

Neighborhood influence and technological change

Anne Case*

Princeton University, Princeton NJ, USA

Received June 1991, final version received February 1992

This paper presents an estimation scheme that allows individuals to be influenced by neighbors when making discrete choice decisions. The model developed is used to test interdependence in farmers' attitudes toward the adoption of new technologies in Indonesia. Strong neighborhood effects are found and appear to be robust to changes in specification. In addition, the results suggest that failure to control for neighbors' influence may bias estimation of parameters of interest.

1. Introduction

When individuals make choices, they are often influenced by the behavior and opinions of people in their immediate environment. Individuals' attitudes about a range of activities – from charitable giving to cheating on income taxes – may develop through contact with others. In modeling the discrete choice behavior of individuals, it will often be important to allow for interdependence in decision-making. This paper will propose an estimation scheme that allows individuals to be influenced by their neighbors. The model developed will be used to test interdependence of farmers' attitudes towards new technologies.

The adoption attitude of neighbors is often an important determinant of whether a farmer chooses to adopt a new technology. Between the time farmers become aware of a new technology and the time they accept or reject its use, the farmers must persuade themselves that the new technology is or is not suited to their needs. During this period, sociologists argue, the farmer 'is likely to seek conviction that his thinking is on the right path from peers by means of interpersonal communication channels' [Rogers and Shoemaker (1971, p. 109)]. In the diffusion of hybrid corn, for example, researchers have found that while most farmers first heard of a new seed from a salesman, the

Correspondence to: Professor Anne Case, Woodrow Wilson School, Princeton University, Princeton, NJ 08544, USA.

*I thank Tim Besley for useful discussions and Luc Anselin, Edward Rhodes and two anonymous referees for comments on an earlier draft of this manuscript.

adoption decision of farmers' neighbors was the most frequent channel of influence [Rogers (1971, p. 55).]

In the applied economics literature, interaction between farmers has been noted as an important element in technology adoption. Studies conducted by the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) suggest that the information provided by other farmers, together with their choices of technologies, are often central to a given farmer's decision to adopt. For example, Foster et al. (1987) note that farmers find each other important sources of information. Mueller et al. (1986), in a study of adoption of chemical pest control in the semi-arid tropics, find that 90% of farmers surveyed had discussed their decisions of whether to use insecticide with other farmers and village extension workers.

However, while much descriptive work suggests neighbors may influence each others' technology choices, the farm household literature on time to adoption has largely ignored the importance of interaction between farmers. As discussed in the surveys of Feder et al. (1985) and Lindner (1987), work in this area has instead focussed on correlating the choice of technology with observable characteristics of a farm household at a point in time. With few exceptions, the farm household literature has used cross-sectional data to test whether the choice of adoption is significantly correlated with a farmer's education, land holdings, family size, or access to credit, without reference to the decisions made by neighbors.

There are several reasons why the incorporation of neighbors' influence is important in the estimation of adoption decisions. First, ignoring neighborhood effects in adoption behavior may bias estimation of parameters of interest. For example, the level of education attained by farmers in a particular area may be relatively high. At the same time, in part due to peer influence, a large fraction of farmers in that area may have adopted a new technology. A cross-section estimation that ignored farmer interaction would overestimate the effects of education on adoption. A policy to increase adoption through education may, then, fail to perform as well as expected and may not justify the resources invested in it.

There are additional reasons why, for policy purposes, an estimate of the magnitude of neighbors' effects is important. If a government or international organization wants to promote the adoption of a new technology, it will want to know the size of the externality associated with convincing one farmer within the village to adopt the technology. Agencies wishing to close the gap between technologies *available* and those *employed* in a particular area may want to become involved in the adoption process at the point at which farmers are persuading themselves and each other of the efficacy of a new technology. The resources these agencies spend persuading given farmers to adopt should reflect the externality these farmers then provide by convincing others to adopt.

This is the idea behind the Training and Visit (T&V) program supported by the World Bank in many developing countries. Farm extension agencies introduce new technologies to 'contact farmers' within each village and these contact farmers, in turn, 'are expected to adopt recommended practices (or at least try them out) and transmit them to other farmers' [Feder and Slade (1984, p. 7)]. An estimate of the magnitude of farmer interaction is important if one wishes to ascertain whether such resources are well spent.

In order to estimate the magnitude of neighbors' influences, and to provide unbiased estimates of other parameters of interest, this paper will present a model in which farmers are allowed to influence neighboring farmers' technology choices. The model provides consistent estimates of both the effects household characteristics have on technology choice and the effects neighbors have on those choices through their attitudes toward the new technology.

The model is tested using data on the adoption of the sickle as the rice harvesting tool in rural Java, Indonesia. The data are from the 1980 Indonesian socio-economic survey, SUSENAS. The estimation results suggest that farmers are strongly influenced by their neighbors. Controlling for observable farm household characteristics, when a given farm's neighbors' anticipated benefits from using the sickle increase, this significantly increases the original farm's anticipated benefits. In addition, the results suggest that if one does not control for neighbors' influence, the effects of farm household characteristics on the likelihood of adoption are significantly overestimated.

We will proceed as follows. Section 2 will present a discrete choice model that allows a farmer's predicted profit from adoption to depend upon that of his or her neighbors. Section 3 will describe the case of sickle adoption in rural Java. Section 4 will introduce the data used in this paper and discuss the estimation results. Section 5 will discuss directions for future research.

2. Modeling

In this section, we will propose a model that allows neighbors to influence one another in their choice of technology. Tests of the model's adequacy in predicting which farmers will adopt the new technology will follow in section 4.

Descriptive work on adoption suggests that, after farmers become aware of a new technology, they develop an attitude about the new technology that determines whether they will adopt it. That is, they develop a 'degree of positive or negative affect' toward the new technology [Ambastha (1986, p. 66)]. This attitude may be influenced by neighbors' attitudes towards the technology; farmers may transmit their enthusiasm or pessimism about new technologies to their neighbors.

In this analysis, the farmer's predisposition toward adoption of the sickle

will depend upon the profits the farmer expects, if he or she adopts the sickle, relative to the profits the farmer expects if he or she continues to use the traditional harvesting tool. We hypothesize that the expected profits from the adoption of the sickle will depend upon farm household characteristics, X . These will be discussed in detail in section 3 below. In addition, in order to allow the possibility that farmers' attitudes toward adoption are interdependent, we will allow farmer i 's expected profits with the new technology, Y_i^* , to depend upon neighbors' expected profits, that is

$$Y_i^* = \phi W_i \cdot Y^* + X_i \beta + u_i. \quad (1)$$

For N farmers observed making a choice on technology, W_i is the i th row of an $(N \times N)$ matrix W that assigns to each farm household its neighbors. The W matrix used here can be characterized: $W = \{w_{ij}\}$ such that $w_{ij} = 1$ if i and j are neighbors, $w_{ij} = 0$ otherwise, and $w_{ii} = 0$, for all i . The rows of W are then normalized such that each observations' neighbors have the same amount of influence, that is, $\sum_j w_{ij} = 1$, all i . In addition, it will be assumed that each neighbor of a given farm carries equal weight, $w_{ij} = w_{ik}$ for non-zero elements (neighbors) k and j for farmer i . If more information were available about the amount of influence each household wields, this could be incorporated into the W matrix.

In what follows, 'neighbors' will refer to farmers who live in the same district in rural Java. Geographic neighbors have been chosen here because, in rural Java, it is likely that farmers have the most contact with farmers that are closest at hand. In other studies, in which mass media or marketing are thought to influence adoption, a different criterion for neighbor assignment might be more appropriate. Furthermore, if one had reason to believe that in addition to geographic proximity some other characteristic of farmers – religion, wealth – affected the extent to which farmers interacted, this could be incorporated into the weighting matrix as well. However, in rural Java, we have no prior reason to believe farmers with particular characteristics are more likely to interact. For this reason, geographic proximity alone will be used to define neighbors. If observations are grouped by district, this characterization of neighbors makes the W matrix block diagonal: The only non-zero elements will appear as a block for households in the same district.

In matrix form, eq. (1) can be written

$$Y^* = \phi W Y^* + X \beta + u, \quad (2)$$

and, if ϕ is less than 1 in absolute value, eq. (2) can be rewritten

$$Y^* = (I - \phi W)^{-1} X \beta + (I - \phi W)^{-1} u$$

$$\begin{aligned}
 &= X\beta + \phi WX\beta + \phi^2 W^2 X\beta + \phi^3 W^3 X\beta \dots \\
 &+ [I + \phi W + \phi^2 W^2 + \dots]u.
 \end{aligned}
 \tag{3}$$

In eq. (3), it becomes clear that a farm household's attitude toward adoption Y^* will be a function of the farm's characteristics, X , neighbors' characteristics, WX , neighbors' neighbors' characteristics W^2X , and so on, with the influence of more distant neighbors dying out.

The matrix $(I - \phi W)$ is also block diagonal. For any district with n observation, we can write the relevant block of $(I - \phi W)$ as

$$(I_n - \phi W_n) = [1 + \phi/(n-1)]I_n - \phi/(n-1)ee' = \theta_1 I_n - \theta_2 ee', \tag{4}$$

where e is an $(n \times 1)$ vector of ones. Consistent with the description of W given above, in this district each farm has $(n-1)$ neighbors, and each neighbor is given equal weight. Thus, $\phi W_n = \phi/(n-1)ee' - \phi/(n-1)I_n$. Using the notation of eq. (4), the inverse of $(I_n - \phi W_n)$ can be conveniently represented as

$$(I_n - \phi W_n)^{-1} = (1/\theta_1) [I_n + \theta_2/(\theta_1 - n\theta_2)ee']. \tag{5}$$

Substituting this into eq. (3), a farmer's predisposition toward the new technology Y^* can be written as

$$Y^* = (1/\theta_1) [X\beta + n\{\theta_2/(\theta_1 - n\theta_2)\}\bar{X}\beta] + (I - \phi W)^{-1}u, \tag{6}$$

where \bar{X} is the matrix of mean household characteristics in the relevant district.

The parameter ϕ is identified by the correlation between a given household's predisposition toward adoption and that household's neighbors' characteristics. The key identifying assumption is that any correlation between neighbors' characteristics and a given household's predisposition toward adoption is due to the direct influence the neighbors have through their own predispositions toward adoption. Correlation between neighbors' characteristics and a given household's error is ruled out by assumption, as is any *direct* effect of neighbors' characteristics on a given farm's predisposition toward adoption.

In this analysis, we do not observe the anticipated profits from adoption that drive farmers' predispositions toward the new technology. We only observe whether the technology was chosen. If the farmer's expected profits Y^* cross the threshold zero, the farmer adopts the technology and an indicator variable, d , takes the value 1. For farmer i ,

$$d_i = \begin{cases} 1 & \text{if } Y_i^* > 0, \\ 0 & \text{otherwise.} \end{cases}$$

The structure chosen for errors, u , determines the likelihood function for

the model. We assume, to begin, that the errors are identically and independently distributed. We will relax this assumption below. In this case, it is clear from eq. (6) that the interdependence of expected profits induces spatial correlation and heteroskedasticity in the errors. This would render estimation of eq. (6), with a standard logit or probit specification, inconsistent. It is possible, however, to compensate for the induced heteroskedasticity and derive consistent estimates for the model in eq. (6).

To do so, note that the variance covariance matrix for eq. (6) is

$$\Omega = E(VV') = (I - \phi W)^{-1} (I - \phi W)^{-1'} \sigma_u^2,$$

where V is the vector of errors, $(I - \phi W)^{-1}u$, and where σ_u^2 is the variance of the error term u . A variance normalized version of eq. (6) can be produced by multiplying both sides of eq. (6) by the inverse of the square root of $\text{diag}(\Omega)$:

$$Y^{**} \equiv (D^*)^{-1} Y^* = (D^*)^{-1} (I - \phi W)^{-1} X\beta + (D^*)^{-1} (I - \phi W)^{-1} u,$$

where D^* is the square root of $\text{diag}(\Omega)$. Using eq. (5), D^* can be written

$$D^* = (1/\theta_1) \text{sqrt} \{ 1 + 2\theta_2/(\theta_1 - n\theta_2) + n\theta_2^2/(\theta_1 - n\theta_2)^2 \}.$$

Multiplication through by $(D^*)^{-1}$ is used to give the model homoskedastic disturbances. Clearly

$$\text{Prob}[d = 1] = \text{Prob}[Y > 0] = \text{Prob}[V > -(I - \phi W)^{-1} X\beta],$$

is equivalent to

$$\text{Prob}[Y^{**} > 0] = \text{Prob}[(D^*)^{-1} V > -(D^*)^{-1} (I - \phi W)^{-1} X\beta]. \quad (7)$$

It is this variance normalized version of the model, presented in eq. (7), that will be estimated below. [See Heckman (1978, appendix B) for a general treatment of this problem, or Heckman (1981, pp. 145–146) for details on the time series analogue.]

The assumption of identically and independently distributed errors may not reflect reality well. For example, parts of Java are mountainous and others flat. Some parts of Java may have been heavily influenced by a government campaign to adopt the technology. These unobservable variables – which are correlated over space – may influence adoption of a new technology. One can allow for spatial correlation in the errors by allowing farmers within a district to all experience a common shock. Within a district, we will allow errors u_n to be correlated:

$$u_n = \rho W_n u + \varepsilon = (I_n - \rho W_n)^{-1} \varepsilon.$$

As an alternative to the model in which neighbors directly influence one another, we will estimate a model in which neighbors' actions are correlated because they share a common shock. That is, we will estimate

$$Y^* = X\beta + (I - \rho W)^{-1} \varepsilon, \quad (8)$$

controlling for heteroskedasticity as described above. We will compare the results of this model with those of eq. (6) above.

Finally, we will allow for both direct influence of neighbors, as in eq. (6), and for spatial correlation in errors:

$$Y^* = (I - \phi W)^{-1} X\beta + (I - \phi W)^{-1} (I - \rho W)^{-1} \varepsilon. \quad (9)$$

The variance covariance matrix for this model is

$$\Omega = (I - \phi W)^{-1} (I - \rho W)^{-1} (I - \rho W)^{-1'} (I - \phi W)^{-1'} \sigma_u^2.$$

Using eq. (5), one can readily incorporate into D^* the additional components of Ω . Results with and without allowance for spatial correlation in the errors will be presented below.

Before estimation results are presented, a discussion of the adoption of the sickle as the rice harvesting tool in Indonesia will be put forward and data to be used in estimation will be introduced.

3. Sickle adoption in Indonesia

In wet rice farming on Java, the traditional harvesting tool is the 'small knife' or 'finger knife'. The small flat blade of the knife, held in the palm of the harvester's hand, cuts rice panicles (seed-heads) individually. Using small knives, 50–150 person days may be needed to harvest 0.5 hectares of land [Stoler (1977, p. 683)]. On Java, the harvest is performed in a very short period of time.

While 62% of farmers surveyed in 1980 reported harvesting with small knives [SUSENAS (1980)], the sickle, long the rice harvesting tool of choice in many other parts of Asia, is beginning to make inroads on Java. It would appear that the sickle's attributes make it an attractive harvest instrument. First and foremost, it reduces the per hectare labor demand for the harvest, and thus harvesting costs, by roughly 50% [Stoler (1977, p. 691)]. In addition, the new high yield varieties (HYV) of rice, which accounted for roughly 75% of the rice harvested on Java in 1980, favor harvest by sickle. HYV rice has shorter stalks which make the panicles harder to cut with a

small knife [Hayama and Hafid (1979, p. 96)]. In addition, to prevent the more fragile HYV rice from shattering, it is preferable to thresh the rice after first harvesting with sickles.

However, the adoption of the sickle as the harvesting tool has been resisted by farmers for a number of reasons. First, the change in harvesting tool tears at the fabric of the *bawon* (shared harvest) system of income distribution. In Indonesian villages, the harvesting of a rice field has traditionally been open to all in the village who wish to bring their small knives and participate in the harvest. That the switch from the small knife to the sickle has led to 'rage of the rural workers who have become redundant' is well documented [Miles (1979, p. 238)]. The social cost of breaking the *bawon* is thought to be an important factor restraining the adoption of the sickle.

An additional reason for hesitation in switching to the sickle may be limits in the employment opportunities available to household members. To the extent that its members may be constrained in their off-farm employment opportunities, the farm household may choose to use its own labor, at home, harvesting rice. We will allow for this in the analysis that follows.

The farmer's selection of a harvesting tool can be modeled as the solution of an expected profit maximization problem. Calling upon the preceding discussion, a farmer's expected profits from sickle adoption may depend not only on the expectations of other farmers with whom a given farmer is conversing, WY^* , but also on the farmer's observable characteristics – including the amount of wetland under cultivation (*LAND*); whether the land was irrigated (*IRR*); the type of seed harvested ($HYV = 1$ if high yield variety seed is planted); and off-farm employment opportunities, as measured by the male household members' non-agricultural earnings (*EARN*). This last variable (*EARN*) may identify both the opportunity for family members off the farm as well as the extent to which the community depends upon the *bawon* system. In areas in which agricultural household members are holding jobs outside of agriculture, the shared harvest system may be less important.

In addition, we are interested in whether correlations exist between adoption of the sickle and those household characteristics often thought to be influential in technology choice. These include a variable indicating whether the household borrowed in order to bring in the harvest (*CAP*); the wealth of the household, proxied here by the value of draft animals and machinery owned by the household (*DRAFT*); the education received by male household members (*ED*); whether there was an agricultural center accessible to the farm (*AGC*); and the household composition, specifically the number of household males in three age categories [males 0–15 (*M015*), males 16–55 (*M1655*), and males older than 55 (*M56P*)]. Expressing the expected profit of farmer i using a finger knife to harvest as Y^f , the farmer's expected profit from sickle adoption Y^s can be written

$$Y^s = Y^f + \phi W(Y^s - Y^f) \\ + f(LAND, IRR, HYV, CAP, ED, AGC, EARN, DRAFT, \\ M015, M1655, M56P) + u.$$

We will assume the expected profit when the sickle is used, over and above the expected profit when the small knife is used, is a linear function of the variables discussed above. Farmer i will choose the sickle if the benefit from adoption ($Y_i^* \equiv Y_i^s - Y_i^f$) is positive. Otherwise, the farmer continues to use the small knife for the harvest. This equation can be written as eq. (3) in section 2, $Y^* = X\beta + \phi WY^* + u$, where X refers to the household characteristics discussed above.

4. Estimation and results

The data used in the analysis are a random sample of rural Javanese farm households from the 1980 survey of SUSENAS. This Indonesian socio-economic survey draws samples randomly from every district (regency) within Indonesia. Districts on Java are roughly the size of counties in the Eastern United States. For this paper, I use a randomly selected subsample which includes 1,664 wet rice producing farms from 84 districts in four rural provinces of Java.¹ As noted above, a given farmer's neighbors are the other farmers surveyed in that farmer's district.

Descriptive statistics for these farm households are presented in table 1. There are significant differences between the sickle and the small knife users on a number of dimensions. Sickle farmers have, on average, close to 50% more wet land than small knife farmers, and are significantly more likely to be growing HYV rice. Sickle farmers are also on average wealthier, as measured by the value of draft animals and machinery they own, and earn on average roughly twice the non-agricultural earnings of small knife users. Furthermore, sickle users are more likely to be located near an agricultural extension center. Sickle farmers on average have a larger number of young males in the household, and fewer older males – although these differences are not significant.

The influence of household characteristics on adoption is often estimated

¹I had access to data on 1,664 wet-rice producing farms. However, only 1,646 of these farms had a positive amount of land under wet-rice cultivation. Of these, 57 farms did not report any value for draft animals and machinery owned. Given the potential importance of wealth as an indicator of adoption, the analysis is restricted to those without missing values for draft animals and machinery value. One household had a missing value for non-agricultural male earnings and was removed. Finally, one district was represented by one household and was removed because it had no neighbors. This left 1,587 farm households for the analysis.

Table 1
Choice of harvest tool in rural Java; descriptive information on household characteristics.^a

Explanatory variables	All households	Small knife households	Sickle households
Total wetland (ha), <i>LAND</i>	0.68 (1.59)	0.52 (0.57)	0.93 (2.41)
HYV seed use, <i>HYV</i>	0.76 (0.42)	0.65 (0.47)	0.93 (0.26)
Males 0–15 yrs., <i>M015</i>	1.06 (1.10)	1.01 (1.04)	1.14 (1.18)
Males 16–55 yrs., <i>M1655</i>	1.22 (0.81)	1.22 (0.82)	1.21 (0.78)
Males ≥ 56 yrs., <i>M56P</i>	0.18 (0.39)	0.19 (0.40)	0.16 (0.38)
Value, draft animals and machinery owned, <i>DRAFT</i>	4,469 (10,943)	3,220 (6,967)	6,388 (14,940)
Level of male education, <i>ED</i>	4.22 (3.28)	4.21 (3.27)	4.26 (3.31)
Male non-agri earnings, <i>EARN</i>	5,684 (80,122)	4,440 (34,346)	7,595 (120,301)
Irrigated land used, <i>IRR</i>	0.24 (0.43)	0.16 (0.36)	0.37 (0.48)
Capital borrowed to bring in the harvest, <i>CAP</i>	0.10 (0.31)	0.11 (0.32)	0.09 (0.28)
Farm is near an agricultural center, <i>AGC</i>	0.83 (0.38)	0.78 (0.41)	0.90 (0.29)
Number of observations	1,587	961	626

Source: SUSENAS 1980.

^aStandard deviations in parentheses. See text for details.

in a standard probit framework which, in effect, constrains the coefficients on neighbors' variables to zero,

$$Y^* = X\beta + u. \quad (10)$$

The results of a standard probit estimation, which will be compared below to those from models that allow for neighbors' influence, are presented in table 2. Here, the left column provides the parameter estimates on household characteristics discussed above, and the right column provides the change in probability of sickle adoption associated with a change in the explanatory variable, evaluated at the sample means. The results are consistent with what was seen in the cross tabulations provided above. Evaluated at the sample means, *ceteris paribus*, a farmer using HYV seed is 43% more likely to use a sickle than a farmer growing traditional seed. Farmers with an additional male household member between the ages of 0 and 15 are significantly more likely to use a sickle, while with an additional household male above the age

Table 2
Choice of harvest tool in rural Java; probit estimates of sickle adoption.

Explanatory variables	Probit estimates		Allowing neighbors' characteristics to enter:	
	Estimates	Change in probability	Estimates ^a	Change in probability ^a
Total wetland (ha), <i>LAND</i>	0.13 (0.05)	0.05	0.07 (0.05)	0.03
HYV seed use, <i>HYV</i>	1.07 (0.09)	0.43	0.79 (0.11)	0.30
Males 0–15 yrs., <i>M015</i>	0.06 (0.04)	0.03	0.04 (0.04)	0.02
Males 16–55 yrs., <i>M1655</i>	–0.04 (0.06)	–0.02	–0.09 (0.07)	–0.03
Males ≥ 56 yrs., <i>M56P</i>	–0.16 (0.09)	–0.06	–0.17 (0.11)	–0.06
Value, draft animals, ^b <i>DRAFT</i>	0.007 (0.004)	0.003	0.007 (0.004)	0.003
Level of male education, <i>ED</i>	–0.02 (0.02)	–0.007	0.01 (0.02)	0.004
Male non-agri earnings, ^b <i>EARN</i>	0.0002 (0.0005)	0.0001	0.0005 (0.0005)	0.0002
Irrigated land used, <i>IRR</i>	0.54 (0.08)	0.21	0.18 (0.10)	0.07
Capital harvest, <i>CAP</i>	–0.36 (0.11)	–0.14	–0.13 (0.12)	–0.05
Agricultural center, <i>AGC</i>	0.35 (0.10)	0.14	0.31 (0.12)	0.12
Neighbors' characteristics included?		No	Yes	
Log-likelihood	–911.32	–	–860.43	–

^aNeighbors' explanatory variables were present in estimation, but are not reported.

^bValues in thousands of rupiahs; standard errors in parentheses; change in probabilities evaluated at sample means.

of 55 the farmer is 6% less likely to adopt the sickle. Evaluated at the sample means, *ceteris paribus*, an increase in the amount of wetland owned increases the probability that the farmer will choose the sickle, as do increases in household wealth, as measured by the value of draft animals and machinery owned. The significance of the household and farm characteristics suggests that these characteristics provide a strong signal of a farmer's predisposition toward adoption. For this reason, neighbors' characteristics should be capable of identifying neighbors' predispositions toward adoption in what follows.

In order to test whether neighbors significantly influence sickle adoption, two types of tests are run. Following Chamberlain (1985), we run probits of

sickle adoption with and without neighbors' characteristics (\bar{X}) as explanatory variables. One test for the importance of neighbors will be to compare the log-likelihood of a model that restricts the coefficients on neighbors' characteristics to equal zero, as in eq. (10) above, with the log-likelihood of a model that allows neighbors' right side variables to enter freely:

$$Y^* = X\beta + \bar{X}\delta + u. \quad (11)$$

Allowing neighbors' characteristics to enter freely provides a fairly robust test of neighbors' influence: Entering neighbors' characteristics separately, the results are less apt to be driven by functional form. The results of these probit estimates are also provided in table 2. A comparison of the log-likelihoods of the models – with and without neighbors' explanatory variables – provides a chi-square test statistic of the joint significance of neighbors' 11 explanatory variables of 102 points. This is significant in a 99.9% confidence interval and suggests that neighbors do influence each other in choice of harvest tool.

A second test of the model is to see if constraining neighbors' variables to enter in the manner implied by eq. (6) significantly lowers the log-likelihood of the model. In rewriting eq. (6),

$$Y^* = (1/\theta_1)X\beta + n\theta_2/(\theta_1(\theta_1 - n\theta_2))\bar{X}\beta + (I - \phi W)^{-1}u, \quad (6')$$

it is clear that this model restricts the coefficient on the neighbors' k th right side variable \bar{X}_k to equal $[n\theta_2/(\theta_1 - n\theta_2)]$ times the coefficient on right side variable X_k . We can compare the log-likelihood from eq. (6) with that from a model that does not constrain the coefficients, such as eq. (11) above, to see if constraining the coefficients to enter in the manner implied by eq. (6) does damage to the information contained in the data.

To see if this is indeed the case, eq. (6) was estimated, controlling for heteroskedasticity as in eq. (7). The results of this estimation, presented in table 3, suggest that the influence of neighbors is strong and significant. Increases in neighbors' predispositions toward adoption result in a significant increase in a given farmer's probability of adoption. In addition, recognition of the neighbors' influence does not break the strong bond between farm household characteristics and predisposition toward adoption, although it does dampen the importance of these characteristics somewhat. For example, use of HYV seed still has a positive and significant effect on adoption of the sickle: Allowing neighbors to influence farmers' attitudes toward adoption, the probability of sickle adoption is, at the sample means, 26% more likely when HYV seed is used. This is significantly lower than the 43% found when neighbors' influence is ignored in estimation. Proximity to an agricultural extension center increases the probability of adoption by 5%, calculated at

Table 3
Choice of harvest tool in rural Java; estimates of sickle adoption.

Explanatory variables	Probit with spatial correlation in latent variable		Probit with spatial correlation in errors	
	Estimates	Change in probability	Estimates	Change in probability
Neighbors' predisposition (ϕ)	0.71 (0.04)	0.28	–	–
Total wetland (ha), <i>LAND</i>	0.03 (0.03)	0.01	0.18 (0.08)	0.07
HVV seed use, <i>HVV</i>	0.65 (0.07)	0.26	1.45 (0.16)	0.58
Males 0–15 yrs., <i>M015</i>	0.07 (0.03)	0.03	0.09 (0.05)	0.04
Males 16–55 yrs., <i>M1655</i>	–0.13 (0.06)	–0.05	–0.08 (0.09)	–0.03
Males \geq 56 yrs., <i>M56P</i>	–0.13 (0.10)	–0.05	–0.24 (0.14)	–0.10
Value, draft animals, ^a <i>DRAFT</i>	0.003 (0.004)	0.001	0.008 (0.006)	0.003
Level of male education, <i>ED</i>	–0.01 (0.01)	–0.004	–0.02 (0.02)	–0.009
Male non-agri ^a earnings, <i>EARN</i>	–0.000 (0.000)	–0.000	0.000 (0.001)	0.000
Irrigated land used, <i>IRR</i>	0.39 (0.06)	0.16	0.87 (0.13)	0.35
Capital harvest, <i>CAP</i>	–0.38 (0.10)	–0.15	–0.48 (0.16)	–0.19
Agricultural center, <i>AGC</i>	0.13 (0.08)	0.05	0.59 (0.16)	0.24
Spatial correlation errors (ρ)	–	–	–0.71 (0.03)	–
Log-likelihood	–871.15	–	–904.48	–

^aValues in thousands of rupiahs; standard errors in parentheses; change in probabilities evaluated at sample means.

the sample means, which can be contrasted with the 14% estimate when neighbors are not included in the analysis. In a similar way, the importance of irrigation and the impact of wealth on adoption are dampened.

Note that constraining the manner in which neighbors' characteristics enter does not have much of an effect on the log-likelihood: With neighbors' characteristics entering in an unconstrained fashion, as in eq. (11) above, the likelihood was –860; constraining neighbors' characteristics to enter solely as determinants of neighbors' predispositions to adoption, as in eq. (6), reduces the likelihood to –871. While the difference in likelihoods is significant, it is not large. In addition, the estimates of changes in probability

of adoption that accompany changes in household characteristics are almost identical from the two models. This suggests that constraining neighbors characteristics to enter through their effect on neighbors' predispositions toward adoption does not remove much information in the system.

The second set of columns in table 3 presents results that allow for spatial correlation in the errors of an adoption equation, as in eq. (8) above. These results suggest that there is *negative* spatial correlation in the errors. The log-likelihood of this model is significantly higher than that from eq. (10), which allows for no form of spatial correlation; the likelihood rises from -911 to -904 . However, note that because the model does not allow for neighbors' direct influence, estimates of the effects of household characteristics are again biased upward. This model suggests that, measured at the sample means, sickle use is 58% more likely if HYV seed is used – compared with an estimate of 26% from eq. (6), a model in which neighbors' influence is taken into account. In a similar way, this model estimates that, on average, sickle use is 24% more likely if a household is near an agricultural center – compared with 5% from the former model.

As spatial correlation in errors is potentially present, we will want to nest both spatial correlation in the latent variable and in the errors within the same model. Again, we use two approaches. First, we allow neighbors' characteristics to enter unconstrained, as in eq. (11) above, while allowing spatial correlation in the errors. (For ease of estimation, the right-hand side variable list was limited to those variables that had t -values greater than 1 in earlier tables.) That is, we estimated

$$Y^* = X\beta + \bar{X}\delta + (I - \rho W)^{-1}\varepsilon. \quad (12)$$

Results of this estimation appear in the first two columns of table 4. Note that including spatial correlation in the errors does not significantly increase the likelihood above that for eq. (11) in table 2 (-859.5 vs. -860.4). This suggests there exists an insignificant amount of spatial correlation in the errors of eq. (12). Note also that the point estimate of spatial correlation in the errors, $\rho = -2.91$, cannot be interpreted as it is in a linear model. As with most probit estimates, the parameter estimates and the variance estimate here cannot be separately identified. The parameter estimates presented here are all normalized by the variance, σ_u^2 :

$$\rho^{\text{est}} = \rho^{\text{true}}/\sigma_u^2.$$

Thus, an estimate of σ_u^2 close to zero is consistent with an underlying value of ρ within the unit circle and an estimated value of $(\rho^{\text{true}}/\sigma_u^2)$ outside the unit circle.

Table 4
 Probits allowing for neighbors' influence and for spatial correlation in errors.

Explanatory variables	Probit allowing neighbors' characteristics and spatial correlation in errors		Probit with neighbors' direct influence and spatial correlation in errors		Linear probability model ^a
	Estimates	Change in probability	Estimates	Change in probability	
Neighbors' predisposition (ϕ)	-	-	0.67 (0.04)	0.27	-
HYV seed use, <i>HYV</i>	0.95 (0.13)	0.38	0.72 (0.14)	0.29	0.24 (0.02)
Males 0-15 years, <i>M015</i>	0.06 (0.04)	0.02	0.08 (0.03)	0.03	0.02 (0.01)
Males 16-55 years, <i>M1655</i>	-0.05 (0.05)	-0.02	-0.17 (0.04)	-0.07	-0.01 (0.01)
Males ≥ 56 years, <i>M56P</i>	-0.12 (0.11)	-0.05	-0.19 (0.09)	-0.08	-0.04 (0.03)
Irrigated land used, <i>IRR</i>	0.29 (0.12)	0.11	0.48 (0.08)	0.19	0.08 (0.03)
Capital harvest, <i>CAP</i>	-0.12 (0.14)	-0.05	-0.42 (0.11)	-0.17	-0.05 (0.03)
Agricultural center, <i>AGC</i>	0.37 (0.14)	0.15	0.15 (0.09)	0.06	0.07 (0.03)
Spatial correlation errors (ρ)	-2.91 (0.34)	-	-0.70 (0.02)	-	-
Neighbors' characteristics included? Log-likelihood	-859.53	Directly: χ^2 -	Only through ϕWY^* -870.07	-	-

^aWith district fixed effects.

We are also interested in results of a model that allows for both spatial correlation in the latent variable and in the errors, as in eq. (9) above. These results are presented in the second set of columns in table 4. Again, the log-likelihood from this model is not significantly higher than the model that excludes spatial correlation in the errors (-870 vs. -871). This provides a second test for spatial correlation in the errors and, again, we reject its presence. Thus while both a model with only spatial correlation in the latent variable and a model with only spatial correlation in the errors obtain likelihoods higher than a model that allows for neither, once they are nested within the same model, only spatial correlation in the latent variable appears to significantly improve the likelihood.

Collectively, these tests suggest that, in the adoption of this technology, neighbors are extremely influential and should not be overlooked when modelling discrete choice adoption behavior. However, these tests of neighbors' influence and spatial correlation in errors are only valid if right-hand side variables are uncorrelated with the errors. To test for correlation between right-hand side variables and errors, we constructed a fixed effect estimator for sickle adoption.² Each district is allowed its own specific effect. Note that these effects absorb the influence of neighbors (WY^*) and spatial correlation in the errors (ρWu). The results of this estimation are provided in the last column of table 4. If household or neighborhood level right-hand side variables were correlated with errors, the coefficients of the linear probability model may be quite different from the predicted probabilities from a probit model that allows spatial correlation in the latent variable (as in column 2 of table 3). Note, however, that the predicted probabilities are almost identical. The linear probability model suggests that HYV seed makes farmers 24% more likely to adopt the sickle, compared to the 26% estimate from the model that allows neighbors' influence; the linear probability model suggests an agricultural center makes a farmer 7% more likely to adopt, compared to the estimate of 5% in the earlier model. In addition, the effects of family demographic variables are almost identical in the two models. The equality of these estimates suggests that correlation between right-hand side variables and errors are not biasing results.

As a final check on how well a model that allows neighborhood influence fits the data, we present results of predicted sickle use from a probit model that does not allow neighbors to influence adoption and from a probit that does. Here, if the index $-X\hat{\beta}$ for the first model and $(I - \hat{\phi}W)^{-1}X\hat{\beta}$ for the second is greater than zero, we predict the household will adopt the sickle. Otherwise, we predict the household continues to use the small knife. Results of these predictions are presented in table 5. Note that the model that allows

²This estimation procedure is only valid as the number of observations per district goes to infinity. Nonetheless, it may provide an interesting comparison with the spatial models.

Table 5
Predicted sickle use.

	Probit estimation without neighbors' influence		Probit estimation with neighbors' influence			
	Actual sickle use		Actual sickle use			
	No	Yes	No	Yes		
Predicted sickle use	No	827	350	No	810	314
	Yes	134	276	Yes	151	312

for neighbors' influence is more successful in predicting adoption. The model that allows neighbor effects makes 17 more mistakes in falsely predicting sickle use, relative to the model with no neighbor effects. However, the model that allows neighbors makes 36 fewer mistakes in falsely predicting small knife use.

It appears that neighbors are important influences in farmers' decisions to adopt new technologies. Neighbors appear to be influential in farmers' attitudes toward adoption. In addition, ignoring interaction between farmers may lead researchers to overstate the influence of household characteristics on adoption decisions: Ignoring farmer interaction could lead one to attribute to household characteristics some influence that actually works through farmers' neighbors.

5. Extensions

There are several important areas in which extensions would be of interest. First, while adoption is taking place over space, it is also taking place over time. Risk averse behavior may lead to time lags in adoption. In addition, adjustment costs may be lower if they are spread over several time periods. Furthermore, it may take farmers time to learn about a new technology. Incorporating the dynamics of adoption into this model will be of particular interest when modeling adoption patterns for technologies in which diffusion is slow and in which correlation between household characteristics and adoption may change over time.

Finally, there are other avenues by which neighbors may influence adoption decisions. It may be that it is the neighbors' actual adoption of technology, rather than their attitude toward it, that influences a farmer. It may be that farmers have unequal influence upon one another: Natural leaders may influence later adopters, but later adopters may have little influence on leaders. I hope to extend the analysis in these directions in future work.

References

- Ambastha, C.K., 1986, Communications patterns in innovation development, Extension and client systems (B.R. Publishing, Delhi, India).
- Chamberlain, G., 1985, Heterogeneity, omitted variable bias, and duration dependence, in J.J. Heckman and B. Singer, eds., *Longitudinal analysis of labor market data* (Cambridge University Press, Cambridge) 3–39.
- Feder, G. and R. Slade, 1984, Contact farmer selection and extension visits: The training and visit extension system in Haryana India, *Quarterly Journal of International Agriculture* 23, no. 1, 6–21.
- Feder, G., R. Just and D. Zilberman, 1985, Adoption of agricultural innovations in developing countries: A survey, *Economic Development and Cultural Change* 28, 119–133.
- Foster, J.H., K.G. Kshirsagar, M.J. Bhende, V. Bhaskar Rao and T.S. Walker, 1987, Early adoption of improved vertisol technology options and double cropping in Begumgunj, Madhya Pradesh (International Crop Research Center for the Semi-Arid Tropics, Patancheru, India).
- Hayami, Y. and A. Hafid, 1979, Rice harvesting and welfare in rural Java, *Bulletin of Indonesian Economic Studies* 15, 94–112.
- Heckman, J.J., 1978, Dummy endogenous variables in a simultaneous equation system, *Econometrica* 46, 931–959.
- Heckman, J.J., 1981, Statistical models for discrete panel data, in: C.F. Manski and D. McFadden, eds., *Structural analysis of discrete data with econometric applications* (MIT Press, Cambridge, MA) 114–178.
- Lindner, R.K., 1987, Adoption and diffusion of technology: An overview, in: B.R. Champ, E. Highley and J.V. Remenyi, eds., *Technological change in post-harvest handling and transportation of grains in the humid tropics* (Press Etching Pty. Ltd., Canberra, Australia).
- Miles, D., 1979, The finger knife and Ockham's razor: A problem in Asian cultural history and economic anthropology, *American Ethnologist* 6, 223–243.
- Mueller, R.A.E., K.G. Kshirsagar and C.S. Pawar, 1986, Advancing new methods for chemical pest control on traditional farms in SAT India (International Crop Research Center for the Semi-Arid Tropics, Patancheru, India).
- Rogers, E.M. and F.F. Shoemaker. 1971, *Communication of innovations*, Second edition (The Free Press, New York).
- Stoler, A.L., 1977, Rice harvesting in Kali Loro: A study of class and labor relations in rural Java, *American Ethnologist* 4, 678–698.
- SUSENAS Data, 1980, Biro Pusat Statistik (Jakarta, Indonesia).