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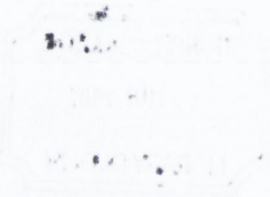
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ESSAYS ON PRODUCTIVITY IN IRISH AGRICULTURE

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Thesis Submitted to Trinity College, Dublin

in fulfilment of the requirements for the degree of

Doctor of Philosophy (Ph.D.)

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For my Mother and Father

In memory of Des

Summary

The focus of this thesis is the measurement of performance in Irish agriculture over the period 1984 to 1998. The methodology applied lies in the broad area of production economics and is located primarily in the microeconometric approach to the estimation of production functions. There is a total of six chapter in the thesis.

Chapter 1 is concerned with the policy motivation for the work and describes the data set used in the analysis.

Chapter 2 covers the core theoretical foundations underpinning the empirical essays presented in Chapters 3, 4 and 5. It also includes a literature review of production theory, defines the concepts of technical efficiency, technical change and productivity growth. The alternative functional forms and the regularity conditions of the frontier production function are also discussed. The remainder of the chapter concentrates on the estimation of frontier production functions. The starting point, in this section, is a review of cross-sectional models for both deterministic and stochastic frontier production functions followed by the development of panel data models.

Chapter 3 contained the first essay called "Technical Change and Efficiency in Irish Agriculture". The empirical analysis quantifies two competitiveness factors, namely, the rate of technical change over time and the relative efficiency of individual farms compared to best practice in the industry. A panel of Irish farms taken from the National Farm Survey over the period 1984 to 1998 isused. The technical change results are weighted to account for differences in the relative contribution of each farm to national output. The results show evidence of technical change, over the period but this is occurring at a decreasing rate for both the weighted and the unweighted results. The exponential weighted rate of technical change is 1.94 (linear 2.58) per cent compared to a value of 0.9 per cent for the unweighted sample and the cumulative growth increases from 13.9 per cent over the period for the unweighted results to 34 per cent for the weighted results.

Significant differences are revealed in the rate of technical change on farms of different types. Farms located in the Eastern region have a mean annual rate of technical change of 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 rate of technical change is greater for farms located in the West and the East (1.15 and 2.21 per cent respectively). Farms in the top size quintile (over 81 hectares of land) have an unweighted average annual rate of technical change of 2.54 per cent annually and a weighted annual rate of 2.24. Weighting technical change gives an annual average rate of technical change of 1.03 per cent compared to an unweighted average annual fall in productivity (which is called technical regress) of -0.8 per cent on farms in the bottom size quintile (less than 22 hectares). Dairy, dairy and other and crop farms experience technical change over the period (at unweighted annual rates of 1.9, 1.3 and 1.75 per cent respectively) while cattle and sheep farms experience technical regress over the same period. Weighting the results show that cattle farms experienced an annual rate of technical progress of 0.5 per cent over the period. While weighting the results for sheep farms indicates technical regress at a rate of -0.02 per cent. Farm efficiency relative to best practice within each farming system, in a particular year, is also considered. The average level of farm efficiency

decreases by 0.4 per cent per annum over the period of the study. The breakdown of the most efficient farms by system of farming shows that 31 per cent are dairy farms while 23 per cent are arable farms. Approximately 52 per cent of the least efficient farms are cattle farms while a further 31 per cent are sheep farms.

Chapter 4 contains an essay called "Does Contact with the Extension Service Improve Farm Level Efficiency?". A smaller sample containing 1603 observations for the years 1995 to 1998 is used for the analysis. The analysis examines the factors associated with differences in technical efficiency across farms. In particular, the impact of contact with the agricultural advisory service on farm-level technical efficiency is explored. A correction of the efficiency model to take account of an endogeneous extension variable is undertaken.

The results indicate that being located in the West of Ireland is associated with an average decrease in efficiency of less than 1 per cent. Larger farm size is associated with a steady decrease in efficiency. Receiving direct payments has a negative impact on efficiency; farms with a share of direct payments 25 percentage points greater than average are, on average, 1 per cent less efficient. Contact with the extension service increass efficiency by 6.5 per cent relative to farms with no contact. The interaction between the level of education and extension contact is found to be statistically insignificant. Farms in contact with the extension service and with a lower than average dependency on direct payments are, on average, a further 6.6 per cent more efficient. Farms that are highly dependent on direct payments and have contact with the extension service are 1.9 per cent less efficient than contact farms with an average dependence on direct payments.

The final essay in Chapter 5, concentrates on the measurement of total factor productivity for Irish milk producing farms. The aim of the chapter is to compare Stochastic Frontier Analysis (SFA) to Data Envelopment Analysis (DEA) in the measurement of total factor productivity (TFP). Both approaches generate estimates of efficiency and technical change. Both methods are used to construct distance functions which are then used to construct a Malmquist TFP index. The analysis is carried out using farm level data on Irish milk producing enterprises for the period 1984 to 1998.

Average technical efficiency in the SFA and DEA models, in 1984 are 81 and 79 per cent respectively. The rank correlation between the SFA and DEA results is 67 per cent which is consistent with other studies in the literature. As expected the variation in efficiency is greater in the DEA due to the influence of white noise. The driving force behind total factor productivity growth over the period comes from technical progress. The DEA results show the TFP index rising by 19 per cent over the fifteen year period of the study compared to 33 per cent for SFA.

The final chapter discusses the policy implications and areas of possible future work. The caveats of the analysis are also presented.

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CHAPTER 1
INTRODUCTION

1.1. BACKGROUND

This research began with a large panel data set on Irish farms, the broad objective of examining farm performance over time and a copy of Gerry Boyle's (1987) PhD thesis on efficiency and technical change in Irish agriculture, which was published by Teagasc. There appeared to be little recent work on micro level productivity measurement in the Irish agricultural literature and so began my quest to fill the gap. The primary goal of the research was to produce statistically sound measures of efficiency and technical change based on a well developed methodology which would have an impact in the policy arena.

There are six chapters in this thesis. This chapter is an introduction to the thesis and outlines the motivation for the analysis to follow. The data set used for the empirical work is also introduced in Chapter 1. Chapter 2 concentrates on the aspects of production theory which form the foundation for the empirical work to follow in the three main chapters of the thesis. These three chapters examine aspects of Irish farm performance over time. The final chapter brings together the main results and policy implications.

1.2. METHODOLOGY

The methodology applied lies in the broad area of production economics and is located primarily in the microeconometric approach to the estimation of production functions known as stochastic frontier analysis (SFA). This is the first time that the Battese and Coelli (1992, 1995) SFA

approach, which uses maximum likelihood estimators, has been applied to Irish farm level data.

There are two potential advantages of the farm level SFA approach. The first is that changes in total factor productivity, due to improvements in technical efficiency (farms moving closer to the frontier), can be separated from shifts in the frontier itself over time which is the more correct measure of technical progress. Although over long periods it might be a reasonable assumption that average farm technical efficiency does not change, this is not necessarily the case over time periods as short as one to two decades. The second is that separate rates of technical progress can be calculated for different farming systems and different regions.

An alternative approach to SFA, know as Data Envelopment Analysis (DEA), is introduced in Chapter 5. DEA is a form of linear programming which is used to estimate efficiency and technical change. While it is important to acknowledge an alternative methodology to the SFA approach in my PhD for completeness reasons, employing DEA also offered a method of checking the robustness of the SFA results. Furthermore, up until the late 1990s, DEA and SFA methodologies have developed along separate paths. However, recent work is attempting to integrate the strengths of both approaches to enhance the quality of the generated results.

1.3. POLICY MOTIVATION

The agricultural sector is of prime importance to the Irish economy. A number of policy changes are contributing to changes in the structure and the production practices of Irish farms. The 1992 MacSharry reforms represented the first major attempt to overhaul the Common Agriculture

Policy (CAP) and these have been followed by the Agenda 2000 reforms. The primary reason for CAP reform has been European Union (EU) budgetary concerns. Also, the EU has attempted to rectify the environmental effects of CAP through the introduction of environmental schemes and through cross compliance eligibility criteria for direct payments to farmers. Direct payments, for particular enterprises have significant important in Irish agriculture. For example, direct payments amounted to 124 per cent of family farm income in the cattle rearing farm system, 128 per cent of family farm income in mainly sheep systems and 83 per cent of family farm income in mainly tillage farm systems (Matthews, 2000). For these farms, meeting the complex eligibility conditions for direct payments has a greater impact on income than lowering production cost leading to resource inefficiency. Therefore, it is conceivable that it is in the interest of the farm operator not to put maximum effort into the achievement of full efficiency if this reduces total income.

The second reason, leading to change in agricultural policy has arisen because the EU has signed up to the Agreement on Agriculture in the Uruguay Round of world trade negotiations. The WTO Agreement has established a number of trade liberalisation disciplines which stipulate the amount and type of government intervention in agricultural markets. As these trade liberalisations are introduced, the EU agricultural sector will find itself competing in a more open market. The ability of the agricultural sector to thrive under liberalisation is made more urgent as the Central and East European Countries prepare to join the EU.

As Matthews (2000) states "the future competitiveness of Irish agriculture depends on access to up-to-date and productive new technologies, on

achieving an optimal structure of production, and on the management skills of its farmers". The empirical analysis carried out in this thesis attempts to quantify two of these competitiveness factors, namely, the rate of technical change over time and the relative efficiency of individual farms compared to best practice in the industry. Chapter 3 focuses on a large panel data set and calculates rates of technical change and efficiency which can be used for further policy analysis.

For example, working from the premise that if research intended to improve productivity actually shows up in higher total factor productivity (TFP) over time, then the benefits of publicly funded research can be quantified. The value of increased TFP lies in the value of the inputs saved to produce the current volume of output or, alternatively, the value of the additional output which can now be produced using the current volume of inputs. Either of these measures can be used as a starting point to estimate the return to agricultural research expenditure.

At the early stages of my research I met with Prof. Jim Phelan (UCD) and had the opportunity to discuss my research on technical efficiency. Jim made two interesting points which shaped the focus of Chapter 4. He pointed out that education was an essential variable missing from the model presented in Chapter 3. The second point emphasised that the farm advisory service was not entirely focused on improving farm level efficiency. Indeed, the role of the advisory service is changing as a result of the changed policy environment for agriculture following the European Union (EU) agricultural policy reforms in 1992 (the MacSharry reforms) and 2000 (the Agenda 2000 reform2). I wanted to explore whether this increased dependence on direct payments has any implications for farm-level

efficiency and for the role of the extension service. If the relationship between efficiency and advisory contact could be established, then it would be possible to analyse the funding structures and the priorities for the advisory service in the future.

The final empirical chapter looks at the rate of TFP for a sample of Irish milk producing farms. The rationale for this chapter is different from the other two empirical chapters in so far as the analysis is concerned with the comparison of two methods for the estimation of TFP, namely, the SFA approach used in the previous chapters and the non parametric method of data envelopment analysis (DEA). The decision to concentrate on milk producing farms stems from the results of Chapters 3 and 4. Dairy farms were found to be more efficient relative to other sectors. Furthermore, the rate of technical progress is also greatest on dairy farms.

The dairy market is highly regulated with both supply control measures and market support in operation. Supply controls are implemented through the quota system, which was introduced in 1984 in response to growing milk surpluses and the accelerating cost of subsidising agriculture. At the time, there was widespread fear that the introduction of milk quotas would reduce innovation, over time, and fossilise the structure of milk production. While, the results presented in Chapters 3 and 4 indicate that dairy farms are more productive, these results are derived using an aggregated output variable. Irish milk producing farms have a relatively homogeneous output and hence some of the data aggregation issues detailed in Chapters 3 and 4 could be avoided.

1.4. THE DATA SET

In every year since 1972 Teagasc (The Irish Agricultural and Food Development Authority) has recorded data from a sample of Irish farms for the purposes of determining the financial situation and relative performance of Irish farms. The survey is called the National Farm Survey (NFS) and Irish data are used in the EU's Farm Accountancy Data Network (FADN) data. Farmers are randomly selected from the farm population based on a statistical sampling procedure and participate voluntarily in the survey.

1.4.1. Collection of Data and Sampling Technique

The NFS is undertaken on an annual basis. The Central Statistics Office (CSO), Census of Agriculture provides the population information on farms in the country. A selection plan is drawn up to represent the major systems of farming and the size of farms within each system by the CSO. From the selection plan a random stratified sample is taken from the population for use in the NFS. The CSO is responsible for the generation of population weights which allow inferences to be made about the population from the data collected on farms in the NFS sample. A number of farms leave the NFS sample every year and the NFS unit in Teagasc request replacement farms from the CSO so that the sample number remains close to 1300 farms. They inform the CSO of the size and system of the farms leaving to help to ensure that the representativeness of the sample is maintained. The last entirely new sample of farms was taken in 1984 and so the result of the farm selection process is that farms can remain in the survey for long periods of time.

1.4.2. Information Collected in the NFS

The data collected in the NFS are published under five main headings and are presented by farm size, farm system, province and status of the farm (part-time or full time-farm). The variables used in this study are listed under the NFS headings.

- *Financial results*: Gross output, direct costs, gross margin, family farm income, net sales, receipts and cash flow. Asset values for machinery, buildings, livestock and land.
- *Resources per farm*: Land owned, size of farm in adjusted acres, utilised agricultural area, total number of livestock units, total number of labour units (family and non family).
- *Gross output and direct payments*: Value of dairy, cattle, sheep, pig, poultry, horse, crops and other output. Amount of direct payments made, the value of inter-enterprise transfers.
- *Direct and overhead costs per farm*: Cost of feed, fertiliser, crop protection, casual labour and overhead costs such as electricity, hired labour, machinery depreciation, machinery running costs, building maintenance.
- *Demographic information*: Age of farmer, change of management, marital status.

1.4.3. Limitations of the Data

There have been a number of changes in both the information collected and in the methods used by the NFS statisticians to calculate a number of variables in the sample. Many of these changes have arisen in response to EU requests for data to be comparable across countries. The most significant of these changes was in 1993 when the method for defining farm systems was changed. It was necessary to redefine, as close as

possible, the pre-1993 classifications into the new 1993 classification. The redefinition of the pre-1993 classifications was based on the share of enterprise outputs in total gross output. Other information such as the contribution of direct payments to gross output and off farm employment information has only been collected in recent years. Care was taken to ensure that the data series were consistent over the period, despite the changes in definitions.

1.4.4. Data Cleaning

An extensive data cleaning process was conducted prior to all analysis. The original data set comprised over 16,000 observations. Outliers were identified using the methods of Hadi (1992, 1994) as these measures are suitable for multivariate data analysis[1]. The data set also contained some data entry errors and incomplete data on some of the socioeconomic variables such as age and education. In general, it was possible to introduce decision rules when dealing with missing data. For example, if age was given in 1984 and not given again until 1994, and if there was no change in farm operator then it was possible to fill in the missing age data. Missing data were not a problem with the production data used to estimate the frontier production function.

1.5. CHAPTER OVERVIEWS

Chapter 2 reviews the core theoretical foundations underpining the empirical essays presented in Chapters 3, 4 and 5. The literature review of

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[1] *The methods developed by Hadi (1992, 1994) are designed for multivariate data. The method involves measuring the distance of an observation to a cluster of points. A base cluster of r points is selected and the cluster is redefined by taking r+1 points closest to the cluster as the new base until the base cluster has r=int(n+k+1/2) points. The distance that is minimised in selecting the k+1 points is a covariance matrix distance on the variables with their medians removed. The method continues until a user specified critical value is introduced. The stopping rule implies that the empiricist must set the critical value and so this method is not a first best method. Nevertheless, it is a good second best solution when the number of data points is large.*

production theory is by no means exhaustive. This approach allows the empirical essays to be papers in their own right, with each essay developing an aspect of the theory and presenting an empirical application. However, the concepts of technical efficiency, technical change and productivity growth are common to all chapters and so are presented in Chapter 2 to keep repetition to a minimum. Similarly, details of the alternative functional forms and the regularity conditions for the estimation of frontier production functions are common to all essays and so they are also discussed in Chapter 2. The remainder of the chapter concentrates on the microeconometric methods used in the estimation of frontier production functions. The starting point is a review of cross-sectional models for both deterministic and stochastic frontier production functions and an outline of some possible estimation techniques. The advantages of panel data over cross sectional data are discussed next and time invariant and time variant specifications of technical efficiency are introduced. Finally, the measurement of technical change over time is presented.

The first essay in Chapter 3 "Technical Change and Efficiency in Irish Agriculture" builds on the work of Boyle (1987). He estimated technical change and efficiency using fixed effects and random effects approaches applied to farm level panel data drawn from the National Farm Survey from 1976 to 1984. The computing power necessary to work with large micro data sets has improved greatly since Gerry Boyle first estimated farm level estimates of technical change and efficiency and my research has benefited greatly due to the advances in computing technology. For example, I was able to estimate a number of alternative frontier production functions and estimate technical change, time variant and invariant estimates of technical efficiency with relative ease. However, the construction and

cleaning of the data set and the methods of variable aggregation still takes a considerable length of time even with the aid of a powerful computer. The master data set is taken from the National Farm Survey over the period 1984 to 1998 and comprised approximately 15,000 observations. The chapter concentrates on measuring technical change and technical progress for all farms in the sample. The analysis presented also examines the different rates of technical change and efficiency across regions, size quintiles and farm system. The factors affecting technical efficiency are also explored.

Unfortunately, two vital variables required for the model explaining technical efficiency, namely, data on education and contact with the farm advisory service, were not available for the entire time period. Data were available on education and contact with the farm advisory service for the period 1995 to 1998 and so this sub-set of data was used for the analysis in Chapter 4. The purpose of Chapter 4 is to extend the analysis beyond the measurement of technical efficiency to explaining the level of efficiency. The analysis explores whether increased dependence on direct payments has any implications for farm-level efficiency and for the role of the farm advisory service. Particular attention is given to the correction, for endogeneity, of the extension variable.

Chapter 5 is the final empirical essay and concentrates on the comparison of two approaches to the measurement, over time, of TFP, SFA which was examined in Chapters 3 and 4 in detail and DEA. This chapter introduces some theoretical concepts which are better placed in Chapter 5 than in Chapter 2. If the results of the two approaches are different, then the robustness of the methods used in Chapter 3 and 4 are questionable. The

data used are a sample of milk producing farms for the period 1984 to 1998.

1.6. SUMMARY

In this Chapter I have outlined the policy motivation for the research. However, given the excellent data set and the changing policy environment there are many areas of productivity measurement which should warrant further analysis. My research represents the first application of the SFA and DEA methods to Irish agricultural data. Furthermore, it adds to the work of Boyle (1987).

The thesis proceeds as follows. Chapter 2 concentrates on the aspects of production theory which form the foundation for the following empirical analysis. Three distinct essays on farm performance over time, each with a separate focus, form the body of the thesis. It is intended that each essay should be readable in its own right but that there is a common thread among all three. The data set used and the methods of variable aggregation are broadly the same in each paper, so there is a certain amount of repetition, although this has been kept to a minimum. Finally, a brief review of the key results and policy implications are presented in the final chapter.

CHAPTER 2
METHODOLOGY

2.1. INTRODUCTION

The aim of this chapter is to cover the core theoretical foundations underpinning the empirical essays presented in Chapters 3, 4 and 5. It will become clear as this chapter progresses that not all theoretical avenues are explored. The rationale for this approach is to allow the empirical essays to be papers in their own right. Each chapter concentrates on a particular aspect of the theory and the theoretical foundations are expanded as required. Nevertheless, the definitions of technical efficiency, technical change and productivity growth, alternative functional forms, regularity conditions and the estimation of production frontiers are common to all essays and so they are discussed in detail here to prevent repetition throughout the thesis. The chapter progresses as follows. Section 2.2 reviews the key production theory concepts and defines efficiency technical change and productivity growth. Section 2.2.3 introduces the frontier production function formally. The functional forms used in the empirical essays and their associated regularity conditions are discussed in Section 2.2.4. The remainder of the chapter concentrates on the estimation of production frontiers. The starting point is a review of cross sectional models for both deterministic and stochastic frontiers and an outline of the techniques used to estimate the frontiers is given in Section 2.3.2 and Section 2.3.3 respectively. The virtues of panel data models are presented in Section 2.4.1. Both time invariant and time variant specifications of technical efficiency are presented and finally the measurement of technical change is found in Section 2.4.5.

2.2. REVIEW OF PRODUCTION ECONOMICS

In the microeconomic approach adopted here productivity growth is assumed to be composed of two elements, technical change and efficiency change (Grosskopf, 1993). Assuming that producers are rational in the neo-classical sense, they will attempt to reach the upper bound of their production possibility set by allocating resources in such a way as to gain the maximum output for the least cost allocation of inputs. If it is possible for the producer to produce the same output with less of at least one input or to use the same inputs to produce more output the producer is said to technically inefficient (Koopmans, 1951). The movement of the producer towards the production possibility set is efficiency change. The addition of a time dimension allows for new innovations to push the production possibility set outwards, that is, allowing technical change to occur. Koopmans (1951) definition of technical efficiency was theoretical and it was not until the work of Debreu (1951) and Farrell (1957) that the measurement of technical efficiency was attempted. Assuming that the production frontier is known, it is possible to illustrate the decomposition of productivity growth into its constituent parts.

In Figure 2-1 three sources of productivity growth can be distinguished. Assume a single farm produces a single output from a vector of inputs. Assume, for simplicity that constant returns to scale apply (removing scale efficiency). Let Y_1 be the output level of Farm A in period 1 and Y_2 be the level of output in period 2. The growth in output for Farm A between the two periods is the distance Y_1-Y_2. This growth has occurred due to changes in three separate elements, that is, changes in input use, changes in technical efficiency and technical progress. Figure 2-1 illustrates the decomposition of the elements of output growth.

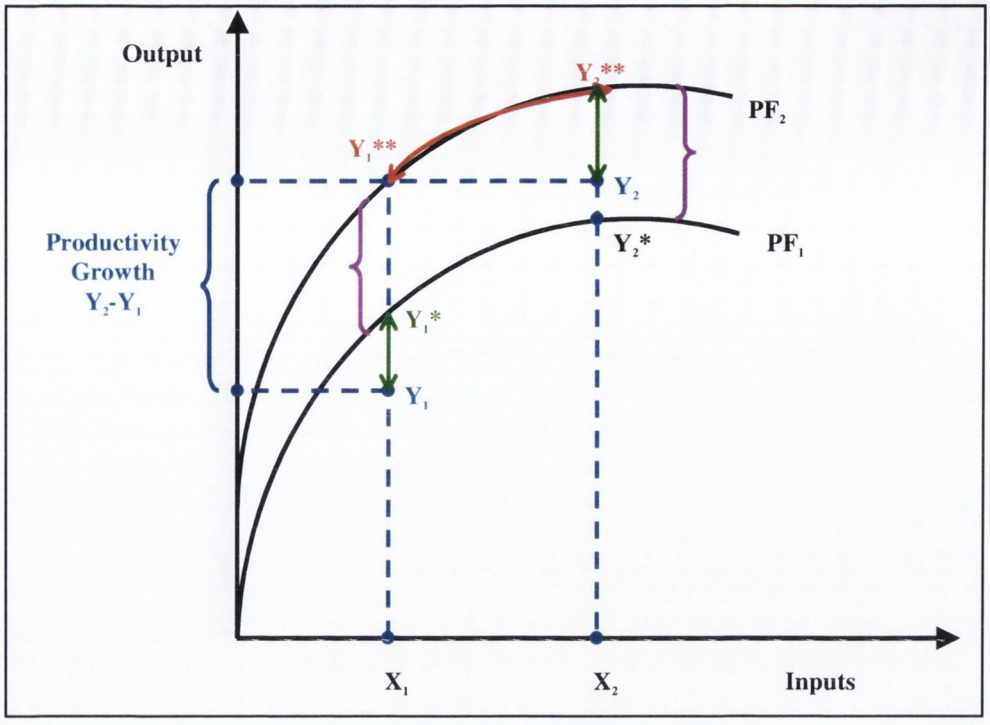


Figure 2-1: Output Growth Over Time

Output growth due to growth in the use of inputs (which cause movements along the frontier production function) is given by the distance Y_1^{**} to Y_2^{**}. In addition to increases in input use growth occurs due to technical change resulting from the introduction of new innovations (which cause a shift in the frontier production function) and changes in technical efficiency (the distance that individual farms are from the frontier). The change in technical efficiency is given by $[(Y_1^{*}-Y_1) +(Y_2^{**}-Y_2)]$ and technical progress is given by $Y_1^{**}-Y_1^{*}$ or $Y_2^{**}-Y_2^{*}$ under the assumption of constant returns to scale. If there are increasing or decreasing returns then the distance $Y_2^{**}-Y_2^{*}$ can be further disaggregated into "pure technical" progress and the effect of economies or diseconomies of scale.

2.2.1. Efficiency

Farrell (1957) decomposes efficiency into technical and allocative (price) efficiency. Technical efficiency in production economics is represented by

the distance of a farm relative to the production frontier. Assume that a farm produces two output x_1 and x_2 and the production technology exhibits constant returns to scale, it is possible to illustrate efficiency using an isoquant and isocost line.

In Figure 2-2 isoquant 1 represents the various combinations of inputs that can be used to produce an efficient level of output. Point A represents the inputs per unit of output of a technically efficient farm (indeed any point along isoquant 1 is an technically efficient point) while point R represents a farm using inputs in the same ratio of Farm A to produce the same level of output. At point E the same level of output is produced but with only a fraction of the inputs used to end up at point R. The fraction is the ratio OA/OR. Technical efficiency measures the ratio which measures the proportion of inputs actually needed to produce output. If the ratio takes a value of one then the farm is perfectly technically efficient.[2] Technical inefficiency can be measured in the same way and is equal to the inverse of the ratio OA/OR, that is, technical inefficiency is equal to 1-OA/OR. The line WW' has a slope equal to the price ratio of the two inputs. Both points A and P are technically efficient points. P is also an allocatively efficient point as it represents the point at which the marginal rate of technical substitution between inputs x_1 and x_2 are equal. In other words at point P the cost minimisation assumption holds (Farrell, 1957). In Figure 2-2 allocative efficiency is measured by the ratio 0A/0W and again allocative inefficiency is measured as 1-OA/OW.

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[2] *A farm is said to be X-inefficient if production does not occur on the boundary of its production possibilities set because of a "lack of effort" or "management slack". In general terms this definition of X-inefficiency is identical to that of technical inefficiency as discussed in Chapter 2. However, as Boyle (1986) points out that the major difference is that X-inefficiency attributes all the deviations from the frontier to one specific factors of production rather than a number of factors.*

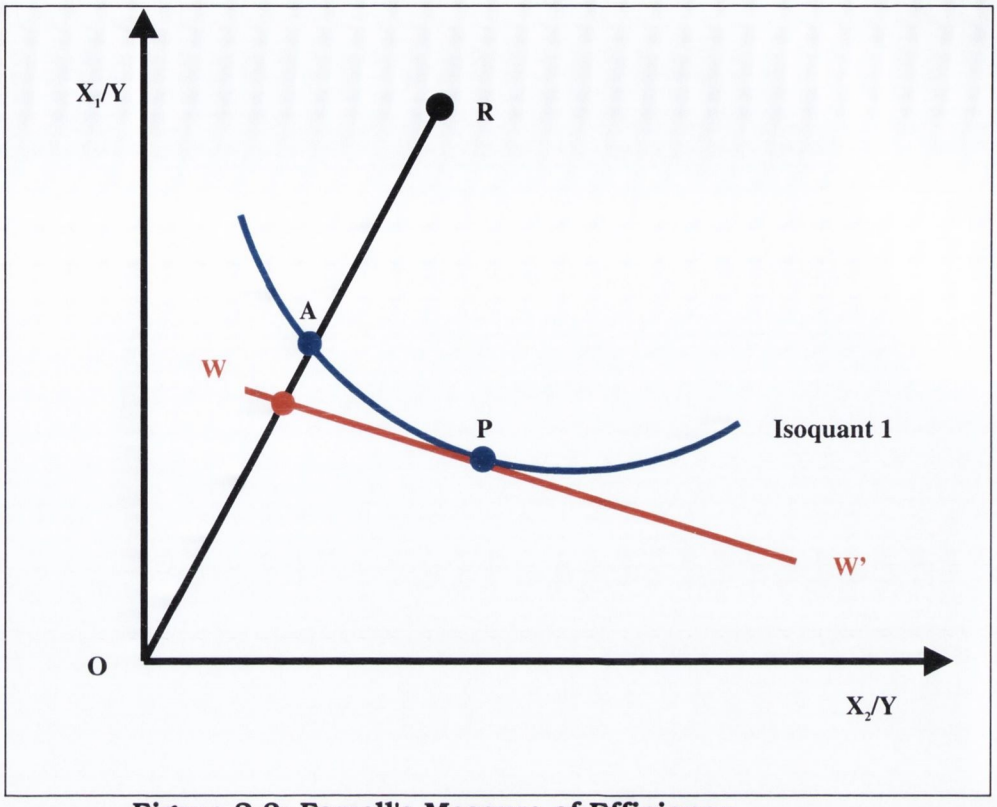


Figure 2-2: Farrell's Measure of Efficiency

2.2.2. Technical Change

Technical change *'refers to the changes in a production process that come about from the application of scientific knowledge* '(Antle & Capalbo, 1982:33). These changes can take the form of changes in the input quality, known as embodied technical change, or the form of new inputs or production techniques known as disembodied technical change. According to Hicks new technologies can be classified '*according as their initial effects are to increase, leave unchanged or diminish the ratio of the marginal product of capital to that of labour*' (Hicks, 1963), that is, they can be capital saving, labour saving or neutral. Assuming the relative factor prices remain constant over time if the new technology reduces the unit cost of all inputs equally then the technical change is said to be neutral. In other words if the marginal rate of technical substitution and the optimal input ratio is unchanged by the new technology then the technology is Hicks neutral

(Hicks, 1963). In Figure 2-3 two inputs capital and labour are used to produce Y_1 output.

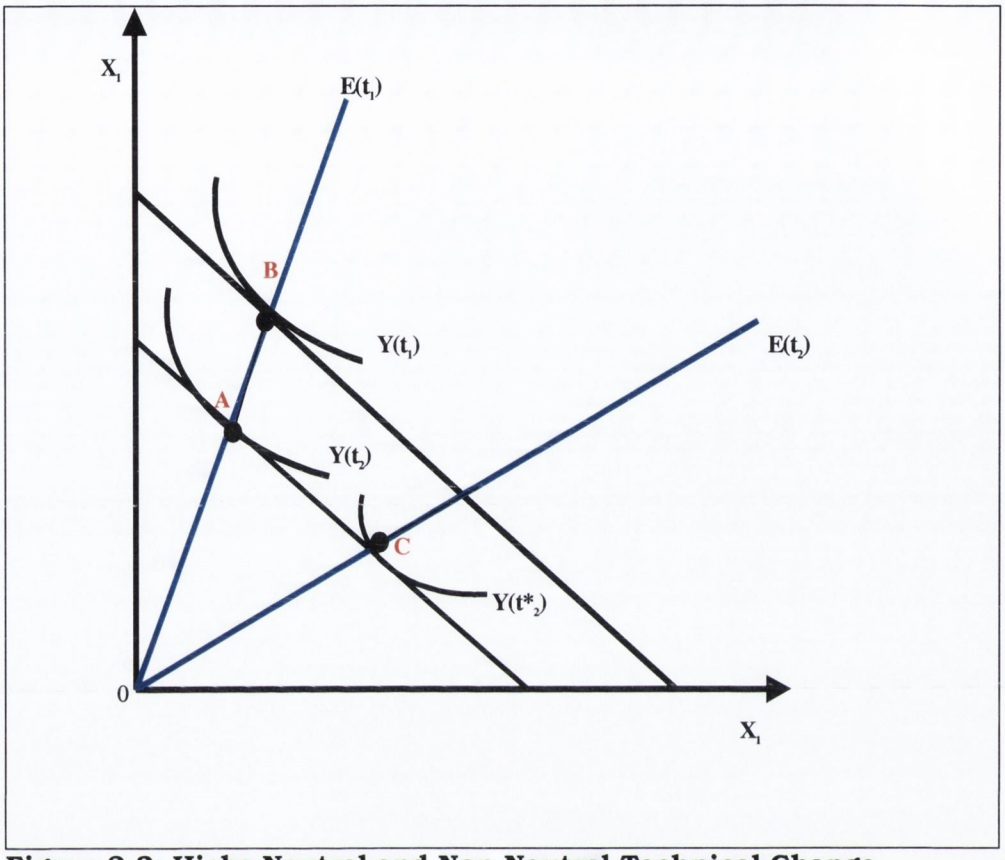


Figure 2-3: Hicks Neutral and Non Neutral Technical Change

A neutral technological change would be represented by the parallel shift inwards of the isoquant $Y(t_1)$ to $Y(t_2)$ as shown in assuming that the farm must remain on its expansion path where it is minimising the cost of production for a given level of output (Antle and Capalbo, 1988; Blackorby et al. 1976). However, should the new technology lead to greater savings on one input than in the other input then technical change is said to be non-neutral or biased (Nadiri, 1970). The farm's initial equilibrium is at B. In the second period new technology is introduced and the farm can move to a new equilibrium C producing the same level of output Y_1 but at a lower cost, represented by the parallel shift inwards of the cost line. In moving from point B to point C the farm changes the ratio of capital to labour. In

this case the new technology is capital saving and the technical change is said to be Hicks biased (non-neutral).

2.2.3. The Properties of Frontier Production Functions

Perhaps the simplest way to consider the production process of a farm is through the production frontier function (Beattie and Taylor, 1985). A farm produces output from a set of inputs. Any combination of inputs that results in output is a technologically feasible production plan. The set of all technically feasible plans is the production possibility set

$$S = \{(x, y) : x \text{ can produce } y\} \qquad 2\text{-}1$$

where S is assumed to model the transformation of inputs $x \in \Re_+^N$ into output $y \in \Re_+^M$. The set of all inputs that can produce output is called the input requirement set and is defined as

$$V(y) = \{x \; in \; \Re_+^n : (y, x) \;\; is \;\; in \;\; S\} \qquad 2\text{-}2$$

where x is a vector of inputs that can produce output. Now consider a single output frontier production function as given by

$$y = f(x) \qquad 2\text{-}3$$

where f is a single valued function such that for a unique combination of inputs there is a corresponding unique level of output, y is output and x is an n dimensional vector of inputs. Underlying the frontier production function given in equation 2-3 is the assumption that the frontier production function will give the maximum output for a given input vector. There are a number of properties which are assumed in the neo-classical theory of production.

1. *If* $x^* \geq x$ *then* $f(x^*) \geq f(x)$ Once there is free disposal of inputs, this implies that the addition of extra units of any input will not lead to a fall in output. This is also referred to as the monotonicity condition.
2. The input requirement set (*V(y)*) is a convex set, that is, $V(y) = \{x : f(x) \geq y\}$. This implies that if there are two input vectors x^1 and x^2 which belong to *V(y)* then any weighted average of x^1 and x^2 is also an element of input requirement set. This is equivalent to saying that the frontier production function is a quasi-concave function.
3. *V(y)* is an non empty set for all *y* greater than zero. This implies that it is always possible to produce any positive output.
4. *V(y)* is a closed set for all y greater than zero. This guarantees the existence of well defined constrained maxima and minima
5. For all non negative and finite *x*, *f(x)* is finite, non negative, real valued and twice continuously differentiable.

Consider again equation 2-3 The actual form of this frontier production function is not given until Section 2.2.4. It is useful to work with the general form and assume a single output and two input (x_j and x_k) case. A unit free measure of the change in output associated with a small change in a single input is given by the output elasticity with respect to the input. For x_j this is

$$E_j^O = \frac{\partial f(x)}{\partial x} \frac{x_j}{y} \qquad 2\text{-}4$$

where $\partial f(x)/\partial x_j$ is the marginal productivity of x_j. To estimate the degree to which a farmer can substitute one input for another while keeping output and any remaining inputs (say x_l) constant we take the total differential of equation 2-5, that is

$$dy = \sum_{j=1}^{n} f_j dx_j \qquad 2\text{-}5$$

Since output is held constant $dy=0$ and the input x_l is held constant implying $dl=0$ so equation 2-6 can be written as

$$\frac{dx_j}{dx_k} = -\frac{f_k}{f_j} \qquad 2\text{-}6$$

This ratio is called the marginal rate of technical substitution.

The elasticity of scale measures how output changes as a particular input bundle is multiplied by a scalar (λ) and is defined as

$$E^S = \frac{\partial \ln f(\lambda x)}{\partial \lambda} \qquad 2\text{-}7$$

E^s is a measure of how output changes along a ray from the origin in n space. This implies that simultaneous input variations do not change the ratio of x_j to x_k. The elasticity of scale is positive for all values of λ greater than or equal to 1, which implies that the frontier production function is strictly increasing in all its arguments. The elasticity of scale is useful as it provides a method of delineating frontier production functions based on the returns to scale. A frontier production function exhibits constant returns to scale if $E^s=1$ and at x, $f(\lambda x)=\lambda f(x)$ for $(\lambda \geq 1)$. A frontier production function exhibits increasing returns to scale if $E^s>1$ implying that at x, $f(\lambda x) \geq \lambda f(x)$ and decreasing returns to scale if $E^s<1$ implying that at x, $f(\lambda x) \leq \lambda f(x)$.

A frontier production function is homogeneous if the returns to scale do not change along a ray from the origin. More formally, a function $f(x)$ is homogeneous of degree t if $f(tx)=\lambda^t f(x)$ for all $t>0$. The homogeneous function

has the following property $y = \sum_j^n x_j f_j$ where, by Euler's theorem, $f_j = \partial f / \partial x_j$.

There are two special cases, when a frontier production function is homogeneous of degree zero, where $f(\lambda x)=f(x)$ and when a frontier production function is homogeneous of degree one, that is $f(\lambda x)= \lambda f(x)$. If a frontier production function is homogeneous of degree one then it exhibits constant returns to scale.

Transforming a frontier production function such as in equation 2-2 allows an n-dimensional analog of the frontier production function while still maintaining the marginal rate of technical substitution between inputs j and k at any given level of the n-dimensional vector of inputs. Equation 2-2 becomes

$$G(x) = h(f(x)) \qquad 2\text{-}8$$

where f is defined as in equation 2-1and h is a twice continuously differentiable, finite, non negative and non-decreasing function. Both f and h have the same marginal rate of substitution. A homothetic frontier production function is a transform of a monotonically increasing homogeneous frontier production function. Homothetic frontier production functions are characterised by isoquants that cut any one ray through the origin and do so with the same slope. The elasticity of substitution of a homothetic frontier production function is a function of output only, that is,

$$E^S = \frac{h(y)}{h'(y)y} \qquad 2\text{-}9$$

In empirical work, where there are n dimensional vectors of inputs, the estimation of the parameters of the frontier production function can be a difficult task due to a lack of sufficient degrees of freedom. If it was not possible to aggregate inputs to reduce the dimensionality of the input vector then many models could not be estimated. Indeed, although not always stated the assumption that inputs are separable underlies the classification of inputs into the three common categories of land, labour, and capital that are so commonly seen in applied work. Not all frontier production functions are separable, only functions that are twice continuously differentiable and quasi-concave are separable. Separability is based on how the marginal rate of technical substitution between two inputs responds to changes in another input. It is also assumed that an input is not separable from itself. For example, if there are three inputs, x_j, x_k and x_l then inputs x_j and x_k are separable from x_l in $f(x)$ if the marginal product of x_j with respect to x_k is equal to the marginal product of x_l with respect to x_k as in equation 2-9.

$$\frac{\partial \ln f_j}{\partial x_k} = \frac{\partial \ln f_l}{\partial x_k} \qquad 2\text{-}10$$

This implies that the slope of an isoquant in j, k space is not affected by what happens in l space. There are two forms of separability, weak separability and strong separability. Assume the frontier production function given in equation 2-2 is twice differentiable and strictly quasi-concave with n inputs denoted by $N=(1,2....,n)$ and is partitioned into r mutually exclusive and exhaustive subsets $(N_1,N_2,...,Nr)$, of a partition set called R. The frontier production function is said to be weakly separable in the partition R when the marginal rate of substitution between any two inputs x_j and x_k from any subset N_s, $s=1,2,....,r$, is independent of the

quantities outside N_s. The separability condition as defined first by Leontief (1947) is given as

$$\frac{\partial}{\partial x_k}\left(\frac{f_j}{f_L}\right)=0 \quad j,L\in N_s, \quad k\notin N_s \qquad 2\text{-}11$$

Weak separability with respect to partition R is necessary and sufficient for the frontier production function $f(x)$ to take the form $f(x^1,x^2,....x^r)$ where x^s is a function of elements of N_s only. A frontier production function is strongly separable if the marginal rate of substitution between any two inputs inside N_s and N_t does not depend on the quantities of inputs outside N_s and N_t, that is,

$$\frac{\partial}{\partial x_k}\left(\frac{f_j}{f_L}\right)=0 \quad for\ all\ j,k\in N_s, and\ k\notin N \qquad 2\text{-}12$$

Strong separability requires that it is necessary and sufficient for $f(x)$ to have the form $f(x^1,x^2,...,x^r)$ where x^s is a function of elements of N_s only. Separability is implicitly assumed in most empirical and theoretical formulations of frontier production functions since without these conditions the aggregation of inputs into a manageable size would not be possible (Nadiri, 1982). This point is particularly important in the analysis to follow in Chapters 3, 4 and 5 since without the assumption of separability the estimation of the production frontier function would be difficult due to degrees of freedom problems.

2.2.4. The Specification of the Translog Frontier Production Function

The true functional form for the production technology is never known. As a result an appropriate functional form must be defined for empirical work. The criteria for selection of a functional form should take account of both the empirical application and the theoretical considerations at hand. While it is desirable that theoretical properties of the production technology hold, it is not essential they hold in all empirical applications. In other words,

while it is theoretically important that the conditions of homogeneity, homotheticity and separability are maintained, it is also desirable for the frontier production function to be sufficiently flexible to accommodate various production structures, and as Coelli et al. (1998) point out, these two objectives may be in conflict. Imposing an inappropriate functional form in a continuous model increases the risk of biases occurring in the estimated parameters of the model.

Early applications of production theory used the log-linear Cobb-Douglas form since it is amenable to econometric estimation; however, it is restrictive in the properties it imposes on the production structure. Put simply the Cobb-Douglas is not a flexible functional form. Flexibility is based on approximation theory where the objective is to provide the first and second order partial derivatives of an unknown function at some point. Most often the Taylor series interpretation is given to the flexible forms such as the translog or Leontief. There are two definitions of flexibility commonly used in the literature. Diewert flexibility also known as local flexibility implies that a functional form represents a second order Taylor series expansion or a second-order differential approximation of an arbitrary function at a particular point. At this point there is no restriction placed on the first or second order derivatives. The main disadvantage of locally flexible forms is that they can lead to large and unknown restrictions at unknown points of expansion. (Fuss et al. 1978; Chambers, 1988). Global flexibility is not prone to this problem and is preferred in empirical work since it is possible to calculate the first and second order partial derivatives of an unknown function at an arbitrary point without imposing *a priori* restrictions on the structure of technology. However, the global approximation properties are usually not known and the notion of a

local approximation is relied upon for practical estimation purposes. A group of flexible functional forms has been suggested in the literature to redress this problem whereby local approximation is achieved through either a point approximation to a function or a second order Taylor series expansion. The translog frontier production function is one of the most frequently used flexible forms and is the form used in the subsequent chapters. Other flexible forms such as the Leontief and generalised quadratic have been suggested but are not explored here. Table 2-1 presents the algebraic form along with the relevant properties of the forms most commonly used, namely, the translog and the Cobb-Douglas frontier production functions (see Diewert (1971) for the Generalized Leontief, Denny (1974) for the Generalised Quadratic and de Janvry (1972) for the Generalised Power). Generally the translog is given by

$$ln\ y = \beta_0 + \sum_j^J \beta_j\ ln\ x_j + \frac{1}{2}\sum_{j=1}^{J}\sum_{k=1}^{K} \beta_{jk}\ ln\ x_j\ ln\ x_k + \varepsilon \qquad 2\text{-}13$$

where $ln\ y$ is the logarithm of the output; $ln\ x_j$ is the logarithm of the jth input; β are the parameters to be estimated and ε are the random disturbances. It should be noted that the Cobb-Douglas functional form is nested within the translog. The Cobb-Douglas is given by

$$ln\ y = \beta_0 + \sum_j^J \beta_j\ ln\ x_j + \varepsilon \qquad 2\text{-}14$$

It is possible to test the null hypothesis that the $\beta_{jk}=0$ for all j, that is, to test the Cobb-Douglas specification against the translog specification. The major properties of the translog and the Cobb-Douglas forms are given in Table 2-1.

Table 2-1:Properties of the Translog and Cobb-Douglas Frontier Production Functions

	Translog	Cobb Douglas
Homogenous	If $\sum_j \beta_j = 1, \sum_k \beta_{jk} = 0$	If $\sum_j \beta_j = 1$
Homothetic	If $\sum_j \beta_{jk} = 0$	Yes
Concave	If $\beta \geq 0, \beta_{jk} \geq 0$	If $\beta \geq 0,\ 0 \leq \beta \geq 1, \sum_j \beta_j < 1$
Monotonic	If $\beta_j + \sum_{j=1}^{J} \beta_{jk} \ln x_j > 0$	If $\beta_j > 0 \quad \forall j$
Separable	Yes	Yes

Each of the properties is discussed in detail below and formally tested in all three empirical chapters to follow. It is essential when estimating a translog frontier production function that the conditions of concavity and monotonicity hold. The translog function is a local approximation, which means that it does not necessarily satisfy the restrictions for frontier production functions globally. Therefore, it is necessary to examine whether or not output increases monotonically with all inputs and that the isoquants are convex. If at least one second-order parameter is different to zero ($\beta_{jk} \neq 0$), there exists a combination of inputs such that neither the convexity nor the monotonicity conditions are satisfied. Usually there are regions in input space where the conditions hold. These well-behaved regions may be large enough so that the translog function can provide a good representation of relevant production possibilities.

2.2.4.1.Monotonicity

For monotonicity the marginal products of inputs should be positive as in equation 2-15.

$$MP_{jit} = \frac{y}{x_{jit}}\left(\beta_j + \sum_{k=1}^{K} \beta_{jk} \ln x_{kit}\right) > 0 \qquad 2\text{-}15$$

The law of diminishing marginal productivity should also apply, that is, the marginal products should be positive and be decreasing in inputs, that is,

$$\left(\beta_j + \sum_{k=1}^{K} \beta_{jk} \ln x_{kit}\right)\left(\beta_j - 1 + \sum_{k=1}^{K} \beta_{jk} \ln x_{kit}\right) < 0 \qquad 2\text{-}16$$

Generally both restrictions should hold at the point of approximation, which is usually the mean. However, for completeness, both positive and diminishing marginal product should be evaluated for each data point in the sample.

2.2.4.2. Curvature

Checking curvature conditions, that is, convexity of the isoquants and concavity of the frontier production function, requires that the signs on the determinants of principal minors of the bordered Hessian matrix are calculated. The bordered Hessian matrix of the first and second-order partial derivatives of the frontier production function should be negative semi-definite at each data point. The first-order partial derivatives of the translog are given by equation 2-15 above and the second order partial derivatives are given by

$$\frac{\partial^2 y_{it}}{\partial x_{jit}^2} = \frac{y_{it}}{x^2_{jit}}\left(\beta_{jj} + S_{jit}\left(S_{jit} - 1\right)\right) \qquad 2\text{-}17$$

for $j=k$, and

$$\frac{\partial^2 y_{it}}{\partial x_{jit}\partial x_{kit}} = \frac{y_{it}}{x_{jit}x_{kit}}\left(\beta_{jk} + S_{jit}S_{kit}\right) \qquad 2\text{-}18$$

for $j \neq k$, where $S_{jit} = \left(\beta_j + \sum_{k=1}^{K} \beta_{jk} \ln x_{kit}\right)$. In other words the diagonal elements of the Hessian matrix should be non-positive. Furthermore, at the point of approximation the principal minors should alternate their sign

from positive to negative, that is, $(-1)^j \left|\overline{H}_j\right| > 0$. Even if the curvature condition does not hold for each data point there usually exists well-behaved regions that are large enough for the translog function to be a good representation of the underlying production process. Evidence from simulation experiments by Wales (1977) indicates that translog estimates of important elasticities are fairly good if the regularity conditions are violated only for a small number of points in the data.

2.3. THE ESTIMATION OF PRODUCTION FRONTIERS - CROSS SECTIONAL MODELS

This section is concerned with the theoretical framework and considers the econometric estimation of technical change and efficiency. The approach taken to measuring efficiency and technical change is discussed first. The deterministic frontier model is then examined with particular focus placed on the limitations of the approach. The stochastic frontier is discussed in considerable detail in Section 2.3.3 with emphasis placed on the alternative estimation techniques and the benefits of this approach over the earlier deterministic models.

2.3.1. The Approach Taken to Measuring Efficiency and Technical Change

Two broad approaches to identifying the relevant frontier function have been developed: econometric[3] and Data Envelopment Analysis[4] (DEA). DEA involves the construction of production frontiers using linear programming with no assumptions made regarding the functional form. As the data are fully exploited without the use of restrictive assumptions DEA can handle multiple input and multiple output situations when prices are not available (Hadley, 1997). More recently, variations of the basic DEA approach have

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[3] *Also called parametric techniques.*
[4] *Also called non-parametric methods or linear programming techniques.*

been used for the decomposition of productivity change into technical progress and efficiency change. The main drawback of DEA is that it is confined to the calculation of deterministic frontiers, that is, DEA attributes all deviations from the frontier to inefficiency. There is no account taken for random shocks and external environmental conditions such as bad weather. There is also considerable difficulty applying the standard specification tests such as those for normality, robustness and model misspecification. More recently, the divide between DEA and econometric techniques such as SFA has become less pronounced as attempts are made to combine the benefits of both approaches. The DEA approach is developed further in Chapter 5.

2.3.2. The Deterministic Frontier Model

Farrell (1957) is credited as the first researcher to measure efficiency empirically using the concept of a production frontier. The foundations for Farrell's (1957) work stem from the theoretical writings on efficiency by Koopmans (1951), Debreu (1951) and Shephard (1953). While Farrell did not use econometric techniques, his work and, in particular, his definition of efficiency has become the foundation for the econometric estimation of production frontiers. Further work by Aigner and Chu (1968) conceptualised the notion of a deterministic production frontier, while Timmer (1971) and Afriat (1972) proposed methods to estimate the deterministic frontier. It was not until Schmidt (1976) showed that the programming estimators of Aigner and Chu were consistent with maximum likelihood estimation with one-sided errors distributed as either exponential or half normal that the association between measures of technical efficiency and one sided error terms began (Kumbhakar and Lovell, 2000: 7).

The early deterministic frontier models were defined for cross-sectional data. Consider a production frontier model with N inputs that are used to produce a single output y, as given by

$$y_i = f(x_i;\beta)TE_i \qquad 2\text{-}19$$

y_i is the output of the *ith* farm, x_i is a vector of non stochastic inputs, β is a vector of unknown parameters and TE_i is technical efficiency. The technical efficiency of the *ith* farm can be obtained by rewriting equation 2-19 as

$$TE_i = \frac{y_i}{f(x_i;\beta)} \qquad 2\text{-}20$$

Technical efficiency is defined as the ratio of the observed output to the maximum feasible output. If the value of $TE_i = 1$ then the observed output is equal to the maximum feasible output. For $TE_i < 1$ then there is a gap between observed output and the maximum feasible output. In other words the farm is technically inefficient. The production frontier is deterministic since the difference between the observed output and the feasible output is attributed to inefficiency. The impact of external shocks, such as adverse weather conditions, are not accounted for in the specification of equation 2-19. The fundamental requirement for the estimation of deterministic frontiers is that no observed output level can be greater than the output level predicted by the estimated best practice frontier (Førsund & Jansen, 1977). To ensure that this requirement is satisfied first substitute $exp(-u_i)$ for TE_i in equation 2-20 to give

$$y_i = f(x_i;\beta)\exp(-u) \qquad 2\text{-}21$$

By assuming $u_i \geq 0$ ensures that the observed output level cannot be greater than the maximum feasible output, that is $y_i \leq f(x_i;\beta)$ and so technical efficiency must be less than or equal to one.

Assuming a suitable functional form for $f(x_i;\beta)$ such as a log linear Cobb-Douglas or translog form, then the model can be easily estimated. Using the log linear Cobb-Douglas form, equation 2-21 be written as a linear regression model with a non-positive error term.

$$\ln y_i = \beta_0 + \sum_n \beta_n \ln x_{ni} - u_i \qquad 2\text{-}22$$

The error term is usually assumed to be independently and identically distributed and to follow a one-sided distribution. (Aigner et al. 1977 ; Young, 1994). It is possible to obtain a farm level measure of technical efficiency using the estimates of the β parameters from the production frontier and the error term. So long as the functional form is log linear, the technical efficiency of the *ith* farm can be predicted by obtaining the ratio of the observed frontier production function values to the corresponding estimated frontier values, that is,

$$TE_i = \frac{y_i}{y_i^*} \qquad 2\text{-}23$$

where the frontier output of the *ith* farm is y_i^*, and the observed output is given by y_i. Replacing y and y* in equation 2-23 gives

$$TE_i = \frac{\exp\left(f\left(x_i;\beta\right) - u_i\right)}{\exp\left(f\left(x_i^*;\beta^*\right)\right)} = \exp\left(-u_i\right) \qquad 2\text{-}24$$

Since the non-positive error term u_i in equation implies that the frontier is bounded above and below by the deterministic quantity $f(x_i;\beta)$, technical efficiency has to take a value between zero and one. The estimation of the deterministic production frontier can be undertaken using a variety of techniques including ordinary least squares (OLS), corrected ordinary least squares (COLS), modified ordinary least squares (MOLS) and maximum likelihood estimation (MLE).

2.3.2.1. Corrected Ordinary Least Squares

The use of corrected ordinary least squares to estimate the deterministic frontier was first proposed by Winsten (1957) in his discussion of Farrell's (1957) seminal efficiency paper and was developed further by Gabrielsen (1975) and Greene (1980). Equation 2-22 is estimated in a two stage process. First ordinary least squares is used to obtain consistent and unbiased estimates of the slope parameters and a consistent but biased estimate of the intercept parameter. The second step involves a correction of the intercept term for bias in the estimated OLS intercept by shifting it upwards until all corrected residuals are non-positive and the largest residual is zero (Lovell, 1993). The COLS intercept is estimated by

$$\hat{\beta}_0^* = \hat{\beta}_0 + \max(\hat{u}_i) \qquad 2\text{-}25$$

where $\hat{u}_i^*$ is the OLS residual so the COLS residuals are given by

$$-\hat{u}_i^* = \hat{u}_i - \max(\hat{u}_i) \qquad 2\text{-}26$$

The corrected residuals are then used to calculate technical efficiency for each farm as $TE_i = \exp(-\hat{u}_i^*)$ such that the efficiency estimates fall in the range $0 < TE_i \leq 1$. COLS requires no assumptions regarding the functional form of the residuals and it generates an estimated frontier production function which lies on or above the data (Kumbhakar and Lovell, 2000). The main caveat of this approach is that the COLS estimated frontier production function is parallel to the OLS frontier (as the correction is made through the intercept). This implies that the structure of the best practice technology is not allowed to differ from that of the production technology centred at the middle. In other words the structure of the

efficient frontier technology is the same for efficient producers as for less efficient producers.

2.3.2.2. Modified Ordinary Least Squares

MOLS follows the same logic as the COLS above. The major difference is that the error term is assumed to follow an explicit one-sided distribution (such as half normal or exponential) and the OLS intercept is modified by the mean of the assumed distribution. Most common is that u_i is half normal. The technology parameters of equation 2-22 are estimated by OLS and the OLS intercept is modified as

$$\hat{\beta}_0^{**} = \hat{\beta}_0 + E(\hat{u}_i) \qquad 2\text{-}27$$

and the error term is defined by

$$-\hat{u}_i^{**} = \hat{u}_i - E(\hat{u}_i) \qquad 2\text{-}28$$

where $E(\hat{u}_i)$ is the mean of the one sided distribution obtained from the moments of the OLS residual. Technical efficiency for the *ith* farm is defined by $TE_i = \exp(-\hat{u}_i^{**})$.

The MOLS frontier faces the same difficulty as the COLS frontier in so far as it does not necessarily bound the data from above as closely as possible since it too is parallel to the OLS frontier. Perhaps a more serious consideration when using the MOLS procedure is that the correction does not guarantee that the frontier will shift far enough to bound a very large OLS residual. If this is the case then it is possible that $[\hat{u}_i - E(\hat{u}_i)] > 0$ which implies that technical efficiency can be greater than one.

2.3.2.3. Maximum Likelihood Estimation

Schmidt (1976) established a link between the linear programming approaches used by Aigner and Chu (1986) and statistical estimation

techniques by imposing a distributional assumption on the u_i. If $u_i \geq 0$ follows an exponential distribution or a half normal distribution then the Aigner and Chu (1986) linear programming estimates are maximum likelihood estimates of the deterministic frontier production function. Greene (1980) suggested the gamma distribution as superior to either the half normal or exponential since it satisfies all the regularity conditions for obtaining asymptotic properties of the ML estimators. The main advantage of MLE is that it allows the structure of the technology to change as between the production frontier and the 'average' production function. However, as with the OLS estimation techniques the deterministic frontier makes no accommodation for noise and attributes all deviations from the frontier production function to technical inefficiency (Lovell, 1993).

2.3.2.4. Limitations of Deterministic Frontier Approaches

The major fundamental and practical problem associated with the estimation of deterministic frontiers is that 'any measurement error, and any other source of stochastic variation in the dependent variable, must be imbedded in the one-sided disturbance. As such, in any sample, a single errant observation can have profound effects on the estimates and this outlier problem is not alleviated by resorting to large-sample results' (Greene, 1993:75). Empirically, Ekanayake & Jayasuriya (1987) demonstrated the pitfalls associated with using technical efficiency measures estimated from deterministic frontiers and they conclude "*they (deterministic frontiers) generally tend to over-estimate the average level of technical inefficiency and the extent of this bias is unknown*" (Ekanayake & Jayasuriya, 1987: 121).

Although, estimation of the frontier production function and the calculation of technical efficiency was popular in the 1970s, the results were not ideal since it was not possible to decompose the residuals into separate estimates of statistical noise and technical inefficiency (Lovell, 1993). An indirect approach to modelling the error term to allow decomposition into technical efficiency and statistical noise was provided by Aigner, Amemiya and Poirier (1976). They suggested a model in which the errors were allowed to be negative and positive but which used weights. The error term is given as

$$u_i = \begin{cases} u_i^* / \sqrt{(1-\theta)}, & \text{if } u_i^* > 0, \quad i = 1,\ldots\ldots\ldots,N. \\ u_i^* / \sqrt{\theta}, & \text{if } u_i^* \leq 0, \end{cases} \qquad 2\text{-}29$$

where u_i is the error term and the parameter θ is taken as a measure of the relative variability of two error sources. The first is a one sided error source due to the difference in the ability of farms to utilise best practice technology, and the second is a symmetric error due to measurement error in y_i. When $\theta = 0.5$ this gives rise to the frontier production function proposed by Aigner et al. (1977). In the deterministic frontier model the weights are assumed to be zero and one and so u_i^* has either a positive or negative truncated normal distribution respectively. Kumbhakar and Lovell (2000) point out that this model was limited since the only weights known were zero and one and the model could not be estimated with other weights. However, the approach was an improvement on the purely deterministic frontier approaches. The main advance in the theory came through the development of the stochastic frontier approach.

2.3.3. The Stochastic Frontier Approach

The stochastic frontier production function 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 is determined by the structure of the production technology - the deterministic production frontier - and by external events, favourable and unfavourable, beyond the control of the farmer (Lovell, 1993:20). Prior to the estimation of the stochastic frontier, it is necessary to make assumptions about the behaviour of the farmer and about the structure of the technology. The stochastic frontier approach will produce biased and inconsistent estimates of the parameters if profit maximisation is assumed as this implies that the input levels are not independent of the error term (Coelli, 1995b). This problem is overcome if it is assumed that the objective of the farm operator is to maximise profit and inputs are treated as exogenous, that is, the input choice decision is made prior to the output decision. In this case maximising profits with given input and output prices is equivalent to maximising output and hence the classical definition of the frontier production function is consistent with the profit maximisation hypothesis (Kumbhakar and Hjalmarsson, 1993). A second method is to assume that the farm is maximising expected rather than actual profits (Coelli, 1995b). Alternatively dual forms of the technology can be used.

The stochastic production frontier approach was simultaneously presented by Aigner et al. (1977) and Meeusen and van den Broeck (1977). This approach allowed random shocks to be taken out of the error term which in deterministic models is used to calculate technical efficiency. Unlike the deterministic frontier defined in equation 2-20 the stochastic production frontier has two components to the error term

$$\varepsilon_i = v_i - u_i \qquad 2\text{-}30$$

so the stochastic frontier can be written as

$$y_i = f(x_i;\beta) + \upsilon_i - u_i \qquad 2\text{-}31$$

where y_i is a scalar output, x is a vector of inputs and β is the vector of parameters to be estimated, υ_i represents statistical noise and is assumed to be independently and identically distributed with a zero mean and variance σ^2_υ. The distributional form of u_i is discussed below but suffice to say at this stage that it represents the factors under the control of the farmer, that is, the inefficiency effects. u_i are assumed to be non-negative and to be distributed independently of υ_i. The error term ε_i is asymmetric since $u_i \geq 0$. Both υ_i and u_i are distributed independently of the regressors. Farmers will operate on their frontier if $u_i=0$ or beneath the frontier if $u_i>0$. If it is assumed that the form of $f(x_i;\beta)$ is a log linear Cobb-Douglas production frontier then equation 2-31 can be written as

$$\ln y_i = \beta_0 + \sum_n \beta_n \ln x_{ni} + \upsilon_i - u_i \qquad 2\text{-}32$$

Using OLS to estimate equation 2-32 produces consistent estimates of the β parameters with the exception the intercept term β_0, and as a result it is not possible to obtain farm level estimates of technical efficiency.

Since u_i is not directly observable then the $E(u_i)$ given ε_i can be calculated once an appropriate distribution for the u_i is employed. Assuming that $u_i \sim iid\ \mathrm{N}^+(0,\sigma_u^2)$, that is, distributed as a half normal (N^+) distribution then the mean or the mode of the conditional distribution can be used to give a point estimate of u_i. Work by Stevenson (1980), Pitt and Lee (1981) and Jondrow et al. (1982) produced log likelihood functions to estimate u_i and showed that when u_i is distributed as the half normal case then the conditional distribution (f) of u_i given ε_i is

$$f(u \mid \varepsilon) = \frac{f(u,\varepsilon)}{f(\varepsilon)} = \frac{1}{\sqrt{2\Pi\sigma*}} \exp\left\{ -\frac{(u-\mu*)^2}{2\sigma_*^2} \right\} \Big/ 1 - \phi\left(-\frac{\mu*}{\sigma*} \right) \qquad 2\text{-}33$$

where

$$\mu* = -\varepsilon\sigma_u^2/\sigma^2 \qquad and \qquad \sigma_*^2 = \sigma_u^2\sigma_v^2/\sigma^2$$

Either the mode or the mean of the conditional distribution can be used to give a point estimate for u_i. The mean is normally used in empirical applications and the point estimates are given by

$$\begin{aligned} E(u|\varepsilon) &= \mu*_i + \sigma* \left[\frac{\phi(\mu*_i/\sigma*)}{1-\phi(-\mu*_i/\sigma*)} \right] \\ &= \sigma^* \left[\frac{\phi(\varepsilon\lambda/\sigma)}{1-\Phi(\varepsilon\lambda/\sigma)} \right] - \left(\frac{\varepsilon\lambda}{\sigma} \right) \end{aligned} \qquad 2\text{-}34$$

where $\Phi(.)$ and $\phi(.)$ are the cumulative distribution and standard normal density function respectively. It is also possible to use the mode to estimate a point estimate for u_i as in

$$M(u_i/\varepsilon_i) = \begin{cases} -\varepsilon\left(\frac{\sigma_u^2}{2} \right) & \text{if } \varepsilon_i \le 0, \\ 0 & otherwise \end{cases} \qquad 2\text{-}35$$

Technical efficiency can be obtained as

$$TE_i = \exp(-\hat{\mu}_i) \qquad 2\text{-}36$$

where $\hat{\mu}_i$ are the point estimates of $E(u_i \mid \varepsilon_i)$ or $M(u_i \mid \varepsilon_i)$. The Battese and Coelli (1988) approach draws on the early work of Jondrow et al. (1982), however an alternative point estimate for u_i is offered

$$E[\exp(-u_i \mid \varepsilon_i)] = \frac{1-\Phi(\sigma* - \mu*_{ii}/\sigma_*)}{1-\Phi(-\mu*_i/\sigma_*)} \exp(\mu*_i + \sigma_*/2) \qquad 2\text{-}37$$

where $\Phi(.)$ is the density function of a standard normal random variable and all other terms are defined as above (Coelli et al. 1998). Kumbhakar and Lovell (2000) point out the technical efficiency estimates obtained from the Battese and Coelli (1988) approach and the Jondrow et al. (1982)

approach can be different. However, the former approach is more widely accepted.

2.3.3.1. Maximum Likelihood Estimation

The parameters of the stochastic frontier production function can also be obtained by maximum likelihood estimation involving a three step procedure. The first stage involves the OLS estimation of β and σ_s^2 where s denotes OLS. All estimators are unbiased except the intercept term and σ_s^2. The second stage involves the evaluation of the likelihood function for a number of values of γ where $\gamma\varepsilon_i = \mu *_i$ in the range 0 to 1 and the adjustment of the OLS estimates for σ_s^2 and β_0 for use in the final stage. The largest log-likelihood values from the second stage are used as starting values in a Davidon-Fletcher-Powell (DFP) iterative maximisation routine to obtain the maximum likelihood estimates (Coelli et al. 1998).

Maximum likelihood estimation has been shown to be more asymptotically efficient than corrected ordinary least square methods (Greene, 1993). Coelli (1995) used Monte Carlo experiments to test the small sample properties of stochastic frontier models and showed that the maximum likelihood estimator is better than corrected least squares when the inefficiency effects in the model are large (i.e. as $\gamma^* \rightarrow 1$) and the relative performance of maximum likelihood estimates improve as the sample size increases. The MLE estimators of β_0, σ^2 and γ are positively biased when γ is near zero and negatively biased otherwise. The bias in γ declines as γ tends to one. However, as sample size increases, the bias variance and mean standard errors decline. Although maximum likelihood estimation techniques have been used extensively to estimate stochastic frontier models there has been little work done on establishing the asymptotic

properties of these models. However, work by Polachek and Yoon (1995) has investigated the consistency of maximum likelihood estimators for panel models in which the error term is normally distributed. In order to decompose the error term ε_i and obtain separate estimates of technical efficiency and statistical noise for each farm in the sample, distributional assumptions on the two error terms must be made and ML estimators used. The υ_i are almost always assumed to be $\upsilon_i \sim iid\ \mathrm{N}(0,\sigma_\upsilon^2)$ and the assumption that υ_i and u_i are distributed independently of each other and the regressors is also standard. There is no *a priori* rationale for the choice of the distributional form for the u_i and this has become one of the criticisms of the stochastic frontier approach. The most common distribution assumptions for the u_i suggested in the literature are

Table 2-2 :Distributional Assumptions for the Technical Efficiency Effect

Half Normal	$u_i \sim iid\ \mathrm{N}^+(0,\sigma_u^2)$
Exponential	$u_i \sim iid\ Exponential$
Truncated Normal	$u_i \sim iid\ \mathrm{N}^+(\mu,\sigma_u^2)$
Gamma Normal	$u_i \sim iid$ Gamma

The exponential and the half-normal distributions forms for u_i are criticised since they have a mode at zero which implies that there is the highest probability that the inefficiency effects are in the neighbourhood of zero (Coelli, et al. 1998). The result of this is that empirically a large number of farms will appear to be highly efficient when in practice they are not. This problem has been overcome by the use of the truncated normal (Stevenson, 1980) and the gamma distribution proposed by Greene (1990). The most common form used is the truncated normal distribution which is a generalisation of the half-normal distribution. The truncated normal is

preferred over the gamma distribution primarily due to its computational simplicity (Coelli et al. 1998). Kumbhakar and Lovell (2000) argue that there is some empirical evidence that the sample mean technical efficiencies are sensitive to the choice of distribution imposed on u_i, however, Greene (1990) has shown that the ranking of efficiencies and the top and bottom deciles of efficiencies are not sensitive to distributional assumptions.

This section has covered the history of the stochastic frontier approach to the estimation of technical efficiency. The move away from the deterministic frontier stemmed from both the need to account for statistical noise in a robust manner and the availability of panel data and software capable of producing results in a time efficient way. The next section introduces the panel data models and explains how the availability of panel data enabled empirical researchers to develop more statistically acceptable results. The specification of the frontier production function is broadly the same, albeit with a time dimension. The major advantages of panel models are the ability to allow technical efficiency to vary over time and technical change to be estimated.

2.4. THE ESTIMATION OF PRODUCTION FRONTIERS - PANEL DATA MODELS

The early applications of the deterministic frontier model discussed above and the stochastic frontier models discussed below were undertaken using cross section data. In recent times the availability of panel data has lead to considerable statistical and modelling advances in the estimation of frontier production functions. Intuitively the cross sectional approach is limited as it provides only a snap shot of a process which is evolving over time and hence this partial approach can be misleading when evaluating

the performance of farms. By following individual farms over time as they alter their output mix or as they enter periods of growth or decline it is possible to make inferences about the dynamics of change, something that is not possible with cross sectional data alone.

2.4.1. The Advantages of Panel Models over Cross Sectional Models

The econometric efficiency of estimates are improved when panel data are used due to the large number of data observations which increase the degrees of freedoms and reduce collinearity among explanatory variables (Baltagi, 1995). Furthermore, panel data uses information on both the intertemporal dynamic and the individual characteristics of the farm and so it is possible to reduce the effects of omitted variables (Hsiao, 1996). Dawson (1985) notes that single period estimates (either deterministic or stochastic) may be inappropriate since resource allocation decisions are frequently long-term investment ones which are based on projections and expectations over more than one production period. Cross sectional data have therefore limited value.

There are three specific problems in the estimation of deterministic and stochastic frontier models that can be overcome with the use of panel data. The first problem is that the technical efficiency of a particular farm (observation) cannot be estimated consistently as the variance of the distribution of technical inefficiency conditional on the whole error term (which can be estimated consistently) does not vanish as the sample size gets larger. With panel data this problem is overcome since the addition of observations on a single farm gives more information than the addition of another farm to the sample. The second problem is that ML estimation of stochastic frontier models using cross sectional data requires normality

assumptions on the components of the error term. The third problem is that assuming inefficiency is independent of the regressors may be incorrect. With panel data these strong normality assumptions are not required. With panel data it is possible to estimate the parameters without the uncorrelated assumption (Schmidt and Sickles, 1984).

While panel data improves the quality of the deterministic frontier estimates it cannot solve the fundamental problem of the deterministic nature of the frontier production function. If random noise is not accounted for, the technical efficiency estimates obtained are simply not accurate. Since deterministic frontiers are rarely estimated now the stochastic frontier approach has become the method of choice for empirical researchers, and it is the method of choice in the three empirical chapters to follow.

2.4.2. Time Invariant Technical Efficiency

The cross sectional stochastic frontier models outlined above can be modified where panel data are available. The general form of the production frontier given in equation 2-31 becomes

$$y_{it} = f(x_{it;}\beta) + \upsilon_{it} - u_i \qquad 2\text{-}38$$

if the efficiency effects are assumed to be time invariant, where y_{it} is output, x_{it} is a vector of inputs, υ_{it} is random noise, u_i is the efficiency effects and t is time. If the efficiency effects are assumed to be time variant then u_i vary over farms and time as in equation 2-39

$$y_{it} = f(x_{it;}\beta) + \upsilon_{it} - u_{it} \qquad 2\text{-}39$$

Estimation of the stochastic production frontier specified in equations 2-38 or 2-39 can be undertaken using a fixed effects or a random effects

approach estimated using either generalised least squares or maximum likelihood estimation. Time invariant models are considered first.

2.4.2.1.Fixed Effects

Fixed effects were used by Schmidt and Sickles (1984) to obtain producer specific estimates of technical efficiency. Consider a Cobb-Douglas frontier production function of the form

$$\ln y_{it} = \beta_0 + \sum_n \beta_{nt} \ln x_{nit} + \upsilon_{it} - u_i \qquad 2\text{-}40$$

The assumption underlying the fixed effects approach is that the u_i's are treated as firm-specific constants. The farm level intercepts can be obtained by introducing (*I-1*) farm specific intercepts as in equation 2-41

$$\ln y_{it} = \beta_0 + \sum_i \gamma_i D_i + \sum_n \beta \ln x_{nit} + \upsilon_{it} - u_i \qquad 2\text{-}41$$

where D_i are dummy variables to account for farm specific effects, β are the parameters to be estimated and υ_{it} is random noise. By assuming that the dummy variables are proxies for unobservable management characteristics of the farm they can be interpreted as a measure of technical efficiency, thus linking the fixed effects approach to the production frontier methodology (Andreakos et al. 1997). Estimation of the model as given in equation 2-41 leads to the generation of a dummy variable for each of the farms in the sample which can be cumbersome if this number is large. If the data are transformed and modelled in deviations from the individual farm means, this transformation removes the need to estimate the individual dummy variables for each farm but does not change the estimator for β. However, this individual farm mean transformation implies that it is not possible to include any time invariant explanatory variables in the model and so the estimator may not be fully efficient (Hallam and Machado, 1995). The result of the mean differencing is a model of the form

$$\ln y_{it} = \beta_{0i} + \sum_{n} \beta \ln x_{nit} + \upsilon_{it} \qquad 2\text{-}42$$

where $\beta_{0i} = (\beta_0 - u_i)$ are the farm specific intercepts and υ_{it} is random noise. Technical efficiency for each farm is calculated as

$$TE_i = \frac{\exp(u_i)}{\max[\exp(u_i)]} \qquad 2\text{-}43$$

where $u_i = (\beta_0 - \beta_{0i})$, max is the highest predicted value for the *ith* farm. This measure is transformed into a technical efficiency index with values ranging from 0 to 1 where 1 is the maximum level of technical efficiency obtained by the most efficient farm. This approach is very similar to the corrected least squares method used for the cross sectional models. The Least Square Dummy Variables (LSDV) estimates of the β_i parameters are consistent as the sample size (I) goes to infinity or time goes to infinity while the β_{0i} intercepts are consistent only if both size and time go to infinity. Although the fixed effects approach assumes that the explanatory variables are strictly exogenous it allows for correlation between the u_i (i.e. technical efficiency) and the explanatory variables. Furthermore, it does not require that the u_{it}'s are normally distributed. The major criticism of the fixed effects approach comes from the fact that the individual specific effects are intertwined with the technical efficiency of the production unit and therefore *"since individual specific effects also capture the effects of inputs that are invariant over time (but vary across production units) and such effects are not inefficiency – it is inappropriate to label the individual-specific effects as technical inefficiency. Policy prescriptions based on such measures may be misleading unless one can disentangle the individual specific effects from inefficiency"* (Kumbhakar and Hjalmarsson, 1993: 256).

2.4.2.2. Random Effects

The key difference between the fixed effects approach and the random effect approaches is the assumption concerning the relationship between the technical efficiency effect and the explanatory variables in the model. The u_i's are non negative, assumed to be uncorrelated with the regressors and with υ_{it} and are randomly distributed with a constant mean and variance but no distributional assumptions are enforced. Random effect models can handle time invariant inputs which overcome the problem of omitted variable bias that can occur with fixed effects. The random effects model is defined by rewriting equation 2-42 as

$$\ln y_{it} = [\beta_0 - E(u_i)] + \ln \sum_n \beta_n n x_{nit} + \upsilon_{it} - [u_i - E(u_i)] \qquad 2\text{-}44$$
$$= \beta_0^* + \sum_n \beta_n n x_{nit} + \upsilon_{it} - u_i^*$$

This model can be estimated using generalised least squares methods and $\hat{u}_i^*$ can be estimated from the residuals using

$$\hat{u}_i^* = \frac{1}{T} \sum_t \left(\ln y_{it} - \hat{\beta}_0^* - \sum_n \hat{\beta}_n \ln x_{nit} \right) \qquad 2\text{-}45$$

where β_0^* and the β_n's have been estimated using GLS. Kumbhakar and Lovell (2000) suggest that the u_i's obtained by normalising $\hat{u}_i^*$ can be used to give technical efficiency as in equation 2-46

$$TE_i = \frac{\exp(u_i)}{\max[\exp(u_i)]} \qquad 2\text{-}46$$

Greene (1993) argues that estimation of equation 2-44 does not produce estimates of technical efficiency (u_i) and that to obtain estimates $E(u_i)$ must be calculated. To do this a distributional assumption must be imposed on u_i. GLS ignores any additional information that might be available about the distribution of the efficiency component in the disturbance term. This leads to a trade off between the gain in efficiency by estimating the frontier

using MLE instead of GLS and the risk of model misspecification resulting from the imposition of an incorrect distributional assumption on the efficiency effects. However, the maximum likelihood estimator is asymptotically more efficient that the GLS approach. Coelli (1995a) investigated the small sample properties of the half-normal frontier model using Monte Carlo experiments and found that the ML estimator to be significantly better than GLS estimators. In practice MLE is favoured over GLS especially since the advent of automated software which has reduced the computational problems of ML frontier estimation. The MLE approach is broadly similar to the ML approach outlined in Section 2.3.2.3 with the only key difference being the random noise component is allowed to vary over time.

2.4.3. Time Varying Technical Efficiency

The above models can be adapted if it is desirable to allow technical efficiency to vary over time. Models can be divided into two main groups, those which make assumptions about the distribution of the technical efficiency effects and those which do not. Cornwell, Schmidt and Sickles (1990) proposed a time variant model where no assumptions are made about the distribution of the technical efficiency effects. Their approach allowed efficiency to vary across time and farms. Inefficiency is defined as

$$u_{it} = \eta_{1i} + \eta_{1i}t + \eta_{1i}t^2 \qquad 2\text{-}47$$

where t is time and η are the farm specific parameters to be estimated. Although this approach does allow the inefficiency to vary over time and over farms it is not possible to decompose technical change from improvements in efficiency over time. This occurs as time appears in both

the frontier production function and the efficiency function and hence it is not possible for all the parameters to be defined (Karagainnis et al. 1999).

Kumbhakar (1990) and Battese and Coelli (1992) developed models with distributional assumptions made about the technical efficiency effects. Kumbhakar (1990) proposed

$$u_{it} = \left[1 + \exp\left(\eta_1 t + \eta_2 t^2\right)\right]^{-1} u_i \qquad i = 1,2,....,N; t = 1,2,....,T \qquad 2\text{-}48$$

where the u_{it} 's are assumed to have a half normal distribution. Battese and Coelli (1988) suggested that

$$u_{it} = \{\exp[-\eta(t-T)]\}u_i \qquad i = 1,2,....,N; t = 1,2,....,T \qquad 2\text{-}49$$

where the u_i's have a generalised truncated normal distribution and η is an unknown parameter to be estimated. It should be noted that since the technical efficiency effects of individual farms at any time period are equal to the same exponential function of the corresponding farm specific efficiency effects in the preceding period, the ordering of farms according to the size of the efficiency effects is the same in all time periods. Implicitly, this implies that the model does not accommodate the situation where a farm may be relatively efficient at the start of the time period and relatively more efficient in later periods (Coelli et al. 1998). Other limitations of the Kumbhakar (1990) and Battese and Coelli (1992) and other similar models such as those proposed by Schmidt and Lee (1993) is that if there is any persistent time-specific inefficiency this could be masked by technical change (Kumbhakar and Hesmati,1995; Karagainnis et al.1999).

Kumbhakar and Hesmati (1995) proposed that

$$u_{it} = U_i + \tau_{it} \qquad 2\text{-}50$$

where τ is the element representing both time and the farm unit. Battese and Coelli (1992, 1995) proposed a model where the stochastic frontier production function is defined as

$$\ln y_{it} = \ln(x_{it} : \beta) + \upsilon_{it} - u_{it} \qquad 2\text{-}51$$

and the efficiency equation is given as

$$u_{it} = g(z_{it}; \gamma) + \varepsilon_{it} \qquad 2\text{-}52$$

where ε_{it} is defined by the truncation of the normal distribution with zero mean and variance such that the point of truncation is $-z_{it}\gamma$. The distributional assumption on ε_{it} is consistent with the distributional assumption on u_{it} that $u_{it} \sim N^{+}(\gamma' z, \sigma_{\mu}^{2})$. The model does not require that the inefficiency effects are identically distributed but they are assumed to be independently distributed such that u_{it} is obtained by truncation at zero of the normal distribution with mean $z_{it}\gamma$ and variance σ_{υ}^{2}. Technical efficiency for the *ith* farmer in the *tth* period is defined as

$$TE_{it} = \exp(-u_{it}) = (-z_{it}\gamma - \varepsilon_{it}) \qquad 2\text{-}53$$

By defining technical inefficiency in this manner Battese and Coelli (1995) were able to model both technical change and time varying efficiency and to overcome the limitation of earlier models which assumed that the temporal pattern of efficiency was the same for all farms (Karagainnis et al. 1999). This specification has been advanced to include interaction terms between input quantities and farm specific factors allowing non neutral stochastic frontiers to be estimated.[5] These models are developed in Chapter 3. If the technical efficiency estimates are used in a second stage regression then this implies that the efficiency effects which are assumed to be

[5] *See Huang and Lui (1994) and Battese and Broca (1998).*

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 period *t*, the technical inefficiency effects (u_{it}) are obtained by the truncation at zero of the normal distribution with a mean $z_{it}\delta$ and a variance σ^2 as in equation

$$u_{it} = \delta_0 + z_{it}\delta_{it} \qquad 2\text{-}54$$

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).[6] By including a time trend in equation 2-54 it is possible to capture the linear change in technical inefficiency over time (Karagiannis et al. 1999; Battese and Coelli, 1995). If all the elements of δ are equal to zero then the model is the half normal distribution specified by Aigner et al. (1997).

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

Finally, it is prudent to ask whether the method of estimation makes a difference to either the average efficiency or the ranking of farms by efficiency score. Gong and Sickles (1989) used a series of Monte Carlo experiments to examine the similarity of rank correlation for technical efficiency obtained by the three panel methods outlined above and found that all gave similar results; however, as the complexity of the production technology increased, the performance of all approaches decreased. Ahmad and Bravo-Ureta (1996) carried out a comparison of methods using data on dairy farms and also found that the correlation was similar in all approaches.

2.4.4. Single Stage Approaches

If the measures of technical efficiency are to be used in a second stage model explaining the level of technical efficiency then the specification of the error term and the efficiency effects detailed above is not adequate. The two stage approach, though widely used, implies that the inefficiency effects which are assumed to be independently and identically distributed in the estimation of the stochastic frontier are a function of the farm specific effects in the second stage, thus violating the assumption that the inefficiency effects are identically distributed. Battese and Coelli (1995) addressed this issue with a single stage model designed to explain the reasons for differences in technical efficiency. Unlike the Battese and Coelli (1992) approach where the efficiency effects are the product of an exponential function of time and non negative firm specific random variables, the technical efficiency effects are specified in the later model, to be a linear function of a vector of farm specific variables and time, together

with an additive random error. This is assumed to be independent over time and farms in which the efficiency equation is given as

$$u_{it} = g(z_{it};\gamma) + \varepsilon_{it} \qquad 2\text{-}55$$

where ε_{it} is defined by the truncation of the normal distribution with zero mean and variance such that the point of truncation is $-\gamma' z_{it}$. The distributional assumption on ε_{it} is consistent with the distributional assumption on u_{it} that $u_{it} \sim N^{+}(\gamma' Z, \sigma_{\mu}^{2})$. The model does not require that the inefficiency effects are identically distributed but they are assumed to be independently distributed such that u_{it} is obtained by truncation at zero of the normal distribution with mean $z_{it}\gamma$ and variance σ_{v}^{2}. By including a time trend in equation 2-55 it is possible to capture the linear change in technical inefficiency over time (Karagiannis et al. 1999; Battese and Coelli, 1995). Technical efficiency for the *ith* farmer in the *tth* period is defined as

$$TE_{it} = \exp(-u_{it}) = (-z_{it}\gamma - \varepsilon_{it}) \qquad 2\text{-}57$$

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 a mean $z_{it}\gamma$ and a variance σ^2. By defining technical inefficiency in this manner, Battese and Coelli (1995) were able to model both technical change and time varying efficiency and to overcome the limitation of earlier models which assumed that the temporal pattern of efficiency was the same for all farms (Karagainnis et al. 1999). This model is developed further in Chapter 4. In this approach, the technical inefficiency effects are specified in the stochastic frontier model and assumed to be independently but *not identically* distributed non-negative random variables.

2.4.5. Technical Change

The rate of technical change is defined as the percentage change in output due to a unit change in time, that is,

$$TC_{it} = \partial y_{it} / \partial t = \varsigma_t + \varsigma_{tt} t + \sum_j^J \xi_{jt} x_{jit} \qquad 2\text{-}57$$

Neutral technical change is given by the first two terms of 2-57 and non neutral technical change is given by the third term (Hesmati, 1996; Niahimizu and Page, 1982). If ζ_t is positive/negative then there is neutral 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 if the sign on ξ_{jt} is greater than zero and input-saving if ξ_{jt} is less than zero.

Caution must be taken with the interpretation of the coefficients on the variables used to capture technical change in the case of time invariant efficiency models and models in which both time varying efficiency and technical change are modelled via a simple time trend (Karagiannis et al. 1999; Lovell, 1996). This occurs because the time trend, which is common to all producers, may capture both neutral technical change and neutral technical efficiency change if the inefficiency effects are not correctly specified. This problem can be minimised, but not removed, by allowing for the interaction of time and the other inputs (Lovell, 1996). Moreover, by allowing the efficiency effects to vary over time and by making the correct distributional assumptions about the efficiency effects, it is possible to disentangle technical change and changes in efficiency. Both the Battese and Coelli (1992, 1995) specifications allow the separation of time variant technical efficiency and technical change by defining technical inefficiency

as a function of a non-linear time trend in the (1992) specification, and by including a time trend as one of the explanatory variables in the inefficiency model in the (1995) specification (see Karagiannis et al. (1999) for a review of other possible specifications).

2.5. CONCLUSION

This chapter has looked at the properties and estimation of frontier production functions. There are a number of important points to carry over into the three essays to come. First is that where possible the frontier production function specified should be tested to ascertain whether or not the underlying properties hold. In the case of the translog frontier production function the conditions of concavity and monotonicity are crucial and they should be tested for at each data point. The second point is the assumptions of separabililty required to aggregate inputs. The third point is that, where possible, the alternative functional forms are tested against each other to find the best representation of the frontier production function using the Irish data set. The next three chapters will each expand on part or all of the theory discussed here. Chapter 3 explores the alternative functional forms for the frontier production function and estimation of time varying and time invariant technical efficiency and technical change. Chapter 4 concentrates on the Battese and Coelli (1995) model which defines efficiency as a function of a number of farm and farmer characteristic variables. Finally, Chapter 5 ties the stochastic frontier literature into the concept of a distance function and also looks at Data Envelopment Analysis as an alternative method for estimating technical efficiency.

CHAPTER 3
TECHNICAL CHANGE AND EFFICIENCY IN IRISH AGRICULTURE

3.1. INTRODUCTION

The Irish agricultural sector has experienced rapid change over the past twenty years. This change has been characterised by increases in average farm size coupled with an increased specialisation in production. However, many farm enterprises remain economically unviable and there is evidence of an increasing dependence on direct payments as a key source of family farm income. Over the next twenty years it is likely that the EU will continue to grow as the Transition Economies enter the union and trade barriers will be removed in line with the WTO agreements leading to a more competitive environment. If Irish agriculture is to succeed and prosper in this environment then there is a need for the sector to improve efficiency and to exploit existing technology. As Matthews states "*future competitiveness depends on access to up-to-date and productive new technologies, on achieving an optimal structure of production and on the management skills of its farmers*" (Matthews, 2000). The motivation for the analysis presented here is to understand the performance of Irish farms over the past fifteen years using a methodology which measures the relative efficiency and rate of productivity growth of farms in a consistent way, while also throwing light on the factors associated with differences in farm performance. 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 in the future.

As well as differences in efficiency levels, it is hypothesised that farms differ in the rate at which productivity is growing over time. Productivity change is identified here as technical change, although it is recognised that increases in total factor productivity may be due to a variety of sources, including improvements in human capital. To date there are no Irish data on farm-specific or system-specific productivity growth rates. This chapter provides such data for the first time.

The chapter proceeds as follows. The alternative specifications of the models estimated are presented in the next section. The chapter concentrates on the econometric methods only, in particular, the stochastic frontier approach. Measures of technical efficiency and technical change are estimated using fixed effects and maximum likelihood techniques for an unbalanced panel of 2,603 farms for the period from 1984 to 1998. The construction of the data set and the limitations of the data are presented in Section 3.3. Specification tests and the results of the analysis are presented in Section 3.4. Elasticities of mean production and returns to scale are also calculated. Section 3.5 explores the importance of different sources of farm level inefficiency. The chapter ends by discussing the policy implications of the results.

3.1.1. Defining Efficiency and Technical Change

There are apparently large differences between farms in the efficiency with which they use their available resources. For example, in 1998, 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 (lu/ha) on average, compared to a gross margin per hectare of €1043 and a stocking density of 1.54 lu/ha for farmers in the top third of the population. 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 hectare may also use relatively few capital and labour inputs. One alternative to partial productivity indices is to use econometric techniques to obtain estimates of efficiency and technical change.

This chapter focuses on the measurement and explanation of differences in technical efficiency between farms. The concept of efficiency is defined using the framework outlined by Farrell (1957) and presented in detail in Chapter 2. Allocative efficiency is not investigated as its measurement would require farm level prices on inputs and outputs which were not available. Technical change as defined in Chapter 2 is also measured and is broken down into neutral and non-neutral technical change. The rate of technical change is calculated for each farm system in the sample.

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

3.2. MODEL SPECIFICATIONS

The models estimated in this chapter are stochastic frontier models. Suppose the frontier production function is given by a general translog functional form incorporating the possibility of non-neutral technical change

$$\ln y_{it} = \alpha + \sum_k \beta_k \ln x_{kit} + 0.5 \sum_k \sum_j \beta_{kj} \ln x_{kit} \ln x_{jit} + \sum_k \xi_k \ln x_{kit} T + \varsigma_t T + \varsigma_{tt} T^2 + u_i + \upsilon_{it} \qquad 3\text{-}1$$

where y_{it} is output for farm i in period t and x_{kit} is the kth input of farm i in period t. α, β_k , β_{kj} ,ξ_k, ζ and ζ_t are the parameters to be estimated. T is time technical change, u_i represents time invariant technical inefficiency and υ_{it} is statistical noise. A number of other functional forms are nested within equation 3-1. By restricting $\xi_k=0$ the model reduces to a translog frontier production function with neutral technical change and by setting $\beta_{kj}=0$ the equation reduces to a Cobb-Douglas frontier production function. These specifications are tested formally.

Time variant technical inefficiency is estimated from

$$\ln y_{it} = \alpha + \sum_k \beta_k \ln x_{kit} + 0.5 \sum_k \sum_j \beta_{kj} \ln x_{kit} \ln x_{jit} + \sum_k \xi_k \ln x_{kit} T + \varsigma_t T + \varsigma_{tt} T^2 + u_{it} + \upsilon_{it} \qquad 3\text{-}2$$

where the parameters are as above and u_{it} represents technical inefficiency which is now allowed to vary over time. Again, the Cobb-Douglas and the neutral technical change specifications are nested in equation 3-2.

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 both equations 3-1 and 3-2 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. While it is possible to measure farm specific productivity growth rates by estimating a separate frontier for each farm system, this was not done. Although the NFS classifies farms into farm systems based on the share of each enterprise in standard gross margin, this does not imply that the farm is producing a single output. In fact, because of the multi-output nature of Irish farms, it is not possible to distinguish clearly between farms of different types. Multiple outputs

are aggregated into a single output (the method aggregation is discussed in Section 3.3.1). This is the justification for assuming that all farm systems have a similar production technology but differ just by an efficiency factor.

The distribution assumptions and characteristics of the models with time invariant and time variant efficiency to be estimated are given in Table 3-1.

Table 3-1: Major Characteristics of Models with Technical Efficiency

Time-Invariant Efficiency	Functional Form	Estimator	Technical Change	One-sided Error Term
Model I	CD	FE	N	—
Model II	CD	FE	NN	—
Model III	CD	BC	N	HN
Model IV	CD	BC	N	TN
Model V	CD	BC	NN	HN
Model VI	CD	BC	NN	TN
Model VII	SCD	FE	N	—
Model VIII	SCD	FE	NN	—
Model IX	SCD	BC	N	HN
Model X	SCD	BC	N	TN
Model XI	SCD	BC	NN	HN
Model XII	SCD	BC	NN	TN
Model XIII	TL	BC	N	HN
Model XIV	TL	BC	N	TN
Model XV	TL	BC	NN	HN
Model XVI	TL	BC	NN	TN
Model XVII	STL	BC	N	HN
Model XVIII	STL	BC	N	TN
Model XIX	STL	BC	NN	HN
Model XX	STL	BC	NN	TN
Model XXI	TL	FE	N	—
Model XXII	TL	FE	NN	—
Model XXIII	STL	FE	N	—
Model XXIV	STL	FE	NN	—
Time-Variant				
Model Ia	CD	FE	N	—
Model IIa	CD	FE	NN	—
Model IIIa	CD	BC	N	HN
Model IVa	CD	BC	N	TN
Model Va	CD	BC	NN	HN
Model VIa	CD	BC	NN	TN
Model VIIa	SCD	FE	N	—
Model VIIIa	SCD	FE	NN	—
Model IXa	SCD	BC	N	HN
Model Xa	SCD	BC	N	TN
Model XIa	SCD	BC	NN	HN
Model XIIa	SCD	BC	NN	TN
Model XIIIa	TL	BC	N	HN
Model XIVa	TL	BC	N	TN
Model XVa	TL	BC	NN	HN
Model XVIa	TL	BC	NN	TN
Model XVIIa	STL	BC	N	HN
Model XVIIIa	STL	BC	N	TN
Model XIXa	STL	BC	NN	HN
Model XXa	STL	BC	NN	TN
Model XXIa	TL	FE	N	—
Model XXIIa	TL	FE	NN	—
Model XXIIIa	STL	FE	N	—
Model XXIVa	STL	FE	NN	—

CD Cobb-Douglas; TL Translog; SCD Cobb-Douglas with farm system dummies; STL Translog with farm system dummies; BC Battese and Coelli MLE; N Hicks neutral technical change; NN Non neutral technical change; HN Half normal distribution; TN Truncated normal distribution.

3.3. 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 that participated in the survey at any time during this period. Farms remain in the sample for on average 5.9 years giving a total number of 14,917 observations.

3.3.1. Data aggregation

Most Irish farms are multi-product enterprises producing a combination of milk, beef cattle, tillage, horses, sheep, pigs or other outputs. There are three main reasons why it was prudent to aggregate the data. On the output side, SFA can only handle a single output. The second reason was to limit the number of right hand side variables in the models as the data on inputs were very disaggregated. To include all the variables in a translog production function would have increased the likelihood of multicollinearity and would not have increased the explanatory power of the model or changed the technical efficiency measures. Furthermore, using very disaggregated data on variable inputs, for example, increases the number of data points with zero values. The translog specification does not handle zero values.[7] This leads to the third justification for the aggregation of inputs and outputs, that it removes the problem of zero values. The aggregation was carried out using implicit quantity indices. The production function was specified using a single output based on the value of the enterprise outputs excluding subsidies and

[7] *This is further discussed in Section 3.3.2*

four inputs; land, labour, capital and variable inputs. Tornqvist Thiel (TT) value indices were first constructed. Implicit quantity indices for output and variable inputs are obtained as the ratio of the TT value indices to an aggregate farm-specific multilateral Tornqvist price index with base period 1996. Individual farm prices were not available, so national prices, taken from the CSO, are used. This index varies over time but not over farms implying that differences in the quality of outputs or inputs are reflected in differences in quantity (Reinhard, 1999 and Caves et al. 1982). The farm-specific price index for output is given as

$$\ln w_{jit} = \sum_{k=1}^{K} 0.5\left(s_{jkit} + \bar{s}_{jkb}\right)\left(\ln w_{jkit} - \ln \overline{w}_{jkb}\right) \qquad 3\text{-}3$$

where

s_{jkit} is the share of output k in total gross output j on farm i in year t;

s_{jkb} is the average share of output k in total gross output j in the base year;

w_{jit} is the price of output k on farm i in year t and

$\overline{w}_{jkb}$ is the average price of output k on farm i in the base year.

The same method is used for the aggregation of variable inputs. Variable inputs include feed, fertilisers, electricity, veterinary fees and transport costs. The land input is measured by the adjusted size of the farm in hectares. As the bulk of Irish farmland is operated by owner-occupiers, a series on the rental value of farmland is not available. The adjustment here is the conversion of rough grazing to pasture equivalent and does not take account of differences in soil

quality among farms. Such differences could therefore show up as differences in technical efficiency among farms. The labour input is measured as the number of labour units used, including family labour, casual and hired labour on the farm. The capital input is measured as the depreciated stock of machinery, land improvements, livestock and buildings with the individual components aggregated using the implicit quantity method. The alternative to this method is to obtain a flow from the services of capital. In both cases the capital index was almost identical as the same price series was used to obtain the flow of services hence the flow figure is proportional to the stock figure.

Table 3-2: Summary Statistics of Variables in the Stochastic Frontier Production Function

Variable	Mean	Std/Mean	Minimum	Maximum
Gross output (€)	61,981	1.26	1942	455,685
Capital (€)	44,425	1.54	83	459,439
Other inputs (€)	30,645	1.56	429	729,338
Size of farm (ha)	55	0.83	4.04	404
Total number of labour units	1.54	1.85	0.05	15.2

The summary statistics of the variables in the models are shown in Table 3-2 above. All production data used in the stochastic frontier analysis were *normalised* around the sample mean, prior to logarithmic transformation, to define the point of approximation. Normalising around the sample mean is performed by dividing all observations by the sample mean as $\ln(y/\bar{y}) = \ln y - \ln \bar{y}$ and $\ln(x/\bar{x}) = \ln x - \ln \bar{x}$. As stated by Friedlaender and Spady (1980) "*since the translog production function can be viewed as a Taylor series approximation around the point (1,1,...,1) or ln(1)=0, a number of important economic calculations are simplified at the point of*

approximation, which corresponds to a hypothetical farm whose values of inputs, technological conditions and generic outputs and qualities are those of the sample arithmetic mean". More importantly, unless the normalisation of the data around the sample mean is undertaken, it is questionable whether the translog parameter estimates could provide sufficiently large *well-behaved* regions so that the true underlying technology could be approximated. All the data were mean corrected prior to estimation of the production frontier so the first order partial derivatives can be interpreted as elasticises of mean output with respect to the input involved.

There are two main caveats with regard to the construction of the data set. The first relates to the assumption that all variables are separable from each other. This is always true especially with agricultural data. Second, a limitation of the translog is that it does not allow any of the variables to be equal to zero and this causes difficulties in the estimation of frontier production functions. The somewhat *ad hoc* technique of adding an arbitrarily small number greater than zero to the value of all outputs and inputs (not just the output involving zeros) is commonly used to salvage the translog. However, if the inputs are in volume terms this approach can lead to bias if it is carried out independently of the units of measurement of the variable concerned. In addition, if the number of zero cases is a significant proportion of the total number of sample observations, then the procedure may result in seriously biased estimators of the parameters of the frontier production function (Battese, 1997). The approach of setting zero outputs to a small positive number has been

shown to be unsatisfactory because quite different estimates of scope economies can be obtained, depending upon how close the number is to zero (Cummins and Weiss, 1998). Battese (1997) suggests using dummy variables for the inputs which have significant zero values. Another option is to use alternative forms to the translog. Cummins and Weiss (1998) and Sherlund et al. (1998) employ modified forms of the generalised Leontief frontier production function. In the data set used for this analysis, zero values were problematic only for variable inputs and in a small number of cases and observations were dropped in these cases and this did not bias the results.

3.4. RESULTS

The individual parameter estimates for all models are reported in Tables 2a to 2e in the appendices. The programme Frontier 4.1, developed by Tim Coelli was used to estimate the models.[8]

Elasticities with respect to mean output and returns to scale are reported in the Appendix and the minimum, maximum, mean and standard deviations between models are given in Table 3-3. For Models III, IV, XIII, XIIIa, XIVa and XIVa the input coefficients on land, representing production elasticities, are negative and in some cases statistically insignificant suggesting that the frontier production function is not well behaved.

For Model II the production elasticity for capital is negative. All of the models with the negative production elasticities technical change is specified as being Hicks neutral, which introduces the possibility of

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[8] *This software can be downloaded from http://www.une.edu.au/febl/EconStud/emet/cepa2.htm*

model misspecification (tests of misspecification are considered below).

Table 3-3: Minimum and Maximum Production Elasticities and Returns to Scale

	Land		Var Inputs		Labour		Capital		RTS	
	Model		Model		Model		Model		Model	
Min	*III*	-0.0196	*VIII*	0.0192	*IX*	0.0795	*II*	-0.0177	XXIII	0.5964
Min(+)	*IIIa*	0.0021					*XXIV*	0.0177		
Max	*VIII*	0.5019[a]	*XIII*	0.8717[a]	*VIa*	0.2442[a]	*XIII*	0.1421[a]	III	1.0684
Std Dev		0.1317		0.1811		0.0374		0.0320		0.1109

The standard deviations from the mean value is greatest for variable inputs and lowest for capital. Returns to scale range from 0.5964 to 1.068 and the standard deviation is 0.1742. This suggests that there is some differences across models with respect to the returns to scale.

3.4.1. Specification Testing

There was no correct starting place for the specification testing as there were no a priori reasons to expect a particular specification. The strategy used in this chapter began by comparing MLE to fixed effects approaches and ended up by testing the alternative distributions of the efficiency effects. The results for the full range of models estimated is presented in the appendices. The main justification for the large number of models estimated was to ensure that specification testing could be carried out in a rigorous manner.

The first stage of testing concentrated on identifying the most appropriate estimation technique. The choice between a fixed effects approach 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. Recall from Chapter 2 that fixed effects allow for correlation between the error term and the explanatory variables while for random effects approaches the explanatory variables and the efficiency must not be correlated. The hypothesis that there was zero correlation between the x variables and the efficiency effect was tested using a Hausman test. The result indicated that the MLE 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 MLE specifications using a log likelihood test. The null hypothesis that $\beta_{ij}=0,\ i\leq j=1,5$ 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 MLE 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 was 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 are no technical inefficiency effects in the model. Again likelihood ratio tests were used. The null hypothesis that there were no inefficiency 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 time invariant, that is, $\eta=0$ was rejected against the alternative that the technical inefficiency effects were time variant for all MLE 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. The coefficient of γ for Model XXa is *0.97* and is statistically significant at the 1 per cent level for the translog with non-neutral technical change. This indicates that the stochastic frontier model is significantly different from the deterministic frontier. Given these results, the translog with non-neutral technical change and farm system dummies (Model XXa) is the best representation of Irish agricultural technology given the alternative specifications considered[9]. These results are presented in Table 3-4.

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[9] *Once the best model for Irish agriculture was determined the testing regime was reversed and the starting point was the best model. This approach was taken to ensure that the starting point was not influencing the model selected.*

Table 3-4: Generalised Likelihood Ratio Tests for Hypothesis for Parameters of the MLE Stochastic Frontier Production Functions for Irish Farming

Null Hypothesis		x	Critical Value	Decision
Hausman Test Fixed Effects 'v' MLE MLE	E(X'U)=0	356	36.4	Accept
OLS v Stochastic Frontier Models	Ho: γ=0	1320	11.91	Reject
Cobb Douglas vs Translog	Ho: β_{ij}=0 i≤j=1,4	166	5.14	Reject
Non-neutral vs Neutral Technical Change	Ho:β_{ijt} = 0	121	9.48	Reject
No System Dummies vs System	H_0: ζ_t=0	1261	5.14	Reject
Time Variant vs Time Invariant	H_0: η=0	940	3.84	Reject
Truncated Normal v Half Normal Distribution	H_0: μ=0	252	3.84	Reject

Tests were also undertaken for heteroscedasticity and normality. A White's test was used to test for heteroscedasticity.[10] The estimated χ^2 value obtained exceeded the critical value and it was concluded that there was no heteroscedasticity in the error variance. The normality assumption was tested using the method outlined in D'Agostino et al. (1990) and it was concluded that the assumption of normality holds.[11]

3.4.1.1.Monotonicity

To define the point of approximation all data were normalised around the sample mean prior to estimation. Normalising the data results in

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[10] *A White's test does not require a normality assumption. The model of interest is estimated the residuals are obtained. The residuals are squared used as the dependent variable in auxiliary regression on the original x variables and x squared and the R^2 is obtained. The sample size (n) is multiplied by R^2 and has a asymptotically a chi squared distribution. If this value exceeds the critical chi-squared value there is no heteroscedasticity. White, H. "A Heteroscedasticity Consistent Covariance Matrix Estimator and a Direct Test of Heteroscedasticity", Econometrica Vol. 48 1980 pp. 817-818.*

[11] *This method is based on measurement of the degree of kurtosis in the data.*

the second term in equation 3-4 summing to zero so the marginal productivity condition is fulfilled once $\beta_j > 0$ for all j.

$$MP_{jit} = \frac{y}{x_{jit}}\left(\beta_j + \sum_{k=1}^{K}\beta_{jk}\ln x_{kit}\right) > 0 \qquad 3\text{-}4$$

Similarly, diminishing marginal productivities require that equation 3-5 is less than zero Again normalising the data simplifies equation 3-5 to $\beta_j(\beta_j - 1) < 0$.

$$\left(\beta_j + \sum_{k=1}^{K}\beta_{jk}\ln x_{kit}\right)\left(\beta_j - 1 + \sum_{k=1}^{K}\beta_{jk}\ln x_{kit}\right) < 0 \qquad 3\text{-}5$$

The monotonicity condition for Model XXa was checked by evaluating equation 3-4 and equation 3-5 at the point of approximation and at each data point. Table 3-5 gives the percentage points violating the monotonicity condition.

Table 3-5: Percentage of Data Points Violating the Monotonicity Condition

Input	Preferred Model
Land	0.3
Labour	9.2
Capital	14.0
Variable Inputs	8.8

3.4.1.2. Curvature Conditions

The curvature condition was confirmed by examining the definiteness of the bordered Hessian matrix of first and second order partial derivatives of the translog frontier production function.[12] The

[12] *The first order partial derivatives must be positive and they form the border of the Hessian.*

first-order partial derivatives of the translog are given by equation 3-4 above and the second order partial derivatives are given by

$$\frac{\partial^2 y_{it}}{\partial x_{jit}^2} = \frac{y_{it}}{x^2_{jit}}\left(\beta_{jj} + S_{jit}\left(S_{jit} - 1\right)\right) \qquad 3\text{-}6$$

for $j=k$, and

$$\frac{\partial^2 y_{it}}{\partial x_{jit}\partial x_{kit}} = \frac{y_{it}}{x_{jit}x_{kit}}\left(\beta_{jk} + S_{jit}S_{kit}\right) \qquad 3\text{-}7$$

for $j \neq k$, where $S_{jit} = \left(\beta_j + \sum_{k=1}^{K}\beta_{jk}\ln x_{kit}\right)$. If the function is concave, which implies that the isoquants are convex, then the bordered Hessian matrix will be negative definite. The bordered Hessian matrix is shown in Table 3-6.

Table 3-6: Hessian Matrix of the First and Second Order Partial Derivatives Averaged over Time and Farms

		f_{jV}	f_{jLab}	f_{jC}	f_{jL}
	0	0.275	0.099	0.02112	0.1112
f_{Vj}	0.275	**-0.3998**	0.335	0.0278	0.024
f_{Labj}	0.099	0.335	**-0.6542**	0.01251	0.01298
f_{Cj}	0.0211	0.0278	0.01251	**-0.02051**	0.0234
f_{Lj}	0.1112	0.024	0.01298	0.0234	**-0.201**

j denotes inputs; f = derivative; v = variable inputs; lab = labour; C = capital; L= land.

The diagonal elements of the Hessian matrices are negative at the point of approximation (the mean) as required for the convexity condition. The curvature condition for negative definiteness requires that the principle minors of the bordered Hessian of the first and second order conditions alternate in sign. The convexity restriction did not hold for all data points, but since it holds at the mean it is possible to assume that there are well-behaved regions large enough to ensure the translog function is a good representation of the data.

3.4.2. Technical Change

Three methods of calculating technical change growth rates (linear, exponential and average) were used in the analysis. The use of an arithmetic averages is the least favoured measure as by definition they give no indication of the rate of change. Exponential and linear growth rates give a more robust indication of the actual growth rate. For completeness all three rates are reported.

The results reported are for the preferred Model XXa only. Two sets of technical change results are discussed. The first set is the unweighted sample results. 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.[13] 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 second set are the sample results weighted by the ratio of gross output to the sample gross output. The weights were applied to account for differences in the relative contribution of each farm to overall national output. Unweighted technical change for Model XXa

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[13] *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.*

was estimated as described in Chapter 2, equation 2-57. All figures reported in Table 3-7 are for the sample mean values by year.

The average annual rate of technical change was 0.9 per cent with a cumulative growth rate of 13.9 per cent over the period. Linear and exponential growth rates were also calculated and were found to be very similar to the mean growth rate over the period at 0.85 and 0.91 respectively.

Table 3-7: The Annual Rate of Unweighted Technical Change by Year and Associated Growth Rates

Year	Neutral Technical Change	Non-neutral Technical Change	Total Technical Change
	%	%	%
1984	1.66	-0.28	1.38
1985	1.53	-0.13	1.40
1986	1.40	-0.07	1.33
1987	1.27	-0.16	1.11
1988	1.14	-0.12	1.02
1989	1.01	-0.01	1.00
1990	0.88	0.17	1.05
1991	0.75	0.18	0.93
1992	0.62	0.07	0.69
1993	0.49	0.17	0.66
1994	0.36	0.19	0.55
1995	0.23	0.32	0.55
1996	0.10	0.45	0.55
1997	-0.03	0.44	0.41
1998	-0.16	0.76	0.60
Sample Mean	0.785	0.100	0.858
Standard Deviation	.0052	.0166	0.0218
Exp. Growth Rate	0.799	0.104	0.912
Linear Growth Rate	0.748	0.103	0.853

Unweighted technical change is decomposed into neutral and non-neutral technical change. There is evidence of technical progress over the period but this is occurring at a decreasing rate. In 1984 technical progress occurred at a rate of 1.37 per cent compared to a rate of 0.60 per cent in 1998. In the period up to 1990 technical

change was dominated by non-neutral technical regress. The same period saw 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 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.

The mean annual rates of unweighted technical change by region, farm system and size of farm in hectares are reported in Table 3-8.

Table 3-8: The Mean Annual Rate of Technical Change by Region, System and Size (Unweighted)

Region	Neutral	Non Neutral	Total
West	0.750	-0.600	0.130
East	0.750	0.580	1.350
System	**Neutral**	**Non Neutral**	**Total**
Dairy	0.750	1.120	1.890
Dairy other	0.750	0.620	1.360
Cattle	0.750	-0.880	-0.220
Sheep	0.750	-1.250	-0.470
Crops	0.750	0.870	1.750
Quintiles of Size	**Neutral**	**Non Neutral**	**Total**
less than 22 ha	0.750	-1.650	-0.800
23 to 33 ha	0.750	-0.580	0.170
34 to 48 ha	0.750	0.090	0.820
49 to 80 ha	0.750	0.860	1.570
80 ha and above	0.750	1.810	2.540

Farms located in the Eastern region had a mean annual rate of technical progress of 1.36 per cent over the period compared to 0.12 per cent annual for farms in the Western region.[14] This is due in part to the presence of non-neutral technical regress over the period for

[14] *The results in Table 3-9 are unweighted and so it is possible that the results are being driven by the size and or system of farming.*

farms in the west. Farms in the top size quintile (over 81 hectares of land) had a higher average rate of technical progress of 1.1 per cent compared to farms in the bottom quintile (less than 22 hectares) that had an average annual rate of technical progress of 0.3 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). It should be noted that the results in Table 3-9 are unweighted and so it is possible that the results are being driven by the size and or system of farming.

Annual rates of technical change by system of farming are given in Table 3-9. Dairy, dairy other and crop farms experienced technical progress over the period (at annual rates of 1.9, 1.4 and 1.75 per cent respectively) while cattle and sheep farms actually experienced technical regress over the same period. The technical regress evident sheep systems throughout the period and in cattle systems from 1990. Tillage farms have seen the most dramatic decline in the average annual rate of technical change over the period, however, slow down was also found on dairy and dairy other farms.

Table 3-9: The Annual Rate of Technical Change by Farm System (Unweighted)

Year	Dairy	Dairy & Other	Cattle	Sheep	Tillage
1984	2.321	1.803	0.082	-0.907	3.456
1985	2.313	1.684	0.141	-0.649	2.321
1986	2.262	1.606	0.244	-0.490	2.231
1987	2.079	1.506	0.083	-0.478	1.985
1988	2.056	1.560	-0.013	-0.456	1.912
1989	2.070	1.586	0.012	-0.408	1.794
1990	2.000	1.547	-0.056	-0.095	1.836
1991	1.856	1.492	-0.067	-0.263	1.760
1992	1.682	1.284	-0.332	-0.436	1.564
1993	1.667	1.061	-0.506	-0.615	1.268
1994	1.713	1.038	-0.456	-0.427	1.249
1995	1.650	1.322	-0.457	-0.499	1.256
1996	1.604	1.014	-0.448	-0.548	1.173
1997	1.513	1.021	-0.471	-0.770	1.081
1998	1.631	1.056	-0.340	-0.631	0.832
Mean	0.019	0.014	-0.002	-0.005	0.017

Figure 3-1 below shows the cumulative growth rate of technical change over the period 1984 to 1998.

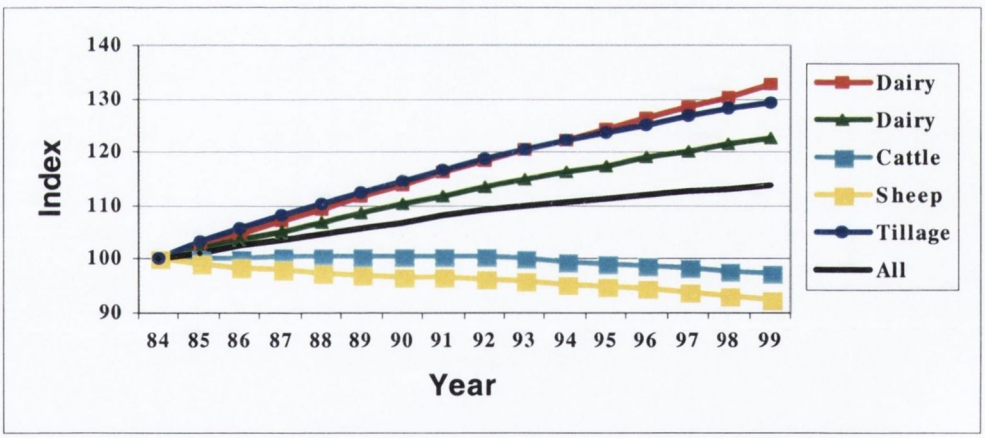


Figure 3-1: Cumulative Growth in (Unweighted) Technical Change (1984-98)

Cattle and sheep farms are showing a cumulative decline over the period. It may be no coincidence that these are the farm systems where direct payments play the most important role in farm incomes (Matthews, 2000). Table 3-10 presents the breakdown of the

unweighted neutral and non-neutral growth rates for each system. For completeness three growth rates are presented: the annual average rate, the exponential rate and the linear rate.

The rate of technical progress, found in dairy, dairy and other and tillage farms, is greater than the rate of technical regress found on sheep and cattle farms. The rate of technical regress is approximately 0.2 per cent and 0.45 per cent on cattle and sheep farms respectively.

Table 3-10: Annual, Exponential and Linear Technical Change Growth Rates (Unweighted)

System	Growth Rate	Neutral TC	Non Neutral TC	Total
Dairy	Average	0.750	1.140	1.890
	Exponential	0.747	1.130	1.880
	Linear	0.799	1.216	2.159
Dairy Other	Average	0.750	0.622	1.372
	Exponential	0.749	0.620	1.370
	Linear	0.799	0.643	1.516
Cattle	Average	0.750	-0.922	-0.22
	Exponential	0.749	-0.932	-0.181
	Linear	0.799	-0.867	-0.180
Sheep	Average	0.750	-1.26	-0.511
	Exponential	0.749	-1.17	-0.460
	Linear	0.799	-1.05	-0.447
Tillage	Average	0.750	0.897	1.647
	Exponential	0.749	0.881	1.696
	Linear	0.799	0.932	1.911

Table 3-11 presents the unweighted and weighted rates of technical change by region and for the entire sample.

Table 3-11: Exponential Growth Rates Technical Change Growth Rates (Weighted and Unweighted)

Region	Exponential Growth Rates	Unweighted	Weighted
National	Total	0.912	1.94
	Neutral	0.749	0.749
	Non Neutral	0.104	1.19
Western	Total	0.133	1.17
	Neutral	0.749	0.749
	Non Neutral	-0.572	0.422
Eastern	Total	1.321	2.19
	Neutral	0.749	0.749
	Non Neutral	0.571	1.45

The weights applied are based on the ratio of gross output to the mean gross output in each year. For example, to weight technical change results for farms in the Western region, weights are based on the ratio of gross output in the Western region to the mean gross output in the Western region in each year. The reason for using separate weights each year is that the number of farms is different in each year.[15]

The weighted linear rate of technical change is 2.58 per cent compared to a value of 0.9 per annum for the unweighted sample and the cumulative growth increases from 13.9 per cent over the period for the unweighted results to 38 per cent for the weighted results. Splitting the time period in two shows a slowdown in the annual rate of technical progress from 1.19 per cent for the period 1984 to 1990 to 0.5 per cent for the period 1990 to 1998. Similarly the weighted results show the rate of change to be 2.7 per cent per annum for 1984 to 1990 compared to 1.9 per cent for the later time

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[15] *The same approach is adopted for the weights applied to farm system and land size categories. It is noted that if the technical change rates estimated are used as national rates then more extensive weights based on farm system and land area should be used as the sample used is based on a stratified random sample. This work is being carried out by the author.*

period. Matthews (2000), using an index number methodology with aggregate data, found an average annual rate of total factor productivity growth in Irish agriculture of 2.3 per cent in the 1980s falling to 0.8 per cent on average in the 1990s.[16] 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.

The regional analysis shows that non-neutral technical change becomes positive for farms in the Western region when the results are weighted by regional gross output (an unweighted growth rate – 0.5 per cent, and a weighted growth rate of 1.17 per cent). Farms located in the Eastern region appear to be experiencing higher rates of technical change growth than farms in the Western region. Table 3-12 gives the exponential growth rates, weighted and unweighted, for each farm system. Comparing the weighted and unweighted exponential growth rates for each farm system shows that for all farm systems the weighted growth rate is greater than the unweighted rate.

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[16] *The work by Matthews (2000) combines the impact of pure technical change, as well as changes in scale, allocative and technical efficiency levels of farms, so the results are not directly comparable with those calculated here.*

Table 3-12: Exponential Weighted and Unweighted Technical Change Growth Rates by Farm system.

System	Exponential Growth Rates	Unweighted	Weighted
Dairy	Total	1.88	2.67
	Neutral	0.749	0.749
	Non Neutral	1.130	1.92
Dairy \other	Total	1.370	2.09
	Neutral	0.749	0.749
	Non Neutral	0.620	1.34
Cattle	Total	-0.181	0.532
	Neutral	0.749	0.749
	Non Neutral	-0.932	-0.216
Sheep	Total	-0.46	-0.027
	Neutral	0.749	0.749
	Non Neutral	-1.17	-0.777
Tillage	Total	1.696	2.065
	Neutral	0.749	0.749
	Non Neutral	0.881	1.316

The change is occurring through changes in non-neutral technical change.[17] The weighted growth rate is 2.67 per cent for dairy farms, 2.09 per cent for Dairy and Other and 2.06 per cent for tillage farms. Weighting the rate of technical change for sheep farms results in a lower rate of non-neutral technical regress from a rate of -0.5 per cent to -0.2 per cent, for unweighted and weighted respectively. Weighting the data for cattle farms leads to a change from regress in total technical change. However, it does not change the non-neutral technical regress. Exponential unweighted and weighted technical change growth rates were also calculated for quintiles of farm size in hectares. As with region and system the weighted results are different for all size categories. The unweighted results are greater in all cases. Weighting the results for size categories is particularly important as a farm can be large in land area but this does not imply

[17] *Neutral technical change is not farm specific and so will not change when the weights are applied.*

that all the land is high quality farming land. Take for example a hill farmer in Donegal, the farm may be large but poor quality land may mean that the vast majority of the land is unsuitable for farming. Similarly, a large dairy farm (in ouput) may be located on a small (in land size) farm.

Table 3-13: Exponential Weighted and Unweighted Technical Change Growth Rates by Quintiles of Farm Size in Hectares

Size Quintiles	Exponential Growth Rates	Unweighted	Weighted
Less that 22 ha	Total	0.347	1.032
	Neutral	0.749	0.749
	Non Neutral	-0.442	0.282
23 to 33 ha	Total	0.881	1.613
	Neutral	0.749	0.749
	Non Neutral	0.061	0.864
34 to 48 ha	Total	0.9031	1.727
	Neutral	0.749	0.749
	Non Neutral	0.153	0.977
49 to 80 ha	Total	1.078	1.884
	Neutral	0.749	0.749
	Non Neutral	0.328	1.134
80 ha and Over	Total	1.16	2.246
	Neutral	0.749	0.749
	Non Neutral	0.410	1.496

Farms less than 22 hectares have an unweighted non-neutral technical change growth rate of –0.4 per cent (technical regress), compared to a weighted rate of 0.28 per cent. Farms in the middle three quintiles (23 to 33 ha, 34 to 48 ha and 49 to 80 ha) have similar increases in the weighted rate of total technical change (1.6, 1.72 and 1.88 per cent respectively). The quintiles at the top and bottom have the largest changes in total weighted technical change growth.

It should be noted that the single time trend used here may not be the best representation of neutral technical change. Karagiannis

(1999) and Hesmati (1996) have suggested multiple time trends and a general time index as possible alternative methods. There is scope to use the results here and to apply National Farm Survey size and system weights to give an aggregate measure of technical change.

3.4.3. Average Technical Efficiency

Efficiency is measured on a scale from 0 to 1 in which lower values represent lower levels of technical efficiency. The mean technical efficiency estimates are higher for the MLE time variant (ranging from 0.60 to 0.71) and time invariant (ranging from 0.58 to 0.70) frontier models than for the fixed effect time invariant (0.21 to 0.36) and time variant models (0.21 to 0.32). Other studies examining technical efficiency in agriculture have shown the fixed effects estimates of technical efficiency to be lower than estimates obtained using maximum likelihood techniques. In an analysis of technical efficiency of farms in North-Western Pakistan, Parikh and Shah (1994) found a mean technical efficiency of 0.96 using maximum likelihood estimation. Hallam and Machado (1995) examined efficiency in Portuguese dairy farms and found the fixed effects average technical efficiency to be 0.57 and the Battese and Coelli maximum likelihood average to be 0.88. Ahmad and Bravo-Ureta. (1996) also found fixed effects average technical efficiency for dairy farms to be lower than MLE specifications.

Average technical efficiency is highest at 0.71 (Model XXa) when non-neutral technical change is included and account is taken for the difference in farm systems. Average technical efficiency of 0.745 was found by Ajubefun et al. (1996) in their study of technical efficiency

in the Japanese rice industry. The distribution of the error term also impacts on the average efficiency measures. The different methods used to estimate technical efficiency also produced differences in the ranking of farms. However, the correlation between the different estimates of technical efficiency is greater than 0.85 for all the MLE models and 0.89 for the fixed effect models. Not surprisingly the correlations between the fixed effects models and the MLE models are lower ranging from 0.50 to 0.70.

The results of the models including 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. Average technical efficiency by farm system is given in Table 3-14.

Table 3-14: Annual Average Technical Efficiency by Farm System 1984 to 1998

Year	Dairy	Dairy Other	Cattle	Sheep	Tillage	All
1984	0.7365	0.7248	0.6765	0.5257	0.7362	0.6799
1985	0.7412	0.7237	0.6923	0.5365	0.7263	0.6840
1986	0.7392	0.7244	0.6889	0.5579	0.7430	0.6906
1987	0.7409	0.7275	0.6878	0.5623	0.7343	0.6905
1988	0.7435	0.7309	0.7010	0.5597	0.7300	0.6930
1989	0.7451	0.7483	0.6985	0.5647	0.7496	0.7012
1990	0.7482	0.7529	0.6849	0.6241	0.7591	0.7138
1991	0.7589	0.7505	0.6745	0.6084	0.7620	0.7108
1992	0.7582	0.7546	0.6743	0.6190	0.7665	0.7145
1993	0.7740	0.7400	0.6380	0.6068	0.7716	0.7060
1994	0.7779	0.7584	0.6062	0.6182	0.7843	0.7090
1995	0.7833	0.7641	0.6059	0.5961	0.7770	0.7052
1996	0.7932	0.7595	0.5825	0.6044	0.7902	0.7059
1997	0.7968	0.7743	0.5867	0.5610	0.7934	0.7024
1998	0.8016	0.7844	0.6075	0.6343	0.8077	0.7271
Mean	*0.7625*	*0.7478*	*0.6537*	*0.58527*	*0.7620*	0.7023
GR	0.6546	0.5308	-1.321	0.9509	0.7153	0.3240

Average efficiency is lowest on sheep farms. At the start of the period average efficiency was 0.52 on sheep farms compared to the average of 0.67 for all farms. However efficiency on sheep farms did improve steadily over the period. While efficiency on cattle farm has declined over the period from 0.67 to 0.60. The average growth rate in efficiency over the period has increased by almost 5 per cent on sheep, tillage and dairy farms, 3 per cent on dairy other farms and declined by 3 per cent on cattle farms. From 1984 until 1992 average efficiency on cattle farms was increasing. However, efficiency starts to decline in the year following the 1992 CAP reforms. The exponential growth rates in technical efficiency show that cattle farms have experienced negative technical efficiency growth rate of 1.3 per cent. The growth rate for sheep farms is almost 1 per cent compared to 0.65, 0.53, 0.71 per cent for dairy, dairy and other and tillage farms respectively. The overall growth rate of 0.32 per cent reflects the negative growth rate for cattle farms.

Movements in average annual efficiencies are compared across farm systems in Figure 3-2, by setting the annual average efficiency of each farm system in 1984 equal to 100.

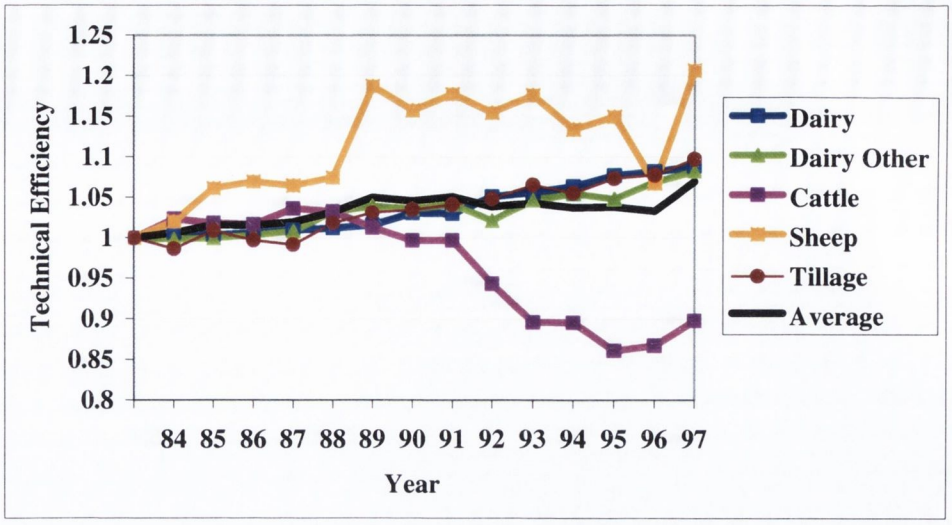


Figure 3-2: Annual Average Technical Efficiency by Farm System (Base year 1984)

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. This is not surprising as the EU structural and less favoured areas aid was introduced in 1988. Cattle farms experienced a significant fall in average technical efficiency in the period after 1991. This could be due to the impact of the MacSharry CAP reforms.

3.5. EXPLAINING TECHNICAL EFFICIENCY

Given the results in Section 3.4.3 an analysis of factors which may explain technical efficiency was undertaken. The following variables were used to explain technical efficiency differences across farms

Z_1 is the age of the farmer

Z_2 is age squared

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

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

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

Z_6 is size of the farm household

Z_7 represents the size of the farm (as a proxy for wealth).

Z_8 is 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. Age squares is included to allow for a non-linearity regarding age to be introduced into the model. The squared terms are included to reflect the fact that, after some point, the year-by-year impacts of increasing age begin to decrease. The sign on the co-efficient on age squared indicates whether or not the impact of age is occurring at an increasing or decreasing rate.

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 positively associated with inefficiency; 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 negative relationship with inefficiency. Farms located in the West of Ireland face geographical and economic disadvantage and so the coefficient is expected to be negative. The regional division of the country into West and East is important for two main reasons. The agricultural sector in the West and East are different in terms of both the output produced and the quality of the inputs (in particular land). There are other differences in infrastructure, and general economic development which would lead to the a priori belief that there would be differences in the rate of technical change between West and East.

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, such data were not available in the data set used. A time trend is included to capture the linear pattern of technical inefficiency 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. Land is included in the model as a proxy for a wealth effect. [18]

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[18] *Land is also included as a factor of production (as a x variable land is influencing output. However, it is used as a Z variable in the efficiency equation not as a factor of production but as a proxy for a wealth effect. The rationale is to try and capture factors which may affect farmers' motivation, hence the wealth effect.*

Model XXa, which was the translog function with non-neutral technical change conditional on the system of farming that the farmer is in, is used for the analysis of the factors associated with technical efficiency. There are two approaches available to explain farmers' technical efficiency. The two stage approach in which the factors thought to explain farmers technical efficiency are regressed on the efficiency scores obtained from the SFA approach. The second approach is the Battese and Coelli (1995) single stage efficiency model as discussed in Chapter 2. In the single stage approach the efficiency scores and the factors explaining efficiency are estimated at the same time. The two stage approach has become largely redundant as, in the estimation of the production function the efficiency effects are assumed to be independently and identically distributed. However, in the second stage the efficiency scores are defined as a function of the farm specific effects thus violating the assumption that the efficiency effects are identically distributed. The single-stage approach was developed to overcome the most frequently cited difficulty with the two stage approach. The single - stage Battese and Coelli model overcomes this caveat. Chapter 4 gives a more detailed account of the difficulties in trying to explain technical efficiency using stochastic frontier approaches. The results of the two stage approach are cited for comparative purposed only as the results are not equivalent.

The results of the two approaches are given in Table 3-15. The signs on the coefficients are the same in the two models for all the explanatory variables except for age and there are only minor

differences in the statistical significance of some of the variables. However, the size of the coefficients varies considerably.

Table 3-15: Results of the Technical Efficiency Analysis for Model XXa

Variables	Single Stage	SE	Two Stage	SE
Age of farm operator	0.0257	0.0100	-0.0002	0.0007
Age squared	-0.0008[a]	0.0001	-9.64e-06	7.54e-06
Debt ratio	0.1742[a]	0.0792	0.0326[a]	0.0033
Off-farm job	-2.9087[a]	0.0792	-0.0914[a]	0.0038
Located in West of Ireland	-3.3381[a]	0.0966	-0.0920[a]	0.0028
Size of farm household	0.3468[a]	0.0119	0.0125[a]	0.0006
Size of farm in ha	-0.0137[a]	0.0004	-0.0003[a]	0.0003
Time	-0.5280[a]	0.0093	0.0003	-0.0223[a]
Adjusted R^2				0.3385

[a] 1% significance level [b] 5% significance level

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, the debt burden, farm size and age. Efficiency was positively associated with the size of farm household. Previous evidence on farm viability 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).[19] Having an off-farm job is negatively associated with efficiency. There are two possible reasons for these results. First, is that the farm is not considered to be economically viable forcing the farm operator into full time employment of the farm. Second, if the farmer is working off the farm then the amount of time devoted to the farm is less and so the farm is less efficiency.

[19] *The term farm viability can be defined in a number of ways. Farms which generate income equal to the average industrial wage are considered to be viable. It is also argued that farms with children in the household have more of an incentive to generate income as they have larger expenditure commitments compared to household with only the farm operator and spouse.*

A higher debt ratio is positively associated with efficiency suggesting that farmers who are borrowing are better managers (though the direction of causation here could also be 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. Time is found to be negatively related to efficiency implying that average efficiency decreased over the time period. This could be due to the changes in the policy environment discussed earlier. In the preferred single stage model age is positively related with efficiency although the variable is not statistically significant in the two stage model.

These results are 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, Abdulai and Huffman, 1998, Andreakos et al. 1997 and Parikh and Shah 1994). It is worth noting that the explanatory variables in the two stage model only explain about 34 per cent of the variance in efficiency scores, indicating the importance of management factors not captured in this analysis. It was not possible to include education as an explanatory variable in the efficiency analysis as the data were not available for the long time period. The impact of education and role of the farm advisory service are explored in the next chapter.

Table 3-16 shows that 51 per cent of farms in the lowest quintile are primarily cattle farms and a further 31.3 per cent are sheep farms.

Table 3-16: Percentage of Most and Least Efficient Farms by System of Farming

System	% Least Efficient	% Most Efficient
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

Thirty one per cent of this group are specialist dairy farms. As 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 3-7 presents some of the characteristics of the top one fifth and bottom one fifth of farms ranked by their technical efficiency score.

Table 3-17: Characteristics of the Most and Least Efficient farms

	Mean	Std Dev/mean	Min	Max
Technical Efficiency				
Least efficient	0.3420	0.1209 (.35)	0.0026	0.5067
Most efficient	0.8910	0.0326 (.03)	0.8424	0.9868
Gross Output per ha				
Least efficient	210.13	299.69 (1.4)	0.0024	2991.08
Most efficient	889.84	561.75 (.63)	14.82	5380.81
Gross Margin per ha				
Least efficient	323.94	211.17 (.65)	-428.19	2049.03
Most efficient	661.81	351.02 (.53)	7.19	2381.99
Family Farm Income per ha				
Least efficient	161.00	147.71 (.91)	-808.50	948.80
Most efficient	388.91	272.13 (.69)	-491.85	1732.76
Capital per ha				
Least efficient	451.69	410.21 (.90)	1.030	4452.51
Most efficient	678.35	508.25 (.74)	3.185	4234.06
Variable Costs per ha				
Least efficient	302.54	247.72 (.81)	4.61	2825.03
Most efficient	487.53	320.42 (.65)	20.97	4213.34
Labour Units				
Least efficient	1.2	.6682 (.55)	.0667	12.57
Most efficient	1.6	.8558 (.53)	.1244	15.25
Livestock Units				
Least efficient	53.70	49.79 (.92)	0.000	732.88
Most efficient	67.15	51.18 (.76)	0.000	385.33
Size of farm in adjusted ha				
Least efficient	49.98	47.73 (.95)	4.04	395
Most efficient	58.32	47.19 (.80)	4.04	397
Borrowing per ha				
Least efficient	122.17	279.05 (2.2)	0.000	3751
Most efficient	293.06	416.76 (1.4)	0.000	3592
Debt Ratio				
Least efficient	.0942	.2028 (2.1)	0.000	3.80
Most efficient	.2323	.3456 (1.4)	0.000	3.46
Age				
Least efficient	52	12.64 (.24)	18.00	85
Most efficient	47	12.04 (.25)	18.00	84
Household Size				
Least efficient	3.5	1.95 (.55)	1.00	13
Most efficient	4.4	1.98 (.45)	1.00	12

Gross output per hectare, gross margin per hectare and family farm income per ha are all higher in the farms ranked in the top 20 per cent of efficiency ratings. Borrowings per hectare and debt ratios are also higher in the most efficient quintile of farms.

3.5.1. Marginal Effects

The coefficients on the explanatory variables give an indication of the direction of the effect of the variable on technical inefficiency. 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 for each of the efficiency variables. These are reported for the preferred single stage model below in Table 3-18.

Table 3-18: Marginal Effects of a Unit Change in Each Factor (%)

Variables	Percentage change In Efficiency
Age of farm operator	1.39
Age squared	-2.31
Debt ratio	0.04 [a]
Off farm job	-3.23 [a]
Located in West of Ireland	-3.75 [a]
Size of farm household	1.54[a]
Size of farm	-0.85 [a]
Time	-4.33 [a]

[a] 1% significance level

Being located in the West of Ireland decreases efficiency by 3.75 per cent (this may be a reflection of the poorer land quality, on average, 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 in 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. 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. Each year in agriculture, represented by time,

has seen efficiency decreasing by 4 per cent over the period reviewed.

3.6. CONCLUSIONS

This chapter presented a methodology for estimating technical efficiency levels and rates of technical change for individual farms using a stochastic production frontier approach and tested whether particular farm-specific factors are associated with differences in technical efficiency. The results suggest that, on average, farms achieve around 60 to 70 per cent of the efficiency level of best practice farms within the system they are in. Comparing farms with best practice within the agricultural sector as a whole (i.e. excluding farm system dummies) does not radically change the result. Using the preferred specification for agricultural technology, the average efficiency level drops from 71 per cent to 65 per cent. This average figure compares to an average of 58 per cent found by Boyle using a different model specification and an earlier time period (1984-86). This suggests that there is considerable scope for either increased output or cost savings if average efficiency levels could be improved.

The chapter investigated a number of factors associated with lower efficiency scores. Farming in the East of the country, age, larger household size and high borrowings were found to be positively associated with 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. These 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. This issue is further pursued in Chapter 4.

The results show evidence of technical change, over the period, but this is occurring at a decreasing rate for both the weighted and the unweighted results. The weighted linear rate of technical change is 2.58 (exponential growth rate is 1.94) per cent compared to a value of 0.9 per cent per annum for the unweighted sample and the cumulative growth increases from 13.9 per cent over the period for the unweighted results to 34 per cent for the weighted results. Splitting the time period in two shows a slow down in the annual rate of unweighted technical progress from 1.19 per cent for the period 1984 to 1990 to 0.5 per cent for the period 1990 to 1998. Similarly the weighted results show the linear rate of change to be 2.7 per cent per annum for 1984 to 1990 compared to 1.9 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 mean annual rate of technical change of 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 rate of technical change is

greater for farms located in the Western and the Eastern regions (1.15 and 2.21 per cent respectively). Farms in the top size quintile (over 81 hectares of land) had an unweighted average annual rate of technical change of 2.54 per cent annually and a weighted annual rate of 2.24. Weighting technical change gives an annual average rate of technical change of 1.03 per cent compared to an unweighted average annual fall in productivity (which is called technical regress) of -0.8 per cent on farms in the bottom size quintile (less than 22 hectares). 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 respectively) while cattle and sheep farms experienced technical regress over the same period. In the latter farm systems direct payments comprise a high proportion of total farm income and it is possible that this result is due to the conditions attached to these payments. Weighting the results showed that cattle farms experienced an annual rate of technical progress of 0.5 per cent over the period. While weighting the results for sheep farms indicated technical regress at a rate of 0.02 per cent.

The causes of these differences in technical change growth rates deserve more extensive investigation, but it is interesting to speculate on the possible contribution of the changes in CAP support mechanisms 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). It is at least plausible that the more recent CAP regulations have acted to the detriment of efficiency and efficiency improvement in Irish agriculture.[20] 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. The role of direct payments is investigated further in the next chapter.

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[20] *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.*

CHAPTER 4
DOES CONTACT WITH THE EXTENSION SERVICE IMPROVE FARM EFFICIENCY?

4.1. BACKGROUND

Chapter 3 discussed in detail the various techniques available to measure technical efficiency and technical change using panel data for Ireland. The purpose of this chapter is to extend the analysis beyond the measurement of technical efficiency towards explaining the level of efficiency. The motivation behind this analysis is to assess whether contact with the agricultural extension service has any impact on farm-level technical efficiency. The role of the extension service is changing as a result of the changed policy environment for agriculture following the European Union (EU) agricultural policy reforms in 1992 (the MacSharry reform) and 2000 (the Agenda 2000 reform). Over half of household income from farming is now in the form of direct payment support financed by the EU's Common Agricultural Policy. The analysis explores whether this increased dependence on direct payments has any implications for farm-level efficiency and for the role of the extension service. Section 4.1.1 discusses a range of issues that have been raised in the general literature evaluating the impact of agricultural extension. These include the conceptualisation of the role of extension, the importance of controlling for possible selection bias and some of the data problems which arise when measuring extension contact. The current operation of the public extension service in Ireland is also briefly reviewed. Section 4.2 discusses the methodology used to estimate the frontier production function and the methods available to explain technical efficiency. Section 4.3 pays particular

attention to the correction for endogeneity of the extension variable. The model estimated is presented in Section 4.4. Section 4.5 outlines the data set used in the production function and concentrates on the criteria used for the selection of variables in the efficiency models. The limitations of the data set are also discussed. Section 4.6 presents the empirical results of the analysis and Section 4.7 details some policy conclusions.

4.1.1. Assessing the impact of agricultural extension

It is generally accepted that extension effects should be estimated in a framework resembling a simulated experiment (Jarmin, 1999; Evenson, 1992). Because few such experiments are available, the approach commonly used is a statistical analysis relying on data measuring extension activities at the farm or regional level. The maintained hypothesis is that extension has a positive effect on farm efficiency. The frontier production function approach assumes that the potential scope for a pay-off on investment in public sector extension depends on the effective gap between current and potential farm efficiency, given the existing "best technology" and "best management" for farms in a particular region. Given a frontier production function at a point in time and evidence that higher levels of technical efficiency (TE) are associated with greater levels of extension contact, the higher output due to higher levels of TE can be interpreted as the pay-off to extension.

A second issue in extension-impact studies is to control for possible estimation bias due to the self-selection of sample farmers. Typically, researchers treat extension contact as an exogenous variable, but if

the more productive farmers are more aware of the value of extension advice, and are more likely to seek out extension contact, then estimates of extension impact are positively biased. Alternatively, it is possible that extension workers themselves might seek out contact with the more productive farmers because of greater job satisfaction or because it is easier to see results. It is also possible that the mandate of the extension service might be specifically to work with the more disadvantaged farmers (particularly if advisory services are privately financed and used by more commercially-minded farmers), in which case the sample-selection bias would be negative. Another possible source of negative bias in estimates of extension impact is indirect or secondary information flows, in which farmers with direct extension contact pass knowledge directly to non-contact farmers, thus reducing the size of the observed efficiency gap between contact and non-contact farmers (Evenson, 1992).

A third problem in extension-impact studies concerns the measurement of extension input. Three issues arise here. First, the assumption that the primary motivation of public extension agents is to improve technical efficiency may not be correct. Extension workers may have other goals such as community development or helping with grant payments, which are not necessarily captured by increases in technical efficiency. In this case it could be argued that the extension service is improving allocative rather than technical efficiency. Second, the meaning of extension contact can differ greatly from farm to farm, varying from a single telephone call during the year to an intensive series of farm visits. Third, farmers may have a choice between public and private extension advisers or consultants. It is important to be

clear whether it is the total impact of advisory services to farmers or just the impact of the public extension service that is being measured.

This chapter examines the impact of the Irish public agricultural extension service at a time of extensive changes in the agricultural policy environment. The main function of the extension service is to maximise the income of farm families. Traditionally, this was achieved by improving output and efficiency, through the use of the most appropriate and up-to-date technology. The reform of the EU's Common Agricultural Policy, which regulates the support provided to Irish farmers, has since 1993, led to a much greater role for direct payments in farm income support, together with the imposition of ceilings on the quantities of production eligible for support.

Direct payments contributed 56 per cent of aggregate income from Irish farming in 1998 and, for particular enterprises, their importance is even greater. For example, direct payments amounted to 124 per cent of family farm income in the cattle rearing farm system, 128 per cent of family farm income in mainly sheep systems and 83 per cent of family farm income in mainly tillage farm systems (Matthews, 2000). For these farms, meeting the complex eligibility conditions for direct payments has a greater impact on income than lowering production costs. For example, payments to livestock farmers are limited by stocking density criteria and higher payments are made to farmers who practice more extensive farming systems. As a result, it may be rational for the farmer to be technically inefficient if the inefficient operation of the farm leads to higher direct payments and, thus, higher family farm income. Maximising income, within production

constraints, both from direct payments and from more efficient farming is now a central theme of extension programmes (Murphy, 1998).

4.1.2. The Irish Extension Service

Public agricultural extension in Ireland dates back to 1823 and, by the 1970s, an extensive network of trained advisers, organised at a county level in all the major farm systems, was in place. The service was centralised in a new organisation ACOT in the 1980s with funding provided by the central government. Cuts in government expenditure resulted in reductions in the number of advisers and the introduction of charging for services. In 1988, extension, education and research services for farmers were brought together in a single organisation called Teagasc, the Agricultural and Food Development Authority. The number of advisers continued to shrink and extension methods focused more on mass media and group techniques. There has been a rise in the number of private agricultural consultants primarily assisting farmer with the qualifying conditions for EU subsidies. This would seem to suggest that the private consultants are helping farmers to improve their allocative efficiency rather than with improving technical efficiency.

In 1994, the extension service was restructured into three units. The Farm Tech Service aimed to raise the competitiveness of commercial farming through encouraging the use of up-to-date technology. The Farm Viability Service provided advice to improve the viability of small-scale farmers through reducing production costs, optimising income from EU direct payments and encouraging participation in a new Rural

Environment Protection Scheme. A third arm provided a Rural Enterprise Service that was focused on area-based community development initiatives and the establishment of alternative farm enterprises and rural businesses. The delivery of advice to farmers is provided through an annual contract for which the client pays a fee. The level of the fee depends on the category of the client (Farm Tech or Viability) and the level of contract the client wishes to pay for. The basic contract entitles a farmer to telephone and 'short office' consultations, access to the adviser for technical information and basic assistance with applications for direct payment schemes. Farmers can pay extra for one or two farm visits, to participate in discussion groups or for longer office consultations. In 1997, Teagasc estimated that approximately 78 per cent of the target client group of commercial farmers (18,000 farmers out of 23,000) had significant contact with the extension service, of which 15,500 were contracted clients. Of the 122,000 farmers targeted for the viability service, over 45,000 (37 per cent) had significant contact with the extension service and 22,000 were contracted clients. Despite the differences in contact numbers, extension time was equally divided (about 45 per cent each) between the two services, with the balance accounted for by the Rural Enterprise and Forestry services (Murphy, 1998). These figures indicate that the extension service is reaching its target client group of commercial farms but is having less success with poorer farms.

This background highlights two factors that are taken into account in the subsequent analysis. First, the contact of farmers with the extension service is not random and the possibility of selection bias needs to be taken into account. Second, it is hypothesised that the role

of the extension service on farms, where direct payments are a more significant source of income, is likely to be different from that on the more commercial farms (in Ireland, these are mainly dairy farms) where direct payments play a less important role. This hypothesis is explicitly tested in the empirical analysis.

4.2. METHODOLOGY

A stochastic frontier approach is used to measure the technical efficiency of a panel of Irish farms over the period 1995 to 1998 and the level of efficiency is explained using a number of explanatory variables. The choice of functional form and estimation of the stochastic frontier has been presented in detail in the preceding chapter. The emphasis here is on the methodological developments which aim to explain the level of efficiency by incorporating the influence of external variables, such as education level of the farm operator, the age of the farm operator and contact with the extension service into the model. Section 4.2.1 details with the alternative models available to explain technical efficiency. At this stage all the external variables in the z vector are assumed to be exogenous variables. Section 4.3 examines the efficiency models when one of the variables is assumed to be endogenous, the specification of the model estimated is presented section 4.4 and the data used in the analysis are discussed in the final section.

4.2.1. Explaining Farm Level Efficiency

Deprins and Simar (1989) and Kumbhakar and Lovell (2000) stress the importance of incorporating external variables correctly into either the frontier production function or the efficiency model. In other words, the researcher must decide whether external variables are in fact

influencing the structure of the frontier production function relative to the way in which efficiency is measured or the level of technical efficiency itself. Consider a production function with a vector of external variables z_i which are assumed to be exogenous to the model. Incorporating z_i into the standard stochastic frontier production function gives

$$\ln y_{it} = \ln(x_{it}, z_{it}, \beta) + \upsilon_{it} - u_{it} \qquad 4\text{-}1$$

where y_{it} is output of the *ith* farm in time period t. x is a vector of the standard input variables and z is a vector of external exogenous variables, v_{it} is random noise and u_{it} is the variable associated with technical efficiency. $v_{it} \sim \text{iid } N(0, \sigma_v^2)$. If the variables included in z influence the structure of the frontier production function then they should be included in the frontier production function as in equation 4-1. The exogenous variables influence performance, (that is, the ability to get the maximum output for a given set of inputs); however, the improvement is not due to gains in efficiency but rather through influencing the structure of the production technology that describes the relationship between the inputs and output. If the exogenous variables are left out of the frontier production function, this will show up as a lower level of technical efficiency. In most cases the decision to specify a variable as a determinant of efficiency rather than a characteristic of the production technology comes down to the researchers *a priori* belief, all the same, inclusion of the variable should be defendable statistically (Kumbhakar and Lovell, 2000).

4.2.2. Two Stage Approaches

Early work on explaining technical efficiency was carried extensively by Kalirajan (1981, 1982, 1989) and involved obtaining the technical

efficiency scores from the stochastic frontier models and carrying out a second stage regression, usually OLS, in which the estimated technical efficiency scores are regressed on the explanatory variables. This approach assumes that the exogenous variables do not influence the frontier production function structure but impact output indirectly through their impact on efficiency. A proliferation of agricultural studies explaining technical efficiency were carried out using the two stage methods (see Capalbo and Antle, 1988 and Kumbkahar and Lovell, 2000 for details). The majority of these studies have been carried out using data from developing countries. The results for the analysis, while not directly comparable to Irish agriculture, do provide a priori reasons for the selection for variables in the Irish model.

There are two statistical caveats to the two-stage method which has lead to the rejection of this approach by most empirical researchers. The most frequently cited difficulty is that in the stochastic frontier estimation the efficiency effects are assumed to be independently and identically distributed but in the second stage the efficiency scores are defined as a function of the farm specific effects thus violating the assumption that the efficiency effects are identically distributed (Battese et al. 1995). Kumbhakar and Lovell (2000) note two further problems with the two-stage approach in explaining technical efficiency. The two-stage approach hinges on the assumption that the x_i variables and the z_i variables are correlated since if they are not then the model has no explanatory power. If a maximum likelihood approach is followed and it is assumed that the x_i and z_i are correlated and z_i is excluded from the MLE estimation then the MLE estimates of the β coefficients and error variance terms are biased. The final

criticism of the two-stage approach is perhaps more fundamental than the other two discussed since it involves the choice of the appropriate estimation technique. Many of the early studies have applied OLS estimation techniques to the second stage regression, however, the dependent variable, technical efficiency, is bounded by zero and one implying that a limited dependent variable model is more appropriate for the second stage regression.

4.2.3. Single Stage Approaches

Pitt and Lee (1981) recognised that the two stage approach was not adequate. They proposed either including the exogenous variables in the frontier production function and jointly estimating the parameters or regressing the farm intercepts on the exogenous variables. Howeever, Deprins and Simar (1989) and Deprins (1989) were the first to address the problems of the two stage approach by offering a single stage approach which overcame the omitted variables and independence problems, albeit in a deterministic framework. The later work by Deprins and Simar (1989) and Deprins (1989) improved on the work of Pitt and Lee (1981). The frontier production function is defined as

$$\ln y_i = \ln(x;\beta) - u_i \qquad 4\text{-}2$$

and the relationship between the efficiency effects and the z_i's as

$$E(u_i|z_i) = exp\,\gamma'(z_i) \qquad 4\text{-}3$$

where β and γ are the parameters to be estimated, $u \geq 0$ is technical inefficiency and $exp(\gamma' z_i)$ expresses the relationship between the efficiency effects and the vector of z_i explanatory variables. Inserting 4-3 into 4-2 and adding a random noise variable gives the single stage model

$$\ln y_{it} = \ln(x_{it} : \beta) - \exp(\gamma' z_i) + \varepsilon_i \qquad 4\text{-}4$$

where ε_i is assumed to have a zero mean and a constant variance. The ε_i do not have to be identically distributed as they depend on z_i. This model can be estimated using MLE or nonlinear least squares. The performance of the farm is calculated as

$$\exp(\varepsilon_i) = \frac{y_i}{f(x_i;\beta)}.\exp(\exp\{\gamma' Z_i\}) \qquad 4\text{-}5$$

where $\frac{y_i}{f(x_i;\beta)}$ is an estimate of technical efficiency and $\exp(\exp\{\gamma' z_i\})$ is the term which adjusts efficiency for the influence of the exogenous variables.

Kumbhakar et al. (1991), Reifschneider and Stevenson (1991), Battese and Coelli (1993, 1995) and Huang and Liu (1994) build on the work by Pitt and Lee (1984) and Deprins (1989) in different ways but all addressed the need for an error term to capture the effects of statistical noise. Kumbhakar et al. (1991) proposed a single stage model given by

$$\ln y_i = \ln(x_i : \beta) + \upsilon_i - u_i \qquad 4\text{-}6$$

where υ_i is identically and independently distributed with a zero mean and a constant variance u_i is the one-sided error term representing technical inefficiency. u_i has two parts, the first $\gamma' z_i$ is a systematic component associated the exogenous variables associated with technical efficiency and an error term to capture white noise as given in equation 4-7

$$u_i = \gamma' z_i + \varepsilon_o \qquad 4\text{-}7$$

Kumbhakar et al. (1991) simplify the estimation of the model by imposing distributional assumptions on u_i and υ_i

[$u_i \sim$ iid $N^+(\gamma' z_i, \sigma_u^2)$ and ($\upsilon_i \sim iid\ N(0, \sigma_\upsilon^2)$ respectively] and assuming that u_i and υ_i are distributed independently of each other but ε_i is not assigned a distributional form. The inefficiency effect must be greater than or equal to zero, that is $u_i \geq 0$, and in turn this requires that $\varepsilon_i \geq \gamma' z_i$. This model can be estimated by MLE. The log likelihood function is a generalisation of the truncated normal model where the term u_i is replaced with the term $\gamma_i z_i$ in the log likelihood function.

Reifschneider and Stevenson (1991) test and reject the hypothesis that the inclusion of the inefficiency function does not change the estimates of the frontier production function parameters. They suggest a model to capture the inefficiency effects as the sum of a non-negative function of the exogenous variables and a non-negative random variable with either a gamma, half normal or exponential distribution. They simplify the estimation of the model by assigning a one sided distribution for the random noise term. According to Kumbhakar and Lovell this simplification comes at a cost. Reifschneider and Stevenson define the production function as

$$\ln y_{it} = \ln(x_{it} : \beta) + \upsilon_i - u_i \qquad 4\text{-}8$$

and the efficiency function as

$$u_i = g(z_i ; \gamma)_i + \varepsilon_i \qquad 4\text{-}9$$

Inserting the efficiency function into the frontier production function gives

$$\ln y_{it} = \ln(x_{it} : \beta) - g(Z_i ; \gamma) \qquad 4\text{-}10$$

The conditions that $g(z_i;\gamma) \geq 0$ and $\varepsilon_i \sim iid\ N^+(0, \sigma^2)$ are sufficient but not necessary for the $u_i \geq 0$. If $\varepsilon_i \geq 0$ which implies that $u_i \geq g(z_i;\gamma)$ and the

inefficiency is at least as great as the minimum possible inefficiency achievable in an environment characterized by the exogenous z variables then the function $g(z_i;\gamma)$ in equation 4-9 can be interpreted as a deterministic inefficiency relationship (Kumbhakar and Lovell, 2000). Hence the Reifschneider and Stevenson (1991) model is the reverse of the Deprins and Simar (1989a,b) model which specified a deterministic frontier production function model with a stochastic inefficiency relationship. The deterministic nature of the inefficiency function is the main draw back of the Reifschneider and Stevenson approach to explaining technical efficiency.

Huang and Liu (1994) have taken the inclusion of exogenous variables in the frontier production function a step further by including interaction terms between the z_i's and the x_i's. Their model is defined for a cross section only as

$$\ln y_i = \ln(x_i : \beta) + \upsilon_i - [g(z_i;\gamma;x_i) - \varepsilon_i] \qquad 4\text{-}11$$

where $u_i = [g(z_i;\gamma;x_i) - \varepsilon_i]$. To ensure that u_i is greater than or equal to zero, ε_i is assumed to be normally distributed with a zero mode and variance σ_ε^2 is truncated from below at a variable truncation point $[-g(z_i;\gamma)]$. The truncation allows ε_i to be less than zero but ensures that u_i is greater than or equal to zero. The result of this in a non-neutral stochastic frontier where the marginal rates of technical substitution and the marginal products of inputs are functions of the farm specific factors.

Battese and Coelli (1992, 1995) proposed a model similar to Huang and Liu (1994) for use with panel data. The stochastic frontier production function is defined as

$$\ln y_{it} = \ln(x_{it} : \beta) + \upsilon_{it} \cdot \qquad 4\text{-}12$$

and the inefficiency equation is given as

$$u_{it} = g(z_{it}; \gamma) + \varepsilon_{it} \qquad 4\text{-}13$$

where ε_{it} is defined by the truncation of the normal distribution with zero mean and variance such that the point of truncation is $-\gamma z_{it}$. The distributional assumption on ε_{it} is consistent with the distributional assumption on u_{it}, namely that $u_{it} \sim N^{+}(\gamma' Z, \sigma_u^2)$. The model does not require that the inefficiency effects are identically distributed but they are assumed to be independently distributed such that u_{it} is obtained by truncation at zero of the normal distribution with mean $z_{it}\gamma$ and variance σ_υ^2. Technical efficiency for the *ith* farmer in the *tth* period is defined as

$$TE_{it} = \exp(-u_{it}) = (-z_{it}\gamma - \varepsilon_{it}) \qquad 4\text{-}14$$

Although alternative approaches to the Battese and Coelli (1993) model have been proposed by Simar, Lovell and Vanden Eeckaut (1994) and Caudill, Ford and Gropper (1995), the Battese and Coelli (1995) model remains the approach of choice in many empirical applications especially in agricultural studies. It is also the approach of choice for the analysis of the relationship between technical efficiency and contact with the extension service presented here. The Battese and Coelli (1995) model allow the mode and the variance of the truncated normal distribution to vary since they are functions of the exogenous variables and this overcomes the violation of the identically distributed assumption. In addition it works well for unbalanced panel data and it

has the additional benefit of allowing the ordering of farms to vary in terms of technical efficiency in each time period which is another improvement on earlier stochastic frontier models. The parameters of the models in the following sections are estimated by the maximum-likelihood method using the program, FRONTIER 4.1.

4.3. ACCOUNTING FOR THE ENDOGENEITY OF FARMER-EXTENSION INTERACTION

In the analysis above it was assumed that all the factors in the z_i were exogenous. Consider the following stochastic frontier production function

$$\ln y_{it} = \ln(x_{it} : \beta) + \upsilon_{it} - u_{it} \qquad 4\text{-}15$$

and technical efficiency equation

$$u_{it} = \delta_0 + \sum_{j=1}^{J} \delta_{ij} z_{ijt} + \chi_{it} c_{it} + \varepsilon_{it} \qquad 4\text{-}16$$

where u_i is efficiency, the z_i's are the farm-specific exogenous variables, to be defined in Section 3.4.4, and c is the contact with the extension service dummy variable taking a value of one if the farmer has contact with the extension service and a value of zero otherwise, and the ε_{it} is the random error. Equation 4-15 assumes that all the farm-specific variables are exogenous. However, contact with the advisory service may be endogenous, in that farmers who are more efficient may seek out contact with the extension service, or the extension service may be working with less-advantaged farmers.

4.3.1. Endogeneity and Ordinary Least Squares Estimation

If estimating equation 4-16 using farm level estimates of technical efficiency u_{it}'s obtained MLE estimation of the frontier production function first and in a separate estimation the factors effecting efficiency are regressed on the u_{it}'s usually using OLS then once the

explanatory variables are exogenous then parameter estimates are statistically sound notwithstanding the comments made in section 4.2.2. This approach to explaining technical efficiency is frequently used in agricultural applications and it is statistically sound. The crucial point is that all the explanatory variables are *exogenous*. However, using OLS in the presence of an endogenous variable on the right-hand side ensures contemporaneous, non-vanishing correlations between the error term and the explanatory variables, even as the sample size tends to infinity (Judge et al. 1988).

Endogeneity can be corrected for using either two-stage least squares or an instrumental variable approach, though there has been little work done in this area in agricultural productivity studies. Work on technical efficiency and extension, undertaken by Bindlish and Evenson (1997) for cross-sectional data and updated for a panel study by Gautam and Anderson (1999), addressed the endogeneity problem using an instrumental-variables approach. While the two-stage approach presents a straightforward route to solving the endogeneity problem, the method has some serious statistical problems outlined in section 4.2.1 which place doubt on the appropriateness of the approach.

4.3.2. Endogeneity and Maximum Likelihood Estimation

In general maximum likelihood estimation can, under appropriate distributional assumptions, provide consistent estimators in the presence of an endogenous variable, despite the fact that its empirical use is hampered by computational complexities such as local maxima and multi-dimensional integrals (Vella and Verbeek, 1998; Alvarez and

Glasgow, 1999). However, the interpretation of the endogeneity problem is not as clear cut when using a single MLE technique such as the Battese and Coelli (1995) approach. Although equation 4-15 and 4-16 are estimated simultaneously by MLE, both are separate functions which should be correctly specified. In section 4.2.1 the importance of whether or not an exogenous variable should appear in the production function or the technical efficiency model was discussed. This point has particular relevance when placed in the context of assessing the impact of extension contact on farm performance. It can be argued that extension contact not only influences farm-level efficiency but also impacts on the structure of the production function. The decision to include a variable in the production function or the efficiency relationship is a judgement call and it was decided that the variable for contact with the extension service should be in the technical efficiency model. In the same way the decision to define a variable in the efficiency equation as endogenous or exogenous is also a judgement call. The *a priori* belief is that the extension contact variable is endogenous, that is, the level of efficiency can be explained by contact with the extension service as in equation 4-16 but it is also possible that contact with the extension service is determined by the efficiency level of the farm resulting in a contact equation as defined by

$$c_{it} = f(u_{it}; \varpi) \qquad 4\text{-}17$$

where c is contact with the extension service, u_{it} is efficiency and ϖ is the parameter to be estimated. To include the extension variable in the efficiency equation with the knowledge that it is endogenous without

controlling for this endogeneity will lead to misspecification of the model and will give rise to spurious results.

4.3.3. Formal Testing for Endogeneity

The use of formal tests for endogeneity have been primarily concerned with least squares estimation. The reliability of these tests in the context of the Battese and Coelli (1995) ML technique is questionable. In an attempt to show empirically that the *a priori* belief that extension is endogenous is correct, a Durbin-Wu-Hausman test was undertaken using estimates from the two stage approach. The test is formed by including the residuals of the endogenous variable, as a function of all exogenous variables, in a regression of equation 4-16. If the co-efficient on the residual variable is significantly different to zero then OLS is not consistent and the variable is endogenous (Davidson and MacKinnon, 1993, Card and Vella, 1994). The P value for the residual variable was 0.0092 suggesting that the variable is indeed endogenous. While it is clear that appropriate estimation technique for the single stage approach is MLE and not OLS the hypothesis that extension contact is endogenous needed to reinforced beyond an *a priori* belief. In an attempt to do this, a comparison of the results of the Battese and Coelli (1995) single-stage efficiency model and the two-stage approach (which involves the estimation of technical efficiency in the first step and regresses the z_i's on the efficiency estimates in the second stage using OLS) was undertaken. Similar coefficient estimates in both were found. This result is not surprising since the single-stage Battese and Coelli (1995) model specifies efficiency to be a linear function of the explanatory variables as in the two-stage approach albeit that the estimation techniques are different.

4.3.4. Possible Solutions

The ideal solution to the endogeneity problem is to replace the offending variable with another variable (an instrument) that is highly correlated with the endogenous variable but not correlated with the error term. The number of farms per county and the number of farms per advisory centre were identified as possible instruments. Each instrument was included as the contact variable, in turn. In both cases, however, neither variables appeared to be significant. Using either of these variables directly as instruments in the presence of a poor correlation between the instruments and the endogenous variable could lead to serious biased estimates (Davidson and MacKinnon 1993; Klepinger et al., 1995). Nelson and Startz (1990a, 1990b) have shown that when the correlation between a single instrument and a single regressor is low the IV estimate of the coefficients on the regressor may appear to be highly significant when the true coefficient is in fact zero. For this reason both variables were rejected as direct instruments but since the two variables are not related to efficiency but are related to contact with the extension service, albeit weakly, they can be used to generate a proxy variable.

To create a proxy, a modified instrumental-variables approach is used. The approach requires that the set of all exogenous variables in the equation of interest, equation 4-15 and at least one other exogenous variable are regressed on the endogenous extension contact variable. Two exogenous variables are included in the model even though only one is required for the system to be identified. The rationale for the inclusion of an extra exogenous variable comes from Klepinger et al.

(1995), who suggest that when possible the set of instruments should be expanded beyond the number required to improve the quality of the resulting proxy. The contact equation is given by

$$c_{it} = \beta_0 + \sum_{j=1}^{J} \beta_j z_{ijt} + \sum_{k=1}^{2} \pi_k w_k + \varepsilon_{it} \qquad 4\text{-}18$$

where c_{it} is the endogenous dummy variable equal to one if the farm has contact and zero otherwise. w represents two exogenous variables unique to the contact equation which are highly correlated with endogenous contact variable but not correlated with efficiency. The variables chosen are the number of farms per county and the number of farms per extension centre. Since the endogenous contact variable is a dichotomous variable and not continuous, a probit model was used in the first stage to obtain an instrument for the extension variable. If least squares was applied to a dichotomous variable, the estimated β-coefficients will be consistent but the error term has a highly non-normal distribution and suffers from heteroscedasticity resulting in inconsistent standard errors (Verbeek, 1999; Robinson, 1985). The probit model is defined as

$$P_i = \int_{-\infty}^{v} \frac{1}{\sqrt{2\Pi}} \exp\left(-\frac{1}{2}\tau^2\right) d\tau \qquad 4\text{-}19$$

where P_i is the probability of a visit from the extension service, Pr(c=1) and τ is a standardised normal variable. The likelihood function for the probit is given by

$$\ln L = \sum_{y=1} \ln \Phi(x_i;\beta) + \sum_{y=1} \ln(1 - \Phi(x_i;\beta)) \qquad 4\text{-}20$$

where $\Phi(.)$ is the cumulative standard normal distribution function (Greene, 1993). The predicted values of the dependent variable are a linear combination of the exogenous variables and these are used as a proxy for the endogenous variable. The endogenous variable is

replaced in the right-hand side of the original equation by the proxy. The proxy is also used instead of the contact variable to create the interaction terms in the efficiency equation (Koutsoyiannis, 1977).

In theory the correction for endogeneity using a proxy variable created in the method above does solve the problem of endogeneity and it does produce estimates of the endogenous variable that are consistent. In practice the proxy can be a poor instrument if there is a weak relationship between the proxy variable and the endogenous variable. This results in large standard errors and the possibility of inconsistencies in the proxy parameter estimate. Furthermore, Bound et al. (1995) demonstrate that in finite samples IV estimates are biased in the same direction as the OLS estimates, with the magnitude of the bias approaching that of OLS as the R^2 between the instruments and the endogenous explanatory variable approaches zero. The alternatives to IV type approaches when the resulting proxy is a poor instrument is to either exclude the endogenous variable from the technical efficiency equation or to assume the contact variable is exogenous. These solutions lead to omitted variable bias or misspecification of the model respectively (Alvarez, 1999; Bound et al. 1995; Davidson and MacKinnon, 1993).

4.4. MODEL SPECIFICATION

A translog production function with neutral technical change is given by equation 4-21 below

$$\ln(y_{it}) = \alpha + \sum_k \beta_k \ln x_{kit} + .5\sum\sum \beta_{kj} \ln x_{kit} \ln x_{jit} + \varsigma T + \xi T^2 + \sum_j \theta_j S_{jit} + \upsilon_{it} - u_{it}$$

where y_{it} is output for farm i in period t, x_{kit} is the k^{th} input of farm i in period t, T and T^2 are time and time squared respectively, S denotes farm system and α, β_k, β_{kj}, ζ ,θ and ξ are parameters to be estimated. Time and time squared are included to account for Hicks neutral technical change. Because of the existence of the milk-quota system, which prevents farmers from entering or increasing dairy production, a series of dummy variables are included to allow the intercept term in the frontier production function to vary by farm system. S_{jit} is the dummy variable for the j^{th} farm system in year t, which has value one if the observation for the i^{th} farm in year t is for the j^{th} farm system, and zero otherwise. This has the effect of defining a separate frontier for each farm system so that efficiency is measured relative to the best practice within a system. The v_{it}s are random errors that are assumed to be identically and independently distributed N(0, σ_v^2), and to be independently distributed of the u_{it}s; the u_{it}s are non-negative time-variant technical inefficiency effects which are defined in equation 4-13 and discussed in detail in Section 4.2.1.

4.5. 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 530 farms in the years, 1995 through 1998, representing farms that participated in the survey at any time throughout the period. Farms were in the sample for, on average, 2.9 years. Outliers were identified using the methods of Hadi (1992, 1994) and excluded from the sample. The removal of outliers and the matching of data gave a final sample

size of 1556 observations. The subsequent sections discuss the selection of variables and the matching of data.

4.5.1. Production Data

Most Irish farms are multi-product enterprises producing a combination of dairy cattle, beef cattle, tillage, horses, sheep, pigs or other outputs. To limit the number of variables in the models it was necessary to aggregate outputs and some of the inputs. This aggregation was carried out using implicit quantity indices as discussed in Chapter 3.

The production function is specified using a single output comprised of the enterprise outputs excluding subsidies and four inputs, land, labour, capital and variable inputs. Implicit quantity indices for output and variable inputs were obtained as the ratio of a multilateral Tornqvist value index (based on the value of outputs and inputs) to an aggregate price index with base period, 1996. Since individual farm prices are not available, national prices, taken from the CSO, are used.

The same method is used for the aggregation of variable inputs. Variable inputs include feed, fertilisers, electricity, veterinary fees, and transport costs. The land input is measured by the adjusted size of farm in hectares. Because the bulk of Irish farmland is operated by owner-occupiers, a series on the rental value of farmland is not available. The adjustment here is the conversion of rough grazing to pasture equivalent and does not take account of differences in soil quality among farms. Such differences could therefore show up as differences in technical efficiency among farms. The labour input is

measured as the number of labour units used, including family labour, casual and hired labour on the farm. The capital input is measured as the stock of machinery, land improvements, livestock and buildings, with the individual components summed using the implicit quantity method.

4.5.2. Construction of the Extension Variable

Data on extension contact is not routinely collected in the NFS. However, in the period being considered, information on extension contact was collected in response to two different questions. In 1996, farmers were asked whether they had contact or not with the extension service in the previous twelve months. In 1997 and 1998, farmers were asked what were their expenditures on extension services. It was assumed that a positive response to the 1996 question meant that the farmer had contact in 1995 and appropriate values for 1996 were interpolated using a set of plausible rules. If the farmer had contact in 1995, 1997 and 1998, then contact was assumed to have occurred in 1996. For other farms the missing value was not replaced as it was not possible to make a judgment on the missing data. In these cases, the data for the year with the missing data were dropped. Similarly, if the farmer had no contact in 1995, 1997 and 1998, then no contact was assumed to have occurred in 1996. For other farms the missing value was not replaced as it was not possible to make a judgment on the missing data. In these cases, the data for the year with the missing data were dropped. The extension variable was constructed by converting positive expenditure on public extension services in 1997 and 1998 to a dummy variable with value one, and zero otherwise. The rationale for this approach is twofold. First, a sliding scale based on

gross margin is used to calculate charges for state extension services so using expenditure levels could give a misleading indication of the amount of contact. Second, it was possible to combine the data with the dummy variables representing extension contact collected in 1996 thus allowing the use of data over four years rather than just two. Lagged terms to account for the impact of extension in the year after the contact are not included for two reasons. The process of lagging the variable with a short series and unbalanced panel data set would have resulted in the loss of observations and auxiliary regressions found the lagged variables to be insignificant in explaining technical efficiency.

4.5.3. Other Variable Selection Issues

Data on the education level of the farm operator is not routinely collected by the NFS An additional survey, carried out in 1999, asked a question on the education level of the farm operator. When these data were matched with the NFS data for the 1995-1998 period the sample size was reduced significantly. The original data set consisted of 2987 observations, but 1230 observations were excluded due to difficulties in the matching of the education and extension data. This reduction in sample size may affect the representativeness of the sample so the models were run with and without the education variable to ascertain if education was important in explaining efficiency and if the model with the larger sample size and education excluded suffered from omitted variable bias. The results suggested that excluding education did lead to an omitted variable bias and this result coincided with the findings of other extension studies (see Huffman, 2000; Philips and Marble, 1986; and Lockheed et al. 1980). Given the importance of education in models that seek to explain extension contact and

efficiency it was decided to accept the loss of data rather than run the risk of excluding a vital variable.

The NFS also contains data on the expenditure of farmers on private consultants. The definition of a private consultant covers a broad range of services such as accountant fees and private agricultural consultants. Although these data were available for the final two years of the sample, they were excluded as it was not possible to determine if the payment was for extension related activities. Nevertheless preliminary analysis using the final two years of data was carried out to check the relationship between private consultants and the public extension service. There was no statistically significant relationship found between the private and public extension variables nor was private extension found to be significant in explaining technical efficiency. These results suggest that although it is desirable to include data on private consultants, there is little evidence that an omitted variable bias is occurring.

4.5.4. Variables Used in the Technical Efficiency Model

The following variables are used to explain technical efficiency differences across farms:

z_1 denotes the age of the farmer;

z_2 denotes the square of the age of the farmer;

z_3 denotes the regional dummy variable that has value 0 for farms located in the West of Ireland, and 1 otherwise;

z_4 denotes the share of direct payments in the gross margin;

z_5 denotes the household size;

z_6 is a dummy variable that has value 1 for farms between 24 and 36 hectares, 0 otherwise;

z_7 is a dummy variable that has value 1 for farms between 37 and 58 hectares, 0 otherwise;

z_8 is a dummy variable that has value 1 for farms greater than 58 hectares, 0 otherwise;

z_9 is a dummy variable that has value 1 for farmers educated to Junior Certificate (approximately up to age 15), 0 otherwise;

z_{10} is a dummy variable that has value 1 for farmers educated to Leaving Certificate or above (approximately up to age 18), 0 otherwise;

z_{11} is a dummy variable that has value 1 if the farm operator has an off-farm job, and 0 otherwise;

z_{12} is the ratio of debt to total farm assets;

z_{13} is a dummy variable that has value 1 if the farm operator had contact with the extension service, and 0 otherwise;

z_{14} is a dummy variable that has value 1 if the farm has over two thirds of its gross margin coming from direct payments and is in contact with the extension service, and 0 otherwise;

z_{15} is a dummy variable that has value 1 if the farm has less than one third of its gross margin coming from direct payments and is in contact with the extension service;

z_{16} is a dummy variable that has value 1 if the farmer has education to Leaving Certificate or above and is in contact with the extension service, and 0 otherwise; and

z_{17} is the variable for time of observation.

Technical efficiency is measured on a scale from 0 to 1, such that higher values represent higher levels of technical efficiency. An

efficiency score of 1 implies that the farm is perfectly efficient. The converse is also true, that is technical inefficiency is also measured on a scale of 0 to 1 with a value of 0 implying the farm is perfectly efficient. The following coefficient signs are hypothesised. There is no a priori expectation on the sign of the coefficients for age. It is possible that older farmers have more experience and therefore are more efficient managers, but it is also possible that older farmers are less concerned with optimising the use of resources under their control. Age squares is included to allow for a non-linearity regarding age to be introduced into the model. The squared terms are included to reflect the fact that, after some point, the year-by-year impacts of increasing age begin to decrease. The sign on the co-efficient on age squared indicates whether or not the impact of age is occurring at an increasing or decreasing rate.

Farms with large households are expected to be more efficient because of the pressure and incentive to achieve a minimum living standard, so a positive coefficient is expected. 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 with a high debt ratio are expected to be more efficient as they need to ensure that the debt can be repaid, so a positive coefficient is hypothesised. Economies of scale may be significant on larger farms and thus the signs on the coefficients for the farm-size variables are hypothesised to be positive.

A negative relationship between efficiency and the share of direct payments in gross margin is expected, as incentives to maximise direct payments may be in conflict with the goal of achieving high levels of technical efficiency. The signs on the education variables are expected to be positive, that is, the better educated the farm operator the more efficient the farm. It is hypothesised that contact with the extension service increases efficiency, so a positive coefficient is expected.

Two sets of interaction variables are included in the model specification. Farmers, who have contact with the extension service but are highly dependent on direct payments, are likely to be less efficient than the omitted group with a medium dependence on direct payments, since it is thought that the farm adviser is not advising on methods to improve efficiency but on maximising farm income with direct payments. Hence, a negative coefficient is hypothesised. The converse is expected for farms that are not dependent on direct payments. In this case, it is hypothesised that contact with the extension service improved efficiency, so a positive coefficient is expected. The sign of the interaction variable between education and extension contact is expected to be positive, suggesting that there are more benefits from extension contact if the farm operator is better educated. The correlation between education and off-farm employment was found to be 0.103 and so no interaction term was included for education and off-farm employment.

To control for differences in regional and farming system characteristics, a number of additional dummy variables are included in the model. Farms located in the West of Ireland face a geographical

disadvantage, due to poorer land quality, and an economic disadvantage, due to rural decline and elderly population. Therefore it is expected that the sign on the region variable should be positive, that is farms located in the West are less efficient. A time trend is included in the model to capture changes in the policy environment over time.

The aggregation method used is detailed in Chapter 3. The summary statistics of the variables in the models are shown in Table 4-1.The ratio of the standard deviation to the mean in Table 4-1 is reported rather than the standard deviation since it allows for comparisons between variables.

All the data have been logged and mean corrected prior to estimation of the frontier production function so that the first-order partial derivatives can be interpreted as elasticities of mean output with respect to the inputs involved, evaluated at mean values.

Table 4-1: Summary Statistics of Variables

Variable	Mean	Std/Mean	Minimum	Maximum
Gross output (€)	63870.84	1.33	4841.24	437918.8
Capital (€)	18003.52	1.28	692.15	135332.4
Variable inputs (€)	30071.06	1.44	2548	210220.5
Size of farm (ha)	58.35	1.21	10.79	646.08
Total number of livestock units	67.95	0.66	0	345.29
Total number of labour units	1.48	0.46	0.69	6.25
Gross Margin per hectare	613.99	0.58	13.89	1800.19
Age of farmer	50	0.22	25	74
Debt to Assets Ratio	0.16	1.45	0	2.16
Direct Payments to Gross Margin	0.38	0.66	0	1.89

4.5.5. Data Limitations

The analysis undertaken in this chapter focuses on technical efficiency. Given the amount of subsidies in Irish agriculture it would seem sensible to examine the role of the extension service in improving the farmers allocative efficiency. However, to measure allocative efficiency requires farm level prices which are not available. It would also be helpful if data on the use of private extension agents was available since it would then be possible to look at the complementarity and substitutability of private and public extension services. The final limitation with respect to extension contact is related to lack of data on the intensity of extension service usage. The decision to model a translog frontier production function for all farms rather than for each farm system was also influenced by the data available. As discussed in chapter 1 most Irish farms are multi-output enterprises and although disaggregated data were available on the output side they were not available on the input side. Estimating separate frontiers for each farm system would have required that assumptions be made about the allocation of inputs between enterprises since very few Irish farms are single enterprise operations.

4.6. EMPIRICAL RESULTS

The results of the uncorrected model and the model corrected for endogeneity are compared in this section. Estimating the model with and without the correction for endogeneity of farmer-extension interaction made almost no difference to the production function parameters. However, important changes were found between the two models in the relative weight and importance of the variables explaining technical efficiency.

4.6.1. Specification Tests

The stochastic model was subjected to a number of statistical tests to find the preferred model for Irish agriculture. The adequacy of the Cobb-Douglas specification was tested using a generalised likelihood-ratio test. The null hypothesis, H_0: $\beta_{ij}=0$, $i \leq j = 1, \ldots, 5$, was strongly rejected. The null hypothesis that there is no technical change, $\zeta_t=\xi_t=0$, was tested and rejected. Finally, the null hypothesis that there are no technical inefficiency effects, $\gamma=0$, is strongly rejected. The estimate for γ is 0.9701 with estimated standard error 0.0034, indicating that the model is significantly different from the deterministic frontier. Given these results, the translog specification with neutral technical change is the preferred model of Irish agricultural technology given the alternative specifications considered.

4.6.1.1. Monotonicity and Convexity

Monotonicity was evaluated at each data point and at the point of approximation. At the point of approximation (the mean) the marginal products for each input are greater than zero and the diminishing marginal productivities are confirmed for each input at the mean. Monotonicity was also checked at each data point. Table 4-2 shows the percentage of data points violating the monotonicity condition.

Table 4-2: Percentage of Data Points Violating the Monotonicity Condition

Input	Corrected Model	Uncorrected Model
Land	2.57	2.12
Labour	4.88	3.64
Capital	6.28	7.25
Variable Inputs	0.00	0.00

The curvature condition was confirmed by examining the definiteness of the bordered Hessian matrix of first and second order partial derivatives of the translog production function. If the function is concave, which implies that the isoquants are convex, then the bordered Hessian matrix will be negative definite. The bordered Hessian matrices for the corrected and uncorrected models evaluated at the mean are given in Table 4-3 and Table 4-4 respectively.

Table 4-3: Hessian Matrix of the First and Second Order Partial Derivatives averaged over Time and Farms (Corrected Model)

		f_{jV}	f_{jLab}	f_{jC}	f_{jL}
	0	0.18045	0.18048	0.69283	0.03110
f_{Vj}	0.18045	**-0.20923**	0.10175	0.01469	0.01212
f_{Labj}	0.18048	0.10175	**-0.0021**	-0.03510	0.11837
f_{Cj}	0.69283	0.01469	-0.03510	**-0.90351**	0.07844
f_{Lj}	0.03110	0.01212	0.11837	0.07844	**-0.24005**

j denotes inputs; f = derivative; v = variable inputs; lab = labour; C = capital; L= land.

Table 4-4: Hessian Matrix of the First and Second Order Partial Derivatives Averaged over Time and Farms (Uncorrected Model)

		f_{jV}	f_{jLab}	f_{jC}	f_{jL}
	0	0.18260	0.17255	0.65915	0.04023
f_{Vj}	0.18259	**-0.21734**	0.11120	0.13421	0.00409
f_{Labj}	0.17255	0.11120	**-0.13360**	-0.01831	0.11075
f_{Cj}	0.65915	0.13421	-0.01831	**-0.27356**	0.00544
f_{Lj}	0.04023	0.00409	0.11075	0.00544	**-0.17224**

j denotes inputs; f = derivative; v = variable inputs; lab = labour; C = capital; L= land.

The diagonal elements of the Hessian matrices are negative at the point of approximation (the mean) in both the corrected and uncorrected models as required for the convexity condition. The curvature condition for negative definiteness requires that the principle minors of the bordered Hessian of the first and second order condition are alternative in sign.

Table 4-5 shows that the principal minors are alternating in sign in both the corrected and uncorrected model. The convexity restriction did not hold for 20.3% per cent of data points, but since it does hold at the mean it is possible to assume that there are well-behaved regions large enough to ensure the translog function is a good representation of the data.

Table 4-5: The Expected and Actual Values for the Principal Minors of the Bordered Hessian

	Expected Sign on the Principle Minors of the Bordered Hessian	Corrected Model Results	Uncorrected Model Results
$\lvert\overline{H}_4\rvert$	Positive	0.000246	0.001612
$\lvert\overline{H}_3\rvert$	Negative	-0.00496	-0.01776
$\lvert\overline{H}_2\rvert$	Positive	0.01351	0.017933
$\lvert\overline{H}_1\rvert$	Negative	-0.03257	-0.03334

4.6.1.2. Parameters of the Production Function

Since the data have been mean corrected prior to estimation of the frontier production function the first-order partial derivatives can be interpreted as elasticities of mean output with respect to the input involved. The elasticities for the preferred corrected model are land (0.180), labour (0.180), capital (0.031) and variable inputs (0.693). The estimate for the returns to scale at the mean input values is estimated to be 1.084.[21] Estimates of the annual percentage change in output resulting from technical change are provided by the first order derivative of equation 4-21 with respect to time. The positive sign on time and the negative sign on time squared indicates that technical change increases until it reaches a maximum at 1.6 years after which it decreases. In other words, productivity increases at a *decreasing* rate after the second year. As expected all farm systems have a lower

[21] *In the corrected model, the corresponding value is 1.054*

intercept term relative to dairy farms. This result suggests that the intercept term is allowing the efficiency of the farm to be measured relative to the best practice within the system. In other words, dairy farms are in general more efficient than sheep farms, so the efficiency of sheep farms should be measured relative to sheep farms and not dairy farms. A second method to correct for farm system effects is to estimate a separate frontier for each farm system. Preliminary results found no marked difference in the parameter estimates for single system production functions than the aggregate model discussed. As discussed in chapter 1 a single frontier is preferred given the multi-output nature of agriculture.

4.6.2. The Probit Model

The results of the probit model used to generate the instrument for the corrected model are interesting in their own right and are presented in Table 4.6.

Table 4-6: Results of the Probit Model Used to Generate the Proxy for Extension

Y=contact	Coeff-icient	Std. Error	z	P>|z|	95% Confidence Interval	
Age	-0.02	0.0191	-1.047	0.295	-0.0573	0.0174
Age squared	0.0002	0.0002	1.052	0.293	-0.0002	0.0006
Household total	-0.0079	0.0175	-0.452	0.651	-0.0422	0.0264
Direct Payments	0.127	0.1963	0.647	0.518	-0.2577	0.5118
Junior Certificate	0.1679	0.0793	2.118	0.034	0.0125	0.3233
Leaving Certificate	0.1289	0.1071	1.204	0.229	-0.081	0.3387
Off farm job	-0.0359	0.0943	-0.381	0.703	-0.2207	0.1489
Dairy Other	-0.1182	0.1108	-1.067	0.286	-0.3353	0.0989
Cattle	-0.6904	0.1298	-5.321	0	-0.9447	-0.4361
Sheep	-0.4245	0.146	-2.907	0.004	-0.7107	-0.1383
Tillage	0.0212	0.1506	0.141	0.888	-0.2739	0.3163
24 to 36 ha	0.6817	0.0945	7.216	0	0.4966	0.8669
36 to 60 ha	0.5995	0.098	6.115	0	0.4073	0.7916
60+ ha	0.9129	0.1076	8.487	0	0.7021	1.1238
Farms per extension	0.004	0.0091	0.437	0.662	-0.0138	0.0218
Farms per county	-140.59	137.92	-1.019	0.308	-410.93	129.746
Constant	0.328	0.4906	0.669	0.504	-0.6336	1.2896
chi2(16)	216.54	*Log Likelihood*	-964.49			
Prob > chi2	0	*Pseudo R^2*	0.1009			

Contact with the extension service was regressed on the exogenous variables in the efficiency model, as well as farm system and two variables that explain contact with the extension service but not farm efficiency. The number of extension centres per county and the number of farms per extension centre in each county are measures of the ease of access to extension services. Being involved in farming on a part-time basis and being in cattle or sheep systems of farming are all negatively related to the probability of having contact with the extension service. The higher the share of direct payments in gross margin increased the probability of contact as did being in the size

category 24 to 36 hectares. Having Junior Certificate education relative to primary education increased the probability of having contact with the extension service, although having Leaving Certificate education relative to primary education was not found to be significant. The higher the number of extension centres in a county increased the probability of contact with the extension service while the higher the number of farmers per extension centre per county reduced the probability of contact. Neither variable were statistically significant in explaining technical efficiency.

The R^2 on probit models tend to be lower than OLS (Verbeek, 2000). The pseudo R^2 for the probit was 0.1009 suggesting that the model has little explanatory power. The low R^2 suggests that the proxy variable is not a good instrument, that is, the goodness of fit is low and so caution is warranted when making inference about the variable replaced by the proxy (Bound et al. 1995). Following the suggestions of Klepinger et al. (1995) a number of other possible instruments were included in the probit equation and the R^2 did improve significantly to 0.4 when county dummies, to try and capture the heterogeneity at county level, were added to the model. The impact of the extra variables on the resulting proxy were not significantly different to the model with no county dummies. When an instrument is not a good proxy there are two options available to the researcher. The level of bias due to the presence of an endogenous variable is accepted or the proxy is used, the quality of the instrument is noted, and the bias is due to a weak instrument is accepted. Either way any inference about the endogenous variable and any policy recommendations made

concerning the variable are issued with some caution (Connelly, 1998; Bound et al. 1995).

4.6.3. Efficiency Measures

Recall that, as the level of efficiency is derived for a model that explicitly recognises the role of farm systems, all efficiency scores are relative to the best practice within a system rather than the best practice overall in the agricultural sector. Average technical efficiency over the period is 0.65. Other work by O'Neill et al. (1999) using similar data over a longer time period found mean technical efficiency estimates ranging from 0.66 to 0.75 depending on the precise specification of the stochastic frontier. This analysis showed that calculating efficiency levels relative to best practice in the sector as a whole reduced the average efficiency score by around 6 percentage points.

4.6.3.1. The Uncorrected Model

The importance of the explanatory factors is first considered using the uncorrected model. The results of both the corrected and uncorrected models are presented in Table 4-7. The age coefficients in the uncorrected model indicate that the minimum value is attained at about age 49 years which is also the average age for the sample. Hence, the relationship between efficiency and age is initially positive and then negative.

Table 4-7:Production Function

	Uncorrected Model			Corrected Model		
	Coefficient	*SE*	*t-ratio*	*Coefficient*	*SE*	*t-ratio*
Constant	0.733	0.054	13.653	0.705	0.050	14.070
Variable inputs	0.659	0.025	26.682	0.693	0.025	28.165
Labour	0.173	0.034	5.017	0.181	0.034	5.359
Capital	0.040	0.014	2.788	0.031	0.014	2.270
Land	0.183	0.026	7.154	0.181	0.024	7.577
Variable inputs^2	0.026	0.042	0.629	0.039	0.042	0.931
Labour^2	0.260	0.078	3.323	0.308	0.079	3.892
Capital^2	0.108	0.059	1.839	0.057	0.056	1.020
Land^2	0.060	0.019	3.224	0.062	0.020	3.178
Vari*Lab	-0.020	0.066	-0.311	-0.040	0.063	-0.638
Var *Cap	0.002	0.041	0.057	0.032	0.039	0.819
Variable inputs*Land	-0.099	0.029	-3.360	-0.109	0.029	-3.806
Labour*Cap	-0.140	0.059	-2.366	-0.149	0.060	-2.478
Labour*Land	0.076	0.039	1.918	0.070	0.038	1.815
Capital*Land	-0.002	0.027	-0.060	0.005	0.027	0.179
Dairy Other	-0.161	0.024	-6.807	-0.167	0.023	-7.340
Cattle	-0.826	0.030	-27.440	-0.603	0.036	-16.742
Tillage	-0.188	0.037	-5.137	-0.197	0.038	-5.194
Sheep	-0.698	0.038	-18.329	-0.622	0.036	-17.392
Time	0.148	0.043	3.482	0.136	0.042	3.239
Time Squared	-0.048	0.017	-2.871	-0.042	0.017	-2.540
Sigma-squared	0.970	0.066	14.618	0.842	0.054	15.526
Gamma	0.974	0.003	310.577	0.970	0.003	287.260

a denotes significance at 1% level; *b* denotes significance at a 5% level and *c* denotes significance at a 10% level

None of the farm size categories were found to be significant in explaining efficiency. The sign of the region variable is as expected indicating that farms located in the West of Ireland are less efficient than farms located in the Eastern part of the country. This factor is probably picking up differences in average soil quality in the two regions as the land variable in the production function is not adjusted for quality. A high debt to asset ratio is positively related to efficiency, as is completing education to Junior Certificate and Leaving Certificate

level relative to completing primary school. Neither household size nor having an off-farm job were found to significantly influence efficiency. The variable for contact with the advisory service is positively associated with technical efficiency and statistically significant at the 1 per cent level. The coefficient of the interaction term for contact and education was found not to be significantly different from zero, suggesting that education level had no effect in influencing the strength of the extension impact. The share of direct payments in gross margin is negatively related to efficiency as expected. Where farms have a low dependency on direct payments (relative to the average level), contact with the extension service is positively related to efficiency. However, farms that are highly dependent on direct payments and have contact with the extension service are less technically efficient than farms with an average level of dependency. Finally, the sign and significance of the time variable suggests that efficiency increases over time.

4.6.3.2. The Corrected Model

The results of the estimated model correcting for endogeneity of farmer extension contact are given in Table 4-7. This discussion looks at the impact of the factors explaining technical efficiency, once endogeneity of farmer-extension contact has been corrected for. Age is initially positively related to efficiency until age 49 years after which age is negatively related to efficiency. The debt ratio continues to have a positive effect on efficiency while location in the West of Ireland and a high dependence on direct payments are negatively related to efficiency. Farm size is now strongly related to efficiency, indicating perhaps that larger farms are under less pressure to optimise the use

of the resources that they control. The size of the coefficient on the contact variable increases by more than twenty times and becomes highly significant. This suggests that when endogeneity of extension contact is not taken into account there is a downward selection bias in the results of the uncorrected model, implying that the extension service is more likely to have contact with relatively inefficient farmers than would be expected on a purely random basis. This may reflect the policy of subsidising access to the extension service for non-commercial farmers as well as the significant resources devoted to the Farm Viability Scheme geared towards these farmers. In the corrected model the education level of the farmers no longer influences their levels of efficiency. Similarly, education does not influence the magnitude of extension impact on technical efficiency as the coefficient of the interaction term is not significantly different from zero. The corrected model also confirms that the impact of extension is different on farms with very low dependence on direct payments than those with very high dependence. The coefficient on the time variable indicates, as in the uncorrected model, that average efficiency improved over the period investigated.

These results may be compared with the findings from other studies of farm-level technical efficiency. Andreakos et al. (1997) found age and education level statistically significant in explaining technical efficiency in a panel analysis of Greek livestock farms. Contact with the extension service and higher education levels were important in explaining technical efficiency in Parikh and Shah's (1994) study of farms in Pakistan. Extension was found to be positively related to technical efficiency in studies by Seyoum et al. (1996), Kalirajan (1991)

and Philips and Marble (1986). However, endogeneity of extension contact by farmers was not corrected for in the latter three studies.

4.6.4. Marginal Effects

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 for each of the efficiency variables. The marginal effects are reported in Table 4-8.

Table 4-8: Marginal Effects of a Unit Change in Each Factor (%) on Efficiency Uncorrected Model

Explanatory Variable	Percentage Change in Efficiency
Age of farm operator (one year increase)	0.00
Farm is located in the West of Ireland (relative to farms in the East)	- 0.72[a]
Share of direct payments in gross margin (one percentage point change in the ratio)	- 2.72[a]
Household size (one additional person)	0.04[c]
Size of farm 25-36ha	0.12
Size of farm 36-60ha	-0.187[c]
Size of farm 60+ha	- 0.21[c]
Debt ratio to assets (one unit change the ratio)	1.58[a]
Farm operator has an off farm job (relative to no job)	- 0.15
Education level of farm operator to Junior Cert. (relative to primary only)	0.29[c]
Education level of farm operator to Leaving Cert (relative to primary only)	0.48
High dependency on direct payments and contact with the advisory service (relative to the medium dependency farms)	- 1.16[a]
Low dependency on direct payments and contact with the advisory service (relative to the medium dependency farms)	3.30[a]
Interaction of education level and contact with the advisory service (relative to primary education and contact)	0.09
Contact with the farm advisory service (relative to no contact)	0.25[a]
Time	0.15[a]

a denotes significance at 1% level; *b* denotes significance at a 5% level and *c* denotes significance at a 10% level

The marginal effects were evaluated at the mean and can be interpreted as elasticities. Dummy variables and were evaluated at zero rather than at the mean and the marginal effect is interpreted as a

one off change in efficiency rather than a unit change. The partial differentials of the efficiency predictor with respect to each of the efficiency were calculated to generate the statistical significance. As with technical efficiency the marginal effects in the uncorrected and corrected model are different, due to the correction for endogeneity and possibly some error resulting from the proxy variable for extension contact. Contact with the farm advisory service increases efficiency by a one off 0.25 percent in the uncorrected model. The results for the corrected model are given in Table 4-9.

Table 4-9:Marginal Effects of a Unit Change in Each Factor (%) on Efficiency Corrected Model

Explanatory Variable	Percentage Change in Efficiency
Age of farm operator (one year increase)	0.00004
Farm is located in the West of Ireland (relative to farms in the East)	- 0.69[a]
Share of direct payments in gross margin (one percentage point change in the ratio)	- 3.98[a]
Household size (one additional person)	0.04[c]
Size of farm 25-36ha	- 1.35[a]
Size of farm 36-60ha	- 1.54[a]
Size of farm 60+ha	- 2.22[a]
Debt ratio to assets (one unit change the ratio)	0.04
Farm operator has an off farm job (relative to no job)	1.11[a]
Education level of farm operator to Junior Cert. (relative to primary only)	- 0.16[c]
Education level of farm operator to Leaving Cert (relative to primary only)	0.52
High dependency on direct payments and contact with the advisory service (relative to the medium dependency farms)	- 1.90[a]
Low dependency on direct payments and contact with the advisory service (relative to the medium dependency farms)	6.56[a]
Interaction of education level and contact with the advisory service (relative to primary education and contact)	- 0.87
Contact with the farm advisory service (relative to no contact)	6.47[a]
Time	0.11[a]

Being located in the West of Ireland is associated with an average decrease in efficiency of less than 1 per cent. Larger farm size is associated with a steady decrease in efficiency. Though statistically significant the effects are not quantitatively important. Relative to

farms less than 25 hectares in size, the very largest farms of 60+ ha are approximately 2 per cent less efficient in their use of resources. The effect of both junior and leaving certificate education level relative to primary education does not have a statistically significant impact on the efficiency level. Receiving direct payments has a negative impact on efficiency; farms with a share of direct payments 25 percentage points greater than average are, on average, 1 per cent less efficient. Contact with the extension service increases efficiency by 6.5 per cent relative to farms with no contact. This is a one off increase. Since the extension contact variable covers contact with Teagasc advisors only, it is possible that non-contact farms may have contact with private consultants. This suggests that the impact of advisory contact per se may be greater than reported here. The interaction between the level of education and extension contact is found to be statistically insignificant. Farms in contact with the extension service and with a lower than average dependency on direct payments increased efficiency by a further 6.6 per cent. Farms that are highly dependent on direct payments and have contact with the extension service are 1.9 per cent less efficient than farms with an average dependence on direct payments. Nonetheless, even this group of farms are, on average, more efficient that those farms which had no extension contact whatsoever.

4.7. CONCLUSIONS

This Chapter reports on analysis to ascertain whether levels of technical efficiency on farms are influenced by contact with the extension service, using a panel of Irish farms. An examination of the literature highlighted the failure in some previous work to take into account the possible selectivity bias of farmers who have contact with

the extension service. A review of the operation of the Irish extension service indicates the potential for selectivity bias in that a significant proportion of its resources are specifically geared to tackling the problems of farm viability on smaller scale farms and the cost of using the extension service is subsidised for these farmers. In addition, it is important to take into account the changed EU policy environment for agriculture where maximising farm income is as much, or more, a matter of claiming eligibility for direct payments rather than improving production efficiency and where it may be rational for a farmer to accept a lower level of technical efficiency if this helps to meet the conditions required to receive direct payments.

The paper derives technical efficiency effects for individual farms by estimating a Battese and Coelli (1995) stochastic frontier production function model and explains these effects using a variety of farm-specific variables, including extension contact and dependence on direct payments. A modified instrumental-variables approach is used to overcome the potential selectivity bias in farmer-extension contact. The probability of contact with the extension service is estimated using a probit model. The probability of contact is found to be significantly negatively influenced if the farm operator had an off-farm job and was involved in low-margin cattle and sheep farming, and positively influenced by a high dependence on direct payments in farm income, by education and by ease of access to extension advisers as measured by the density of extension coverage in each county. When this probability of extension contact was included in the regression explaining technical efficiency effects rather than actual extension contact, the estimated impact of extension contact on farm level

efficiency jumped more than twenty times and became even more statistically significant. Extension contact is estimated to increase technical efficiency by 6.5 per cent when selectivity bias is taken into account. This is evidence for the hypothesis that the Irish extension service is more likely to have contact with relatively inefficient farmers who impart a downward bias to the direct measurement of the contact-inefficiency relationship.

Other factors found to be significant in explaining efficiency include farm size (which is negatively related to efficiency), a high debt burden and the farmer's age both of which are positively related to efficiency. A marked negative relationship between dependence on direct payments and efficiency was also found. Direct payments have been introduced unevenly in EU agricultural policy. Significant direct payments are made to cattle, sheep and cereal producers but support to dairy farmers continues to be provided entirely through market price support. However, because efficiency is measured relative to best practice within that system, the dependence on the direct payments variable is not simply picking up the possibility that some farming systems make more efficient use of resources than others. Rather, it appears to reflect the fact that eligibility for payments may require a farmer to deliberately pursue less efficient production practices (such as extensification, or feeding animals over the winter period in order to qualify for a deseasonalisation premium). To the extent that these production practices confer non-priced environmental benefits reflects a measurement error in the specification of the output variable in the production function. However, in Ireland it is likely that the environmental benefits arising from direct payment schemes are

relatively small so ignoring them is not likely to lead to a misleading interpretation.

The changing role of the extension service in a situation where direct payments now make up the majority of income for a majority of farmers was also explored. Relative to farms with an average level of direct payment receipts, the impact of the extension service on efficiency was to increase efficiency by a further 6.5 per cent on farms with a low dependence on direct payments. These are the more commercial farms who are using the extension service for productivity-oriented advice. On the other hand, extension contact on farms with a very high dependence on direct payments was associated with a decrease in technical efficiency of almost 2 per cent relative to farms with an average dependence on direct payments. It is most likely that these farms are using the extension service mainly for assistance in applying for grant aid, and that where assistance is sought, measured technical efficiency decreases.

These findings have important policy implications, although that they shall be viewed with some caution due to the issues raised in section 4.6.2. The positive association between dependence on direct payments and farm technical inefficiency suggests that reform of the EU agricultural policy is encouraging a less competitive agricultural sector and one which will find it more difficult to face up to the more market-oriented policy regime which may result from WTO negotiations on agricultural trade liberalisation. In assessing the overall benefits to Ireland from the operation of the EU's Common Agricultural Policy, it would be important to offset the negative effect on agricultural

productivity of the direct payments regime against the value of the inflow of funds into Ireland arising from the EU financing of direct payment supports. Indeed, it may be that a high dependence on direct payments not only raises inefficiency but also slows down the take-up of technical innovations and thus the rate of technical change over time, although this hypothesis has not been explored in this paper.

The negative association between extension contact and technical efficiency, especially on the more commercial farms, suggests that there is a high pay-off to extension advice on these farms. While a benefit-cost ratio to public extension expenditure is not attempted in this paper, the fact that over three-quarters of all eligible commercial farmers have signed up to participate in the commercially-oriented Farm Tech Service offered by the extension service suggests that this advice is valued. On the other hand, it is clear that many farmers now rely on the extension service for advice and assistance in applying for direct payment supports. Technical efficiency on farms with a high dependence on direct payments that have extension contact is even higher than on farms with an average dependence on direct payments with extension contact. Nevertheless, even on the former group of farms a comparison of the sizes of the marginal effects suggests that their overall efficiency is still higher compared to farms without any extension contact. This suggests that even where the primary purpose of extension contact is assistance with grant payments there is a positive productivity benefit from this contact.

CHAPTER 5
A COMPARISON OF SEA AND DEA MALMQUIST TOTAL FACTOR PRODUCTIVITY INDICIES FOR IRISH MILK PRODUCING FARMS

5.1. INTRODUCTION

The first two essays in Chapters 3 and 4 focused on econometric methods for the estimation of technical change and efficiency. The aim of this chapter is to compare Stochastic Frontier Analysis (SFA) to Data Envelopment Analysis (DEA) in the measurement of total factor productivity (TFP). Both approaches will generate estimates of efficiency and technical change. SFA draws on microeconometric techniques and involves the imposition of a number of restrictive assumptions regarding the structure of the technology. DEA employs linear programming methods which exploit the data fully without the need for the restrictive assumptions required for econometric frontier analysis. Both methods are used to construct distance functions which are then used to construct a Malmquist TFP index. The distance function approach is taken as it allows for multi-output and multi-input production technologies and does not require behavioural assumptions of profit maximisation or cost minimisation. Furthermore, unlike Tornqvist and Fisher TFP indices, price data are not required to construct the Malmquist index. One aim of this work is to evaluate the robustness of the SFA results by using another approach with different assumptions, albeit restrictive ones.

The analysis is carried out using farm level data on Irish milk producing farms for the period 1984 to 1998. In Chapters 3 and 4 it was clear that at the micro level milk producing farms were on average more efficient than other farm systems and had higher rates of technical progress. At a macroeconomic level the Irish dairy sector is important not only to the agricultural sector, but to the economy as a whole. Ireland is more than self sufficient in milk products and produces large surpluses for export. The share of dairy products in total agricultural exports has been rising steadily at a time when agricultural exports as a share of total exports has been declining. In 1998 dairy products accounted for 20 per cent of total agricultural exports and were worth €1,311.9 million to the Irish economy. The dairy sector provides significant farming and non farming employment. There are approximately 40,000 dairy farmers,7,500 people are employed directly in the dairy food industry and many others are employed in the distribution and retailing of dairy products. Keane (1995) estimated that over 5 per cent of the total employed in Ireland are working in the dairy industry.

This Chapter begins with an overview of Irish dairy farming and the policy environment in which it operates. Next, the distance function is introduced and the development of the Malmquist TFP index is discussed. The data used in the analysis and the method of variable aggregation are outlined. A single output, multi-input model is defined and estimated using SFA and DEA and the results of the models are compared. Finally some policy recommendations are made.

5.1.1. Irish Milk Producing Farms

Milk producing farms can be divided into two main groups. A farm is called a specialist dairy farm if over 70 per cent of its standardised gross margin is obtained through milk production. Farms that combine milk production with another enterprise, usually cattle rearing, are classified as a 'dairy and other' farm. Milk can also be produced on a smaller commercial basis on farms not classified as either specialist dairy or dairy and other. Specialist dairy farms are considered to be more efficient and more technically progressive than other farm systems and this is confirmed by the microeconomic analysis presented in the previous two chapters. Some 65 per cent of specialist dairy farms and 38 per cent of dairying and other have a gross margin per hectare of €984 or above compared to 26 per cent for tillage farms and 12 per cent for cattle farms. Family farm income is on average higher than other farm systems and higher than the average industrial wage McCarthy (2000). Income per family labour unit is presented in Table 5-1.

Table 5-1: Income per Family Farm Labour Unit (Specialist Dairy Farms) 1999

Family Farm Income per Labour Unit	Lowest Third	Middle Third	Top Third
Income per Labour Unit (€)	4,170	13,375	37,050
Yield per Cow (gallons)	834	994	1,102
Number of Cows per Farm	21	37	59
Farm Size (ha)	22	36	49

It is clear that there is considerable variation in income per labour unit depending on the number of cows, farm size and yield per cow. Nevertheless 95 per cent of dairy farms are considered to be demographically viable (NFS, 1998).[22] The average age of a dairy farm

[22] *Percentage of farm households which have at least one member below 45 years of age.*

operator is lower than the national average age for the agricultural sector as a whole. There is also a higher percentage of spouses with off farm jobs on dairy farms.

5.1.2. The Policy Environment

The dairy market is highly regulated with both supply control measures and market support in operation. Supply controls are implemented through the quota system which was introduced in 1984 in response to growing milk surpluses and the accelerating cost of subsidising agriculture. The aim of the quota system was to reduce the volume of milk produced while maintaining farm incomes through price supports. Each member state was allocated a reference quantity and this was then distributed to milk producers. At the time there was widespread fear that the quota system would create a massive bureaucracy, stifle milk production and reduce innovation. However, the alternative to quotas was a reduction in support prices paid to farmers leading to reductions in incomes, which was politically unacceptable. The quota system has been adjusted and modified considerably since its introduction but the policy objective remains the same as it did in 1984. Ireland's milk production quota is currently 1,118.5 million gallons which is distributed among just over 40,000 quota holders. Milk produced above the quota allocation results in the payment of fines called milk *super levies*. There have been considerable changes in the number of quotas holders and the quantity of quota held since the introduction of the quota system in 1984.[23] The number of quota holders has fallen by 20 per cent since 1988 and there has

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[23] *Although the quota system was introduced in 1984 reliable figures on the number of quota holders and the size of quota held were not available until 1988.*

been a marked decline in the number of small quota holders. Of the 50,000 quota holders in 1988, 65 per cent held a quota of less than 20,000 gallons compared to 46 percent in 1997. The reduction in the number of quota holders is primarily due to the exit of quota holders with less than 20,000 gallons. The changes in quota holder numbers occurred as farms were permitted to leave out quota and the restrictions tying land to quota was relaxed.

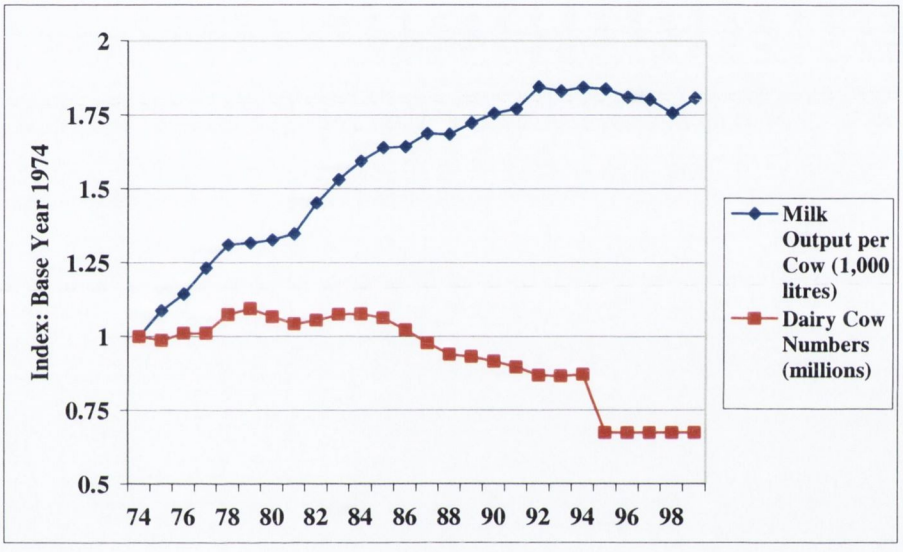


Figure 5-1:Index of Dairy Cows Numbers and Milk Output per Cow in Ireland 1974 to 1999

Quotas have been tied to land but they can be leased either on a long term basis with land or on a temporary basis without land. Many small quota holders lease out their quota. In 1997 almost 8 per cent of quota holders leased their quota with land and a further 13 percent availed of the temporary quota scheme and leased quota without land. The ability to lease and buy quota not tied to land has contributed to the concentration of quota held by large producers. For example, in 1997, 17 percent of the quota was held by 46 per cent of quota holders and

22 per cent by 6 per cent of quota holders. The number of dairy cows decreased steadily since the introduction of the quota period. At the same time milk output per cow has risen although there has been a levelling of this increase since 1992 (Fingleton, 1995). The trends in milk output per cow and dairy cow numbers are shown in Figure 5-1. Donnellan (2001) points out that the decline in dairy cow numbers was greater than the cut in milk production required under the quota. It is the case that the quota system is indeed reducing the volume of milk produced. *Ex ante* increased yields per cow are expected due to improvements in feed and herd quality, however, there has been a stagnation of yields which is counter intuitive even under the constrained output requirements of the quota regime.[24]

Even with the quota system there exists excess supply of milk on the EU market requiring price support and trade levies. The price support mechanism works at three levels. The *target price* is a notional price which EU policy makers expect farmers to receive for milk products in the following year. The target price is primarily used to set the super levy payments but historically the market price for milk has tracked the target price. Usually excess supply of milk products, such as butter and skimmed milk powder, end up in intervention stores. Intervention gives the option to sell excess supply of milk products at a reduced rate known as the *intervention price*. The intervention price acts as a minimum product price at the wholesale level for milk products. In theory, intervention stock should be sold once the market price had recovered. In practice, intervention has resulted in the accumulation of large stocks of products leading policy makers to

[24] *Donnellan points out that this could be due to unreliable statistics.*

encourage exports. Export refunds compensate farmers for the lower world price relative to the EU internal price making the export of excess supply attractive to producers. Since EU prices for milk products are greater than world prices a *minimum import price* exists to prevent displacement by non-EU imported products.

The CAP has certainly improved the standard of living for agricultural communities by supporting incomes. However, the increase in living standards has occurred at a cost. In addition to the cost to the taxpayer of the CAP, the support price mechanism has lead to the perverse situation whereby inefficient farms are financially better off when staying in production rather than leaving the industry. The more efficient farms continue to intensify production leading to large surpluses in many agricultural products but, perhaps more worrying , is the damage to the environment.

The 1993 MacSharry reforms represented the first major attempt to overhaul the CAP and these were followed by the Agenda 2000 CAP reforms. The primary reason for CAP reform has been budgetary in nature. Nevertheless the EU has attempted to rectify the environmental effects of the CAP through the introduction of environmental schemes and through cross compliance eligibility criteria for payments. The Agenda 2000 Berlin Agreement reforms will reduce the level of price support to dairy farms but will not impact on the dairy sector until 2005. Donnellan (2001) argues that the reduction of milk price support will be offset by introduction of direct payments and the increased quota allocations, leaving the value of the milk sector unchanged.

The secondary reason for reform has arisen because the EU has signed up to the Agreement on Agriculture in the Uruguay Round of world trade negotiations. The WTO Agreement on Agriculture has established a number of trade liberalisation measures which stipulate the amount and type of government intervention on agricultural markets. As these trade liberalisation measures are introduced the EU agricultural sector will find itself competing on the open market. Although the major trade liberalisation measures are yet to impact fully, commentators recognise that the agricultural sector must prepare to be more competitive if it is to survive on the open market. The ability of the agricultural sector to thrive under trade liberalisation is made more urgent as the Central and East European Countries (CEEC) prepare to join the EU.

Teagasc and the Department of Agriculture, Food and Rural Development are attempting to encourage the dairy sector to improve its efficiency and performance. One aspect of this is to allow free trade in quotas. Although the UK, Sweden and Denmark are all moving towards a free market system for the trading of quotas, Ireland is moving more slowly. The Minster of Agriculture has encouraged the freeing up of the market for quota by allowing the sale of quota without land. Furthermore, recent changes to the quota scheme have been targeted towards increasing the size of quota on farms under 55,000 gallons and encouraging young farmers with under 35,000 gallons to remain in production. Labour has become scarce as young men leave the farm to work elsewhere for higher wages. Teagasc's chief dairy advisor Dermot McCarthy has suggested that intensification of dairy

production is required. Dairy farms need to increase their scale of operation by a third and become more efficient if their incomes are to be maintained. In addition McCarthy asserts *"to get best labour and economic efficiency and improvement in working conditions, we should encourage amalgamation of small units through partnerships to bring production unit quota size up towards 80,000 to 100,000 gallons"* (McCarthy, 2000).

To ensure that policy is formulated in the optimal way, accurate information of technical change and technical efficiency in the dairy sector is presented. The analysis presented in this chapter is intended to contribute to this goal. The use of DEA and SFA will ensure that any difference in the results of the two methods are highlighted. Furthermore, it also allows the robustness of the results on technical change and efficiency to be compared to those found in chapter 3 for dairy farms. The next section of this chapter presents the theory underlying the estimation of TFP using Malmquist distance functions.

5.2. METHODOLOGY

The Malmquist distance function was first presented in a consumer context by Sten Malmquist (1953) and in a producer context by Shephard (1953).[25] However, it was not until Shephard's 1970s work *Theory of Cost and Production Functions* that the distance function became popular in production theory primarily due to its duality with the cost function. Caves, Christensen and Diewert (1982) produced what is considered to be a seminal paper where they introduced the Malmquist Total Factor Productivity index, based on the Malmquist

[25]*Debreu (1951) formulated the distance function two years before Malmquist or Shepard. However, Debreu did not develop the duality relationships which underpin the empirical application of distance functions (Russell, 1998).*

distance function. Early applications of the Malmquist TFP index were undertaken by Nishimizu and Page (1982) using parametric estimation, and by Pittman (1983) and Färe, Grosskopf, Lindgren and Roos (1989) using linear programming. The latter work is important as it recognized that the distance function was the reciprocal of Farrell's (1947) measure of technical efficiency and that it was possible to decompose the Malmquist index into changes in efficiency and changes in frontier technology over time.

5.2.1. Distance Functions

The notion of distance functions is crucial to the construction of Malmquist TFP indices. A distance function allows the measurement of multi-input and multi-output production technologies without the need to impose behavioural assumptions and can be specified relative to input vectors or output vectors. An input distance function characterises the production technology by looking at a minimal proportional contraction of the input vector, given an output vector.[26] Let

$$S^t = \left\{\left(x^t, y^t\right): x^t \text{ can produce } y^t\right\} \qquad 5\text{-}1$$

define the technology set S for time period t where S^t is assumed to model the transformation of inputs $x^t \in \Re_+^N$ into output $y^t \in \Re_+^M$. The input distance function, which involves the scaling of the input vector (by ρ), is defined on the set $L(y)$

$$D_I^t(y,x) = inf\left\{\rho : \left(\rho x^t\right) \in L(y)\right\} \qquad 5\text{-}2$$

where *inf* is the lower bound, the input set $L(y)$ a subset of S^t represents the set of all input vectors x, which can produce the output vector y.

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[26] *This section draws on work by Fare and Grosskopf (2000).*

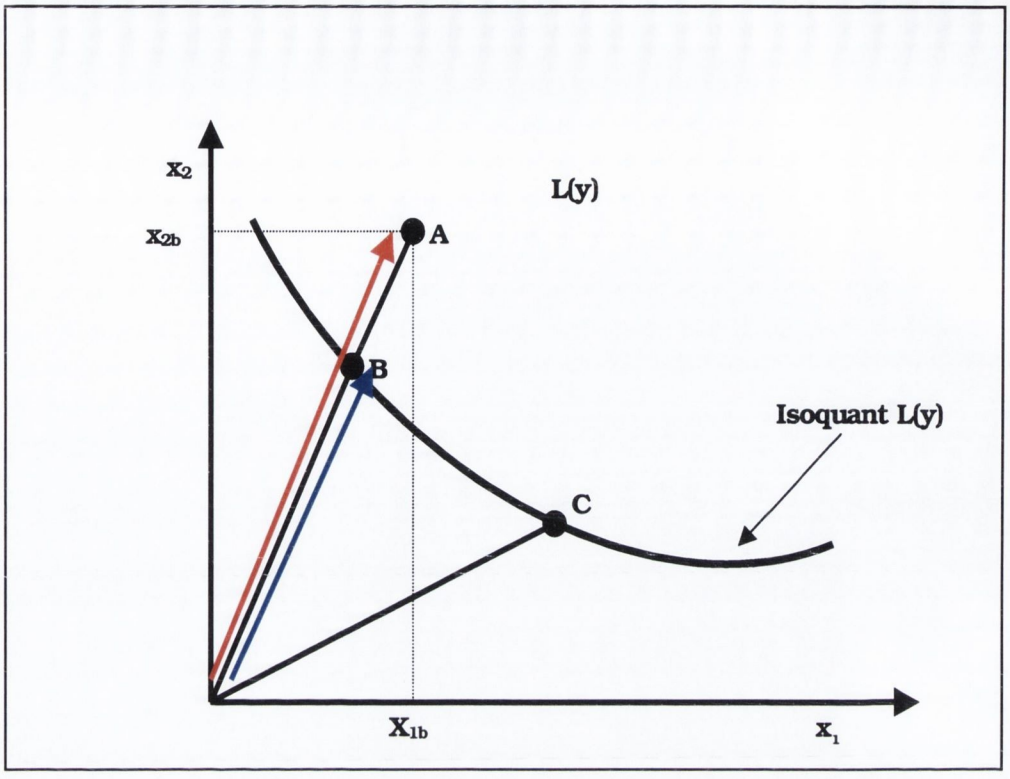


Figure 5-2: Input Distance Function and Input Requirement Set

For each y, the input set $L(y)$ is assumed to be closed and convex. Inaction is possible, that is, $0 \in L(y)$, and $L(y)$ satisfies strong disposability of inputs and output. Strong disposability requires that if $x \in S(x)$ and $y^* \leq y$ then $y^* \in S(x)$. The input distance function D_I is non decreasing in x and increasing in y, and is linearly homogeneous in y. If $x^t \in L(y)$ then $D_I^t = (y^t, x^t) \leq 1$ and if x is in the isoquant of y then $D_I^t = (y^t, x^t) = 1$. Figure 5-2 illustrates the input distance function. Assuming a given output vector, the inputs set $L(y)$ is the area bounded from below by the isoquant $L(y)$. Let point A define the production point where farm A used x_{1b} input X_1 and x_{2B} of input X_2 to produce the output vector y. The value of the distance function from point A is equal to the distance ρ=0B/0A.

In other words, the input distance function measures the largest possible decrease in the input vector, given the output vector and given that the contracted input vector must still be a part of the input set. The imposition of constant returns to scale leads to the useful result that the input distance function is the reciprocal of Farrell's measure of technical efficiency

$$D_I^t\left(y^t, x^t \mid C, S\right) = 1/F_I\left(y^t, x^t \mid C, S\right) \qquad 5\text{-}3$$

where D_I^t represents the input orientated distance function, F_I is Farrell's measure of efficiency, C is constant returns to scale and S is strong disposability of inputs. Similarly the output distance function is defined as

$$D_O^t\left(x^t, y^t\right) = \inf\left\{\phi : \left(x^t, y^t/\phi\right) \in P(x)\right\} \subset S^t \qquad 5\text{-}4$$

For each x, the output set $P(x)$ is closed and convex and, unlike the input set $L(y)$, is bounded, that is, unlimited levels of outputs cannot be produced with a given set of inputs. Strong disposability of inputs and outputs is assumed and inaction is possible. The output distance function is non-decreasing in y and increasing in x, and is linearly homogeneous in y. If $y^t \in P(x)$ then $D_O^t = \left(x^t, y^t\right) \leq 1$ and if y is on the frontier then $D_O^t = \left(x^t, y^t\right) = 1$, that is, the output distance function measures the largest possible proportional increase in the output vector given the input vector and given that the expanded output vector must still be part of the output set. As with the input distance function the addition of the constant returns to scale assumption leads to the definition of the output orientated distance function as the reciprocal of Farrell's measure of technical efficiency, that is,

$$D_O^t(x^t, y^t \mid C,S) = 1/F_o(x^t, y^t \mid C,S) \qquad 5\text{-}5$$

5.2.1.1. Distance Functions and the Malmquist Total Factor Productivity Index

The discussion above highlights three essential properties of distance functions that makes them useful in the calculation of Malmquist TFP indices. The first states that when constant returns to scale and strong disposability of inputs and outputs are imposed, by definition, the output and input distance functions are homogeneous of degree one in y and x respectively, that is,

$$D_I^t = (y^t, \rho x^t \mid C,S) = \rho D_I^t(y^t, x^t \mid C,S), \rho > 0 \qquad 5\text{-}6$$

and

$$D_O^t = (x^t, \lambda y^t \mid C,S) = \lambda D_O^t(x^t, y^t \mid C,S), \lambda > 0 \qquad 5\text{-}7$$

The second property states that where the distance functions satisfy constant returns to scale, the distance functions are homogeneous of degree minus one in x and y respectively, that is,

$$D_I^t = (\rho y^t, x^t \mid C,S) = (1/\rho) D_I^t(y^t, x^t \mid C,S), \rho > 0 \qquad 5\text{-}8$$

and

$$D_O^t = (\lambda x^t, y^t \mid C,S) = (1/\lambda) D_O^t(x^t, y^t \mid C,S), \lambda > 0 \qquad 5\text{-}9$$

The final property states that when the distance functions satisfy global constant returns to scale, the input and the output distance functions are reciprocals, that is,

$$D_I^t(y^t, x^t \mid C,S) = 1/D_O^t(x^t, y^t \mid C,S) \qquad 5\text{-}10$$

Figure 5-3 illustrates the relationship between the input and output orientated distance functions using the single input single output assumption. The input distance function scales the point *(x,y)* in the input direction (due West) until the boundary is reached. The output

distance function scales the point *(x,y)* in the output direction (due North) until the boundary is reached.

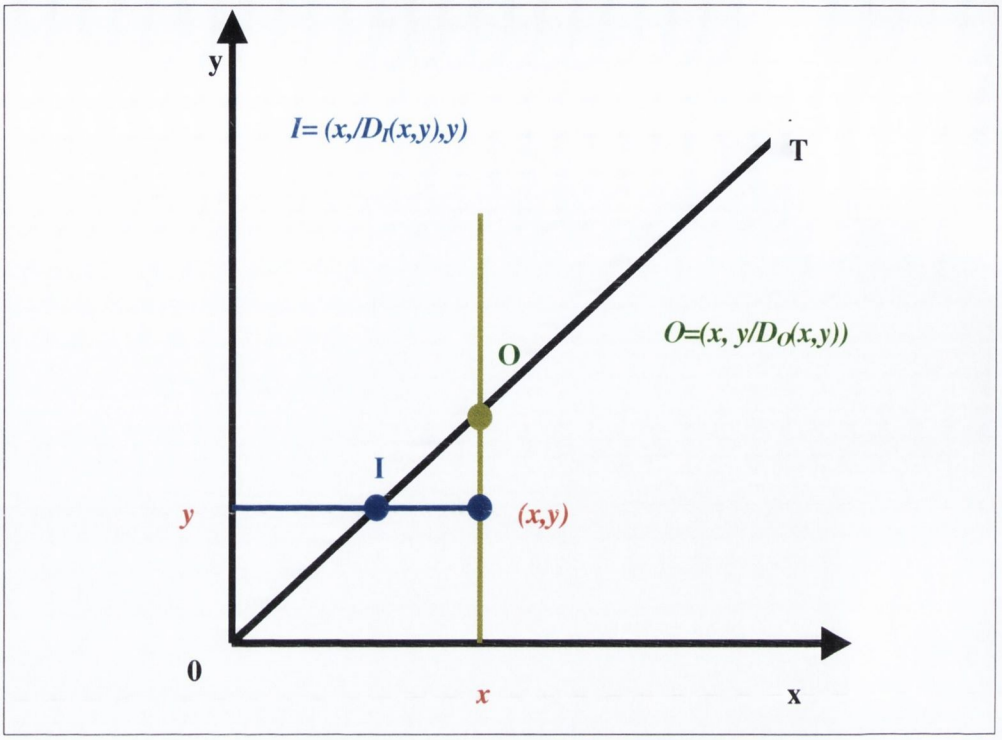


Figure 5-3: Input and Output Distance Functions

To demonstrate how distance functions can be used to calculate total factor productivity between period *t* and *t+1* the model is simplified to a single input and single output case. Strong disposability of inputs and outputs and constant returns to scale are assumed. The analysis is confined to the input orientated case although the results are also shown for the output orientated distance function. The model can be refined for the multi-input and multi-output case. Total factor productivity growth is an index of the average products (the ratio of input to output) in each period over time as given by

$$TFP = \frac{y^{t+1}/x^{t+1}}{y^t/x^t} \qquad 5\text{-}11$$

(x^t, y^t) is the input and output combination in period t and (x^{t+1}, y^{t+1}) is the observed input and output combination in period *t+1*. The input

distance function relative to the reference technology from period t can be defined as

$$TFP = \frac{y^{t+1}/x^{t+1}}{y^t/x^t} = D_I^t\left(x^{t+1}, y^{t+1}\right)/D_I^t\left(x^t, y^t\right) \qquad 5\text{-}12$$

which is equal to

$$M_I^t = D_I^t\left(y^{t+1}, x^{t+1}\right)/D_I^t\left(y^t, x^t\right) \qquad 5\text{-}13$$

Equation 5-13 compares data from period t and period $t+1$ but the best practice frontier is measured relative to the period t data. Values of M_I^t greater than one indicate improvements in productivity between periods t and $t+1$. It is possible to calculate the best practice frontier relative to the $t+1$ technology. The input distance function relative to the reference technology from period $t+1$ is defined as

$$M_I^{t+1} = D_I^{t+1}\left(y^{t+1}, x^{t+1}\right)/D_I^{t+1}\left(y^t, x^t\right) \qquad 5\text{-}14$$

Taking the geometric mean of the period t TFP index and the period $t+1$ TFP index gives an ideal index. The Malmquist TFP index between two periods is defined as

$$M_I\left(y^{t+1}, x^{t+1}, y^t, x^t\right) = \left[\frac{D_I^{t+1}\left(y^t, x^t\right)}{D_I^{t+1}\left(y^{t+1}, x^{t+1}\right)} \times \frac{D_I^t\left(y^t, x^t\right)}{D_I^t\left(y^{t+1}, x^{t+1}\right)}\right]^{0.5} \qquad 5\text{-}15$$

$D_I^t\left(y^t, x^t\right)$represents the distance from the period t observation to the period t technology and $D_I^{t+1}\left(y^{t+1}, x^{t+1}\right)$ represents the distance from the period t+1 observation to the period t+1 technology. The early work by Caves, Christensen and Diewert (1982) on the construction of the Malmquist TFP index was based on the assumption that the firm was both technically and allocatively efficient, that is, $D_I^t\left(y^t, x^t\right) = D_I^{t+1}\left(y^{t+1}, x^{t+1}\right) = 1$. However, by assuming that there are inefficiency effects in the model, that is, $D_I^t = \left(y^t, x^t\right) \leq 1$ and $D_I^{t+1} = \left(y^{t+1}, x^{t+1}\right) \leq 1$, it is possible to rewrite equation 5-15 in the form

$$M_I(y^t, x^t, y^{t+1}, x^{t+1}) = \frac{D_I^{t+1}(y^t, x^t)}{D_I^t(y^{t+1})}\left[\frac{D_I^t(y^{t+1}, x^{t+1})}{D_I^{t+1}(y^{t+1}, x^{t+1})} \times \frac{D_I^t(y^t, x^t)}{D_I^{t+1}(y^t, x^t)}\right]^{0.5} \quad 5\text{-}16$$

where

$$\frac{D_I^{t+1}(y^t, x^t)}{D_I^t(y^{t+1}, x^{t+1})} \quad 5\text{-}17$$

represents the output orientated measure of technical efficiency between years *t* and *t+1* and technical change is captured by

$$\left[\frac{D_I^t(y^{t+1}, x^{t+1})}{D_I^{t+1}(y^{t+1}, x^{t+1})} \times \frac{D_I^t(y^t, x^t)}{D_I^{t+1}(y^t, x^t)}\right] \quad 5\text{-}18$$

Similarly, the output orientated Malmquist index between years *t* and *t+1* is given by

$$M_O(x^t, y^t, x^{t+1}, y^{t+1}) = \frac{D_O^{t+1}(x^t, y^t)}{D_O^t(x^{t+1}, y^{t+1})}\left[\frac{D_O^t(x^{t+1}, y^{t+1})}{D_O^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_O^t(x^t, y^t)}{D_O^{t+1}(y^t, y^t)}\right]^{0.5} \quad 5\text{-}19$$

and is decomposed into technical efficiency change between periods *t* and *t+1*

$$\frac{D_O^{t+1}(x^{t+1}, y^{t+1})}{D_O^t(x^{t+1}, y^t)} \quad 5\text{-}20$$

and technical change between periods *t* and *t+1*

$$\left[\frac{D_O^t(x^{t+1}, y^{t+1})}{D_O^{t+1}(x^{t+1}, y^{t+1})} \times \frac{D_I^t(x^t, y^t)}{D_O^{t+1}(x^t, y^t)}\right] \quad 5\text{-}21$$

The Malmquist TFP index is illustrated in Figure 5-4.

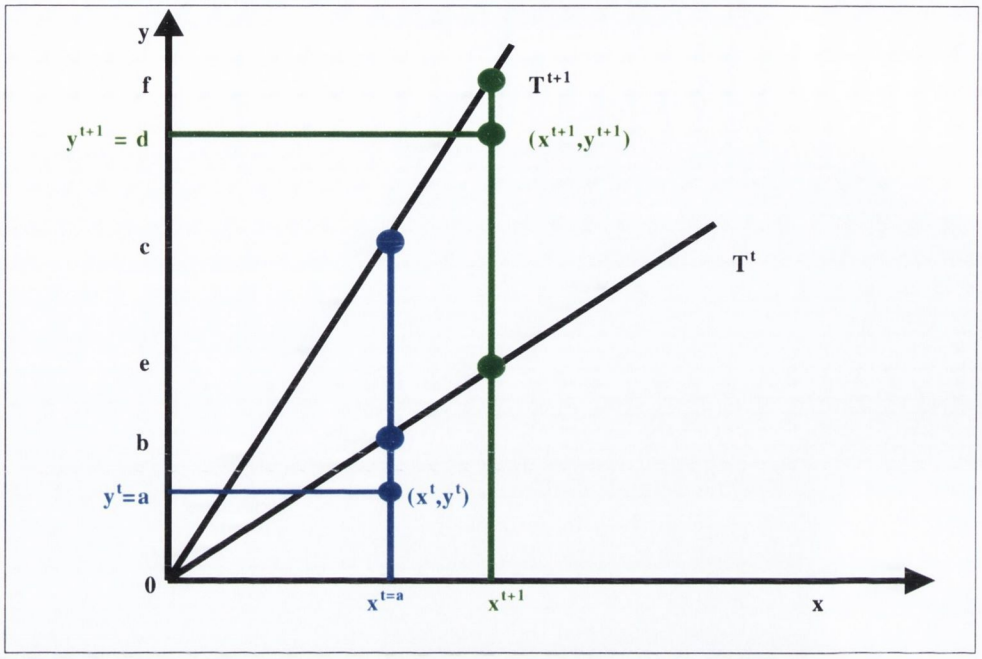


Figure 5-4 : The Output Orientated Malmquist Total Factor Productivity Index

There are two observations of inputs and outputs (x^t, y^t) and (x^{t+1}, y^{t+1}). The points T^t and T^{t+1} which are on the boundary of the frontier production function. At these points production is technically efficient. If however the observed output falls short of the maximum output possible then production is technically inefficient. The maximum possible output is obtained by increasing output northwards while remaining on the appropriate production possibility set. In period *t* the actual output (x^t, y^t) is less than the maximum possible (b, x^t). This is represented by the first term in equation 5-22.

$$M_O\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \left(\frac{0d}{0f}\frac{0b}{0a}\right)\left(\frac{0f}{0e}\frac{0c}{0b}\right)^{0.5} \qquad 5\text{-}22$$

The second term is technical change between period *t* and *t+1*, that is the distance the production frontier has shifted over time.

5.2.1.2.Returns to Scale

The decomposition of the Malmquist TFP index presented here is obtained under the assumption of CRS. This restrictions are imposed by normalising the outputs and inputs by dividing across by any one of the inputs such that there is homogeneity in inputs, that is, $\sum_{i}^{J} \beta_j = 1$, $\sum_{k=1}^{K} \beta_{jk} = 0$ and $\sum_{jt}^{J} \beta_{jt} = 0$ and the property of homotheticity $\sum_{k=1}^{K} \beta_{jk} = 0$ also holds (Chambers, 1988).

It should be noted that the appropriateness of the CRS restriction has been raised as the main caveat of the Malmquist TFP decomposition, in that the imposition of CRS ignores the potential contribution of scale economies to productivity change. Grifell-Tatje and Lovell (1995) and Coelli et al (1998) argue that the CRS assumption is required when applying either SFA or DEA techniques while Cuesta and Orea (1999) have suggested that the assumption of CRS is only necessary when applying DEA techniques.

Färe, Grosskopf, Norris and Zhang (1994), Ray and Desli (1997) and Grifell and Lovell (1999) have addressed this problem in the non-parametric context by measuring distance function values corresponding to constant and variable returns to scale technologies. By comparing two different observations that correspond to the most productive scale size in each period, it is possible to obtain an indirect measure of scale economies through the introduction of scale efficiencies. Scale efficiency measures the productivity at the observed input bundle relative to what is attainable at the so-called most

productive scale size, which is the input bundle where productivity reaches a maximum (Banker, 1984).

On the parametric side, Balk (1999) proposed a decomposition of the Malmquist TFP index based on estimation of translog distance functions with variable returns to scale based on the results of Ray (1999). More recently Orea (2000) attempts to address the problem by drawing on Diewert's (1976) exact index number approach to the derivation of productivity change measures. This allows the contribution of scale economies to productivity growth to be measured without any reference to scale efficiency. Orea (2000) argues that this method is suitable for the more restrictive Cobb-Douglas functional form.

5.3. THE ESTIMATION OF MALMQUIST TFP

The distance functions required for the Malmquist TFP index can be estimated using either Stochastic Frontier Analysis or Data Envelopment Analysis. SFA can be restrictive as a functional form for the production function and a distributional form for the inefficiency term must be specified. However, SFA does take account of statistical noise and it is possible to conduct conventional hypotheses tests. DEA does not require the specification of a functional form for the production function, but it does not account for statistical noise and standard hypothesis testing is not possible. The SFA model is discussed first and the assumptions underlying the model are outline in detail. Subsequently, the DEA model is introduced.

Given that the models to be estimated are restricted to constant returns to scale then either an input or an output orientated distance function can be applied since the input and output distance functions are reciprocals. For the remainder of the chapter only input distance functions are discussed.

5.3.1. Stochastic Frontier Analysis

The translog functional form is widely accepted as it is conceptually simple and imposes no *a priori* restrictions on the structure of technology. A translog production function which also takes account of non neutral technical change is given by

$$\ln y_{it} = \alpha + \sum_k \beta_k \ln x_{kit} + .5\sum_k \sum_j \beta_{kj} \ln x_{kit} \ln x_{jit} + \sum_k \xi_k \ln x_{kit} T + \varsigma_t T + \varsigma_{tt} T^2 + u_i + \upsilon_{it} \qquad 5\text{-}23$$

where the disturbance term is defined as

$$\varepsilon_{it} = v_{it} - u_{it} \qquad 5\text{-}24$$

and y_{it} is output for farm i in period t, and x_{kit} is the kth inputs of farm i in period t. α, β_k and β_{kj} are the parameters to be estimated. $-u_{it}$ represents time variant technical efficiency and v_{it} is statistical noise. υ_{it} is assumed to be independently and identically distributed with a zero mean and variance σ^2_v. The error component u_{it} is assumed to be non-negative and distributed independently of υ_{it}. u_{it} represents the factors under the control of the farmer while the υ_{it} represent non farm factors such as weather as well as statistical noise.

The efficiency effects are assumed to be distributed as

$$u_{it} = \{\exp(-\eta(t-T))\}u_i \qquad 5\text{-}25$$

where the u_i's have a generalised truncated normal distribution and η is an unknown parameter to be estimated.[27] Technical efficiencies for each farm in each year are predicted as the conditional expectation of $exp(u_{it})$ given the value of ε_{it}, that is,

$$TE_{it} = E(\exp(u_{it})/\varepsilon_{it}) \qquad 5\text{-}26$$

Recall that $TE_{it} = D_I^t(y^t, x^t)$ and $TE_{it+1} = D_I^{t+1}(y^{t+1}, x^{t+1})$ therefore the change in technical efficiency between period t and $t+1$ is

$$\text{Efficiency Change} = \frac{TE_{it+1}}{TE_{it}} = \frac{D_I^{t+1}(y^{t+1}, x^{t+1})}{D_I^{t+1}(y^t, x^t)} \qquad 5\text{-}27$$

where TE_{it+1} is the efficiency of the ith farm in the $t+1$ period and TE_{it} is the efficiency of the ith farm in the t period. If technical change is estimated as non-neutral then the technical change index may vary for different input vectors. Hence a geometric mean is used to estimate the technical change index between periods s and t. Technical change is given by

$$\left[\left(1+\frac{\partial f(x_{it}, t, \beta)}{\partial t}\right)\times\left(1+\frac{\partial f(x_{it+1}, t+1, \beta)}{\partial t+1}\right)\right] = \left[\frac{D_I^t(y^{t+1}, x^{t+1})}{D_I^{t+1}(y^{t+1}, x^{t+1})}\times\frac{D_I^t(y^t, x^t)}{D_I^{t+1}(y^t, x^t)}\right]^{0.5} \qquad 5\text{-}28$$

The partial derivatives of the production function with respect to time (evaluated at each particular data point) enable the calculation of a technical change index between periods t and t for the ith farm.

$$Technical\ Change = TC_{it+1}/TC \qquad 5\text{-}29$$

It is essential that technical change is appropriately defined in the production function. Otherwise, if there is any persistent time-specific inefficiency in the model it could be masked by technical change

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[27] *Kumbhakar (1990) and Battese and Coelli (1992) developed models which made distributional assumptions about the technical inefficiency effects. Kumbhakar (1990) proposed as* $u_{it}=[1+\exp(\eta_1 t+2_i t^2]^{-1}u_I\ i=1,2,\ldots,N;\ t=1,2,\ldots\ldots,T$ *where the u are assumed to have a half normal distribution.*

(Kumbhakar and Hesmati,1995; Karagainnis et al.1999).[28] The elasticity of output with respect to time can be interpreted as the rate of technical change (Heshmati, 1996; Capalbo and Antle, 1988), that is,

$$\frac{\partial \ln y_{it}}{\partial t} = \sum_{k=1}^{K} \varsigma_k \ln x_{kit} + \varsigma_t + \psi t + \varepsilon_{it} \qquad 5\text{-}30$$

If $\sum_{k=1}^{K} \varsigma_k \ln x_{kit} = 0$ then equation 5-30 is a measure of Hicks neutral technical change.[29] This can be interpreted as a neutral-shift of the production frontier which cannot be attributed to any particular input.

5.3.2. Data Envelopment Analysis

DEA is a linear programming approach developed and refined by Charnes et al.(1978), Banker et al. (1984) and Fare et al. (1985, 1994). DEA is an alternative to the SFA method for obtaining the distances required to compute the Malmquist TFP index. The Malmquist TFP index measures the change in total factor productivity between two data points by calculating the ratio of the distances of each data point relative to a common technology. As with the distance functions the DEA linear programme can be output or input orientated. Assume data on K inputs and M outputs, for N farms. x_i represents the column vector of inputs for the *ith* farm and y_{it} represents the column vector of outputs for the *ith* farm. X is the K×N input matrix for and Y is the M × N output matrix all N farms in the sample. The input orientated distances are obtained by the solution of the four linear programmes for each farm listed below

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[28] Other specifications such as that of Kumbhakar (1990) and Lee and Schmidt (1993) require the same specification of technical change in the production function.

[29] Also referred to as pure or autonomous technical change. Furthermore t^2 can be included. Technical change can be positive or negative.

$$\left[D_I^t\left(y^t, x^t\right)\right]^{-1} = \min_{\theta\lambda} \theta,$$
$$st \; -\theta y_i^t + Y^t \geq 0, \qquad 5\text{-}31$$
$$x_i^t - X^t\lambda \geq 0,$$
$$\lambda \geq 0$$

$$\left[D_I^{t+1}\left(y^{t+1}, x^{t+1}\right)\right]^{-1} = \min_{\theta\lambda} \theta,$$
$$st \; -\theta y_i^{t+1} + Y^{t+1} \geq 0, \qquad 5\text{-}32$$
$$x_i^{t+1} - X^{t+1}\lambda \geq 0,$$
$$\lambda \geq 0$$

$$\left[D_I^{t+1}\left(y^t, x^t\right)\right]^{-1} = \min_{\theta\lambda} \theta,$$
$$st \; -\theta y_i^t + Y^{t+1} \geq 0, \qquad 5\text{-}33$$
$$x_i^t - X^{t+1}\lambda \geq 0,$$
$$\lambda \geq 0$$

$$\left[D_I^t\left(y^{t+1}, x^{t+1}\right)\right]^{-1} = \min_{\theta\lambda} \theta,$$
$$st \; -\theta y_i^{t+1} + Y^t \geq 0, \qquad 5\text{-}34$$
$$x_i^{t+1} - X^t\lambda \geq 0,$$
$$\lambda \geq 0$$

where θ is a scalar and λ is a N × 1 vector of constraints. The value θ will be the less than or equal to one and represents the efficiency score for the *ith* farm. If θ is equal to one then the farm is on the frontier and is technically efficient. In linear programmes 5:33 and 5:34 the production points are compared to technologies from different time periods. In these cases the θ need not be less than or equal to one as in Farrell's measure of efficiency. The data point could lie above the feasible production if technical progress has occurred.

The results of the Linear Programmes (LP) provide farm level technical efficiency change and technical change for each pair of years in the sample. The N × (3T-2) LPs were solved for each of the 1,166 farms in the sample for each time period and technical change and efficiency were calculated for each pair of years in the sample using the DEA package OnFront. Technical efficiency change is measured as the ratio of efficiency in the two time periods.

$$Efficiency\ Change = \frac{TE_{it+1}}{TE_{it}} = \frac{D_I^{t+1}\left(y^{t+1}, x^{t+1}\right)}{D_I^{t+1}\left(y^t, x^t\right)} \qquad 5\text{-}35$$

Technical change is measured as

$$Technical\ \ Change\ \ TC_{it+1}/TC_{it} = \left[\frac{D_I^t\left(y^{t+1}, x^{t+1}\right)}{D_I^{t+1}\left(y^{t+1}, x^{t+1}\right)} \times \frac{D_I^t\left(y^t, x^t\right)}{D_I^{t+1}\left(y^t, x^t\right)} \right]^{0.5} \qquad 5\text{-}36$$

OnFront will only estimate a TFP index directly when a farm stays in the survey from year one to the final year. So the technical change and technical efficiency were estimated on a year on year basis, working with pairs of years. This resulted in some loss of observations for farms which appeared in a single year or for farms that appeared in the sample in non-consecutive years.

It should be noted that the method of calculating the distance functions for the measurement of technical efficiency and technical change are the same once the estimates of technical change and technical efficiency are calculated.. Cumulative chained indices of TFP, technical change and technical efficiency change were calculated results from both DEA and SFA.

5.4. DATA

Farms included in the National Farm Survey sample include 18.5 per cent classified as specialist dairy farms, there are another 13.4 per cent 'dairy and other' farms and a further approximately 0.5 per cent of farms producing some dairy products. The analysis focuses on both specialist milk producing farms and farms where milk is not the predominant output but is produced in large enough quantities for sale. Hence, the sample excludes farms producing less than 18,925 litres of milk (5,000 gallons) per annum.

The inputs used are

- The number of dairy cow livestock units (x_1). Livestock units use feed demand equivalents based on the amount of feed each animal type consumes and these technical equivalents do not vary over time.
- Variable costs (x_2). Variable costs associated with milk production is an index composed of veterinary expenses, electricity, machinery operating expenses and miscellaneous expenses.
- Labour (x_3). The total amount of labour units includes family labour, casual and hired labour. Labour data were not available on the share of labour allocated to milk production, therefore, the share was allocated based on the share of milk production in total output.
- Feed Units (x_4). The total number of feed units allocated to milk production was available. Feed units are comprised of the forage area and feed concentrates.
- Capital (x_5) The capital input was also allocated as a share of milk production in total output. The capital input associated with milk production is comprised of the value of farm buildings, machinery and land improvements at the start of the year, plus purchases less sales and net of depreciation.

A concern arises from the method used to allocate the share of capital, variable and labour inputs to the dairy enterprise. Assuming a one to one ratio of costs to output is not ideal however, it is a reasonable alternative given the data limitations. To reduce the number of explanatory variables in the model, implicit quantity indices for capital and variable inputs are obtained as the ratio of their value to an

aggregate multilateral Tornqvist price index based on 1991=100. Since individual farm prices are not available, national prices taken from the CSO are used. This index varies over time but not over farms, implying that differences in the quality of outputs or inputs are reflected in differences in quantity Full details of the aggregation method are given in Chapter 3. Summary statistics are given in Table 5-2.

Table 5-2: Summary Statistics of Variables in the SFA and DEA Analysis

Variable	Mean	Std/mean	Min	Max
Pooled 1984-1998				
Number of dairy livestock units	39.14	0.84	0.25	441
Milk Output in Gallons	37348	1	4999	499603
Feed Acres	69.8	0.81	0.37	788.14
Variable inputs (€)	9782	1.35	38	150026
Capital	45130	1.03	3530	500436
Total number of labour units	2.5	0.81	0.25	13.5
1984 N=632				
Number of dairy livestock units	39.4	0.9	3.16	356
Milk Output in Gallons (€)	43855	1.37	4999	446006
Feed Acres	72	0.88	5.274	758
Variable inputs (€)	7230	1.38	265	80793
Capital	43240	1.1	0	500436
Total number of labour units	2.6	0.72	0.251	13.63
1998 N=477				
Number of dairy livestock units	41.8	0.68	0.75	204
Milk Output in Gallons (€)	53527	0.99	4999	261815
Feed Acres	69.5	0.64	2.52	3701
Variable inputs (€)	12303	1.12	59.69	80516
Capital	47448	0.87	0	264498
Total number of labour units	2.67	0.65	0.024	13.48

As in the two previous chapters all data used in the stochastic frontier analysis were *normalised* around the sample mean, prior to logarithmic transformation, to define the point of approximation. Estimates of

technical change and efficiency were chained to form a Malmquist TFP index as outlined in Section 5.3.

5.5. EMPIRICAL RESULTS

It is important to reiterate the goal of this chapter prior to discussing the results. The primary goal was to compare the results of the DEA and SFA measures of TFP. These measures were obtained under the restrictive assumption of constant returns to scale. In the SFA case a translog production function with non-neutral technical change was estimated and CRS was imposed data prior to estimation. The CRS restriction may not adequately reflect the nature of dairy farming which *a priori* be expected to demonstrate increasing returns to scale. As discussed in section 5.2.1 there are alternative models proposed in the literature which leave open the option of repeating the analysis under variable returns to scale (VRS) in the future. Nevertheless, it is possible to make some broad policy interpretations based on the results.

5.5.1. Specification Tests

The MLE stochastic frontier model was subjected to a number of likelihood tests to find the preferred model for the sample of milk producing farms. The validity of the translog over the Cobb Douglas specification was tested. The null hypothesis that $\beta_{ij}=0_i,\ i\leq j=1,5$ was strongly rejected. As such the translog production technology is considered to be a better representation of farm technology than the Cobb Douglas specification in the case of the stochastic frontier model. The null hypothesis that the technical inefficiency effects are time invariant and have a half-normal distribution, that is, $\eta=\mu=0$,is rejected against the null that the technical inefficiency effects are time

variant and have a truncated normal distribution. Finally, the null hypothesis that there are no technical inefficiency effects in the model is tested using a likelihood ratio test of the one sided error. Again the null hypothesis $\gamma=0$ is strongly rejected. The coefficient of γ is 0.74 and the standard error is 0.07 for the translog with non-neutral technical change. This indicates that the model is significantly different from the deterministic frontier. Finally, the specifiction of neutral technical change was rejected in favour of the specifiction with non-neutral technical change. Given these results, the translog with non-neutral technical change is the best representation of dairy data given the alternative specifications considered.

5.5.1.1. Monotonicity

The translog function is only a local approximation, implying that it does not necessarily satisfy the restrictions for production functions globally. Therefore, it was necessary to examine whether output increases monotonically with all inputs. Monotonicity was evaluated at each data point and at the point of approximation. There was no violation of the condition for all variables in the production function except for labour which had a 10.2 per cent violation. Hence the function can be deemed to satisfy the necessary condition for monotonicity at the majority of the data points.

5.5.1.2. Convexity

The curvature conditions require that the isoquants be convex which is equivalent to the production set being concave. Curvature can be confirmed by examining the bordered Hessian matrix of first and second order partial derivatives of the translog production function.

Table 5-3: Hessian Matrix of the Second Order Partial Derivatives Averaged Over Time and Farms

	f_{jS}	f_{jL}	f_{jF}	f_{jV}	f_{jC}
f_{Sj}	**-0.23485**	-0.09405	0.054404	0.093697	0.015841
f_{Lj}	-0.09405	**-0.49305**	-0.01879	0.03061	0.009042
f_{Fj}	0.054404	-0.01879	**-0.09015**	0.014776	0.004415
f_{Vj}	0.093697	0.03061	0.014776	**-0.02563**	0.001112
f_{Cj}	0.00257	0.015191	0.004415	0.001112	**-0.00464**

If the function is concave then the bordered Hessian matrix will be negative definite. Greene (1993) points out that the convergence criteria for the MLE estimation requires the bordered Hessian to be invertible, that is, negative definite, the condition was confirmed by checking that the bordered Hessian matrix was negative definite at the point of approximation, and for each data point. Table 5-3 below shows that the diagonal elements of the Hessian matrix averaged, over time and farms, are negative. The convexity restriction did not hold for 15 per cent of data points. However, it is clear from Table 5-3 that the condition holds at the mean. Furthermore, the principal minors of the Hessian matrix alternate their sign supporting the curvature condition. It is possible to assume that there are well-behaved regions that are large enough for the translog function to be a good representation.

5.5.2. Technical Efficiency

Average technical efficiency in the SFA and DEA models in 1984 were 81 and 79 per cent respectively. The rank correlation between the SFA and DEA results is 67 per cent. Figure 5-5 gives the annual average efficiency levels for the SFA and DEA results.

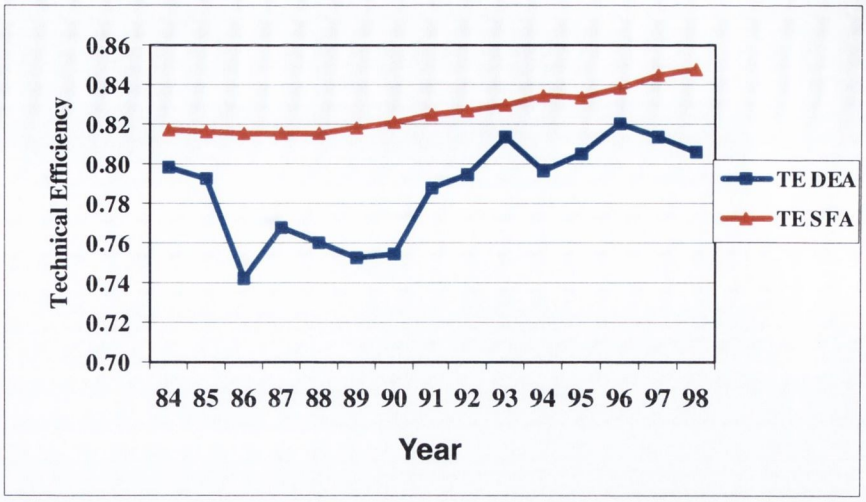


Figure 5-5: DEA and SFA Annual Average Efficiency Levels 1984 to 1998

As expected the variation in efficiency is greater in the DEA due to the influence of white noise. SFA and DEA average technical efficiency fell after the introduction of quotas in 1984. Average efficiency started to rise again in 1990 and the upward trend has continued. The 1992 McSharry reforms did not result in the marked changes in average efficiency seen in the years following the original introduction of quota restrictions. This result is not surprising as dairying was not effected by the 1992 reforms. The introduction of quotas in 1984 would have had a major impact on the structure of the dairy sector. Cumulative chained indices of the DEA and SFA technical efficiency results are presented in Table 5-4.

Table 5-4: SFA and DEA Chained Cumulative Indices of Technical Efficiency, Technical Change and Total Factor Productivity

	Stochastic Frontier Analysis			Data Envelopment Analysis		
Year	**TE**	**TC**	**TFP**	**TE**	**TC**	**TFP**
1984-85	100	100	100	100	100	100
1985-86	99.84	100.59	100.43	95.89	100.94	96.79
1986-87	99.55	101.39	100.93	100.05	98.49	98.54
1987-88	99.29	102.38	101.66	100.18	101.45	101.64
1988-89	99.06	103.59	102.61	101.88	103.81	105.76
1989-90	99.08	105.00	104.03	102.25	98.12	100.33
1990-91	99.41	106.64	106.01	108.64	103.67	112.63
1991-92	100.16	108.49	108.66	110.44	98.42	108.69
1992-93	101.15	110.59	111.87	109.06	99.87	108.92
1993-94	102.40	112.95	115.66	103.93	105.83	109.99
1994-95	104.22	115.57	120.45	104.61	112.79	117.99
1995-96	106.01	118.47	125.59	106.14	111.11	117.94
1996-97	108.36	121.65	131.82	106.46	114.06	121.43
1997-98	111.59	125.16	139.66	103.94	119.27	123.96
Growth Rates						
Linear	0.79	1.91	2.87	0.63	1.31	2.01
Exponential	0.76	1.74	2.52	0.62	1.23	1.85

The chained DEA indices are more volatile than the SFA indices, however, the general trends in efficiency, technical change and total factor productivity are the same. Technical efficiency growth rates over the period for the DEA and SFA results are 0.45 and 0.29 per cent respectively. The index of DEA efficiency rises by 1.83 per cent over the period and by 3.74 per cent for SFA results. Technical efficiency remains almost constant for the entire period of the study however the level of technical efficiency is relatively high at the start of the study. This suggests that milk producing farms are operating near the frontier. In other words, they are highly efficient and so there is little room for gains in efficiency.

5.5.3. Technical Change

The SFA results show a rise in the technical change index of 29 per cent over the period with a growth rate of 2.04 per cent per annum. The DEA results show a rise in the technical change index of 16.86 and a growth rate of 1.37 per cent. Figure 5-6 compares the upward trend in technical progress in the SFA and DEA results.

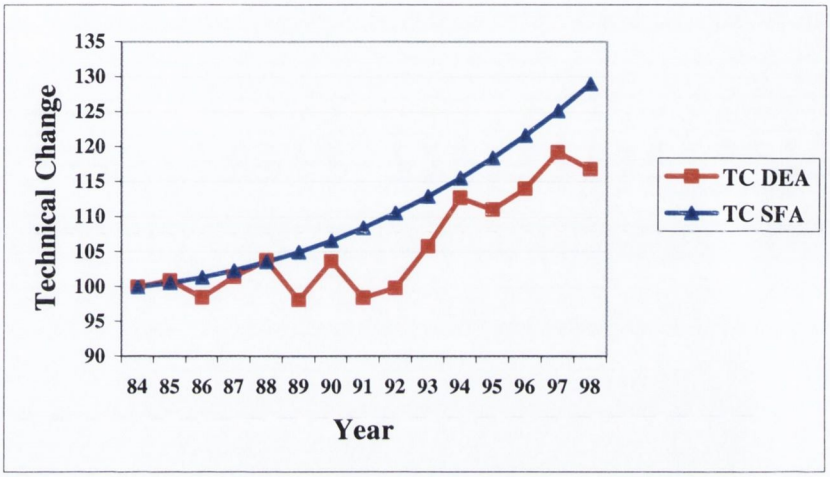


Figure 5-6: DEA and SFA Chained Cumulative Indices of Technical Change

The DEA results indicate relatively stagnant technical progress up to 1992 but with a steady increase over the later years.

The technical change estimates obtained here were compared to the unweighted rate of technical change estimated in Chapter 3. The rate of technical change taken from chapter 3 was approximately 2 per cent per annum compared to 1.4 per cent from the DEA approach and 2.04 per cent for SFA. It should be noted that the results from Chapter 3 were obtained under the assumption of VRS while the results here results from the imposition of CRS.

5.5.4. Total Factor Productivity

Aggregating the technical change and technical efficiency for each year gives the Malmquist TFP index. Both the DEA and SFA results indicate that TFP is being driven almost entirely by technical change over the period.

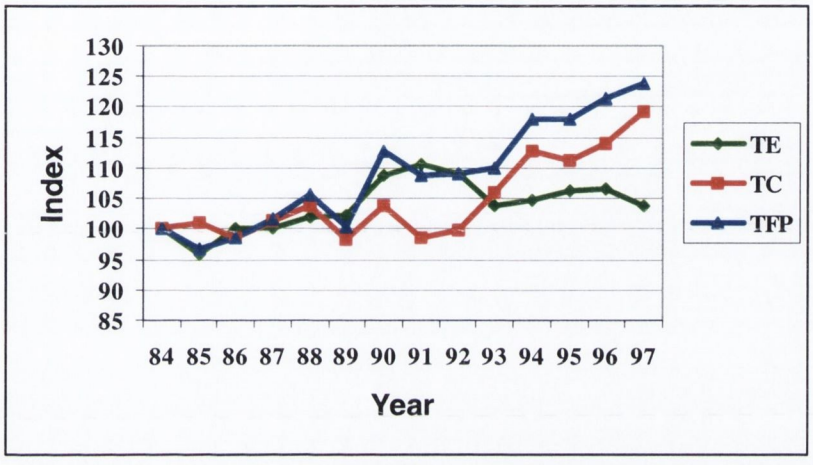


Figure 5-7: The DEA Malmquist TFP Index and its Components

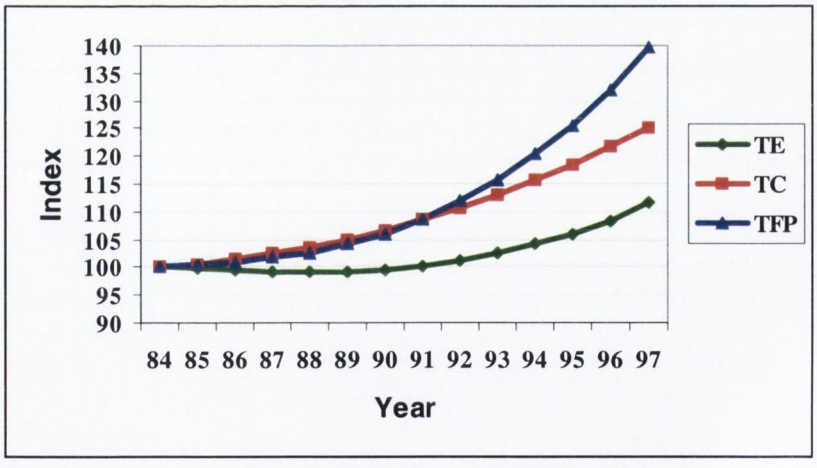


Figure 5-8: The SFA Malmquist TFP Index and its Components

From 1990 to 1998 there is evidence of TFP growth due to small improvements in technical efficiency and technical progress. The TFP index rises by 33.84 per cent over the period with a growth rate of 2.39

per cent per annum. The DEA results show the TFP index rising by 19 per cent over the fifteen year period of the study. The TFP growth rate is 2.02 per cent which is lower than the SFA results. Examining the DEA results graphically shows swings in technical efficiency and technical change over the period (Figure 5-7). During the early part of the study technical change and technical efficiency are moving together. In the period until 1990 to 1994 technical efficiency improvements drive TFP growth. However, in the post 1994 era technical change takes over as the driving force behind TFP growth.

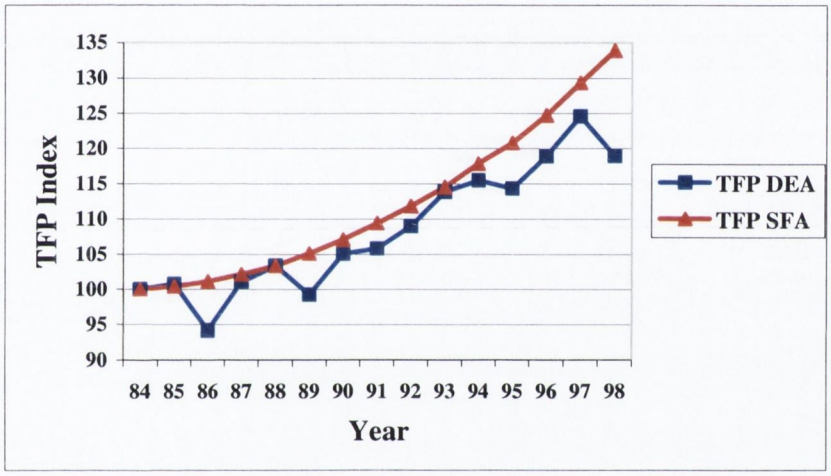


Figure 5-9: DEA and SFA Malmquist Indices of TFP Change 1984 to 1998

Although the underlying components of TFP growth are different for the SFA and DEA results the overall change in TFP is similar. This pattern of TFP growth is illustrated in Figure 5-9. The DEA TFP results do rise and fall over the period however the trend in TFP is upwards as in the SFA results. The SFA results show that TFP rises by 29.33 per cent up to 1997 and by 24.59 per cent for the DEA results over the same period. The exception is 1998 when the SFA and DEA results diverge. However, since we do not have data for the period after 1998 it

is not possible to determine whether or not this divergence is due to statistical noise or some other process.

The results for milk producing farms are very similar to the efficiency results presented in Chapter 3. Recall that in Chapter 3 an aggregate production frontier was estimated with different intercepts for each of the farm systems. The correlation between the annual average efficiency of dairy farms from the aggregate production frontier and the estimates for milk producing enterprises presented in this chapter is 98 per cent. The correlation based on the ranking of efficiency for individual farms is lower at 85 per cent. These results are reassuring given the concerns about the use of an aggregate production frontier raised in Chapter 3.

These results can be compared with studies of dairy farms elsewhere. Hadley et al. (2000) using data on UK dairy farms found an average TFP growth rate of 2.4 per cent per annum which. Kumbhakar and Heshmati (1995) found mean technical efficiency of 81 per and technical progress at a rate of 1.8 per cent for Swedish Dairy farms, and Ahmad and Bravo-Ureta (1996) found similar trends for both technical change and efficiency in studies of Portuguese dairy farms The Irish TFP results are consistent with these studies, the average rate of TFP growth was found to be 2.39 per cent per annum. Recent work by Cuesta and Orea (1999) using FADN data for Spanish farms found technical progress of 13.6 per cent and declining technical efficiency for the period 1987 to 1991. This is lower than the technical progress rate for Irish dairy farm which was found to be 29 per cent over the period. It is possible that the difference in the TFP rate

between Ireland and Spain can be explained in part by the large reductions in State expenditure on dairy research. There has also been changes in the focus of the extension service in Spain which has seen a move away from improving farm performance and a move towards assistance with EU income support schemes.

5.5.5. The Similarity of the DEA and SFA Results

The results presented above show that the cumulative TFP growth rates using SFA is 5 percentage points higher than the DEA rate. The rate of technical change estimated using SFA is higher than the DEA results and the converse is true for technical efficiency. As expected the DEA results are more volatile over time compared to the SFA results and this is particularly so for the DEA technical change results. It is possible to conclude (albeit cautiously) that the results of the SFA are robust given the similarity between the DEA results and the results for dairy farms in Chapter 3.

5.6. CONCLUSIONS

This chapter considered two methods of calculating total factor productivity, namely the non parametric method of DEA and the parametric method of SFA, and applied them to a sample of Irish milk producing farms under the assumption of constant returns to scale. The results of the DEA and SFA analysis undertaken in this chapter are broadly similar suggesting that the two methods are robust. However, it is not possible to test for robustness statistically. Furthermore, the SFA results are similar to those for milk producing

farms reported in Chapter 3, which were based on an aggregate output variable and intercept dummies to account for system differences.

Fingleton (1995:1) states "It was predicted by several commentators that the introduction of milk quota in 1984 would *fossilise the structure of milk production* over time. This did not happen in the EU and neither did it happen in Ireland". Average efficiency under DEA and SFA is above 70 per cent in almost all years. This suggests that on average milk producing farms in the post quota period recovered from this major structural change to the dairy industry. In the period directly after the introduction of quota technical efficiency change was stagnant and total factor productivity growth was being driven by technical progress. Working from the premise that technical progress occurs due to research and gains in technical efficiency come from contact with the extension service then in the future allocation of funds between research on one hand and extension on the other should be levied in favour of research. Nevertheless, it could be argued that the farm advisory service prevented declines in technical efficiency in the post quota period. Indeed both the research and farm advisory service were undertaking research and advising dairy farms on the optimal profit maximising output mix prior to the implementation of the quota system. Furthermore, there have been increases in technical efficiency over the latter part of the period under study.

Despite the reality of WTO conditions on trade and price support, there appears to be significant optimism among dairy specialists for the future of the industry. Agenda 2000 has secured a reasonable price for milk which will remain in place until 2008, albeit with a trend towards

the world market price for milk (McCarthy, 2000). The Irish dairy sector can maintain a competitive edge if the focus of research is moved into improving the quality of milk products. At farm level, there is a need for farmers to maintain and increase farm profit through maintaining and increasing technical efficiency, with an emphasis on meeting the high food quality standards required by the large creameries.

The analysis presented in this chapter is a starting point for future work. Clearly efficiency and technical change on dairy farms needs to be modelled with the restrictions of constant returns to scale removed. Indeed there is scope for analysis of all the major farm systems but that remains another days work.

CHAPTER 6
CONCLUSIONS

6.1. INTRODUCTION

This concluding chapter aims to present a short overview of the key points in the thesis, discuss the policy implications, comment on the major caveats in the work and to suggest future work.

6.2. THESIS SUMMARY

Chapter 2 covered the core theoretical foundations underpinning the empirical essays presented in Chapters 3, 4 and 5. The literature review of production theory, defined the concepts of technical efficiency, technical change and productivity growth. The alternative functional forms and the regularity conditions of the frontier production function were also discussed in Chapter 2. The starting point was a review of cross-sectional models for both deterministic and stochastic frontier production functions and and then panel data models were developed. The remainder of the chapter concentrated on the estimation of frontier production functions.

Chapter 3 contained the first essay called "Technical Change and Technical Efficiency in Irish Agriculture". The empirical analysis quantified two competitiveness factors, namely, the rate of technical change over time, and the relative efficiency of individual farms compared to best practice in the industry. A panel of Irish farms taken from the National Farm Survey over the period 1984 to 1998 were used

resulting in 14,917 data points. The Battese and Coelli (1992, 1995) approach had not been applied to Irish farm level data before this work.

The results show evidence of technical change over the period, but this is occurring at a decreasing rate for both the weighted and the unweighted results. The linear weighted rate of technical change was 2.58 (exponential rate is 1.94) per cent compared to a value of 0.9 per cent per annum for the unweighted sample and the cumulative growth increases from 13.9 per cent, over the period, for the unweighted results to 34 per cent for the weighted results. Splitting the time period in two shows a slow done in the annual rate of unweighted technical progress from 1.19 per cent for the period 1984 to 1990, to 0.5 per cent for the period 1990 to 1998. Similarly the weighted results show the rate of change to be 2.7 per cent per annum for 1984 to 1990 compared to 1.9 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 East had a mean annual rate of technical change of 1.35 per cent over the period, compared to a mean annual rate of 0.13 per cent for farms in the West. The weighted mean rate of technical change is greater for farms located in the West and the East (1.15 and 2.21 per cent respectively). Farms in the top size quintile (over 81 hectares of land) had an unweighted average annual rate of technical change of 2.54 per cent annually and a weighted annual rate of 2.24. Weighting technical change gives an annual average rate of technical change of 1.03 per cent compared to an unweighted

average annual fall in productivity (which is called technical regress) of -0.8 per cent on farms in the bottom size quintile (less than 22 hectares). 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 respectively) while cattle and sheep farms experienced technical regress over the same period. In the latter farm systems direct payments comprise a high proportion of total farm income and it is possible that this result is due to the conditions attached to these payments. Weighting the results showed that cattle farms experienced an annual rate of technical progress of 0.5 per cent over the period. While weighting the results for sheep farms indicated technical regress at a rate of -0.02 per cent.

Farm efficiency relative to best practice within each farming system in a particular year was also considered. Results indicate that farms within a farming system achieve, on average, around 65 per cent of the efficiency level of best practice farms within that system. This figure fell to approximately 60 per cent if farm efficiency was measured relative to the most efficient farms in the sample overall. The average level of farm efficiency has been decreasing by 0.4 per cent per annum over the period of the study. This implies that the gap between productivity on best practice farms and farms in general has been growing over the period. The breakdown of the most efficient farms, by system of farming, shows that 31 per cent are dairy farms while 23 per cent are arable

farms. Approximately 52 per cent of the least efficient farms are cattle farms, while a further 31 per cent are sheep farms.

Chapter 4 contained an essay called "Does Contact with the Extension Service Improve Farm Level Efficiency ?" A smaller sample containing 1603 observations for the years 1995 to 1998 was used for the analysis. Again a stochastic frontier approach was used to estimate efficiency and technical change. The analysis examined the factors associated with differences in technical efficiency across farms. One interest was the impact of direct payments. Over 20 per cent of revenue and over 50 per cent of income from farming are now derived from direct payment support financed by the EU's Common Agricultural Policy. In particular, the impact of contact with the agricultural advisory service on farm-level technical efficiency was explored. Two approaches were used, in the first the extension variable is treated as an exogenous variable in the efficiency equation while the second approach treats extension contact as endogeneous. The correction of the efficiency model to take account of an endogeneous extension variable is rarely attempted as it is difficult to find a suitable proxy for the endogenous variable. Chapter 4 explored the endogeneity problem in detail and the empirical model was adjusted econometrically in an attempt to rectify the problem.

The results indicate that being located in the West of Ireland is associated with an average decrease in efficiency of less than 1 per cent. Larger farm size is associated with a steady decrease in efficiency. The effect of both junior and leaving certificate education relative to primary

education, does not have a statistically significant impact on the efficiency level. Receiving direct payments has a negative impact on efficiency; farms with a share of direct payments 25 percentage points greater than average are, on average, 1 per cent less efficient.

It is possible that the role of the extension service is changing as a result of the changed policy environment for agriculture following EU agricultural policy reforms in 1992 (the MacSharry reform) and 1999 (the Agenda 2000 reforms). Contact with the extension service increased efficiency by 6.5 per cent relative to farms with no contact. The interaction between the level of education and extension contact was found to be statistically insignificant. Farms in contact with the extension service and with a lower than average dependency on direct payments were on average a further 6.6 per cent more efficient. Farms that are highly dependent on direct payments and have contact with the extension service are 1.9 per cent less efficient than contact farms with an average dependence on direct payments.

The final essay, in Chapter 5, concentrated on the measurement of total factor productivity for Irish milk producing farms. The aim of the chapter was to compare Stochastic Frontier Analysis (SFA) to Data Envelopment Analysis (DEA) in the measurement of total factor productivity (TFP). Both approaches generate estimates of efficiency and technical change. SFA draws on microeconometric techniques and involves the imposition of a number of restrictive assumptions regarding the structure of the technology. DEA employs linear programming methods which exploit the

data fully without the need for the restrictive assumptions required for econometric frontier analysis. Both methods were used to construct distance functions which were then used to construct a Malmquist TFP index. The analysis was carried out using farm level data on Irish milk producing farms for the period 1984 to 1998.

In Chapters 3 and 4 it was clear that, at the micro level, milk producing farms were on average more efficient than other farm systems and had higher rates of technical progress. Average technical efficiency in the SFA and DEA models in 1984 were 81 and 79 per cent respectively. The rank correlation between the SFA and DEA results is 67 per cent which is consistent with other studies in the literature. As expected the variation in efficiency is greater in the DEA due to the influence of white noise. Technical efficiency remains almost constant for the entire period of the study, however, the level of technical efficiency is relatively high at the start of the study. This suggests that milk-producing farms are operating near the top of the frontier. In other words, they are highly efficient and so there is little room for gains in efficiency. The driving force behind total factor productivity growth over the period is coming from technical progress. The DEA results show the TFP index rising by 1.9 per cent over the fifteen year period of the study. The TFP growth rate is 2.02 per cent, which is lower than the SFA results. It should be noted that although technical progress is dominating growth in productivity it is doing so at a declining rate. Technical progress is being driven most likely by research expenditure.

6.3. POLICY IMPLICATIONS

There are a number of policy implications related to the results presented here which warrant discussion. The first paper concentrated on measuring technical change and efficiency over the period from 1984 to 1998. The average efficiency level for the preferred model (translog with non-neutral technical change and system dummies) was estimated at 71 per cent. This result suggests that there is considerable scope for either increased output or cost savings if average efficiency levels could be improved. Farming in the East of the country, age, larger household size and high borrowings were found to be positively associated with efficiency, while having an off-farm job and larger farm size were negatively associated with efficiency. From a policy perspective these results do give important insights into the determinants of farmers' behaviour. However, the results only account for a proportion of the observed variance in efficiency levels. It is worth noting that the 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.

Overall, the weighted average rate of technical change, measured by the shift in the frontier of best practice farms, is 1.95 per cent annually. There is evidence that the rate of technical change has been slowing down over the period. Overall productivity growth has been slower than this because the average level of farm efficiency (the average distance farms are away from the frontier) has been decreasing by 0.4 per cent per annum. This evidence suggests that, in the short term, efforts to halt

the decline in average efficiency levels, perhaps through farm advisory work, would have a high pay-off compared to research expenditure. However, the long term pay off for research compared to advisory services is less clear. There was also evidence that the rate of technical change has been slowing down over the period.

Farms located in the Eastern region had a mean annual rate of technical progress of 1.36 per cent over the period compared to 0.12 per cent annual for farms in the Western region. This is due in part to the presence of non-neutral technical regress over the period for farms in the west. Farms in the top size quintile (over 81 hectares of land) had a higher average rate of technical progress of 1.1 per cent compared to farms in the bottom quintile (less than 22 hectares) that had an average annual rate of technical progress of 0.3 per cent.

The causes of these differences in technical change growth rates deserve more extensive investigation. The decline in the rate of technical progress coincides with the cuts in the research funding experience in the mid 1980s. If technical progress continues to occur at the current declining rate there are serious implications for the future competitiveness of Irish agriculture. Ireland needs to be at the forefront of the agricultural industry at international levels if it is to prosper when price support goes and when the transition countries enter the EU.

It is also interesting to speculate on the possible contribution of the changes in CAP support mechanisms in the 1990s. Not only has the role

of direct payments in farm income support increased in importance, but also a growing share of direct payments is now contributed by schemes with direct production-limiting impacts (extensification, rural environmental payments). It is at least plausible that the more recent CAP regulations have acted to the detriment of efficiency and efficiency improvement in Irish agriculture. If corroborated, it is an important argument to be taken into account in assessing the balance of advantage of the CAP to Ireland.

The negative association between dependence on direct payments and farm technical efficiency suggests that reform of EU agricultural policy is encouraging a less competitive agricultural sector. Again, the concern is that the agricultural sector will find it more difficult to face up to the more market-oriented policy regime which may result from WTO negotiations on agricultural trade liberalisation. Indeed, it may be that the high dependence on direct payments not only reduces efficiency, but also slows down, the take-up of technical innovations and is thus responsible for the decreasing rate of technical change over time.

Significant direct payments are made to cattle, sheep and cereal producers, but support to dairy farmers continues to be provided entirely through market price support. However, because efficiency is measured relative to best practice within each system, the dependence on the direct payments variable is not simply picking up the more efficient use of resources by some farming systems. Rather, it appears to reflect the fact that eligibility for payments may require a farmer to

deliberately pursue technically less efficient production practices (such as is required to qualify for REPS or extensification payments). Policy makers need to be aware that there is an evident tension between short-run income support or environmental objectives and long-run competitiveness.

The positive association between advisory contact and technical efficiency suggests that there is a high pay-off to extension advice. The fact that over three-quarters of all eligible commercial farmers have signed up to participate in the "Farm Tech Service" offered by the extension service suggests that this advice is valued by them. On the other hand, it is clear that many farmers now rely on the extension service for advice and assistance in applying for direct payment supports. Comparing farms with extension contact, technical efficiency is lower on farms with a higher than average dependence on direct payments. Nevertheless, efficiency is still higher than on farms with no extension contact. This suggests that there is a positive productivity benefit from extension contact even when the primary purpose of this contact is assistance with qualification for direct payments.

The results for the milk producing farms indicate that technical efficiency has remained almost constant for the entire period of the study. This should be interpreted in the context that the level of technical efficiency is relatively high at the start of the study. This suggests that milk producing farms are operating near the frontier. In other words, they are highly efficient and so there is little room for gains

in efficiency. The driving force behind total factor productivity growth over the period is coming from technical progress. It appears that, on average, milk producing farms in the post quota period recovered from this major structural change to the dairy industry. In the period directly after the introduction of quota technical efficiency change was stagnant and total factor productivity growth was being driven by technical progress. Working from the premise that technical progress occurs due to research and gains in technical efficiency come from contact with the extension service, then any future allocation of funds between research on one hand and extension on the other hand should be levied in favour of research. However, it could be argued that the farm advisory service prevented declines in technical efficiency in the post quota period. Both the research and farm advisory service were undertaking research and advising dairy farms on the optimal profit maximising output mix prior to the implementation of the quota system and this appears to have assisted dairy farms to increase TFP.

6.4. CAVEATS AND FUTURE WORK

The results presented in this thesis represent a small area of research. I have by no means exploited the data set fully and there are a number of issues which I have not been able to solve with a first best solution. Nevertheless, the body of work does represent a significant contribution to the literature on productivity in Irish agriculture.

The most pertinent issue is to try and model allocative efficiency explicitly. The data aggregation method used is a good second best in the absence of price data, but it has to be acknowledged there may be some

allocative efficiency intertwined with technical efficiency. Given sufficiently detailed price data this problem could be overcome. Orea (2000) has developed an approach to the measurement of allocative efficiency through an alternative decomposition of total factor productivity estimated under variable returns to scale. This model has not been applied empirically at this stage, but it seems to offer a logical theoretical approach

It is also important to note that extension workers may have other goals, such as community development or helping with grant payments, which are not necessarily captured by increases in technical efficiency. The inclusion of direct payment variables and their interaction with contact with the advisory service has given an indication that the extension service may be pursuing goals other than technical efficiency.

There are environmental benefits arising from the less extensive farming methods encouraged by the present agricultural policy. Quantifying the negative effects on agricultural productivity and the positive effects on the environment of the direct payments regime are important issues in assessing the overall benefits to Ireland from the operation of the EU's Common Agricultural Policy. Research on environmental impacts would be a natural progression from this research.

At the start of my research I had hoped to be able to calculate system level rates of return to agricultural research and extension. However, cost data does not seem to be available for system specific costs. A cost-

benefit ratio to public extension and research expenditure could be carried out by weighting the results found in Chapter 3 and using aggregate national level data on the costs of research and extension.

I have concentrated on the SFA method to calculate technical change and technical efficiency and only used DEA methods in the final empirical chapter. DEA offers an alternative approach to the measurement of productivity. It does not require the imposition of a production function form which is its main advantage. It would seem apt to use DEA to replicate the models estimated using SFA to check the consistency of the results.

Finally, every time I think I have mastered the measurement of technical change and efficiency there is a new development or an alternative approach to be tried. I had, due to time pressures, to end my research somewhere. I hope that this research will, in some way, assist agricultural policy makers as they shape the future of Irish agriculture.

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APPENDIX

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CHAPTER 3: Input Elasticities and Returns to Scale

Model	Size	SE	Labour	SE	Variable Input	SE	Capital	SE
I	0.2551[a]	0.030	0. 0889[a]	0.021	0. 4411 [a]	0.024	0.0321[a]	0.015
II	0.4645[a]	0.034	0.0709[a]	0.027	0.1198[a]	0.038	-0.018	0.020
III	-0.020	0.016	0.1212[a]	0.018	0.8573 [a]	0.014	0.1095 [a]	0.009
IIIa	0.002	0.121	0.1610[a]	0.015	0.7779[a]	0.011	0.1163[a]	0.008
IV	-0.0312[b]	0.016	0.1224[a]	0.017	0.8664[a]	0.013	0.1068[a]	0.009
IVa	0.003	0.012	0.1595[a]	0.015	0.7843[a]	0.012	0.1157[a]	0.720
IX	0.1493[a]	0.015	0.080	0.017	0.705	0.014	0.091	0.008
IXa	0.1326[a]	0.012	0.1241[a]	0.015	0.6903[a]	0.012	0.101	0.007
V	0.2418[a]	0.024	0.1737[a]	0.033	0.4438[a]	0.022	0.1143[a]	0.015
Va	0.0379[b]	0.019	0.2437[a]	0.028	0.6792[a]	0.018	0.1025[a]	0.013
VI	0.2374[a]	0.024	0.1742[a]	0.033	0.4550[a]	0.002	0.1156[a]	0.015
VIa	0.0381[b]	0.018	0.2442[a]	0.028	0.6830[a]	0.018	0.1008[a]	0.013
VII	0.2845[a]	0.029	0.0737[a]	0.024	0.3601[a]	0.021	0.0374[b]	0.015
VIII	0.5019[a]	0.034	0.1095[a]	0.038	0.019	0.027	-0.006	0.020
X	0.1615[a]	0.014	0.0769[a]	0.016	0.7074[a]	0.013	0.0865[a]	0.008
Xa	0.1208[a]	0.013	0.1287[a]	0.014	0.6876[a]	0.011	0.1043[a]	0.007
XI	0.3781[a]	0.023	0.1486[a]	0.033	0.3539[a]	0.021	0.1034[a]	0.015
XIa	0.1753[a]	0.019	0.2057[a]	0.027	0.5805[a]	0.019	0.0962[a]	0.012
XII	0.398[a]	0.022	0.1451[a]	0.032	0.3558[a]	0.020	0.1017[a]	0.014
XIIa	0.1823[a]	0.018	0.2035[a]	0.027	0.5799[a]	0.018	0.0949[a]	0.012
XIII	-0.0843[a]	0.016	0.1316[a]	0.020	0.8717[a]	0.015	0.1421[a]	0.010
XIIIa	-0.018	0.012	0.1593[a]	0.016	0.7749[a]	0.012	0.1336[a]	0.008
XIV	-0.0814[a]	0.016	0.1318[a]	0.019	0.8633[a]	0.015	0.1377[a]	0.010
XIVa	-0.0222[c]	0.013	0.1606[a]	0.017	0.7791[a]	0.012	0.0134[a]	0.008
XIX	0.3685[a]	0.024	0.1294[a]	0.034	0.3522[a]	0.022	0.1260[a]	0.016
XIXa	0.2088[a]	0.020	0.1658[a]	0.028	0.5548[a]	0.019	0.1115[a]	0.013
XV	0.1962[a]	0.025	0.1635[a]	0.035	0.4679[a]	0.023	0.1359[a]	0.017
XV1a	0.0368[c]	0.020	0.2140[a]	0.029	0.6795[a]	0.019	0.1146[a]	0.014
XVa	0.0146[b]	0.020	0.2130[a]	0.029	0.6751[a]	0.019	0.1160[a]	0.014
XVI	0.1962[a]	0.023	0.1597[a]	0.034	0.4703[a]	0.022	0.1357[a]	0.016
XVII	0.1004[a]	0.015	0.0908[a]	0.019	0.7042[a]	0.015	0.1277[a]	0.010
XVIIa	0.1155[a]	0.013	0.1249[a]	0.016	0.6690[a]	0.012	0.1283[a]	0.008
XVIII	0.1128[a]	0.015	0.0878[a]	0.018	0.6790[a]	0.015	0.1238[a]	0.009
XVIIIa	0.1153[a]	0.013	0.1241[a]	0.016	0.6726[a]	0.012	0.1264[a]	0.008
XX	0.3655[a]	0.022	0.1274[a]	0.032	0.3626[a]	0.021	0.1224[a]	0.015
XXa	0.2015[a]	0.020	0.1664[a]	0.028	0.5592[a]	0.019	0.1096[a]	0.013
XXI	0.0168[a]	0.030	0.0793[a]	0.022	0.5291[a]	0.025	0.0651[a]	0.017
XXII	0.4217[a]	0.039	0.1276[a]	0.029	0.1170[a]	0.039	0.0108[a]	0.022
XXIII	0.0202[a]	0.030	0.0671[a]	0.025	0.4440[a]	0.022	0.0651[a]	0.016
XXIV	0.4649[a]	0.035	0.1051[a]	0.038	0.0740[a]	0.029	0.018	0.021

APPENDIX

CHAPTER 3 : Production Function Coefficients Table 1a

	I	II	III	IIIa	IV	IVa	V	Va
Constant	0.1771[a] 0.0166	0.1447[a] 0.0163	0.8391[a] 0.0199	0.4890[a] 0.0156	0.7386[a] 0.0183	0.4572[a] 0.0155	0.8013[a] 0.0192	0.4886[a] 0.01642
Size (hectares)	0.2551[a] 0.0299	0.4645[a] 0.0342	-0.0196 0.0162	0.0021 0.1214	-0.0312[b] 0.0156	0.0033 0.0122	0.2418[a] 0.0241	0.0379[b] 0.01890
Labour	0. 0889[a] 0.0210	0.0709[a] 0.0267	0.1212[a] 0.0178	0.1610[a] 0.0152	0.1224[a] 0.0174	0.1595[a] 0.0153	0.1737[a] 0.0332	0.2437[a] 0.0279
Variable inputs	0. 4411[a] 0.0242	0.1198[a] 0.0382	0.8573[a] 0.0141	0.7779[a] 0.0113	0.8664[a] 0.0129	0.7843[a] 0.0117	0.4438[a] 0.0218	0.6792[a] 0.0183
Capital	0.0321[a] 0.0148	-0.0177 0.0198	0.1095[a] 0.0088	0.1163[a] 0.0076	0.1068[a] 0.0088	0.1157[a] 0.7203	0.1143[a] 0.0154	0.1025[a] 0.0125
size^2								
Labour^2								
var^2								
capital^2								
SL								
SV								
SC								
LV								
LC								
VC								
Time	-0.0055 0.0045	0.0076[c] 0.0044	-0.0113[b] 0.0043	0.0060 0.0039	-0.0119[a] 0.0043	0.0023 0.0041	0.0034 0.0043	0.0136[a] 0.0041
Time^2	- 0.0044[a] 0.0005	-0.0068[a] 0.0005	-0.0042[a] 0.0005	0.0010[b] 0.0005	-0.0039[a] 0.0005	0.0010[c] 0.0005	-0.0068[a] 0.0005	0.0012[b] 0.0005
VT		0.0500[a] 0.0023					0.0519[a] 0.0021	0.0195[a] 0.0022
ST		-0.0329[a] 0.0024					-0.0327[a] 0.0022	-0.0077[a] 0.0022
LT		-0.0073[b] 0.0038					-0.0084[b] 0.0033	-0.0139[a] 0.0031
CT		0.0036[b] 0.0017					-0.0015 0.0015	0.0021 0.0014
Dairy Other								
Cattle								
Sheep								
Crops								
σ2			1.0608[a]	3.3865	0.3013[a]	0.1189[a]	1.045[a]	2.8297[a]
gamma			0.7913[a]	0.9446[a]	0.9262[a]	0.9842[a]	0.8032[a]	0.9335[a]
mu			0	0	-3.3414[a]	-6.844[a]	0	0
eta			0	-0.1062[a]	0	-0.1113[a]	0	-0.9540[a]
R^2	0.6766	0.6737						
LLF \ **F**	**226.76**	**241.53**	-12310	-11315	-12238	-11226		-11252

a Significance at 1%; b Significance at 5%; c Significance at 10%; LLF log likelihood function

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CHAPTER 3 : Production Function Coefficients Table 1b

	VI	VIa	VII	VIII	IX	IXa	X	Xa
Constant	0.7165[a]	0.4505[a]	0.4652[a]	0.3882[a]	1.0342	0.6064[a]	0.9304[a]	0.6316
	0.01602	0.01455	0.0236	0.2311	0.0223	0.01701	0.0213	0.0180
Size (hectares)	0.2374[a]	0.0381[b]	0.2845[a]	0.5019[a]	0.1493[a]	0.1326[a]	0.1615[a]	0.1208[a]
	0.0236	0.0184	0.0294	0.0339	0.0153	0.0122	0.01443	0.01272
Labour	0.1742[a]	0.2442[a]	0.0737[a]	0.1095[a]	0.0795	0.1241[a]	0.0769[a]	0.1287[a]
	0.0332	0.0282	0.0238	0.0376	0.0168	0.01469	0.0163	0.0144
Variable inputs	0.4550[a]	0.6830[a]	0.3601[a]	0.0192	0.7053	0.6903[a]	0.7074[a]	0.6876[a]
	0.0021	0.0180	0.0210	0.0265	0.0138	0.0115	0.0130	0.0114
Capital	0.1156[a]	0.1008[a]	0.0374[b]	-0.0061	0.0913	0.1007	0.0865[a]	0.1043[a]
	0.0150	0.0127	0.0145	0.0195	0.0081	0.0072	0.0081	0.0069
$size^2$								
$Labour^2$								
var^2								
$capital^2$								
SL								
SV								
SC								
LV								
LC								
VC								
Time	0.0029	0.0107[a]	0.0022	0.0144[a]	0.0027	0.0092[b]	0.0017	0.1229[a]
	0.0042	0.0039	0.0045	0.0044	0.0043	0.0041	0.0043	0.0040
$Time^2$	-0.0066[a]	-0.0014[a]	-0.0049[a]	-0.0071[a]	-0.0053[a]	-0.0002	-0.0505[a]	0.1214
	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005
VT	0.0518[a]	0.0200[a]		0.0476[a]				
	0.2001	0.0021		0.0023				
ST	0.0332[a]	-0.0080[a]		-0.0341[a]				
	0.0022	0.0022		0.0024				
LT	-0.0086[b]	-0.0138[a]		-0.0073[b]				
	0.0033	0.0031		0.0037				
CT	-0.0017	0.0019		0.0028[c]				
	0.0015	0.0014		0.0017				
Dairy Other			-0.1067[a]	-0.1032[a]	-0.146[a]	-0.0925[a]	-0.1411[a]	-0.8682[a]
			0.0206	0.0199	0.0169	0.0145	0.0164	0.0145
Cattle			-0.6124[a]	-0.5423[a]	-0.7340[a]	-0.4927[a]	-0.7139[a]	-0.4800[a]
			0.0299	0.0292	0.0205	0.0181	0.0196	0.01829
Sheep			-0.6207[a]	-0.5202[a]	-0.8255[a]	-0.6506[a]	-0.7909[a]	-0.6572[a]
			0.0352	0.0343	0.0241	0.0207	0.0230	0.0204
Crops			-0.3730[a]	-0.2879[a]	0.3148[a]	-0.2355[a]	-0.2947[a]	-0.2348[a]
			0.0353	0.0344	0.0224	0.0178	0.0211	0.01767
$\sigma 2$	3.0158[a]	9.5485[a]			0.7339[a]	8.9271[a]	1.9544[a]	0.2662[a]
gamma	0.9311[a]	0.9804[a]			0.7112	0.9795	0.8921[a]	0.9310[a]
mu	-3.351[a]	-6.1193[a]			0	-5.9141[a]	-2.6409[a]	0
eta	0	-0.0984[a]			0	-0.1264[a]	0	-0.1212[a]
R^2			0.7674	0.7584				
LLF \ F	-11755	-11163	**192.79**	**206.81**	-11571	-10652	-11468	-10778

a Significance at 1%; b Significance at 5%; c Significance at 10%; LLF log likelihood function

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CHAPTER 3 : Production Function Coefficients Table 1c

	XI	XIa	XII	XIIa	XIII	XIIIa	XIV	XIVa
Constant	0.9575a	0.6257[a]	0.8738[a]	0.5973	0.7296[a]	0.4370[a]	0.0649[a]	0.3998[a]
	0.0219	0.0185	0.02050	0.0171	0.0214	0.0168	0.0205	0.0161
Size (hectares)	0.3781[a]	0.1753[a]	0.398[a]	0.1823[a]	-0.0843[a]	-0.0176	-0.0814[a]	-0.0222[c]
	0.0232	0.0192	0.0215	0.0182	0.0159	0.0124	0.01577	0.0125
Labour	0.1486[a]	0.2057[a]	0.1451[a]	0.2035[a]	0.1316[a]	0.1593[a]	0.1318[a]	0.1606[a]
	0.0327	0.0271	0.0315	0.0274	0.0196	0.0163	0.0194	0.0167
Variable inputs	0.3539[a]	0.5805[a]	0.3558[a]	0.5799[a]	0.8717[a]	0.7749[a]	0.8633[a]	0.7791[a]
	0.0213	0.0185	0.0200	0.0179	0.0151	0.0115	0.0146	0.0120
Capital	0.1034[a]	0.0962[a]	0.1017[a]	0.0949[a]	0.1421[a]	0.1336[a]	0.1377[a]	0.01340[a]
	0.0148	0.0121	0.0143	0.0121	0.0103	0.0082	0.0102	0.0083
$size^2$					-0.0564[c]	-0.1494[a]	-0.0311	-0.1304[a]
					0.0314	0.0240	0.0309	0.0239
$Labour^2$					0.1032[a]	0.0521	0.1063[a]	0.0517
					0.0369	0.0342	0.0365	0.0350
var^2					0.3462[a]	0.1513[a]	0.3351[a]	0.1573[a]
					0.0278	0.0219	0.0282	0.0217
$capital^2$					0.0354[a]	0.0187[b]	0.0334[a]	0.0212[b]
					0.0113	0.0092	0.0111	0.0092
SL					-0.0117	0.0512[b]	-0.0174	0.0503[c]
					0.0308	0.0258	0.0304	0.0259
SV					-0.1483[a]	-0.0317[c]	-0.1593[a]	-0.0445[a]
					0.0216	0.0167	0.0213	0.0168
SC					0.0509[a]	0.0479[a]	0.05190[a]	0.0462[a]
					0.0142	0.0117	0.0140	0.0118
LV					-0.0805[a]	-0.1007[a]	-0.0720[a]	-0.0960[a]
					0.0270	0.0230	0.0266	0.0225
LC					0.0247	0.0130	0.0191	0.0090
					0.0193	0.0162	0.0187	0.0164
VC					-0.0399[a]	-0.0122	-0.0396[a]	-0.0133
					0.0145	0.0111	0.0146	0.0110
Time	0.0164[a]	0.0219[a]	0.01482[a]	0.0185[a]	-0.0077[c]	0.0076[c]	-0.0081[c]	0.0050
	0.0043	0.0041	0.0042	0.0041	0.0077	0.0040	0.0043	0.03969
$Time^2$	-0.0077[a]	0.0023[a]	-0.0074[a]	-0.0025[a]	-0.0048[a]	0.0007	-0.0045[a]	0.0005
	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005	0.0005
VT	-0.1341[a]	-0.0906[a]	-0.1301[a]	0.0202[a]				
	0.0164	0.01501	0.01572	0.0021				
ST	-0.6749[a]	-0.4884[a]	-0.6605[a]	-0.0102[a]				
	0.0203	0.0184	0.01883	0.0021				
LT	-0.7669[a]	-0.6587[a]	-0.7386[a]	-0.0128[a]				
	0.0241	0.0206	0.02189	0.0031				
CT	-0.2512[a]	-0.2241[a]	-0.2407[a]	0.0007				
	0.0220	0.0184	0.0207	0.0014				
Dairy	0.04662[a]	0.0204[a]	0.0469[a]	-0.0947[a]				
Other	0.0021	0.0021	0.0020	0.0149				
Cattle	-0.0319[a]	-0.0113[a]	-0.0329[a]	-0.4980[a]				
	0.0021	0.0021	0.0020	0.0182				
Sheep	-0.0093[a]	-0.0129[a]	-0.0093[a]	-0.6497[a]				
	0.0032	0.0031	0.0032	0.0208				
Crops	-0.00187	0.0011[a]	-0.0021	-0.2228[a]				
	0.0015	0.0014	0.0014	0.0179				
σ2	0.7227[a]	2.1798[a]	1.9554[a]	7.1743[a]	1.051[a]	3.3320[a]	3.135[a]	11.791[a]
gamma	0.7236[a]	0.9154[a]	0.8984[a]	0.9744[a]	0.7946	0.9439	0.9314[a]	0.9842[a]
mu	0	0	-2.650[a]	-5.2880	0	0	-3.417[a]	-6.183[a]
eta	0	-0.1082[a]	0	-0.1130[a]	0	-.1069[a]	0	-0.1120[a]
R^2								
LLF \ **F**	-11181	-10717	-11071	-10589	-12140	-11233	-12071	-11143

a Significance at 1%; b Significance at 5%; c Significance at 10%; LLF log likelihood function

APPENDIX

CHAPTER 3 : Production Function Coefficients Table 1d

	XV	XVa	XVI	XVIa	XVII	XVIIa	XVIII	XVIIIa
Constant	0.7322[a]	0.4430[a]	0.6490[a]	0.4044[a]	0.9316[a]	0.5913[a]	0.8367[a]	0.5595[a]
	0.0213	0.0183	0.0196	0.0183	0.02355	0.0188	0.0222	0.0174
Size (hectares)	0.1962[a]	0.0146[b]	0.1962[a]	0.0368[c]	0.1004[a]	0.1155[a]	0.1128[a]	0.1153[a]
	0.0245	0.0196	0.0227	0.0199	0.01549	0.0125	0.0149	0.0125
Labour	0.1635[a]	0.2130[a]	0.1597[a]	0.2140[a]	0.0908[a]	0.1249[a]	0.0878[a]	0.1241[a]
	0.0347	0.0288	0.0336	0.0292	0.0187	0.0156	0.0179	0.0158
Variable inputs	0.4679[a]	0.6751[a]	0.4703[a]	0.6795[a]	0.7042[a]	0.6690[a]	0.6790[a]	0.6726[a]
	0.0229	0.0189	0.0223	0.0192	0.0147	0.0118	0.0149	0.0117
Capital	0.1359[a]	0.1160[a]	0.1357[a]	0.1146[a]	0.1277[a]	0.1283[a]	0.1238[a]	0.1264[a]
	0.0166	0.01365	0.0161	0.0138	0.0097	0.0078	0.0093	0.0079
size^2	-0.1527[a]	-0.1749[a]	-0.1235[a]	-0.1522[a]	-0.1041[a]	-0.1687[a]	-0.0748[a]	-0.1526[a]
	0.0315	0.0250	0.0304	0.0258	0.0288	0.0217	0.0287	0.0220
Labour^2	0.0889[b]	0.0406	0.0807[b]	0.0419	0.0931[b]	0.0495	0.0926[a]	0.0506[c]
	0.0372	0.0354	0.0361	0.0370	0.0358	0.0331	0.0351	0.0321
var^2	0.1330[a]	0.0107[a]	0.1316[a]	0.1094[a]	0.2751[a]	0.1247[a]	0.2720[a]	0.1338[a]
	0.0268	0.0226	0.0258	0.0230	0.0262	0.0205	0.0262	0.0203
capital^2	0.0320[a]	0.0240[b]	0.0310[a]	0.0259[a]	0.0395[a]	0.0303[a]	0.0392[a]	0.0328[a]
	0.0108	0.0094	0.0105	0.0094	0.0105	0.0085	0.0104	0.0084
SL	-0.0197	0.0345	-0.0288	0.0325	0.0214	0.0606[b]	0.0113	0.0577[b]
	0.0307	0.0267	0.0297	0.0274	0.0292	0.0245	0.0287	0.0245
SV	-0.0080	0.0001[a]	-0.0173	-0.0113	-0.0886[a]	-0.0012	-0.1047[a]	-0.1544
	0.0218	0.0181	0.0208	0.0185	0.0202	0.0157	0.0196	0.0156
SC	0.0360[b]	0.0450[a]	0.0332[b]	0.0434[a]	0.0476[a]	0.0457[a]	0.0500[a]	0.0459[a]
	0.0142	0.0121	0.0139	0.0123	0.0136	0.0112	0.0321	0.0112
LV	-0.0443[c]	-0.0754[a]	-0.0340	-0.0682[a]	-0.0762[a]	-0.0911[a]	-0.0629[b]	-0.0822[a]
	0.0269	0.0238	0.0261	0.0245	0.0255	0.0215	0.0247	0.0211
LC	0.0180	0.0152	0.0142	0.0090	0.0265	0.0211	0.0224	0.0162
	0.0188	0.0166	0.0183	0.0175	0.0184	0.0155	0.0175	0.0152
VC	-0.0096	-0.0030	-0.0106	-0.0140	-0.0436[a]	-0.0253[b]	-0.0442[a]	-0.0269[a]
	0.0133	0.0112	0.0128	0.0115	0.0134	0.0103	0.0136	0.0101
Time	0.0034	0.0142[a]	0.0029	0.0117[a]	0.0043	0.0126[a]	0.0035	0.0102[a]
	0.0044	0.0042	0.0043	0.0040	0.0043	0.0039	0.0042	0.0038
Time^2	-0.0068[a]	-0.0013[b]	-0.0066[a]	-0.0016[a]	0.0028[a]	-0.0000[a]	-0.0022[a]	-0.0002
	0.0005	0.0005	0.0005	0.0005	0.0002	0.0003	0.0002	0.0002
VT	0.0488[a]	0.0194[a]	0.0489[a]	0.0188[a]				
	0.0022	0.0024	0.0021	0.0022				
ST	-0.0327[a]	-0.0111[a]	-0.0330[a]	-0.0108[a]				
	0.0023	0.0024	0.0021	0.0023				
LT	-0.0064[c]	-.0.100[a]	-0.0064[c]	-0.0099[a]				
	0.0035	0.0033	0.0034	0.0033				
CT	-0.0002	0.0035[b]	-0.0005	0.0034[b]				
	0.0016	0.0015	0.0016	0.0015				
Dairy					-0.1430[a]	-0.0971[a]	-0.1371[a]	-0.1003[a]
Other					0.0168	0.0142	0.0165	0.0144
Cattle					-0.7124[a]	-0.4939[a]	-0.6929[a]	-0.5029[a]
					0.0204	0.0177	0.0195	0.0175
Sheep					-.07928[a]	-0.6603[a]	-0.7629[a]	-0.6536[a]
					0.0240	0.0200	0.0231	0.0198
Crops					-0.3011[a]	-0.2567[a]	-0.2802[a]	-0.2500[a]
					0.0228	0.0175	0.0214	0.0176
σ2	1.012[a]	2.7685[a]	2.9601[a]	9.477	0.7232[a]	2.632[a]	1.9940[a]	8.8361[a]
gamma	0.7983[a]	0.9325[a]	0.9313[a]	0.9804[a]	0.7172[a]	0.9309[a]	0.8970[a]	0.9795[a]
mu	0	0	-3.332[a]	-6.0965[a]	0	0	-2.6749[a]	-5.8838[a]
eta	0	-0.0967[a]	0	-0.1004[a]	0	-0.1238[a]	0	-0.1289[a]
R^2								
LLF \ **F**	-11743	-11169	-11672	-11083	-11426	-106807	-11320	-10549

a Significance at 1%; b Significance at 5%; c Significance at 10%; LLF log likelihood function

APPENDIX

CHAPTER 3 : Production Function Coefficients Table 1e

	XIX	XIXa	XX	XXa	XXI	XXII	XXIII	XXIV
Constant	0.9075[a]	0.5993[a]	0.8164[a]	0.5650[a]	0.0301	0.0704[a]	0.3151[a]	0.3152[a]
	0.0230	0.0195	0.0214	0.0192	0.0222	0.0218	0.0278	0.0272
Size	0.3685[a]	0.2088[a]	0.3655[a]	0.2015[a]	0.0168[a]	0.4217[a]	0.0202[a]	0.4649[a]
(hectares)	0.0238	0.0201	0.0222	0.0198	0.0302	0.0385	0.0298	0.0354
Labour	0.1294[a]	0.1658[a]	0.1274[a]	0.1664[a]	0.0793[a]	0.1276[a]	0.0671[a]	0.1051[a]
	0.0336	0.0280	0.0324	0.0279	0.0218	0.0288	0.0247	0.0382
Variable	0.3522[a]	0.5548[a]	0.3626[a]	0.5592[a]	0.5291[a]	0.1170[a]	0.4440[a]	0.0740[a]
inputs	0.0218	0.0188	0.0205	0.0189	0.0252	0.0388	0.0218	0.0285
Capital	0.1260[a]	0.1115[a]	0.1224[a]	0.1096[a]	0.0651[a]	0.0108[a]	0.0651[a]	0.0177
	0.0156	0.0129	0.0151	0.0129	0.0166	0.0215	0.0163	0.0212
$size^2$	-0.1890[a]	-0.2048[a]	-0.1598[a]	-0.1843[a]	0.0768	-0.0353	0.0814[c]	-0.0341
	0.0286	0.0230	0.0271	0.0230	0.0500	0.0495	0.0495	0.0487
$Labour^2$	0.0787[b]	0.0363	0.0777[b]	0.0361	0.0297	0.0280	0.0355	0.0340
	0.0358	0.0333	0.0352	0.0334	0.0450	0.0439	0.0441	0.0433
var^2	0.0951[a]	0.0753[a]	0.0960[a]	0.0830[a]	0.3777[a]	0.1264[a]	0.3603[a]	0.1255[a]
	0.0250	0.0215	0.0239	0.0215	0.0341	0.0346	0.0335	0.0341
$capital^2$	0.0354[a]	0.0336[a]	0.0348[a]	0.0360[a]	0.0330[b]	0.0226	0.0305[b]	0.0207
	0.0100	0.0089	0.0081	0.0089	0.01564	0.0152	0.0153	0.0149
SL	0.0004[c]	0.0418[c]	-0.0085	0.0356	-0.0478	-0.0249	-0.0348	-0.0188
	0.0291	0.0251	0.0282	0.0249	0.3852	0.0376	0.0378	0.0371
SV	0.0383[c]	0.0396[b]	0.0215	0.0241	-0.1324[a]	0.0048	-0.1214[a]	0.0177
	0.0201	0.0169	0.0194	0.0168	0.0284	0.0288	0.0278	0.0284
SC	0.0340[b]	0.0413[a]	0.0337[b]	0.0425[a]	0.0123	0.0053	0.0062	0.0003
	0.0135	0.0116	0.0133	0.0116	0.0193	0.0188	0.0190	0.0185
LV	-0.0405[c]	-0.0687[a]	-0.0315	-0.0567[a]	-0.0583[c]	-0.0333	-0.064[b]	-0.0396
	0.0253	0.0222	0.0246	0.0223	0.0328	0.0324	0.0322	0.0319
LC	0.0213	0.0250[c]	0.0205	0.0203	0.0529[b]	0.0319	0.0448[c]	0.0251
	0.0179	0.0159	0.0172	0.0160	0.0259	0.0251	0.0254	0.0247
VC	-0.0180	-0.0199[c]	-0.0178	-0.0223[a]	-0.0269	0.0044	-0.0295[c]	0.0013
	0.0123	0.0107	0.0119	0.0107	0.0191	0.0187	0.0187	0.0184
Time	0.0155[a]	0.0214[a]	0.0145[a]	0.0179[a]	-0.0032	0.0072[c]	0.0045[a]	0.0142[a]
	0.0044	0.0042	0.0042	0.0039	0.0045	0.0044	0.0045	0.0044
$Time^2$	-0.0038[a]	-0.0012[a]	-0.0036[a]	-0.0013[a]	-0.0051[a]	-0.0069[a]	-0.0056[a]	-0.007[a]
	0.0002	0.0003	0.0002	0.0002	0.0005	0.0005	0.0005	0.0005
VT	0.0448[a]	0.0208[a]	0.0442[a]	0.02022[a]		0.0472[a]		0.0450[a]
	0.0021	0.0022	0.0021	0.0022		0.0024		0.0024
ST	-0.0335[a]	-0.0162[a]	-0.0330[a]	-0.0148[a]		-0.0320[a]		-0.0337[a]
	0.0022	0.0022	0.0021	0.0021		0.0025		0.0025
LT	-0.0066[c]	-0.0084[a]	-0.0067[b]	-0.0085[b]		-0.007[c]		-0.0070[b]
	0.0034	0.0032	0.0033	0.0032		0.0038		0.0038
CT	-0.0005	0.0031[b]	-0.0005	0.0028[c]		0.0034[b]		0.0027[c]
	0.0015	0.0015	0.0015	0.0014		0.0018		0.0017
Dairy	-0.1484[a]	-0.1067[a]	-0.1434[a]	-0.1086[a]			-0.1059[a]	-0.1060[a]
Other	0.0165	0.0153	0.0158	0.0152			0.0205	0.0199
Cattle	-0.6837[a]	-0.5084[a]	-0.6709[a]	-0.5163[a]			-0.5940[a]	-0.5405[a]
	0.0202	0.0184	0.0191	0.0183			0.0297	0.0291
Sheep	-0.7655[a]	-0.6682[a]	-0.7448[a]	-0.6591[a]			-0.5956[a]	-0.5172[a]
	0.0238	0.0207	0.0223	0.0205			0.0350	0.0343
Crops	-0.2716[a]	-0.2551[a]	-0.2568[a]	-0.2469[a]			-0.3397[a]	-0.2796[a]
	0.0225	0.0190	0.0212	0.0186			0.0351	0.0343
σ2	0.6980[a]	2.1387[a]	1.8009[a]	6.974[a]				
gamma	0.7164[a]	0.9146	0.8909[a]	0.9741				
mu	0	0	-2.533a	-5.2131a				
eta	0	-0.1111a	0	-0.1155a				
R^2					0.6770	0.6900	0.7588	0.7686
LLF \ **F**	-11079	-10608	-10970	-10482	**102.26**	**124.25**	**109.09**	**123.44**

a Significance at 1%; b Significance at 5%; c Significance at 10%; LLF log likelihood function