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The influence of management characteristics on the technical efficiency of wheat farmers in eastern England

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Abstract

Technical efficiency of wheat farms in eastern England is measured through the estimation of a stochastic frontier production function using panel data for the 1993–1997 crop years. Variations in the technical efficiency index across production units are explained through a number of managerial and farm characteristic variables following Battese and Coelli (1995) [Empirical Econ. 20, 325–332] and incorporating the spirit of Rougoor et al. (1998) [Agric. Econ. 18, 261–272]. The technical efficiency index across production units ranges from 62 to 98%. The objectives of maximising annual profits and maintaining the environment are positively correlated with, and have the largest influence on, technical efficiency. Moreover, those farmers who seek information, have more years of managerial experience, and have a large farm are also associated with higher levels of technical efficiency. Future studies that seek to explain variation in technical efficiency should include further aspects of the managerial decision-making process.

Keywords: Technical efficiency; Managerial capacity; Wheat yields

1. Introduction

Numerous studies have identified wide variation in the physical and financial performance achieved by farmers and farm managers operating within the same environmental and economic constraints. Kay and Edwards (1994) argue that in many instances this difference in performance is due to variation in management. However, unlike land, labour and capital, management is not directly observable; subsequently this complicates any analysis that attempts to explain the influence of management on farm performance. Kay and Edwards define the functions of management as planning, implementation and control. Rougoor et al. (1998) have renewed the debate on how to measure the ability of a farmer to influence his/her farm results. Rougoor et al. (1998) broadened the definition of management and group management capacity into two components: personal aspects (e.g. drives, motivations, abilities and biographical facts) and aspects of the decision-making process (e.g. the practices and procedures in planning, implementation and control of decisions). It is argued that these two components are linked because the personal aspects of the manager may influence his/her ability to follow a decision-making process. Moreover, accounting for only one of these two components is argued to be a necessary but not sufficient condition

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if management is to be measured correctly. Rougoor et al. (1998) argue that a manager may possess high personal skills yet fail to achieve high performance if the decision-making process is poor. Following a well-defined process helps a decision-maker to make a decision in a logical and organised manner that will, on average, lead to better results (Rougoor et al., 1998).

Empirical studies that seek to quantify the influence of management on farm technical performance generally attempt to explain variation in technical efficiency as a function of management ability through the inclusion of biographical variables in the analysis (e.g. Battese et al., 1996). Such studies have gone some way towards quantifying the impact of management on farm performance yet are open to the criticism that they ignore aspects of the decision-making process as defined above. Other studies conclude that to gain a greater understanding of the influence of management requires more detailed information about management decision-making and ability in addition to biographical data (Wilson et al., 1998). Rougoor et al. (1998) reinforce this view and conclude that a logical next step in defining farmers' management capacity would be to include aspects of the decision-making process when explaining variation in technical efficiency levels amongst farmers.

The focus of this study is to explain the influence of management on the technical performance of wheat farmers in eastern England. The study differs from much previous research into the estimation and explanation of technical efficiency by including variables that relate to both personal aspects and aspects of the decision-making process of the farmer as suggested by Rougoor et al. (1998). The data used in this research are taken from two related sources: production data collected as part of a study into the economics of cereal production and an attitudinal questionnaire collected specifically to obtain data on aspects of managerial capacity.

The structure of the paper is as follows. Section 2 describes the surveys from which the data sample analysed is derived and defines and provides summary statistics for the variables that enter the model. In Section 3 the inefficiency effects model is specified and empirical results from this are presented and discussed in Sections 4 and 5. The final section summarises the findings of this research.

2. The data

Cereal production in Great Britain is concentrated in eastern England. The climate of eastern England is favourable to arable rather than livestock production, and subsequently, the eastern region of England contains nearly 50% of the cereal area of Great Britain (MAFF, 1997). For this reason the data used in this study are drawn from this region of England.

The production data used are taken from survey information collected for a study of the economics of cereal production conducted for the Ministry of Agriculture, Fisheries and Food (MAFF) as part of their series of special studies in agricultural economics (Asby, 1998). The survey was conducted over the years 1993–1997 inclusive. Farmers took part in the survey on a voluntary basis, receiving no payment for supplying the information. Farmers who took part in the survey received a detailed analysis of data for the financial and technical performance of their cereal production together with benchmark comparisons. Only data from farmers who took part in the survey from 1993 to 1997 inclusive are used in this study. Physical and financial information was collected from the farmer during on-farm visits conducted by farm business researchers. These visits were conducted over the period when the crop was being sown, harvested and marketed. During these visits the researcher, in conjunction with the co-operating farmer, recorded data on outputs and inputs down to the Gross Margin level only for the years 1994–1997 with labour and machinery data solely being available for the first year of the survey (1993) (Davidson and Asby, 1995).

Output data were recorded by the quality of grain sold, tonnes produced of each quality per farm and price obtained. For practical reasons the amount of data collected on individual inputs varied. For seed, both the quantity used and cost per tonne (by variety) was collected. Similar information was collected on fertiliser usage with the quantity applied further broken down into its constituent parts (the amount of nitrogen, phosphates and potassium). However, only the cost of crop protection materials (which are defined as applications of herbicides, fungicides, insecticides, growth regulators and slug pellets) was collected because such practices as tank-mixing and varied application rates made collection of the physical quantities unviable. Since labour and machinery

Table 1
Mean annual values for yield and inputs, 1993–1997[a]

Year	No. of farms	Yield (tonnes/ha)	Seed (£/ha)	N P K (kg/ha)	Crop protection (£/ha)	Labour (h/ha)	Machinery (h/ha)
1993	71	8.04 (1.37)	51.20 (12.18)	270.40 (95.61)	99.92 (26.45)	9.46 (2.69)	139.74 (35.94)
1994	72	7.96 (1.31)	54.70 (14.45)	278.49 (75.39)	99.35 (26.99)	9.46 (2.67)	139.00 (36.24)
1995	72	8.15 (1.19)	44.37 (10.72)	288.60 (70.81)	106.23 (31.86)	9.39 (2.59)	139.12 (36.15)
1996	74	8.38 (1.22)	42.26 (9.14)	285.93 (75.55)	104.50 (27.62)	9.43 (2.65)	138.23 (36.05)
1997	73	7.96 (1.48)	47.20 (10.72)	277.18 (67.63)	107.16 (31.48)	9.46 (2.65)	138.07(36.27)
Total obervations=362							

[a] Standard deviations shown in parentheses. Labour and machinery data based on 1993 per ha utilisation (annual averages differ due to changes in the number of observations, and the composition of the sample in each year).

data (both being measured in terms of the hours of each that were applied to the wheat crop) are only available for 1993 we assume that per ha utilisation of these inputs remains fixed over the period.

In order to provide a consistent measure of output (since the sampled farms produced a wide variety of grades of wheat) feed wheat equivalents were derived by first calculating the mean annual price for feed wheat within the sample and then dividing this price into the gross return for wheat of all qualities on each farm. Table 1 gives a broad description of the data, showing changes between 1993 and 1997. Yield is calculated from the total tonnes produced per farm as tonnes of feed wheat equivalent per ha of wheat area. Inputs are given per ha of wheat area, as costs for seed and crop protection, as kilograms for fertiliser and in hours of labour and machinery use. The cost of seeds was used to capture differences in quality of purchased and farm-saved seed (for which physical units were not available). Both seed and crop protection costs are deflated using appropriate indices to 1993 prices. [1] The number of farms included in the panel data set varies slightly from year to year because a small number of farmers in the set did not grow wheat in every year considered.

Table 1 shows the means and standard deviations for outputs and inputs for the years 1993–1997 for this sample. Note that yield, seed costs and crop protection costs have remained fairly stable over the 5-year period. Fertiliser application showed more variation with usage increasing in 1995 and 1996 and falling again in 1997.

Variation in levels of input use among farms for each year is relatively small. This is possibly due to farmers applying these inputs following recommended application rates per ha (where manufacturers and/or advisors make recommendations). Given this small variation in application rates we would expect that efficiency differences among farms are also likely to be small and that these differences will be explained by either factors which remain beyond control of the farmer, e.g. climatic and locational variations (which are not explored here because of data limitations) or differences in the management input on each farm. This small variation in application rate also raises issues for model formulation. Variables defined as annual levels of inputs were found to be very highly collinear with land area and each other (with correlation coefficients of 0.9 and above), hence the variables which enter the stochastic frontier production function analysis are defined on a per ha basis in an attempt to mitigate multicollinearity problems. This problem is common in empirical agricultural production analysis although it is particularly acute in this case where single enterprise (rather than whole farm) data is utilised. The implications of using a yield function, rather than the more conventional production function, are discussed further in Section 3.2.

Management data was gathered by conducting face-to-face interviews with farmers/managers who had participated in the MAFF survey continuously over the period 1993–1997. The results of this survey

[1] The seed deflator is from the MAFF Index of purchase prices of the means of agricultural production. The crop protection deflators (which are detailed by type, e.g. herbicides, fungicides, etc.) were supplied by MAFF York (Branch A, Market Prices, Stats C&S).

Table 2
Definition of variables hypothesised as influencing technical efficiency

Variable	Definition
AREA	Total area of each farm (ha)
EXP	No. of years of managerial experience
FED	Dummy variable=1 if decision maker has had some form of higher education (diploma, degree, etc.) and 0 otherwise
PMAX	Dummy variable=1 if farmer ranks profit maximisation as 1 or 2 in answer to business objectives
ENV	Dummy variable=1 if farmer ranks maintaining the environment as 1 or 2 in answer to business objectives
INFSEEK	Number of information sources the farmer utilises of the 16 listed in the questionnaire
TIME	Linear time trend (1=1993 to 5=1997)

produced the sample of 74 farms for which production data is summarised in Table 1. The face-to-face interviews specifically asked farmers about their number of years of managerial experience, whether they had undertaken further education, their use of advisors and consultants and their methods of acquisition of technical information. In addition, the farmers were asked to rank in order of importance to them the following four business objectives: maintain way of life, maximise annual profits, maintain environment and increase farm size/business.

From the responses received, a number of variables were formulated which were hypothesised as possibly having a role in explaining differences in levels of technical efficiency among farms. Definitions of these variables are outlined in Table 2, while Table 3 provides summary statistics.

Of the variables defined in Table 2, experience, further education, profit maximisation and maintaining the environment relate to the personal aspects of managerial capacity as defined by Rougoor et al. (1998). Of these, the first two can be considered as biographical characteristics whilst the latter relate to the drives which motivate farm decision-makers. To capture aspects of the decision-making process, farmers were asked to identify from where they obtained technical information about crop husbandry practices from a list of 16 possible sources grouped into four categories as follows:

1. personal: independent advisor, merchant's advisor, other farmers, others;
2. written: farming press, MAFF literature, Home-Grown Cereals Authority (HGCA) literature, commercial literature, others;
3. electronic: internet, others;
4. others: HGCA conferences, other conferences, local agronomy groups, farmer meetings, others.

An 'information seeker' variable was constructed by summing the number of these 16 sources that farmers stated as using. This measure provides an indication of practices and procedures in planning and will have a direct influence on implementation and control of decisions or aspects of the decision-making process in general.

Table 3 shows that the average number of years of managerial experience was approximately 20. Only 21% of the sample had undertaken further education, 88 and 17%, respectively, ranked maximising annual profit and maintaining the environment as one or two in their ranking of objectives, whilst an average of seven information sources, of the 16 listed, were used by farmers.

It should be noted that this managerial survey was undertaken in 1997 and it is assumed that the responses received in this year relating to managerial objectives and sources of information hold over the period of analysis, i.e. 1993–1997. Given that the identity of the major decision-maker for each farm does not change

Table 3
Summary statistics for variables hypothesised as influencing technical efficiency, 1993–1997

Variable	Mean	Standard deviation	Maximum value	Minimum value
AREA	209.86	183.59	1231.47	8.09
EXP	19.80	10.43	45	1
FED	0.21	0.41	1	0
PMAX	0.88	0.33	1	0
ENV	0.17	0.37	1	0
INFSEEK	7.09	2.50	12	1
TIME	3.02	1.41	5	1

over this period this does not seem an unreasonable assumption to make.

3. Technical inefficiency effects model and specification

3.1. Model

The Battese and Coelli (1995) technical inefficiency effects model is an extension of the more usual stochastic error component frontier function which allows for identification of factors which may explain differences in efficiency levels between observed decision-making units. The conventional stochastic frontier approach involves estimation of a function with a composite error term, including a symmetric and a one-sided component (following Aigner et al. (1977) and Meeusen and van den Broeck (1977)). In the case of the frontier production function, the symmetric component represents random variations in production due to factors outside the control of the farmer (such as climate, measurement error, etc.) and is assumed to be independently and identically distributed as $N(0, \sigma^2)$. The one-sided component is associated with technical inefficiency of production and measures the extent to which observed output deviates from potential output given a certain level of inputs and technology. Commonly it has been assumed that this component has an identical and independent half-normal distribution, although a variety of other distributional specifications are possible (Greene, 1997). A detailed review of the approach can be found in Greene (1997).

The model proposed by Battese and Coelli (1995) builds upon Kumbhakar et al. (1991) and Reifschneider and Stevenson (1991) and extends to panel data the work of Huang and Liu (1994) who formulated a non-neutral stochastic frontier production function model, for cross-sectional data, in which the one-sided inefficiency effects are specified as a function of firm-specific factors and input variables, believed to influence technical inefficiency. The technical inefficiency effect, for the i-th firm in the t-th time period, u_{it}, is defined by the truncation (at zero) of the $N(\mu_{it}, \sigma_u^2)$ distribution where the firm specific mean, μ_{it}, is specified as follows:

$$\mu_{it} = \delta_0 + \delta' z_{it} \quad (1)$$

where z_{it} is a column vector of technical inefficiency explanatory variables and the δs are unknown parameters which are to be estimated.

3.2. Specification

Following the recommendation of Battese and Broca (1997) we employ a general specification for the model as a starting point and test for simpler formulations within a formal hypothesis testing framework. Hence the stochastic frontier production function is specified here as a translog function with the following initial form,

$$\ln y_{it} = \alpha_0 + \sum_{k=1}^{5} \alpha_k \ln x_{kit} + \sum_{k=1}^{5}\sum_{j=1}^{5} \alpha_{kj} \ln x_{kit} \ln x_{jit} + \alpha_t t + \alpha_{tt} t^2 + \sum_{k=1}^{5} \alpha_{kt} \ln x_{kit} t + v_{it} - u_{it}, \quad (2)$$

where ln denotes natural logarithms, y_{it} represents wheat yield for the i-th farm in the t-th year, x_1 is expenditure (£) per ha on seeds, x_2 the kilograms of plant nutrients per ha, x_3 the cost of crop protection products per ha, x_4 the hours of labour per ha, x_5 the hours of machinery per ha, t the linear time trend (1993=1, ..., 1997=5), v the random error which is assumed independent and identically distributed $N(0, \sigma_v^2)$, and αs the parameters to be estimated. The technical inefficiency effects, u_{it}, are defined in Eq. (1) where the z variables correspond to those listed in Table 2.

Specification of Eq. (2) in terms of per ha variables imposes homogeneity of degree one on the production technology and hence constant returns to scale. As noted earlier, this was done on pragmatic grounds in order to reduce the effects of multicollinearity which severely affected estimates of the parameters of the conventional production function (many estimated parameters were statistically insignificant, and some calculated production elasticities for the translog form were negative). Constant returns to scale in arable production is a somewhat brave assumption to make, however, a Wald test for constant returns to scale for a conventional translog production function including land as an input variable (together with the levels of the input variables defined above and total production of wheat as the dependent variable) significantly failed

Table 4
Generalised likelihood ratio tests of hypotheses for parameters of the stochastic frontier production function and inefficiency effects model[a]

Test	Null hypothesis	λ	Critical value	Decision
1	H_0: $\alpha_t=\alpha_{tt}=\alpha_{kt}=0$	4.53	14.07	Accept H_0
2	H_0: $\gamma=\delta_0=\cdots=\delta_7=0$	93.49	16.27	Reject H_0
3	H_0: $\delta_1=\delta_2=\cdots=\delta_7=0$	50.05	14.07	Reject H_0
4	H_0: $\delta_7=0$	0.123	3.84	Accept H_0

[a] All tests performed at 5% significance.

to reject the null hypothesis that the sum of production elasticities was greater than or less than one.[2]

The unknown parameters of Eqs. (1) and (2) in addition to σ_v^2 and σ_u^2 can be estimated simultaneously using maximum-likelihood — see Battese and Coelli (1993) for details of the likelihood function.[3] Predictions of technical efficiency (TE) are calculated according to the following expression:

$$\mathrm{TE}_{it} = \exp(-u_{it}). \tag{3}$$

These predictions are made using the conditional expectation of Eq. (3), given the composed error $(v_{it} - u_{it})$ and evaluated using the estimated parameters presented in Section 4 (Jondrow et al. (1982) and generalised by Battese and Coelli (1988)).

4. Results

4.1. Hypothesis tests and parameter estimates

The model parameters are estimated using the FRONTIER 4.1 program (Coelli, 1996). The preferred model results from the outcome of a sequence of hypothesis tests that are detailed in Table 4.[4]

The first null hypothesis (Test 1) is accepted, indicating that no statistically significant technical change occurs in the sample over the period. Test 2 explores the null hypothesis that each farm is fully technically efficient and hence that systematic technical inefficiency effects are zero.[5] This is strongly rejected, as is the following null hypothesis which tests whether the variables included in the inefficiency effects model have no effect on the level of technical inefficiency. Finally, Test 4 accepts the null hypothesis that there are no statistically significant time effects within the technical inefficiency model.

After these tests the preferred model is a translog frontier function with no time effects and an inefficiency effects model that is also without time effects. Parameter estimates for this model are given in Table 5.

Elasticities of mean output with respect to the k-th input are calculated from the maximum-likelihood estimates for the parameters of the stochastic frontier using the expression given in Eq. (4).[6]

$$\varepsilon_{x_k} = \alpha_k + 2\alpha_{kk}\bar{x}_{kit} + \sum_{j\neq k}\alpha_{kj}\bar{x}_{jit} \tag{4}$$

These are estimated as 0.515 (t-statistic=1.73) for seeds, 0.00605 (t-statistic=0.175) for fertilisers, 0.118 (t-statistic=4.28) for crop protection, −0.032 (t-statistic=−1.05) for labour and 0.099 (t-statistic=2.88) for machinery. Given the constant returns to scale specification of the function these imply an elasticity for land of 0.757 (t-statistic=11.55).

4.2. Technical efficiencies

Fig. 1 shows the frequency distribution of production-unit-specific technical efficiency, averaged over the period for which each farm appears in the sample. Predicted technical efficiencies range from a minimum of 49.51% to a maximum of 98.01%, the mean value being 87.01% with a standard deviation of 10.52%. More than 74% of the sampled farms have mean efficiency scores that are 85% or greater.

[2] However, given the multicollinearity problems associated with estimation of this function the results of this test must be treated with some caution.

[3] The likelihood function is expressed in terms of the variance ratio $\gamma \equiv \sigma_u^2/\sigma_s^2$, where $\sigma_s^2 \equiv \sigma_u^2 + \sigma_v^2$.

[4] These are undertaken using the likelihood ratio test. This has the form $\lambda=2(\ln L_1 - \ln L_0)$ where $\ln L_0$ is the value of the log likelihood under the null hypothesis and $\ln L_1$ the corresponding value under the alternative hypothesis. It has an approximate chi-square distribution with degrees of freedom equal to the number of independent constraints (Judge et al., 1985).

[5] If γ=0 is involved in the null hypothesis (H_0), then the likelihood ratio statistic has asymptotically a mixed chi-square distribution, if H_0 is true (Coelli, 1995), the critical value for this test is taken from Kodde and Palm (1986) (p. 1246; Table 1).

[6] Elasticities are calculated at the mean values of the input variables over the whole of the sample.

Table 5
Maximum-likelihood estimates for the parameters of the stochastic frontier and inefficiency effects model

Variable	Parameter	Coefficient	Standard error	t-Statistic
Stochastic frontier				
Constant	α_0	−2.944	1.827	−1.611
$\ln x_1$ (seed £/ha)	α_1	−2.816	0.773	−3.641
$\ln x_2$ (fertiliser kg/ha)	α_2	1.056	0.814	1.297
$\ln x_3$ (crop protection £/ha)	α_3	2.636	0.838	3.145
$\ln x_4$ (labour h/ha)	α_4	0.1003	0.9118	0.110
$\ln x_5$ (machinery h/ha)	α_5	0.3298	0.8195	0.402
$\ln x_1 \times \ln x_1$	α_{11}	0.2300	0.0564	4.075
$\ln x_1 \times \ln x_2$	α_{12}	0.2612	0.0960	2.720
$\ln x_1 \times \ln x_3$	α_{13}	−0.0208	0.0706	−0.294
$\ln x_1 \times \ln x_4$	α_{14}	−0.0184	0.1033	−0.178
$\ln x_1 \times \ln x_5$	α_{15}	−0.0500	0.1207	−0.414
$\ln x_2 \times \ln x_2$	α_{22}	0.1562	0.0602	2.594
$\ln x_2 \times \ln x_3$	α_{23}	−0.3913	0.0819	−4.775
$\ln x_2 \times \ln x_4$	α_{24}	−0.3033	0.0810	−3.742
$\ln x_2 \times \ln x_5$	α_{25}	−0.2685	0.1123	−2.390
$\ln x_3 \times \ln x_3$	α_{33}	−0.0799	0.0441	−1.810
$\ln x_3 \times \ln x_4$	α_{34}	−0.0460	0.0829	−0.555
$\ln x_3 \times \ln x_5$	α_{35}	0.1240	0.1131	1.096
$\ln x_4 \times \ln x_4$	α_{44}	−0.0400	0.0463	−0.864
$\ln x_4 \times \ln x_5$	α_{45}	0.4137	0.1242	3.330
$\ln x_5 \times \ln x_5$	α_{55}	−0.00278	0.08514	−0.0326
Inefficiency model				
Constant	δ_0	0.798	0.152	5.261
AREA	δ_1	−0.001175	0.000412	−2.853
EXP	δ_2	−0.005394	0.002252	−2.396
FED	δ_3	−0.02124	0.05624	−0.378
PMAX	δ_4	−0.3598	0.1126	−3.197
ENV	δ_5	−0.3932	0.1202	−3.272
INFSEEK	δ_6	−0.0410	0.0126	−3.259
Variance parameters				
Sigma-squared	σ_s^2	0.0626	0.0149	4.191
Gamma	γ	0.9117	0.0317	28.770
Log (likelihood)		221.224		

5. Technical efficiency and managerial capacity

The results detailed in Section 4 show that the majority of cereal farmers in this sample are operating relatively close to the fully efficient frontier. This is an unsurprising conclusion given that the summary statistics for the sample show that there is little variation in yields and input application rates. Despite this fact parameter estimates for the stochastic frontier and technical inefficiency effects model show that systematic technical inefficiency effects exist and that these are, in part, explained by the variables included in the model.

The parameter estimates for the inefficiency model presented in Table 5 only indicate the direction of the effects these variables have upon inefficiency levels (where a negative parameter estimate shows that the variable has a positive effect on efficiency). Quantification of the marginal effects of these variables on technical efficiency is possible by partial differentiation of the technical efficiency predictor with respect to each of the inefficiency effects variables. Battese

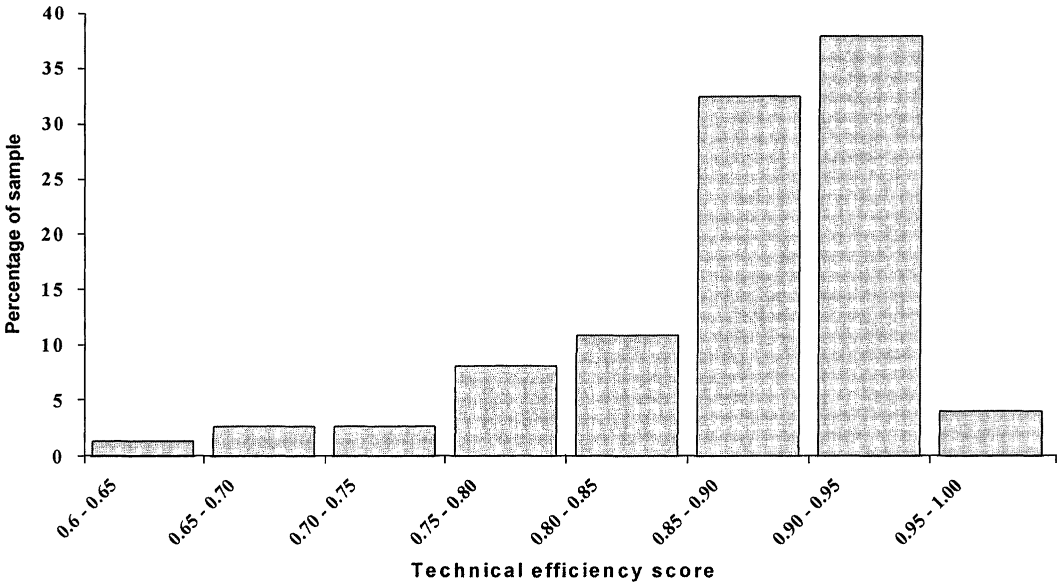

Fig. 1. Frequency distribution of predicted technical efficiencies.

and Coelli (1993) show that for the i-th firm in the t-th time period, technical efficiency is predicted using the conditional expectation

$$\mathrm{TE}_{it} = E[\exp(-u_{it})|E_{it} = e_{it}]$$
$$= \exp(-\mu_* + \tfrac{1}{2}\sigma_*^2)\left(\frac{\Phi[(\mu_*/\sigma_*) - \sigma_*]}{\Phi(\mu_*/\sigma_*)}\right) \quad (5)$$

where

$$\mu_* = (1-\gamma)z_{it}\delta - \gamma e_{it}, \quad \sigma_*^2 = \gamma(1-\gamma)\sigma_s^2,$$
$$e_{it} = v_{it} - u_{it}$$

and Φ represents the distribution function of the standard normal random variable. Table 6 presents the results of differentiating Eq. (5) with respect to each of the inefficiency effects variables (evaluated at their mean values or with a value of one for dummy variables and where the residuals, e_{it}, are calculated at the mean values of the dependent and independent variables in the stochastic frontier function).

Table 6
Marginal effects of inefficiency effects model variables

Variable	Coefficient	Standard error	t-Statistic
AREA	0.0000563	0.0000111	5.080
EXP	0.0002586	0.0000996	2.596
FED	0.00102	0.00270	0.377
PMAX	0.0173	0.0041	4.194
ENV	0.0188	0.00363	5.188
INFSEEK	0.00196	0.000477	4.122

Table 6 shows that all these variables have a positive effect on levels of efficiency and that all, apart from the further education variable (FED), have a statistically significant effect. Note that for those variables constructed as dummy variables (FED, PMAX and ENV), the coefficient estimated represents a one-off shift in efficiency rather than a true marginal effect.

The two variables representing farmer business objectives (PMAX and ENV: profit maximisation and maintaining the environment) have a statistically significant impact on levels of technical inefficiency, i.e. farmers who rank these objectives highly are more efficient than those who do not, generally of the order of 2% more efficient. Those farmers who are classified as information seekers are also more efficient than those farmers who consult fewer information sources, at a statistically significant level. Whilst we might expect that the profit maximising and information seeking variables would have a positive effect on levels of technical efficiency, it is less immediately clear why this should also be the case for those farmers who rank maintaining the environment as an important objective. One possible explanation is that farmers who are environmentally aware, practice a more efficient use of inputs than those who are less environmentally aware.

The model also shows that managers with more experience and those with some form of further education are likely to be less inefficient than those managers with fewer years of experience and lower levels of education, although the estimated coefficient for the latter is statistically insignificant, and the effect in both cases is very small. The coefficient estimate associated with the AREA variable is also very small, although it is highly significant statistically and reinforces the findings of other UK specific studies (Dawson, 1985; Wilson et al., 1998) that technical inefficiency increases as farm size decreases. Given that the constant returns to scale model specification employed here, this is an interesting result, and may arise from the ability of larger farms to negotiate bulk buy discounts for the two inputs which are defined in cost terms (seeds and crop protection) which would then be reflected in lower costs per ha than those for smaller farms.

6. Summary

Technical inefficiency in wheat yields in eastern England has been estimated and the variation in technical inefficiency explained using variables representing a number of managerial biographical details, managerial drives and motivations and practices and procedures with respect to business planning. The results indicate that the majority of wheat farmers in eastern England operate close to maximum technically feasible yield levels and that there is limited potential to improve technical efficiency.

Variables constructed to represent managerial business objective, profit maximisation and concern for maintaining the environment, are shown to have a significant and positive effect on levels of technical efficiency. Moreover, increasing farm size and seeking information are also associated with higher levels of efficiency. The information-seeking variable was included in this research to examine the influence of aspects of the managerial decision-making process. Our findings indicate that aspects of the decision-making process do influence technical efficiency. This reinforces the suggestion of Rougoor et al. (1998) that further studies should include more information on aspects of the managerial decision-making process if they are to successfully measure farmers' management capacity.

The results presented both reinforce findings from previous studies that examine the issue of technical efficiency and also highlight some of the factors that affect technical efficiency. Perhaps of most contemporary interest is that those farmers who consider maintaining the environment as an important objective achieve higher levels of technical efficiency. The results of this study therefore suggest that practices and business objectives that seek to maintain the environment may, indirectly, lead to an improvement in technical efficiency.

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