HOW BIG IS YOUR NEIGHBORHOOD? SPATIAL IMPLICATIONS OF MARKET PARTICIPATION BY SMALLHOLDER LIVESTOCK PRODUCERS

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Abstract

Identifying ways to increase market participation by smallholder producers requires identifying variables that influence market access. This is usually achieved using probit estimation. An important phenomenon affecting entry decision-making is the entry decision of a ‘similar’ household, where similarity is measured in terms of ‘location.’ When neighborhood influences are significant, it is important to allow for them in discrete decision contexts, such as probit estimation. This paper, therefore, assesses the magnitude of neighborhood influences in smallholder decisions concerning market entry. The empirical model is based on a cross-section of (110) farms situated in northern Philippines, visited (twice) in the 2000-2001 production year (a panel of 220 observations). The vehicle for analysis is a Bayesian formulation of a standard probit model, but one that allows for spatial autoregression in the decision vector. Estimation requires a Metropolis-step addition to a basic Gibbs sampling algorithm and generates useful insights concerning quantities that are important for market-access policy. (154 words).

Keywords: market access, neighborhood effects, spatial econometric model, Bayesian estimation. (9 words).

Journal of Economic Literature Classifications: O18, R15, C11

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I. Introduction

The Philippine livestock sector is undergoing structural changes in response to a changing market environment. This is happening in the context of the so-called Livestock Revolution, namely, the projected increase in per capita meat and milk consumption in developing countries, brought about by increasing incomes, rising population, and rapid urbanization (Delgado et al. 1999). Potentially, there are many different pathways in which this structural change may be directed, all of which have direct implications on smallholder producers. One direction could be towards the path of increasing concentration of production among a few, that is, the emergence of industrial type systems characterized by high capital inputs and economies of scale, that could potentially drive smallholders from the market. One other direction could be towards greater vertical integration of smallholders with large producers, thus promoting a more equitable and environmentally sustainable development of the livestock sector (FAO, 2000). Given that the Philippines is at the cusp of this development pathway at the moment, it is important that the right policies are put in place to ensure that the smallholders share a return within the development process. Of particular concern is the extent to which smallholders are participating in this expanding market and the underlying factors that enable them to participate.

Several studies have looked at market access/participation and identified critical policy variables for market entry by smallholders (see, for example, Holloway et al.

2001a and 2001b, Holloway and Ehui 2001, Holloway et al. 2000a and 2000b). It has been shown that the number of extension visitations, adoption of crossbred cows, and distance to market are important factors that precipitate entry in milk markets in Ethiopia (Holloway et al. 2001a, 2000a). These covariates have also been discovered to be important in other settings. Specifically, in the present context, previous work (Lapar et al. 2002) observes that animal stocks, financial resources, and human capital accumulation are important determinants of smallholder decision-making and that increases in them engender participation in livestock markets. Each of these studies ignores the possible existence of externalities arising in the entry decision-making process, that is, existence of possible neighborhood effects. Spatial aspects or 'neighborhood effects' of market participation could have potentially important implications for policies targeted towards increased participation by smallholders. The logic is simple. An estimated quantity of a particular household resource that is required to precipitate entry could engender greater impacts than in the absence of neighborhood effects. Hence, the existence of neighborhood effects can influence conventional cost-benefit calculations.

It is thus the objective of this paper to investigate the existence of these neighborhood effects using the Philippine data. Section II discusses the neighborhood phenomenon and section III outlines the spatial, autoregressive probit estimation. Section IV presents the data, section V presents the results and section VI concludes.

II. Neighborhood effects of market participation

The farm household literature has shown that a farmer's discrete decision making is largely influenced by certain household characteristics (Feder et al. 1985). However, it ignores the importance of interaction among farmers, and how this interaction may affect an individual farmer's decisions. The possibility that the behavior and characteristics of one's neighbors have an effect on one's behavior has long been a topic of interest among sociologists, and has recently received growing attention among economists as well (Ludwig et al. 2000). The latter's interest stems from the need to obtain accurate estimates of the impacts of particular variables of interest on certain economic outcomes, for example, adoption of new technologies and employment, among other items. Empirical work that does not include information about neighborhoods may likely overstate the (direct) influence of individual and household characteristics, say, on economic outcomes. This has subsequent important implications on policy recommendations that come out of the empirical results.

Neighborhood effects of market participation may arise from information provided by participant neighbors about markets, prices, product quality and quantity. This is in a way, the impact of social capital provided by participant neighbors. The effect of local social norms is also one way by which neighborhood effects may be manifest. For example, in areas where livestock raising is an accepted way of life, the social composition of the neighborhoods may directly influence a farmer's attitude towards engaging in similar socially acceptable activities. Thus, one may observe contiguous areas where the majority of farmers may be engaged in pig raising, poultry raising, or beef cattle production. This is particularly true in several locations in the Philippines. While it can be argued that these could be just the result of agroecology and/or certain economic and policy variables, such as better infrastructure, higher levels of education, market pull, among others, it is worthwhile to examine the extent to which the 'neighborhood' is also largely responsible for these outcomes, and thereby make adjustments to account for the magnitude of this externality in the ensuing policy recommendations. In summary, excluding neighborhood effects can lead to biases concerning the impacts of policy outcomes on smallholder adoption choices, and it is important to take account of the spatial aspects of economic decision making when formulating policy.

Case (1992) examines neighborhood effects in the context of technology adoption, using an estimation scheme that allows individuals to be influenced by neighbors when making discrete choice decisions. This is applied to survey data on sickle adoption in Java, Indonesia. The results show strong neighborhood effects, and suggest that failure to control for neighbors' influence may bias estimation of parameters of interest. Following the Case model, Holloway et al. (2002) investigate neighborhood effects in adoption of high-yielding rice varieties in Bangladesh, and find evidence of significant neighborhood effects, particularly with respect to inter-household differences in marginal probabilities of entry. While both models are applied in the context of adoption, a similar approach may be employed to investigate neighborhood effects in market participation, as both adoption and market participation are discrete choice decisions within a utility-maximizing framework.

A Bayesian approach to estimating spatial autoregressive limited dependent variable models such as the probit and Tobit is presented by LeSage (2000). He uses a Gibbs sampling (Markov chain Monte Carlo) method to estimate heteroskedastic spatial autoregressive and spatial error probit and Tobit models. In the development of an estimable model of neighborhood effects and in its implementation we follow closely the ideas generated by LeSage (2000). The one difference concerns a particular feature of the economic environment with which the data are generated. This feature is the size of the geographic area in relation to the market-selling decision and the possibility that the entire sample, as opposed to the individual compartments within it, could be considered a single 'neighborhood.' This feature of the study has more than academic interest. For example, in targeting public resources (for example, extension activities) to particular regions it is important to have some understanding of the extent to which pro-active agents influence neighbors and the extent to which this ‘ripple-effect’ is passed on and the range of its geographic dispersion. This idea motivates a formal test for the existence of neighborhoods within the sample as opposed to an alternative whereby the entire geographic domain can be considered the ‘neighborhood.’ The approach requires computation of posterior probabilities (or Bayes factors) in favor of the null and competing hypotheses and, following recent work by Chib (1995, 1998) is implemented through routine application of Gibbs-sampling and Metropolis-Hastings algorithms (see Holloway et al. 2002 for a primer on Bayesian spatial autoregressive models of which the present application is an example). The interested reader is referred to Chib (1995 and 1998) for details about the algorithm and to Casella and George (1992) and Greenberg and Chib (1994) for introductory reading on the power of Markov chain Monte Carlo methods and their use in Bayesian estimation. Related works that are useful for what follows are Gelfand and Smith (1990), Gelfand et al. (1991) and Chib and Greenberg (1992).

III. Estimating the Magnitudes of Neighborhood Effects

An estimable model of market participation evolves in three steps. First, we specify the household’s relationship between its discrete choice about entry and its characteristics; second, we include the possibility that neighboring decisions may impact the household’s own decisions; third, we formulate a statistical model based on probit techniques. In each of the three steps, the important component of the exercise is an underlying relationship between entry, household characteristics, and a latent, normal random variable that represents the household’s willingness or, better, its propensity to engage in market activities concerning livestock that it produces. Hence, for households i = 1, 2, .., N, we denote this propensity to enter z_i, and observe its relationship between characteristics $\mathbf{x}_i$ (a k-vector), the decision-behavior of remaining households $z_1, z_2, .., z_{i-1}, z_{i+1}, .., z_N$, and a random effect, u_i, which is assumed to have a normal distribution and (the usual restriction for identification) unit variance. Hence, the market access decision is represented by the model

(1) $$z_i = \rho \, \mathbf{w}_i \, \mathbf{z}_{-i} + \mathbf{x}_i \, \boldsymbol{\beta} + u_i.$$

Here, parameter ρ denotes a spatial autoregression effect that influences decision-making within the household. Its impact on the propensity of household i to adopt the market-entry strategy is affected by two terms, namely $\mathbf{w}_i$ and $\mathbf{z}_{-i}$, with the remaining terms, $\mathbf{x}_i\boldsymbol{\beta}$ denoting controls for household differences and the u_i denoting error. The first component, $\mathbf{w}_i$ denotes the ith row in a spatial-weight matrix (which we will term $\mathbf{w}$) that is designed to associate the specific pattern of neighborhood effects corresponding to household i. The design of row $\mathbf{w}_i$ is discussed in detail in Case (1992) and involves identifying those respondents within the survey that are deemed to have a 'proximity' to the household in question such that they are potential 'neighbors' where the context in question defines proximity. Hence, in what follows, it is important to recognize that the components of the weight, $\mathbf{w}_i$ are assigned by the investigator and are, therefore, considered data. Of course, in view of its importance, it would be desirable to estimate the components of the weight $\mathbf{w}_i$ but this does not seem possible at the present state of knowledge or, at least, without additional restrictive parameterisations. Hence, in what follows, we pursue Case's strategy for assigning the 'weights', which is to make the weight vector binary, with zeros corresponding to non-neighbors and ones corresponding to neighbors, with the exception of zeros corresponding to own-effects. Formally, row i of $\mathbf{w}$ has the structure $\{ w_{ij} = 1$ if households i and j are neighbors and $w_{ij} = 0$ if i and j are not neighbors or $i = j \}$. Case proposes the normalization $\sum_j w_{ij} = 1$, which amounts to normalizing elements in a particular row by the sums of their neighborhood effects, but we will discuss alternative normalizations subsequently.

The remaining items in the latent-response set-up in (1) that deserve explanation are the covariate impacts $\boldsymbol{\beta}$. These effects control for the presence of differences across the households' resources and are, therefore, household homogenous. The interpretation is the common one in household production data. Each of the households has the same innate propensity to enter the market ($\boldsymbol{\beta}$) but, due to differences in household resources ($\mathbf{x}_i$) and the random error (u_i), the actions observed by individual households will be different. Hence, because they delimit the extent to which individual resources influence the latent propensity to enter, the covariate impacts, $\boldsymbol{\beta}$ and the spatial autoregression parameter ρ are important for policy. These parameters are the focus of the empirical inquiry.

Equation (1), the observation equation, is the starting-point for empirical investigation. Because equation (1) is assumed to hold for all respondents in the survey, we can stack observations and rearrange terms into the matrix system

(2) $$\mathbf{z} = \rho\, \mathbf{w}\, \mathbf{z} + \mathbf{x}\, \boldsymbol{\beta} + \mathbf{u},$$

where $\mathbf{z} \equiv (z_1, z_2, .., z_N)'$ denote the household propensities to enter the market; $\mathbf{w} \equiv (\mathbf{w}_1', \mathbf{w}_2', .., \mathbf{w}_N')'$, $\mathbf{w}_1 \equiv (w_{11}, w_{12}, .., w_{1N})$, $\mathbf{w}_2 \equiv (w_{21}, w_{22}, .., w_{2N})$, .., $\mathbf{w}_N \equiv (w_{N1}, w_{N2}, .., w_{NN})$, denotes the household-specific spatial weights; $\mathbf{x} \equiv (\mathbf{x}_1', \mathbf{x}_2', .., \mathbf{x}_N')'$, $\mathbf{x}_1 \equiv (x_{11}, x_{12}, .., x_{1N})$, $\mathbf{x}_2 \equiv (x_{21}, x_{22}, .., x_{2N})$, .., $\mathbf{x}_N \equiv (x_{N1}, x_{N2}, .., x_{NN})$, denote observations on the household-specific effects; and $\mathbf{u} \equiv (u_1, u_2, .., u_N)'$ denotes the random effects. We assume that the error terms are iid normal so that $\mathbf{u}$ has the distribution $N(\mathbf{0}, \mathbf{I}_N)$.

The investigator observes data **x** and assigns data **w** and observes data $\mathbf{y} \equiv (y_1, y_2, .., y_N)'$ which are the discrete choices such that $y_i = 1$ if household i enters the market and $y_i = 0$ otherwise. We do not observe ρ or $\boldsymbol{\beta}$ and so, our interest lies in the form of the joint posterior for the unknown quantities, after observing the data, which we denote $\pi(\rho, \beta \mid \mathbf{y}, \mathbf{w}, \mathbf{x})$. One feature of this representation is the absence of the latent data **z**, which, by definition, is not observed. In this regard, an important step in inference is to estimate these latent quantities as part of the estimation exercise. Hence, we refer to the posterior $\pi(\rho, \beta \mid \mathbf{y}, \mathbf{w}, \mathbf{x})$ as the posterior corresponding to the observed data likelihood and refer to the formulation $\pi(\rho, \beta, \mathbf{z} \mid \mathbf{y}, \mathbf{w}, \mathbf{x})$ as the posterior corresponding to the complete data likelihood to signify the important fact that the latter has augmented the former and contains both missing and observed data. The advantages of augmenting models with latent data are highlighted in a series of influential papers by Siddartha Chib and co-authors and the spatial probit model which we now estimate is by no means an exception.

The essential steps involve three important observations. One observation is that, due to an integration implied by the fact that the probit model is generated by a probability signifying the likelihood that a particular agent will enter the market, the marginal probability density functions implied by the observed data likelihood $\pi(\rho, \beta, \mathbf{z} \mid \mathbf{y}, \mathbf{w}, \mathbf{x})$ are intractable in the sense that they cannot be derived in closed form from the joint posterior. The second point to note is that, although the posterior corresponding to the complete-data likelihood $\pi(\rho, \beta, \mathbf{z} \mid \mathbf{y}, \mathbf{w}, \mathbf{x})$ is also intractable, each of its fully conditional distribution functions is available in closed form. Third, each of these fully conditional distributions is easy to sample from. Hence, although the posterior density of interest is complicated, it is possible to simulate draws from this density by exploiting a relationship between the full conditional distributions. These observations make way for a robust estimation of household neighborhood effects using Markov chain Monte Carlo methods (Gibbs sampling in particular) following the seminal work by LeSage (2000). Our estimation is based closely on the algorithm exploited by him with minor modifications to suit our data-generating environment. We outline the basic algorithm and subsequent modifications in Annex 1.

IV. Data

We use data obtained from a household survey to estimate the model and apply the estimation algorithms described above. The survey was conducted in Don Montano, the study site of the Crop-Animal Systems Research Project (CASREN).[1] One of the objectives of the CASREN project is to generate technology and policy options to increase the productivity and economic viability of smallholder crop-animal systems in rainfed areas. The study of policy options focuses on identifying ways to improve the market participation of smallholder livestock producers in the area.

Don Montano is a crop-livestock producing village in the Philippines, and is one of 58 barangays[2] in the Municipality of Umingan in the province of Pangasinan, within the northern Luzon Island of the archipelago. It has a total population of 1,738 persons in 329 households, or an average household size of 5 - 6 members. The majority of farmers (about 99 percent) have an average land holding of 1.5 ha. Rice, corn, onion, peanut, mungbean, and vegetables are the major crops grown. Smallholder farmers in the area commonly raise beef cattle, buffalo, goat, pig, and poultry.

Barangay Don Montano is divided into 14 sections, locally referred to as sitio or purok. (see Figure 1). A sitio or purok consists of about 10-20 households. It is not a political unit, hence, there are no formal political structures within. More often than not, any form of organizations in a sitio or purok is functioning in an informal set up.

Interactions among households within these groups as well as with households belonging to adjacent sitios or puroks are more frequent than those who live farther away, say two or three sitios away. However, it is observed that households within the entire barangay itself freely interact with one another, albeit at different levels. Those who live close to each other have more frequent interactions than those who live quite a distance away. Hence, while the 'neigborhood' may be defined as the entire barangay, there are varying degrees to which 'neighbors' interact with one another across the various sitios or puroks within the barangay. Given that there are no reasons to believe that socio-cultural factors such as religion or political affiliations may create a different level of 'neighborhood', the use of this administrative boundary to define neighborhood may be justified.

Primary data were collected from a sample of smallholder livestock producers and non-producers using structured questionnaires. The survey instruments include both combined and separate questionnaires for producers and non-producers, a questionnaire on technology adoption, and a survey form for recording daily food consumption during a one-week period. A total of 110 households (consisting of 75 smallholder/backyard livestock producers and 35 non-producers) were interviewed. These households were randomly picked from a list of households that was generated from a census to determine the sample population. The complete interview that was executed in two rounds was designed to generate information on general household characteristics, production, consumption, sales, transactions costs, credit, technology adoption, and perceptions about livestock production.

The descriptive statistics of variables that characterize the sample households in the study site are presented in Table 1. The figures suggest that livestock producers are slightly older, more educated, have access to more family labor, have higher household income, have more assets (including residential buildings, vehicles, farm equipment, furniture, household appliances), and have larger farm size than non-producers. Producers are also predominantly farmers producing rice and onion. Both producers and non-producers obtain at least half of their household income from non-farm sources, with non-producers having a larger share than producers. Among producers, slightly less than half sold livestock in 2000, and slightly less than one-fourth did during the first half of 2001.

V. Results

Table 2 presents the estimates of the spatial probit model for market participation including the spatial autoregression parameter (ρ). Confidence intervals (highest posterior density intervals) at the 90 percent percentile are reported in parentheses. The posterior means estimate of the spatial autoregression parameter is 0.30 and is significantly different from zero, indicating a strong, positive neighborhood effect among the Don Montano respondents. This suggests that the individual farmer's decision to participate in the market is influenced by the actions of his/her neighbor/s in the purok. Figure 2 shows the distribution of the empirical estimates of the spatial autoregression parameter, or the neighborhood effect, in the Philippine data.

The dependent variable in the spatial probit model is binary, where $y = 1$ if the household reported sales during the year being studied, and 0 otherwise. The set of covariates that are potentially expected to influence market participation are grouped into the following classes, as follows: Transaction Costs, Demography, Intellectual Capital, Financial Capital, and Physical Capital.

Transaction costs are hypothesized to impede market participation because they impose added cost burdens to the efficient conduct of market entry activities. Distance to markets is considered as a proxy for transaction costs and is hypothesized to negatively affect market participation; that is, the farther away a household is from the market, the more difficult and costly it would be to get involved. Initial runs of the model, however, did not produce fruitful results for this variable as it has performed poorly in terms of its statistical significance. Since non-inclusion of this variable did not significantly change the estimated coefficients of the other covariates, it was excluded in the final set of covariates.

Demography is represented by the number of household members. In traditional agrarian studies, it was shown that household members represent labor resources and, hence, are posited to be directly related to engagement in agricultural activities. In this particular case, however, the opposite effect is obtained, where larger households are less likely to participate in markets (i.e., negative and statistically significant coefficient). This result is interpreted to suggest that contrary to traditional expectations, larger households are more exposed to risks of subsistence pressure especially when the composition is largely of younger and older members and only a few are productive members. This subsequently requires the household to devote more resources to meeting the subsistence requirements of its members and hence limiting whatever is left available to undertake non-subsistence activities. It is recognized that the data set on hand is limited in further decomposing this hypothesized effect, given that there is no information to disaggregate the household size composition of respondents. This presents an opportunity for further empirical investigation when appropriate information may be available.

Intellectual capital stock in the household is posited to be positively related to market participation. However, this expectation may be reversed when there are competing and more remunerative employment opportunities available in the area that require skills that are enhanced by more education. In the current investigation, the effects of intellectual capital is captured in the variables 'education' (number of years of schooling of the household head and the spouse) and 'extension' (access to extension services), both of which are statistically significant. The negative coefficient of education is contrary to the usual expectation that was exhibited in a similar study in Ethiopia where education was shown to be positively promoting market entry by smallholder dairy producers (Holloway et al. 2000). This suggests the strong competing effect of diverting skills to other off-farm employment opportunities as the level of education increases within the household in this particular data set. It is further observed that the area is accessible to major urban centers where employment opportunities are prevalent, thereby providing empirical support to this conjecture. Furthermore, the differential impact of education may also arise from externalities due to differences in risks associated with different types of commodities, as different commodities may require different levels of skills. The extension variable, on the other hand, has a positive coefficient, suggesting that exposure to extension agents strongly exerts a positive influence on market participation and this is consistent with expectations.

Financial capital include other income by household members other than the household head and spouse, remittances from other household members, income by household members other than the household head and spouse, and income from crop production. Of these income variables, only crop income exhibited a negative coefficient. Hence, while all the other income variables are contributing positively to the household's decision to participate in markets, crop income suggests otherwise. This signals a dominant competing influence exerted by crop production, suggesting that when households find crop production to be more profitable than otherwise, they are less likely to engage in livestock-related activities. This may appear to be a valid empirical support for a hypothesis on specialization; however, the present inquiry does not have adequate information to further look into the details of this result. This is an open research question that is worthwhile pursuing in a more appropriate data set. On the other hand, the positive influence of the other financial capital variables indicate the importance of financial security in enabling smallholders to cope with both production and consumption risks.

Animal stocks as represented by number of cattle, buffalo, goat, pig, and chicken constitute the physical capital of the households. It is shown that market participation is strongly influenced by the number of cattle, buffalo, pig, and chicken, while number of goat did not significantly figure in the market participation decision and was therefore subsequently excluded from the final set of covariates. These results suggest that households with more animals are more likely to accumulate more marketable surplus and hence are more likely to engage in marketing activities. This has important implications on policies that are directed towards promoting the adoption of productivity-enhancing technologies that are directed at increasing farm productivity and hence, animal stocks.

VI. Conclusions

This study has investigated the spatial aspects of market participation decisions of smallholder livestock producers in order to find out if this has a significant influence in engendering market entry and its subsequent policy ramifications. Empirical estimates of the spatial probit model suggest that neighborhood effects are significantly influential in motivating household decisions to participate in markets. Thus, market participation decisions are influenced by observed decisions of other farmers within the vicinity and not just by other factors that include household resources such as intellectual, financial and physical capital stocks that are obtained in the usual market participation modeling exercise. This finding is particularly important in estimating the potential impacts of knowledge diffusion on farmer decisions, and that failure to consider this influence will likely overestimate the attributed effects of other factors in engendering market participation. Farmers are more likely to imitate their neighbors' success stories, all other things constant. It is, thus, well advised to consider this phenomenon in designing policy interventions in order to fine-tune the expectations of policy impacts and hence devise more realistic options.

Footnotes

[1] This study is one component of the project that is being funded by the Asian Development Bank under a Regional Technical Assistance (RETA) Grant.

[2] A barangay is the smallest political unit in the Philippines.

[3] A Spanish term for rich landed farmer.

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Table 1. Characteristics of Livestock Producers and Non-Producers in the Study Site (Barangay Don Montano, Umingan, Pangasinan, Luzon Island, Phillipines).

Characteristic	Producer (N = 75)	Non-Producer (N = 35)
Age		
Household Head	47	45
	(13.9)	(17.2)
Spouse	43	38
	(13.1)	(13.7)
Educational Attainment		
Household Head	9	8
	(3.0)	(3.0)
Spouse	9	10
	(2.5)	(3.3)
Gender Household Head (percent)		
Male	71	30
	(95)	(86)
Female	4	5
	(5)	(14)
Household Members	5	4
	(1.73)	(2.09)
Available Family Labor	2.97	2.66
(aged between 15-69 years old)	(1.38)	(1.33)
Main Occupation (percent)		
Farmer	80	26
Farm laborer	4	30
Housekeeper	3	9
Government Employee	5	3

Private Employee	8	20
Overseas Worker	0	6
None	0	6
Household Income (peso)	55,094	60,903
Percent from:	(54,628)	(91,104)
Crop Production	29	3
Sale of Livestock	6	0
Farm Labor	3	4
Non-Farm	53	76
Remittances	9	17
Household Assets (peso)	33,109	26,874
	(69,711)	(53,568)
Farm Size (ha.)	0.99	0.63
	(0.88)	(0.32)
Cropping Proportions (frequency)		
Rice	62	12
Onion	39	5
Corn	4	-
Sweet Potato	1	-

Numbers in parentheses are standard errors. Data are from the survey enacted for the project 'Policy Options for Improving the Market Participation of Smallholder Livestock Producers,' April-May, 2001.

Table 2. Spatial-probit equation estimates.	
Members	-0.44
	(-0.59, -0.29)
Education	-0.10
	(-0.12, -0.08)
Extension	0.51
	(0.22, 0.81)
Otherinc	0.01
	(0.002, 0.01)
Remitinc	0.01
	(0.003, 0.02)
Memberinc	0.01
	(0.0002, 0.01)
Cropinc	-0.01
	(-0.02, -0.004)
Cattle	0.38
	(0.29, 0.47)
Buffalo	0.37
	(0.20, 0.55)

Pig	0.54
	(0.38, 0.71)
Chicken	0.04
	(0.03, 0.05)
ρ	0.30
	(0.15, 0.50)
Numbers in parentheses are 90% confidence intervals.	

Figures

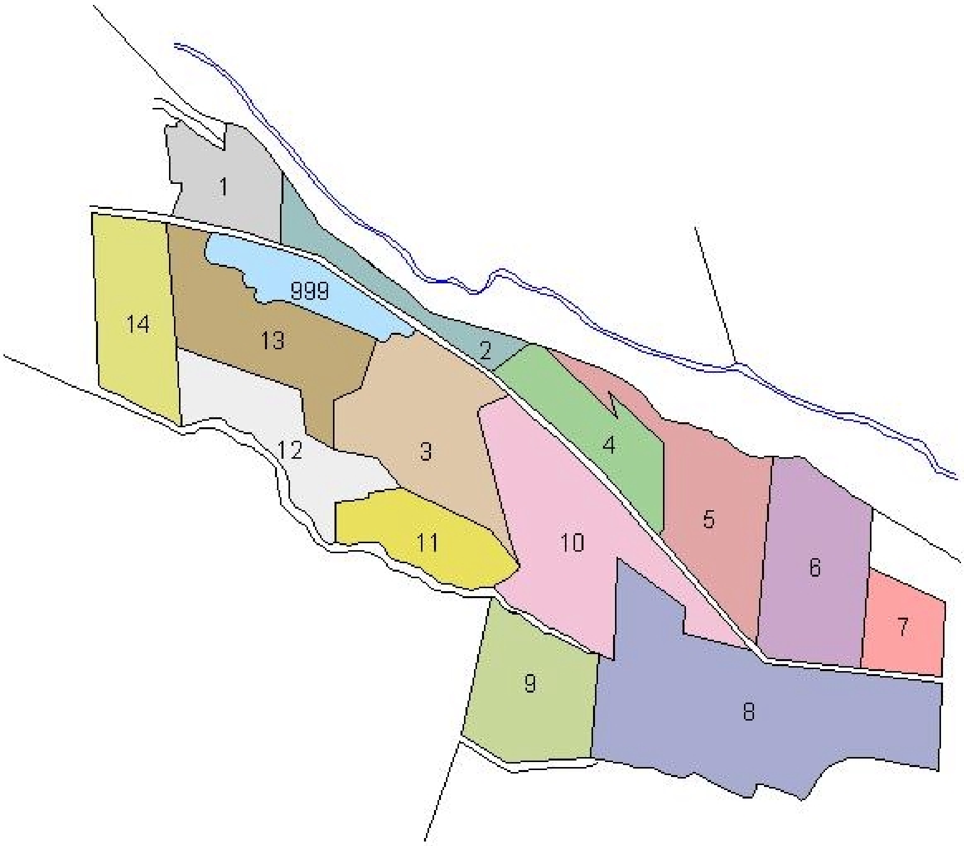

Figure 1. Map of Don Montano showing boundaries between sitios or puroks

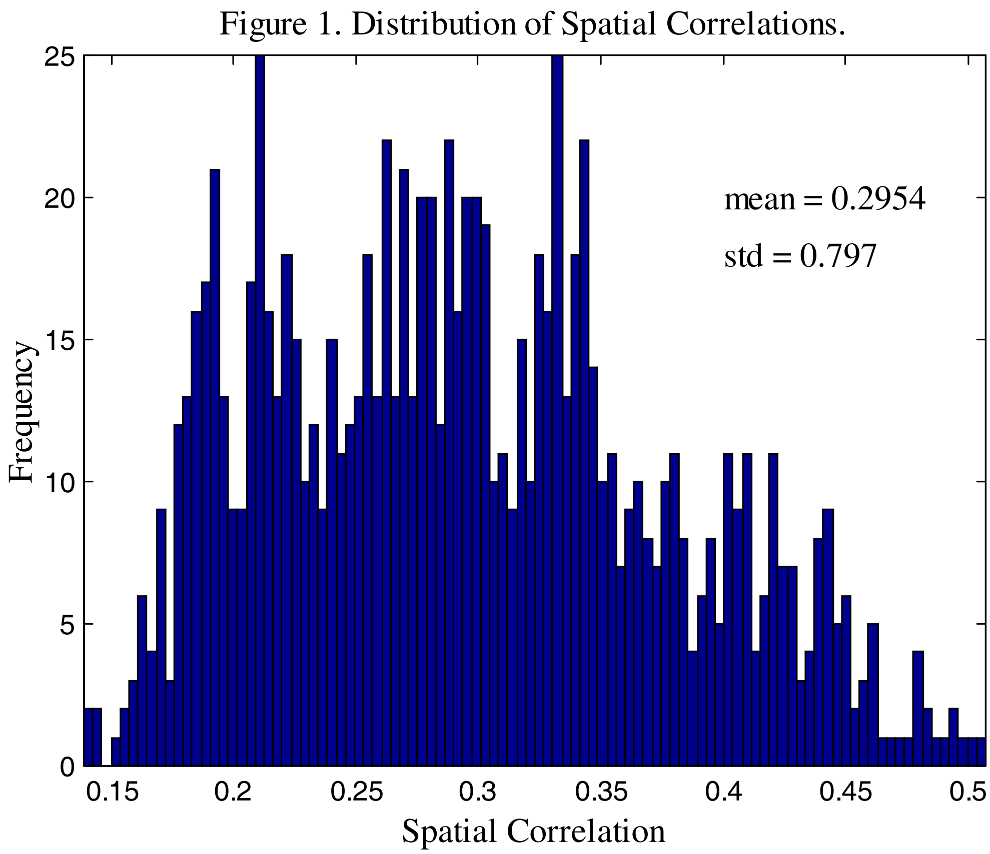

Figure 2. Distribution of Spatial Correlations in the Sample Data.

Annex

Annex 1. Details of the Basic Gibbs Sampling Algorithm and the Metropolis Step Procedures.

Step 1: Select starting values $\boldsymbol{\beta}^{(s)}$, $\rho^{(s)}$ and $\theta^{(s)}$, s = 0.

Step 2: Draw $\mathbf{z}^{(s)} \sim$ Normal($\mathbf{E_z}^{(s)}$, $\mathbf{V_z}^{(s)}$), truncated so that $z_i^{(s)} \leq 0$ if $y_i = 0$ (that is, if the household does not adopt) and truncated so that $z_i^{(s)} \geq 0$ if $y_i = 1$ (the household adopts), where $\mathbf{E_z}^{(s)}$ and $\mathbf{V_z}^{(s)}$ are defined with respect to $\boldsymbol{\beta}^{(s)}$ and $\rho^{(s)}$, above.

Step 3: Draw $\boldsymbol{\beta}^{(s)} \sim$ Normal($\mathbf{E_\beta}^{(s)}$, $\mathbf{V_\beta}^{(s)}$), where $\mathbf{E_\beta}^{(s)}$ and $\mathbf{V_\beta}^{(s)}$ are defined with respect to $\mathbf{z}^{(s)}$ in step 2 and $\rho^{(s)}$ in step 1.

Step 4: Draw $\rho^{(s+1)}$ using a Metropolis step (outlined below). (which steps?)

Step 5: Repeat steps 1-4 until s equals some predetermined limit, say S^1, beyond which convergence is assured.

Step 6: Repeat steps 1-8 (shouldn't this be 1-6, or am I missing something?) until s equals some predetermined limit, say S^2, and collect output { $\mathbf{z}^{(s)}$ s = 1, 2, .., S^2 }, { $\boldsymbol{\beta}^{(s)}$ s = 1, 2, .., S^2 }, { $\rho^{(s)}$ s = 1, 2, .., S^2 }.

The basic algorithm could be implemented without further complication were it not for the appearance of an irregular (conditional) density for the autocorrelation parameter, ρ. However, what complications there are can be easily circumvented by applying procedures outlined in LeSage (p. 24). These procedures area also outlined in greater detail in Chib and Greenberg (1995) and in Gelman et al. (1995). Essentially, the Metropolis step involves selecting a step parameter which, in turn, controls an acceptance criterion for an accept-reject sampling scheme involving draws from a uniform and one other candidate density. As in LeSage (2000), we apply the normal distribution as the candidate density. Experiments suggested that the normal distribution works well in the application to the Philippine data. The step rule, however, proved more troublesome. The step rule is a parameter, h, which adjusts the draws in the random walk

$$(3) \qquad r = \rho^{(s)} + h\,z,$$

where r denotes the candidate for the new draw for ρ; $\rho^{(s)}$ denotes the current value; z denotes a draw from the candidate (normal) density; and h denotes the step control parameter. Selection of h is important because it ultimately affects the rate of acceptance (rejection) of the candidate draws and, hence, the speed of convergence to the target distribution. Experimentation suggested that a control value of approximately h = 0.1 worked satisfactorily, and the reports of the results that follow are obtained under this selection value. Experiments with alternative starting values suggest that the posterior means estimates are robust, and that convergence is obtained after about 200 rounds of the algorithm. It remains to be seen, however, whether this experience can be replicated under alternative sets of data.

The outputs in the last step of the algorithm can be used to calculate means and variances of the respective distributions, or plot histograms as indications of locations of scales of any of the posterior quantities of interest. In the reports that follow we select the burn-in and collection phases of the algorithm to be S_1 = 5,000 and S_2 = 5,000, respectively. However, even with this highly conservative burn-in phase the entire estimation procedure took only about 5 minutes of real time on a DELL™ machine running a Pentium™ IV processor at 2.0 gigahertz with commands executed in MATLAB™ version 5.1.0.421. All computer code is available upon request.