MEASURING AND EXPLAINING FARM INEFFICIENCY IN A PANEL DATA SET OF MIXED FARMS

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ABSTRACT
This paper aims to estimate a translog stochastic frontier production function in the analysis of a panel of 150 mixed Catalan farms in the period 1989-1993, in order to attempt to measure and explain variation in technical inefficiency scores with a one-stage approach. The model uses gross value added as the output aggregate measure. Total employment, fixed capital, current assets, specific costs and overhead costs are introduced into the model as inputs. Stochastic frontier estimates are compared with those obtained using a linear programming method using a two-stage approach. The specification of the translog stochastic frontier model appears as an appropriate representation of the data, technical change was rejected and the technical inefficiency effects were statistically significant. The mean technical efficiency in the period analyzed was estimated to be 64.0%. Farm inefficiency levels were found significantly at 5% level and positively correlated with the number of economic size units.

Keywords: technical efficiency, stochastic frontier approach, agricultural economics, frontier productions, farm efficiency

JEL: C23

1. Introduction

The measurement of technical inefficiency in the agricultural sector of developing and developed countries has received renewed attention since the late eighties from an increasing number of researchers, as the frontier approaches to efficiency measurement have become more popular. There have been a vast number of applications of frontier methodologies to empirical studies at the farm-level data in a large number of countries. For a review of empirical applications in agricultural economics, see Battese (1992), Bravo-Ureta and Pinheiro (1993) and Coelli (1995).

The introduction of the frontier approach in agricultural economics has raised the level of analysis and broadened the range of efficiency hypotheses that can be formulated and tested. Empirical applications of the frontier approach in agricultural economics are clearly relevant in view of its important policy implications for developed and developing countries: i.e., investigating the effect of reforms upon various agricultural sectors, or the effect of public subsidies on technical efficiency and technical change, etc.

The production frontier approach to technical inefficiency measurement makes it possible to distinguish between shifts in technology from movements towards the *best-practice* frontier. By estimating the best-practice production function (an unobservable function) this approach calculates technical efficiency as the distance between the frontier and the observed output. Two different groups of techniques have been used to measure technical efficiency under the frontier approach, which differ in the assumptions imposed on the data: non-parametric linear programming techniques (Data Envelopment Analysis, DEA), and the parametric stochastic frontier approach (SFA).

The advantage of frontier analysis is that it provides an overall, objectively determined, numerical efficiency value and ranking of individual farms that is not otherwise available. The stochastic frontier approach allows observations to depart from the frontier due to both random error and inefficiency, whereas DEA-type models measure random error as part of inefficiency, that is, they confuse random error with inefficiency (any departure from the frontier is measured as inefficiency). In a survey of applications of frontiers to agriculture between 1985 and 1994, Coelli (1995) observed the dominance of parametric methods in the agricultural economics literature (28 of the 38 papers reviewed employed the stochastic frontier approach). The implicit assumption in DEA that all deviations from the frontier are due to inefficiency is difficult to sustain at the farm level in the presence of measurement error, missing variables, unmeasured environmental factors influencing production such as the weather, etc.

Technical inefficiency scores obtained from the production frontier approach have a very limited utility for policy and management purposes if empirical studies do not investigate the sources of inefficiency. Panel data studies also offer a number of significant potential advantages over cross-section studies in the estimation of production frontiers and the measurement of efficiency. In Table 1 we identify a number of studies on agricultural efficiency measurement that have appeared in economic journals since 1995. This does not constitute a comprehensive survey of frontier applications to agriculture; it lists only those papers applying a production frontier approach to individual farms and investigating the sources or factors explaining technical inefficiency using a panel data set. Those papers exploring temporal patterns of farm inefficiency scores but not their determinants are not included in Table 1. Papers analyzing the sources of inefficiency with aggregate production functions are also excluded (see Yao and Liu, 1998; or Tian and Wan, 2000, as interesting applications).

[Table 1]

Despite the growing number of papers devoted to efficiency measurement in agricultural economics in recent years, we identified only five studies examining farm-level efficiency and investigating the possible sources of inefficiency with panel data sets. As observed in previous literature reviews of agricultural efficiency, a large amount of published papers restrict their attention to efficiency measurement without considering its determinants. And, as previously noted, panel data sets are not predominant even among the more recent papers. Furthermore, as was observed in the surveys of Battese (1992) and Coelli (1995), this literature has focused its attention on farms located in developing countries. There is no clear reason why farms in developed countries have not deserved more interest among economics researchers, specially in view of the pervasive presence of many forms of government intervention in the agricultural sector of these countries.

As observed in Table 1, the stochastic production frontier is the predominant approach among those few studies investigating inefficiency sources in farm-level panel data sets. The parametric literature has investigated the determinants of technical inefficiency variation among farms by regressing the predicted inefficiencies (residual analysis), obtained from a stochastic frontier, upon a vector of farm-specific factors, such as firm size, age and education of manager, etc., in a two-stage approach (in Table 1: Ferrantino and Ferrier, 1995; Álvarez and González, 1998). Two-step procedures to estimate the determinants of technical inefficiency used in the parametric literature suffer from a fundamental contradiction. The second stage involves the specification of a regression model for the predicted technical inefficiency effects, which contradicts the identical and independent distribution assumption of the first stage. The Battese and Coelli (1995) inefficiency effects model overcomes this contradiction and allows the simultaneous estimation of the parameters of the stochastic frontier and the inefficiency model.

Some important issues appear in the application of production frontier techniques to farm-level panel data sets which may influence measured inefficiency. Misspecification in production frontier models for individual farms may arise as the result of error measurement, omitted outputs and input heterogeneity. Other problems may also be present, such as those related to the functional form or the specification of the strictly one-sided error term representing efficiency deviations from the frontier. Misspecification is partially accommodated by the random error term in the non-frontier production function. However, in parametric frontier estimates, specification biases are quite likely to influence the systematic part of the composable error term, thereby biasing the level and distribution of the efficiency residual.

Specification biases in farm-level frontier functions may arise from choosing which variables to include and exclude from the model, how disaggregated these variables should be, and how much structure to impose on their hypothesized relationship with output. In general, farms are multi-output firms, with varying degrees of concentration of their production in some specific products. However, this fact has received little attention in the agricultural frontier literature. Non-parametric approaches such as DEA perform well when production involves more than one product, but they are deterministic. However, stochastic production frontiers applied in agricultural economics used only one output measure, ignoring multi-output production. In most previous studies, this problem has been overcome by restricting the frontier identification and efficiency comparisons to those farms specialized in the production of the same products. In this case, output is represented by one variable that is measured in physical units (quantities of rice, wheat, corn, milk, etc.).

In order to account for multi-output farm production and to allow building production frontiers for firms in the agricultural sector that produce a mixed range of products or that are specialized in different products, monetary values of agricultural output could be proposed. The advantage of using monetary values of agricultural output is that they accommodate the fact that farms are involved in several agricultural activities. Notwithstanding, in this latter case the researcher has to choose which monetary measure of agricultural output, between those employed in economic accounts, to use: total output, gross output, final output or agricultural value added (Ay and Prasada Rao, 1992). Battese and Coelli (1995) used the total value of output to deal with this problem, but the value added would be more in line with national accounts criteria. However, the other papers surveyed in Table 1 used physical measures of output. The use of monetary measures of output has implications for the interpretation of inefficiency scores: they tend to reflect not only technical inefficiency but a mixture of technical and allocative inefficiency in production.

Another issue that has received little attention in this literature is the presence of input heterogeneity. The level of aggregation in the measurement of inputs imposed by data availability is the cause of this type of problem. The use of aggregate physical input measures usually makes it impossible to measure differences in input quality such as soil quality, machinery, equipment, etc. In many cases, rough physical measures such as the number of cows are used as a proxy of capital. A possible solution to reduce input heterogeneity problems is to obtain accurate monetary measures of all the inputs used in the production process and, especially, accurate economic information on fixed and variable capital. As farms make little use of accounting (Poppe, 1991), this alternative to heterogeneous physical input measures requires the availability of sophisticated economic databases that are uncommon in the agricultural sector. In addition, the use of monetary input values in estimating inefficiency scores also contributes to obtaining production inefficiency measures rather than technical inefficiency scores.

The principal aim of this paper is to estimate a translog stochastic frontier production function in the analysis of 150 mixed Catalan farms in the period 1989-1993, in order to attempt to measure and explain variation in technical inefficiency scores with a one-stage approach. The model uses gross value added as the output aggregate measure. Total employment, fixed capital, current assets, specific costs and overhead costs are introduced into the model as inputs. Monetary output and input measures are obtained following the methodology of the Farm Accountancy Data Network (FADN) procedures established by the European Commission. The model allows technical inefficiency to vary over time, and inefficiency effects to be a function of a wide set of explanatory variables, in which size and specialization play an important role.

This study differs from previous works on efficiency and productivity measurement in the agricultural sector in two respects. First, it estimates stochastic inefficiency scores for a panel data set of mixed individual farms in a European Community country using accurate accounting input and output information from the FADN. And, second, it applies to a panel of individual mixed farms in a developed country the approach developed by Battese and Coelli (1995) in which the inefficiency effects are modeled as an explicit function of a number of firm-specific and environmental variables (i.e., location, concentration, specialization, size, public subsidies, etc.) which are thought to influence the level of technical inefficiency.

Technical inefficiency scores obtained by estimating the stochastic function are also compared with those obtained using a non-parametric and non-stochastic approach, Data Envelopment Analysis (DEA). Other studies have compared the efficiency scores and rank correlations between these methods or measured the consistency of the methods in identifying the units in the most and least efficient quartiles.

To our knowledge, this paper is the first to estimate technical efficiency for a sample of farms that are not specialized in the same product, using homogeneous and reliable accounting input and output measures. It is also the first to estimate the sources of inefficiency with the Battese and Coelli (1995) model for a panel data set of farms located in a developed country.

The paper continues with the following structure. Section 2 outlines the stochastic frontier approach with the inefficiency effects model. The empirical specification of the model is presented in Section 3. Empirical results derived from this model and discussion are presented in Section 4. The empirical results allow us to present efficiency scores, and factors explaining efficiency. The final section summarizes the findings of this research.

2. The Stochastic Production Frontier Function

Our method constructs a best-practice frontier from the data in the sample (i.e., we construct a frontier for the sample of observation units and compare individual farms with that frontier). Frontier approaches do not necessarily observe the *true* (unobserved) technological frontier, only the best-practice reference technology. An observation is technically inefficient if it does not minimize its input given its output. Efficiency scores of unity imply that the individual farms in a given year (the unit of observation) are on the frontier in the associated year. Efficiency scores lower than unity imply that the farm is below the frontier: in this case, a further proportional increase in output is feasible, given productive factor quantities and technology. We assume that each farm attempts to maximize output from a given set of inputs.

We consider a panel data model for inefficiency effects in stochastic production frontiers based on the Battese and Coelli (1995) model. Our stochastic production frontier model allows: (i) technical inefficiency and input elasticities to vary over time in order to detect changes in the production structure; and (ii) inefficiency effects to be a function of a set of explanatory variables the parameters of which are estimated simultaneously with the stochastic frontier. Time-invariant efficiency would be an unrealistic assumption given that elimination of slack compresses the efficiency distribution, while generation of slack works the opposite way (Kumbhakar et al., 1997). The approach is stochastic, and farms can be off the frontier because they are inefficient or because of random shocks or measurement errors. Efficiency is measured by separating the efficiency component from the overall error term.

Having data for i farms in year t for input and output data (X_{it}, Y_{it}), the stochastic frontier production function model with panel data is written as:

$$Y_{it} = f(X_{it}; \boldsymbol{b}_t) \cdot e^{(V_i - U_{it})} \qquad (1)$$

where Y_{it} is the farm output at the t-th observation (t=1,2,...,T) for the i-th farm (i=1,2,...,n);

f(·) represents the production technology;

X_{it} is a vector of input quantities of the i-th farm in the t-th time period;

β_t is a vector of unknown parameters in the t-th time period;

V_{it} are assumed to be independent and identically distributed random errors, which have normal distribution with mean zero and unknown variance σ^2_V);

U_{it} are non-negative unobservable random variables associated with the technical inefficiency in production, such that, for the given technology and level of input, the observed output falls short of its potential output.

In the technical inefficiency effects model the error term is composed of the following two components: technical inefficiency effect and statistical noise. A farm-specific effect is not explicitly considered in the estimated production function model because it would be considered as *persistent* technical inefficiency, which implies that we do not consider the existence of unobserved systematic effects which vary across states in the production function (Heshmati et al., 1995).

The technical inefficiency effect, U_{it}, could be specified as:

$$U_{it} = z_{it}\boldsymbol{d} + W_{it} \qquad (2)$$

where U_{it} are non-negative random variables which are assumed to be independently distributed as truncations at zero of the $N(m_{it}, \sigma^2_U)$ distribution;

m_{it} is a vector of farm-specific effects, with $m_{it}=z_{it}\delta$;

z_{it} is a vector of variables which may influence the efficiency of the farm;

δ is a vector of parameters to be estimated;

W_{it}, the random variable, is defined by the truncation of the normal distribution with mean zero and variance σ^2, such that the point of truncation is $-z_{it}\delta$.

An estimated measure of technical efficiency for the i-th farm in the t-th time period may be obtained as:

$$TE_{it} = \exp(U_{it}) \qquad (3)$$

The unobservable quantity U_{it} may be obtained from its conditional expectation given the observable value of $(V_{it}+U_{it})$ (Jondrow et al., 1982; Battese and Coelli, 1988).

Inefficiency scores obtained from the stochastic translog production frontier are compared with those obtained using a linear programming approach. In this study we also use a non-parametric method based on Data Envelopment Analysis (DEA) to compute efficiency scores in the described panel data set. DEA is a linear programming methodology which uses data on the input and output quantities of a group of states to construct a piece-wise linear surface over the data points. A detailed description of the DEA approach to efficiency measurement may be found in Färe, Grosskopf, and Lovell (1994). This frontier surface is constructed by solving a sequence of linear programming problems, one for each state in the sample. In the output oriented case, the DEA method seeks the maximum proportional increase in output production, with fixed input levels.

Having data for i farms in the time period analyzed, the linear programming problem that is solved for the i-th farm in year t, having input and output data (x^{it}, y^{it}), in an output orientated DEA model with variable returns (VRS) to scale, is computed as follows (Färe, Grosskopf, and Lovell, 1994):

$$
\begin{aligned}
& \max_{\lambda,\phi} \ \phi \\
\text{subject to} \quad & -\phi y^{it} + Y\lambda \geq 0 \qquad (5) \\
& x^{it} - X\lambda \geq 0 \\
& e^{T}\lambda = 1 \\
& \lambda \geq 0
\end{aligned}
$$

where X is a matrix of input quantities for all farms in year t,
Y is a matrix of output quantities for all farms in year t,
x^{it} is a vector of input quantities for the i-th farm and year t,
y^{it} is a vector of output quantities for the i-th farm and year t,
λ is a vector of weights,
e^{T} is a row vector of ones, and
ϕ is a scalar.

ϕ^{-1} is a technical efficiency score which varies between zero and one. In the non-parametric programming approach, any departure from the frontier is considered as inefficiency.

3. Empirical Specification

Data.- Our data consists of a panel of observations on 150 mixed farms in Catalonia (Spain) from 1989 to 1993. The source of information is the FADN. The FADN provides annual statistics on the state of agriculture in the EU based on a sample of almost 60,000 EU farms. Data are collected by surveying a rotating sample of farms. The FADN's field of observation covers professional farms as defined in the farm structure survey of the EU, and excludes smaller farms below FADN thresholds. A full description of FADN procedures and methodology can be found in European Commission (1990, 1997, 1998). All data of farms in the FADN are tested and follow the same methodology and accounting standards. The FADN provides the most suitable data for our study that is currently available.

The “Xarxa Comptable Agrària de Catalunya” (XCAC) is the subsidiary of the FADN in Catalonia, Spain, and follows its methodology. The XCAC provided us with data relating to the performance of 180 individual Catalan farms from 1989 to 1993. Omitted variables and unreliable information reduced the panel data set to 150 observations.

Table 2 identifies the variables in the analysis, and also shows summary statistics.

[Table 2]

Variables in the production function model.- The specification of a production function requires the definition of only two types of variables: the output of farm production and the inputs employed in the production process. Empirical measurement of output in agricultural production is not as controversial as it could be in services production, but the agriculture literature on production functions offers a range from physical quantities of output to the monetary value of the output. As has been previously argued in this paper, given multi-output production we reject physical quantities of output as a measurement tool. Instead, we use gross farm income (GFI) as the output measure of farm production. As the European Commission (1991a:34) states, gross farm income is a concept close to value added (GVA), according to national accounts criteria of value added in a nation or industry. Farm output is an inappropriate measure to compare low levels of output of extensive farms with intensive farms presenting high outputs and intermediate consumptions. In contrast with farm output, GFI allows comparisons between extensive and intensive farms. In our case, we consider that gross farm income has the advantage of including in the output measure subsidies arising from current productive activity, given that the EU agricultural policy relies heavily on subsidies. This indicator corresponds to the payment for fixed factors of production supplied by the agricultural sector, whether they be external or family factors. As a result, holdings can be compared irrespective of the family/non-family nature of the factors of production employed. The output measure has been deflated using the agricultural GDP deflator and it has been expressed in 1989 pesetas.

Inputs employed in farm production are represented in this study by five variables: fixed capital (FIXEDK), current assets (CURRASSETS), annual work units (AWU), specific costs (SPECIFCOSTS), and overhead costs (OVERHEAD). Four of these variables are measured in monetary terms in order to avoid quality differences in input measures (input heterogeneity), as observed in other studies, and to allow inclusion of all inputs employed in the production process. All monetary values have been expressed in 1989 pesetas and are deflated by the most suitable category in the series of input prices paid by the agricultural sector published by Spanish Agricultural Ministry. The advantage of using monetary values as input measures is that we obtain a measure that is closer to productive efficiency than to technical efficiency, given that input paid prices may affect the inefficiency measures.

FIXEDK is the amount of fixed assets employed by the farm. It includes monetary values of agricultural land, forest capital, buildings, machinery and values at closing valuation of breeding livestock. CURRASSETS is the amount of current assets employed by the farm. It includes monetary values at closing valuation of all non-breeding livestock and crop and livestock products, and other circulating capital, such as amounts receivable in the short term and cash balances.

AWU is the total labor input employed by the farm, family labor included, expressed in annual work units, which means full-time worker equivalents in the region under consideration and on the same type of holding. A person who spends his entire annual working time employed on the holding represents one annual unit, even if his actual working time exceeds the mentioned normal annual working time.

SPECIFCOSTS is the amount of supply costs linked to specific lines of production. It includes monetary values of the cost of crop-specific inputs (for example, seeds, fertilizers, crop protection, etc.), feed and other livestock-specific costs, and specific forestry costs.

OVERHEAD is the amount of supply costs linked to productive activity but not linked to specific lines of production. It includes monetary values of current costs of machinery and buildings, energy expenses, costs linked to contractors, water, insurance and other farming overheads.

The average temporal evolution of inputs and outputs of the 150 Catalan farms is depicted in Table 3.

[Table 3]

Variables in the inefficiency effects model.- In our model, unexplained systematic production differences are attributed to inefficiency. Several types of factors may explain inefficiency variation.

We define 15 environmental factors grouped into 5 categories that may potentially explain the level of inefficiency:

- Group1: General information on the farm
    - Age of the farmer (AGE)
    - Percent of family work units to annual work units (FWU/AWU)
    - Economic size units (ESU)
- Group 2: Characteristics of farm production
    - Extensive farming (EXTENSCR)
    - Permanent crops (PERMCROP)
    - Dairy and drystock (DAIRYDRY)
    - Pigs and poultry (PIGPOULT)
    - Herfindhal concentration index (CONCHERZ)
    - McBean Index of production stability (MCBEAN)
- Group 3: Tenancy and characteristics of utilized agricultural area
    - Percent of rented utilized agricultural area (RENTEDUA)
    - Percent of irrigated utilized agricultural area (IRRUAA)
- Group 4: Farm location
    - Location in mountain zone (MOUNTZO)
    - Location in less favored zone (LESSFAZO)
- Group 5: Financial status
    - Percent of current subsidies on total output (CURRSUBS)
    - Ratio of debt to assets (LIABILTO)

AGE is expressed in years and it is an indicator of experience. FWU/AWU indicates the family orientation of the farm. Thus, low values in this ratio mean professional farmers managing modern farms with a substantial amount of hired labor. The European Commission (1991a) found this variable interesting and valuable. It is expected that more experienced and professional farmers will have better skills enabling more effective decision making and assuring the efficiency of their farms.

ESU is a standard measure of size used in the FADN methodology. Size is poorly assessed with physical measures such as utilized agricultural area or livestock units. However, monetary values of farm output are a misleading indicator of size, because they are influenced by windfall market prices included in output valuation. The ESU defines the economic size of an agricultural holding on the basis of its potential gross added value (total standard gross margin). To determine the total standard gross margin, coefficients established at the level of the different regions of the Union for the different lines of productions are taken as a basis. The total standard gross margin, expressed in ECU's, is divided by the ESU coefficient, which corresponds to ECU 1200. In the context of the existing family farms predominant in Western agriculture, large farms allow economies of scale due to large-scale production. Larger farms can advantageously adopt technological advances and innovations. Larger size entails better capital and technological endowments, which result in better farm performance and efficiency.

Four dummy variables indicate the type of farming of farms in the sample. Farms where the predominant type of farming is extensive crops are indicated with EXTENSCR, permanent crops and horticulture with PERMCROP, dairy and drystock farming with DAIRYDRY, pigs and poultry farming with PIGPOULT, and mixed farming with the dummy variable omitted.

CONCHERZ indicates the output concentration of a farm, calculated by means of the Herfindahl index with the values of 22 different items of farm output. Allen and Lueck (1998) argue that random production shocks from nature and market risks generate opportunities for product diversification in farms. This mitigates the reduction in income produced by random effects even though it may reduce farm efficiency. MCBEAN is an indicator of production stability, measured with the McBean Index. This is the average difference between the farm output in individual years and the three-year moving average centered on the same year, expressed as a percentage of the moving average. The calculation offers a single value for every farm in the whole five-year period, showing a higher value for higher output instability. The European Commission (1993) found that it is a useful measure of the stability of farm income and production around a trend. We hypothesize that high output instability generates inefficiency.

RENTEDUA indicates the percentage of utilized agricultural area of the farm. Farmers will be unlikely to invest in land improvements of rented land, thus contributing to inefficiency. IRRUAA indicates the percentage of irrigated utilized agricultural area of the holding. Dry weather and water shortages handicap farming in Mediterranean countries, because they limit farms to a few types of farming and reduce farm productivity. Higher inefficiency is expected for higher values of this variable.

We use the dummy variables LESSFAZO and MOUNTZO to refer to farm location in less favored and mountain zones respectively, while the omission of the dummy variable indicates farms located in normal zones. The FADN classifies agricultural holdings in less favored or mountain zones, when the majority of the agricultural area of the holdings are situated in these areas within the meaning of Article 3(4) and (5) of Directive 75/268/ECC. It is expected that farms situated in less favored and mountain zones will be less efficient, because they are handicapped by low potential for crop diversification, and poorly endowed in terms of infrastructure and services, etc. The European Commission (1994) found better performance on farms located in normal zones than those located in these areas.

The percentage of current subsidies on total output (CURRSUBS) indicates the relative importance of current subsidies in a farm. This variable is included in the model because gross farm income includes current subsidies received by farms, and they are an important share of income in some farms (European Commission, 1994).

The ratio of debt to assets (LIABILTO) is a classical indicator of debt burdens. The financial structure of farms is not related with their economic efficiency, but heavily indebted farms with financial burdens are highly vulnerable to the frequent random effects that lead to shortfalls in income. When a farm faces a reduction in its revenues because prices fall or the climate affects production, income and cash flow subsequently fall. The farm is unable to service its debts. Consequently, the farm needs to increase debts or obtain liquidity through land sales, by depleting inventories or effecting disadvantageous sales. This was noted by Foster and Rauser (1991), who found that financially stressed farmers take inefficient decisions. We hypothesize that indebtedness will contribute to farm inefficiency.

Table 4 presents the temporal evolution of factors explaining inefficiency.

[Table 4]

Specification of the production function model.- To render the model operational and to limit the restrictive properties imposed on the production process, the following translog production function is chosen and tested against the restricted Cobb-Douglas functional form:

where y is the log of gross value added, and x is a vector of the logarithms of the 5 inputs

$$y_{it} = \boldsymbol{b}_0 + \sum_{j=1}^{5} \boldsymbol{b}_j x_{jit} + \boldsymbol{b}_t t + \sum_{j=1}^{5} \sum_{h=1}^{5} \boldsymbol{b}_{jh} x_{jit} x_{hit} + \boldsymbol{b}_{tt} t^2 +$$

$$+ \sum_{j=1}^{5} \boldsymbol{b}_{jt} x_{jit} t + V_{it} + U_{it}, \quad (3)$$

considered; and where the technological change can be specified as an additional input (time trend, t) representing the rate of technical change or the shift in the production function over time. This specification makes it possible to consider time varying coefficients, and non-neutral technical change.

4. Results

4.1 Estimates of the Production Function

Following Battese and Coelli (1995) maximum likelihood estimation (performed using FRONTIER 4.1; Coelli, 1996) was employed to simultaneously estimate the parameters of the stochastic production frontier and the technical inefficiency effects model. The program automatically checks the OLS residuals for correct skewness before proceeding to a maximum likelihood estimate of the frontier. The results of this procedure corresponding to the translog production function are presented in Table 5. The variance parameters are expressed in terms of $\gamma \equiv \sigma^2_U / (\sigma^2_U + \sigma^2_V)$. The estimates of the first-order coefficients of the variables in the translog function cannot be directly interpreted as output elasticities.

[Table 5]

A number of statistical tests were carried out to identify the appropriate functional forms and the presence of inefficiency and its trend. As a misspecification analysis we used the log-likelihood ratio tests (LR) (Kumbhakar et al., 1997). LR tests were performed to test various null hypotheses as listed in Table 6. The first test shows that, given the specification of the technical inefficiency effects model, the null hypothesis that the Cobb-Douglas functional form is preferred to the translog is rejected. The null hypothesis is rejected by the test at the 5% level and hence all results presented here refer solely to the translog. Also, in test 2, the null hypothesis that there is no technical change in the period 1989-1993 for production in Catalan farms is accepted. Hence, technical change is not present in the preferred model presented in Table 5.

Tweeten (1969) observed that the persistence of low resource returns in agriculture is a complex matter, but it is mainly explained by the possibility of adopting economies of size. He said that technical changes and increasing productivity in agriculture are related to the ability of farmers to expand their farms, which, in its turn, depends on the rate at which farmers can abandon farming and find employment outside agriculture. The fact that our data corresponds to a period of recession partly explains our finding of the absence of technical change. This is in accordance with the results of Ball et al. (1991), who found significant technical change for each member country of the European Union from 1967 to 1988, but the rate of cost reduction achieved by adopting best-practice techniques slowed dramatically by the late 1980's. On the other hand, as Schmitt (1991) argues, since most farm tasks are not susceptible to supervision or monitoring, the enlargement of farms is limited to family governance, a fact that limits increases in farm size and technical change. Finally, the persistence and spread of part-time farming allows the existence of inefficient farms and hinders the introduction of technical change in the agricultural sector.

The null hypothesis explored in test 3 is that each farm is operating on the technically efficient frontier and that the systematic and random technical inefficiency effects are zero. The null hypothesis that γ is zero is rejected, suggesting that inefficiency was present in production and that the *average* production function is not an appropriate representation of the data. The estimate of γ indicates that the proportion of the one-sided error component in the total variance of the composed error term is as high as 91%. Thus, inefficiencies in production are the dominant source of random errors.

Finally, tests 4 and 5 consider the null hypothesis that the inefficiency effects are not a function of the explanatory variables. Again, the null hypothesis is rejected, confirming that the joint effect of these variables on technical inefficiency is statistically significant. However, the null hypothesis that the constant term in the inefficiency effects model is zero is accepted, and therefore it is not included in the preferred model.

[Table 6]

Since the coefficients of the translog production functions do not have any direct interpretation, we calculate the elasticities of output with respect to each of the inputs as the first derivative of the output with respect to each input. Input elasticities vary both over time and between farms. The elasticity of scale (returns to scale) is calculated from the sum of the input elasticities. In Table 7 we report mean input elasticities and returns to scale. The signs of the elasticities conformed to expectations. Standard errors of these elasticities are also reported in Table 7. Since the t-statistics based on the estimated elasticities and their standard errors are around 2 for variable capital, labor and overheads, the hypothesis of zero input elasticity is rejected for these inputs. However, this hypothesis cannot be rejected in the case of fixed capital and specific inputs. The mean value of the short-run elasticity of scale (RTS) is near unity, suggesting that Catalan farms operate with constant returns to scale. The hypothesis of unitary returns to scale cannot be rejected at the 5% level.

[Table 7]

The mean technical efficiency of the 150 Catalan farms in the period 1989-1993 is estimated to be 64.0% (Table 8). That is, over the period analyzed, the average farm produced only 64.0% of maximum attainable output. Mean efficiency by year presents an overall decreasing trend from 1990 to 1993. Average efficiency by year decreased from the highest level in 1990 (0.671) to the lowest level in 1993 (0.605). This means that, according to the stochastic production frontier, the contribution of the efficiency change to total factor productivity after 1990 was a reduction in productivity growth.

[Table 8]

To test the robustness of the efficiency scores obtained from the stochastic frontier, efficiency measures for each state in each period were computed using the DEA linear programming approach. We compare the efficiency scores and rank correlations between the two methods. The average technical efficiency scores using the linear programming method is 0.614. Average DEA efficiency scores for each year between 1989 and 1993 are lower than those obtained from the stochastic frontier (Table 8). The results in Table 8 show that the choice of methodology has an important impact on the average efficiency scores. DEA efficiency scores are much lower than those obtained from the stochastic frontier. DEA estimates are lower because the stochastic frontier approach allows farms to depart from the frontier due to both random error and inefficiency, whereas DEA measures random error as part of inefficiency.

Comparison of the scores obtained from the two methods indicates that the choice of methodology has a major effect on the estimated average efficiency scores. More important than the absolute values of the scores is the ranking of farms in terms of efficiency. Kendall's tau statistic and Spearman's rho statistic are presented along with the mean efficiency scores for the stochastic and linear programming efficiency measures in Table 8. Both the rank correlation coefficient and Kendall's tau statistic indicated that the null hypothesis of no significant correlation between the two efficiency measures is rejected at the 5% significance level considering the mean of all years. Thus, even though the non-parametric method produces lower efficiency scores than the econometric model, they produce comparable efficiency rankings for the average scores.

4.2 Estimates of the Inefficiency Function

Given the differences in efficiency between farms, it is appropriate to ask why some farms achieve a relatively high efficiency score whilst others are less efficient. The inefficiency function provides some explanations for variation in efficiency levels between Catalan farms in the period 1989-1993. It should be noted that since the explained variable in the inefficiency function is the mode of inefficiency, a positive sign on a parameter in Table 5 indicates that the associated variable has a negative effect on efficiency and a negative sign indicates a positive efficiency effect. Thus, farms with a larger size (economic size units) tend to be more efficient. Economic size (ESU) appears as the only significant variable at the 5% level in the inefficiency effects model. These results confirm our expectations that larger size entails better capital and technological endowments, which result in better farm performance and efficiency.

Table 9 reinforces this conclusion: larger farms are more efficient, for the average of all years and almost invariably for every year. It suggests the existence of economies of scale. Kalaitzandonakes et al. (1992) built a latent variable model to reconcile the lack of clear evidence between firm size and technical efficiency from previous studies. They supported a positive relationship between the two variables with a study of a sample of 50 Missouri grain farms. They suggested that this relationship does not reflect exploitation of scale economies, but merely suggests that firm size summarizes the effects of factors that are directly related with both technical efficiency and firm growth, for example, entrepreneurial ability, education, farming experience and other personal attributes of the firm manager. We explicitly sought to include other available variables in the model in order to isolate the influence of size, and our findings seem to confirm the exploitation of economies of scale. However, we cannot rule out the possibility that size summarizes other hidden information not included in the inefficiency effects model.

On the other hand, different measures of size have traditionally been found to be positively correlated with viability (Adelaja and Rose, 1988) and with higher farm income (Brangeon et al., 1994). The studies of the European Commission (1991a, 1991b) also found better performance and viability for larger farms, where the size was measured in ESU.

At a lower level of significance, the variables RENTEDUA and PERMCROP appear as positively and negatively, respectively, associated with farm inefficiency. The significant positive relationship of RENTEDUA confirms our expectations that farms with a large proportion of rented land would show low efficiency, because farmers will be unlikely to invest in land improvements of rented land. The significant relationship between farms with predominantly permanent crops and efficiency with respect to farms with mixed farming confirms the preference that is felt for specialization in intensive crop farming in Catalonia, when a minimum amount of arable land, preferably irrigated, and a minimum amount of funds for investment are available. When this is not the case, farmers mix intensive crops with livestock, which do not need arable land. Furthermore, specialization in extensive crops, or combinations of extensive with intensive crops, is a practice for old farmers who do not expect the next generation to continue in the holding. When possible, farmers specialize in more efficient intensive crops.

The non-significant relationship between IRRUAA and efficiency suggests that the availability of irrigated land is less important than the size and the type of farming applied to the land. The non-significant relationship between CONCHERZ and efficiency suggests that specialization is less important than the type of farming in which the specialization is applied.

Our hypotheses about farm location and instability of output are not confirmed. A possible explanation for this is that, after years of decreasing in the number of farms in mountain and less favored areas, the remaining farms make use of large amounts of agricultural land and resources. They have reached an efficient size. In addition, insurance policies adopted by farmers and product diversification mitigate the effects of output instability.

The non-significant relationship for variable CURRSUBS suggests that the CAP criteria for subsidies are more closely related to assuring farm income than efficiency. The results reveal that the financial structure of the farm does not interfere with its efficiency.

The non-significance of the variable AGE suggests the complexity of measuring experience with the variable AGE. Experience provides management skills, but the most experienced and aged farmers usually have a low education level. Research by Wadsworth and Bravo-Ureta (1992) and Brangeon et al. (1994) found a threshold of farmer age at which the probability of failure is the lowest and beyond which it increases again. As we could not obtain data on the educational level of the farmers in our sample, the results of variable AGE may summarize some hidden information.

[Table 9]

5. Conclusion

This paper set out to provide estimates of inefficiency in a panel of mixed Catalan farms and to explain variation in inefficiency between farms through decisions concerning a wide range of environmental factors. A translog stochastic frontier production function with inefficiency effects is applied. The results indicate that inefficiency was present in production, and that the traditional *average* response function and the Cobb-Douglas functional form are not an appropriate representation of the data. Parametric and non-parametric estimation methods have been evaluated using two criteria: average efficiency scores, and rank correlation of efficiency scores.

The findings indicate that the choice of efficiency estimation method can make a significant difference in relation to average efficiencies. DEA estimates are expected to be lower in general than econometric estimates. Also, the rankings are only partially well preserved between the econometric and mathematical programming method.

Technical change in the mixed Catalan farms over the period analyzed is rejected at the 5% level. Thus, our results indicate that farm technology was stagnant over the period. Consequently, output change can only be attributed to input change or efficiency change. Significant input elasticities at the 5% level are obtained for variable capital, labor and overheads. However, input elasticities are not different from zero at the 5% level for fixed capital and specific costs. The hypothesis of unitary returns to scale cannot be rejected.

The mean technical efficiency is estimated to be only 64.0% according to the stochastic production frontier. The results of the inefficiency effects model suggest that economies of scale represented by the number of economic size units (ESU) is negatively correlated with inefficiency. ESU is the only variable in the inefficiency effects model that is significant at the 5% level. The one-sided error component representing inefficiency accounts for 91% of the error term.

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Table 1. **Some Recent Applications of Stochastic Production Frontiers (SPF) to Farm-Level Efficiency Measurement**

Authors (year)	Method	Observation units	Output (s)	Inputs	Possible determinants of inefficiency
Ferrantino and Ferrier (1995)	SPF with a residual analysis (two-stage approach)	239 firms in the Indian vacuum-pan sugar industry, 1980-81 to 1984-85	Sugar (metric tons)	Milling capacity; boiling capacity; generating capacity; sucrose in cane	Organizational form (private, cooperative or public); length of the factory's crushing season in days (duration); experience; Domestic equipment only; foreign equipment only
Battese and Coelli (1995; 1996)	SFP with technical inefficiency effects (one-stage approach)	125 Indian paddy farmers, 1975-76 to 1984-85	Monetary value of output	Land; proportion of irrigated land; labor; bullocks; non-labor costs	Age; schooling; year
Battese, Malik and Gill (1996)	SPF with technical inefficiency effects (one-stage approach)	139 wheat farmers in Pakistan, 1986-87 to 1988-89 and 1990-91	Wheat harvested	Land; labor; amount of hired labor; fertilizer (dummy); hours of land preparation; tractor, plowings; wheat seed sown; owner/tenant; year	Age; school; adult (ratio of adult males to the total household size); year
Battese and Broca (1997)	SPF with technical inefficiency effects (one-stage approach)	80 wheat farmers in Pakistan, 1986-87 to 1988-89 and 1990-91	Wheat harvested	Fertilizer (dummy); land; labor; wheat seed sown; year	Age; school; owner/tenant; constrained by credit availability; year
Álvarez and González (1998)	SPF with residual analysis (two-stage approach)	82 Spanish dairy farms, 1986-1995	Milk	Labor cost; land; cows; feed cost; forage cost	Age; artificial meadow; genetic level; silo; other familiar income sources; area

Table 2. **Summary Statistics for Variables in the Stochastic Frontier Models (n=750)**

Variable	*Sample Mean*	*Standard Deviation*	*Minimum*	*Maximum*
Gross Farm Income (GFI)	2886359.9	2994909.2	59435.9	28192436.0
Fixed Capital (FIXEDK)	21119861.0	23892971.7	835330.0	202029101
Current assets (CURRASSETS)	5466574.2	6819053.8	22010.0	42136360.0
Annual work units (AWU)	1.53	0.73	0.36	5.06
Specific costs (SPECIFCOSTS)	5432896.9	6819053.8	6709.0	59669208.0
Overhead costs (OVERHEAD)	846171.5	997886.1	7768.0	7632975.0
Age of the farmer (AGE)	47.19	11.15	19.00	70.00
Family work units (FWU)	89.50	19.06	0.00	100.00
Herfindhal concentration index (CONCHERZ)	0.58	0.23	0.10	1.00
% of rented utilized agricultural area (RENTEDUA)	7.87	21.46	0.00	100.00
% of irrigated utilized agricultural area (IRRUAA)	33.39	41.05	0.00	100.00
Location in mountain zone (MOUNTZO)	0.05	0.21	0.00	1.00
Location in less favored zone (LESSFAZO)	0.41	0.49	0.00	1.00
Extensive farming (EXTENSCR)	0.17	0.37	0.00	1.00
Permanent crops (PERMCROP)	0.49	0.50	0.00	1.00
Dairy and drystock (DAIRYDRY)	0.03	0.18	0.00	1.00
Pigs and poultry (PIGPOULT)	0.13	0.33	0.00	1.00
Economic size units (ESU)	22.58	20.24	1.00	140.00
McBean Index (MCBEAN)	15.13	10.67	2.23	49.50
% of current subsidies on total output (CURRSUBS)	9.23	15.64	0.00	163.71
Ratio of debt to assets (%) (LIABILTO)	5.65	10.54	0.00	64.82

Table 3. **Development of Production in Catalan Farms (average values)**

	1989	*1990*	*1991*	*1992*	*1993*
Gross Farm Income (GFI)	2854355	2828176	2883240	2998056	2867973
Fixed Capital (FIXEDK)	24590548	23370654	20017458	18599465	19021181
Current assets (CURRASSETS)	4728126	4585455	5294366	6184206	6540718
Total employment (AWU)	1.56	1.49	1.52	1.56	1.55
Specific costs (SPECIFCOSTS)	5373472	5256624	5247272	5546954	5740164
Overhead costs (OVERHEAD)	677039	751952	853156	936363	1012347
GFI per employed person	1758276	1909172	1915938	1900286	1874558
Fixed capital per person	16595396	16614358	13744355	12064403	13073222
Variable capital per person	3451040	3466232	3977437	4153738	4458609

Table 4. **Evolution of Factors Explaining Inefficiency**

FACTORS	1989	1990	1991	1992	1993
Age of the farmer (AGE)	46.02	46.66	47.46	47.39	48.41
Farmers aged less than 35 (AGE1)	0.15	0.14	0.13	0.13	0.11
Farmers aged more than 60 (AGE2)	0.11	0.14	0.16	0.17	0.19
Family work units (FWU)	89.20	89.88	89.93	88.80	89.71
Herfindhal concentration index (CONCHERZ)	0.58	0.64	0.57	0.58	0.55
% of rented utilized agricultural area (RENTEDUA)	7.70	7.66	7.61	8.14	8.25
% of irrigated utilized agricultural area (IRRUAA)	32.20	33.47	33.77	33.12	34.39
Location in mountain zone (MOUNTZO)	0.05	0.05	0.05	0.05	0.05
Location in less favored zone (LESSFAZO)	0.41	0.41	0.41	0.41	0.41
Extensive farming (EXTENSCR)	0.17	0.17	0.15	0.16	0.17
Permanent crops (PERMCROP)	0.50	0.49	0.50	0.47	0.47
Dairy and drystock (DAIRYDRY)	0.03	0.04	0.03	0.03	0.03
Pigs and poultry (PIGPOULT)	0.13	0.12	0.12	0.13	0.14
Economic size units (ESU)	22.97	23.13	24.61	20.61	21.57
McBean Index (MCBEAN)	15.13	15.13	15.13	15.13	15.13
Coefficient of variation of total output (COEFVAR)	0.25	0.25	0.25	0.25	0.25
% of current subsidies on total output (CURRSUBS)	3.30	8.72	8.27	9.44	16.44
Ratio of debt to assets (%) (LIABILTO)	4.8	5.17	5.69	6.42	6.17

Table 5.

Maximum-Likelihood Estimates of Parameters of the Translog Stochastic Frontier Production Function (Preferred Model)

Variable	*Parameter*	*Coefficient*	*Standard Error*	*t-ratio*
Stochastic Frontier Model:				
Constant	β_0	9.2865	6.1837	1.502
FIXEDK	β_1	0.0529	0.3571	0.148
CURRASSETS	β_2	1.5164	0.4332	3.500***
AWU	β_3	0.6716	1.2235	0.549
SPECIFCOSTS	β_4	0.0255	0.3875	0.066
OVERHEAD	β_5	-1.5506	0.6954	-2.230**
Inefficiency effects model:				
AGE	δ_1	-0.0028	0.0055	-0.519
FWU	δ_2	0.0030	0.0037	0.807
CONCHERZ	δ_3	0.2225	0.2736	0.813
RENTEDUA	δ_4	0.0092	0.0054	1.688*
IRRUAA	δ_5	0.0025	0.0020	1.228
MOUNTZONE	δ_6	-0.8622	0.5652	-1.526
LESSFAZO	δ_7	-0.0847	0.1524	-0.556
EXTENSCR	δ_8	-0.3784	0.2739	-1.381
PERMCROP	δ_9	-0.6855	0.3992	-1.717*
DAIRYDRY	δ_{10}	-0.4161	0.4875	-0.853
PIGPOULT	δ_{11}	-0.2290	0.28019	-0.817
ESU	δ_{12}	-0.0396	0.0185	-2.131**
MCBEAN	δ_{13}	0.0085	0.0062	1.378
CURRSUBS	δ_{14}	0.0034	0.0038	0.878
LIABILTO	δ_{15}	-0.0098	0.0093	-1.050
YEAR	δ_{16}	0.0357	0.0447	0.800
Variance parameters:				
	σ^2_S	0.9258	0.3202	2.890***
	γ	0.9101	0.0250	36.384***
Loglikelihood Function		-545.39		

Notes: The t-ratios are asymptotic t-ratios. The coefficients corresponding to the cross-product of the input variables in the translog production function are not presented in this table.
*** $p<0.001$; ** $p<0.05$; * $p<0.1$.

Table 6. **Generalized Likelihood-Ratio Tests of Hypothesis for Parameters of the Stochastic Frontier Production Function**

Test	***Null Hypothesis (H_0)***	***Loglikelihood***	***Value of l***	***Critical Value***	***Decision (at 5% level)***
1	$H_0 : \beta_{jh} = 0$	-568.7	56.2	32.08	Reject H_0
2	$H_0 : \beta_t = \beta_{tt} = \beta_{jt} = 0$	-544.2	7.0	13.40	Accept H_0
3	$H_0 : \gamma = \delta_0 = ... = \delta_{15} = 0$	-606.7	132.4	26.98	Reject H_0
4	$H_0 : \delta_1 = ... = \delta_{15} = 0$	-561.4	41.4	25.69	Reject H_0
5	$H_0 : \delta_0 = 0$	-541.9	2.4	2.71	Accept H_0

Notes: λ: likelihood-ratio test statistic, $\lambda=-2\{\log[\text{Likelihood}(H_0)] - \log[\text{Likelihood}(H_1)]\}$. It has an approximate chi-square distribution with degrees of freedom equal to the number of independent constraints. The asymptotic distribution of hypothesis tests involving a zero restriction on the parameter γ has a mixed chi-squared distribution. The critical value for this test is taken from Kodde and Palm (1986), Table 1, page 1246.

Table 7. **Overall Mean Input Elasticities and Returns to Scale**

	Elasticities	*Standard error*
Fixed capital	0.092	0.139
Variable capital	0.254	0.112
Labor	0.376	0.162
Specific inputs	0.024	0.072
Overheads	0.228	0.112
Returns to scale	0.974	0.161

Table 8. **Mean Efficiency Values by Year**

Year	*Mean SF scores (std. dev.)*	*Mean DEA scores (std. dev.)*	*Kendall's tau (significance)*	*Spearman's rho (significance)*
1989	0.631 (0.194)	0.615 (0.255)	0.1024 (0.000)	0.7514 (0.000)
1990	0.671 (0.189)	0.602 (0.270)	0.1495 (0.000)	0.8095 (0.000)
1991	0.656 (0.186)	0.627 (0.261)	0.0576 (0.003)	0.8288 (0.000)
1992	0.636 (0.187)	0.648 (0.272)	0.0348 (0.022)	0.7388 (0.000)
1993	0.605 (0.206)	0.576 (0.276)	0.0256 (0.050)	0.6382 (0.000)
Mean of all years	0.640 (0.193)	0.614 (0.266)	0.0669 (0.000)	0.7343 (0.000)

Table 9. **Stochastic Inefficiency Scores by Farm Size**

Farm size (ESU)	*1989*	*1990*	*1991*	*1992*	*1993*	*All years*
1 to 7	0.568 (0.193)	0.599 (0.183)	0.541 (0.187)	0.608 (0.187)	0.552 (0.189)	0.575 (0.187)
8 to 14	0.544 (0.180)	0.680 (0.162)	0.603 (0.196)	0.630 (0.172)	0.555 (0.208)	0.602 (0.188)
15 to 25	0.626 (0.168)	0.656 (0.215)	0.671 (0.160)	0.587 (0.232)	0.651 (0.179)	0.640 (0.191)
³ 26	0.725 (0.191)	0.719 (0.172)	0.730 (0.167)	0.712 (0.140)	0.664 (0.224)	0.712 (0.180)

Note.- Standard errors in parentheses. ESU = economic size units.