specific variables including a comparison of the best local variety to improved varieties of maize in terms of cost of seed, yield, resistance to storage pests, draught resistance, palatability, etc.

Socioeconomic characterization of farm households in the study area

An average farm household in the survey area consists of seven members with corresponding man-equivalent[3] units of five, the main source of labor supply for farm work because of lack of a class of landless laborers and limited cash to hire labor (Table 1). The majority of households (77%) are headed by males. Mean ages of the 300 household heads interviewed in the Manica, Sussundenga and Chokwe districts are, respectively, 46, 45 and 55 years. Whereas over 70% of the sampled household heads in Manica and Sussundenga districts have formal education, less than 50% of those in the Chokwe district are literate.

[3] Man-equivalents used were defined as follows: Household members less than 9 years = 0; 9 to 15 years or above 49 years = 0.7; and 16 to 49 = 1. (Compiled after Runge-Metzger 1988)

Mean household incomes in Manica, Sussundenga and Chokwe districts are, respectively, Medicais (Mt) [4] 8.7 million, Mt10 million and Mt 11.7 million. Crops and livestock sales contribute about 27%, 36% and 44% to income in the three districts, respectively, reflecting the important role of agriculture in the livelihoods of farm households. Household earnings from employment in the formal and informal (artisanal activities[5]) sectors account for over 50% of total income in each district (with the highest of 72% in Manica district). As households receive and also give out remittances, the estimated net income from remittances in the three districts ranged from Mt 15,500 in Manica, Mt 330,000 in Chokwe to Mt 830,000 in Sussundenga (or 0.2%, 3% and 8% of total household income, respectively). Across all districts, about 20% of the estimated total household expenditures of Mt 6.1 million, Mt 5.4 million and Mt 14.2 million in Manica, Sussudenga and Chokwe districts, respectively, are invested in farm inputs such as seed, fertilizer, implements, etc. Corresponding expenditures in maize seeds were Mt 428,000, Mt 174,000 and Mt 382,000 representing 7%, 3.2% and 2.7% of total household expenditure, respectively.

An estimated 80% of the total family farm size of five hectares is cultivated annually and the remainder put under fallow for an average of a year only (due to the high population pressure on arable land). The three most important determinants of cultivated farm sizes in Manica district, where many farmers are more eager than in the other two districts to grow improved varieties, are unavailability of seed (38%), cash to purchase complementary inputs (21%), and unavailability of family labor-force (19%), while in Sussundenga and Chokwe districts, unavailability of labor (32% and 33%, respectively), cash to purchase complementary inputs (20% and 37%, respectively) and seed (21% and 18%, respectively) constrain choice of

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[4] The Mozambican currency is called Medicais (Mt). The exchange rate in May 2005 was: 1US$ = Mt 18,000.
[5] Artisanal activities include fitting mechanic work, etc.

cultivated farm size. Similar reasons are responsible for 34% of farmers reducing their farm sizes over the years compared with 9% who increased because of improved access to seed. Partly due to their relatively smaller household sizes, female headed households especially in Sussundenga and Chokwe districts tend to cultivate relatively smaller farm sizes compared with their male counterparts (Figure 1). In addition to growing maize for home consumption and the market, farmers also grow sorghum, millet and beans on less than 40% of the total cultivated area. As a risk management strategy, households keep livestock averaging 6.4 TLU[6] (made up of 0.2 sheep, 0.4 pigs, three cattle, four goats and 12 fowls) on average.

Typically farmers spread maize yield risk by planting more than one variety on their fields. Important varieties include Matuba (25%), SC513 (18%), PAN64 (12), and Sussuma (5%) usually procured from village markets located between 12 and 16 km away (which are sometimes inaccessible due to floods) or saved from the previous harvest. In the 2003/04 cropping season, about 83%, 58% and 22% of farmers in Manica, Sussundenga and Chowkwe districts, respectively, planted improved varieties. As a measure of area under improved varieties, however, estimated adoption rates were, respectively, 23%, 8% and 5% during the same year compared with 30%, 18% and 21% within the past five years. The main reasons for the relatively high dis-adoption rates were (1) unsatisfactory performance of improved varieties (39%), (2) unavailability of preferred improved seed (30%), (3) lack of cash to purchase improved seed (30%), and (4) other related problems (1%). The choice of specific varieties is sometimes influenced by extension staff of the Ministry of Agriculture (MoA) or non-governmental organizations (NGO) such as World Vision and Care Internationals through field

[6] A TLU (Tropical Livestock Unit) is an animal unit that represents an animal of 250 kg liveweight, and 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).

days and demonstrations. Ironically, over two-thirds of the farmers interviewed never had any contact with extension staff during the cropping season meanwhile more than 50% of those who had, made at least three contacts.

Staffs of MoA and NGOs are also instrumental in organizing farmers into associations and groups to bargain for better services (Table 1) although over 80% of farmers rely on equity capital to finance their farm operations due largely to unavailability of credit sources (44%) and lack of collateral to guarantee any loans (37%). Only 13% of households in Manica district and 4% each in Sussundenga and Chokwe districts received either cash or input credits. In Manica district, however, 4% received both cash and input credits. Relatives are the main sources of cash credit with virtually no interest while NGOs provide input credits to be repaid in output of specified quantity agreed upon at the time of lending.

Testing for spatial dependence

As a result of interactions among farmers across geographical locations, spatial heterogeneity is likely. The presence or absence of spatial heterogeneity has implications for spatial modeling. For example, in the case of extreme spatial heterogeneity, every region or spatial scale would be considered to be unique, and thus no general statements could be formulated while in the case of spatial homogeneity, relationships of interest are essentially the same in all regions, and thus formulations derived for any scale can be effectively transposed to every other scale (Anselin, 1990). This means the necessity to test for the presence of spatial heterogeneity in technology adoption modeling and where necessary implement a spatial Tobit model.

By definition, spatial autocorrelation or 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 for the error term at other locations. In general, spatial autocorrelation is given as: $E[y_i y_j] \neq 0$ or $E[\varepsilon_i \varepsilon_j] \neq 0$ for any neighboring locations *i* and *j*. The null hypothesis is homoskedastic or uncorrelated errors, that is, $H_0 : \rho = 0$. Two alternative hypotheses are possible. One pertains to the dependent variable referred to as spatial lag and 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 autocorrelation is that the 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 ($y = X\beta + \varepsilon$, where $\varepsilon = \lambda W\varepsilon + \xi$) or a moving average form ($\varepsilon = \lambda W\xi + \xi$), 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, consequently, inferences based on *t* and *F* statistics will be misleading and indications of fit based on R^2 will be incorrect.

Following Anselin and Hudak (1992) the data described in Table 2 were first tested for spatial dependence in SHAZAM using the Lagrange multiplier error (LMerr) and Lagrange Multiplier lag (LMlag) with inverse distance weights as spatial weights matrix. The former, which is related to the spatial error, is an asymptotic test, which follows a χ^2 distribution with one degree of freedom while the latter, which is related to spatial lag, is valid under normality and asymptotic conditions and is distributed as a χ^2 variate with one degree of freedom.

The estimated LM (lag) and LM (err) values of 6.1849 (ρ=0.0129) and 1.8506 (ρ=0.1737), respectively, suggest that the null hypothesis of homoskedastic or uncorrelated errors can be rejected in favor of a spatial lag and hence the need to account for spatial dependence in the modeling process.

Specification of a spatial Tobit model

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

$$y_t = x_t\beta + e_t \quad \forall\, t \in T \qquad \ldots (1)$$

where y is a (T x 1) vector of observations, x a known (T x K) design matrix, β a (K x 1) vector of unknown coefficients, and e a (T x 1) identically and independently distributed (*iid*) 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 correlation, the error term violates the classical assumptions of the ordinary least squares. That is, e is no longer *iid* 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 or correlation.

Restricting ourselves to spatial dependence, the influence of spatial neighbors in technology decision making can be accounted for in the classical statistical models by reformulating the model as a first order spatial autoregressive (AR) model (ibid) of the form:

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

where ρ_1 is a scalar interpreted as the spatial AR correlation coefficient of the lagged dependent variable, W_1 an (N x N) weight (or proximity) matrix, and all other variables as described above. 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 weight matrix W_1. Spatial correlation is positive if $\rho_1 > 0$, negative if $\rho_1 < 0$ and no correlation if $\rho_1 = 0$. The u 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,

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

where ε is a (N x 1) *iid* 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 correlation is positive if $\rho_2 > 0$, negative if $\rho_2 < 0$ and no correlation if $\rho_2 = 0$.

Incorporating the spatial structures of (2) and (3) into the linear regression model (1) transforms the model into the standard spatial AR model:

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

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 (Case, 1992) $\Omega = [diag[E(\varepsilon^* \varepsilon^{*T})]]^{-\frac{1}{2}}$ to produce a transformed model with unit variance disturbances as:

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

It is important to note that while the variance normalizing transformation alters the dependent variable to adjust for spatial relationship in the variables, it does not influence the censoring point of zero nor does it alter the physical interpretation of the Tobit model coefficient β although the β values adjust to reflect the influence of spatial correlation.

In specifying censored regression in the presence of spatial dependence/correlation using a Tobit model, modifications are necessary to account for the spatial effects of the variables. To capture the spatial dependence, let the expected decision to adopt a maize variety by a farmer in location *i* be influenced by farmer in adjacent location *j*. In the spatial Tobit model censored at zero, the relationship can be represented as:

$$E(Y_i^* \mid Y_i^* > 0) = x^*\beta + E(\mu_i^* \mid Y_i^* > 0) \qquad \ldots (6)$$

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

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

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

Empirical results

A spatial Tobit model was specified and estimated with the proportion of maize area under improved varieties regressed on a spatial lag and selected exogenous variables reported in Table 2. A standard Tobit model was also estimated with similar variables excluding the spatial lag for comparison. As reported in Table 3, the log-likelihood function values of -199.7246 and -258.2080 for the spatial Tobit and standard Tobit models, respectively, and the relatively smaller standard errors for the former model suggest that the spatial Tobit is a better fit between the two. Moreover, the highly significant spatial lag coefficient (value = 2.2216; ρ = 0.0000) indicates that the standard Tobit model is inefficient for ignoring spatial dependence.

The estimated results from both models suggest that farm size, access to credit, yield and cost of seed significantly influence improved maize variety adoption at less than 1% error probability (Table 3). In general, farmers are risk averse and therefore are very cautious about devoting some portions of their fields to an untried new variety. Consequently the proportion of area devoted to the new varieties is positively related to farm size as hypothesized. Farmers with relatively larger farms are willing to experiment with new improved varieties compared with those with smaller ones.

For farmers to maximize the benefits from adopting an improved variety, they need money to invest in complementary inputs such as fertilizer and timely weeding in addition to paying for relatively expensive improved seed. Hence moving a farmer from a situation of no access to credit to access would significantly improve adoption decisions. As expected, increasing improved seed cost by a unit over the local ones would discourage farmers from adopting such varieties.

As noted earlier, farmers grow maize for consumption and cash income and would prefer higher yielding varieties for more grains and higher revenues allowing them to depend less on handouts. Consequently, the perceived superior yield of improved varieties over the local ones positively influenced the adoption and use intensity of improved maize varieties in Mozambique. That is, farmers sufficiently convinced that the improved varieties would yield higher than their local varieties at given conditions would have a significant impact on adoption and use intensity of improved maize varieties.

Differences between the two models existed in the spatial Tobit model suggesting that at the 5% level of error probability, distance to market and age of household head significantly influence maize variety adoption decisions among farmers in Mozambique while the standard Tobit model results indicated significantly positive influence of household labor-force and palatability on farmers' decisions to adopt at 1% and 5% error probabilities, respectively, which seems debatable. Adopting an improved crop variety may only increase labor requirements marginally (during harvesting because of increased yields) and thus unlikely to have a significant impact on adoption decisions especially that harvesting takes place during off-labor peak period when the marginal value product of labor is negligible or even zero. Similarly, in a situation where farm households are not food self-sufficient, it is unlikely that palatability would play a significant role in technology adoption decisions. On the other hand, older people are less amenable to change and therefore age can have a significantly negative impact on variety adoption decisions as rightly predicted by the spatial Tobit model. Access to market is an important variable as it influences the prices farmers receive when they sell their maize. As hypothesized, distance negatively influenced farmers' adoption decision making. The farther away farmers are from output markets the less likely they would be willing to invest in improved, high yielding varieties.

Policy implications

The empirical model presented earlier can be used to draw economic implications for maize improvement strategies in southern Africa. The effects of changes of given attributes and characteristics of farmers on adoption probabilities and use intensities can be obtained by decomposing the marginal effects following a Tobit decomposition framework suggested by McDonald and Moffitt (1980). Let E(P) be the expected value of the proportion of adoption across all observations conditional on the maize farmer being above the threshold limit. That is, we are concerned about use intensities of maize farmers who have already adopted an improved variety. Given the probability of adoption as F(z), where $z = XP / \sigma$, the relationship between these variables can be shown to be:

$$E(P) = F(z) * E(P) \qquad \ldots (8)$$

For a given change in the level of a specific characteristic of interest, the effects on farmer adoption behavior can be broken down into two parts by differentiating (8) with respect to the specific characteristic change:

$$\partial E(P)/\partial X_i = F(z)\{\partial E(p)/\partial X_i\} + E(p)\{\partial F(z)/\partial X_i\} \qquad \ldots (9)$$

Multiplying through by $X_i / E(P)$, the relation in (9) can be converted into elasticity form as:

$$\{\partial E(P)/\partial X_i\}X_i / E(P) = F(z)\{\partial E(p)/\partial X_i\}X_i / E(P) + E(p)\{\partial F(z)/\partial X_i\}X_i / E(P) \qquad \ldots (10)$$

Re-arranging (10) by using (8), the following decomposed elasticity equation can be obtained:

$$\{\partial E(P)/\partial X_i\}X_i / E(P) = \{\partial E(p)/\partial X_i\}X_i / E(P) + \{\partial F(z)/\partial X_i\}X_i / F(z) \qquad \ldots (11)$$

Therefore, total elasticity of a change in the level of any given characteristic (which is assumed to be directly linked to adoption) consists of two effects: (a) the change in the elasticity of the use intensities of the improved maize varieties for those maize farmers that are already adopters, and (b) the change in the elasticity of the probability of being an adopter.

Limiting ourselves to the spatial Tobit model for the marginal analysis, the results showed that convincing farmers that a given improved maize variety would give a unit more yield than the local one would increase adoption rate by 18% and intensity of use by 10% (Table 4). This suggests the need to intensify field demonstrations involving all categories of farmers rather than skewing it for only the elderly, the rich and those in leadership positions. However, if farmers in leadership positions could be motivated to act as trainers, then they could be used as conduits to widen the coverage of extension messages.

Making credit accessible to farmers would increase adoption and intensity of use of improved maize varieties in Mozambique by 24% (16% being the probability of adoption and 8% the intensity of use of the varieties). But lack of access to credit by farmers has been an age old problem in the developing countries. Financial institutions are reluctant to advance credit to farmers for varied reasons including lack of appropriate collateral to guarantee the loan, high administrative cost of the loan and high default rates among farmers. So how might farmers be assisted to access credit?

It has been demonstrated in Ghana that an Inventory Credit Program (ICP) implemented by TechnoServe (detailed in Langyintuo, 2005) has the potential of creating confidence between farmers and financial institutions thus allowing farmers to have access to farm credit from such institutions using their collective grains in a community warehouse as collateral. Soon after harvest when farmers are in dire need for cash to meet immediate cash needs but prices of grains are at the lowest, farmers take loans (at the market interest rate) from the financial institution equivalent to about 75% of the value of the grains they store in the community warehouse as collateral to meet such needs. The grains in the warehouse are sold when prices are favorable usually during the lean season when all crops have been planted and new ones yet to be harvested. This affords farmers to pay back their loans (with interest) and still make profit. Such innovative marketing strategies, apart from creating avenues for farmers to access credit as well as affording them the benefit of grain price movement, also assure local level food security stocks. Therefore, ICP could be exploited to improve the financial wellbeing of farmers, improved variety adoption, and livelihoods of farm households.

As in most developing countries, farmers are cash-trapped with limited options for borrowed capital. Therefore, increasing improved seed price by a unit over the local variety would decrease the adoption rate by 12% and area under the improved variety by 6%. One way of addressing this problem is to offer farmers competitive grain prices to justify their investment in seed. One reason why small scale farmers depending on agriculture are often cash-trapped is the fact that the majority of them sell off their grains soon after harvest when prices collapse to meet immediate family needs (as noted above). Affording farmers the opportunity to keep their produce beyond the harvesting period when prices are at their lowest and yet be able to meet the cost of medical bills, school fees, etc which compel them to sell their grains at that time would be helpful. The ICP program discussed earlier on could be one of the ways forward. Another option could be the Cereal Bank (CB) concept operating in Kenya (Okello, 2004). The CB allows farmers to access competitive markets without compromising on their immediate cash needs. Government and development agents should exploit such marketing opportunities to stimulate output markets to enhance adoption rates of improved maize varieties, especially that decreasing the distance to market by one unit has the potential of increasing the adoption rate and use intensity of improved varieties by 0.4%.

Targeting younger farmers as opposed to older ones would marginally increase the adoption rate and use intensity of improved maize varieties by only 0.4%. Policy makers should endeavor to encourage extension staff to extend their services to all categories of farmers especially the younger ones to increase adoption rates of improved technologies.

Although increasing farm size by a unit would increase adoption and use intensity of improved varieties by 6%, it is unrealistic to advocate expanding cultivated areas because of population pressure on land, potential loss of crop biodiversity and possible land degradation. Instead, one may argue for crop intensification, which would effectively increase cultivated land area without recourse to the problems associated with cropped area expansion.

Conclusion

These results make a compelling case for increased field demonstrations to show all categories of farmers the yield advantage of improved varieties over local ones in Mozambique. To further improve the uptake of improved varieties would require making credit available to farmers to address the high improved seed costs. Additionally, farmers should be assured of competitive output prices through innovative marketing strategies such as CBs and ICPs. That in itself would address in part the high cost of improved seed. Since farmers would be better rewarded for their investment in seed and subsequently be willing to invest more in improved seed albeit being higher priced than the local ones.

In conclusion, it may be noted that the significance of the paper is in its demonstration of the need to include spatial dependence in technology adoption models where neighborhood influences are suspected. Such an approach would give more credence to the results and limit the errors in suggesting areas to emphasize in individual or group targeting. The results thus have implications beyond the study area. Furthermore, the paper contributes to the scanty literature on the application of spatial econometrics in agricultural technology adoption modeling.

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Table 1: Descriptive statistics of survey districts in Mozambique, 2004

Statistic	District: Manica	Sussundenga	Chokwe	Whole sample
Household size	6.4 (3.12)	6.8 (3.81)	7.7 (4.05)	6.9 (3.71)
Man-equivalent units	4.5 (2.22)	5.0 (2.74)	5.4 (2.83)	5.0 (2.63)
Total farm land (ha)	3.55 (2.61)	4.86 (3.78)	5.32 (5.92)	4.57 (4.38)
Total cropped land (ha)	3.05 (2.20)	3.55 (2.71)	4.26 (3.66)	3.62 (2.95)
Proportion of cropped land on improved maize varieties	0.23 (0.23)	0.08 (0.13)	0.05 (0.14)	0.12 (0.19)
Mean fallow years	0.95 (1.65)	2.58 (2.20)	0.73 (1.27)	1.42 (1.93)
Man-land ratio	2.54 (1.86)	1.91 (1.37)	2.13 (1.45)	2.19 (1.59)
Tropical livestock units (TLU)	5.34 (9.98)	7.64(15.48)	6.16(8.70)	6.38(11.76)
Age of household head	46.1 (14.3)	45.6 (14.2)	55.0 (13.5)	48.9 (14.6)
Female headed-house holds (%)	13	14	43	23
Membership of association (%)	11	21	23	18
Percent illiterates	20	29	53	34

Note: In parenthesis are the standard deviations.

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

Variable	Definition	Mean
IMPROPN (Dependent)	Proportion of cropped area on improved varieties	0.12 (0.19)
GENDER$^{-/+}$	A binary variable with 1 if household head is a male and zero otherwise.	0.77 (0.42)
AGEHH$^{-/+}$	Age of household head.	48.89 (14.6)
EDUCN	Years of formal education of household head.	1.82 (0.71)
MEUNIT	Household labor-force in man equivalent units.	4.96 (2.63)
ASSOCN	A binary variable with 1 if household head belongs to a farmers' association and 0 otherwise.	0.18 (0.39)
CROPLAN	Total cropped area in physical units.	3.62 (2.95)
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)
OPTMKT^{-}	Distance to output markets in physical units.	14.24 (17.3)
CREDACC	A binary variable with 1 if household head had access to credit and 0 otherwise.	0.13 (0.34)
RKCOST	A binary variable with 1 if household head perceives that the improved maize seed is cheaper than the best local variety and 0 otherwise	0.83 (0.38)
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.

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

Variable	Coefficient	
	Standard Tobit specification	Spatial Tobit specification
WIMPVA (Spatial lag)	-	3.5401***
GENDER (Base = Female)	0.1232	0.2631
AGEHH	-0.0053	-0.0125***
EDUCHH	-0.0620	-0.1876
MEUNIT	0.0772***	0.0527
ASOCN (Base = Not a member)	0.0107	-0.1763
CROPLAN	0.0825***	0.1983***
EXTCON (Base = Less than three contacts per year)	0.3128	0.2790
OPTMKT	-0.0345	-0.0115**
CREDACC (Base = No access to credit)	0.7809***	0.7827***
RKCOST (Base = Local variety)	-0.4850***	-0.5946***
RKYIELD (Base = Local variety)	1.5003***	0.9439***
RKSTPEST (Base = Local variety)	-0.2038	-0.1469
RKPALAT (Base = Local variety)	0.3376**	0.1403
CONSTANT	-0.9053	-1.4708***
Dependent Variable		
IMPROPN	1.1964	1.5935
Predicted probability of Y > limit given average X(I) =	0.4899	0.5226
Observed frequency of Y > limit =	0.5433	0.5433
Log-likelihood function =	-258.2080	-199.7246
Squared correlation between observed and expected values =	0.42523	0.6719

Note: *** Significant at 1% level of error probability

** Significant at 5% level of error probability

Table 4: Decomposition of elasticities from spatial Tobit results

Variable	Probability of adoption	Expected use intensity	Marginal change
Age of household head	-0.0025	-0.0013	-0.0038
Cropped land	0.0391	0.0206	0.0597
Distance to market	-0.0024	-0.0015	-0.0039
Access to credit	0.1552	0.0811	0.2363
Seed cost	-0.1172	-0.0616	-0.1788
Grain yield	0.1860	0.0978	0.2838

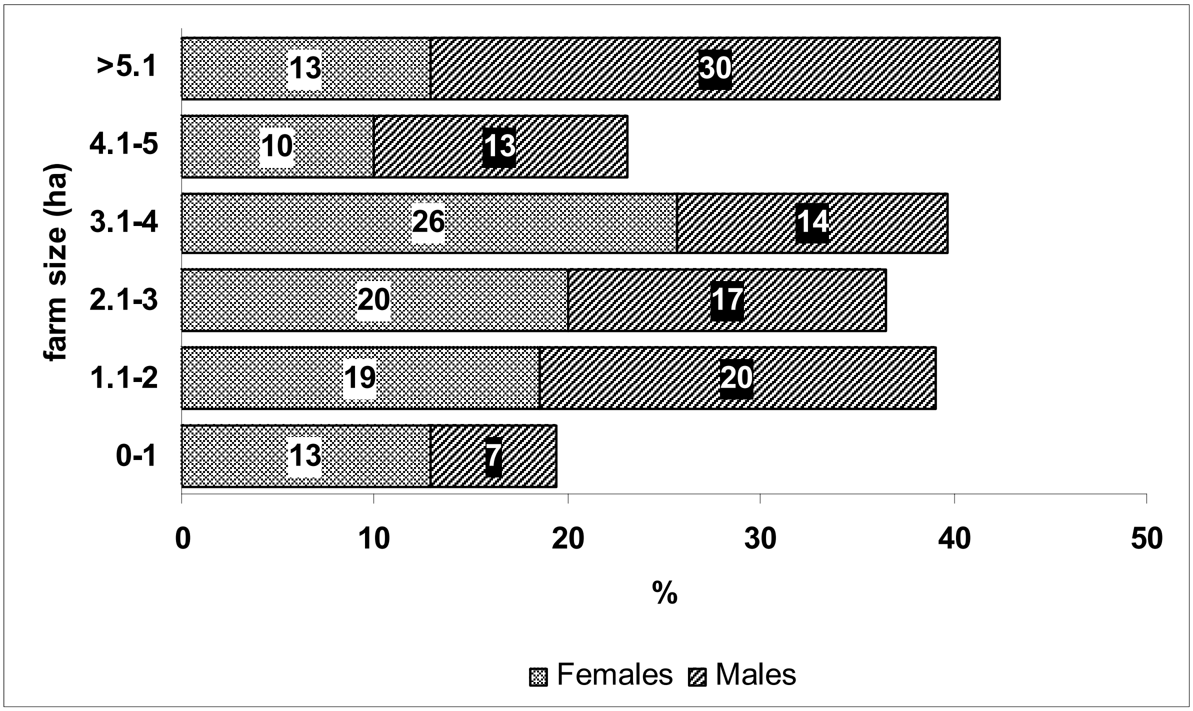

Figure 1: Distribution of farm sizes by gender of household head in Mozambique, 2004