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Soil conservation and technical efficiency among hillside farmers in Central America: a switching regression model*

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The main objective of this paper is to evaluate and analyse technical efficiency (TE) levels for hillside farmers under different levels of adoption of soil conservation in El Salvador and Honduras. A switching regression model is implemented to examine potential selectivity bias for high and low level adopters, and separate stochastic production frontiers, corrected for selectivity bias, are estimated for each group. The main results indicate that households with above-average adoption show statistically higher average TE than those with lower adoption. Households with higher adoption have smaller farms and display the highest partial output elasticity for land. Constraints in the land and credit markets are likely explanations for these differences. In addition, all estimated models show that TE has a positive and significant association with education and extension.

Key words: Central America, soil conservation, stochastic frontiers, switching regression, technical efficiency.

1. Introduction

Traditional agricultural practices in hillsides and the expansion of agriculture in Central America have been identified as major sources of watershed degradation in the region. Soil erosion, which has negative impacts on farm productivity and environmental quality, is a very serious problem. Several authors, including Arellanes and Lee (2003), and Kaimowitz (2001), report the severe social, environmental and economic consequences that arise from environmentally unsustainable traditional production practices in the region. Johnson and Baltodano (2004) highlight the reduction in quality of vast areas of agricultural land and the consequent decrease in farm productivity and rural income.

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In an effort to improve the environmental conditions in rural Central America, and to reduce poverty among hillside producers, local governments with the support of international donors have undertaken several natural resource management programs during the last two decades. Two such initiatives that involve significant public spending are the Environmental Program for El Salvador (PAES) and the Natural Resource Management Program in Honduras (CAJON). These programs promoted the conservation of renewable natural resources and particularly soil conservation in the upper watershed of the Lempa River in El Salvador and in the Cajón watershed in Honduras. These programs also sought to improve the socioeconomic conditions of the rural population in the areas of intervention.[1]

Despite the targeted effort and financial resources invested in promoting soil conservation under these two programs, the rates of adoption and the factors influencing farmers' decisions to adopt the new technologies vary among beneficiaries (Bravo-Ureta *et al.* 2006a). This variation provides an opportunity to measure the magnitude of the expected gains in productivity resulting from different levels of adoption of soil conservation practices. This type of analysis is useful for policy decision-making because it facilitates the understanding of the circumstances under which promoting alternative soil conservation technologies may have their greatest impacts (Fuglie and Bosch 1995). Consequently, the main objective of this paper is to measure and analyse technical efficiency (TE) levels for rural-hillside households under different levels of soil conservation adoption in El Salvador and Honduras.

Separate production models for alternative groups of farms within the sample are estimated. Freeman *et al.* (1998) indicate that the estimation of separate models is warranted if the level of adoption varies randomly among farms. However, Sriboonchitta and Wiboonpongse (2004) and Pattanayak and Mercer (1998) contend that the adoption of a new technology is a voluntary choice exercised by the farmer. Thus, classifying farms into arbitrary groups and then estimating separate production models for each group could generate a self-selection problem leading to biased parameter estimates.

Pattanayak and Mercer (1998) clarify that the type of self-selection just noted is different from the more traditional case where data for non-adopters is not available. In our case, self-selection could arise from classifying farms into arbitrary groups. Maddala (1983) indicates that partitioning the data into subsamples might lead to observations that are no longer random draws from the population, because the data in each subsample might depend on the variables affecting the adoption of the technology under analysis. Therefore, to account for the potential self-selection bias that may arise in the models to be estimated in this study, a switching regression framework is implemented.

[1] For more details on the PAES and CAJON Project please refer to Bravo-Ureta *et al.* (2003).

The rest of this paper is divided into five additional sections. The next section presents the theoretical framework, followed by a description of the empirical model and the dataset. The subsequent section presents and discusses the main results of this analysis while the last section provides some concluding remarks.

2. Switching regression model

In broad terms, a switching regression model corrects for self-selection bias by introducing a set of self-selectivity variables into the production model. In doing so, the first step in this model is to determine the factors influencing farmers' decisions to adopt soil conservation. Consistent with Freeman *et al.* (1998) the level of adoption of soil conservation can be described by a criterion function, which is postulated to be associated with exogenous household socioeconomic variables as follows:

$$A_i = \delta' Z_i + u_{0i} \tag{1}$$

where A is the level of adoption of soil conservation, subscript i denotes farm-households, Z is a vector of exogenous variables, δ are the unknown parameters and u_0 is the disturbance term.

Petersen (2001) indicates that to obtain robust results it is best to classify the dataset into a few broad groups because defining several narrow groups may reduce significantly the variation within subgroups thus affecting the statistical significance of the econometric estimates. Therefore, we divided the sample into two adoption levels – HIGH and LOW – with the median level of adoption in the sample as the breakpoint.[2] By dividing the sample in two subgroups, the dependent variable can be redefined as a dichotomous variable (i.e. $A = 1$ for a relatively high level of adoption and 0 for a lower level of adoption) and the parameters in Equation (1) can then be estimated as a Probit model.

The second step in the switching regression model is to estimate production functions for the two groups of farmers. These production functions can be expressed as:

$$Y_{1i} = \beta_1' X_{1i} + u_{1i} \qquad \text{if } A = \text{HIGH} \tag{2}$$

$$Y_{2i} = \beta_2' X_{2i} + u_{2i} \qquad \text{if } A = \text{LOW} \tag{3}$$

where Y_1 and Y_2 represent output for farm-households with high and low levels of adoption of soil conservation, respectively. X_1 and X_2 are vectors of

[2] In this classification, all those cases that are equal to or higher than the median level of adoption, which is 0.5, are included in the HIGH group ($n = 328$) while all observations below the median are in the LOW group ($n = 311$).

exogenous variables, β_1 and β_2 are unknown parameters, and u_1 and u_2 are random disturbance terms.

Maddala (1983) indicates that estimating the unknown parameters, β_1 and β_2, using OLS, yields inconsistent estimates because the expected values of the error terms, conditional on the sample selection criterion, are non-zero. Furthermore, he argues that the random disturbance terms, u_0, u_1 and u_2 (Equations (1)–(3), respectively), are assumed to have a trivariate normal distribution with zero mean and non-singular covariance matrix. Thus, in order to obtain unbiased estimates it is necessary to estimate Equations (1)–(3) simultaneously using maximum-likelihood techniques.

The estimation of this system of equations using maximum-likelihood is feasible but complicated. To simplify the estimation, Lee (1978) suggests a two-step method where self-selectivity is treated as a missing variable problem. In this model, the error terms are assumed to have a joint-normal distribution with the following covariance matrix:

$$\mathrm{Cov}(u_1, u_2, u_0) = \begin{bmatrix} \sigma_1^2 & \sigma_{12} & \sigma_{10} \\ \sigma_{12} & \sigma_2^2 & \sigma_{20} \\ \sigma_{10} & \sigma_{20} & \sigma_0^2 \end{bmatrix} \tag{4}$$

where $\sigma_i^2 = \mathrm{var}(u_i)$ and $\sigma_{ij} = \mathrm{cov}(u_i, u_j)$, $i \neq j$.

Based on these assumptions, the expected values of the truncated error terms are equal to:

$$\mathrm{E} = (u_1 \mid_{A=1}) = \mathrm{E}(u_1 \mid_{u_0 > -Z'\delta}) = \sigma_{10} \frac{\phi(Z_i'\delta)}{\Phi(Z_i'\delta)} \equiv \sigma_{10} W_1 \tag{5}$$

$$\mathrm{E} = (u_2 \mid_{A=0}) = \mathrm{E}(u_2 \mid_{u_0 \leq Z'\delta}) = \sigma_{20} \frac{-\phi(Z_i'\delta)}{1 - \Phi(Z_i'\delta)} \equiv \sigma_{20} W_2 \tag{6}$$

where Z and δ are, respectively, the vector of exogenous variables and the estimated parameters from Equation (1), and ϕ and Φ are the probability density and the cumulative distribution functions.

Thus, consistent with Lee (1978), the revised system of equations can be depicted as:

$$Y_{1i} = \beta_1' X_{1i} + \sigma_{10} W_{1i} + \varepsilon_{1i} \qquad \text{if } A = \text{HIGH} \tag{7}$$

$$Y_{2i} = \beta_2' X_{2i} + \sigma_{20} W_{2i} + \varepsilon_{2i} \qquad \text{if } A = \text{LOW} \tag{8}$$

where W_1 and W_2 are the self-selectivity variables derived, respectively, in Equations (5) and (6). The coefficients of these variables provide estimates of the covariance terms σ_{10} and σ_{20}. If the covariances are non-zero then the estimation of Equations (2) and (3) would be biased due to self-selection.

Otherwise, Equations (7) and (8) will collapse to Equations (2) and (3) (Pitt 1983; Fuglie and Bosch 1995). The terms ε_1 and ε_2 are the residuals for Equations (7) and (8) and have zero conditional mean. Freeman *et al.* (1998) show that these residuals are heteroscedastic and they suggest estimating Equations (7) and (8) by weighted least square (WLS) to obtain efficient parameters.

Sriboonchitta and Wiboonpongse (2004) maintain that the methodology described above can also be used to modify the stochastic production frontier (SPF) model in order to estimate efficient parameters in the presence of self-selectivity bias. Consequently, using the SPF framework, Equations (7) and (8) are expressed as follows:

$$Y_{1i} = \beta_1' X_{1i} + \sigma_{10} W_{1i} + v_{1i} - \mu_{1i} \qquad \text{if } A = \text{HIGH} \tag{9}$$

$$Y_{2i} = \beta_2' X_{2i} + \sigma_{20} W_{2i} + v_{2i} - \mu_{2i} \qquad \text{if } A = \text{LOW} \tag{10}$$

where v_i is a random variable reflecting noise and other stochastic shocks entering into the definition of the frontier, and μ_i captures the technical inefficiency (TI) relative to the stochastic frontier. The maximum-likelihood estimation of Equations (9) and (10) produces consistent parameter estimates for the SPFs.

A further refinement is to analyse the extent to which certain variables are correlated with the inefficiency term μ_i. To accomplish this, a desirable option is the one developed by Battese and Coelli (1995) where, in a single-stage maximum-likelihood approach, the TI effects are estimated as a function of farm-specific variables. Hence, using this approach, the parameters of the production frontier as well as those of the TI factors are estimated jointly. Thus, TI can be estimated by incorporating the following expression in the frontier model:

$$\mu_i = \alpha_0 + \sum_{n=1}^{m} \alpha_n F_{ni} + e_i \tag{11}$$

where μ_i is the inefficiency effect defined as a normal random variable truncated at zero, F_{ni} is a vector of household-specific variables, the α are unknown parameters and e_i is random noise, assumed to be independently distributed.

3. Empirical model

As indicated earlier, the first step in estimating the switching regression model is to investigate farmers' decisions to adopt soil conservation. According to neoclassical theory, farmers would adopt new technologies provided the associated expected economic benefits are positive. The literature also document other reasons that motivate farmers to adopt new technologies (see Feder and Umali 1993; Rogers 1995 for detailed reviews of this area of research).

Typically, the variables affecting the adoption of a new technology have been classified into the following groups: human capital; structural factors and social capital. Human capital variables often included in adoption models are age, gender, education, literacy, agricultural experience and training. Among structural factors, farm size, land tenure and credit have been widely analysed. Also, recent studies have focused on evaluating the effect of access to social networks and institutions on farmers' perceptions of a new technology and on the adoption process (e.g. Shultz *et al.* 1997; Winters *et al.* 2004). Studies focusing specifically on the adoption of soil conservation technologies suggest that farmers' perceptions of soil erosion problems in their area, household attributes and assets, plot slope and location are relevant in the development of an appropriate model (Lindner 1987).

Based on the literature and the available data, the adoption function used in this study can be summarised as follows. First, the dependent variable in the Probit model (Equation (1)) is a dichotomous variable reflecting the level of adoption of soil conservation practices on the farm. As explained in Section 2, this variable takes the value of 1 (high adoption) if the farm puts 50 per cent or more of its cultivated land under soil conservation practices (i.e. crop residue mulching, minimum tillage, crop rotation, green manure and/or contour tillage) or 0 otherwise (low adoption). The explanatory variables in this model include both continuous and dummy variables. These variables have been selected to characterise, in the best way possible, the factors governing farmers' decision to adopt soil conservation. To account for a possible project effect a set of dummy variables is included in this model; namely, *Paes 1*, *Paes 2* and *Paes 3* (*Cajón* is the excluded category). PAES is treated as three projects because each of these subprojects was managed by separate organisations each with its own methodologies and approaches to extension services.

The second-step in the switching regression model is to estimate the SPF model for farms under high and low levels of adoption of soil conservation (i.e. Equations (9) and (10), respectively). In general, productivity analyses in peasant economies are usually undertaken at the farm-level (Bravo-Ureta *et al.* 2007). However, using the farm as the unit of analysis to study productivity in developing countries has come under scrutiny. Specifically, Chavas *et al.* (2005) argue that performing efficiency studies at the farm-level in an environment with market imperfections may be inappropriate. Chavas and coauthors contend that farm-level analyses neglect possible labour allocation inefficiency between farm and non-farm activities, and that decisions regarding both of these activities are often made jointly.

It is important to indicate that traditional farm-level analysis usually includes off-farm earnings as an explanatory variable in the production frontier. However, this strategy has been criticized for potentially introducing endogeneity bias because both farm and non-farm activities may be correlated with the same unobserved variables (Jolliffe 1998). Typically, the literature has addressed this problem by implementing instrumental variables. In contrast, a household-level productivity model includes off-farm income as part of the dependent variable (or variables if a multioutput approach is used) in the productivity model, which avoids the potential endogeneity problem (Chavas *et al*. 2005).

Therefore, a household-level productivity model is implemented in this study. In doing so, the dependent variable in the second-stage is the total value of household production. This variable, measured in US dollars, represents the sum of a household's agricultural production (including self-consumption) and off-farm earnings. The values for agricultural production are calculated based on total production quantities and selling prices reported by the farmers. Off-farm earnings are measured as the total value of income generated outside of the farm by household members. It includes income accruing from either employment in the rural non-farm labour market, self-employment in the local non-farm sector, or employment in the farm labour market.

Following common practice, the explanatory variables included in the household production model reflect mostly farm characteristics and production inputs (Coelli and Battese 1996; Gorton and Davidova 2004, among others). In this study, the labour used in farm production is disaggregated into family and hired labour. This division of agricultural labour is consistent with the view that, in developing countries, family and hired labour may not be perfect substitutes (Taylor and Adelman 2003). Thus, these two types of labour should be considered separately in the characterisation of a production model. Due to data restrictions, *Off-farm labour* is measured as the number of people in the household over the age of 15 with off-farm jobs. As in the Probit model, a set of dummy variables are included to account for any unobserved project effects. To correct for potential selectivity bias the frontier functions include the self-selectivity variables W_1 and W_2, as discussed in Section 2.

The specification of the inefficiency effects component includes several socioeconomic, structural and social capital variables selected both on the basis of the data available and on the literature. To measure the influence of extension on inefficiency the number of annual visits made by an extension worker to the farm (*Extension*) and the number of years that the farmer has been associated with the project (*Years*) are also included. The variable *Participation* is used to assess the effect of access to social networks and institutions on TI. Lastly, following González and López (2007), the variables *Credit* and *Ownership* are included to measure the impact of financial and land markets. Table 1 presents a summary description of each variable used in this study.

4. Data

The data used in this study consist of detailed household-level information obtained from surveys administered to farmers participating in the PAES and CAJON projects. These projects have sought to increase household

Table 1 Variable definition

Variable	Model	Definition
Dependent variables		
Adoption	A	Level of adoption of soil conservation practices (dummy, HIGH = 1, LOW = 0)
Production	P	Total household production (US$)
Farm characteristics		
Land	A/P	Total number of Manzanas devoted to agricultural production (1 Mz = 0.7 hectares)
Slope	A/P	1 if the average slope is greater than 15% (dummy)
Ownership	A/I	1 if the household owns at least part of the farm (dummy)
Practices		Percentage of total land with soil conservation practices
Household characteristics		
Family size	A	Number of people in the household
Credit	A/I	1 if the household has access to financial credit (dummy)
Purchased inputs	P	Total expenditure in variable inputs (US$)
Family labour	P	Total family labour (working days)
Hired labour	P	Total hired labour (US$)
Off-farm labour	P	Number of people in the household over the age of 15 with off-farm jobs
Household head characteristics		
Age	A/I	Age of the household head (years)
Education	A/I	Average level of education (years) for household's members ≥10 years old
Gender	A/I	1 if the household head is a man (dummy)
Perception	A	1 if farmer is aware of the erosion problem in the area
Participation	A/I	1 if the household head participates in an organisation (dummy)
Project characteristics		
Extension	A/I	Number of visits by an extensionist to the farm
Years	A/I	Number of years involved with the project
Paes 1	A/P	1 if household is in PAES 1 (dummy)
Paes 2	A/P	1 if household is in PAES 2 (dummy)
Paes 3	A/P	1 if household is in PAES 3 (dummy)
Cajón	A/P	If household is in CAJON (dummy, excluded category)

A, Adoption model; P, Production model; and I, Inefficiency Effects model.

income through improved soil productivity, the adoption of conservation technologies and product diversification through a series of activities and instruments, including farm extension programs, education and training, community engagement, targeted investments under cost sharing mechanisms, marketing assistance and environmental awareness programs.

The households included in the dataset were selected randomly from lists of producers associated with each project and the farmers were interviewed between May and August 2002. The data from El Salvador include 530 households drawn from a listing of all beneficiaries located in 102 communities of the Lempa River Watershed. In Honduras, 210 households associated with the 240 communities participating in the CAJON project were interviewed. In sum, the database has 740 observations; however, all surveys with missing or incomplete data necessary for this study were excluded from the analysis. Thus, the final dataset contains 639 observations.[3]

The descriptive statistics presented in Table 2 reveal several important points. For instance, the typical project participant operates about 6 Mz (4.2 hectares). In addition, most of the farmers (70 per cent) own more than 50 per cent of the land they operate. They are middle-aged men (83 per cent) and have very limited access to rural credit and formal education.

An interesting pattern is found between the two groups of households (high and low adopters). In general, farmers with a higher percentage of land under soil conservation practices are younger, better educated and have higher household income. Conversely, farmers with a lower share of land under conservation practices are larger and have higher levels of off-farm income. These statistics appear to confirm the findings presented by Bravo-Ureta *et al.* (2006b), Solís and Bravo-Ureta (2005) and Sanders *et al.* (1995) who suggest that, in Central America, more conservative producers retreat to subsistence crops – where they use few inputs generating low returns – and engage in as much off-farm work as they can, in order to obtain the necessary means to support their families.

5. Results and discussion

5.1 First-stage: Probit model

Table 3 presents the maximum-likelihood estimates of the Probit model. This table displays the estimated coefficients along with their respective marginal effects (MEs). The MEs measure the change in the probability of adoption due to a one unit change of a specific explanatory variable. The MEs for the dummy variables are estimated by taking the difference between the value of the prediction when the exogenous variable equals 1 and when it equals 0. By contrast, the MEs for the continuous variables are estimated as ME = $\phi(\delta Z)\delta$, where ϕ is the probability density function, Z is the vector of exogenous variables and δ are the estimated parameters (Maddala 1983). The MEs for both kinds of variables are measured at the mean value of the regressors.

As is shown in Table 3, the model correctly predicts farmers' decisions to adopt soil conservation practices for 75 per cent of the observations and the likelihood ratio test rejects the null hypothesis that all slope coefficients are equal to zero at the 5 per cent level. The main results of the Probit model can

[3] A thorough analysis of the deleted observations revealed no systematic pattern with respect to any variable used in the analysis. Thus, no biases are expected from the data cleaning that preceded model estimation.

Table 2 Descriptive statistics

Variable	ALL				HIGH				LOW			
	Mean	SD	Max	Min	Mean	SD	Max	Min	Mean	SD	Max	Min
Practices	0.5	0.5	1.0	0.0	0.7	0.7	1.0	0.5	0.3	0.2	0.5	0.0
Age	48.0	14.5	88.0	19.0	46.4	14.1	85.0	19.0	49.5	14.1	88.0	19.0
Education	3.6	2.2	13.5	0.0	3.7	2.3	13.5	0.0	3.3	2.1	12.0	0.0
Gender	0.9	–	–	–	0.9	–	–	–	0.9	0.3	–	–
Family size	5.3	2.4	10.0	1.0	5.4	2.5	10.0	1.0	5.2	2.4	10.0	1.0
Land	5.9	13.5	181.0	0.4	2.8	2.8	26.0	0.4	8.8	18.1	181.0	0.6
Slope	0.6	–	–	–	0.6	–	–	–	0.6	0.5	–	–
Ownership	0.7	–	–	–	0.8	–	–	–	0.6	0.5	–	–
Extension	2.0	1.1	3.0	0.0	1.9	1.1	3.0	0.0	2.1	1.1	3.0	0.0
Years	3.1	1.1	6.0	0.0	3.1	1.1	6.0	0.0	3.1	1.2	6.0	0.0
Credit	0.3	–	–	–	0.3	–	–	–	0.2	0.4	–	–
Perception	0.81	–	–	–	0.93	–	–	–	0.69	–	–	–
Participation	0.6	–	–	–	0.6	–	–	–	0.6	–	–	–
Purchased inputs	657.8	997.6	13 727.2	42.0	799.9	1286.5	13 727.2	44.4	507.9	508.5	4183.3	42.0
Family labour	43.5	53.8	583.3	3.4	47.1	64.0	583.3	3.4	39.7	40.0	278.3	3.9
Hired labour	20.3	33.5	360.3	0.0	24.6	40.4	360.3	0.0	15.6	23.4	171.9	0.0
Off-farm labour	3.0	2.0	8.0	1.0	2.8	1.9	7.0	1.0	3.5	2.3	8.0	1.0
Paes 1	148	–	–	–	97	–	–	–	58	–	–	–
Paes 2	162	–	–	–	83	–	–	–	79	–	–	–
Paes 3	155	–	–	–	64	–	–	–	84	–	–	–
Cajón	174	–	–	–	84	–	–	–	90	–	–	–
No. households	**639**				**328**				**311**			

Table 3 First-stage Probit model

Variable	Coefficient	SE	ME
Constant	3.807**	1.873	–
Age	–0.050	0.168	–0.020
Education	0.053**	0.023	0.021
Gender	0.091	0.150	0.036
Family size	–0.015	0.021	–0.006
Land	–0.121*	0.017	–0.047
Slope	–0.056	0.106	–0.056
Ownership	0.412*	0.127	0.412
Extension	0.099**	0.046	0.039
Years	0.018	0.053	0.007
Credit	0.001	0.001	0.001
Perception	0.075**	0.029	0.075
Participation	–0.038	0.116	–0.038
Paes 1	0.228**	0.108	–
Paes 2	0.205***	0.125	–
Paes 3	0.066	0.231	–
Likelihood ratio test	**36.1****		–
Percentage of correct predictions	**75.2%**		–

*** 10%, ** 5% and * 1% level of significance.
Notes: The dependent dichotomous variable reflects the level of adoption of soil conservation.

be summarised as follows. Individually, 8 out of the 16 estimated parameters are statistically different from zero and most of them present signs consistent with what would be expected. For instance, *Education* and *Extension* are positive and significant parameters. This finding is consistent with the idea that human capital formation, through formal education, agricultural training and technical assistance, is essential in helping farmers to better understand the attributes of new technologies (Feder and Umali 1993; Rogers 1995).

Ownership displays a positive and significant effect on the level of adoption of soil conservation. Specifically, households who own at least some of the land they farm are 41 per cent more likely to adopt soil conservation practices than those who do not.[4] Shultz *et al.* (1997) and Lutz *et al.* (1994) argue that ownership reduces risk and consequently enhances expected returns encouraging farmers to invest in more productive technologies. However, the empirical literature presents mixed results in this regard. In fact, contradictory outcomes are reported by Ramírez and Shultz (2000) and Lee and Stewart (1983).

The positive and significant effect of *Perception* indicates that those producers who express knowledge of the erosion problem on their farms have a higher probability of investing in soil conservation practices than those who are unaware of this problem. The former group of farmers has approximately

[4] Farm owners include all those households that report having legal title on at least part of the land they operate. Conversely, no owners are all those who either rent or have no legal title for their plots.

an 8 per cent higher probability of investing in conservation than the latter group. These results suggest that environmental awareness is an important precondition for adopting conservation technologies. Similar findings have been reported by Mbaga-Semgalawe and Fomer (2000).

Land presents a negative and significant parameter, revealing an inverse relationship between the probability of investing in soil conservation and total area cultivated. Rogers (1995) explains that, in many cases, producers with smaller farms tend to be more innovative in their production techniques. Deininger *et al*. (2003) indicate that, in developing countries, an imperfect rural land market can lead to smaller farms than desired and, in these cases, family labour is in abundance and available to implement alternative production methods.

The dummy variables *Paes 1*, *Paes 2* and *Paes 3* capture the individual effects of these projects with respect to *Cajón* (omitted category). All three PAES projects present positive parameters and two out of the three are statistically significant. These results suggest that farmers associated with PAES are more likely to adopt soil conservation practices than those linked with CAJON. A possible explanation for this result might be the different strategies used by these projects to promote the adoption of soil conservation technologies among their beneficiaries. For example, the PAES project introduced various incentives to assist farmers in the adoption process (e.g. extension assistance, cost sharing mechanisms, marketing support), whereas the CAJON project's major subsidy was the provision of extension assistance.

5.2 Second-stage: efficiency analysis

Table 4 contains the second-stage estimates of the switching regression model used in this paper. Three different SPFs were estimated to evaluate the effect of investing in soil conservation on household productivity. The HIGH and LOW models analyse productivity among farms with corresponding levels of adoption of soil conservation practices. These models incorporate the self-selectivity variables W_1 and W_2 generated in the fist-stage analysis. If there is no selectivity bias then the parameters associated with W_1 and W_2 would not be statistically different from zero and direct estimation of the production model for each group would be adequate (Freeman *et al*. 1998).

As mentioned earlier, the incorporation of the self-selectivity variables into the production models introduces heteroscedasticity (Fuglie and Bosch 1995). Therefore, the Lee *et al*. (1980) procedure is implemented to calculate the correct asymptotic covariance matrix and thus obtain robust estimates for the standard errors. For comparison, an SPF was also estimated for the entire sample (ALL).

Preliminary comparisons led to the rejection of the Cobb–Douglas in favour of the translog (TL) functional form; hence, the analysis below is based on the TL. Following common practice, all variables in the TL models are normalised by their geometric mean (GM). Thus, the first-order coefficients

Table 4 Second-stage stochastic production functions

Variable	ALL		HIGH		LOW	
	Coef.	SE	Coef.	SE	Coef.	SE
Constant	−3.045*	0.492	−4.208*	0.547	−3.018*	0.325
Land	0.078***	0.054	0.144***	0.080	0.047***	0.027
Purchased Inputs	0.244*	0.098	0.243*	0.098	0.254*	0.111
Family Labour	0.312*	0.048	0.326*	0.062	0.228**	0.108
Hired Labour	0.109	0.079	0.076	0.077	0.144***	0.080
Off-Farm Labour	0.078***	0.028	0.089**	0.038	0.081**	0.040
Slope	0.009	0.009	0.011	0.014	0.005	0.012
W_1	–	–	0.163***	0.094	–	–
W_2	–	–	–	–	0.218***	0.136
Paes 1	0.301*	0.082	0.323*	0.078	0.277*	0.083
Paes 2	0.316*	0.094	0.322*	0.071	0.297*	0.112
Paes 3	0.228**	0.108	0.291**	0.153	0.111**	0.055
Quadratic and interaction terms excluded due to space limitations						
Inefficiency model						
Constant	−2.985***	1.268	−2.794*	*0.757*	1.781***	0.988
Age	0.007	0.012	0.002	*0.003*	0.005	0.007
Education	−0.412*	0.175	−0.715**	*0.340*	−0.301**	0.126
Gender	−0.996**	0.504	0.708**	*0.317*	−0.729**	0.365
Extension	−0.439***	0.237	−0.312***	*0.162*	0.201**	0.088
Years	0.104	0.154	0.031	*0.038*	0.036	0.050
Credit	−0.215	0.447	−0.211	*0.196*	−0.227***	0.134
Ownership	0.701	0.558	0.598***	*0.311*	0.111	0.120
Participation	−0.235	0.344	−0.122	*0.136*	−0.076	0.210
Sigma-squared $\sigma^2 = \sigma_v^2 + \sigma_u^2$	**0.621***	***0.128***	**0.842***	***0.111***	**0.595***	**0.066**
$\gamma = \sigma_u^2/\sigma^2$	**0.805***	***0.051***	**0.672***	***0.071***	**0.832***	**0.048**
Log-likelihood	**−540.85**	–	**−675.36**	–	**−715.89**	–
Returns to scale	**0.82**	–	**0.87**	–	**0.75**	–
Mean	**0.77**	–	**0.83**	–	**0.74**	–

*** 10%, ** 5% and * 1% level of significance.
Notes: The dependent variable is total household income, measured in US$.

Table 5 Tests of hypothesis for the inefficiency effects

Models	Null hypothesis	Test	Conclusion
ALL	–	34.28	Reject
HIGH	H_0: $\gamma = 0$	27.63	Reject
LOW	–	28.34	Reject

can be interpreted as partial production elasticities at the GM. The three SPF models satisfy monotonicity at the GM given that all partial elasticities of production are positive. In addition, the bordered Hessian matrices at the GM are negative semidefinite for all three models implying diminishing marginal productivities and thus concavity (Chambers 1988).

The values for σ^2 and γ are reported at the end of Table 4. The null hypothesis $\gamma = 0$ is rejected in all cases (Table 5) which suggests that TI is indeed stochastic. Moreover, the value for γ is statistically significant and ranges from 0.672 to 0.832, which indicates that inefficiency is an important contributor to observed output variability.

The parameters for the self-selectivity variables W_1 and W_2 are statistically significant, which supports the estimation of the SPF using the switching regression approach. Furthermore, Fuglie and Bosch (1995) suggest that the signs of the parameters for W_1 and W_2 have important economic interpretations. Assuming profit maximisation, these authors conclude that if these parameters display the same sign, as is the case here, households with higher adoption levels also have higher output. Thus, our results suggest that investing in soil conservation is an appropriate alternative for improving total household production among the sampled farmers.

The results show that out of the 25 estimated coefficients, 16 and 14 are significant at least at the 10 per cent level in the HIGH and LOW SPF models, respectively. In addition, 15 out of the 24 estimated coefficients in the ALL model are significant at least at the 10 per cent level. The significance of several cross products and squared terms confirms the selection of the TL over the Cobb–Douglas specification.

In general, the estimated production elasticities follow similar patterns in the three estimated models; however, their magnitudes differ. Table 4 shows that, at the GM, *Family Labour* and *Purchased Inputs* contribute the most to the total value of household production. Specifically, model HIGH displays the largest partial elasticity for *Family Labour*, while model LOW presents the largest partial elasticity for *Purchased Inputs*.

The three variables used to evaluate the effect of labour on output display positive parameters in all estimated models. Nevertheless, the statistical significance of these parameters varies. For instance, the parameters for *Family Labour* and *Off-Farm Labour* are statistically different from zero in all cases. However, the parameter for *Hired Labour* is significant only in model LOW.

It is important to indicate that the effect of labour on output presents mixed results in the literature. For example, Kompas and Che (2006), González (2004) and López and Valdéz (2000) report positive and significant effects of labour on output among dairy producers in Australia, and peasant farmers in Colombia and Central America, respectively. By contrast, no significant effects are reported by Alvarez *et al*. (2007) in northern Spain, Wadud and White (2000) in Bangladesh and Squires and Tabor (1991) in Indonesia.

Farm size presents positive but small effects in all estimated models. Indeed, the partial elasticity for *Land* in model HIGH is 0.144, indicating that a 10 per cent rise in total cultivated area could increase total household production by 1.44 per cent. Lastly, all project dummy variables display positive coefficients suggesting that farmers associated with *Paes* (1–3) have higher levels of productivity than those working with *Cajón*.

At the GM, returns to scale are equal to 0.87, 0.82 and 0.75 for models HIGH, ALL and LOW, respectively, which suggests the presence of decreasing returns to scale (DRTS). Chavas *et al*. (2005) indicate that in household-level analyses, the presence of DRTS implies that household resources are 'too large' for the prevailing technology. Given that the farms under analysis are small in terms of land area, the source of DRTS is most likely due to the relatively large number of adults in the households. Chavas *et al*. (2005) suggest that this problem may be offset by promoting off-farm employment opportunities.

The empirical results also show that the average levels of TE are 0.83, 0.77 and 0.74 for models HIGH, ALL and LOW, respectively. Based on paired *t*-tests, the differences among these means are statistically different from zero suggesting that, on average, households with higher adoption levels also exhibit higher TE. These results also reveal considerable inefficiency for the LOW group which, on average, could reduce the use of inputs by 26 per cent and still generate the same level of earnings. It is important to indicate that these TE levels are well within the range reported by Bravo-Ureta *et al*. (2007) in their meta-regression analysis of TE studies in agriculture. These authors show that the average TE for stochastic studies in Latin America is approximately 78 per cent. The distribution of farmers among the different TE intervals is presented in Figure 1. This graph shows that 82 per cent of the farmers in the HIGH group achieve TE levels of 70 per cent or higher. This percentage decreases to 54 per cent for farmers in the LOW group.

Table 4 also presents the inefficiency effects for the three models. Following common practice, the analysis is performed in terms of TE instead of TI which is equivalent to assuming that the inefficiency effects parameters display the opposite sign as the one shown in Table 4. As expected, *Education* and *Extension* display positive and statistically significant effects in all three models which is consistent with other published results (i.e. Abdulai and Eberlin 2001; González and López 2007).

The gender of the household head affects TE significantly in all three models. More precisely, female-headed households achieve lower levels of efficiency than male-headed households. Similar outcomes have been reported in the

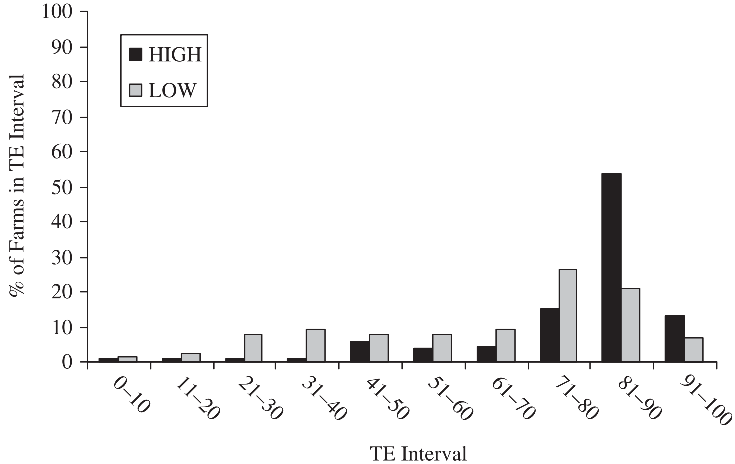

Figure 1 Technical efficiency (TE) score by level of adoption of soil conservation.

literature and different arguments have been advanced to explain this result. For instance, López and Valdés (2000) suggest that this finding may be related to the different kinds of production activities performed by male and females in Central America. González (2004) argues that gender inequalities, prevalent in rural Latin America, limit women's access to information, land, capital and other inputs, and this can adversely affect TE. This difference could also be explained by the fact that females perform household activities that usually go unmeasured. Generally, in less developed areas, female household-heads are not only in charge of their family business but they also take care of basic household needs; namely, child care, cooking, cleaning, wood and water fetching, and so on. However, to test this hypothesis detailed intrahousehold information is required, which is not available for this study. This is an area that merits further research.

Credit presents a positive effect on household efficiency but it is statistically significant only in the model LOW. Previous studies show mixed results with regards to the effect of credit assistance on productivity (e.g. Yadav and Rahman 1994; Deininger *et al.* 2004). Nonetheless, our analysis suggests that households with lower adoption of soil conservation may be credit constrained. Therefore, extension programs should focus credit assistance on this group of households where additional funds have the potential of having a positive and significant effect on productivity improvement.

Finally, the coefficient for *Ownership* is negative in all models but statistically significant only in the HIGH model. This suggests that TE decreases with land ownership, contradicting the neoclassical notion that land ownership is an economic incentive for farmers to improve productivity. Nevertheless, this seemingly contradictory finding has been reported in other studies (e.g. Byiringiro and Reardon 1996; Deininger *et al.* 2004). Deininger *et al.* (2003)

claim that this result could be explained by the prevalence of imperfect rural land markets, which may restrict farmers' access to land, including those that may be the most technically efficient in a given geographical area.

6. Summary and concluding remarks

This study has assessed the connection between the adoption of soil conservation practices and farmers' TE by comparing two groups of farm households, high and low adopters, located in hillside regions of Honduras and El Salvador. A specific methodological and empirical issue addressed on this paper is the determination of whether there is an unobserved mechanism at work that might lead farmers to self-select into one of these two groups. If such a mechanism is at work then the conventional estimation of separate production models for each group may lead to biased parameter estimates.

A switching regression approach was used to test for a systematic difference between the two groups. This approach corrects for the potential self-selectivity problem using a two-stage procedure. First, a Probit model is estimated to evaluate the variables affecting the adoption of soil conservation practices among the sampled households and to derive self-selectivity variables. These self-selectivity variables are then introduced into two SPFs to compute unbiased estimators. The empirical analysis corroborates that a systematic difference exists between the two groups of households under study.

The results can be summarised as follows. First, the Probit model indicates that education, soil erosion awareness and frequency of rural extension visits play a positive and significant role in determining the level of adoption of conservation practices. Land ownership also displays a positive and significant effect. By contrast, farm size shows a negative and significant effect on adoption, indicating that smaller farms have a higher probability to be engaged in soil conservation activities than larger ones.

The second-step analysis reveals that producers with higher adoption of soil conservation also exhibit higher average TE. Moreover, these producers have the smallest farms and present the highest partial elasticity of production with respect to total cultivated land. These results suggest the presence of a failure in the land market in the region under analysis. Deininger *et al.* (2003) claim that market failures in less-favourable areas restrict access to land to many efficient rural producers. Vogelgesang (1998) suggests that a workable approach to handle these market failures is to strengthen the rental land market and to offer farmers the necessary financial support so that they can afford to rent additional land.

Conversely, farms with less soil conservation display the highest elasticities for purchased inputs and hired labour. In addition, access to credit is found to be a factor in explaining the sources of inefficiency, suggesting the presence of cash constraints. Thus, resource management projects should consider enhancing credit access to these households as a strategy to encourage the adoption of soil conservation practices and to improve efficiency.

All production models exhibit positive and significant effects of education and extension on TE. These results are not surprising since the average level of formal education among the sampled households is only 3.6 years. Furthermore, the analysis reveals substantial inefficiency for household production in El Salvador and Honduras, indicating considerable potential for profitability improvement. Thus, rural development projects in the region should focus on improving farmers' human capital by supporting agricultural training, extension and educational programs.

Finally, households associated with PAES not only show higher average levels of TE than those working with CAJON but they also display a higher probability of adopting soil conservation technologies. These differences are likely due to the unique strategies, methodologies and incentives used in each project. This is an important issue that requires further work. However, to isolate the impact of project design and implementation it is necessary to have a much richer dataset, including a control group, than the one available in this study.

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