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Technical Change and Efficiency in Irish Agriculture*

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Abstract: This paper calculates average technical efficiency levels and rates of technical change for Irish agriculture using an unbalanced panel of 2,603 farms drawn from the Irish National Farm Survey over the period 1984 to 1998. An average technical efficiency level of between 65 and 70 per cent with a slight upward trend over the period was found. The efficiency of individual farms is positively associated with the size of the farm household, the ratio of debt to assets and the farmer's age, and negatively related to being located in the West of Ireland, having an off-farm job and size of farm. Technical progress is observed at an unweighted rate of approximately 0.9 per cent and a weighted rate of 2.1 per cent per annum over the 1984-98 period. There is evidence that this rate of growth has been slowing over time. Technical progress was considerably faster on farms in the East of the country compared to Western farms, on larger farms compared to smaller ones, and on dairy and tillage farms compared to cattle and sheep farms.

I INTRODUCTION

A consistent feature of Irish agricultural performance is the apparently large differences between farms in the efficiency with which they use their available resources. For example, in 1998, National Farm Survey data showed that farmers in the lowest third of the population had a gross margin per hectare of €484 and a stocking density of 1.13 livestock units per hectare

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(lu/ha), on average, compared to a gross margin per hectare of €1,043 and a stocking density of 1.54 lu/ha for farmers in the top third of the population (Teagasc, 1999). Partial productivity indicators of this kind can be misleading in comparing relative efficiency across farms as farmers may use different combinations of fixed inputs. For example, farmers with a low level of gross margin per ha may also use relatively few capital and labour inputs. In assessing the factors associated with farm efficiency, it is important to measure efficiency differences accurately. This paper uses a methodology which measures the relative technical efficiency of farms in a consistent way while also throwing light on the factors associated with these differences. Understanding the reasons why these differences occur can be a valuable aid to policy makers in designing policies to improve the overall efficiency and competitiveness of the agricultural sector.

Overall economic efficiency can be decomposed into the product of technical, allocative and scale efficiency (Kumbhakar and Lovell, 2000). A farm is said to be technically efficient if it uses the available inputs in the most effective way in order to produce the maximum output. Technical inefficiency is a measure of the possible reduction in input use to produce the same level of output. When producing a single output, a farm is allocatively efficient if it uses the optimum proportion of each input to produce maximum output, given input prices. Allocative inefficiency is a measure of the possible reduction in cost of using the correct input proportions.[1] A farm is said to be scale efficient if it produces output at a level that minimises the average cost of production. This paper focuses on the measurement and explanation of differences in technical rather than allocative or scale efficiency between farms. Investigation of allocative efficiency requires farm-specific prices on outputs and inputs which were not available in the dataset used by the authors. We do not address scale efficiency explicitly as it is less amenable to policy intervention than technical efficiency.

In order to measure technical efficiency as defined above, it is first necessary to define the production frontier. A production frontier is defined in terms of the maximum output that can be achieved from a set of inputs given the technology available to the farm. Underlying the frontier approach is the assumption that if a farm is operating at a point inside the frontier then it is technically inefficient (Coelli *et al.*, 1998). Once the frontier has been defined the position of any farm relative to the frontier can be gauged and interpreted as a measure of its relative efficiency. The frontier can shift over time (i.e.

[1] In the case of multiple-output farms, it is also possible to have output allocative inefficiency where there is production of an inappropriate output mix in the light of prevailing output prices.

technical change) and the position of farms relative to the frontier can also change over time (i.e. changes in technical efficiency).

As well as differences in efficiency levels, it is hypothesised that farms differ in the rate at which productivity is growing over time. To date, there are no Irish data on farm-specific or system-specific productivity growth rates and this paper provides such data for the first time. Productivity change is here identified with technical change although it is recognised that increases in total factor productivity can also involve scale efficiency change and allocative efficiency change. Technical change refers to shifts in the production frontier over time due to application of new innovations and technology. Shifts in the frontier can be neutral or non-neutral. Neutral technical change is represented by a parallel upward shift of the frontier. Technical change is defined as non-neutral if it affects the marginal rate of technical substitution between inputs. The paper examines the relative importance of changes in average technical efficiency and technical change which may have implications for the allocation of resources between research and extension, for example.

The estimation of farm level efficiency and technical change has received considerable attention from researchers (for applications specific to agriculture see Kalirajan *et al.*, 1996; Kumbhakar *et al.*, 1991; Hallam and Machado, 1996; Parikh and Shah 1994; Taylor and Shonkwiler, 1986). Two broad approaches to identifying the relevant frontier function have been developed: parametric and non-parametric (see Coelli *et al.*, 1998 for an introduction to this literature). Although parametric techniques, unlike the non-parametric ones, require the imposition of assumptions regarding the technology structure and cannot easily handle multiple outputs, they possess the advantage that conventional tests of hypotheses can be conducted. This paper concentrates on the parametric stochastic frontier approach and models technical efficiency and technical change using maximum likelihood techniques for a unbalanced panel of 2,603 farms for the period from 1984 to 1998.

The paper extends a previous Irish study by Boyle (1987) who estimated efficiency effects from cross-section stochastic frontiers using Irish farm data for 1979-1983 and examined the factors associated with differences in efficiency levels between these farms. Papers by Ahmad and Bravo-Ureta (1996), Dawson (1985) and Greene (1993) show that measures of technical efficiency can vary greatly depending on the estimation technique and the specification of the production frontier. A variety of models with differing assumptions are first tested to determine the most appropriate representation of the technology of Irish farms. Using the preferred model, estimates of average technical efficiency and technical change are derived. The sources of farm level efficiency are also explored.

II METHODOLOGY

The stochastic approach assumes 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 model first specified by Aigner *et al.* (1977) and Meeusen and Van den Broeck (1977) and modified for panel data by Pitt and Lee (1981) is given as

$$y_{it} = f(x_{it};\, \beta) + v_{it} - u_{it} \tag{1}$$

where y_{it} is output, x_{it} is a vector of inputs, v_{it} is random noise, u_{it} is the efficiency effects and t is time. The efficiency effects may be assumed invariant over time ($u_{it} = u_i$ for all t) or may be assumed to vary over farms and over time as in Equation (1). Estimation of the stochastic production frontier specified in Equation (1) can be undertaken using a fixed effects or a random effects approach estimated using either generalised least squares or maximum likelihood (ML) estimation. The choice of method is not innocuous. The fixed effects approach assumes that the efficiency effects and the independent variables are uncorrelated. As Boyle (1987) points out, this is a strong assumption. One could argue that efficient farmers are more likely to use more of certain resources, such as fertilisers or capital equipment.

There is no a priori justification for the distribution of the error term u_{it} in either the time variant or time invariant models. Early models assumed a half normal distribution which implies relatively low technical inefficiency scores. This is because the half normal distribution has a mode at zero which implies that there is the highest probability that the inefficiency effects are near zero (Coelli *et al*., 1998; Greene 1993). Stevenson (1980) suggested that the mean of zero in the half normal distribution was unnecessarily restrictive. By truncation at zero of the normal distribution with mean μ and variance σ^2 an alternative distribution, the truncated normal distribution, is possible.

The ML estimation in this paper is based on the Coelli (1992 and 1995) specifications. These approaches allow for the estimation of time invariant and time variant technical efficiency. Time invariant technical efficiency is defined as $TE_i = \exp(-u_i)$. By assuming that the efficiency effects are distributed as

$$u_{it} = \{\exp[-\eta(t - T)]\}u_i \quad i = 1, 2, \ldots , N;\ t = 1, 2, \ldots , T \tag{2}$$

where the u_i's are distributed as general truncated normal random variables as above and η is an unknown scalar, time variance can be introduced into the model. If the value of η is positive (negative) then the inefficiency effects are decreasing (increasing) over time (Coelli *et al*., 1998).

Suppose the frontier production function is given by a general translog functional form incorporating the possibility of non-neutral technical change

$$ln\ y_{it} = \alpha + \sum_k \beta_k\ ln\ x_{kit} + 0.5 \sum_k \sum_j \beta_{kj}\ ln\ x_{kit}\ ln\ x_{jit} + \sum_k \xi_k\ ln\ x_{kit}\ t + \zeta_t t + \zeta_{tt} t^2 + u_{it} + v_{it} \tag{3}$$

where y_{it} is output for farm i in period t, x_{kit} is the kth input of farm i in period t, t is time technical change, α, β_k, β_{kj}, ξ_k, ζ and ζ_t are the parameters to be estimated, u_{it} represents time variant technical efficiency and v_{it} is statistical noise. A number of other functional forms are nested within Equation (3). By restricting $\xi_k = 0$ the model reduces to a translog frontier production function with neutral technical change. By setting $\beta_{kj} = 0$ the equation reduces to a Cobb-Douglas frontier production function. By restricting $u_{it} = u_i$ for all t implies that the efficiency effects are invariant over time. These specifications are tested formally.

The rate of technical change is defined from Equation (3) as the percentage change in output due to a unit change in time, that is,

$$TC_{it} = \partial y_{it}/\partial t = \zeta_t + \zeta_{tt}\ t + \sum_j^J \xi_{jt}\ x_{jit} \tag{4}$$

Neutral technical change is given by the first two terms of Equation (4) and non-neutral technical change is given by the third term (Hesmati, 1996; Nishimizu and Page, 1982). If ζ_t is positive/negative then there is technical progress/regress over the period. The sign on ζ_{tt} determines whether or not technical change is taking place at an increasing or decreasing rate. Technical change is said to be input-using in the j^{th} input if the sign on ξ_{jt} is greater than zero and input-saving in the j^{th} input if ξ_{jt} is less than zero.

Two routes are possible in investigating the determinants of technical efficiency variation among the farms in the sample. The first involves the estimation of the technical efficiency effects as described above and regressing these on a set of farm specific characteristics. This approach, though widely used, implies that the efficiency 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 efficiency 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 the Battese and Coelli (1995) model. In this approach the technical efficiency effects are specified in the stochastic frontier model and assumed to be independently but *not identically* distributed non-negative random variables. For the ith farm in the tth period the technical efficiency effects (u_{it}) are obtained by the truncation at zero of the normal distribution with mean $Z_{it}\delta$ and variance σ^2 as in Equation (5).

$$\mu_{it} = \delta_0 + Z_{it}\,\delta_{it} \tag{5}$$

where Z is a vector of farm specific variables and δ are the unknown parameters to be estimated. Unlike the Battese and Coelli (1992) model where the efficiency effects are the product of an exponential function of time and non-negative firm specific random variables, the technical efficiency effects in the Battese and Coelli (1995) model are specified to be a linear function of a vector of farm specific variables and time, together with an additive random error which is assumed to be independent over time and among farms (Battese and Coelli, 1993).[2] By including a time trend in Equation (5) it is possible to capture the linear change in technical efficiency over time (Karagiannis *et al.*, 1999; Battese and Coelli, 1995). If all the elements of the δ vector are equal to zero then the model is the half normal distribution specified by Aigner *et al.* (1997).

Specialist dairy farms are the highest-income farm system and are often considered to be more productive than the other systems of farming in Ireland for that reason. Because the existence of the milk quota system prevents farmers from entering or increasing dairy production, a series of dummy variables is included in Equation (3) to allow the intercept term in the production frontier to vary by farm system. This has the effect of defining a separate frontier for each farm system so that efficiency is now measured relative to the best practice within a system.[3]

This review of model specification issues has drawn attention to the variety of assumptions which can be made about the nature of the underlying production frontier for Irish agriculture. They include: whether the efficiency effects are better modelled as fixed or random effects; assumptions about the distribution of the efficiency effects (half-normal or truncated normal); whether the production function is Cobb-Douglas or translog; whether technical change is non-neutral or not; and whether farm system influences the position of the frontier or not. A rigorous testing of these alternative specifications was carried out to determine the preferred model for Irish

[2] The likelihood function for the Battese and Coelli (1995) model is given in Battese and Coelli (1993).

[3] Boyle (1987) uses a similar argument when including involvement in a dairy farm system as a variable potentially explaining efficiency differences between farms.

agriculture. This preferred model was then used to estimate the importance of the factors influencing technical efficiency and farm system-specific rates of technical change. All models are estimated using the programme Frontier 4.1 (Coelli, 1996).[4]

III DATA

The data used are taken from the Irish National Farm Survey (NFS). Farmers are randomly selected from the farm population and participate voluntarily in the survey. The data set comprises a sample of 2,603 farms in the years 1984 to 1998, representing farms which participated in the Survey at any time during this period.[5] Farms remain in the sample for on average 5.9 years giving a total number of 14,917 observations.

Most Irish farms are multi-product enterprises producing a combination of milk, beef cattle, tillage, horses, sheep, pigs or other outputs. The production function was specified using a single output based on the value of the enterprise outputs excluding subsidies and four inputs; land, labour, capital and variable inputs. There are two reasons why it was necessary or prudent to aggregate the data. On the output side, the stochastic frontier approach can only handle a single output. Second, the translog specification cannot handle zero values. Using more disaggregated data for variable inputs, for example, increases the number of data points with zero values and the necessity to make *ad hoc* adjustments to get round this problem. Aggregation of inputs and outputs removes the problem of zero values in estimating the production functions in the majority of cases. The cost of aggregation is the separability assumptions which are implicitly made in the production function specification used. Aggregating to a single output assumes input-output separability implying that the producer's choice of output mix is independent of the levels of inputs. Aggregating input groups assumes that the marginal rate of substitution between inputs within the group is independent of the quantities of inputs outside the group (Boyle, 1987). The bias arising if this assumption does not hold is minimised by the use of Tornqvist-Theil indices to perform the aggregation.

Output, variable input and capital stock variables for each farm were aggregated as follows. Tornqvist-Theil (TT) value indices were first constructed for each of the variables. Implicit quantity indices are then obtained as the ratio of the TT value indices to an aggregate farm-specific

[4] This programme can be downloaded from http://www.une.edu.au/econometrics/cepanews.htm.

[5] The original data set consisted of 3,359 farms. 552 farms were excluded due to missing socio-economic data. Outliers were identified using the methods of Hadi (1992 and 1994). Once true outliers were removed the sample reduced to 2,603.

multilateral TT price index with base period 1996 (Boyle (1987) discusses the advantages of different index number formulae and advocates the use of superlative index numbers such as the Divisia index to which the TT index is a discrete approximation). Since farm-specific prices were not available, the CSO national price indices were used in the construction of the farm-specific TT price indices. Because these indices vary over time but not over farms, differences in the quality of outputs or inputs are reflected in differences in quantity (Reinhard, 1999; Caves *et al*., 1982).

The land input is measured by the adjusted size of farm in hectares. Because the bulk of Irish farmland is farmed by owner-occupiers, a series on the rental value of farmland is not available. The adjustment made 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. The variable inputs aggregate was constructed as described above. Variable inputs include feed, fertilisers, electricity, veterinary fees, and transport costs. Capital input includes the stock of machinery, land improvements, livestock and buildings, with the individual components summed using the implicit quantity method. Livestock are valued as the average of the opening and closing inventories. Machinery is the closing inventory valued at the cost of replacement, while the value of land improvement and buildings is based on market value as estimated by the farmer. The summary statistics of the variables in the models are shown in Table 1. All the production data were mean corrected using the sample means prior to estimation of the production frontier so the first order partial derivatives can be interpreted as elasticities of mean output with respect to the input involved.

Table 1: *Summary Statistics of Variables in the Stochastic Production Function*

Variable	*Mean*	*Std/Mean*	*Minimum*	*Maximum*
Gross output (£)	48,804	0.99	1,529	358,807
Capital (£)	34,980	1.21	65	361,763
Other inputs (£)	24,130	1.23	338	574,282
Size of farm (ha)	55	0.83	4.04	404
Total number of labour units	1.54	1.85	0.05	15.2
Age	48.7	0.25	16	86
Debt ratio	0.183	2.21	0	23.4
Household total	3.9	0.52	0	13

An additional set of variables is used to explain technical efficiency differences across farms. These include:

Z_1: the age of the farmer;

Z_2: age squared;

Z_3: a debt ratio of the total farm borrowings to the total value of assets on the farm;

Z_4: a dummy variable where having an off-farm job = 1 and 0 otherwise;

Z_5: a dummy for region where being located in the West of Ireland = 1 and 0 otherwise;

Z_6: size of the farm household in numbers of individuals;

Z_7: size of the farm in hectares;

Z_8: a time trend.

The following coefficient signs are hypothesised. There is no a priori expectation on the sign for age. It is possible that older farmers have more experience and therefore are more efficient but it is also possible that older farmers are less concerned with optimising the use of resources under their control thus giving a negative coefficient. The expected sign for off-farm employment is also ambiguous. Farm operators who engage in off-farm employment spend less time on the farm which may be negatively associated with efficiency; on the other hand, off-farm employment may absorb underemployed labour resources and improve the experience and human capital of the farm operator, thus leading to a positive relationship with efficiency. Farms located in the West of Ireland face physical disadvantages and so this coefficient is expected to be negative.

Farms with large households are thought likely to be more efficient because of the pressure and incentive to achieve a minimum living standard. Farms with a high debt ratio are also expected to be more efficient as they need to ensure that the debt can be repaid. The education level of the farm operator would be an appropriate variable to include in a model explaining technical efficiency; however, this information was not available in the data set used. A time trend is included to capture the linear pattern of technical efficiency over time. Some authors have suggested that time may be capturing learning by doing or lagged reactions to changes in the policy environment. Hence, there is no a priori expectation of the sign on the time trend. Farm size is included as a factor explaining efficiency not as a production factor (where it appears in the frontier production function) but as a proxy representing the ease with which farmers can efficiently utilise lumpy factors of production (including both own labour and capital). As such, a positive relationship with efficiency is anticipated. Alternatively, it may proxy a wealth effect whereby farmers’ motivation to maximise efficiency is reduced with larger assets, in which case a negative relationship will be found.

IV RESULTS

Model Specification Tests

There is no correct starting place for the specification testing.[6] The first stage of testing concentrated on identifying the most appropriate estimation technique. The choice between a fixed effects or a random effects approach is dependent on whether or not the explanatory (x) variables and the efficiency effects (from the error term) are uncorrelated. Fixed effects allow for correlation between the error term and the explanatory variables while for random effects approaches the explanatory variables and the efficiency effect must be uncorrelated. The hypothesis that there was zero correlation between the x variables and the efficiency effect was tested using a Hausman test. ML specifications were favoured over the fixed effects ones.

The second stage of testing concentrated on the validity of the translog over the Cobb-Douglas specification within the ML specifications using a log likelihood test. The null hypothesis that $\beta_{ij}=0,\ i \leq j=1,4$ was strongly rejected. Therefore, the translog production technology is considered to be a better representation of farm technology than the Cobb-Douglas specification.

The third stage of testing used log likelihood tests to examine the alternative specifications of technical change within the family of ML translog models. The null hypothesis that there was neutral technical change was rejected in each case against the alternative hypothesis of non-neutral technical change.

The fourth stage of testing used a log likelihood test to determine if the models with farm system dummies were preferred to models with no system dummies. The null of no farm system dummies was rejected.

The fifth stage of testing was used to test the null hypothesis that there were no technical efficiency effects in the model. Again likelihood ratio tests were used. The null hypothesis that there were no efficiency effects, that is, the one sided error $\gamma=0$, was strongly rejected.

The final stage of testing concerned the nature and distribution of the efficiency effects. The null hypothesis that the technical efficiency effects were

[6] The results for the full range of models estimated and the test results can be obtained from the authors.

time invariant, that is, $\eta=0$, was rejected against the alternative that the technical efficiency effects were time variant for all ML specifications. The null hypothesis that the technical efficiency effects have a half-normal distribution, that is, $\mu=0$, is rejected against the null that the technical efficiency effects have a truncated normal distribution. Given these results, the translog with non-neutral technical change and farm system dummies is the best representation of Irish agricultural technology given the alternative specifications considered.[7] The parameter estimates for this model are shown in Table 2. There is no evidence of heteroscedasticity or non-normality in the data.[8]

Farm Efficiency

Efficiency is measured on a scale from 0 to 1 in which lower values represent lower levels of technical efficiency. Average technical efficiency using the preferred model amounted to 0.70 over the period, and showed a slight upward trend (from 0.68 in 1984 to 0.72 in 1998). In order to throw light on the importance of the factors affecting efficiency, a comparison of the characteristics of the top one-fifth and bottom one-fifth of farms ranked by their technical efficiency score was undertaken (Table 3). Gross output per ha, gross margin per ha and family farm income per ha are all higher in the farms ranked in the top 20 per cent of technical efficiency ratings. Borrowings per ha and debt ratios are also higher in the most efficient quintile of farms, although the direction of causation might be questioned here. Thirty-one per cent of the top quintile are specialist dairy farms, which is a higher proportion than in the sample as a whole. Because the technical efficiency scores are calculated relative to best practice in each system, this figure implies that the variation in efficiency scores among dairy farmers is relatively smaller than for other systems, in that a higher proportion of dairy farmers end up in this top quintile. Table 4 shows that 51 per cent of farms in the lowest quintile are primarily cattle farms and a further 31 per cent are sheep farms.

[7] Once the best model for Irish agriculture was determined the testing regime was reversed and the starting point was the best model. This was then compared against the alternative specification for all the dimensions considered. This approach was taken to ensure that the starting point was not influencing the model selected. Checks that the monotonicity condition and curvature restrictions held for the preferred model were also satisfactory.

[8] The estimated χ^2 value obtained using White's test exceeds the critical value and it was concluded that there was no heteroscedasticity in the error variance. The normality assumption was tested the method outlined in D'Agostino *et al.* (1990).

Table 2: *Parameter Estimates for the Preferred Production Frontier Model*

	Coefficient	*Standard Error*
Constant	0.5595[a]	0.0174
Size (hectares)	0.1153[a]	0.0125
Labour	0.1241[a]	0.0158
Variable inputs	0.6726[a]	0.0117
Capital	0.1264[a]	0.0079
Size^2	–0.1526[a]	0.0220
Labour^2	0.0506[c]	0.0321
Variable^2	0.1338[a]	0.0203
Capital^2	0.0328[a]	0.0084
Size x labour	0.0577[b]	0.0245
Size x variable	–0.1544	0.0156
Size x capital	0.0459[a]	0.0112
Labour x variable	–0.0822[a]	0.0211
Labour x capital	0.0162	0.0152
Variable x capital	–0.0269[a]	0.0101
Time	0.0102[a]	0.0038
Time^2	–0.0002	0.0002
Dairy Other	–0.1003[a]	0.0144
Cattle	–0.5029[a]	0.0175
Sheep	–0.6536[a]	0.0198
Crops	–0.2500[a]	0.0176
σ^2	8.8361[a]	
Gamma	0.9795[a]	
Mu	–5.8838[a]	
Eta	–0.1289[a]	
Log likelihood function	–10,549	

a: Significance at 1 per cent; b: Significance at 5 per cent; c: Significance at 10 per cent;
σ^2 is the variance parameter.
Gamma (γ) indicates the degree to which the residual variation is due to inefficiency effects.
Mu ($\mu \neq 0$) Implies that the distribution of the inefficiency effects is truncated normal.
Eta ($\eta \neq 0$) Implies that the technical efficiency effects vary over time.

Table 3: *Characteristics of the Most and Least Inefficient Farms*

	Mean	*Std Dev (std/mean)*	*Minimum*	*Maximum*
Technical Efficiency				
Most inefficient	.3420	.1209 (.35)	.0026	.5067
Least inefficient	.8910	.0326 (.03)	.8424	.9868
Gross Output per ha				
Most inefficient	210.13	299.69 (1.4)	.0024	2991.08
Least inefficient	889.84	561.75 (.63)	14.82	5380.81
Gross Margin per ha				
Most inefficient	323.94	211.17 (.65)	–428.19	2049.03
Least inefficient	661.81	351.02 (.53)	7.19	2381.99
Family Farm Income per ha				
Most inefficient	161.00	147.71 (.91)	–808.50	948.80
Least inefficient	388.91	272.13 (.69)	–491.85	1732.76
Capital per ha				
Most inefficient	451.69	410.21 (.90)	1.030	4452.51
Least inefficient	678.35	508.25 (.74)	3.185	4234.06
Variable Costs per ha				
Most inefficient	302.54	247.72 (.81)	4.61	2825.03
Least inefficient	487.53	320.42 (.65)	20.97	4213.34
Labour Units				
Most inefficient	1.2	.6682 (.55)	.0667	12.57
Least inefficient	1.6	.8558 (.53)	.1244	15.25
Livestock Units				
Most inefficient	53.70	49.79 (.92)	0	732.88
Least inefficient	67.15	51.18 (.76)	0	385.33
Size of farm in adjusted ha				
Most inefficient	49.98	47.73 (.95)	4.04	395
Least inefficient	58.32	47.19 (.80)	4.04	397
Borrowing per ha				
Most inefficient	122.17	279.05 (2.2)	0	3751
Least inefficient	293.06	416.76 (1.4)	0	3592
Debt Ratio				
Most inefficient	.0942	.2028 (2.1)	0	3.80
Least inefficient	.2323	.3456 (1.4)	0	3.46
Age				
Most inefficient	52	12.64 (.24)	18	85
Least inefficient	47	12.04 (.25)	18	84
Household Size				
Most inefficient	3.5	1.95 (.55)	1	13
Least inefficient	4.4	1.98 (.45)	1	12

Table 4: *Percentage of Least and Most Inefficient Farms by System of Farming*

System	*Per Cent Most Inefficient*	*Per Cent Least Inefficient*
Dairy	4.76	31.04
Dairy Other	9.62	17.70
Cattle	51.17	16.93
Sheep	31.33	11.10
Crops	3.12	23.23
Total	100.0	100.0

The farm system dummies show the intercept term for dairy and other, cattle, sheep and tillage farms to be lower and statistically different to that of dairy farms as expected (Table 2). Average efficiency is lowest on sheep farms. Movements in average annual efficiencies are compared across farm systems in Figure 1, by setting the average efficiency of each farm system in 1984 equal to 100. Technical efficiency has remained almost constant for dairy, tillage and dairy and other farms over the period, although the average level of technical efficiency is relatively high compared to sheep and cattle farms. Technical efficiency on sheep farms has grown from the start of the period under study with a significant jump upward after 1988, while cattle farms experienced a significant fall in average technical efficiency in the period after 1991.

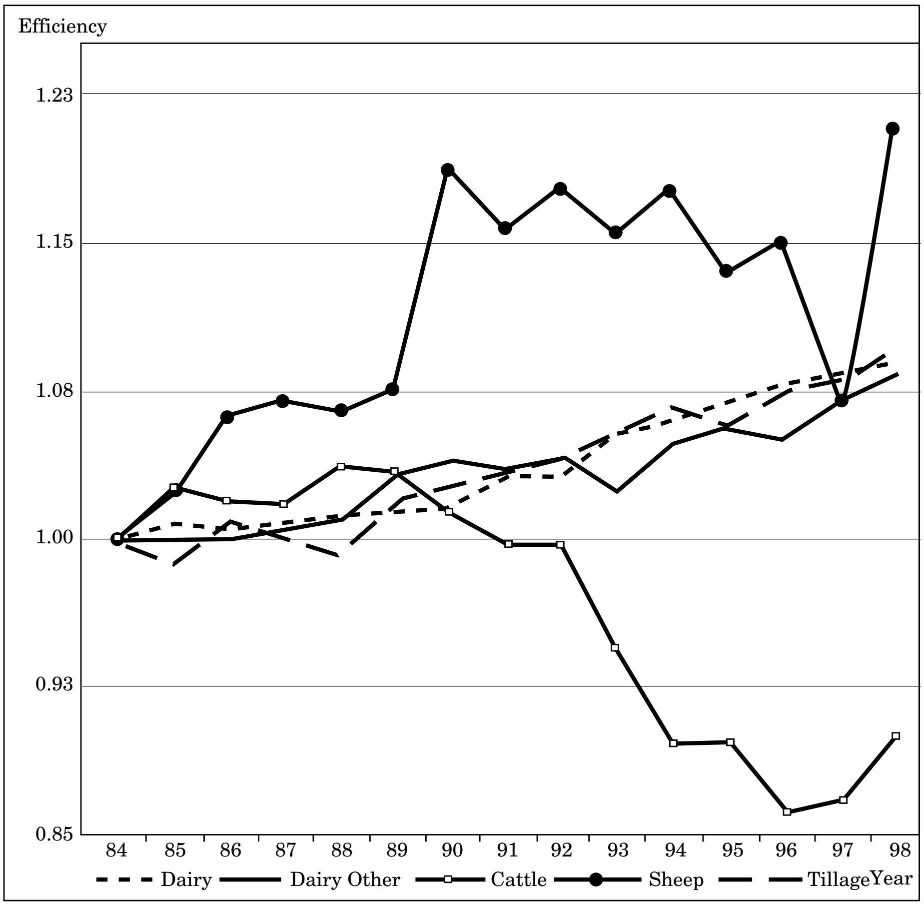
Table 5: *Results of the Technical Efficiency Analysis*

Variables	*Coefficient*	*SE*	*Marginal effect*
Age of farm operator	0.0257	0.0100	1.39
Age squared	–0.0008[a]	0.0001	–2.31
Debt ratio	0.1742[a]	0.0792	0.04[a]
Off-farm job	–2.9087[a]	0.0792	–3.23[a]
Located in West of Ireland	–3.3381[a]	0.0966	–3.75[a]
Size of farm household	0.3468[a]	0.0119	1.54[a]
Size of farm in ha	–0.0137[a]	0.0004	–0.85[a]
Time	–0.5280[a]	0.0093	–4.33[a]

a: 1 per cent significance level.

In the regression analysis, variables which appear significant in explaining differences in technical efficiency across farms include household size, having an off-farm job, being located in the West of Ireland, the debt burden and farm size (Table 5). The relationship between age and efficiency

Figure 1: *Annual Average Technical Efficiency by Farm System (1984 = 1000)*



does not appear to be significant although the slight positive relationship, if it exists, becomes considerably weaker, the older the farmer. Efficiency is positively associated with farm household size. Previous evidence has shown that farms where there are children are more likely to be economically viable than farms with only the farm operator and spouse (Frawley and Commins, 1996).[9] This result highlights that one factor underpinning their greater economic viability is the more efficient utilisation of farm resources on these farms. Having an off-farm job is negatively associated with efficiency. This is a noteworthy result as taking up off-farm employment might be expected to

[9] A farm is said to be economically viable if the family farm income is sufficient to remunerate the family labour on the farm, plus a 5 per cent return for non-fixed assets, and the labour input is greater than 0.75 of a labour unit. (Frawley and Commins, 2000).

lead to a more efficient allocation of labour time on the farm. This effect appears to be outweighed by the farmer having less time to attend to the practical tasks of managing the farm in an efficient manner.

A higher debt ratio is positively associated with efficiency suggesting that farmers who are borrowing are better managers (though the direction of causation could also operate in the other direction, with the better managers more likely or more able to borrow). Larger farms are found, on average, to make less efficient use of their resources. The lower efficiency of larger farms may reflect either the fact that some large farms are associated with relatively poor land (hill farms) or that large farmers are under less income pressure to optimise the use of their resources. The coefficient on the time trend is found to be negatively related to efficiency. This is not inconsistent with the finding that average efficiency has been increasing over time because the influence of time alone is conditional on the values of other explanatory factors remaining constant. Just why time alone is negatively related to efficiency remains unexplained. For example, it may represent a delayed response to policy adjustments, but other explanations are also possible.

Table 6: *Estimates of Technical Change (Annual Rates, Per Cent)*

Category		*Unweighted*	*Weighted*
National	Total	0.91	1.19
	Neutral	0.80	0.80
	Non-neutral	0.10	1.94
Size			
Less that 22 ha	Total	0.35	1.03
23 to 33 ha	Total	0.88	1.61
34 to 48 ha	Total	0.90	1.73
49 to 80 ha	Total	1.08	1.88
80 ha and Over	Total	1.16	2.25
Region			
Western	Total	0.13	0.42
Eastern	Total	1.32	2.19
System			
Dairy	Total	1.88	2.67
Dairy/Other	Total	1.37	2.09
Cattle	Total	–0.18	0.53
Sheep	Total	–0.46	–0.03
Tillage	Total	1.70	2.07

These results can be compared to those of Boyle (1987) using earlier Irish farm data who estimated the determinants of efficiency using a two-stage approach. Boyle found similar effects for household structure and off-farm employment, but not for age or farm size, although except for farm size none of his variables were statistically significant. Surprisingly, he found that the dairy system, relative to other production activities, had a significant negative effect on efficiency. Our results are also broadly consistent with other studies of technical efficiency among farmers although the size of farm effect differs from that found in these studies (Hadley *et al*., 2000; Andreakos *et al*., 1997; Parikh and Shah, 1994).

The coefficients on the explanatory variables give an indication of the direction of the effect of the variable on technical efficiency. By differentiating each of the explanatory variables in the efficiency model with respect to the technical efficiency predictor it is possible to calculate the marginal effect (at the mean) for each of the efficiency variables (Table 5). Being located in the West of Ireland decreases efficiency by 3.75 per cent (this may be a reflection of the poorer average land quality in the West of Ireland as no account was taken of differences in land quality in the land variable in the frontier production function) while having an off-farm job decreases efficiency by 3.23 per cent. An extra hectare of land decreases efficiency by 0.85 per cent. Age is positively related to efficiency with a one year increase in age increasing efficiency by 1.39 per cent suggesting that older farmers are more experienced at managing an efficient farm, but this effect is not statistically significant. An additional household member increases efficiency by a quarter of a per cent. A unit increase in the debt to assets ratio increases efficiency by almost 0.04 per cent. The marginal effect of time (calculated at the mean) is associated with a 4 per cent reduction in efficiency.

Technical Change Estimates

Estimates of technical change for all farms and disaggregated by size, region and system are shown in Table 6. Technical change is decomposed into neutral and non-neutral technical change. Both weighted and unweighted estimates are reported. The unweighted estimates are a simple average for all farms in the sample. Weighted estimates are obtained by weighting the farm-specific technical change rates by each farm's contribution to gross output, and better reflect the overall impact of technical change in each category.[10]

[10] This is true only to the extent that the sample used is representative of the population of all farms. Because the NFS sample is stratified by size and by system, the weighted averages using sample weights are likely to be biased estimates of the true national rates of technical change. It would be possible to gross up the farm-specific rates of technical change by the sampling (population) weights used each year in the NFS, but the general trends reported in the text are unlikely to be seriously affected.

Because there is a positive correlation between size of farm (measured in terms of gross output) and technical change, weighted averages are higher than the unweighted averages.

The average annual rate of technical change was 0.9 per cent (unweighted) and 2.1 per cent (weighted) over the 1984-98 period. However, technical change was higher in the earlier part of the period compared to the later part, indicating that the rate of technical progress is slowing down. The annual rate of unweighted technical change fell from 1.19 per cent for the period 1984 to 1990 to 0.5 per cent for the period 1990 to 1998 (the corresponding weighted figures are 2.3 per cent per annum and 1.5 per cent, respectively). In the period up to 1990 technical change was characterised by non-neutral technical regress but neutral technical progress. The reverse has been the case since 1990 when non-neutral technical change turned positive and has been increasing, while the rate of neutral technical change has been slowing and turned negative (unweighted) in 1997 and 1998. The signs on the coefficients for land and labour are negative suggesting that technical change is both land and labour saving while the signs on the coefficients for variable inputs and capital are positive indicating that technical change is variable input and capital using. A slowdown in the rate of technical change was also observed by Matthews (2000) using an index number methodology with aggregate data. He calculated an annual rate of total factor productivity growth (which combines the impact of technical change with other sources of productivity change) in Irish agriculture of 2.3 per cent per annum in the 1980s falling to 0.8 per cent annually in the 1990s.

Farms located in the Eastern region had an annual unweighted rate of technical progress of 1.3 per cent over the period compared to 0.1 per cent annually for farms in the Western region (the corresponding weighted averages are 2.2 per cent and 0.4 per cent, respectively). There is also a clear positive correlation between technical change and farm size (in hectares). Dairy, dairy other and crop farms experienced technical progress over the period at unweighted annual rates of 1.9, 1.4 and 1.7 per cent respectively (the weighted averages are 2.7, 2.1 and 2.1 per cent). Cattle and sheep farms experienced technical regress (unweighted) over the same period. However, when weighted by gross output, technical change in the cattle sector turns positive if low (0.5 per cent annually) while it appears to have been absent in the sheep sector.

V CONCLUSIONS

This paper applied a stochastic production frontier model to an extensive panel of Irish farms to estimate technical efficiency levels and rates of technical change for individual farms. It also tested whether particular farm-specific factors are associated with differences in technical efficiency. Our results suggest that, on average, farms achieve around 70 per cent of the efficiency level of best practice farms within the system they are in. If farms are compared with best practice within the agricultural sector as a whole, the average efficiency level drops from 70 per cent to 65 per cent. This average figure compares to an average of 58 per cent found by Boyle (1987) using a different model specification and an earlier time period (1979-83). An average score of 65 per cent suggests that there is considerable scope for either increased output or cost savings if average efficiency levels could be improved.

The paper investigated a number of factors associated with higher efficiency scores. Farming in the East of the country, larger household size and high borrowings were found to be positively associated with technical efficiency, while having an off-farm job and larger farm size were negatively associated with efficiency. Two points might be made about these explanatory factors. First, although they give important insights into the determinants of farmers' behaviour, they are not, in themselves, policy levers which the government is in a position to use. Second, together, they account for only a minor proportion of the observed variance in efficiency levels. Observed differences in management performance may be more highly correlated with education and other human capital variables but, unfortunately, data on such variables were not available in the data set available to us. Boyle (1987) found contact with the advisory service to be strongly associated with higher efficiency, though the educational attainment of the farm operator was not statistically significant.

We find an unweighted average rate of technical change, measured by the shift in the frontier of best practice farms, of 0.9 per cent annually and a weighted average of 2.1 per cent. Splitting the time period in two shows a slow down in the annual rate of unweighted technical progress from 1.2 per cent for the period 1984 to 1990 to 0.5 per cent for the period 1990 to 1998. For the weighted results, the corresponding figures are 2.3 per cent per annum for 1984 to 1990 compared to 1.5 per cent for the later time period.

Significant differences were revealed in the rate of technical change on farms of different types. Farms located in the Eastern region have a higher rate of technical change than farms in the Western region. The unweighted mean annual rate of technical change for farms in the Eastern region is 1.35 per cent over the period compared to a mean annual rate of 0.13 per cent for farms in the Western region. The weighted mean rates are 2.21 and 1.15 per cent, respectively. Farms in the top size quintile (over 81 hectares of land) had an unweighted average annual rate of technical change of 1.16 per cent and a weighted annual rate of 2.24 per cent. For farms in the bottom size quintile (less than 22 hectares), the unweighted annual average rate of technical change was 0.35 per cent and the weighted average rate 1.03 per cent. Thus, disparities in the rate of uptake of new technologies appear to be contributing to the observed polarisation of Irish agriculture (Frawley and Commins, 1996). Dairy, dairy and other and crop farms experienced technical change over the period (at unweighted annual rates of 1.9, 1.3 and 1.75 per cent and weighted rates of 2.67, 2.09 and 2.07 per cent, respectively). Technical change on cattle and sheep farms was much slower. Weighting the results showed that cattle farms experienced an annual rate of technical progress of 0.5 per cent over the period, while for sheep farms slight technical regress at a rate of 0.02 per cent was found.

The causes of these differences in technical change growth rates and their change over time deserve more extensive investigation, but it is interesting to speculate on the possible contribution of the changes in CAP support mechanisms in the 1990s. The apparent slow-down in technical change might be due to cutbacks in research expenditure which occurred in the 1980s, or to the greater regulation of agriculture and use of direct payments to support farm incomes which was introduced by the MacSharry CAP reforms in the 1990s. Not only has the role of direct payments in farm income support increased in importance, but a growing share of direct payments is now contributed by schemes with direct production-limiting impacts (extensification, rural environmental payments). These schemes have had their greatest impact on cattle and sheep farms, which have also experienced the lowest technical change over the period. It is at least plausible that the more recent CAP regulations have acted to the detriment of efficiency and efficiency improvement in Irish agriculture.[11] If corroborated, it is an important argument to be taken into account in assessing the balance of advantage of the CAP to Ireland and to Irish agriculture.

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[11] To the extent that extensification and the Rural Environment Protection Scheme have resulted in non-priced environmental benefits, then the calculated slow-down in productivity growth reflects the failure to properly measure these benefits as part of the output of agriculture in the frontier production function framework. It is arguable, however, that these schemes have operated in Ireland primarily as income support rather than as environmental schemes, so this argument does not invalidate the argument made in the text.

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Before the industrial revolution, agriculture was the most important economic activity of traditional societies. The spread of industrialization processes, first throughout a large part of the...Â Allen RC (1982) The efficiency and distributional consequences of eighteenth century enclosures.Â Kopsidis M, Hockmann H (2010) Technical change in Westphalian peasant agriculture and the rise of the Ruhr, circa 1830â€“1880. Eur Rev Econ Hist 14(2):209â€“237CrossRefGoogle Scholar. Kopsidis M, Wolf N (2012) Agricultural productivity across Prussia during the industrial revolution: a ThÃ¼nen perspective. This report investigates technical change and levels of technical efficiency on Irish farms using National Farm Survey (N.F.S.) data. It also examines whether levels of technical efficiency are influenced by contact with the extension service.Â The apparent slow-down in technical change in Irish agriculture is clearly a cause for concern and warrants further investigation. It might be due to cutbacks in research expenditure which occurred in the 1980s, or to the greater regulation of agriculture and the impact of the shift to direct payments to support farm incomes which was introduced by the MacSharry CAP reforms in the 1990s. Figure 2 The Rate of Technical Change. 114 112 110 108 106 104 102 100. This paper calculates average technical efficiency levels and rates of technical change for Irish agriculture using an unbalanced panel of 2,603 farms drawn from the Irish National Farm Survey over the period 1984 to 1998. An average technical efficiency level of between 65 and 70 per cent with a slight upward trend over the period was found. The efficiency of individual farms is positively associated with the size of the farm household, the ratio of debt to assets and the farmer?s age, and negatively related to being located in the West of Ireland, having an off-farm job and size of farm. Technical progress is observed at an unweighted rate of approximately 0.9 per cent and a weighted rate of 2.1 per cent per annum over the 1984-98 period.