Farm Technical Efficiency and Extension

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Abstract

This paper presents a methodology for estimating technical efficiency levels for individual farms using both a fixed effects panel model and a stochastic production frontier approach. It tests whether the estimated technical efficiency levels are associated with measures of contact with the advisory service. The approach is applied to a panel of 307 farms drawn from the Irish National Farm Survey over the period 1984 to 1994. The results show evidence that extension contact has had a positive impact on agricultural output.

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Introduction

The work reported in this paper is part of a wider project which seeks to estimate the impact of state-funded agricultural research and extension on Irish agricultural output and productivity as a step towards calculating a rate of return to these activities. In this paper, we focus specifically on the impact of the extension service in providing advice to farmers, whether by on-farm visits or through farmer participation in training courses run by the advisory service. This paper has a primarily technical focus in comparing alternative specifications of extension impact. Specifically, we take a stochastic frontier approach to estimate technical efficiency (TE) levels for individual farms using a fixed effects panel model and a maximum likelihood approach (Battese and Coelli 1992 specification) and test whether the estimated technical efficiency levels are associated with measures of contact with the advisory service. The choice of estimation technique depends on the assumptions made about the model. The maximum likelihood estimator is more efficient if the assumption of independence of the regressors and the technical efficiency effects holds and if the distribution of the technical efficiency effects is specified.

Two broad methods have dominated economic approaches to measuring extension efficiency (Birkhaeuser and Feder, 1991). In the experimental approach, the performance of groups of farms which have contact with the advisory service is compared with the performance of farms which have not had contact. In a pure experiment, farms would be assigned randomly to the two groups. In practice, researchers are often faced with two self-selected groups (e.g. farms which have chosen to join a scheme which gives them access to extension advice and farms which do not join). Previous Irish studies have shown that contact with the advisory service and information-seeking activities impact significantly on the rate of technical change and efficiency in Irish farms (Frawley, 1985; Boyle, 1987). More recent studies indicate that contact with the advisory service is a positive factor in increasing gross margin on farms participating in specific development programmes (Leavy, 1991; Leavy et al, 1997). The difficulty in interpreting results of this kind lies in knowing how much the self-selection has biased the outcomes observed.

The second economic method is to try to account for differences in output across units (countries, states, regions, farms) in terms of differences in the use of conventional inputs (e.g. land, labour, capital) and non-conventional inputs (R&D expenditure, education and training (E&T) expenditure) by fitting a production function to data on output and inputs. Such studies generally show high and positive rates of return to E&T expenditure, ranging from 20 to 100 per cent (see Birkhaeuser and Feder., 1991 for a review). However, these studies have their own problems, including data issues such as measurement error and aggregation bias, and conceptual issues to do with the nature of the precise relationship between extension expenditure and the increase in output. With individual farm-level data, the productivity decomposition approach entails two stages. In the first stage a total factor productivity index is computed for each farm. This is interpreted as an index of production efficiency. In the second stage the total factor productivity index is regressed on extension and other variables.

More recent work in production economics seeks to define the 'best practice' frontier production function and to measure the distance individual farms are from this frontier. This distance is interpreted as a measure of the level of technical inefficiency of that farm. This approach is illustrated in Figure 1. Three sources of agricultural output growth can be distinguished. In addition to increases in conventional inputs (which cause movements along the production function) and increases in non-conventional inputs (which cause a shift in the frontier production function), changes in output can also be due to changes in technical efficiency (the distance that individual farms are from the frontier). In Figure 1, the growth in output for Farm A over the two periods is the distance Y_1-Y_2 and this growth has occurred due to changes in its three separate elements, that is

$$\text{Output Growth} = \Delta \text{ inputs} + \Delta \text{ technical efficiency} + \text{technical progress}$$

Output growth due to growth in the use of inputs is given by Y_2^{**}-Y_1^{**}. The change in technical efficiency is given by $[(Y_1^*-Y_1) + (Y_2^{**}-Y_2)]$ and technical progress is given by Y_1^{**}-Y_1^* or Y_2^{**}-Y_2^* under the assumption of constant returns to scale. If there are increasing or decreasing returns then the distance Y_2^{**}-Y_2^* can be further disaggregated into "pure technical" progress and the effect of economies/ diseconomies of scale.

This conceptualisation of agricultural growth suggests two channels of impact for extension in terms of production agriculture. The first channel is to assist in the dissemination of new technologies to farmers as a way of increasing agricultural productivity, thus speeding up the adoption or use of new technology and practices. The second channel is the role of extension in improving human capital and the management skills of farmers, thus assisting individual farmers to improve their level of technical efficiency. In a static context, both channels would have the effect of moving farmers closer to the frontier. In a dynamic context, where the frontier itself is moving, the role of extension in diffusing innovation is underestimated by focusing solely on changes in technical efficiency.

This paper uses panel data on 307 Irish farms for the period from 1984 to 1994 to measure each farm's level of technical efficiency relative to the best practice farms in the sample, and then seeks to identify whether contact with the extension service is a significant variable in explaining technical efficiency differences across farms. The role of extension in improving human capital is a frequently cited objective of extension services (farmers' schooling and public extension are substitutes for efficiently processing information about new technology that affects productivity, Huffman and Evenson, 1993) and separate attention to this aspect is justified. If a positive impact of extension on technical efficiency is found, then in principle the value of this productivity gain can be measured and compared to the investment in extension and training. The resulting rate of return would then be a minimum rate of return to extension and training investment given that it ignores any (positive) contribution to moving the frontier production function upwards over time.

Methodology

The key to measuring the technical efficiency of individual farms is identifying the relevant frontier function. Two broad approaches to this have been developed: parametric and non-parametric (see Coelli et al., 1998 for an introduction to this literature). In turn, parametric methods can be deterministic or stochastic. The stochastic approach works on the basis that there are some non-farm specific factors, such as good weather, which may increase the output of the farm above the envelope of the frontier function. The stochastic frontier is determined by the structure of the production technology - the deterministic production frontier - and by external events, favourable and unfavourable, beyond the control of the farmer (Lovell,1993:20). This paper models time invariant and time-variant technical efficiency using a fixed effects framework to estimate the former and the stochastic frontier approach developed by Battese and Coelli (1992) to estimate the latter.

The stochastic frontier model[1] is given as

$$\ln(y_{it}) = a + x_{it} b + e_{it} \quad \textbf{(1)}$$

and the disturbance term is defined as

$$e_{it} = v_{it} - u_{i}, \qquad i = 1,\dots\dots,N \qquad t = 1,\dots\dots,T \quad \textbf{(2)}$$

where v_{it} is assumed to be independently and identically distributed with a zero mean and variance σ^2_v. The error component u_i is assumed to be non-negative and distributed independently of v_{it}. u_i represents the factors under the control of the farmer while the v_{it} represent the non-farm factors such as weather as well as statistical noise. For T=1 the model is a simple cross section stochastic frontier as specified by Aigner et al (1977). For T>1 it is possible to rewrite the model and estimate using either a fixed effects approach or alternatively using maximum likelihood techniques. [2] By defining

$$E(u_i) = m > 0 \qquad a^* = a - m, \qquad u_i^* = u_i - m \tag{3}$$

such that the u_i's are identically and independently distributed with a mean of 0 then equation (1) above can be rewritten as

$$y_{it} = a^* + x_{it}b + n_{it} - u_i^* \tag{4}$$

The error terms v_{it} and u_i now have a mean of zero. Now defining

$$a_i = a - u_i = a^* - u_i^* \tag{5}$$

the model can be rewritten as

$$y_{it} = a_i + x_{it}b + n_{it} \tag{6}$$

It is assumed that v_{it} is normally distributed but there is no a priori rationale for the choice of the distributional form for the α_i and the choice is between the half-normal or the exponential distribution (Coelli, 1995).

Estimation of the stochastic frontier as specified in equation (6) can be undertaken using a number of estimation techniques. The fixed effects method was one of the first approaches taken using panel data (Aigner et al 1977). The general form of the fixed effects model is given as

[1] This section follow Schmidt and Sickles (1984) closely.

$$\ln(y_{it}) = a + \sum_i g_i D_i + \sum_k b \ln x_{kit} + u_{it} \qquad \text{(7)}$$

where is y_{it} is output, x_k are inputs and D_i are dummy variables to account for farm specific effects. β is estimated using least square dummies variable estimation and t is time. By assuming that the dummy variables are a proxy for unobservable management characteristics of the farm they can be interpreted as a measure of technical efficiency, thus linking the fixed effects model to the production frontier methodology (Andreakos et al., 1997). Estimation of the model as given in equation (7) leads to the generation of a dummy variable for each of the farms in the sample which can be cumbersome if this number is large. In this study the number of farms in the data set is 307 so the data were transformed and modelled in deviations from the individual farm means. This transformation removes the need to estimate the individual dummy variables for each farm but does not change the estimator for β. However, this individual farm mean transformation means that it is not possible to include any time invariant explanatory variables in the model and so the estimator may not be fully efficient (Hallam & Machado, 1995). The result of the mean differencing is a fixed effects model of the form

$$\ln(y_{it}) = a + \sum_k b \ln x_{kit} + u_i + u_{it} \qquad \text{(8)}$$

where u_i accounts for farm specific effects which can be interpreted as a measure of technical efficiency. Equation (8) is in the same form as equation (6) above although an intercept term is included in equation (8). Technical efficiency for each farm is calculated as

$$TE_i = \frac{\exp(u_i)}{\max[\exp(u_i)]} \qquad \text{(9)}$$

where max is the highest predicted value for the *i*th farm. This measure is transformed into a technical efficiency index with values ranging from 0 to 1 where 1 is the maximum level of technical efficiency obtained by the most efficient farm. The statistical package STATA has been used to estimate the fixed effect model and the time invariant technical efficiency estimates.

[2] This seemed possibly significant for this study as it is not possible to include a variable for farm system in the model using the fixed effects approach.

Although the fixed effect approach assumes that the explanatory x variables are strictly exogenous it allows for correlation between the u_i's (i.e. technical efficiency) and the explanatory x variables. The measures of technical efficiency obtained by this method are time invariant.[3]

Work by Jondrow et al (1982) produced an alternative prediction technique based on the stochastic frontier using the conditional distribution of u_i given ε_i to estimate the farm level technical efficiencies. The mean or the mode of the conditional distribution can be used to give a point estimate of u_i. In the half normal case the conditional distribution of u_i given ε_i is shown to be that of a normal variable truncated at zero.[4] Jondrow defines

$$s^2 = s_m^2 + s_v^2, \qquad m_* = -s_m^2 e \big/ s^2, \qquad s_* = s_m^2 s_n^2 \big/ s^2 \tag{10}$$

The mean of the conditional distribution is given as

$$\mathrm{E}(u|e) = s_* \left[\frac{f(el/s)}{1 - F(el/s)} \right] - \left(\frac{el}{s} \right) \tag{11}$$

where f is the standard normal density and F is the conditional density function, and $-u_*/\sigma_* = \varepsilon\lambda/\sigma$ and $\lambda = \sigma_\mu/\sigma_v$.

The Battese and Coelli (1995) approach draws on the early work of Jondrow. However, they state that the best predictor of u_i is in fact

$$E[\exp(-u_i \mid e_i)] = \frac{1 - \Phi(s_A + ge_i / s_A)}{1 - \Phi(ge_i / s_A)} \exp(ge_i + s_A / 2) \tag{12}$$

where $g = s_m^2 / (s_m^2 + s_v^2)$ and γ lies in the range 0 to 1, $s_A = \sqrt{g(1-g)}s_S^2$, $e =_i \ln(y_i) - x_i b$ and $\Phi(.)$ is the density function of a standard normal random variable (Coelli et al., 1998). This approach also allows for the estimation of time variant technical efficiency and this formulation is incorporated in the programme Frontier 4.1 which has been used in this paper to estimate the farm level technical efficiencies. The parameters of the stochastic frontier production function are obtained by maximum likelihood estimation involving a three step procedure. The first stage

[3] For time varying fixed effect models see Cornell et al (1990) and Lee and Schmidt (1993).

involves the OLS estimation of β and σ_s^2. All estimators are unbiased except the intercept term and σ_s^2. The second stage involves the evaluation of the likelihood function for a number of values of γ in the range 0 to 1 and the adjustment of the OLS estimates for σ_s^2 and β_0 for use in the final stage. Finally, the largest log-likelihood values from the second stage are used as starting values in a Davidon-Fletcher-Powell (DFP) iterative maximisation routine which obtains the maximum likelihood estimates (Coelli et al.,1998). Maximum likelihood estimation has been shown to be more asymptotically efficient than corrected ordinary least square methods (Greene, 1993).[5]

A key difference between the fixed effects approach and the stochastic frontier approach is the assumption concerning the relationship between the technical efficiency effect and the explanatory variables in the model. The Battese and Coelli stochastic approach assumes that there is zero correlation between the u_{it}'s and the explanatory x variables. In the case of the fixed effects model the assumption that the regressors are uncorrelated with the technical efficiency is relaxed. Also the fixed effects estimator of the technical efficiency effects is consistent only as T gets large but the β estimates are consistent as T or N increases.

Model Specification

Five models are used in this paper to obtain estimates of technical efficiency. Model I is a fixed effects Cobb Douglas production function as given by

$$\ln(y_{it}) = a + \sum_k b_k \ln x_{kit} + VT + u_i + u_{it} \qquad \textbf{(13)}$$

where y_{it} is output for farm i in period t, x_{kit} is the *k*th input of farm i in period t, and α, β_k ξ are parameters to be estimated. Time (T) is included to account for smooth technical change, u_i represents time invariant technical efficiency and ν_{it} is statistical noise. Model II is a stochastic frontier model as defined by Battese and Coelli (1992)

$$\ln(y_{it}) = a + \sum_k b_k \ln x_{kit} + VT + u_{it} - u_{it} \qquad \textbf{(14)}$$

[4]Other specifications of the distribution of the error term are possible. The choice is arbitrary.
[5] For finite sample evidence see Coelli (1995).

where y_{it} is output for farm i in period t, x_{kit} is the *k*th inputs of farm i in period t. α, β_k ξ are the parameters to be estimated. T is included to account for smooth technical change, $-u_{it}$ represents time variant technical efficiency and ν_{it} is statistical noise. This function is estimated using maximum likelihood techniques.

Model III and Model IV are both simplified translog production functions. Model III is a fixed effects model in which the production function is defined as

$$\ln Y_i = a + \sum_{k=1}^{5} b_k \ln X_{kit} + \sum_{k=1}^{5} x_k \ln X_{kit} T_k + VT + VT^2 + u_i + u_{it} \qquad (15)$$

where y_{it} is output for farm i in period t, x_{kit} is the *k*th input of farm i in period t and α, β_k ξ are parameters to be estimated. u_i represents time invariant technical efficiency and ν_{it} is statistical noise. The amount of multicollinearity in the model is controlled by using the simplified translog form which assumes that inputs are separable from each other but not from time (Ahmad & Bravo-Ureta, 1996). The assumption of separability implies that use of one input is not tied to the use of another input but the use of inputs is related to time. If the cross products were restricted to zero and time inseparability was not assumed then the model would simply be a Cobb Douglas production function. While there is some a priori justification for restricting the cross products in the translog production function to zero to reduce multicollinearity there remains the possibility of omitted variable bias (Alston et al.,1998). Model IV is the time variant simplified translog production function given by

$$\ln Y_i = a + \sum_{k=1}^{5} b_k \ln X_{kit} + \sum_{k=1}^{5} x_k \ln X_{kit} T_k + VT + VT^2{}_i + u_{it} - u_{it} \qquad (16)$$

where all parameters are defined as in equation (11) above except for the last term, $-u_{it}$ which represents factors under the control of the farmer which are now allowed to vary over time. This is estimated using maximum likelihood techniques.

Specialist dairy farms are often considered to be more productive than the other systems of farming in Ireland. For this reason a series of dummy variables are included in Model V to allow the intercept term in the production frontier to vary by farm system. This has the effect of defining an separate frontier for each farm system so that efficiency is now measured relative to the best practice within a system.

$$\ln Y_i = a + \sum_{k=1}^{5} b_k \ln X_{kit} + \sum_{k=1}^{5} x_k \ln X_{kit} T_k + \sum_{j=1}^{5} v_j D_{jit} + VT + VT^2 +_i u_{it} - u_{it} \qquad (17)$$

Explaining Technical Efficiency

Two routes are possible in investigating the determinants of technical efficiency variation among the farms in the sample. The two stage approach adopted involves the estimation of the technical efficiency effects from both models and regressing these on a set of farm specific characteristics. This approach, though widely used, implies that the inefficiency effects which are assumed to be independently and *identically* distributed in the estimation of the stochastic frontier are a function of the farm specific effects in the second stage, thus violating the assumption that the efficiency effects are identically distributed (Battese and Coelli.,1995). The inefficiency effects would only be identically distributed if the coefficients of the farm specific factors are simultaneously equal to zero (Coelli et al., 1998). It is possible to overcome this problem by the use of a single stage maximum likelihood approach (Battese and Coelli, 1995). The technical inefficiency effects are specified to be a function of a vector of farm specific variables and a random error and a single stage maximum likelihood estimation technique is used to estimate the parameters of the production frontier and of the technical inefficiency variables simultaneously. For the purpose of comparison the results of the Battese and Coelli single stage technical inefficiency model are also applied to Model IV and V.

The second stage model used to explain the level of technical efficiency is given by

$$TE_{it} = d_0 + \sum_{j=1}^{J} d_{ij} Z_{ij} \qquad (18)$$

where the Z_i variables are a series of farm specific effects hypothesised to influence the level of technical efficiency and TE is technical efficiency of the *i*th farm in period t.

The single stage approach to the estimation of technical inefficiency is a modification of the maximum likelihood estimation technique outlined above. In the Battese and Coelli approach the technical inefficiency effects are specified in the stochastic frontier model and assumed to be independently but *not identically* distributed non- negative random variables. For the *i*th farm in the *t*th period the technical inefficiency effects (u_{it}) is obtained by the truncation at zero of the normal distributions with a mean μ_{it} and a variance σ^2 where

$$m_{it} = d_0 + \sum_{j=1}^{J} d_{ij} Z_{ij} \qquad \textbf{(19)}$$

As in equation (18) above Z is a vector of farm specific variables and δ are the unknown parameter to be estimated.

The data

The main source of data is the Irish National Farm Survey (NFS). Farmers are randomly selected from the farm population and participate voluntarily in the survey. The data set comprises of a sample of 307 farms in the years 1984 to 1994 taken from the NFS[6] and which also completed an additional survey relating to contact with the extension service. [7]

Most Irish farms are multi-product enterprises producing a combination of dairy, cattle, tillage, horse, sheep, pig or other output. The volume of gross output (Y) is the total volume of gross output of the individual farms in each year including coupled direct payments. Five inputs are used in the study: land, labour, livestock, capital and variable inputs. Using 1994 as the base year all inputs and outputs were deflated by the appropriate price series obtained from the CSO. Because the bulk of Irish farmland is farmed by owner-occupiers, a series on the rental value of farmland is not available. Instead, the land input is measured by the adjusted size of farm in acres. The adjustment here is the conversion of rough grazing to pasture equivalent and does not take account of differences in soil quality between farms. Such differences could therefore show up as differences in technical efficiency between farms. Labour input is measured as the number of labour units used, including family labour, casual and hired labour on the farm. Livestock input is measured as the total number of livestock units. Livestock units use feed demand equivalents based on the amount of feed each animal type consumes and these technical equivalents do not vary over time. Capital input is measured as the flow of services from machinery, land improvements and buildings. The service flow is calculated by adding together capital depreciation, the opportunity cost of capital and the cost of repairs and running expenses. Other intermediate inputs is calculated as the sum of intermediate inputs such as electricity, veterinary fees, and transport costs. The summary statistics of the variables in the model are shown in Table 1.

[6] Pig farms have been excluded from the analysis as they are considered to be atypical in the farming sector.

[7] The authors wishes to thank Tom Kirley for access to this data set.

The following variables were used in explaining technical efficiency differences across farms:

Z_1 is the age of the farmer

Z_2 is a dummy variable where a visit from an advisor in the past year = 1 and 0 otherwise

Z_3 is a dummy variable where if the farmer participated in a training course = 1 and 0 otherwise

Z_4 is a dummy variable where having a successor for the farm = 1 and 0 otherwise

Z_5 represents the size of the farm (used to capture economies of scale)

Z_6 is a dummy variable representing education where 1 = having completed education to leaving certificate level or beyond and 0 otherwise.[8]

Z_7 represents the growth in gross margin on each farm over the previous 10 year period.

TE is measured on a scale from 0 to 1 in which higher values represent higher levels of technical *efficiency*. The following coefficient signs are hypothesised. A visit from an advisor is expected to have a positive coefficient, that is, farms with advisory contact are expected to be more technically efficient. Similarly, farmers who attend a course are hypothesised to be more technically efficient as a result. Economies of scale may be significant on larger farms and thus the sign on the coefficient of the farm size variable is hypothesised to be positive.

Farmers who have experienced more rapid growth in gross margins in the recent past are assumed to operate with more modern equipment and to be more aware of best practices as a result and thus the sign on the growth variable is expected to be positive. Higher age is hypothesised to lead to less effort and less concern with optimising the use of resources under the farmer's control and thus a negative coefficient is hypothesised. Farmers with a higher level of education are expected to be more efficient and again a positive coefficient is expected. An appropriate variable to include would be whether the farmer engaged in off-farm employment or not. Data on this were not available but it will be partially taken into account in the labour input variable.

The individual parameter estimates taken from the Battese and Coelli maximum likelihood estimation of the simplified translog production frontier are land .56; labour .17; livestock. 25; capital .19; and variable inputs .40. All the parameter estimates are positive as expected and statistically significant at a 5% level. The parameters for the fixed effects model

[8] The variable for education was taken from the household budget survey.

are also positive and statistically significant except for the labour which has the expected positive sign but which is not statistically significant at a 5% level.

Results

Results for the two stage approach are presented first and the estimates obtained are then compared to the single stage approach. The Cobb-Douglas specification is very parsimonious with respect to degrees of freedom but imposes strong assumptions on the nature of the farm technology. The translog production function is a more flexible functional form than the Cobb Douglas function and it also takes account of interactions between variables and allows for non-linearity in the parameters. However, when estimating the traditional translog production function multicollinearity among the explanatory variables is usually present. For this reason a simplified translog specification was chosen. The validity of the translog over the Cobb Douglas specification was tested using a generalised log likelihood ratio test.[9] The null hypothesis that the $\xi_k=0$ was strongly rejected.[10] So the translog production technology is considered to be a better representation of farm technology than the Cobb Douglas specification in the case of the stochastic frontier model. The production function requires that the first derivatives with respect to all of the inputs are greater than or equal to zero and this is found to be the case in all of the models estimated in this study. There is no evidence of heteroscedasticity in the data.[11]

Finally the null hypothesis that there are no technical inefficiency effects in the model is tested using a likelihood ratio test of the one sided error. The null hypothesis is strongly reject as the LR test statistic is 1767.04 which is greater than the mixed χ^2_1 value of 3.84.

Dawson (1985) and Ekanayake and Jayasuriya (1987) point out that measures of technical efficiency will vary greatly depending on the estimation technique and the specification of the production frontier. The average technical efficiency measures by model are presented in Table 2. In this study the mean technical efficiency estimates are higher for the Battese and Coelli (1992) stochastic frontier models (ranging from .66 to.75) than for the fixed effect models (.35). This would seem to suggest that allowing technical efficiency estimates to vary over time as in the Battese and Coelli (1992) specification is important in estimating technical efficiency. Average technical efficiency is highest at .74 when account is taken for the difference in farm systems. The results of the first stage maximum likelihood estimation of Model V showed the

[9] It was not possible to carry out an equivalent test for the fixed effect model.

[10] The LR test statistic 168.54 which is greater than the upper five percent point for the χ^2_{12} distribution which is 21.02

[11] The estimated χ^2 value obtained using a refined White's test exceeds the critical value χ^2_{3376} and it was concluded that there was no heteroscedasticity in the error variance.

intercept term for specialist dairy farms, dairy and other systems, and tillage farms to be higher and statistically different to that of cattle farms.[12] Sheep farms have a lower intercept term than cattle farms and this is also statistically significant. Other studies examining technical efficiency in agriculture have shown the fixed effects estimates of technical efficiency to be lower than estimates obtained using the Battese and Coelli maximum likelihood technique. In an analysis of technical efficiency in North-Western Pakistan Parikh and Shah (1994) found a mean technical efficiency of .96 using maximum likelihood estimation. Hallam and Machado (1995) found the fixed effects average technical efficiency to be .57 and the Battese and Coelli maximum likelihood average to be .88 and Taylor and Shonkwiler (1986) found average technical efficiency using maximum likelihood to be .71. Average technical efficiency of .745 was found by Ajubefun et al (1996) in their study of technical efficiency in the Japanese rice industry.

The different methods used to estimate technical efficiency also produced differences in the ranking of farms. However, the correlation between the different estimates of technical efficiency is greater than .85 for all the models except the Battese and Coelli translog with system dummies included. The correlation here is lower ranging from .58 to .7. This is not surprising given the different specification of Model V which is the only model estimated to include farm system dummies. The correlation matrix for the five estimates of technical efficiency is reported in Table 3.

Given the different technical efficiency measures obtained the second stage regression of technical efficiency on farm specific factors was undertaken for all five models. The results are given in Table 4. Variables which appear significant in explaining differences in technical efficiency across farms include recent growth in the size of the farm business, the education level of the farmer and whether the farmer has a successor for the farm, all of which appear with the hypothesised sign. The coefficients on the two key extension coefficients are positively related to technical efficiency and statistically significant at a 1% level.

The results are consistent with other studies of farm level technical efficiency. Andreakos et al (1997) found age, the presence of a farm successor and education level statistically significant in explaining technical efficiency in a panel analysis of Greek livestock farms. A Cobb Douglas production frontier was used in the Andreakos et al model (1997) and farm size was found to be statistically insignificant. Contact with the extension service and higher education levels were important in explaining technical efficiency in Parikh and Shah's (1994) study of farms in Pakistan.

[12] See W. Dunne and R O'Neill (1996) for an analysis of efficiency in the beef sector post CAP reforms.

Since the two stage approach violates the assumption that the technical inefficiency effects are identically distributed the single stage Battese and Coelli technical inefficiency approach was repeated for Model IV and Model V. To aid in the comparison of the parameter estimates the technical efficiency measures for Model IV and V have been subtracted from 1 to give the technical inefficiency measures. Table 5 gives the results of the single stage technical inefficiency model obtained from Frontier 4.1 and the two stage results obtained by regressing technical inefficiency on the farm specific factors.

It is worth noting that the signs on the coefficients are the same in the two models for all the explanatory variables and there are only minor differences in the statistical significance of some of the variables. However, the size of the coefficients vary considerably between the two models. In the single stage model IV the co-efficient for variable on participation in a training course is -0.16151 compared to –0.0569 in the two stage model. Similarly for the Model V specification the co-efficient on the participation in a training course variable is almost seven time greater in the single stage approach than in the two stage approach. It would appear that with this data set there is a significant difference in the size of the co-efficient for one of the key variables needed to calculate the rate of return to extension depending on the estimation method used.. Hence it can be said that the choice of model to explain technical inefficiency will have an impact on the rate of return calculated.

Conclusions

This paper presented a methodology for estimating technical efficiency levels for individual farms using both a fixed effects panel model and a stochastic production frontier approach and tested whether the estimated technical efficiency levels are associated with measures of contact with the advisory service. The results from all the models tested show that having contact with the advisory service through either a visit from the farm advisor or participating in a training course is significant in explaining the level of technical efficiency. Other significant factors are age of the farm operator, having a farm successor and having a higher level of education. There is evidence that the technology available on dairy and tillage farms is different to that of cattle farms - as seen through the higher intercept term in the production frontier - and that sheep farms relative to cattle farms have a lower production frontier. These rankings of farm system are important when analysing the impact of the extension service in Ireland since the operation of the extension service is divided along farm system lines. These results hold for both the single stage and two stage models. This is the first time that the

Battese and Coelli (1992 & 1995) two stage technical efficiency and single stage technical inefficiency methodology has been applied to Irish farm level data.

Although, it is possible to conclude that this sample of Irish farms shows evidence that extension contact has had a positive impact on the performance of farms there are a number of caveats to these results which need to be addressed before these coefficient estimates can be used to estimate rates of return to public investment in the advisory service. The most important is possible endogeneity of farmer-extension interactions. In other words, it may be that the more efficient farms have deliberately sought out contact with the advisory service. In further work, it would be useful to handle this problem of endogeneity econometrically.[13] A second problem is that the measure of extension contact is a crude one. It is not possible to tell from the data the number of visits by the extension worker or the intensity of the contact the advisor had with the farmer. A third issue is that some extension contacts may not be motivated by farm production considerations but by other factors, such as providing assistance on environmental management or claiming government supports. A fourth issue is that extension may impact on agricultural output in ways which are not captured by changes in farm technical efficiency. A fifth issue is that the measure of technical efficiency reflects errors in measuring conventional inputs and, if these are correlated with the extension variables, this could bias the estimation process. Future work will try to address some of these issues.

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Appendix A

Table 1
Summary Statistics of Variables in the Stochastic Production Function

Variable	**Mean**	**Std/Mean**	**Minimum**	**Maximum**
Gross output (£)	51015.00	1.14	1334.00	433225.00
Capital (£)	13849.00	1.07	294.00	114383.00
Other inputs (£)	23995.00	1.32	385.00	268342.00
Size of farm (ha)	57.89	0.97	8.38	646.08
Total number of livestock units	75.32	0.78	11.67	411.67
Total number of labour units	1.64	0.49	0.38	6.70

Table 2
Average Technical Efficiency

	Type of model	**Technical Efficiency Effect**	**Mean Technical Efficiency**	**Min**	**Max**	**Std. Dev.**
Model I	FE , CD	Time Invariant	.3508	.1269	1	.1463
Model II	BC, CD	Time variant	.6726	.2939	.9922	.1627
Model III	FE, TL	Time invariant	.3549	.1352	1	.1447
Model IV	BC, TL	Time variant	.6663	.3076	.9925	.1623
Model V	BC,TL,SD	Time variant	.7451	.3713	.9918	. 1288

FE fixed effects; BC Battese and Coelli (1992) stochastic frontier; CD Cobb Douglas; TL Translog. SD farm system dummy variable

Table 3
Correlation Matrix for the Technical Efficiency Measures

	FE, CD	**FE, TL**	**BC, CD**	**BC, TL**	**BC, TL, SD**
FE, CD	1.000				
FE, TL	.9987	1.000			
BC, CD	.8857	.8970	1.000		
BC, TL	.8802	.8937	.9983	1.000	
BC, TL, SD	.5865	.5959	.6996	.7013	1.000

Table 4.
Results of the Technical Efficiency Analysis

Variables	**Model I CD FE**	**Model II CD BC**	**Model III TL FE**	**Model IV TL BC**	**Model V TL BC SD**
Participated in a training course	0.0402*	0.0557*	0.0407*	0.0568*	0.0342**
Had a visit from the advisory service	0.5535*	0.0295*	0.0518*	0.0251**	0.1867*
Education level	0.0675*	0.0692*	0.0650*	0.0659*	0.0186*
Has a successor for the farm	0.0908*	0.1099*	0.0893*	0.1063*	0.0573*
Growth in gross margin	0.0069*	0.0073*	0.0068*	0.00073*	0.0051*
Size of farm in ha	0.0002*	-0.0000	0.0002*	-0.0000	-0.0000***
Age of farm operator	-0.0019*	-0.0027*	-0.0018*	-0.0026*	-0.0018*
r^2	0.2938	0.2640	0.2813	0.2459	0.1387

* 1% significance level ** 5% significance level *** 10% significance level

Table 5
Comparison of Two Stage and Single Stage Technical Inefficiency Results

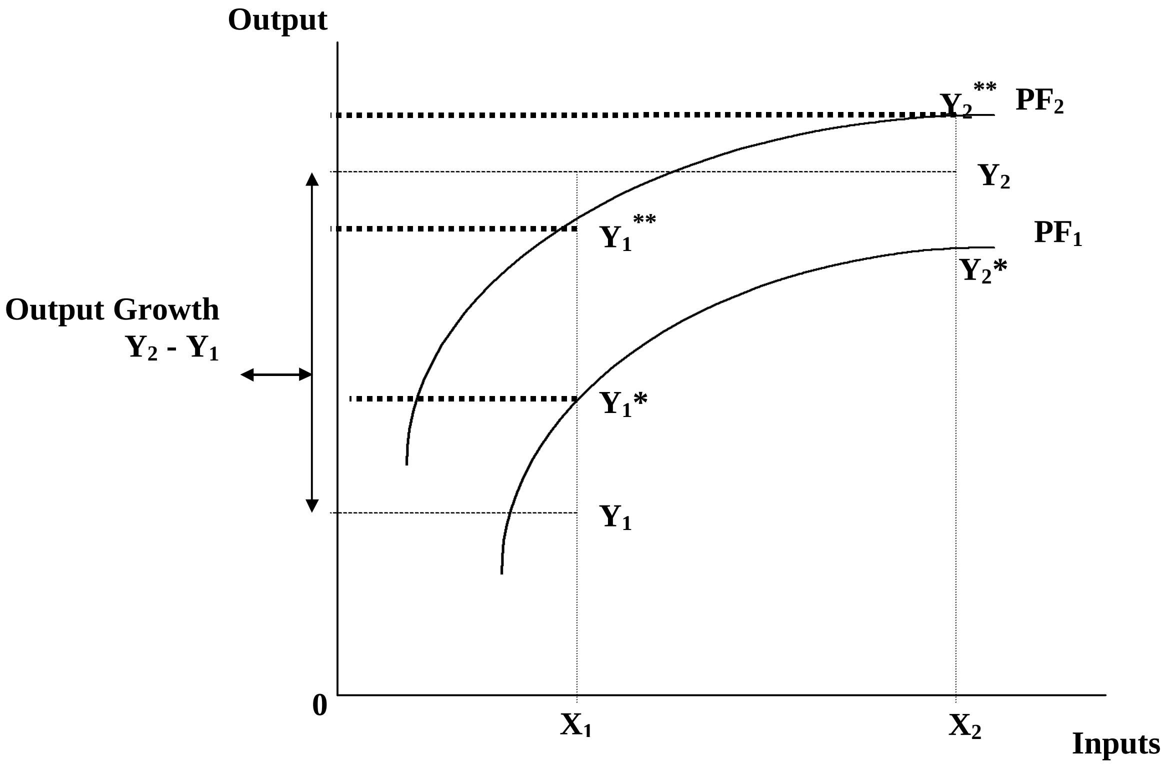
	Model IV TL BC		**Model V TL BC SD**	
Variables	Two Stage	Single Stage	Two Stage	Single Stage
Participated in a training course	-0.0569*	-0.1651*	-0.0343*	-0.2308**
Had a visit from the advisory service	-0.0235**	-0.0235**	-0.0175**	-0.2609**
Education level	-0.0639*	-0.2075**	-0.0278*	-0.2882**
Has a successor for the farm	-0.1103*	-0.2639**	-0.0600*	-0.4299**
Growth in gross margin	-0.0073*	-0.0147**	-0.0052**	-0.0492**
Size of farm in ha	0.0000	0.0005**	0.000***	0.0003
Age of farm operator	0.0029*	0.0056**	0.002*	0.0176**

* 1% significance level ** 5% significance level *** 10% significance level

Appendix B

Figure 1[14]

Production Frontier



[14] This figure is adapted from Kalirajan et al, (1996)

Appendix C

Frequency Distributions of Technical Efficiencies

Chart 1

Frequency Distribution of Technical Efficiencies Model 1

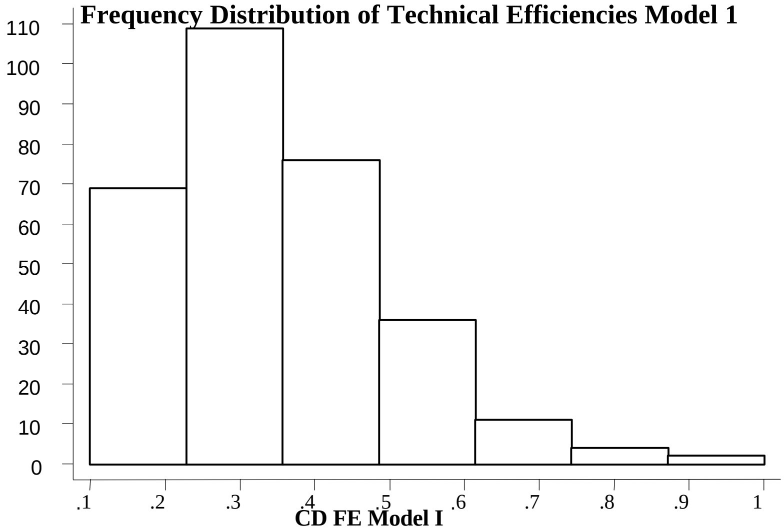


Chart 2

Frequency Distribution of Technical Efficiencies Model II

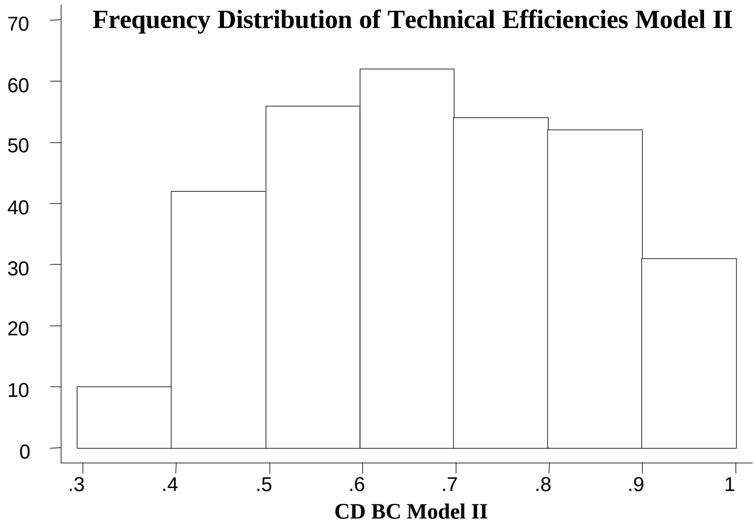


Chart 3

Frequency Distribution of Technical Efficiencies Model III

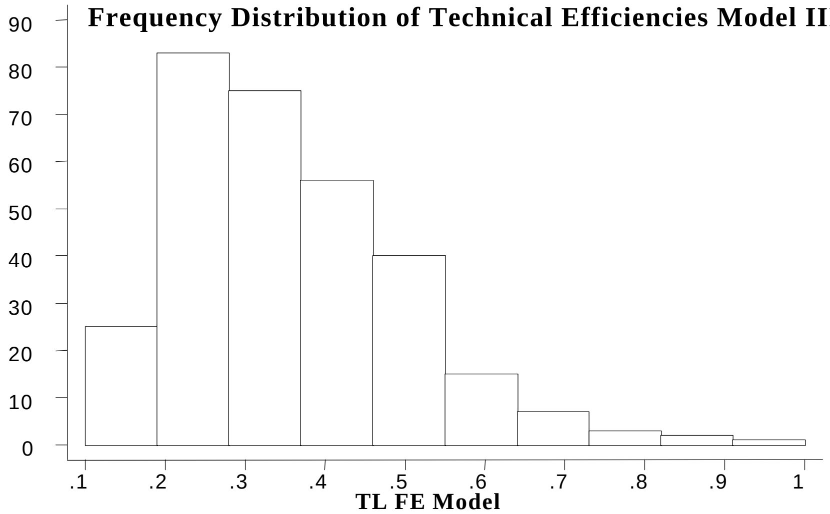


Chart 4
Frequency Distribution of Technical Efficiencies Model IV

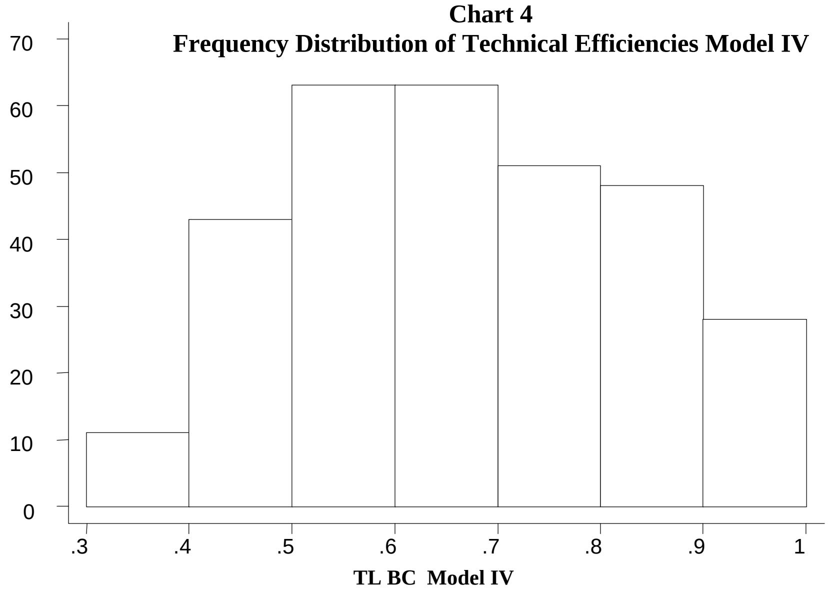


Chart 5
Frequency Distribution of Technical Efficiency