TECHNICAL EFFICIENCY IN IRISH MANUFACTURING INDUSTRY, 1991-1999

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Abstract: This paper measures the technical efficiency levels in the Electrical and Optical Equipment industry in Irish manufacturing sector and examines the factors that could affect these levels utilising a stochastic production frontier approach over the period 1991-99 using firm-level panel data. Using the model outlined by Battese and Coelli (1995) we find that investment intensity and labour quality play an important role in explaining technical inefficiency levels in all sub-sectors of the Electrical and Optical Equipment industry. We found no significant relationship between export intensity and the technical inefficiency levels of individual firms in all but one sector, namely Television and Radio Receivers industry.

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1 Introduction

The Irish economy has been characterised by high rates of economic growth and low unemployment rates relative to other EU countries during the last decade. One of the main contributors to this overall high rate of growth in the Irish economy has been Irish manufacturing industry, which experienced exceptionally high growth rates in terms of both employment and output during the period. This success in achieving higher rates of growth in output relative to employment has brought substantial increases in labour productivity of both foreign and domestic firms.

Although labour productivity is one of the most commonly used measures for analysing performance of firms or industries, it only gives a partial picture of performance. Another approach taken in the literature in measuring performance of firms or industries has been to estimate production functions in order to measure general productivity. A common assumption that is used in estimating production functions is that producers operate on their production functions, namely all producers are technically efficient.

The alternative approach that is adopted in the literature starts with the presumption that not all producers are technically efficient and involves the estimation of production functions, which is known as stochastic production frontier analysis. This paper uses a stochastic production frontier approach to measure technical efficiency in manufacturing firms in Ireland over the period.

Using firm level Census of Production panel data we examine how technical efficiency levels in manufacturing firms in the Electrical and Optical Equipments industry changed over the period 1991-1999. This sector played an important role in the development of Irish manufacturing industry since the 1970s. We also examine the factors that might have affected the changes in the technical efficiency levels of firms in this industry.

This paper comprises the following: the next section summarises the approach taken in the literature to modelling inefficiency using the stochastic production frontier approach; it also includes a discussion of some of the studies that utilised this approach. Section 3 describes the data and outlines the application of stochastic frontier approach in measuring technical efficiency in Irish manufacturing industry. Section 4 presents the results from the estimation of technical efficiency. We conclude with a summary in Section 5.

2 Determining Inefficiency: Methodology and Literature

2.1 Methodology

Typical models of production function analysis start with a production function and in these models producers are assumed to operate on their production functions, maximising output using the available inputs. Empirical analysis of production functions have long used different least squares techniques in which error terms were assumed to be symmetrically distributed with zero means and the only source of departure from the estimated function was assumed to be statistical noise. These analyses considered productivity only and did not deal with technical efficiency. However, the pioneering work of Koopmans (1951) provided a definition of technical efficiency suggesting that not all producers were technically efficient and since that time we have seen increasing number of studies modelling production functions with the assumption that not all firms might be operating efficiently.

Before proceeding with the theoretical and empirical studies in the literature that followed Koopmans, it is useful to provide informal definitions of productivity, technical efficiency and technical change, which are widely used in these studies. More importantly it is important to show the differences between productivity and technical efficiency concepts, which are often used interchangeably.[1]

[1] For more details see O'Neill (2002).

Productivity is defined as the ratio of the output(s) that a firm produces to the input(s). There are different measures of productivity used in empirical studies such as labour productivity and capital productivity, which are known as partial productivity measures since they relate output to a single input such as labour or capital. An alternative measure used in empirical studies is total factor productivity, which relates output to all the inputs used in the production process.

In order to demonstrate the difference between productivity and technical efficiency definitions we can use a simple production process where a single input (x) is used to produce a single output (y).[2]The line OF in Figure 1 represents a production frontier, which defines the relationship between input and output. The production frontier represents the maximum output attainable from each input level. Hence it reflects the current state of technology in producing that output. Firms operate either on the frontier, in which case they are technically efficient, or beneath the frontier, in which case they are technically inefficient. Point A represents an inefficient firm whereas points B and C represent efficient firms. The firm at point A is technically inefficient because it is not producing as much output as potentially it could given the level of inputs it employs.

The distinction between technical efficiency and productivity is illustrated in Figure 2 where productivity at a particular data point is measured as a ray

[2] This section heavily draws on from Coelli *et al.*(1999)

through the origin. The slope of this ray is *y/x* and hence provides a measure of productivity. If the firm operating at point A moves to the technically efficient point B, the slope of the ray will be greater, implying higher productivity at point B. However, by moving to point C, the ray from the origin is at a tangent to the production frontier and hence defines the point of maximum possible productivity and represents the optimal scale. Thus a firm may be technically efficient but may still be able to improve its productivity. Another concept that is widely used in empirical studies is the technical change, which involves advances in technology and can be represented by an upward shift in the production frontier.

Early Developments in the Frontier Analysis:

Farrell (1957) was the first to measure productive efficiency empirically. Using data on US agriculture he defined cost efficiency and decomposed it into its technical and allocative parts using linear programming techniques rather than econometric methods. His work using linear programming eventually led to the development of data envelopment analysis (DEA) and this method is widely used in the literature as a non-parametric non-stochastic technique.

Farrell's work also led to the development of stochastic frontier analysis which involved estimating deterministic production frontiers, either by means of linear programming techniques or by modification to the least squares techniques. Initial studies on efficiency using deterministic production frontier models assumed the error term was not affected in any way by statistical noise and thus represented inefficiency.

Following Farrell (1957), Aigner and Chu (1968) considered the idea of a deterministic production frontier using a parametric frontier function of Cobb-Douglas form defined as:

$$\ln y_i = c_i b - u_i \qquad i=1,2, \ldots,N. \tag{1}$$

where y_i is the output for the i-th firm, χ_i is a vector of inputs, β is a vector of unknown parameters of the intercept and the slope terms and u_i is non-negative random variable associated with technical inefficiency. The measure of efficiency is given as the ratio of the observed output of the i-th firm to the potential output defined by the frontier function and is outlined as:

$$TE_i = \frac{y_i}{\exp(c_i b)} = \frac{\exp(c_i b - u_i)}{\exp(c_i b)} = \exp(-u_i) \tag{2}$$

Following Aigner and Chu (1968) there have been other studies in the literature using the same approach by applying different estimation techniques. Early studies used the Corrected Ordinary Least Squares (COLS) method to estimate the production frontier, which involved the estimation of the model in two stages where parameter estimates are obtained in the first stage using Ordinary Least Squares (OLS) method and the intercept term is corrected by shifting it upwards until all residuals are non-positive and the largest residual is zero, in the second stage (Lovell, 1993). These corrected residuals are then used to calculate technical efficiency for each producer. The main drawback of this method was the implication of both efficient and inefficient producers having the same structure of frontier technology.

In order to overcome this drawback of the COLS method, an alternative method known as Modified Ordinary Least Squares (MOLS) was proposed. It involved the assumption that the error term followed a one-sided distribution.

Schmidt (1976) argued that if the error term associated with the technical inefficiency effects followed a one side distribution such as exponential or half normal, then linear programming estimates proposed by Aigner and Chu (1968) were maximum likelihood estimates of the deterministic frontier model, which led to the widely use of maximum likelihood estimation techniques in stochastic production frontier analysis.

Although these early studies tried to estimate technical inefficiency, their approach was deterministic in the sense that no allowance was made for the possible influence of measurement error and other statistical noise on the estimated production frontier. In other words all the deviations from the frontier were assumed to be the result of technical inefficiency.

Stochastic Frontier Models:

The stochastic production frontier model was suggested by Aigner *et al.* (1977) and Meeusen and van den Broeck (1977). Both studies proposed the use of composed error terms associated with frontiers, which included a traditional symmetric random noise component and a new one-sided inefficiency component in order to overcome the problems associated with the deterministic approach.[3] Their models were defined as:

$$y_i = \chi_i\beta + (v_i - u_i) \qquad i=1, 2, \ldots, N \qquad (3)$$

In this model the random error, v_i, accounts for measurement error and other random factors and is independently and identically distributed with mean zero and constant variance, σ_v^2. The u_i that accounts for technical efficiency is independent of the v_i, and is assumed to be independently and identically distributed exponential or half-normal.[4]

The early empirical studies in the literature used cross-section data. Using a panel data approach, this model was broadened by Pitt and Lee (1981). This specification, involving the use of panel data allows the investigation of both technical change and technical efficiency change over time. Their model can be defined as:

$$y_{it} = \chi_{it}\beta + (v_{it} - u_{it}) \qquad i=1\ldots N,\ t=1\ldots T \qquad (4)$$

where y, χ, β, v and u are defined as in Equation 3 with the introduction of time period t in the model.

[3] The only difference between the two models was the assumption of the distribution of the one-sided error term. Meeusen and van den Broeck assumed an exponential distribution to u, whereas Aigner et al used both half-normal and exponential distributions.

[4] There have also been different distributional forms suggested in the literature, such as the truncated normal (Stevenson (1980)) and the two-parameter gamma (Greene (1990)).

Early studies using this approach assumed that technical inefficiency effects are time-invariant, namely $u_{it} = u_i$. This approach, with the assumption of time-invariant technical inefficiency, did not fully utilise the advantages associated with using panel data where individual enterprise's efficiency levels can be estimated for several years.[5]

Battese and Coelli's (1992) study on the paddy farmers in India proposed a time-varying model for the technical efficiency effects in the stochastic frontier production for panel data, where the u_is were assumed to be an exponential function of time which involved only one unknown parameter. They defined technical efficiency as the ratio of a farm's mean production to the corresponding mean production if the farm utilised its level of inputs efficiently. In this study the maximum-likelihood estimates of the parameters of the model and the predictors of technical efficiency were calculated using the computer program **Frontier**.[6]

The Battese and Coelli (1992) method can be outlined as follows:

$$y_{it} = \chi_{it}\beta + (v_{it} - u_{it}) \qquad i=1\ldots N,\ t=1\ldots T \qquad (5)$$

where y_{it} is the log of production of the i-the enterprise in the t-th time period, χ_{it} is a vector of input quantities of the i-th firm in time t and β is a vector of unknown parameters. The error tem is composed of two parts. The first part v_{it} are random variables assumed to be identically and independently distributed

[5] As Coelli, Rao and Battese (1998) point out, the pattern of technical efficiency effects can change over time.
[6] Details of the programme can be found in Coelli (1996)

(iid) N~ (0, σ^2) and independent from u_{it}. The u_{it} are defined by Battese and Coelli (1992) as:

$$u_{it}= \exp(-\eta\,(t-T))u_i \qquad (6)$$

These are non-negative random variables, which are assumed to account for technical inefficiency in production and to be identically and independently distributed as truncations of zero of the N (0, σ^2) distribution, where η is a parameter to be estimated, which determines whether inefficiencies are time varying or time invariant. This model replaces σ^2_v and σ^2_u with $\sigma^2=\sigma^2_v+\sigma^2_u$ and $\gamma=\sigma^2_u/(\sigma^2_v+\sigma^2_u)$. The parameter γ must have a value between 0 and 1 for use in an iterative maximisation process.

It was recognised in the literature that if efficiency varied across producers or over time, which was proposed in the time-variant inefficiency models, then it was possible to examine the determinants of efficiency variation. Early empirical studies that investigated the determinants of technical inefficiencies among enterprises used a two-stage approach where estimates of the stochastic frontier model were obtained in the first stage and then the estimated values of technical inefficiency were regressed on a vector of explanatory variables. This approach contradicted the assumption of identically distributed inefficiency effects and in order to overcome this drawback Kumbhakar, Ghosh and McGuckin (1991) and Reifschneider and Stevenson (1991) specified stochastic frontier models where the inefficiency effects were defined in the model and all parameters were estimated in a single Maximum-Likelihood procedure. Battese and Coelli (1995) extended their model so that it included the estimation of the parameters of the factors believed to influence the technical efficiency levels of producers and applied this approach to panel data. This model assumed the technical inefficiency effects to be independently, but not identically, distributed non-negative random variables, obtained by the truncation of the N ~ (μ_{it}, σ^2) distribution where

$$\mu_{it}= Z_{it}\delta \tag{7}$$

in which Z_{it}s are the explanatory variables assumed to have an effect on the technical efficiency levels of individual enterprises and δ is a vector of unknown parameters.

2.2 Early Applications

Until recently, most of the empirical applications in the literature measuring technical efficiency using stochastic frontier production function approach have been in agricultural economics and operational research (mainly dealing with state-owned enterprises, non-profit organisations and the banking sector). Examples from the agricultural economics literature include Sidhu (1974) on the efficiency of wheat production in India, Battese and Corra (1977) on the efficiency of paddy farmers in India, Färe *et al.* (1985a) on the efficiency of Philippine agriculture, Battese and Coelli (1988), Kumbhakar *et al.* (1991) examining technical efficiency using data on US dairy farms, Battese and Coelli (1992) using data on Indian paddy farmers, Heshmati and Kumbhakar (1994) analysing technical efficiency of Swedish dairy farms and O'Neill et al. (2001) examining farm technical efficiency in Irish agriculture.

Examples of the application of technical efficiency analysis on state-owned enterprises include Atkinson and Halvorsen (1984) and Färe *et al.* (1985b) on the technical efficiency of electricity generation units in the US, Bhattacharyya *et al.* (1994) studying the technical efficiency of water utilities and Deprins *et al.* (1984) on the labour efficiency of post offices in the US. We also see the application of stochastic production frontier functions in the analysis of transportation sector with the studies of Deprins and Simar (1989) and Gathon and Perelman (1992) using data on railways.

2.3 Applications to Manufacturing Sector

There has been a surge in the studies examining technical efficiency of the manufacturing industries recently, with the increased availability of micro data on manufacturing sectors. Although one of the early studies in the literature appeared in 1980s by Pitt and Lee (1981) analysing the technical efficiency of Indonesian weaving industry using panel data, most studies examining efficiency in manufacturing industries using the stochastic production function approach have used cross-sectional data sets. Cheng and Tang (1987) using data on the Taiwanese electronics sector for 1980 and Hill and Kalirajan (1993) using data for 1986 on Indonesian garment industry are two examples of studies measuring technical efficiency utilising the stochastic production frontier approach with cross-section data sets.

Harris (1991) used a frontier production function approach to estimate efficiency in Northern Ireland manufacturing sector for the year 1987-88 using cross-section data from a survey of 140 manufacturing companies. He found that the mean technical efficiency in Northern Ireland was approximately 80%. He also found that foreign-owned firms were more productive than the domestic firms and that increasing returns to scale were important.

Sheehan (1997) using sample data from the Annual Census of Production (ACOP) covering 404 companies examined technical efficiency in firms in Northern Ireland over the period 1973-85 utilising a stochastic production function approach. Sheehan found that average technical efficiency increased from 65 per cent in 1973 to 79 per cent in 1985. In addition to the technical efficiency estimates provided, this study also analysed the factors that account for the observed levels of efficiency using a two-stage estimation approach where the technical inefficiency is estimated in the first stage and these technical inefficiency estimates are used as dependent variables in the second-stage. Sheehan found that foreign ownership was an important factor in determining average efficiency levels in the manufacturing sector of Northern Ireland.

Harris (1999a) studied productive efficiency in five UK manufacturing industries, namely, Electronic Data Processing Equipment, Motor Vehicles, Aerospace, Brewing and Malting and Newspapers, for the period 1974-94 using data from the ACOP and employing a stochastic production frontier approach.

He found that plants in Data Processing Equipment, Motor Vehicles and Aerospace were relatively around the higher end of the efficiency distribution whereas plants in Brewing and Newspaper sectors had much lower levels of efficiency compared to the frontier. He also found that scale effects and foreign ownership had a positive effect in determining technical efficiency. In a more extended study of efficiency in UK manufacturing sector, Harris (1999b) provides estimates for over 200 manufacturing sectors using the same approach. In addition to the five leading sectors of UK manufacturing he estimates average efficiency levels for all of the 2 digit sectors and selected 4-digit industries. Using estimates from Harris (1999b), Harris (2001) compares the differences in efficiency of manufacturing firms in Northern Ireland and other UK regions. He finds that Northern Ireland had generally the lowest level of average efficiency throughout the period 1974-94. The results were consistent both at the aggregate level and the industry level. Examination of different ownership groups showed that foreign plants operating in Northern Ireland had higher efficiency levels compared to their domestic counterparts. However plants in Northern Ireland overall performed relatively less well than plants in other UK regions across all ownership groups.

Using three digit data from the UK Census of Production for the period 1984-92, Driffield and Munday (2001) examined the determinants of technical efficiency in UK manufacturing industry, focusing particularly on the role of foreign investment and spatial agglomeration of similar industry activities. They found that foreign ownership is a determinant of technical efficiency in UK manufacturing industry, although the effect varies according to industry characteristics. In sectors that are relatively more productive and regionally concentrated, the effect of foreign investment on the technical efficiency of domestic industry is found to be higher.

Mahadevan (2000) studied the technical efficiency of 28 three digit manufacturing industries in Singapore from 1975-94 using a Cobb-Douglas production function and stochastic production frontier approach. This study showed that on the average Singapore's manufacturing industries were operating at 73 per cent of their potential output level and showed that capital intensity and labour quality were important factors in determining the efficiency levels.

Marcos and Galvez (2000), in their study of the Spanish manufacturing industry, utilise the stochastic production frontier approach and examine technical efficiency levels using data on 855 Spanish firms in 15 manufacturing sectors over the period 1990-94. They found that Spanish firms were on the average 60 per cent efficient.

In their study of the technical efficiencies of firms in the Indonesian garment industry, Battese *et al.* (2001) use stochastic frontier models for firms in five different regions of Indonesia for the period 1990 to 1995 and find that there are substantial efficiency differences among the garment industry firms across the five regions. Lundvall and Battese (1998) using an unbalanced panel of 235 Kenyan manufacturing firms in the Food, Wood, Textile and Metal sectors and utilising stochastic production frontier approach, estimated technical efficiency levels in Kenyan manufacturing industry and investigated whether technical efficiency is related to firm size and age. They found that the mean technical efficiency increases with size in all sectors and that there was no direct effect of age on efficiency.

As we can see from the different examples of technical efficiency studies in the literature using the stochastic production frontier approach, there are various applications on manufacturing. Some of the studies used cross-section data while others utilised panel data approach with the availability of data. We can also see that different studies took various approaches in using the level of data where we see studies using firm-level data, 2 and 3-digit industry level data and regional data. [7]

3 Measuring Technical Efficiency in Irish Manufacturing Industry

In this section using, data from the Census of Industrial Production (CIP), we measure technical efficiency levels in Electrical and Optical Equipment sector (NACE 30-33) of Irish manufacturing industry for the 1991-1999 period, using a stochastic production function that allows each plant to have different levels of efficiency in different years for the period. We also investigate the factors that determine efficiency with the one-step approach where parameters of the variables that explain efficiency are included in the model with the estimates of the stochastic production function.

[7] We have to make a distinction between the studies using firm level data and presenting their results at 2 or 3-digit level and studies which use 2 or 3-digit level data in order to get the results.

Electrical and Optical Equipment sector plays an important role in Irish manufacturing industry. In 1991 this sector accounted for about 16 per cent of total manufacturing employment in Ireland and this has increased to over 25 per cent by 1999. This industry consists of four individual two-digit NACE industries, which are Office Machinery and Computers (NACE 30), Electrical Machinery and Apparatus (NACE 31), Radio, Television and Communications Equipment (NACE 32) and Medical, Precision and Optical Instruments (NACE 33). Table 1 shows the levels of employment in these four sectors and their share in total manufacturing employment in the Irish manufacturing sector. In all four sub-sectors we see that employment has increased more than the average increase in total manufacturing employment over the 1991-1999 period, which resulted in an increase in the share of employment, accounted for by these sectors in total manufacturing employment.

An important feature of the Electrical and Optical Instruments industry in Ireland is the dominance of foreign firms in terms of both employment and net output. This feature is the result of the Irish industrial development policy, which recognized in the 1970s that this sector could provide an important role in the development of Irish manufacturing industry and encouraged foreign firms in this sector to locate in Ireland. Although foreign companies locating in Ireland have been, to a great extent, responsible for developing this sector, there has been important development on the indigenous side of the sector. Foreign firms still account for over 80 per cent of employment in this industry, but we can see from Table 2 that employment levels in Irish firms in the four sub-sectors of the industry have increased dramatically during the 1991-99 period. The highest increase has been in the Medical, Precision and Optical Equipments industry with a 236 per cent rise. Overall, domestic firms increased their employment levels in the Electrical and Optical Equipments sector by 106 per cent compared to a 15 per cent increase in total manufacturing employment in Irish firms during the period.

An investigation of labour productivity levels in domestic firms in this sector shows that over the period 1991-99, labour productivity has increased by 48 per cent compared to an average rise of 37 per cent in the labour productivity levels of Irish manufacturing firms. Table 3 shows that three of the four sub-sectors in the industry have experienced much higher growth rates in their labour productivity levels compared to the average growth with the only exception of Office Machinery and Computers industry which showed an 8 per cent rise.[8] The highest increase in productivity of domestic firms in these sub-sectors has been in the Radio, Television and Communications and Medical, Precision and Optical industries with 74 per cent and 70 per cent, respectively.

It has been argued in the literature that the high presence of foreign firms in these sectors as a result of industrial policy followed since the 1970s has had a positive effect on the development of indigenous firms.[9] Görg and Ruane (1998)

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[8] It has to be noted that Office Machinery and Computers sector had already higher productivity levels than the other three sub-sectors in 1991 as well as the total manufacturing industry average.

[9] Cogan and Onyemadum (1981) argue, based on a small case-study survey of a number of Irish-owned firms in the electronics sector, that foreign MNCs act as "incubators" for indigenous firms with previous employees of MNCs acting as the main initiators for a number of Irish-owned electronics firms.

investigate the development and the determinants of inter-firm linkages between electronics[10] firms in Ireland and domestic sub-suppliers using firm level data for 1982 to 1995 and find that foreign-owned electronic firms in Ireland source, on average, 24 per cent of their inputs in Ireland and that firms in the electronics industry in Ireland have increased their backward linkages over time.

In using stochastic frontier analysis when measuring technical efficiency one of the difficulties that arise is the problem of heterogeneity in the outputs of producers. In order to reduce this heterogeneity we carry out our analysis at selected individual 4-digit sub-sectors of the Electrical and Optical Equipment sector since stochastic frontier analysis assumes a technology frontier common to all firms in an industry and using data at a more aggregated industry level could violate this assumption. The selected industries are presented in Table 4.

3.1 Model Specification

There are basically two common functional forms of production function used in the literature in studying technical efficiency using stochastic production frontier functions, namely Cobb-Douglas and general translog functional forms. Since the Cobb-Douglas specification is nested in the translog model we start with the translog specification in our analysis and define it in Equation 8 as:

$$\ln y_{it} = b_0 + \sum_j b_j \ln c_{jit} + b_T t + b_{TT} t^2 + \sum_j b_{Tj} t \ln c_{jit} + \sum_{j \le k}\sum b_{kj} \ln c_{jit} \ln c_{kit} + v_{it} - u_{it} \quad (8)$$

[10] This study uses data from Forfás Irish Economy Expenditure Survey database. Forfás is the policy and advisory board for industrial development in Ireland. We note that the Forfás classification of the electronics sector used in that study is quite different than the CSO NACE classification used here.

where the subscripts i and t indicate plant and time; y is the output; χ_j is a vector of inputs and subscripts j and k index inputs. The v-random errors are assumed to be independently and identically distributed and independent of the u–terms that are plant specific technical inefficiency in production. In this model year of observation (t) and its interaction with input variables are included in a way to specify both neutral and non-neutral technical change, respectively.

In this specification if β_{kj}, the second-order terms, are all equal to zero then the model reduces to the standard Cobb-Douglas form. In our analysis we start with the general translog model and using generalised likelihood ratio tests, we can specify whether general translog or Cobb-Douglas specification should be used in the analysis.

The inclusion of time as a variable allows for the shifts of the frontier over time, which is interpreted as technical change. In this model, technical change is input k using (saving) if β_{Tj} is positive (negative). Technical change is neutral if all β_{Tj}s are equal to zero. Using generalised likelihood tests we can test the significance of the neutral and non-neutral technical change in the model.

In this study the FRONTIER 4.1 software program developed by Coelli (1994) is used. It enables us to undertake a one-step estimation of the stochastic frontier model as well as the parameters of the variables included to explain efficiency.

We are mainly interested in the γ, μ and η parameters among the model parameters estimated when using FRONTIER 4.1. The γ parameter is the variance-ratio parameter, which is important in determining whether a stochastic production frontier is a superior measure to the traditional average production function.[11] The μ parameter determines the distribution the inefficiency effects have, either a half-normal distribution or a truncated normal distribution. The η parameter determines whether the inefficiencies are time varying or time invariant.[12] Various tests of hypotheses of the parameters in the frontier function can be performed using the generalised likelihood ratio-test statistic, defined by

$$\lambda = -2\,[\ell(H_0)-\ell(H_1)] \tag{9}$$

where $\ell(H_0)$ is the log-likelihood value of a restricted frontier model, as specified by a null hypothesis, H_0 ; and $\ell(H_1)$ is the log-likelihood value of the general frontier model under the alternative hypothesis, H_1. This test statistic has approximately a chi-square distribution (or a mixed chi-square) with degrees of freedom equal to the difference between the parameters involved in the null and alternative hypotheses. If the inefficiency effects are absent from the equation, as specified by the null hypothesis H_0: $\gamma=0$, then the statistic λ is approximately distributed according to a mixed chi-square distribution.[13]

[11] Specifically, the average production function has a gamma value of zero, meaning there is no technical inefficiency. On the other hand the full frontier model without the v_{it} term is assumed when the value of γ is one.
[12] A η parameter value that is significantly different from zero indicates time varying inefficiencies.
[13] In this case, critical values for the generalised likelihood-ratio test are obtained from Table 1 in Kodde and Palm (1986).

4.4 Empirical Results

Using data from the CIP for selected 4-digit Irish manufacturing industries in the Electrical and Optical Equipment sector for the period 1991-1999, frontier translog production functions are estimated for each of them, which is defined as:

$$\ln y_{it} = b_0 + \sum_{j=1}^{2} b_j \ln c_{jit} + b_T t + b_{TT} t^2 + \sum_{j=1}^{2} b_{Tj} t \ln c_{jit} + \sum_{j \le k}^{2} \sum_{k=1}^{2} b_{kj} \ln c_{jit} \ln c_{kit} + v_{it} - u_{it} \quad (10)$$

where the subscripts i and t represent the i-th plant and the t-th year of observation, respectively; y represents real net output in 1985 prices (deflated by Producer Price Indices); c_1 represents total employment; c_2 is the capital variable which is proxied by the amount fuel and power used in 1985 prices (deflated by energy component of Wholesale Price Index)[14], t and t^2 are time trends to take account of technical progress; v_{it} are random errors assumed to be identically and independently distributed and independent from the u_{it} which are non-negative unobservable random variables associated with the technical inefficiency of production.

Following Battese and Coelli (1995), technical inefficiency is defined by:

$$u_{it} = d_0 + d_1 z_{1it} + d_2 z_{2it} + d_3 z_{3it} + w_{it} \quad (11)$$

[14] Since capital stock figures are not available from the CIP we use this measure as a proxy, which is often utilised in the literature. See Sjoholm (1998) and Kearns (2000)

where plant level technical inefficiency u_{it} is influenced by the labour quality (z1), investment intensity (z_2) and the export intensity (z_3) variables. Labour quality variable is proxied by the ratio of skilled workers to unskilled workers and expected to have a negative effect on the technical inefficiency levels of firms. Following the nomenclature of the CIP, we define technical and administrative workers as skilled, and industrial workers as unskilled. Investment intensity is measured by the ratio of net capital additions of the firm during the year to total employment and export intensity is measured by the percentage of output exported. We expect both these variables to have a negative impact on the technical inefficiency levels of firms In this specification ω_{it} are unobservable independently distributed random variables obtained by truncation of the normal distribution with zero mean and unknown variance. The mean of u_{it} is assumed to vary both across plants and time.[15] An important explanatory variable, which could be included in the model in explaining technical inefficiency levels of firms in the Electrical and Optical Equipment sector, is the foreign ownership variable but, direct comparison of productivity levels of foreign and domestic firms in Irish manufacturing industry can result in biased results due to overstated output figures by foreign firms. Also it is very difficult to assume that foreign firms operating in Irish manufacturing industry, which are subsidiaries of MNEs, share the same technology frontier as domestic firms. For this reason we did not include foreign ownership variable in the model where we try to explain the technical efficiency levels and the model is estimated only for Irish firms, where we try to explain technical efficiency levels. The other variable, which

[15] The inclusion of the variables reflects the availability of data in the CIP surveys. In other studies variables are included to reflect competitive factors in the industry such as market share and profitability. (See Harris (1999a).

could have an important role in explaining the inefficiency levels of domestic firms in Electrical and Optical Equipment industry, is the presence or entry of foreign firms in this sector. Since our analysis is carried out at the individual 4-digit sectors and this variable experiences very little change over the 1991-99 period we were unable to include it in our analysis.

Before interpreting the results of stochastic production frontier function we carry out various specification tests in order to see the most suitable model for the analysis and present the results of these tests in Table 5. Testing for the validity of the translog over Cobb-Douglas specification using a log likelihood ratio test, we cannot reject the null hypothesis that Cobb-Douglas frontier is an adequate representation.[16] Given the Cobb-Douglas specification of the frontier function, we then carried out likelihood ratio tests to see whether there was neutral or non-neutral technical change. The null hypothesis of no technical change was rejected in all of the industries whereas neutral vs. non-neutral technical change hypothesis was only rejected in the Medical and Surgical Equipment and Television and Radio Receivers sectors.

The third null hypothesis that there are no technical inefficiency effects in the model, that is $\gamma=0$, was rejected by the data for all sub-sectors. This result shows that average production function specification in which all firms are assumed to be technically efficient is not an adequate representation for all sub-sectors of the

[16] This result is not surprising given the multicollinearity problems associated with the translog production function specifications. (See Harris 1999a). The second order and cross parameter estimates of the translog production function were all statistically insignificant for all sectors reflecting the fact that multicollinearity is present in this specification.

Electrical and Optical Equipments industry in Irish manufacturing sector. The last hypothesis involved the nature and distribution of inefficiency effects in the frontier model. The null hypothesis that the inefficiency effects have half-normal distribution, $\mu=0$ could not be rejected in all industries.

Maximum likelihood estimates of the parameters of the stochastic frontier model using an unbalanced panel data for each industry are presented in Table 6.[17] The results show that the elasticity of output with respect to labour dominates over capital. The size of the elasticity of output with respect to capital varies from 0.11 in the Computers and Other Information Processing Equipment sector to 0.25 in the Television and Radio Receivers industry. This coefficient is positive and statistically significant in all sectors. Labour elasticity of output is positive and statistically significant in all sectors and the size of the coefficient is in the range of 0.66 in Television and Radio Receivers industry to 0.95 in Electricity Distribution and Control Apparatus.

We can see from the results that there is evidence that the stochastic frontier model is an appropriate specification since γ is closer to 1 and highly significant in all sectors. Hence the inefficiency effects are important, as indicated in Table 5 also, with the rejection of the null hypothesis that $\gamma=\delta=0$. As to the signs attached to the inefficiency model we see that the investment intensity variable has a negative and significant effect in all sectors reflecting the fact that inefficiency levels and investment intensity are negatively related. Export

[17] The top and bottom 1 percentiles of firms are excluded from the analysis in order to remove the effect of outliers in the analysis

intensity variable has a positive effect but insignificant effect in all but one sector, namely Radio and Television Receivers industry where it has a negative and significant sign which shows that in this sector technical inefficiency decreases with the higher export intensity in the individual firms.[18] The sign of the skill intensity variable, which is used a proxy for labour quality, has a significant and negative effect only in the Radio and Television Receivers and Medical and Surgical Equipment industry showing that high quality labour is important in these two sectors in reducing inefficiency levels.

In terms of technical change we see that there is neutral technical progress in all of the sectors and we see some evidence of non-neutral technical change in the sub-sectors of Radio, Television and Communications and Medical and Surgical Equipment industries. This non-neutral technical change is labour using in the Medical and Surgical Equipment and Television and Radio Receivers sectors whereas it is capital using in the Electronic Valves and Other Electronic Components industry.

We also estimated the technical inefficiency levels in the six sub-sectors of the Electronic and Optical Equipment industry using Equation 8, where the results are presented in Table 7. The estimated technical efficiency effects decreased over the period 1991-99 only for Electronic Valves and Other Electronic Components and Television and Radio Receivers industries. On the other hand

[18] These insignificant results on export intensity variable could be explained by the industrial policy followed in this sector since 1970s, which encouraged foreign firms to establish linkages with their domestic counterparts especially in the electronics industry which means that firms in this sector could be supplying the foreign firms in this sector in Ireland rather than trying to export their products.

in all of the other industries we see that the technical inefficiency effects are estimated to increase over time. We see that efficiency has considerably increased in two of the sectors over the period. These sectors are the Electronic Valves and Other Electronic Components, which had average efficiency levels of 0.48 in 1991 that increased to 0.63 in 1999 and the Television and Radio Receivers industry whose efficiency levels have increased from 0.69 in 1991 to 0.75 in 1999. On the other hand we see that technical efficiency levels of Electric Motors and Generators and Medical and Surgical Equipment industries have declined over the period. This result could be due to the fact that these two sectors have experienced higher technical change than the other sectors in the industry, which could have pushed the production frontier in these sectors further for some firms in the industry making them relatively more inefficient in 1999 than their levels in 1991.

5 Summary and Conclusion

This paper has explored the technical efficiency levels in the Electrical and Optical Equipment industry in Irish manufacturing sector and the factors that could affect these levels utilising a stochastic production frontier approach over the period 1991-99 using firm-level panel data.

The model used is that outlined by Battese and Coelli (1995) which determines the causes of inefficiency simultaneously, rather than employing a two-step approach whereby efficiency estimates are obtained in the first step and are then regressed on a set of determinants. Our analysis showed that technical efficiency levels have increased in two sectors, namely Electronic Valves and Other Electronic Components and Radio and Television Receivers whereas Electric Motors and Generators and Medical and Surgical Equipment industries have experienced a decline in the average technical efficiency levels over the period 1991-99.

We found that investment intensity plays an important role in explaining technical inefficiency levels in all sub-sectors of the Electrical and Optical Equipment industry. Our results show that investment intensity reduces technical inefficiency levels of firms in all of the sub sectors. We found no significant relationship between export intensity and the technical inefficiency levels of individual firms in all but one sector, namely Television and Radio Receivers industry. As outlined above as well, this result could be due to the linkages policy that has been pursued in this sector in order to encourage the development of supplier relationship between foreign and domestic firms with the aim of developing the indigenous companies, which could have resulted in low export intensity levels in individual firms. We also showed that labour quality plays an important role in determining efficiency levels in some sectors.

Overall these results show that investment intensity and labour quality play an important role in reducing technical inefficiency levels of the indigenous firms in the Electrical and Optical Equipments industry in Irish manufacturing sector. Another important variable, which could have an effect in determining technical efficiency levels, is the foreign presence variable, which could not be included in our analysis due to the analysis being carried out separately for each 4-digit industry where the foreign presence variable shows little variation during the period.

Tables

Table 1: Employment Levels in Electrical and Optical Equipments Industry and Its Share in Total Manufacturing Employment

	Employment Levels				Employment Share			
	1991	1995	1999	1991-1999 (% Change)	1991	1995	1999	1991-1999 (% Change)
Electrical Machinery	10278	12395	14564	42	5.2	5.6	5.8	12.1
Medical, Precision and Optical	9299	11818	16618	79	4.7	5.4	6.7	41.3
Office Machinery and Computers	8019	14420	19923	148	4.1	6.5	8.0	96.5
Radio, Television and Communications	4887	7230	13357	173	2.5	3.3	5.4	116.1
Electrical and Optical Equipments	32483	45863	64462	98	16.5	20.8	25.9	56.9
Total Manufacturing	196878	220578	248971	26	100.0	100.0	100.0	26

Table 2: Employment Levels of Irish firms in Electrical and Optical Equipments Industry and Their Share in the Sector

	Employment Levels				Employment Share			
	1991	1995	1999	1991-1999 (% Change)	1991	1995	1999	1991-1999 (% Change)
Electrical Machinery	2467	3364	4426	79	24.0	27.1	30.4	26.6
Medical, Precision and Optical	745	1274	2504	236	8.0	10.8	15.1	88.1
Office Machinery and Computers	1252	2042	2321	85	15.6	14.2	11.6	-25.4
Radio, Television and Communications	759	1073	1502	98	15.5	14.8	11.2	-27.6
Electrical and Optical Equipments	5223	7753	10753	106	16.1	16.9	16.7	3.7

Table 3 Labour Productivity Levels of Irish Firm in Electrical and Optical Instruments Industry, 1991-1999										
	1991	1992	1993	1994	1995	1996	1997	1998	1999	1991-1999
Electrical Machinery	17.5	17.8	16.4	18.9	19.9	20.3	20.7	22.3	25.6	46%
Medical, Precision and Optical	25.5	32.4	36.5	32.7	31.3	37.6	45.3	42.9	43.4	70%
Office Machinery and Computers	28.8	29.6	26.9	28.3	22.6	31	26	28	31.1	8%
Radio, Television and Communications	19.8	16.7	21.2	19.8	19.2	25	25.4	33	34.4	74%
Electrical and Optical Equipments	21.7	22.0	22.5	23.7	22.4	26.8	27.0	29.3	32.1	48%
Manufacturing Average	24.6	24.9	25.9	26.7	26	27.8	29.2	30.3	33.5	37%

Table 4 Sub-Sectors of Electrical and Optical Equipment Industry and Corresponding NACE Codes			
Electrical and Optical Equipment Industry (30-33)			
Office Machinery and Computers (30)	Electrical Machinery and Apparatus (31)	Radio, Television and Communication Equipment (32)	Medical, Precision and Optical Equipment (33)
Computers and Other Information Processing Equipment (3002)	Electric Motors and Generators (3110) Electricity Distribution and Control Apparatus (3120)	Electronic Valves and Tubes and Other Electronic Components (3210) Television and Radio Receivers (3230)	Medical and Surgical Equipment (3310)

Notes: Numbers in brackets are corresponding 2-digit and 4-digit NACE classification codes

Table 5: Generalised Likelihood-Ratio Tests of Hypotheses for Parameters of the Stochastic Production Functions

Null Hypothesis, H_0:	3002	3110	3120	3210	3230	3310	Critical Value[1]
$\beta_{ij}=0$ i,j=1,2[2]	4.20	5.68	7.92	2.94	3.60	3.58	9.48
$B_3=0$[3]	4.51*	6.42*	13.76*	10.24*	14.25*	8.44*	3.84
$\beta_{j3}=0$ j=1,2[4]	2.15	3.45	1.28	4.12	7.90*	13.81*	5.99
$\gamma=\delta_{o}=\delta_{1}=\delta_{2}=\delta_{3}=0$[5]	24.72*	37.92*	41.17*	33.10*	21.28*	22.38*	10.37
$\mu=0$[6]	1.12	2.57	3.16	2.41	1.68	1.24	3.84
$\eta=0$[7]	5.47*	6.23*	5.47*	15.47*	6.98*	6.54*	3.84

Notes: 1) Values of the generalised likelihood-ratio statistic (λ) are given in the table.
Values, which exceed the critical value in the table, are significant at the 5% level and are marked by an asterisk (*)
2) Cobb-Douglas specification, Critical Value $\chi^2_{0.05,6}$
3) No technical Change $\chi^2_{0.05,1}$
4) Neutral vs. Non-Neutral Technical Change $\chi^2_{0.05,2}$
5) No inefficiency effects $\chi^2_{0.05,5}$. The critical value for the test involving $\gamma=0$ are obtained from Table 1 of Kodde and Palm (1986) where the degrees of freedom are q+1 and q is the number of parameters which are specified to be zero. (See Coelli et al. 1998)
6) Inefficiency effects are assumed to be half-normal $\chi^2_{0.05,1}$
7) Inefficiency effects are time invariant $\chi^2_{0.05,1}$

Table 6: Maximum-Likelihood Estimates for Parameters of the Stochastic Frontier Inefficiency Models

		3002	3110	3120	3210	3230	3310
Intercept	β_0	10.03*	8.7*	10.55*	9.8*	8.26*	13.8*
		(0.45)	(0.22)	(0.21)	(0.70)	(0.95)	(0.49)
Capital	β_1	0.11*	0.15*	0.03	0.12**	0.25*	0.14*
		(0.48)	(0.04)	(0.02)	(0.07)	(0.12)	(0.05)
Labour	β_2	0.77*	0.78*	0.95*	0.83*	0.66*	0.87*
		(0.58)	(0.05)	(0.03)	(0.21)	(0.21)	(0.09)
Time	β_3	0.03*	0.06*	0.03*	0.08*	0.12**	0.05*
		(0.01)	(0.01)	(0.01)	(0.01)	(0.07)	(0.01)
Capital*Time	β_4	-	-	-	0.009**	-0.004	-0.006*
					(0.005)	(0.02)	(0.002)
Labour*Time	β_5	-	-	-	-0.002	0.011*	0.003*
					(0.02)	(0.002)	(0.001)
<u>Other ML Parameters</u>							
Sigma-squared	σ^2	1.44*	1.34**	1.24*	0.79*	0.93*	0.88**
		(0.51)	(0.71)	(0.64)	(0.28)	(0.15)	(0.33)
Gamma	γ	0.77*	0.92*	0.90*	0.89*	0.92*	0.91*
		(0.08)	(0.31)	(0.05)	(0.04)	(0.09)	(0.05)
Log-Likelihood		-244.14	-49.81	-134.42	-46.17	- 107.64	-63.01
LR One-sided error		24.72	37.92	41.17	33.10	21.28	22.38
Inefficiency Effects							
Constant	δ_o	0.74	-8.3	1.73	-5.8*	2.87	-10.4*
		(1.40)	(43.16)	(0.98)	(0.22)	(1.96)	(2.3)
Skill	δ_1	-0.70	0.40	0.76	-0.07*	- 0.48**	-0.12*
		(0.56)	(2.06)	(0.43)	(0.24)	(0.07)	(0.04)
Investment Intensity	δ_2	-0.17**	-0.68*	-0.78*	-0.58*	-0.07*	-0.13*
		(0.11)	(0.18)	(0.36)	(0.18)	(0.02)	(0.04)
Exports	δ_3	0.29	0.15	0.49	0.06	-0.33*	0.08
		(0.32)	(1.34)	(0.38)	(0.10)	(0.15)	(0.06)

Table 7 Technical Efficiency Levels

	3002	3110	3120	3210	3230	3310
1991	0.64	0.75	0.73	0.48	0.69	0.72
1992	0.67	0.71	0.74	0.51	0.73	0.75
1993	0.66	0.68	0.74	0.43	0.76	0.72
1994	0.67	0.66	0.70	0.46	0.70	0.74
1995	0.61	0.67	0.68	0.48	0.68	0.69
1996	0.64	0.63	0.68	0.48	0.88	0.64
1997	0.62	0.67	0.68	0.46	0.86	0.62
1998	0.61	0.67	0.72	0.54	0.75	0.60
1999	0.63	0.64	0.71	0.63	0.75	0.59

Figures

Figure 1 Production Frontiers and Technical Efficiency

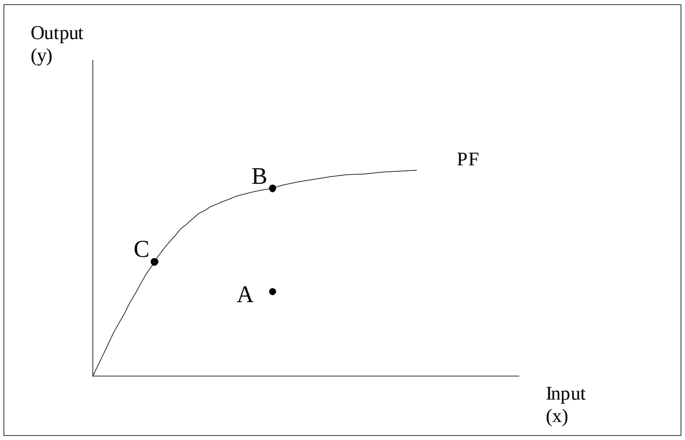
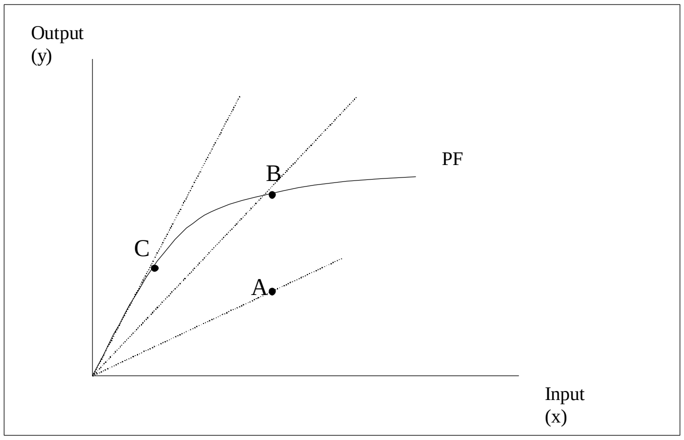


Figure 2 Productivity and Technical Efficiency



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