Journal of Agricultural Economics, Vol. 58, No. 1, 2007, 128–151

Evaluating the Productivity Performance of Agricultural Enterprises in Ireland using a Multiple Output Distance Function Approach

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(Original submitted July 2005, revision received April 2006, accepted July 2006.)

Abstract

This paper uses a distance function approach to measure and decompose productivity growth of Irish agriculture between 1984 and 2000 for four principal farming systems. The technology used by each system is found to be sufficiently different as to warrant a system-by-system approach. The overall rate of productivity growth in Irish agriculture is found to be just over 1% for this period, but there are significant differences between systems. Sheep systems had the highest rate of productivity growth followed by dairy and tillage. Productivity in cattle farms fell during this period although there is evidence that this trend has been reversed in more recent years.

Keywords: *Decomposition*; *generalised Malmquist index*; *Irish agricultural sector*; *output distance function*.

JEL classifications: *D24*, *Q12*, *O3*.

1. Introduction

With the shift in the European Union (EU) to a more market-oriented policy regime for agriculture following the Agenda 2000 and Luxembourg Agreement reforms in 1999 and 2003, respectively, greater attention is now being given to the underlying competitiveness of agriculture in each Member State in an effort to learn how each might fare in the new policy environment. Evidence suggests that, in the past, Ireland has fared badly in terms of technology-based productivity growth, a

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key component of competitiveness, unlike the majority of other EU countries where productivity growth improved after joining the EU (Leetmaa *et al.*, 2004).[2] Recent studies suggest that there has been a further erosion of Ireland's competitiveness in the late 1990s and early 2000s, based on a variety of cost competitiveness indicators (Boyle, 2002; Thorne, 2004).[3] These trends have led to some concern about the future viability of farming in Ireland in the face of increasing costs and falling prices.

Over any time period other than the very shortrun, and under conditions approximating free trade, the main reason for divergent trends in cost competitiveness is differences in the rate of productivity growth across countries. For Ireland, there is evidence which suggests deterioration in the productivity performance of the agricultural sector over time, contributing to competitiveness losses. For example, Matthews (1999/2000) found an annual rate of total factor productivity growth in Irish agriculture of 2.3% per annum in the 1980s falling to 0.8% annually in the 1990s. Similarly, O'Neill *et al.* (2002) observe that productivity growth slowed from an estimated 2.3% annually between 1984 and 1989 to an annual average rate of 1.5% between 1990 and 1998. In this context, the importance of improving the efficiency and productivity of the Irish agricultural sector was underlined in a recent expert report for the Irish government on the future of Irish agriculture (Department of Agriculture and Food, 2004).

Against this background, the focus of this paper is on measuring the productivity performance of the Irish agricultural sector. The novelty of our contribution is that we make use of a very extensive dataset – a representative sample of around 1,200 farms every year between 1984 and 2000 – to measure and compare productivity growth in each of the main farming systems in Ireland, in an attempt to ascertain where the significant problems lie. O'Neill and Matthews (2001) were the first to use Irish data of this kind, applying a stochastic frontier approach to estimating productivity growth. In assuming a common production technology across all farm systems they produce an aggregate index of productivity growth for the agricultural sector as a whole. This paper extends this work by presenting, for the first time, estimates of productivity growth for the four principal farming systems – dairy, tillage, sheep and cattle. It also provides a comprehensive decomposition of total factor productivity growth for the four farm systems, allowing us to understand the factors driving productivity growth to a greater extent than previous studies of this kind in Ireland.

The rest of this paper is structured as follows. In section 2 we review some productivity concepts and outline the methods used to measure productivity growth and decompose it into its components. In section 3 the data are described, and the empirical results are presented in section 4. The paper concludes with a summary of the main findings and outlines some implications of the results.

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[2] In fact, there is evidence to suggest that, on average, the level of total factor productivity growth in EU countries exceeded that of the United States up to the 1980s. A worrying trend is the widening of the gap in favour of the US since the early 1990s (see Leetmaa *et al.*, 2004 for an overview).

[3] Cost competitiveness indicators include measures such as the relative costs in Ireland (converted to a common currency) of producing a unit quantity (e.g. a litre of milk) or the relative costs in Ireland compared with the value of output produced (Boyle, 2002).

2. Method

This paper follows methods similar to those applied by Irz and Thirtle (2004) for the output case (see also Newman and Matthews, 2004, Chapter 2). The producible output set can be defined as the set of all outputs that can be feasibly produced using the set of all inputs. Formally, let $P^t(\mathbf{x}^t)$ represent the set of all output vectors, $\mathbf{y}^t$, that can be produced using the input vector, $\mathbf{x}^t$, at time t, $t = 1, 2,\ldots,T$

$$P^t(\mathbf{x}^t) = \{\mathbf{y}^t : \mathbf{x}^t \text{can produce } \mathbf{y}^t\}. \tag{1}$$

The output distance function is defined on the output set, $P^t(\mathbf{x}^t)$ as (Coelli *et al.*, 1998):

$$D_o^t(\mathbf{x}^t, \mathbf{y}^t) = \min\{\delta : \mathbf{y}^t/\delta \in \mathrm{P}^t(\mathbf{x}^t)\}. \tag{2}$$

Specifically, δ measures the inverse of the amount by which the production of all output could be increased using the given input vector $\mathbf{x}$ with the technology in use in time t.[4] For the most efficient farms, that is those producing at the outer limit of the producible output set, $\delta = 1$, while for inefficient farms $\delta < 1$.

A productivity index can be constructed based on changes in the distance function over time. First, changes in efficiency are captured by movements along the distance function towards the producible output set. As a farm becomes more efficient, it moves up the output distance function towards the production possibilities curve (a change in technical efficiency). Second, technical change is measured by an outward shift in the producible output set over time measured through observing the behaviour of the 'best practice' farm every year. Finally, if a farm exploits scale economies its position on the production possibilities curve changes and a change in the average level of productivity is observed (a change in scale efficiency).

By assuming an appropriate functional form, in this case translog,[5] and imposing the homogeneity property (Kumbhakar and Lovell, 2000, p. 32), a multiple output distance function can be estimated using econometric methods by expressing the distance function in terms of one of the outputs.[6]

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[4] It is also possible that the data could be represented using an input orientation. However, in any year the production problem for the farmer is how to maximise the returns from his given set of fixed inputs, particularly land and capital, and as such the output-oriented specification is intuitively more appealing. In contrast, the dairy system has been subject to quota limitations over the sample period. However, the quota system restricts industry-level output but not farm-level output as quota can be transferred between farms and non-dairy enterprises can be expanded, so the output orientation is also used. Regardless, the finding of virtually constant returns to scale in the empirical results for this system means that output and input orientations will yield the same technologies (Orea *et al.*, 2004).

[5] The translog is a flexible functional form in that it does not impose *a priori* particular values on the elasticity of substitution between inputs and outputs. It also allows the elasticity of scale variable to vary at different sizes of the farm enterprise (Coelli *et al.*, 1998). The translog functional form is generally the most widely accepted in the literature because of its flexibility.

[6] See Irz and Thirtle (2004) for details of how imposing the homogeneity property allows for the econometric estimation of the distance function.

$$
\begin{aligned}
-\ln y_{Mi}^t &= \alpha_0 + \sum_{m=1}^{M-1} \alpha_m \ln\left(\frac{y_{mi}^t}{y_{Mi}^t}\right) + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{n=1}^{M-1} \alpha_{mn} \ln\left(\frac{y_{mi}^t}{y_{Mi}^t}\right) \ln\left(\frac{y_{ni}^t}{y_{Mi}^t}\right) + \sum_{k=1}^{K} \beta_k \ln x_{ki}^t \\
&\quad + \frac{1}{2}\sum_{k=1}^{K}\sum_{l=1}^{K} \beta_{kl} \ln x_{ki}^t \ln x_{li}^t + \sum_{k=1}^{K}\sum_{m=1}^{M-1} \delta_{km} \ln x_{ki}^t \ln\left(\frac{y_{mi}^t}{y_{Mi}^t}\right) + \omega_0 t + \frac{1}{2}\omega_{00} t^2 \\
&\quad + \sum_{k=1}^{K} \omega_{kt} t \ln x_{ki}^t + \sum_{m=1}^{M-1} \omega_{mt} t \ln\left(\frac{y_{mi}^t}{y_{Mi}^t}\right) - \ln D_{oi}^t \\
&= \mathrm{TL}\left(\mathbf{x}_i^t, \frac{\mathbf{y}_i^t}{y_{Mi}^t}, t\right) - \ln D_{oi}^t
\end{aligned}
\tag{3}
$$

where 'TL' stands for translog. By setting $-\ln D_{oi}^t = u_i^t$ and appending a symmetric error term, v_i^t, we obtain a stochastic output distance function (Coelli and Perelman, 1996):

$$
-\ln y_{Mi}^t = \mathrm{TL}\left(\mathbf{x}_i^t, \frac{\mathbf{y}_i^t}{y_{Mi}^t}, t\right) + u_i^t + v_i^t \quad \text{where} \quad u_i^t = u_i \exp[-\eta(t-T)] \tag{4}
$$

are time-varying inefficiency effects measured by the parameter η.[7] Maximum likelihood estimation will produce consistent parameter and inefficiency estimates based on the stochastic output distance function. The model is estimated using Stata/S.E. Version 8.0 (Stata Corporation, 2003).

The purpose of estimating the distance function is that the estimated parameters can be used to construct a measure of productivity. The type of productivity index considered in this analysis is the output-oriented Malmquist productivity index which focuses on the maximum level of outputs that could be produced using a given input vector and a given production technology relative to the actual observed level of output (Coelli *et al.*, 1998).

Following the methods of Balk (1998), a Malmquist productivity index can be constructed based on observed changes in the output distance function over time, as presented in equation (5):

$$
\ln M_{oi} = \left(\ln D_{oi}^{t+1} - \ln D_{oi}^t\right) - \frac{1}{2}\left(\frac{\partial \ln D_{oi}^{t+1}}{\partial t} + \frac{\partial \ln D_{oi}^t}{\partial t}\right). \tag{5}
$$

The first term on the right-hand side of equation (5) measures the change in technical efficiency from one period to the next, that is movements along the distance function, while the second term captures shifts in technology, that is shifts in the production possibilities curve. The Malmquist productivity index requires the assumption of constant returns to scale, and so has been criticised as being an inaccurate measure of total productivity change as it ignores the potential contribution of scale economies. Orea (2002) generalises the Malmquist-type productivity index to

[7] v_i^t are assumed to be independent and identically distributed (i.i.d.) $N(0, \sigma_v^2)$ and independent of u_i^t, and u_i are assumed to be (i.i.d.) as truncations at zero of the $N(\mu, \sigma_u^2)$ where μ, the mean of the truncated distribution, is an unknown parameter to be estimated.

incorporate the effect of scale economies into the measurement of productivity change.

$$\ln G_{oi} = \ln M_{oi} + \frac{1}{2}\sum_{k=1}^{K}\left\{\left(-\sum_{k=1}^{K}\frac{\partial \ln D_{oi}^{t+1}}{\partial \ln x_{ki}} - 1\right)\varepsilon_{ki}^{t+1} + \left(-\sum_{k=1}^{K}\frac{\partial \ln D_{oi}^{t}}{\partial \ln x_{ki}} - 1\right)\varepsilon_{ki}^{t}\right\}\ln\left(\frac{x_{ki}^{t+1}}{x_{ki}^{t}}\right) \tag{6}$$

where

$$\varepsilon_{ki}^{t} = \frac{\partial \ln D_{oi}^{t}/\partial \ln x_{ki}}{\sum_{k=1}^{K}\partial \ln D_{oi}^{t}/\partial \ln x_{ki}}.$$

The parameter estimates of the econometric model presented in equation (4) are used to compute values for the components of this productivity index. Efficiency change, given by the first part of equation (5), is measured by the change in the value of the distance function from one period to the next:

$$\mathrm{EC}_i = \ln D_{oi}^{t+1} - \ln D_{oi}^{t}. \tag{7}$$

Technical change, given by the second part of equation (5), measures the change in the distance function from one period to the next, having controlled for farm-level inefficiencies. As such, the computation of the technical change index involves the parameters associated with the time elements of the distance function presented in equation (3):

$$\begin{aligned}\mathrm{TC}_i &= 0.5 \times \left(\frac{\partial \ln D_{oi}^{t}}{\partial t} + \frac{\partial \ln D_{oi}^{t+1}}{\partial t}\right)\\ &= 0.5 \times \left\{\left(\omega_0 + \omega_{00}t + \sum_{k=1}^{K}\omega_{kt}\ln x_{ki}^{t} + \sum_{m=1}^{M}\omega_{mt}\ln y_{mi}^{t}\right)\right.\\ &\quad \left. + \left(\omega_0 + \omega_{00}(t+1) + \sum_{k=1}^{K}\omega_{kt}\ln x_{ki}^{t+1} + \sum_{m=1}^{M}\omega_{mt}\ln y_{mi}^{t+1}\right)\right\}.\end{aligned} \tag{8}$$

Finally, the effect of changes in scale on the distance function is computed using the second part of equation (6), the relevant component of which is:

$$\varepsilon_{ki}^{t} = \frac{\partial \ln D_{oi}^{t}/\partial \ln x_{ki}}{\sum_{k=1}^{K}\partial \ln D_{oi}^{t}\partial \ln x_{ki}} = \frac{\beta_k + \frac{1}{2}\sum_{l=1}^{K}\beta_{kl}\ \ln x_{li}^{t} + \sum_{m=1}^{M}\delta_{km}\ \ln y_{mi}^{t} + \varpi_{kt}t}{\sum_{k=1}^{K}\left(\beta_k + \frac{1}{2}\sum_{l=1}^{K}\beta_{kl}\ \ln x_{li}^{t} + \sum_{m=1}^{M}\delta_{km}\ \ln y_{mi}^{t} + \varpi_{kt}t\right)}. \tag{9}$$

3. Data

The data used are taken from the National Farm Survey (NFS) (Teagasc, 1984–2000), an annual survey of a sample of Irish farms collected by Teagasc, the Irish Agriculture and Food Development Authority. Farmers are selected using stratified random sampling from the farm population and participate voluntarily in the survey. The full dataset comprises 20,139 observations on a total of 3960 farms that participated in the survey at any time during the 17 years. Within the survey, farms

Table 1
Description of farm systems

Dairy	Farms engaged in specialist milk production and those that combine milk production with some other activity
Tillage	Farms engaged in specialist cereals, oilseeds and protein crops, general field cropping or field cropping combined with grazing livestock
Sheep	Specialist sheep farms and sheep and cattle combined where sheep is the dominant enterprise
Cattle	Includes cattle rearing which are specialist cattle farms mainly involved in rearing, other specialist cattle farms mainly involved in fattening and other mixed livestock

are classified in terms of farm system.[8] In this paper, four systems of farming are considered: dairy, tillage, sheep and cattle.[9] The types of farms within each system are described in Table 1.

3.1. Description of outputs

The dataset is disaggregated into four independent sub-sets. Two outputs are distinguished in each sub-sample, the main enterprise output and other output. In each sub-sample a small number of observations were eliminated because of misreporting errors. Each dataset also excludes a small number of farms that produce just one output to accommodate the translog multiple output distance function model.[10] While this does not affect the dairy system sample (where cattle output is an inevitable by-product of milk production), for the tillage system it excludes 297 observations, for the sheep system it excludes 201 observations and for the cattle system it excludes 1,815 observations. For the tillage and sheep systems, the exclusion of these observations does not compromise the representativeness of the sample as the reduced sample produces the same population-weighted mean values as the original sample. However, because there is a significant number of cattle farms that fall into the single output category, they are modelled separately to ‘other’ cattle farms as a ‘specialist’ group, using a stochastic frontier approach.[11] Results from both models

[8] The method of classifying farms into farming systems is based on the EU farm typology as set out in the Commission Decision 78/463 and its subsequent amendments. Each type of farm animal and each crop hectare are assigned a standard gross margin. Farms are then grouped according to the proportion of the total standard gross margin of the farm which comes from the main enterprises after which the systems are named.

[9] Pigs and poultry are excluded from this analysis.

[10] The translog specification cannot accommodate zero observations on any of the outputs or the inputs. The implications of dropping these observations have not been explored in this paper. The potential for sample selection bias and how it can be adjusted for in models of this kind could be explored in future work (see, e.g. Weaver and Lass, 1989).

[11] Using a likelihood ratio test, proposed by Battese *et al.* (2004), it is found that significant technology differences exist between ‘specialist’ and ‘other’ cattle farms, thus justifying such a disaggregation (see section 4).

are combined to produce an overall index of total factor productivity growth for the cattle system.

In all cases, with the exception of milk output, which is expressed in gallons, output in the NFS is only given as a value figure. In the case of sheep, cattle and tillage output, EU production subsidies are excluded from the value figures. Implicit volume indices are then computed by deflating the adjusted value of output by the appropriate national price series (see the Appendix). In most cases, where enterprise output is homogenous, this method will produce a reasonable approximation of output quantities. However, in the case of the cattle enterprise, output in individual farms is heterogenous in terms of the age and quality of animals, and using a single national average price index for finished cattle to deflate the value of output is unlikely to produce an accurate approximation to the quantity of output produced. A further problem in our approach to measuring output in the cattle system relates to the incidence of direct payments. We subtract the value of direct payments from the value of cattle output before deflating by the national index of cattle prices to obtain a volume measure. However, two farms may have the same level of cattle output but get very different prices for this output depending on whether they have collected the special beef premium payments or not. In the absence of farm-specific prices, it is not possible to adjust for this incidence issue. Thus, the output on individual cattle farms may be under- or over-quantified and as such caution must be exercised in analysing results relating to this system.

In each farm system, other outputs (not directly related to the primary enterprise of the farm type) are aggregated into a volume measure by summing their values and deflating the total value of other output by an aggregate farm-specific Tornqvist price index as described in the Appendix.

3.2. Description of inputs

Four inputs are considered: land, labour, capital and variable costs. Land is measured by the adjusted size of farm in hectares. The adjustment converts rough grazing to pasture equivalent but does not take account of differences in soil quality between farms which thus becomes one of the factors affecting their efficiency score. The labour input measures the total number of labour units employed. The capital input, expressed in 2000 values, includes the stock of machinery valued at replacement cost, land improvement and buildings given a market value as estimated by the farmer, and livestock value, which is an average of opening and closing inventories. Finally, variable costs include fertilisers, seed, crop protection, the purchase of concentrates, the maintenance of livestock, utilities, transport, the hire of machinery, the upkeep of land and the maintenance of buildings. These costs are deflated using appropriate price indicators to convert them to volume measures and are aggregated using the implicit quantity method outlined in the Appendix.[12] Descriptive statistics for the NFS sample of farms by each of the main farming systems are presented in Table 2.

[12] As farm-specific price data are unavailable, the potential for allocative inefficiencies cannot be incorporated into the analysis. This leads to some unknown bias in the technical efficiency estimates presented.

Table 2
Descriptive statistics

	Dairy (n = 8,103)	Tillage (n = 2,252)	Sheep (n = 3,454)	Cattle (n = 5,278)
Enterprise output	36,753	43,722	7,331	24,838
	(36,715)	(56,067)	(7,383)	(28,756)
	Gallons	€ value	€ value	€ value
Other output	27,847	29,058	9,748	4,031
(€ value)	(28,701)	(32,752)	(11,915)	(9,268)
Size (ha)	52.40	80.33	70.61	58.87
	(37.76)	(61.15)	(85.04)	(49.61)
Labour units	1.75	1.87	1.27	1.48
	(0.85)	(1.16)	(0.52)	(0.76)
Capital (€ value)	124,766	115,541	49,953	81,477
	(107,774)	(107,988)	(44,706)	(77,888)
Variable costs	37,216	39,993	11,011	22,164
(€ value)	(34,708)	(33,971)	(10,055)	(20,514)

Note: Mean values with standard deviations in parentheses.

3.3. Aggregation to population averages

These data are collected on a stratified sample of Irish farms. For each farm system, six stratifications, based on farm size, are used. Each year, the sample is selected in such a way that all size groups in each system are represented. Within each group, a number of farms, representative of farms of similar size, are surveyed. This sample selection method has implications for the way in which the sample microdata are aggregated to produce statistics or indices that relate to the true population of farms. The NFS provides data on the population of farms in each size group, in each system, in each year. These data are used to construct weights for each group which quantify the representation of that group in the overall population. These weights are applied in aggregating the microdata so that the resultant statistics and indices reflect those of the underlying population.[13]

3.4. Relationship between outputs and inputs

Table 3 presents an index indicating how the mean level of outputs and inputs per farm, adjusted in this way, has changed over the sample period for each system of farming.

Between 1984 and 2000, on average, the production of the main output in each system has increased. Most notably, enterprise output in farms in the sheep system has more than doubled. For the tillage and cattle systems the production of other output has declined suggesting that, on average, tillage and cattle producers have become more specialised over the sample period. For the dairy and sheep systems,

[13] For the tillage and sheep models, where the samples used are based on the NFS system classifications, the aggregation of the microdata and results into representative statistics and indices is relatively straightforward. However, for the dairy and cattle models, whose samples deviate somewhat from the NFS definitions, this aggregation is more complex. Details of the weighting procedure applied to these models are available from the authors.

Table 3
Percentage change in mean output and input levels 1984–2000
(weighted to reflect population totals)

	Enterprise output	Other output	Size	Labour units	Capital	Variable costs
Dairy	65.21	111.00	33.36	5.81	113.14	108.66
Tillage	83.52	−15.69	13.50	−4.37	15.74	45.25
Sheep	115.10	88.10	36.65	2.21	102.78	189.97
Cattle	33.74	26.08	7.42	−2.63	54.65	64.35

the production of other output has increased, more than doubling in the case of the dairy system. This latter finding reflects the impact of quota restrictions which has restricted the ability of dairy farms to use their resources to expand in milk production. Part of the increase in the mean levels of output is due to the increase in the average size of farms over time. This increase is most notable for dairy and sheep farms which have increased by an average of 33% and 37%, respectively. Tillage farms increased in size by almost 14% while the cattle system exhibited a smaller change in farm size, with an increase of around 7%. The dairy and sheep systems both experienced an increase in the average number of labour units employed, albeit by a small amount. All systems exhibit an increase in the amount of capital employed and in variable costs per farm.

4. Results

4.1. Specification testing

Prior to arriving at the final specification of the models, a range of alternative specifications are considered. The first set of specification tests considers the extent to which technology differences exist between the various systems of farming to ascertain whether analysing systems of farming separately is necessary. This is achieved by comparing the log-likelihood value of an aggregate stochastic production function model using a pooled dataset and a single-aggregate output measure with the sum of the individual log-likelihood values for the same model estimated separately for each farm system (see Battese *et al.*, 2004). The result of this test, presented in Table 4, concludes that significant technology differences exist between each system of farming, justifying the system-by-system approach to analysing Irish agriculture presented in this paper. In the same context, to ascertain the extent to which the decomposition of the dairy and cattle systems to 'other' and 'specialist' sub-systems is warranted, a test comparing the log-likelihood from a pooled model with the sum of the individual log-likelihoods for 'specialist' and 'other' sub-systems modelled separately is conducted, with the same conclusion (see also Table 4). For the dairy system, the distance function specification is used to perform this test.

Second, we check for the theoretical consistency of the estimated stochastic output distance functions (and production function for specialist cattle production). As discussed by O'Donnell and Coelli (2005) in the context of the stochastic output distance function and Sauer *et al.* (2006) in the context of the stochastic production function, if the estimated parameters violate the assumptions of monotonicity, quasi-convexity and convexity in the case of the former, and monotonicity and quasi-concavity

Table 4

Testing for technology differences

H$_0$: All farms share the same technology
H$_A$: Significant technology differences exist
Test statistic: 8,326.22
Critical value: 164.69
Reject null at 1% significance

H$_0$: 'Specialist' and 'other' dairy farms share the same technology
H$_A$: Significant technology differences exist
Test statistic: 378.45
Critical value: 53.49
Reject null at 1% significance

H$_0$: 'Specialist' and 'other' cattle farms share the same technology
H$_A$: Significant technology differences exist
Test statistic: 330.99
Critical value: 44.31
Reject null at 1% significance

in the case of the latter, elasticities and technical efficiency estimates can be misleading. As revealed in Table 5, all partial derivatives of the distance function are of the appropriate sign at the sample mean with few violations of the monotonicity assumption throughout the sample as a whole. In addition, curvature assumptions are also satisfied at the mean where we find quasi-convexity in inputs and convexity in outputs. However, the estimated stochastic production function for specialist cattle production does not perform so well. As Table 6 illustrates, the monotonicity assumption is violated because of the negative partial derivative on the labour input evident at the mean and for 44% of the sample. In addition, the estimated model fails to satisfy the curvature assumption at the point of approximation. Therefore, caution should be exercised in interpreting all results relating to the specialist cattle system.

The third set of tests aims to provide a more empirical justification for the use of the distance function approach over other common approaches to analysing productivity such as deterministic approaches or a stochastic frontier approach. In the case of the former, the stochastic approach is compared with a mean output distance function approach estimated by imposing the restriction that the inefficiency terms are equal to zero (Irz and Thirtle, 2004). As presented in Table 7, likelihood ratio tests lead to a rejection of these restrictions implying that a stochastic rather than a deterministic approach is more appropriate. In the case of the latter, a test of the separability of the outputs and inputs can be conducted by imposing the restrictions on the model that the coefficients on all cross-terms between inputs and outputs are equal to zero (Irz and Thirtle, 2004). The results of these tests are also presented in Table 7. In all cases the restrictions are rejected, providing evidence that the distance function approach is superior to the stochastic production function approach which requires aggregation.

The fourth set of tests relates to the choice of specification of the stochastic output distance function. In each model, the main enterprise output is chosen as the dependent variable and the variable of normalisation for the other output. First, the translog specification is tested against a Cobb–Douglas specification, with the former

Table 5
Theoretical properties of estimated distance functions

	Dairy spec.	Dairy other	Tillage	Sheep	Cattle other
$\partial \ln D/\partial \ln x_1$					
Mean	−0.12	−0.12	−0.36	−0.06	−0.18
% positive	4.79	6.39	1.38	28.87	5.08
$\partial \ln D/\partial \ln x_2$					
Mean	−0.08	−0.08	−0.09	−0.07	−0.08
% positive	2.31	2.02	12.43	10.77	5.95
$\partial \ln D/\partial \ln x_3$					
Mean	−0.31	−0.32	−0.15	−0.40	−0.37
% positive	0.00	0.22	12.21	0.26	2.43
$\partial \ln D/\partial \ln x_4$					
Mean	−0.48	−0.51	−0.49	−0.42	−0.36
% positive	0.00	0.03	0.00	0.35	0.09
$\partial \ln D/\partial \ln y_1$					
Mean	0.77	0.58	0.64	0.49	0.75
% negative	0.00	0.47	0.04	0.87	0.00
$\partial \ln D/\partial \ln y_2$					
Mean	0.23	0.42	0.36	0.51	0.25
% negative	0.67	0.31	1.38	2.29	4.10
Quasi-convexity in inputs	Satisfied at mean	Satisfied at mean	Satisfied at mean	Satisfied at mean	Satisfied at mean
Convexity in outputs	Satisfied at mean	Satisfied at mean	Satisfied at mean	Satisfied at mean	Satisfied at mean

***Notes*:** ln D is the log of the distance function, ln x_1 is the log of land inputs, ln x_2 is the log of labour inputs, ln x_3 is the log of capital inputs, ln x_4 is the log of variable inputs, ln y_1 is the log of enterprise output and ln y_2 is the log of other output.

Table 6
Theoretical properties of estimated production function (specialised cattle)

$\partial \ln y/\partial \ln x_1$	
Mean	0.21
% negative	0.33
$\partial \ln y/\partial \ln x_2$	
Mean	−0.001
% negative	44.19
$\partial \ln y/\partial \ln x_3$	
Mean	0.41
% negative	0.17
$\partial \ln y/\partial \ln x_4$	
Mean	0.32
% negative	0.55
Quasi-concavity	Violated at mean

***Notes*:** ln y is the log of output, ln x_1 is the log of land inputs, ln x_2 is the log of labour inputs, ln x_3 is the log of capital inputs, ln x_4 is the log of variable inputs.

Table 7

Testing the distance function approach

Stochastic vs. deterministic approach
Restriction: $\gamma = \eta = 0$

Model	Log-likelihood restricted model	Log-likelihood unrestricted model	Test statistic	Result $\chi^2_{2,0.01} = 9.21$
Dairy spec.	1,727.28	2,903.56	2,352.55	Reject
Dairy other	717.47	1,498.68	1,562.41	Reject
Tillage	−85.14	286.76	743.81	Reject
Sheep	−1,161.67	−691.65	940.03	Reject
Cattle other	−761.18	−755.37	11.63	Reject
Cattle spec.	−1,375.88	−803.08	1,145.60	Reject

Stochastic frontier production function vs. stochastic distance function approaches: separability of inputs and outputs
Restriction: $\delta_{km} = 0$

Model	Log-likelihood restricted model	Log-likelihood unrestricted model	Test statistic	Result $\chi^2_{4,0.01} = 13.28$
Dairy spec.	2894.87	2903.56	17.38	Reject
Dairy other	1488.16	1498.68	21.04	Reject
Tillage	275.78	286.76	21.98	Reject
Sheep	−701.83	−691.65	20.36	Reject
Cattle other	−777.43	−755.37	44.12	Reject

being chosen on the basis of likelihood ratio testing procedures. Second, likelihood ratio tests are used to test for the neutral and non-neutral technical change components, with the conclusion that both components are appropriate to each of the models considered. Finally, the appropriateness of the time-varying inefficiency model is tested by comparing it against a time-invariant model with the former deemed appropriate in all cases. The results of each of these tests are presented in Table 8.

4.2. Technology representation

The translog stochastic output distance function with neutral and non-neutral technical change components is chosen as the most appropriate specification for all models with the exception of the 'specialist' cattle model which is estimated using a translog stochastic production frontier with neutral and non-neutral technical change components. Table 9 presents the results of these models for Irish farms in the period 1984–2000.

In all cases, $\hat{\gamma}$, the share of technical efficiency in total variance is significant and high, indicating that inefficiency effects exist thus adding further justification for the use of the stochastic model. $\hat{\eta}$, the parameter associated with time in the inefficiency effects, is negative and statistically significant at the 1% level, implying a significant negative change in the technical efficiency effects over time. For all models with the exception of the sheep system, $\hat{\mu}$ is statistically significant implying that the inefficiency term follows the distribution of a normal random variable with a non-zero mean. For the sheep system, where $\hat{\mu}$ is not statistically significant, the technical efficiency effects are assumed to follow a half-normal distribution with mean zero.

Table 8

Testing the technology representation

Translog vs. Cobb–Douglas
Restriction: $\alpha_{mn} = \beta_{kl} = \delta_{km} = \omega_{kt} = \omega_{mt} = 0$

Model	Log-likelihood restricted model	Log-likelihood unrestricted model	Test statistic	Result $\chi^2_{20,0.01} = 37.57$
Dairy spec.	2,653.62	2,903.56	499.88	Reject
Dairy other	1,138.98	1,498.68	719.40	Reject
Tillage	−165.79	286.76	905.11	Reject
Sheep	−1442.66	−691.65	1502.02	Reject
Cattle other	−1194.38	−755.37	878.02	Reject
Cattle spec.	$\beta_{kl} = \omega_{kt} = 0$ −837.00	−803.08	67.84	$\chi^2_{14,0.01} = 29.14$ Reject

Neutral technical change vs. no technical change
Restriction: $\omega_0 = \omega_{00} = 0$

Model	Log-likelihood restricted model	Log-likelihood unrestricted model	Test statistic	Result $\chi^2_{2,0.01} = 9.21$
Dairy spec.	2,794.67	2,887.83	186.32	Reject
Dairy other	1,398.93	1,481.93	165.99	Reject
Tillage	241.04	273.79	65.49	Reject
Sheep	−822.56	−708.97	227.20	Reject
Cattle other	−777.13	−770.94	12.38	Reject
Cattle spec.	−812.87	−808.14	9.47	Reject

Neutral and non-neutral technical change vs. neutral technical change
Restriction: $\omega_{kt} = \omega_{mt} = 0$

Model	Log-likelihood restricted model	Log-likelihood unrestricted model	Test statistic	Result $\chi^2_{5,0.01} = 15.09$
Dairy spec.	2,887.83	2,903.56	31.46	Reject
Dairy other	1,491.93	1,498.68	33.51	Reject
Tillage	273.79	286.76	25.95	Reject
Sheep	−708.97	−691.65	34.63	Reject
Cattle other	−770.94	−755.37	31.14	Reject
Cattle spec.	$\omega_{kt} = 0$ −808.14	−803.08	10.11	$\chi^2_{4,0.05} = 9.49$ Reject

Time-varying inefficiency effects $\eta = 0$

Model	Log-likelihood restricted model	Log-likelihood unrestricted model	Test statistic	Result $\chi^2_{1,0.01} = 6.63$
Dairy spec.	2,897.22	2,903.56	12.69	Reject
Dairy other	1,477.65	1,498.68	42.05	Reject
Tillage	278.29	286.76	16.94	Reject
Sheep	−728.87	−691.65	74.45	Reject
Cattle other	−768.47	−755.37	26.20	Reject
Cattle spec.	−805.75	−803.08	5.34	$\chi^2_{1,0.05} = 3.84$ Reject

Table 9
Parameter estimates of output distance functions 1984–2000

	Dairy spec.	Dairy other	Tillage	Sheep	Cattle spec.	Cattle other
Constant	−0.24*** (0.02)	−0.14*** (0.02)	−0.15*** (0.03)	0.09*** (0.03)	0.32*** (0.05)	−0.19*** (0.04)
Outputs						
$\ln y_1$	$\underline{0.75}$	$\underline{0.50}$	$\underline{0.62}$	$\underline{0.46}$		$\underline{0.72}$
$\ln y_2$	0.25*** (0.01)	0.50*** (0.02)	0.38*** (0.01)	0.54*** (0.01)		0.29*** (0.01)
$(\ln y_1)^2$	$\underline{0.14}$	$\underline{0.31}$	$\underline{0.08}$	$\underline{0.19}$		$\underline{0.10}$
$(\ln y_2)^2$	0.14*** (0.01)	0.31*** (0.01)	0.08*** (0.003)	0.19*** (0.00)		0.10*** (0.003)
$(\ln y_1)(\ln y_2)$	$\underline{0.29}$	$\underline{0.63}$	$\underline{0.17}$	$\underline{0.37}$		$\underline{0.20}$
Inputs						
$\ln x_1$	−0.18*** (0.02)	−0.14*** (0.03)	−0.26*** (0.04)	−0.04** (0.02)	0.18*** (0.06)	−0.14*** (0.03)
$\ln x_2$	−0.13*** (0.02)	−0.13*** (0.03)	−0.11*** (0.03)	−0.06 (0.04)	−0.19** (0.08)	−0.15*** (0.04)
$\ln x_3$	−0.24*** (0.02)	−0.35*** (0.03)	−0.16*** (0.03)	−0.49*** (0.03)	0.44*** (0.07)	−0.34*** (0.04)
$\ln x_4$	−0.49*** (0.02)	−0.45*** (0.03)	−0.60*** (0.04)	−0.34*** (0.03)	0.35*** (0.06)	−0.46*** (0.03)
$(\ln x_1)^2$	0.18*** (0.03)	0.14*** (0.04)	−0.10 (0.08)	0.18*** (0.02)	0.07 (0.06)	0.12*** (0.03)
$(\ln x_2)^2$	−0.08*** (0.03)	−0.03 (0.06)	−0.07 (0.05)	−0.08 (0.08)	−0.06 (0.06)	−0.05 (0.04)
$(\ln x_3)^2$	0.08** (0.04)	−0.14*** (0.05)	−0.06* (0.03)	−0.20*** (0.04)	0.15*** (0.03)	−0.26*** (0.04)
$(\ln x_4)^2$	−0.03 (0.03)	−0.18*** (0.04)	0.06 (0.07)	−0.22*** (0.04)	0.28*** (0.07)	−0.25*** (0.05)
$(\ln x_1)(\ln x_2)$	−0.01 (0.05)	−0.02 (0.07)	0.24** (0.11)	−0.08 (0.05)	0.08 (0.11)	0.07 (0.07)
$(\ln x_1)(\ln x_3)$	−0.19*** (0.05)	−0.29*** (0.07)	0.09 (0.08)	−0.22*** (0.05)	0.02 (0.10)	−0.04 (0.07)
$(\ln x_1)(\ln x_4)$	−0.05 (0.04)	0.04 (0.05)	−0.11 (0.12)	0.001 (0.04)	−0.23** (0.11)	−0.12** (0.05)
$(\ln x_2)(\ln x_3)$	−0.09 (0.06)	0.03 (0.08)	−0.12* (0.06)	0.23** (0.09)	−0.04 (0.11)	−0.04 (0.09)
$(\ln x_2)(\ln x_4)$	0.15*** (0.05)	0.01 (0.07)	−0.01 (0.09)	−0.16** (0.08)	0.02 (0.12)	0.04 (0.08)
$(\ln x_3)(\ln x_4)$	−0.01*** (0.06)	0.37*** (0.08)	0.05 (0.08)	0.36*** (0.08)	−0.31*** (0.10)	0.43*** (0.08)
Inputs–outputs						
$(\ln x_1)(\ln y_1)$	$\underline{0.07}$	$\underline{0.11}$	$\underline{0.10}$	$-\underline{0.06}$		$-\underline{0.06}$
$(\ln x_2)(\ln y_1)$	$\underline{0.02}$	$-\underline{0.005}$	$-\underline{0.08}$	$\underline{0.005}$		$\underline{0.02}$
$(\ln x_3)(\ln y_1)$	$\underline{0.02}$	$\underline{0.07}$	$-\underline{0.01}$	$-\underline{0.02}$		$\underline{0.09}$
$(\ln x_4)(\ln y_1)$	$-\underline{0.05}$	$-\underline{0.15}$	$\underline{0.003}$	$\underline{0.05}$		$\underline{0.01}$
$(\ln x_1)(\ln y_2)$	−0.07*** (0.02)	−0.11*** (0.04)	−0.10*** (0.03)	0.06*** (0.01)		0.06*** (0.02)

Table 9
(*Continued*)

	Dairy spec.	Dairy other	Tillage	Sheep	Cattle spec.	Cattle other
$(\ln x_2)(\ln y_2)$	−0.02 (0.03)	0.005 (0.05)	0.08*** (0.03)	−0.005 (0.03)		−0.02 (0.02)
$(\ln x_3)(\ln y_2)$	0.0206 (0.03)	−0.07 (0.05)	0.01 (0.02)	0.01 (0.03)		−0.09*** (0.02)
$(\ln x_4)(\ln y_2)$	0.05*** (0.03)	0.15*** (0.04)	−0.003 (0.03)	−0.05*** (0.02)		−0.01 (0.02)
Technical change						
t	−0.002 (0.002)	−0.01*** (0.003)	−0.03*** (0.004)	−0.07*** (0.00)	−0.02*** (0.009)	0.005 (0.005)
t^2	−0.001*** (0.0002)	−0.001*** (0.0003)	0.001*** (0.0005)	0.003** (0.001)	0.002** (0.001)	−0.001* (0.0005)
$(\ln y_1)t$	<u>0.002</u>	<u>0.008</u>	−<u>0.003</u>	−<u>0.001</u>		−<u>0.002</u>
$(\ln y_2)t$	−0.002*** (0.001)	−0.008*** (0.002)	0.003*** (0.001)	0.001 (0.001)		0.002*** (0.001)
$(\ln x_1)t$	0.006*** (0.002)	0.001 (0.002)	−0.02*** (0.004)	0.003 (0.002)	0.003 (0.005)	0.002 (0.003)
$(\ln x_2)t$	0.005*** (0.002)	0.007*** (0.003)	0.003 (0.003)	−0.003 (0.005)	0.02*** (0.006)	0.007* (0.004)
$(\ln x_3)t$	−0.006*** (0.002)	0.002 (0.003)	−0.007*** (0.002)	0.005 (0.003)	−0.001 (0.005)	−0.01*** (0.003)
$(\ln x_4)t$	0.0001 (0.002)	−0.006*** (0.003)	0.02*** (0.004)	−0.01*** (0.003)	−0.002 (0.006)	0.006** (0.003)
Other parameters						
Sigma squared	0.04*** (0.003)	0.07*** (0.01)	0.12*** (0.01)	0.70*** (0.07)	0.97*** (0.19)	0.19*** (0.03)
$\hat{\gamma}$	0.74*** (0.02)	0.83*** (0.02)	0.75*** (0.02)	0.92*** (0.01)	0.89*** (0.02)	0.67*** (0.04)
$\hat{\mu}$	0.34*** (0.03)	0.24*** (0.04)	0.60*** (0.06)	Restricted to zero	−1.86*** (0.45)	0.23** (0.10)
$\hat{\eta}$	−0.01*** (0.003)	−0.03*** (0.004)	−0.02*** (0.005)	−0.05*** (0.005)	−0.02* (0.01)	−0.03*** (0.01)
Log-likelihood	2,904	1,499	268	−685	−806	−755

***Notes*:** $\ln y_1$ is the log of enterprise output, $\ln y_2$ is the log of other output, $\ln x_1$ is the log of land inputs, $\ln x_2$ is the log of labour inputs, $\ln x_3$ is the log of capital inputs, $\ln x_4$ us the log of variable inputs, t is the time trend, $\hat{\gamma}$ is an estimate of the share of technical efficiency in total variance, $\hat{\mu}$ is the estimated mean of the truncated normal distribution of the random component of the inefficiency effects and $\hat{\eta}$ is the estimated parameter associated with time in the inefficiency effects. Underlined parameters are calculated using the homogeneity restriction detailed in the Appendix. Parameter estimates for the 'specialist' cattle system are from the estimation of a stochastic production frontier. ***Indicates significance at the 1% level, **indicates significance at the 5% level, *indicates significance at the 10% level. Standard errors are given in parentheses.

Table 10
Estimated input and output distance elasticities

	Dairy spec.	Dairy other	Tillage	Sheep	Cattle other	Cattle spec.
Enterprise output	0.77	0.58	0.64	0.49	0.75	–
Land	0.12* (0.07)	0.12 (0.08)	0.36** (0.14)	0.06 (0.16)	0.18* (0.11)	0.21*** (0.06)
Labour	0.08** (0.04)	0.08** (0.04)	0.09 (0.10)	0.07 (0.06)	0.08 (0.05)	−0.001 (0.08)
Capital	0.31*** (0.05)	0.32*** (0.10)	0.15 (0.14)	0.40*** (0.13)	0.37** (0.18)	0.41*** (0.09)
Variable costs	0.48*** (0.04)	0.51*** (0.10)	0.49*** (0.13)	0.42*** (0.12)	0.36*** (0.12)	0.32*** (0.12)
Returns to scale	0.99	1.03	1.09	0.95	0.99	0.94

Notes: ***Indicates significance at the 1% level, **indicates significance at the 5% level, *indicates significance at the 10% level. Standard errors are given in parenthesis.

For each of the models estimated, between 64% and 75% of the parameter estimates are significant at least at the 10% significance level. The data are mean-corrected prior to the estimation of the model and as such the estimated coefficients can be used to construct input and output elasticities. These are presented in Table 10. Most are significant and all bar one are of the appropriate sign. Capital and variable inputs are the most prominent inputs in all farm systems with the exception of tillage where, as expected, land is a more important factor than capital, given its larger elasticity. Land is less important in other farm systems such as sheep but plays a significant role in the input structure of the cattle system, particularly for farms involved in specialist cattle production. Labour has the lowest share in inputs and is insignificant in the tillage, sheep and cattle systems, and negative and insignificant in the specialist cattle system. This latter result could indicate significant underemployment of labour, most likely on the smaller farms. The estimated distance elasticities for output reveal that the share of the main enterprise output in each system dominates production: 77% for specialist dairy farms, 58% for other dairy farms, 64% for tillage farms and 75% for other cattle farms. The only exception is sheep production where sheep output constitutes only 49% of total output produced in the system. The scale elasticity for the output distance function is measured as the negative of the sum of the input elasticities and measures the proportional increase in outputs as a result of an increase in inputs of the same proportion (Färe and Primont, 1995). All systems of farming experience almost constant returns to scale, though with slightly increasing returns to scale observed on tillage farms and slight decreasing returns to scale on sheep and specialist cattle farms.

4.3. Productivity analysis

The parameters of the distance function are used to estimate the generalised Malmquist index of total factor productivity, given by equation (6), and its decomposition into technical change, efficiency and scale effects, given by equations (7), (8) and (9), respectively, for each farm in each system. Within each system, the farm-level productivity indexes and their components are aggregated to represent the population of farms as described in section 3. The results are presented in Table 11. Productivity performance is presented in terms of linear growth rates, estimated by

Table 11

Productivity change index and decomposition on Irish farms 1984–2000 (weighted to reflect population totals)

	Technical change	Efficiency	Malmquist	Returns to scale	Generalized Malmquist
Dairy	122.91	99.15	121.87	99.82	121.65
		Linear growth rates (%)			
1984–2000	1.42	−0.19	1.21	−0.01	1.20
1984–1989	0.65	0.24	0.90	−0.01	0.89
1989–1995	1.48	−0.49	0.96	−0.01	0.95
1995–2000	2.32	0.18	2.50	−0.01	2.48
Tillage	137.94	82.46	113.74	100.70	114.54
		Linear growth rates (%)			
1984–2000	2.40	−0.99	0.97	0.07	1.06
1984–1989	3.03	−1.20	1.60	0.12	1.74
1989–1995	2.51	−1.49	0.41	−0.09	0.31
1995–2000	1.54	−0.60	0.49	−0.04	0.45
Sheep	181.68	73.16	132.91	96.40	128.13
		Linear growth rates (%)			
1984–2000	5.25	−1.63	2.33	−0.10	2.14
1984–1989	6.44	−0.41	5.92	−0.63	5.08
1989–1995	5.46	−1.28	3.17	0.16	3.29
1995–2000	3.34	−3.23	−2.92	−0.11	−3.00
Cattle	96.59	97.51	94.18	96.62	91.00
		Linear growth rates (%)			
1984–2000	−0.21	−0.46	−0.64	−0.21	−0.84
1984–1989	−1.06	0.09	−0.98	−0.28	−1.25
1989–1995	−0.21	−0.93	−1.08	−0.13	−1.18
1995–2000	0.65	0.04	0.67	−0.09	0.57

Note: Base = 1984 (100.00).

fitting a linear regression line to the productivity trend, for the sample period as a whole and for three sub-periods, 1984–1989, 1989–1995 and 1995–2000.

There are marked differences both in overall productivity performance and the trend in productivity change across systems. These differences are further illustrated in Figure 1. The sheep system exhibits the most impressive performance because of an early burst in productivity growth rates. Total factor productivity grew by 28% over the sample period at a linear rate of 2.1% per annum. However, the decomposition of productivity growth rates into three different time periods illustrates that productivity gains have been exhausted since the mid-1990s. The cattle system, on the other hand, experienced the poorest performance of all systems. In total, productivity fell by 9% over the sample period with negative linear growth of 0.8% per annum. However, positive productivity growth between 1995 and 2000 is evidence of a recovery in the productivity performance of the system in the latter portion of the sample period. Productivity grows slowly in the dairy farm system at the begin-

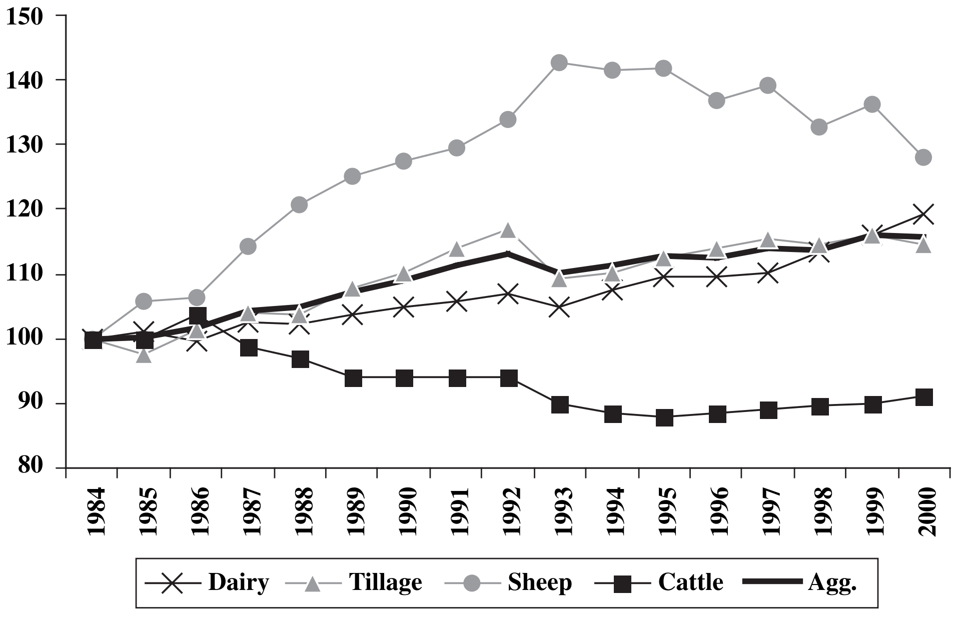

Figure 1. System-by-system decomposition of total factor productivity trend for Irish agriculture

ning of the period with productivity gains of 0.9% per annum. However, in more recent years of the sample period, productivity grew at a linear rate of almost 2.5% per annum, yielding an overall increase in total factor productivity of almost 22% for the sample period as a whole. The tillage system shows the reverse pattern with a gradual loss of momentum in productivity gains in the later years of the sample period. In total, productivity grew by 14.5% over the sample period.

Hadley (2006) estimates similar models for various systems of farming in the UK for the period 1982–2002 with similar results. In order to understand what drives this growth, it is necessary to examine the decomposition of the index into its various components. In the Irish case, the overall growth in productivity in the dairy, tillage and sheep systems is driven by technical progress, leading to outward shifts in the 'best practice' frontier between 1984 and 2000 of 23%, 38% and 82%, respectively. This latter figure is particularly noteworthy and suggests that very rapid innovation in the sheep enterprise took place during this period. In contrast, the 'best practice' frontier in the cattle system exhibits an inward shift of just over 3%. This however, is due to the poor performance of the 'specialist' cattle system, with the 'other' cattle system experiencing some technical progress at a linear rate of 0.3% per annum. Hadley's results are similar in that productivity improvements over time are due to technical change, but he observes the fastest rates of progress on farms specialised in arable production and slower rates of progress on livestock-producing farms. The more extreme trends observed within the sheep and cattle systems in the Irish case are not evident in the UK results.

The efficiency gap between the average farm and the best practice farm declined for all systems. Where there is accelerating technical progress, a decline in average efficiency levels, indicating an increase in the gap between the best practice farm and the average farm, is expected because it is probable that the most efficient farms would adapt to technical change earlier than less efficient farms. The dairy system experiences little change in average efficiency levels over the sample period, with some improvement in average efficiency levels observed in the later period. This is a strong performance given that the best practice frontier improved by 23%, at an accelerating rate over the sample period. This implies that in this system not only are the best practice farms improving but the average farm also manages to keep up with these improvements. This is less so for the tillage and sheep systems where the decline in average efficiency levels is greater. Technical progress was faster in these systems than in the dairy system and the average farm had more difficulty in keeping up with the best practice farms. For the sheep system, the decline in efficiency levels is particularly pronounced in the last 4 years of the sample. The dramatic fall in efficiency levels post-1995 offset much of the outstanding technical progress which took place in the system to produce mediocre productivity growth for the sample period as a whole. The very poor performance of the cattle system is once again highlighted by the increase in the gap between the average farmer and the best practice farmer despite an inward shift in the best practice frontier. Caution, however, must be exercised in analysing results relating to the cattle system because of the heterogenous nature of enterprise output in the system and the homogenous way in which it is quantified in this analysis. Hadley also finds a decline in mean efficiency scores across all systems, with the decline most pronounced for arable farming and sheep production in particular. Once again the poor performance of the cattle system in the Irish case is not evident in the UK results.

Scale effects are negligible in the dairy system and contribute very little to productivity growth in the tillage system. However, for both sheep and cattle systems scale effects contribute negatively to productivity growth.

By weighting the results for each system by their contribution to total output in the population, an aggregate measure of the productivity performance of Irish agriculture is estimated. Overall productivity in Irish agriculture grew by 21.1% over the sample period at a linear rate of just over 1% per annum. Boyle (1987) estimated an annual total productivity growth rate of just over 1% for the 1960–1982 period, suggesting that productivity growth between 1960 and 2000 has remained fairly steady. In this study, however, total factor productivity fell from an estimated growth rate of 1.5% for the 1980s to 0.7% for the 1990s. The former is consistent with Bureau *et al.*'s (1991) estimate of productivity growth of 1.35% annually for the 1973–1989 period. Matthews (1999/2000) and O'Neill *et al.* (2002) found a similar decline in the productivity performance of the sector over time.

5. Concluding Discussion and Implications

In aggregate, the agricultural sector experienced productivity growth of 21.1% for the 1984–2000 period, at a linear rate of just over 1% per annum. There is evidence, however, of a slowdown in growth in the 1990s, a worrying trend given that recent policy developments make it more important than ever for the sector to improve its competitiveness. The study shows that clear differences exist in the productivity performance of different farming systems in Ireland. Sheep farming exhibits the most impressive performance because of an early burst in productivity growth rates. However, productivity gains have been exhausted since the mid-1990s and there has been no further productivity growth since then. Dairy farming has improved its productivity performance throughout the period, albeit from what might be considered a weak performance in the second half of the 1980s. Tillage also performed well at the beginning of the period but productivity performance has been relatively poor in recent years. Cattle farming performs poorly throughout.

While it is not the purpose of this paper to explain why we observe these trends, because the model cannot add anything to such a discussion, we can hypothesise why the observed trends may exist. Because our sample starts in 1984, we have no evidence on the productivity growth performance of the Irish dairy sector before the introduction of the dairy quota regime in that year. Nonetheless, productivity growth of 0.9% annually in the 1984–1990 period is the lowest of the three periods examined, and may reflect the productivity cost of the dislocation and adjustments required on dairy farms immediately following the introduction of the quota regime. It should also be recalled that our productivity estimates are for farming systems as a whole rather than for the principal commodity which defines the system. As Table 3 showed, non-dairy output on dairy farms grew almost twice as fast as milk output. On many dairy farms, this represented a diversification into cattle farming particularly in the early years of the quota period. While this was justified by the direct payments on offer to support this enterprise, the apparent absence of productivity growth in the cattle enterprise over this period would have had the effect of lowering the estimated productivity growth for the dairy system as a whole. On this interpretation, the acceleration of productivity growth on dairy farms in subsequent periods may reflect the re-establishment of more 'normal' growth rates as farmers learned to live with the quota regime and as the regime in recent years has become less restrictive.

Similarly, the relatively poor performance of the tillage system between 1989 and 1995 compared with 1984 to 1989 may reflect the adjustment problems associated with the introduction of the MacSharry reforms to the CAP. The system, however, managed to recover from this lapse exhibiting faster growth rates between 1995 and 2000. After a spectacular productivity performance in the early years, a slowdown in productivity growth in the sheep system is also evidenced post-1992. Total ewe numbers more than doubled between 1984 and 1992, partly in response to improved profitability following the opening of the French market to Irish lamb in 1980. Sheep numbers began to fall after the introduction of the ewe premium quota scheme in 1992. While there was a steady growth in the lambing percentage throughout the whole period, productivity may also have been adversely affected after 1992 by the growth of extensification payments and agri-environment payments. Both schemes would have encouraged farmers to make less efficient use of their resources for production *per se*. In the case of the extensification scheme, the incentive was to reduce sheep numbers per hectare in return for higher levels of direct payments. In the case of the Rural Environmental Protection Scheme, higher levels of on-farm costs would be associated not with greater levels of physical output but with environmental improvements which are not captured in the output variable used in the analysis. A similar attempt to maximise premium income rather than efficiency or productivity could also explain the cattle system findings. The poor productivity performance of the cattle system was associated with a strong premium-driven expansion in the suckler cow herd from 410,000 in 1981 (when the Suckler Cow Premium was introduced) to peak at just under 1,200,000 in 1998. Extensification payments and stocking rate restrictions required for eligibility for premium payments for male animals post-1992 would also have contributed to the distortion of incentives. If this is the case then the introduction of decoupling in 2005, which eliminates the incentive for farmers to manage their livestock enterprises with a view to maximising direct payment receipts, could lead to a rebound in productivity growth. Evidence from New Zealand suggests that total factor productivity growth averaged only 1.5% annually during its high subsidy period (1972–1984), but since the elimination of subsidies productivity has improved to 2.5% per annum (Lattimore, 2006).[14]

Data are not to hand on the productivity performance of other EU countries, which would be necessary to come to a conclusion on how relative competitiveness has changed, but in absolute terms the overall productivity performance of Irish agriculture between 1984 and 2000 is poor. Hadley (2006), for example, reports rates of technical change for England and Wales for arable farms in the range 3.7–5.2% annually, and for livestock farms (excluding pigs and poultry) of between 2.0% and 3.3%. Productivity growth would be a little lower because he found a fall in mean technical efficiency in each farm system apart from cereals. It is unlikely that productivity growth rates of the magnitude recorded in this study will be sufficient to maintain farm incomes in the face of a stagnant or declining price of output and inflationary increases in costs. The poor performance of the cattle system is particularly worrying, even taking the data qualifications in this system into account. It suggests that considerable structural change will be required in the sector if it is to successfully compete in a more market-oriented environment.

Finally, there are two caveats to this study that should be highlighted. First, our estimates depend on the quality of the data and whether they are consistent with the requirements of the theoretical model we use, in particular, that both inputs and outputs are homogeneous across both space and over time. Deflation with the appropriate price indicators removes some of the difficulties of having to use value aggregates of these variables. Nonetheless, there have undoubtedly been improvements in the quality of inputs (and possibly also in outputs) which are not captured in the data used for estimation. This is a common problem in productivity analysis; such quality improvement is captured in the technical progress variable and may lead to an overestimation of the 'true' underlying rate of technical progress. There may also be some variation in input and output quality across farms at a point in time. Variations in input quality will be captured in the measure of inefficiency. Over time, assuming that opportunities to improve the quality of inputs are equally open to all farms, then those that do not adjust will (arguably appropriately) be recorded as being more inefficient than those that do avail of these opportunities. In relation to variations in output quality, this may be particularly severe in the cattle system given the heterogeneous outputs of this system in Ireland (calves, weanlings, store or fat animals of different ages and breeds). Using a single price deflator to extract a

[14] Hennessey and Thorne (2005) report that 20% of beef farmers intend to reduce production post-decoupling and a further 13% intend to quit production completely. The impact that this will have on future productivity performance will depend on which farms these constitute. There is some evidence which suggests that smaller less efficient farms will leave the system in which case we would expect an improvement in overall productivity levels of the system as a whole. However, given that the sector has never before operated in such a policy environment, historical data of the kind used in this analysis can give us little indication of how the sector will react to these changes.

volume measure from the value data on the cattle enterprise introduces a form of measurement error that will be picked up in the error term of the production/distance function. We assume that the measurement error is randomly distributed across farms, does not change over time and is uncorrelated with the inefficiency effects and other inputs, and thus there is no reason to expect that the average efficiency measure for the system, and our measure of how it changes over time, will be biased. Nevertheless, we would urge some caution in the interpretation of the results for the cattle system, given the presence of this measurement error.

A second caveat of this study relates to the exclusion of observations from the tillage and sheep systems that do not produce 'other' output, aside from the main enterprise output. These observations are excluded to accommodate the translog specification. While only a relatively small number of observations are concerned and the weighted sample mean values are not affected, their exclusion could lead to sample selection bias which has not been controlled for in this analysis. An exploration of potential approaches for testing and controlling for sample selection bias in distance function models of the kind presented in this paper is left to future research.[15]

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[15] Weaver and Lass (1989) present an estimation strategy for dealing with corner solutions in cross-section samples of farm-level production decisions. This is an obvious starting point for future work in this area.

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Appendix

Implicit quantity method of aggregation

The implicit quantity index, used for aggregating output and variable inputs, is obtained as the ratio of the value of output to an aggregate farm-specific Tornqvist price index with base period 1990. As individual farm prices are not available, national prices taken from the Compendium of Irish Agricultural Statistics, 2001 (Central Statistics Office, 2001) are used. In the aggregation of outputs, for example, the Tornqvist price index is

$$\ln w_{it} = \sum_{m=1}^{M} 0.5(s_{mit} + \bar{s}_{mb})(\ln w_{mt} - \ln w_{mb})$$

where s_{mit} is the share of output m in total output on farm i in year t, $\bar{s}_{mb}$ is the average share of output m in the base year b, w_{mt} is the price of output m in year t, and w_{mb} is the price of output m in the base year b.

Dividing the value of total output by this index produces an implicit quantity measure. The same procedure is used for the aggregation of variable inputs.

Homogeneity restrictions imposed in estimating the multiple output distance function and used to estimate enterprise output parameters

Homogeneity in outputs implies that $D_o^t(x^t, \lambda y^t) = \lambda D_o^t(x^t, y^t)$. This requires the following restrictions:

$$\sum_{m=1}^{M} \alpha_m = 1, \quad \sum_{n=1}^{M} \alpha_{mn} = 0, \quad \sum_{m=1}^{M} \delta_{km} = 0 \quad \text{and} \quad \sum_{m=1}^{M} \omega_{mt} = 0$$

where $m = 1, 2,\ldots,M$ and $k = 1, 2,\ldots,K$.