THE EFFECT OF SOIL CONSERVATION ON TECHNICAL EFFICIENCY: EVIDENCE FROM CENTRAL AMERICA

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ADOPTION OF SOIL CONSERVATION PRACTICES AND TECHNICAL EFFICIENCY AMONG HILLSIDE FARMERS IN CENTRAL AMERICA: A SWITCHING REGRESSION MODEL

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Abstract: This study evaluates technical efficiency (TE) levels for rural households under high and low levels of investments in soil conservation in El Salvador and Honduras. To correct for potential self-selectivity bias a household-level switching regression framework is implemented to estimate separate stochastic production frontiers for the two groups of households under analysis. The main results indicate that a systematic difference exists between the two studied groups. Specifically, households with higher levels of investments in soil conservation show higher average TE than those with a lower level of investments. Constrains in the rural land and credit markets appear to be the reason behind these differences. Our estimations indicate that for farms with lower levels of investments in soil conservation access to credit is a significant factor explaining the sources of inefficiency. Conversely, households with higher levels of investments in soil conservation present the highest partial output elasticity for land, the highest levels of TE and the smallest farms. This result could suggest the presence of a market failure in the land market which is denying access to land to the more efficient producers.

Keywords: Stochastic Frontiers; Technical Efficiency; Switching Regression; Central America; Soil Conservation

I. OVERVIEW

Traditional agricultural practices in hillsides and the expansion of the agricultural frontier in Central America have been identified as major sources of watershed degradation in the area. In particular, soil erosion, which has negative impacts on farm productivity and environmental quality, is considered to be the most serious problem. Several authors, including Arellanes and Lee (2003), Kaimowitz (2001), and Conroy, Murray and Rosset (1996), have shown 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 of these programs that deserve special attention because of the significance of the investments in terms of public spending are the Environmental Program for El Salvador (PAES) and the Natural Resource Management Program in Honduras (CAJON). Both programs, which have recently concluded, were aimed at conserving renewable natural resources in the upper watershed of the Lempa River in El Salvador and in the Cajón watershed in Honduras, respectively. An underlying objective of these programs was also to improve the socioeconomic conditions of the rural population in their area of influence. In doing so, these programs have promoted the use of soil conservation techniques and the adoption of a more diversified cropping pattern as their main strategy (Bravo-Ureta *et al*, 2003).

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' decision to adopt the new technologies vary sharply among beneficiary farmers (Cocchi, 2004). This variation provides an opportunity to measure the magnitude of the expected gains in productivity resulting from different levels of investments in soil conservation. 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 goal of this study is to evaluate and analyze technical efficiency levels for rural-hillside households under different levels of investments in soil conservation in El Salvador and Honduras.

To pursue this goal it will be necessary to estimate separate production functions for alternative groups of farms within the survey sample. Freeman, Ehui and Jabbar (1998) indicate that this estimation could be feasible if the levels of investments vary randomly among the studied farms. However, Sriboonchitta and Wiboonpongse (2004), and Pattanayak and Mercer (1998) indicate that this might not be the case in this kind of analysis since the adoption of a new technology is a voluntary choice exercised by the household. Thus, classifying farms into arbitrary groups and then estimating individual production functions for each group of farms could generate a self-selection problem in which case the estimated parameters would be biased.

Pattanayak and Mercer (1998) argue that this self-selection bias is different from the traditional one in which data for nonadopters is not available. In our case, the self-selection issue arises from the arbitrary classification of farms into groups. Maddala (1983) explains that by creating such subsamples the observations in each subset will no longer be randomly selected from the population given that the data in each subsample now depends 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 proposed. Generally speaking, this methodology uses a two-step approach in which a choice model is first used to determine the factors affecting farmers' decision to adopt a new technology. Next, based on the results of the choice model a set of self-selectivity variables is generated following Lee (1978). The latter variables are then incorporated into the productivity model in order to correct for the potential self-selection problem and thus compute unbiased parameters.

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 data set. The subsequent section presents and discusses the main results of this analysis while the last section provides some concluding remarks.

II. SWITCHING REGRESSION MODEL

In general terms, a switching regression model corrects for self-selection bias by introducing a set of self-selectivity variables into the productivity model. In doing so, the first step in this model is to determine the factors influencing farmers' decisions to invest in soil conservation.

Following Freeman, Ehui and Jabbar (1998) the level of investment in soil conservation can be described by a criterion function, which is postulated to be associated with exogenous household socioeconomic variables as follows:

$$I_i = \delta^{'} Z_i + u_{0i} \qquad (1)$$

where subscript i denotes farm-households, I is the level of investment in soil conservation, Z is a vector of exogenous variables, δ are the unknown parameters and u_o is the disturbance term.

Petersen (2001) indicates that to obtain robust results it is best to classify the data set into a few broad groups. This author argues that the separation of the data into several narrow groups may reduce significantly the variation among observations within each subgroup thus affecting the statistical significance of the econometric outcomes. Therefore, in our study two investment levels are proposed - high and low - with the sample mean as the breakpoint. By doing so, the dependent variable is now dichotomous (i.e., I = 1 for a high level of investment and 0 otherwise) and the parameters in equation (1) can be estimated using a choice model such as the probit.

The second step in the switching regression model is to compute production functions for the two groups of farmers (i.e., farmers with high and low levels of investment in soil conservation). These production functions can be expressed in reduced form as:

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

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

where Y_1 and Y_2 represent output levels for farm-households with high and low levels of investments in soil conservation, respectively, X_1 and X_2 are vectors of exogenous variables, β_1 and β_2 are the unknown parameters, and u_1 and u_2 are random disturbance terms (Feder *et al*, 1990).

Maddala (1983) indicates that estimating the unknown parameters, β_1 and β_2, using OLS will yield inconsistent estimates because the expected values of the error terms, conditional on the sample selection criterion, are non-zero. Furthermore, he argue that the random disturbance terms, u_0, u_1 and u_2 (equations 1, 2 and 3, respectively) are assumed to have a trivariate normal distribution with zero mean and non-singular covariance matrix. Thus, in order to obtain unbiased estimators it will be necessary to estimate equations (1), (2) and (3) simultaneously using maximum likelihood techniques.

The estimation of this system of equations via maximum likelihood is feasible but complicated. To simplify the calculations, Lee (1978) suggests a two-step estimation method where he treats self-selectivity 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 σ_1^2=var(u_1), σ_2^2=var(u_2), σ_0^2=var(u_0), σ_{12}=cov(u_1,u_2), σ_{10}=cov(u_1,u_0) and σ_{20}=cov(u_2,u_0).

Based on these assumptions, the expected values of the truncated error terms $(u_1|I=1)$ and $(u_2|I=0)$ are equal to:

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

$$(u_2|I=0)=\mathrm{E}(u_2|u_0\le -Z'\delta)=\sigma_{20}\frac{-\phi(Z_i^{'}\delta)}{1-\Phi(Z_i^{'}\delta)}\equiv\sigma_{20}W_2 \tag{6}$$

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

Therefore, based on Lee (1978), the revised system of equations can be expressed as follows:

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

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

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 nonzero then the estimation of equation (2) and (3) would be biased due to self-selection. Otherwise, equations (7) and (8) will collapse to equations (2) and (3), respectively (Fuglie and Boch, 1995; Pitt, 1983). Finally, ε_1 and ε_2 are the new residuals with zero conditional mean. Freeman, Ehui and Jabbar (1998) show that these residuals are heteroscedastic and suggest estimating equations (7) and (8) by Weighted Least Square (WLS) to obtain efficient parameters.

Sriboonchitta and Wibonnpongse (2004) suggest that the methodology described above can also be used to modify the stochastic production frontier (SPF) model in order to estimate efficient parameters under self-selectivity bias. Coelli (1995) states that the SPF is preferable to the average production function method because the former provides the shape of the technology for the best performing decision-making units. Thus, the frontier approach allows us to evaluate the effective gap between current farm productivity and the potential productivity level given the technology available in a specific geographical area.

Consequently, using the SPF method proposed by Aigner, Lovell, and Schmidt (1977), and Meeüsen and van den Broeck (1977), equations (7) and (8) may be expressed as follows:

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

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

where v_i, is a random variable reflecting noise and other stochastic shocks entering into the definition of the frontier, such as weather, luck, etc., and u_i captures the technical inefficiency relative to the stochastic frontier. The maximum likelihood estimation of equations (9) and (10) will produce consistent parameter and efficiency estimates for the stochastic production frontiers.

A further refinement is to analyze the extent to which certain variables are correlated with the inefficiency term u_i. To accomplish this, the most common option is the one developed by Battese and Coelli (1995) where, in a single-stage maximum likelihood approach, the technical inefficiency 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 technical inefficiency factors are estimated jointly. Thus, technical inefficiency 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 u_i are the inefficiency effects defined as normal random variables truncated at zero, F_{ni} is a vector of household-specific variables, α_n are unknown parameters and e are unobservable random variables, assumed to be independently distributed.

III. EMPIRICAL MODEL

As indicated earlier, the first step in estimating the switching regression model is to investigate farmers' decisions to invest in soil conservation. According to neoclassical theory, farmers would adopt new technologies as long as these technologies bring net economic benefits (Scherr, 2000; Saín and Barreto, 1996). However, it is well documented that the reason why farmers adopt a new technology goes beyond the neoclassical rationale. Since the pioneering work by Ryan and Gross (1943), a wealth of studies has analyzed the variables affecting the adoption of new technologies in the agricultural sector. Detailed reviews of this literature can be found in Lichtenberg (2001), Rogers (1995), Feder and Umali (1993), Lindner (1987), and Feder, Just and Zilberman (1985).

Typically, the variables affecting the adoption of a new technology have been classified into the following groups: 1) human capital; 2) structural factors; and 3) social capital (Rogers, 1995). With respect to human capital, it is customary to evaluate the effect of age, gender, education, literacy, agricultural experience and training. Among structural factors, farm size, land tenure and credit have been widely analyzed. Lastly, recent studies have focused on evaluating the effect of access to social networks and institutions on a farmer's perception of a new technology and their subsequent effect on the adoption process (e.g., Winters, Crissman, and Espinosa, 2004; Shultz, Faustino and Melgar, 1997).

With regards to the adoption of soil conservation technologies, previous research and economic theory suggest that variables such as farmers' perceptions of soil erosion problems in the area, household attributes and assets, plot slope, land use patterns and location are relevant in the development of an appropriate model (Lichtenberg, 2001; Lindner, 1987).

Based on the literature and the available data, the adoption function used in this study can be summarized as follows. First, the dependent variable in the probit model (equation 1) is a dichotomous (*dummy*) variable reflecting the level of investment in soil conservation practices in the farm. This variable takes the value of 1 if the farm puts more than 50% of its surface under soil conservation practices (i.e., crop residual mulching, minimum tillage, crop rotation, green manure and/or contour tillage) or 0 otherwise. A 50% level was selected because it is the average level of investment in soil conservation among the sampled households. In addition, the 50% point divides the sample into to two groups of approximately equal size.

The explanatory variables, including both continuous and *dummy* variables, are: AGE, the age of the household head; EDUCATION, the average level of education for household members that are 10 years of age or older[2]; GENDER, a *dummy* variable equal to 1 if the household head is a male; FAMILY SIZE, the total number of people in the household; LAND, the total area of cultivated land measured in Manzanas (1 Mz = 0.7 hectares); SLOPE, a *dummy* variable equal to 1 if the average slope in the farm is greater than 15%; OWNERSHIP, a *dummy* variable equal to 1 if the household owns more than 50% of the land cultivated; FREQUENCY, the number of visits made by an extensionist to the farm during the last agricultural year; YEARS, the number of years that the farmer has participated in the projects under study; CREDIT, a *dummy* variable equal to 1 if the farm uses credit; PERCEPTION, a *dummy* variable equal to 1 if the farmer expresses awareness and knowledge of the erosion problem in the area; and PARTICIPATION, a *dummy* variable equal to 1 if the household head participates in a social organization (e.g., farmer's and community associations).

To account for a possible project effect a set of *dummy* variables are included in this model (i.e., PAES 1, PAES 2 and PAES 3, with CAJON as the excluded category). PAES is treated as three separate projects because each one of these subprojects has been implemented in different agroecological regions of the Lempa River watershed and executed by independent extension programs, 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 investment in soil conservation (i.e., equations 9 and 10, respectively). In general, productivity analyses in peasant economies are usually undertaken at the farm-level (Thiam, Bravo-Ureta and Rivas, 2001). However, using the farm as the unit of analysis to study productivity in developing countries has come under scrutiny. Specifically, Chavas, Petrie and Roth (2005) argue that performing efficiency studies at the farm-level in an environment with market imperfections may be inappropriate. These authors contend that farm-level analyses neglect possible labor allocation inefficiency between farm and non-farm activities and that the decisions regarding both of these activities are often made jointly.

In addition, it is important to indicate that farm-level analysis usually includes off-farm earnings as an explanatory variable in the production frontier. However, this strategy has been

[2] Rogers (1995) indicates that in rural areas in less developed countries, children that are 10 or older have, in general, sufficient reading and writing skills to help their parents in several household and business related activities.

criticized for potentially introducing endogeneity bias because both farm and non-farm activities may be correlated with the same unobserved variables. Typically the literature has addressed this problem by implementing instrumental variables (Jolliffe, 1998). In contrast, the household-level model proposed by Chavas, Petrie and Roth (2005) includes off-farm income as part of the dependent variable (or variables if a multi-output approach is used) in the productivity model, which controls for the potential endogeneity problem.

Therefore, a household production model along the lines proposed by Chavas, Petrie and Roth (2005) 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 were calculated based on total production quantities and selling prices reported by the farmers. Off-farm earnings were 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 labor market, self-employment in the local non-farm sector, or employment in the farm labor market.

The literature shows that the variables that affect farm and household production most significantly can be classified into two broad groups: 1) farm characteristics; and 2) production inputs (Gorton and Davidova, 2004; Bravo-Ureta and Pinheiro 1997; Coelli and Battese, 1996). Specifically, the explanatory variables included in the frontier production models are: LAND; SLOPE; and, PURCHASED INPUTS equal to the total expenditure in variable inputs (US$) including the cost of seeds, fertilizer and pesticides. Total labor has been divided into three different categories. The labor used in farm production is disaggregated into FAMILY LABOR, measured in worker days, and HIRED LABOR, measured in US dollars. This division of agricultural labor is consistent with the view that, in developing countries, family and hired labor may not be perfect substitutes and thus should be considered separately in the characterization of a production function (Taylor and Adelman, 2004). In the absence of data on off-farm labor, the total number of people in the household over the age of 15 (ADULTS) was used as a proxy for labor availability. A similar approach can be found in Chavas, Petrie and Roth (2005). As in the probit model, the *dummy* variables PAES 1, PAES 2 and PAES 3 are included to account for any project effects. To correct for the potential selectivity bias the frontier functions include the self-selectivity variables W_1 and W_2, discussed in Section II.

Finally, the specification of the inefficiency effects component includes several socioeconomic, human and social capital variables selected based on the available data and on the literature (Gorton and Davidova, 2004; Coelli and Battese, 1996; Kalaitzandonakes and Dunn, 1995; Bravo-Ureta and Pinheiro, 1993). The variables AGE, EDUCATION and GENDER are included to account for any possible effect of farmers' characteristics on efficiency. In addition, FREQUENCY and YEARS are used to evaluate the effect of the extension program on this model, and the variables CREDIT, OWNERSHIP and PARTICIPATION are included as proxies for managerial ability and social capital. Table I presents a summary description of each variable used in the analysis.

IV. DATA

The data used in this study consist of detailed household-level information obtained from surveys administered to farmers participating in the PAES (El Salvador) and CAJON (Honduras) projects. These projects have sought to increase household 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, and environmental awareness programs.

The households included in the data set were selected randomly from lists of producers associated with each project and the interviews were conducted between May and August 2002. The data from El Salvador include a total of 530 farm 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 whole database has 740 observations; however, all surveys with missing or incomplete data necessary for this study were excluded from the analysis. Thus, the final data set encompasses a total of 639 observations[3].

Table II presents the descriptive statistics for the whole data set as well as for the two groups of households under analysis (i.e., households with high and low levels of investment in

[3] A thorough analysis of the deleted observations revealed no systematic pattern with respect to farm size, household income or any of the other key socioeconomic variables used in the analysis. In addition, the deleted observations are distributed evenly among the projects. Thus, no biases are expected from the data cleaning that was necessary to estimate the models for this study.

soil conservation). The descriptive statistics reveal several important points. For instance, the average total household income reaches $2,110.6 of which 25% comes from off-farm activities. The typical project participant operates about 6 Mz (4.2 hectares). In addition, most of the farmers (70%) own more than 50% of the land they operate, are middle-aged men (83%) and have very limited access to rural credit and formal education.

An interesting pattern is found between the two groups of households under analysis. In general, farms with a higher percentage of their land under soil conservation practices are the youngest, have a higher average level of education and higher household income. Conversely, the farms with a lower percentage of their land under soil conservation practices are larger and have higher levels of off-farm income. These statistics appears to confirm the findings presented by Solís and Bravo-Ureta (2005) and Sander, Southgate and Lee (1995) who suggest that, in less-developed countries, 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.

V. RESULTS AND DISCUSSION

This section presents the results obtained with the switching regression model. The next subsection describes the empirical results of the probit adoption model, followed by a discussion of the outcome of the efficiency analysis.

A. First-Stage: Probit Model

Table III presents the maximum likelihood estimates of the probit model. This table displays the estimated coefficients along with their respective marginal effects. Marginal effects measure the change in the probability of adoption due to a one unit change of a specific explanatory variable. The marginal effects 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 (STATA, 2003). By contrast, the marginal effects (M.E.) for the continuous variables are estimated using the following formula:

$$\text{M.E.} = \phi(\delta Z)\delta \qquad (12)$$

where ϕ is the probability density function, Z is the vector of exogenous variables and δ are the estimated parameters. The marginal effects are measured at the mean value of the regressors (Madalla, 1983).

As is shown in Table III, the model correctly predicts farmers' decision to invest in soil conservation practices for 75.2% of the observations. In addition, the likelihood ratio test reveals that jointly all slope coefficients are statistically different from zero at the 5% level. The main results of the probit model can be summarized as follows. Individually, eight 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, the average level of education of the household and the frequency of visits by an extensionist to the farm present 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 (Rogers, 1995; Feder and Umali, 1993).

OWNERSHIP displays a positive and significant effect on investments in soil conservation. Specifically, farmers who own most of the land they operate are 41% more likely to adopt soil conservation practices than those who either rent or have no legal title on their plots. Shultz, Faustino and Melgar (1997), and Lutz, Pagiola and Reiche (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), Lee and Stewart (1983), and de Herrera and Saín (1999).

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. More precisely, the former group of farmers has approximately 8% higher probability to invest in conservation than the latter group. These results suggest that environmental awareness is an important pre-condition for the adoption of conservation technologies. Similar findings have reported by Mbaga-Semgalawe and Fomer (2000), and Norris and Batie (1987).

LAND presents a negative and significant parameter revealing an inverse relationship between the probability to invest 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, Zegarra and Lavadenz (2003) indicate that, in developing countries, an imperfect rural land market can lead to smaller farms than desired and, in these cases, family labor is in abundance and available to implement alternative production methods. However, it is important to note that the opposite outcome was reported by Westra and Olson (1997), and Bonnard (1995).

The *dummy* variables PAES 1, PAES 2 and PAES 3 capture the individual effects of these projects with respect to the CAJON project (the omitted variable). 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 working 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 instance, PAES introduced an array of incentives, such as subsidies and cost sharing mechanisms, to assist farmers in the adoption process. On the other hand, CAJON only employed subsidized inputs on its extension programs.

B. Second-Stage: Productivity Analysis

Table VI contains the second-stage estimates of the switching regression model developed 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 analyze productivity among farms with corresponding levels of investments in soil conservation practices. These models include the self-selectivity variables W_1 and W_2 estimated from the results obtained in the fist-stage of this analysis. If self-selection is not present then the parameters associated with W_1 and W_2 are not statistically different from zero and the direct estimation of the production model for each group of farmers should yield unbiased estimates (Freeman, Ehui and Jabbar, 1998).

As mentioned in Section II, the incorporation of the self-selectivity variables into the productivity model introduces heteroscedasticity (Fuglie and Bosch, 1995). Therefore, the Lee, Maddala and Trost (1980) procedure was implemented to calculate the correct asymptotic covariance matrix in order to obtain robust estimates for the standard errors. Goetz (1990) indicates that even though this correction is typically avoided in the empirical literature, uncorrected standard errors could be overstated by more than 200% if the appropriate correction is not performed. For comparison, a SPF was also estimated for the entire sample (ALL).

The SPF models were estimated using the *translog* functional form given that in preliminary analyses the Cobb-Douglas specification was rejected. Following common practice, all variables in these models are normalized by their geometric mean prior to estimation. Thus, the first-order coefficients can be interpreted as partial production elasticities at the geometric mean of the sample (Alvarez and Arias, 2004). At the point of approximation, the three SPF models satisfy monotonicity and convexity. Monotonicity is verified by the positive value of all partial elasticities of production. On the other hand, the bordered Hessian matrixes, at the point of approximation, are negative semi-definite for all three models implying diminishing marginal productivities and thus convexity (Chambers, 1988).

The values for σ^2 and γ are reported at the end of Table VI. The null hypothesis that γ = 0 is rejected in all cases (Table V) which suggests that technical inefficiency is indeed stochastic. Moreover, the value for γ is statistically significant and ranges from 0.672 to 0.832, which indicates that inefficiency is highly significant in determining the output levels and variability.

The parameters for the 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 (i.e., σ_{10} and σ_{20}) have important economic interpretations. Assuming profit maximization, these authors conclude that if σ_{10} and σ_{20} display the same sign, which is the case reported in this analysis, households with higher levels of adoption of the new technology also have higher levels of total output. Thus, these results indicate that investing in soil conservation is an appropriate alternative for improving total household production among the sampled farmers.

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

In general, the estimated production elasticities follow similar patterns in the three estimated models; however, their magnitudes differ. Table VI shows that, at the geometric mean of the data, FAMILY LABOR and PURCHASED INPUTS contribute the most to the total value of household production. Specifically, model HIGH displays the largest partial elasticity for FAMILY LABOR, while model LOW presents the largest elasticity for PURCHASED INPUTS.

The three variables used to evaluate the effect of labor on output display positive parameters in all estimated models. Nevertheless, the statistical significance of these parameters varies among them. For instance, the parameters for FAMILY LABOR and ADULTS are statistically different from zero in all cases. However, the parameter for HIRED LABOR is significant only in model LOW. It is important to indicate that the effect of labor on productivity presents mix results in the literature. For example, González (2004), and López and Valdéz (2000) report positive and significant effects of labor on output among peasant farmers in Colombia and Central America, respectively. By contrast, no significant effects are reported by Alvarez and Arias (2004), Wadud and White (2000), Ahmad and Bravo-Ureta (1995), and Squires and Tabor (1991) in their studies in Northern Spain, Bangladesh, Northeastern USA and Indonesia, respectively.

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% rise in total cultivated area could increase total household production by 1.44%. Lastly, all project variables display positive coefficients suggesting that farmers associated with PAES (1, 2 and 3) have higher levels of productivity than those working with CAJON.

At the point of approximation, the returns to scale are equal to 0.87, 0.82 and 0.75 for models HIGH, ALL and LOW, respectively. These results suggest the presence of decreasing returns to scale (DRTS) among the sampled households. Chavas, Petrie and Roth (2005) indicate that in household-level analyses, the presence of DRTS implies that household resources are 'too large' for the technology implemented. Given that the farms under analysis are small in terms of land area, the source of DRTS is most likely due to the average number of adults per household. Chavas, Petrie and Roth (2005) suggest that this problem may be offset by promoting off-farm employment opportunities in the area.

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 households with higher levels of investment in soil conservation exhibit, on average, higher TE as well. These results also reveal considerable inefficiency levels where, on average, households could, in theory, reduce the level of inputs from 16.0% to 25.0% 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* (2004) 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 0.78.

Table VI also presents the determinants of technical inefficiency for each of the models estimated. Following common practice the interpretation of the parameters is performed with respect to their effect on efficiency. In doing so, the estimated coefficients are analyzed as if they display the inverse sign. As expected, EDUCATION and FREQUENCY display positive and statistically significant effects in all three models. Gorton and Davidova (2004), and Abdulai and Eberlin (2001) suggest that improvements in human capital enhance household efficiency by offering peasants the necessary means to achieve more with the available resources and the existing technology.

The gender of the household head affects TE significantly in all three models. More precisely, female-headed households present lower levels of efficiency than male-headed households. Similar outcomes have been reported by several authors including Deininger, Castagnini and González (2004), González (2004), Fleming and Lummani (2001), López and Valdés (2000), and different hypothesis have been proposed to explain this result. For instance, López and Valdés (2000) suggest that this finding does not necessarily mean that females are less efficient but 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 the access of women to information, land, capital and other inputs and this can adversely affect TE. This difference could also be explained by unmeasured non-economic activities performed by females in the household. 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, etc. However, to test this hypothesis detailed intrahousehold information is required, which is not available for this study; thus, this area merits further research.

CREDIT presents a positive effect on household efficiency but it is statistically significant only in the model LOW. The literature shows mixed results with regards to the effect of credit assistance on productivity (e.g., Deininger, Castagnini and González, 2004; Binam *et al,* 2003; Yadav and Rahman, 1994). Nonetheless, the outcomes of this analysis suggest that households with low levels of investment in soil conservation may be credit constrained. Therefore, extension programs should take advantage of this situation and focus credit assistance on this group of households where credit presents a positive and significant effect for 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 their production technologies. Nevertheless, this seemingly contradictory finding has been reported in other studies (e.g., Deininger, Castagnini and González, 2004; Binam *et al*, 2003; Byiringiro and Reardon, 1996, among others). Deininger, Zegarra and Lavadenz (2003) claim that this result could be explained by the prevalence of imperfect rural land markets, which may restrict access to land to farmers, including those that may be the most technically efficient in a given geographical area.

VI. SUMMARY AND CONCLUDING REMARKS

The purpose of this study was to assess the connection between the adoption of soil conservation practices on household technical efficiency by comparing two types of rural farm-households in hillside regions of Honduras and El Salvador. A switching regression approach was used to test if there is a systematic difference between households with high and low levels of investment in soil conservation. A specific methodological and empirical issue addressed on this paper is the determination of whether there is an unobserved mechanism at work that leads farmers to self-select into 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 model corrects for this potential self-selectivity problem using a two-stage procedure. First, a probit model is estimated to evaluate the variables affecting soil conservation investments among the sampled households. Then, based on the results of the probit model, a set of self-selectivity variables are estimated. Finally, those self-selectivity variables are introduced into two stochastic production frontiers to account for the potential self-selectivity problem and compute unbiased estimators. The empirical analysis corroborates previous assumptions that a systematic difference exists between the two groups of households under study.

The results can be summarized 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, land 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 levels of investments in soil conservation also exhibit higher average technical efficiency. These producers also 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 market failure in the land market in area under analysis. Deininger, Zegarra and Lavadenz (2003) claim that market failures in less-favorable areas denies 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 lower levels of investment in soil conservation display the highest elasticities for purchased inputs and hired labor. In addition, accessibility to financial credit is found to be a factor in explaining the sources of inefficiency, suggesting the presence of credit constraints. Thus, resource management programs should consider targeting credit programs to these households as a strategy for development and productivity improvement as well as for helping farmers to undertake the initial investments to adopt soil conservation techniques. Improved access to financial resources will also allow this group of farmers to acquire more inputs and to hire external labor.

All three models show positive and significant effects of education and extension on technical efficiency. 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 area should focus on improving farmers' human capital by supporting agricultural training, extension and educational programs.

Finally, households associated with the PAES projects not only show higher average levels of technical efficiency than those working with CAJON but they also display a higher probability of investing in soil conservation technologies. These differences are likely due to the unique strategies, methodologies and incentives used in each of the two projects. 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 data set, including a control group, than the one available for this study.

TABLE I

VARIABLE DEFINITION

Variable	Definition
Age	Age of the household head
Education	Average level of education for household's members ≥10 years old
Gender	1 if the household head is a man (*dummy*)
Family Size	Number of people in the household
Land	Total number of Manzanas devoted to agricultural production
Slope	1 if the average slope is greater than 15% (*dummy*)
Ownership	1 if the household owns more than 50% of the farm (*dummy*)
Frequency	Number of visits by an extensionist to the farm
Years	Number of years involve with the projects
Credit	1 if the household uses financial credit (*dummy*)
Perception	1 if farmer is aware of the erosion problem in the area
Participation	1 if the household head participate in an organization (*dummy*)
Household Income	Total household income (US$)
Off-Farm Income	Wage labor in off-farm activities (US$)
Purchased Inputs	Total expenditure in variable inputs (US$)
Family Labor	Total family labor (working days)
Hired Labor	Total hired labor (US$)
Adults	Number of people in the household over the age of 15
Practices	Percentage of total land with soil conservation practices
PAES 1	Household involved with PAES 1 (*dummy*)
PAES 2	Household involved with PAES 2 (*dummy*)
PAES 3	Household involved with PAES 3 (*dummy*)
CAJON	Household involved with CAJON (*dummy*)

TABLE II
Descriptive Statistics

Variable	All				High Level of Investment				Low Level of Investment			
	Mean	St Dev	Max	Min	Mean	St Dev	Max	Min	Mean	St Dev	Max	Min
Practices	0.5	0.5	1.0	0.0	0.7	0.7	1.0	0.5	0.3	0.2	0.6	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	--	--
Frequency	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	--	--	--
H. Income	2,110.6	2,763.6	40,131.6	110.3	2,347.9	3,134.9	40,131.6	200.0	1,860.4	2,286.8	26,313.8	110.3
Off-Farm Income	541.0	1,015.9	13,750.0	0.0	517.4	1,180.5	13,750.0	0.0	565.9	808.0	7,125.0	0.0
Purchased Inputs	657.8	997.6	13,727.2	42.0	799.9	1,286.5	13,727.2	44.4	507.9	508.5	4,183.3	42.0
Family Labor	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 Labor	20.3	33.5	360.3	0.0	24.6	40.4	360.3	0.0	15.6	23.4	171.9	0.0
Adults	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	--	--	--
CAJON	174	--	--	--	84	--	--	--	90	--	--	--
No. of Households	***639***				***328***				***311***			

TABLE III
First-Stage Probit Model

Variable[1]	Coefficient	St Error	Marginal Effect
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
Frequency	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.
[1] The dependent variable is a dichotomous variable reflecting the level of investment in soil conservation.

TABLE IV
Second-Stage Stochastic Production Functions

Variable[1]	Parameter	ALL		HIGH		LOW	
		Coef.	SD	Coef.	SD	Coef.	SD
Constant	β_0	-3.045***	*0.492*	-4.208***	*0.547*	-3.018***	*0.325*
Land	β_L	0.078*	*0.054*	0.144*	*0.080*	0.047*	*0.027*
Purchased Inputs	β_C	0.244***	*0.098*	0.243***	*0.098*	0.254***	*0.111*
Family Labor	β_F	0.312***	*0.048*	0.326***	*0.062*	0.228**	*0.108*
Hired Labor	β_H	0.109	*0.079*	0.076	*0.077*	0.144*	*0.080*
Adults	β_A	0.078*	*0.028*	0.089**	*0.038*	0.081**	*0.040*
Slope	β_S	0.009	*0.009*	0.011	*0.014*	0.005	*0.012*
W_1	σ_{10}	--	--	0.163*	*0.094*	--	--
W_2	σ_{20}	--	--	--	--	0.218*	*0.136*
PAES 1	β_1	0.301***	*0.082*	0.323***	*0.078*	0.277***	*0.083*
PAES 2	β_2	0.316***	*0.094*	0.322***	*0.071*	0.297***	*0.112*
PAES 3	β_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	δ_0	-2.985*	1.268	-2.794***	*0.757*	1.781*	*0.988*
Age	δ_A	0.007	0.012	0.002	*0.003*	0.005	*0.007*
Education	δ_E	-0.412***	0.175	-0.715**	*0.340*	-0.301**	*0.126*
Gender	δ_G	-0.996**	0.504	0.708**	*0.317*	-0.729**	*0.365*
Frequency	δ_V	-0.439*	0.237	-0.312*	*0.162*	0.201**	*0.088*
Years	δ_Y	0.104	0.154	0.031	*0.038*	0.036	*0.050*
Credit	δ_C	-0.215	0.447	-0.211	*0.196*	-0.227*	*0.134*
Ownership	δ_T	0.701	0.558	0.598*	*0.311*	0.111	*0.120*
Participation	δ_P	-0.235	0.344	-0.122	*0.136*	-0.076	*0.210*
Sigma-squared	σ^2	0.621***	*0.128*	0.842***	*0.111*	0.595***	*0.066*
Gamma	γ	0.805***	*0.051*	0.672***	*0.071*	0.832***	*0.048*
log-likelihood		-540.85		-675.36		-715.89	
Mean TE		***0.77***		***0.83***		***0.74***	
Returns to Scale		***0.82***		***0.87***		***0.75***	

* 10% level of significance, ** 5% level of significance, ***1% level of significance.

[1] The dependent variable is total household income, measured in US dollars.

TABLE V
Inefficiency Effects Hypothesis Testing

Models	Null Hypothesis	Test Statistic	Conclusion
ALL		34.28	Reject
HIGH	H_0: γ =0	27.63	Reject
LOW		28.34	Reject

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