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Technical efficiency in electricity generation - the impact of smallness and isolation of island economies*

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Abstract

This paper conducts a comparative technical efficiency analysis of electricity generators in 16 small island economies using panel data, and two methodologies: data envelopment analysis (DEA) and stochastic frontier analysis (SFA). The results indicate neither apparent differences in the production structure between islands and non-islands electric utilities, nor any evidence suggesting that they are less technically efficient. At a theoretical level, our results suggest that benchmarking of small islands, using non-island generating utilities as comparators, is both feasible and desirable given the lack of historical generation data for most small islands. On a more empirical basis, our study bridges an important gap in research on the efficiency of small and interconnected electricity systems.

JEL Classification: D20; L25; L94; N70

Keywords: Electricity; SFA; Malmquist DEA; small islands

1. Introduction

This paper seeks to study technical efficiency in electricity generation of a sample of small island economies. Economies of scale in electricity generation partly explain why small island electricity generators have been state-owned and vertically integrated. Recent developments in restructuring and privatisation of electric utilities around the world have generated considerable interest among many small islands to adopt similar policies. Some have already privatised, while others are planning to restructure. However, there are considerable doubts as to what path electricity reforms in small islands should take. Both theoretical and empirical

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analyses are lacking in predicting what type of reform will best suit small and isolated systems, and whether there is any way to avoid resource-hungry and costly regulation for such systems.

Three major problems plague small islands in their effort to liberalise power markets. First, there is the problem of smallness of size. The introduction of wholesale markets is not feasible in small countries, where, at best, only a small number of generating companies can be supported, leading to an oligopolistic situation. Given the relatively limited scope for restructuring of small power systems, the problem hinges on effective regulation of such systems. But many small islands have a poor history of accounting and data collection, and it is important to investigate how to overcome the lack of electricity generation statistics, say, by using data from other islands and non-islands. This promising attempt of analysing how far yardstick competition can be introduced, using other electric systems as comparators, formally referred to as the system of yardstick regulation (Shleifer, 1995), however, requires that a given decision making unit (DMU) be compared with a like DMU. The view we adopt in this paper is that perfect likeness, which may never exist, is not a binding constraint, and benchmarking will be feasible if differences between electricity generating systems can be properly and fully accounted for.

Second, there is the problem of geographical isolation. Most small islands that we know of have very little prospects to interconnect with an intercontinental power grid. This problem is coupled with low levels of reliability since they cannot import power (Mayer, 2000). There is no published record of the impact of interconnection on efficiency. Our present study intends to partially bridge this gap in both theoretical and empirical research.

Third, it appears that many small islands are not only common by size but by historical development. Many islands have similar colonial histories, similar resource bases (primary production), and a heavy dependence on imported energy resources. This could imply that it potentially easier to compare islands with other islands for benchmarking purposes.

There have been major efforts, with the help of the World Bank, to restructure the power sector of many small islands. Although many have proposed privatisation as the end goal of liberalisation, there have been doubts as to whether it is the only available tool for reform. For instance, it does not seem that privatised electricity generation in Trinidad and Tobago has yielded better results so far (Domah, 2002). The biggest challenge that small islands have yet to face is the introduction of competition in generation.

This paper aims to test the null hypothesis of the existence of identifiable technical inefficiency among decision-making units (DMUs) involved in fossil-fired thermal electricity generation. This is achieved using an international sample of electricity generating utilities, and using two distinct state-of-the-art methodological approaches, viz., data envelopment analysis (DEA) and stochastic frontier methodology (SFA). Such an efficiency analysis will enable us to infer if small islands are significantly different from non-islands, and whether benchmarking is an option that should be explored, given that these islands also suffer from diseconomies in electricity sector regulation (as pointed out in Domah, 2002).

After more than two years of actual field work and data collection, the present study is an analysis of technical efficiency of a 7-year (1994 to 2000) panel physical data of 16 islands and 121 US investor-owned utilities. This paper is divided into 6 sections. Section 2 presents a short overview of efficiency analyses of electricity generation. Section 3 briefly sets out the two methodologies used in this paper. Section 4 provides a brief description of the type and sources of data used. Results are presented and discussed in section 5. Some implications of the results for small island economies and some concluding comments are set out in section 6.

2. Brief Review of Empirical Studies

An increasing number of recent studies on efficiency of electricity generation in developed countries are using frontier methods such as DEA and SFA. These have involved the estimation of both production and cost functions. The vast majority of these studies are US-based. Kopp and Smith (1980) estimate stochastic frontier production functions for 43 US coal-fired electric power plants. They consider three alternative functional forms; three estimation methods; and also divide their data into two capital vintage groups, finding that all three factors have an influence upon the measures of mean technical efficiency.

A comprehensive review of literature and past studies of the electricity sector is provided in Pollitt (1995), where use is made of four alternative methodologies to assess technical and productive efficiencies in an international sample of electric utilities. Pollitt (1996) uses DEA to assess the efficiency of nuclear power generators in five countries: the UK, Canada, Japan, South Africa and US. This study was followed by several other studies of international comparisons of electric utilities, such as Zhang and Bartels (1998) on New Zealand, Australia and Sweden. Although efficiency studies of the generation sector of developed countries abound, analyses of smaller systems and of developing countries' generating systems are lacking.

Mayer (2000) uses non-frontier regression analysis to study reliability problems of small islands in electricity generation. He concludes that the inability of most Caribbean and Pacific islands to tap power from an inter-continental transmission grid has meant that these islands have significantly larger capacity margins in order to meet a given reliability criterion.

Frontier applications for developing countries are also very few. Meibodi (1998) employs both DEA and SFA to estimate technical efficiency in electricity generation. He uses Iranian data combined with data from World Bank. The conclusion reached is that a substantial proportion of the variation in efficiency within the electricity industry in developing countries is due to a factor related to the size of plant. Most of the highly efficient power plants are found to be relatively large. The results also indicate that increasing returns to scale prevail in the electricity generation of most developing countries. Whiteman (1995) uses DEA in an attempt to benchmark electricity systems of developing countries using the World Bank data used by Meibodi (1998), but his study is flawed in two important ways. First it makes use of only two inputs (labour and capital). Secondly, it uses four outputs. For a cross-section dataset, this meant that the final outcome was a large number of countries lying on the frontier (48 out of 85 countries). The present paper is an exercise to bridge this gap in empirical research on developing countries.

3. Frontier Production Functions and Efficiency Measurement

3.1. SFA Specification

The Stochastic Frontier Methodology (SFA) uses statistical techniques to estimate a production function and to estimate efficiency relative to this frontier.

A number of empirical studies have estimated stochastic frontiers and predicted firm-level efficiencies using these estimated functions. The predicted firm-level efficiencies are then used in a two-stage regression (usually a Tobit regression) upon firm-specific variables (such as ownership characteristics, load factors, age of generating plants, type of fuel used, etc.) in an attempt to identify some reasons for the differences in predicted efficiencies between DMUs in the industry. The two-stage method has long been recognised as a useful exercise, but this procedure may be inconsistent in its assumptions regarding the independence of the inefficiency effects in the two estimation stages. The two-stage estimation procedure is unlikely to provide estimates that are as efficient as those that could be obtained using a single-stage estimation procedure (Coelli, 1996b).

Stochastic frontier models in which the inefficiency effects (u_i) are expressed as an explicit function of a vector of firm-specific variables and a random error were proposed by Kumbhakar, Ghosh and McGukin (1991) and Reifschneider and Stevenson (1991). The model presented in equation (1) is a modified Battese and Coelli (1995) model that we use in our analyses, which also allows for the use of panel data. The error term consists of the two terms (v_i) and (u_i), whereby the former accounts for the noise in the regression and is assumed to be normally distributed. The technical inefficiency term (u_i) is usually modelled as a half-normally distributed term. Equation (1) is a full-translog stochastic function and is self-explanatory.

$$ln(Y_i) = \beta_0 + \beta_1 ln(L_i) + \beta_2 ln(K_i) + \beta_3 ln(F_i) + \beta_4 ln(L_i)^2 + \beta_5 ln(K_i)^2 + \beta_6 ln(F_i)^2 + \beta_7 ln(L_i)ln(K_i) + \beta_8 ln(L_i)ln(F_i) + \beta_9 ln(K_i)ln(F_i) + \beta_{10} ln(L)(t) + \beta_{11} ln(K)(t) + \beta_{12} ln(F)(t) + \beta_{13}(t) + \beta_{14}(t)^2 + v_i - u_i, \quad i = 1,2,\ldots,N. \tag{1}$$

where Y_i = electricity generated (in GWh) by the i^{th} plant.

L_i = Labour employed (total number of employees);

K_i = installed generation capacity (MW);

F_i = Fuel consumption;

t = time;

ln refers to the natural logarithms;

β_I are unknown parameters to be estimated.

v_i are iid, and $N(0,\sigma_v^2)$ random errors, and are assumed to be independently distributed of the

u_i which are non-negative random variables associated with technical inefficiency, which are assumed to be independently distributed, such that the distribution of u_i is obtained by truncation at zero of the normal distribution with mean m_i and variance σ_u^2, where;

$$m_i = \delta_0 + \delta_1 GWh\text{-}PC_i + \delta_2 NCUS_i + \delta_3 C_i + \delta_4 Island + \delta_5 Connect \qquad (2)$$

where, $GWh\text{-}PC_i$ = Per Capita Consumption of Electricity;

$NCUS_i$ = Number of Customers Connected (a measure of size);

C_i = Capacity Factor (a measure of capacity utilisation);

Island = Dummy (Island=1, other=0);

Connect = Dummy (Interconnected=1, not interconnected=0);

δ_i are unknown (technical inefficiency) parameters to be estimated.

In FRONTIER 4.1 (Coelli, 1996b) parameterisation is used whereby σ_v^2 and σ_u^2 are replaced with $\sigma^2 = \sigma_v^2 + \sigma_u^2$ and $\gamma = \sigma_u^2 /(\sigma_v^2 + \sigma_u^2)$. The gamma coefficient, therefore, will allow us to infer as to what proportion of the total error term is actually accounted for by technical inefficiency.

The aim of estimating a stochastic frontier is to calculate the efficiency score of a given DMU relative to the frontier and is defined as:

$$Score_i = \frac{E\left(Y_i^* \middle| U_i, X_i\right)}{E\left(Y_i^* \middle| U_i = 0, X_i\right)} \qquad (3)$$

where X_i represents the set of inputs used, Y_i^* is the production of the i^{th} firm, which is equal to Y_i when the dependent variable is in original units and will be equal to e^{Y_i} when the dependent variable is in logarithms. The values of $Score_i$ will take the values of between zero and one. $Score_i$ is calculated as $e^{(-Ui)}$ (Battese and Coelli, 1988). A given value of $Score_i$, say 0.67, implies that the given firm can reduce the use of all inputs equi-proportionately by 33% maintaining output at a given level.

3.2. Data Envelopment Analysis (DEA)

Data envelopment analysis (DEA) is a non-parametric linear programming technique for measuring technical efficiency of a multiple-input-multiple-output DMU. In what follows, we present the methodology as described in Coelli (1996a).

The model is usually illustrated as follows. Assume that there is data on K inputs and M outputs on each N DMU. For the i^{th} decision making unit (DMU) these are represented by the vectors x_i and y_i, respectively. The K x N input matrix, X, and the M x N output matrix, Y, represent the data of all N firms. The purpose of DEA is to construct a non-parametric envelopment frontier over the data points such that all the observed points lie on or below the production frontier.

The input orientated DEA problem may be specified as:

$$
\begin{aligned}
& min_{\ \theta,\lambda}\ \theta \\
& st \quad -y_i + Y\lambda \geq 0, \\
& \quad \theta \bullet x_i - X\lambda \geq 0, \\
& \quad \lambda \geq 0.
\end{aligned}
\tag{4}
$$

where θ is a scalar and λ is a N x 1 vector of constants. The value of θ obtained will be the efficiency score for the i^{th} DMU. It reflects the amount by which the i^{th} DMU can proportionally reduce inputs, without leaving the production possibility space. It will satisfy $\theta \leq 1$, with a value of 1 indicating a point on the frontier and hence a technically efficient DMU.

The constant returns to scale (CRS) assumption is only appropriate when all DMUs are operating at an optimal scale. However, the use of CRS models when not all DMUs are operating at optimal scale will result in measures of TE (technical efficiency) which are confounded by scale efficiencies (SE). The use of a variable returns to scale (VRS) specification will permit the calculation of TE devoid of these SE effects. The CRS linear programming problem can easily be modified to account for VRS by adding the convexity constraint $N1'\lambda = 1$ (where NI is an N x 1 vector of ones) to equation (4). For a detailed exposition see Coelli (1996a).

Environmental Variables

In electricity generation, load factor, age of plants and fuel type may be construed as environmental variables since the managers of the units may not have any influence on these factors. Similarly, a generator in an isolated island economy has no choice as to the scale of operation than those dictated by the restricted market size. In environmental variables efficiency measure the DMU is compared to a constructed frontier along which the values of the environmental variables are equal to those of the units being analysed (Pollitt, 1995). In DEAP 2.1 environmental variables enter as either outputs or inputs depending on the orientation that is adopted. In an input-orientated DEA, the environmental variables will be introduced as ‘outputs’.

3.3. Dynamic DEA and Malmquist Indices of Productivity Change

Panel data allows total factor productivity change (TFP) indices to be calculated using DEA. These indices can be decomposed into two components: the technical efficiency change (which occurs when a DMU moves towards a given efficiency frontier) and technical change (which occurs due to a DMU moving towards a new technically efficient frontier which has shifted from a previously efficient frontier). Since productivity is now being measured across a large number of isoquants, each being efficient at some given point in time, the linear programs must be adjusted or modified in order to account for time. These DEA-like programs allow us to calculate the so-called Malmquist index of productivity change (Coelli, 1996a).

This idea is clearly exposed in Fare, Grosskopf, Lindgren and Roos (1989) specification of an output-based Malmquist productivity change, expressed as a geometric mean of two output-based Malmquist indices, as given in equation (5). An input-orientated measure of the index can be similarly defined as pointed out by Grosskopf (1993), and is based on the same principle as the output-orientated formulation.

$$m_o\left(y_{t+1}, x_{t+1}, y_t, x_t\right) = \left[\frac{d_o^t\left(x_{t+1}, y_{t+1}\right)}{d_o^t\left(x_t, y_t\right)} \times \frac{d_o^{t+1}\left(x_{t+1}, y_{t+1}\right)}{d_o^{t+1}\left(x_t, y_t\right)}\right]^{1/2} \tag{5}$$

This equation represents the productivity of the production point (x_{t+1}, y_{t+1}) relative to the production point (x_t, y_t). d_o represents the distance functions from the frontier. A value greater than unity will indicate positive TFP growth from period t to period $t+1$. The Malmquist equation (5) is composed of two productivity indices. One index uses period t technology (shown in the superscript of d) and the other uses the $t+1$ period technology. The subscript in m and d indicates that this is an output-based definition of the index.

The DEAP 2.1 program computes five measures: technical efficiency change relative to a CRS technology (EFFCH), technological change (frontier shifts) abbreviated as TECHCH, pure technical efficiency change relative to a VRS technology (PECH), scale efficiency change (SECH) and total factor productivity change (TFPCH).

We implement DEA in two ways described in Table 1 below. In Model 1, the DEA scores are generated from a 1-output-3-inputs linear program. These scores are then used in a second-stage (Tobit) regression whereby the regressors are per capita electricity consumption (GWh-PC), number of customers (NCUS), capacity utilisation factor (C), and two dummy variables (ISLAND and CONNECT). In model 2, DEA is implemented using 5 environmental variables, which are the variables used in second-stage regression.

Table 1: Inputs and Output (s) in DEA Models

MODEL 1		***MODEL 2***	
Inputs	***Output (s)***	***Inputs***	***Output (s)***
Labour	Units Generated (MWh)	Labour	Units Generated (MWh)
Installed Capacity (MW)		Installed Capacity	***Environmental Variables***
Fuel		Fuel	GWh-PC
			NCUS
			C
			ISLAND
			CONNECT

GWh-PC: Per Capita Consumption of Electricity
NCUS: Number of Customers Served by Utility
C: Capacity Factor (capacity utilisation)
ISLAND: Dummy (Island =1)
CONNECT: Isolated=0, interconnected=1.

4. Data

Our dataset consists of a sample of 16 small islands' generators and 121 US investor-owned utilities involved in electricity generation. Small islands generators are all monopolies and vertically-bundled, except Trinidad and Tobago which divested its generating activity (in 1994) into a new privately owned company (PowerGen). US utilities involved purely in sale for resale (SFR) have been dropped out. Moreover, only steam generation is included in the sample to ensure comparability with the islands' thermal electricity generating data. In fact, our efficiency analyses of electricity generation is restricted to fossil-fired thermal generation only, so as to ensure, as far as is possible, that the comparisons are being made for similar technologies. There may be variations among countries even in the menu of technological choices within the category of fossil-fired generation but it is the only sensible thing to do if fuel inputs are to be measured in BTU. It is also assumed that all the US-based utilities are interconnected via a transmission grid, over which power can be exchanged. The data covers the period 1993-94 through 1999-2000 and was downloaded from FERC[1] website. In Table 2, we present some descriptive statistics of the two groups of DMUs, islands and non-islands. A full list of the DMUs used in our analyses may be obtained from the author.

Table 2: Descriptive Statistics

	L	K	F	Y	NCUS
Non-Islands					
N = 121					
Minimum	39	26.4	20001.39	1.373	6198
Maximum	4456	415001.7	825840859	138609	4622570
Mean	916.29	7402.6	88333200.5	20474.9	680431.4
Std. Error	85.94	3420.9	11729564.8	2196.26	68608.02
Std. Deviation	945.31	37629.6	129025212	24158.84	811781.1
Islands					
N = 16					
Minimum	37	6.6	77797.55	10.16	1496
Maximum	1408	2275	87217106.5	8958.21	460865
Mean	354.10	456.3	17606398.9	1627.79	162603.3
Std. Error	97.67	154.9	6431624.6	605.12	36059.29
Std. Deviation	390.70	619.8	25726498.5	2420.47	144237.1

5. Results and Analysis

5.1: Preliminary Data Analysis: Partial Productivity Measures

A brief overview of the 7-year panel indicates that overall labour productivity is much larger for non-islands than for islands. This can be indicative of the fact that there is a minimum threshold number of labour units required to run a generating utility, beyond which relative factor indivisibility of labour becomes less significant. This, therefore, implies that small islands may face a significant disadvantage in labour employment due to the overall small scale of operations. The trend (and difference) in net units of electricity generated per unit of labour in generation is depicted in Figure 1.

Regarding the productivity of capital (installed capacity), the net generation per unit of installed capacity (MW) shows that islands fare less well relative to non-islands, but that the

[1] The data are downloadable at http://rimsweb2.ferc.fed.us/form1viewer/, and all files are in relational database structure. Other data for the US utilities including Hawaii was extracted from UDI (1998).

gap between the two groups are not too significant. There is a wider variation in the capital productivity for non-islands. These trends are depicted in Figure 2.

Figure 1: Labour Productivity in Generation

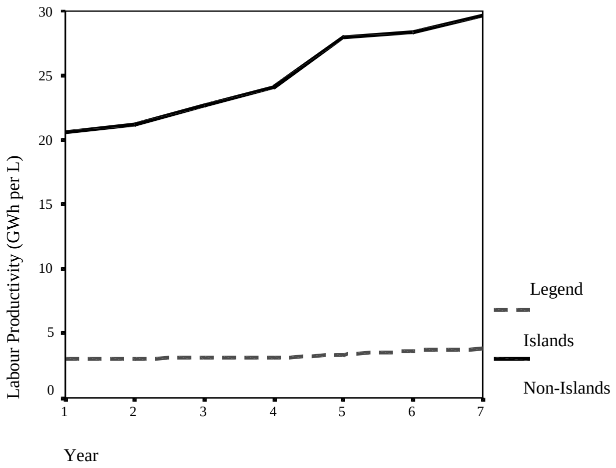
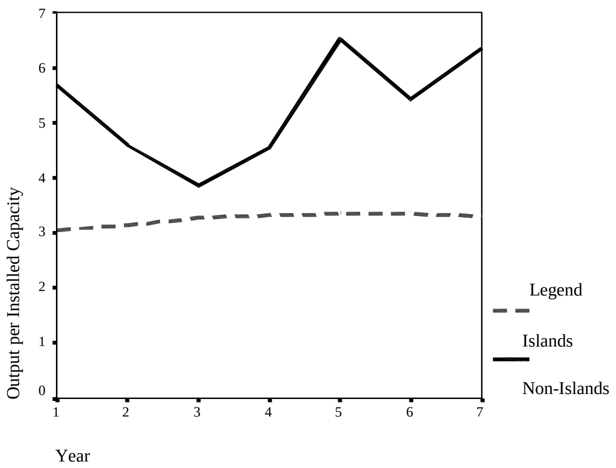


Figure 2: Generation Capacity Utilisation



5.2: Results from Stochastic Frontier Analyses

In this section SFA results of the translog equation (1) is estimated. The three time (t) variables help to test whether there has been Hicks' neutral technical change (HNTC) over the 7-year time period. This would allow us to infer as to whether technical progress (if any) has favoured the use of any given input as opposed to any other input (For a brief explanation of HNTC see Appendix 2). The results are presented in Table 3, which also contains a summary of the likelihood tests at the end.

Three main results should be of interest here. Firstly, the best functional form for the industry is an HNTC translog function. Secondly, we identify significant technical inefficiencies in the industry. Almost all deviations from the frontier are explained by differences in technical inefficiency rather than noise. Such inefficiencies are explained by system size (NCUS) and capacity utilisation (C). Finally, we found that there are no apparent and significant differences between the production structure of islands and non-islands. Below we explain these results in more detail.

5.3: Choosing a Preferred Functional Model Specification?

Firstly, we test whether the Hicks' neutral technical change (HNTC) is valid. This test involves imposing the restriction β_{10}=β_{11}=β_{12}=0 on the translog model. The likelihood test ratio λ (given at the bottom of Table 3) is 5.45. The critical (5%) chi-square value (χ_3^2) is equal to 7.81. The null hypothesis of neutral technical change cannot be rejected; hence we can conclude that HNTC functional form is a better specification for the SFA.

Table 3: SFA and OLS Regression Results

	TRANSLOG		*HNTC (Hicks' Neutral)*		*Cobb-Douglas*		*OLS*
	Single-Stage	*2-Stage*	*Single-Stage*	*2-Stage*	*Single-Stage*	*2-Stage*	
Intercept (β_0)	-11.6796 (1.1440)*	-7.4146 (2.2831)*	-11.155 (1.0318)*	-6.7120 (1.3811)*	-3.3066 (0.256)*	-3.9153 (0.4892)*	-13.9683 (1.9027)*
β_1	0.9837 (0.3257)*	0.4495 (0.5311)	1.2062 (0.2796)*	0.3786 (0.3983)	0.0486 (0.0271)	0.1684 (0.0446)*	0.9256 (0.4768)
β_2	1.4734 (0.2575)*	1.5687 (0.3651)*	1.4736 (0.2377)*	1.9828 (0.3039)*	0.6400 (0.0298	0.4366 (0.0472)*	1.0629 (0.3517)*
β_3	0.6443 (0.1335)*	0.2529 (0.2410)	0.5539 (0.1129)*	0.0975 (0.1777)	0.4288 (0.0178)*	0.5019 (0.0391)*	0.9949 (0.2236)*
β_4	-0.0315 (0.0216)	0.0218 (0.0369)	-0.0332 (0.0189)	0.0132 (0.0343)			-0.0270 (0.0315)
β_5	0.0497 (0.0210)*	0.0127 (0.0184)	0.0453 (0.0172)*	0.0126 (0.0179)			-0.0082 (0.0182)
β_6	0.0437 (0.00713)*	0.0397 (0.0103)*	0.0460 (0.0067)*	0.0477 (0.0099)*			0.0247 (0.0099)*
β_7	0.1184 (0.0339)*	0.0210 (0.0467)	0.1283 (0.0280)*	0.0360 (0.0410)			0.1423 (0.04293)*
β_8	-0.0820 (0.0275)*	-0.0339 (0.0426)	-0.0939 (0.0249)*	-0.0282 (0.0296)			-0.0857 (0.0382)*
β_9	-0.1449 (0.0249)*	-0.1010 (0.0312)*	-0.1440 (0.0233)*	-0.1311 (0.0284)*			-0.0885 (0.0287)*
β_{10}	0.0151 (0.0127)	-0.0068 (0.0164)					0.0022 (0.0185)
β_{11}	0.0053 (0.0172)	0.0237 (0.0189)					0.0189 (0.0214)
β_{12}	-0.0186 (0.0131)	-0.0197 (0.0148)					-0.0218 0.0170
β_{13}	0.1540 (0.1541)	0.1300 (0.1737)	-0.0350 (0.0469)	-0.0708 (0.0596)			0.1424 0.2024
β_{14}	0.0097 (0.0055)	0.0148 (0.00758)**	0.0097 (0.0058)	0.0144 (0.0073)**			0.0157 0.0088
Intercept (δ_0)	-3.3122 (0.7666)*				-1.1729 0.6410		
δ_1	0.0002 (0.0003)		-0.0004 (0.0003)		-0.0011 (0.0003)*		

δ_2	0.0000 (0.0000)*		0.0000 (0.0000)*		0.0000 (0.0000)		
δ_3	-0.3164 (0.0448)*		-0.3356 (0.0499)*		-0.4200 (0.0253)*		
δ_4	-8.0639 (1.6824)*		-9.5219 (-2.3612)		-10.798 (2.2232)*		
δ_5	-13.9128 (2.1419)*		-15.145 (-3.7639)		-10.867 (2.0408)*		
σ^2	9.9854 (1.539)*	2.4356 (0.1377)*	9.5128 (2.0566)*	3.0878 (0.3245)*	8.0713 (1.1163)*	2.3312 (0.2361)*	0.8828
$\gamma=\sigma_U^2/(\sigma_V^2+\sigma_U^2)$.	0.9835 (0.0016)*	0.7606 (0.0178)*	0.9810 (0.0041)*	0.8152 (0.01303)*	0.9747 (0.0039)*	0.7348 (0.0338)*	
μ		-2.722 (0.3981)*		-3.1731 (1.0047)*		-2.6176 (-0.4914)	
LLF	-993.75	-1209.43	-996.48	-1213.14	-1060.22	-1242.03	-1293.41
λ		431.35	5.45	438.79	128	496.56	594
χ^2 Critical Value (5%)		14.0671	7.8147	16.9190	21.0261	28.8693	14.0671
Decision		*Accept translog model with TE terms*	*Accept HNTC against translog*	*Reject model in favour of HNTC with TE effects*	*Reject model in favour of HNTC function*	*Reject model in favour of TE effects*	*Reject model in favour of translog function*

Likelihood Test Ratio Statistic (λ) = -2(LLF(Ho)-LLF(Ha))
Standard Errors in parentheses
Translog OLS has restrictions such that $\gamma=\delta_0=\delta_1=\delta_2=\delta_3=\delta_4=\delta_5=0$; and
Stochastic Cobb-Douglas, $\beta_4=\beta_5=\beta_6=\beta_7=\beta_8=\beta_9=0$
* Significant at 1%, ** Significant at 5%

The second likelihood ratio test that we carry out involves whether a Cobb-Douglas production function is preferred over the HNTC specification. This hypothesis involves a test of the restrictions that $\beta_4=\beta_5=\beta_6=\beta_7=\beta_8=\beta_9=0$. The value of the log-likelihood function fell substantially from –996 to –1060. This provides a likelihood ratio test statistic of 128, which exceeds the χ_6^2 critical value of 12.59 by a large amount. Thus we confidently reject the Cobb-Douglas form in favour of the translog model. It therefore appears that the extra effort involved in estimating and analysing the translog (HNTC) form is warranted in this instance.

5.4: Is there Technical Inefficiency in this Industry?

The third test that we perform on the SFA results in Table 3 is to test the null hypothesis that there is no technical inefficiency in this industry. This is equivalent to imposing the restrictions that $\gamma=\delta_0=\delta_1=\delta_2=\delta_3=\delta_4=\delta_5=0$. The likelihood ratio statistic is calculated to be 594, which is larger than the critical χ_7^2 value of 14.07. This allows us to retain a model that accounts for technical inefficiency.

From our preferred model (Translog HNTC), we have a gamma-statistic ($\gamma=\sigma_U^2/(\sigma_V^2+\sigma_U^2)$) of 98.1% for the single-stage stochastic model. This suggests two things; the first is that 98% of variations in the data between DMUs can be considered as due to inefficiency and the rest 2%

is pure 'noise'. Second, all predicted technical inefficiency is fully accounted for by the TE variables (δ_i) used in the single-stage stochastic regression. This is an important deduction, indicating that there are identifiable efficiency differences between DMUs, and this will render an exercise into benchmarking very valuable.

From the preferred single-stage HNTC model, we can also conclude that there are two significant factors influencing efficiency: NCUS (number of customers) and C (capacity utilisation). Although the two dummy variables (Island and Connect) are significant in the full-translog functional form, they are not significant in the HNTC specification.

5.5: Summary of Input Elasticities

SFA allows the calculation of input elasticities and helps make deductions on the production function. All elasticity estimates are calculated around the means of the two main groups: islands and non-islands[2]. The output elasticity of capital is equal to 0.067 for islands and 0.083 for non-islands, and both these values are not statistically significant different between themselves and from zero. These elasticity values are not too different from those reported by Coelli (1996c). Positive but higher output elasticity with respect to installed capacity was also reported by Lovell and Schmidt (1980) and Kopp and Smith (1980).

Labour elasticity has positive signs and are the largest reported elasticity values among the inputs. For the sample of islands, this elasticity is equal to 0.3698 and 0.1953 for non-islands. This result is very different to elasticity values reported by Lovell and Schmidt (1980), with very low labour elasticity. We observe that islands have significantly larger labour elasticity of output. This may be due to the relatively large amount of labour employed relative to capital (as illustrated in Figure 1 above).

With regards to the elasticity of fuel inputs, we note a significant difference between islands and non-islands (–0.112 and –0.563, respectively). This result is important in explaining that fuel input is not a significant binding constraint on production efficiency, compared to more important capital and labour inputs, which are actually combined with fuel to produce electricity. *Ceteris paribus*, adding more fuel to a fixed (and/or small) generating capacity, or alternatively, on larger generating systems which have much lower margins, does not

[2] For a brief explanation of these elasticity concepts, see Appendix 3.

necessarily contribute positively to total (net) output. Coelli (1996c) reports fuel elasticity that is greater than the other input elasticities, and our present analysis yields significantly different results.

Given that our results are unexpectedly different from other studies, we need a word of caution in interpreting the elasticity results for policy recommendations. Our elasticity results are derived from a translog production function, an over-specification of which (such as with interaction terms like cross-products, as in equation 1) can influence the predicted elasticity values. For instance, our Cobb-Douglas specification (in column 6 of Table 3) indicates that all input elasticities have positive values, with installed capacity and fuel having higher elasticities. But all the results do suggest that all the input elasticities have values that are less than unity. All the elasticity values have orders of magnitude that are not too different between the groups of islands and non-islands or between interconnected and isolated ones (not reported for reason of space). This consistency in elasticity magnitudes between the two groups of DMUs allows us to infer that production technologies are not too dissimilar between islands and non-islands and hence an exercise in benchmarking is valid from the perspective of comparing 'like with like'.

The elasticity of scale (κ) for islands is equal to 0.325, which indicates mildly decreasing returns to scale (low fuel elasticity driving these results). Non-islands, which are generally much larger than islands' DMUs, operate at greater decreasing returns to scale with κ=-0.285. However, our Cobb-Douglas specification indicates that the elasticity of scale is greater than unity (=1.117) indicating mildly increasing returns. With regards to the rate of technical progress, the results show that the value was negative for the first 5 periods and became positive at 0.38 for the last year. This result is in contrast to the Malmquist DEA results (see section 5.7 below), which shows a general progress over the whole time period except in the 3rd year. This is probably due to the functional form specification of the SFA analysis. (Comment 16: p.20 above 7.6: discussion on DRS and IRS not entirely clear).

5.6: DEA and SFA Results on Differences in Efficiency Scores

Results from DEA are in general agreement with our SFA results. Here we only explain any divergence in the two sets of results. Table 4 gives a summary of t-tests conducted on the efficiency scores derived from DEA and SFA between interconnected and isolated systems. Considering, first, the DEA technical efficiency, there is a difference between CRS TE and

VRS TE. It is observed that interconnected systems, generally, do have a much higher efficiency than isolated ones. Similar tests were conducted for the two groups, viz., islands and non-islands and these results are summarised in rows11 through 16 in Table 5. Non-islands are able to better choose an optimal scale than islands, and hence have a better scale efficiency than the latter. This result agrees with our introduction relating to the lesser scope of islands to choose restructuring as a policy option in situations where scale economies are significant.

However, it makes more sense to analyse the VRS TE scores in Table 5 (row 15, columns 3 and 4) indicates islands to have higher TE score (of 0.35) compared to non-islands with an efficiency score of 0.23. Efficiency scores generated by SFA indicate no major difference from DEA scores. However, considering the other efficiency scores, there is evidence for non-islands to perform better than islands (probably because all the latter DMUs are also interconnected). This, obviously, does not suggest that interconnection is a necessity, but that the necessary adjustments need to be made if interconnected islands are to be compared to isolated ones. This should necessarily be cast as an ‘environmental’ variable in analyses of island economies benchmarking of electricity generators.

5.7: Malmquist Efficiency Change

For reasons of space, only the differences in efficiency change between islands and non-islands are reported. Table 5 reports a set of one-tailed statistical tests on the efficiency measures and efficiency change measures of possible differences between islands and non-islands. Similarly, tests of differences in means and in variances between interconnected and isolated systems carried out reveal no differences in results.

Pure efficiency change (PECH), which is the change in VRS TE, differs between islands and non-islands in two out of 8 tests. This result is based on a year-to-year change in VRS TE. A composite measure of this change (PECHS) is based on a geometric mean of the PECH for the 7-year period and indicates that 5 out of 8 tests reveal a statistically significant difference between islands and non-islands. Non-islands have experienced an average improvement in PECHS of 3.69% while islands show no change in VRS TE over the period. The latter’s stagnation is mostly due to interconnected islands’ sluggish performance. We may tentatively suggest that after interconnection, the small islands may have lost their drive to achieve efficiency improvements as they could easily rely on an alternative power-generating source.

Table 4: Summary of Differences in Means of Efficiency Scores4

		Interconnected	*Isolated*
CRS TE (DEA)	Mean Score	.0968	.0182
	D.f.	125	
	t-statistic	7.8132	
	Significant	***At 1%***	
VRS TE (DEA)	Mean Score	.2295	.3585
	D.f.	125	
	t-statistic	-1.0687	
	Significant	***No***	
SE (DEA)	Mean Score	.6208	.1895
	D.f.	22	
	t-statistic	-7.8318	
	Significant	***At 5%***	
SFA scores	Mean Score	.6533	.41456
	D.f.	14	
	t-statistic	-3.8469	
	Significant	***At 5%***	

With regards to CRS TE change between the two groups, all tests reveal no difference between islands and non-islands. The composite measure EFFCHS also reveals no difference. An analysis of the change in scale efficiency shows that there is no difference between islands and non-islands. Differential efficiency change between islands and non-islands is not explained by scale efficiency change for the two groups. This conclusion is supported by 7 out of 8 tests carried out. Nevertheless, the composite scale change (SECHS) for islands was 2.48% per annum and .008% for non-islands.

Technological change (TECHCH) which is represented by frontier shifts, based on a year-to-year comparison has not favoured islands as opposed to non-islands. However, TECHCHS indicates that there is a difference between islands and non-islands. Islands experience a change of 5.5% per annum and non-islands' technological change grew at 3.38% per annum. For the whole sample of countries, there was positive technological progress over the whole period except in the 3rd year.

The overall measure of technical efficiency change that is reported is total factor productivity change (TFPCH). On a year-to-year basis, there does not seem to be any difference between islands and non-islands. However, the seven-year average does show that islands experienced a growth of 9.8% and it was 6.8% for non-islands. The difference is significant in 7 out 8 tests carried out.

Table 5: Summary of Differences of Malmquist Efficiency

	Measure	Mean Score Non-Islands	Mean Scores Islands	Levene F	T-test t	Kruskal-Wallis χ^2	Median Scores χ^2	Yates' Continuity χ^2	Jonckheeree-Terpstra JT	Mann-Whitney-Wilcoxon	Kolmogorov-Smirnov Z
1	EFFCH	1.0852	0.8975	0.41 (.522)	0.263 (.793)	0.754 (.385)	0.041 (.889)	0.009 (.925)	0.868 (.385)	-0.868 (.385)	1.065 (.207)
2	TECHCH	1.2474	1.1550	2.739 (.098)**	1.639 (.102)	1.508 (.220)	1.67 (.196)	1.401 (.236)	-1.228 (.220)	-1.228 (.220)	1.713 (.006)*
3	PECH	1.1261	0.9753	6.834 (.009)*	3.202 (.001)*	0.004 (.949)	0.628 (.428)	0.468 (.494)	-0.064 (.949)	-0.064 (.949)	2.014 (.001)*
4	SECH	0.9678	0.9245	0.199 (.655)	0.037 (.813)	0.546 (.460)	0.287 (.592)	0.183 (.669)	0.739 (.460)	-0.739 (.460)	1.669 (.008)*
5	TFPCH	1.3391	1.0239	1.899 (.169)	0.753 (.452)	2.638 (.104)	4.608 (.032)*	4.154 (.042)*	-1.1624 (.104)	-1.1624 (.104)	1.989 (.001)*
6	EFFCHS	1.0282	1.0241	0.219 (.640)	0.056 (.955)	0.095 (.758)	0.943 (.332)	0.497 (.481)	-0.308 (.758)	-0.308 (.758)	0.827 (.501)
7	TECHCHS	1.0270	1.0553	18.66 (.000)*	-0.404 (.692)	6.851 (.009)*	6.592 (.010)*	5.297 (.021)*	-2.617 (.009)*	-2.617 (.009)*	1.524 (.019)*
8	PECHS	1.0369	0.9991	14.047 (.000)*	3.364 (.001)*	1.806 (.179)	13.191 (.000)*	11.329 (.001)*	-1.344 (.179)	-1.344 (.179)	1.816 (.003)*
9	SECHS	0.9973	1.0249	0.094 (.759)	-1.494 (.138)	1.433 (.231)	1.16 (.291)	0.612 (.434)	1.197 (.231)	-1.197 (.231)	0.724 (.671)
10	TFPCHS	1.0562	1.0989	8.925 (.003)*	-0.396 (.697)	6.641 (.010)*	9.993 (.002)*	8.382 (.004)*	-2.577 (.010)*	-2.577 (.010)*	0.784 (.003)*
11	Translog	0.6919	0.4957	0.773 (.381)	3.298 (.001)*	10.275 (.001)*	7.07 (.008)*	5.726 (.017)*	-3.205 (.001)*	-3.205 (.001)*	1.919 (.001)*
12	HNTC	0.6533	0.4146	0.183 (.669)	4.095 (.000)*	13.771 (.000)*	10.18 (.001)*	8.554 (.003)*	-3.711 (.000)*	-3.711 (.000)*	2.038 (.000)*
13	Cobb-Douglas	0.7017	0.5348	0.453 (.502)	2.993 (.003)*	17.276 (.000)*	13.857 (.000)*	11.984 (.001)*	-4.156 (.000)*	-4.156 (.000)*	2.293 (.000)*
14	CRS TE	0.0986	0.0265	2.882 (.092)**	2.742 (.007)*	22.457 (.000)*	13.857 (.000)*	11.948 (.001)*	-4.739 (.000)*	-4.739 (.000)*	2.694 (.000)*
15	VRS TE	0.2253	0.3496	6.633 (.011)*	-1.453 (.165)	1.063 (.303)*	0.004 (.951)	0.042 (.838)	1.031 (.303)	-1.031 (.303)	1.06 (.211)
16	SE	0.6208	0.1895	9.526 (.002)*	9.24 (.000)*	23.216 (.000)*	18.098 (.000)*	15.91 (.000)*	-4.818 (.000)*	-4.818 (.000)*	2.59 (.000)*

These tests were carried out using SPSS 10.0 statistical package.
EFFECH: Technical efficiency change relative to a CRS technology
TECHCH: Technological change
PECG: Pure technical efficiency change relative to a VRS technology
SECH: Scale efficiency change
TFPCH: Total factor productivity change
* Significant at 5%, ** Significant at 10%, prob. values in parentheses.

On the issue of relative isolation of islands, the analysis of efficiency change reveals a few interesting points. Interconnected islands (Jersey, Guernsey and Isle of Man) experienced technological change of about 7.47% over the seven-year period while isolated islands regressed by 2.2%. To some extent this is a coincidence with the period over which interconnection happened or when interconnection capacity improved. On the front of TFP change, interconnected islands show a 12.6% change while isolated ones show only 8.7%. SECH was much higher in interconnected islands (2.76%) than isolated ones (1.4%). And finally, PECH regressed by 0.12% for interconnected islands and improved for isolated islands (1.4%).

Interconnection caused technological change for small islands but these same islands failed to realise pure efficiency gains (reaching the frontier) as fast as isolated islands did. Nevertheless, TFP change favoured islands especially those that are interconnected. Interconnection improves the chance for better capacity utilisation and allows DMUs to choose more optimal generation capacity.

5.8: Tobit Analysis of Efficiency Scores

Tobit analyses are performed on efficiency scores as a second-stage regression of scores on the technical efficiency parameters. It is noted that this second-stage regression does yield some differences in the factors that explain efficiency differences between islands and non-islands. The results are presented in Table 6. The only factor explaining efficiency differences, common to all methods, is capacity utilisation (C).

Table 6: Tobit Analysis of Regression Results

	CRSTE (DEA)	*VRSTE (DEA)*	*SCALE (DEA)*	*TRANSLOG*	*HNTC*
α_0 (intercept)	0.5137 (.6917)	.9793 (.6875)	1.9851 (.7009)*	1.9462 (.6997)*	1.7688 (.6980)*
α_1 (GWh-PC)	0.3279 (1.4755)	5.269 (.5338)*	-6.1008 (1.518)*	-1.532 (1.4737)	-1.8647 (1.4751)
α_2 (NCUS)	-0.5578 (1.244)	.1306 (.1184)	0.8653 (1.245)	0.1404 (1.2437)	0.9014 (1.2449)
α_3 (C)	1.4423 (.4921)*	-1.322 (.48615)*	3.2121 (.5188)*	3.3689 (.5213)*	3.2625 (.5187)*
α_4 (island)	-0.7432 (.5979)	.90266 (1.524)	-2.3167 (.6125)*	0.0453 (.5961)	-0.4148 (.5966)
α_5 (connect)	-0.1328 (.6408)	.20745 (.6409)	-0.6228 (.6419)	1.0663 (.6439)	0.7756 (.6425)
Sigma	10.084 (.6145)*	4.1902 (.24815)*	4.1016 (.2489)*	6.3828 (.3856)*	6.0306 (.36432)*
Loglik	242.1879	127.7881	123.0952	185.4437	177.6686

* Significant at 5%

VRS TE results indicate that average electricity consumption is a significant factor which affects scale efficiency in this industry. Considering scale efficiency parameters, islands tend to have lower efficiency scores than non-islands, which explain the negative sign of the island parameter in the Tobit analysis. This suggests that islands have scale inefficiency relative to non-islands. SFA results show that they are mostly influenced by capacity utilisation. The most sensible results are derived from the Tobit analysis of HNTC SFA scores, whereby island parameter has the correct negative sign and interconnection dummy has the correct positive sign. However, both these parameters are not statistically significant, suggesting that in general, there does not tend to be significant differences between islands and non-islands and between interconnected islands as opposed to isolated ones. Such results, in fact, suggest that the benchmarking of small islands' generators with non-islands' generators is theoretically feasible and methodologically sound.

5.9: Returns to Scale

About 90% of non-island DMUs face increasing returns as shown in Table 7. Even interconnection does not necessarily overcome islands' sub-optimal scale of operation.

Table 7: Returns to Scale

	Likely CRS	*Likely DRS*	*Likely IRS*	*Total*
Non-Island	3 (2.5) [8390]	10 (8.3) [16289]	108 (89.2) [5897]	121
Island			16 (100) [338]	16
Total	*3 (2.2)*	*10 (7.2)*	*124 (90.5)*	*137*
Non-Interconnected			13 (100)	13
Interconnected	3 (2.4)	10 (8.1)	111 (89.5)	124
Total	*3 (2.2)*	*10 (7.2)*	*124 (90.5)*	*137*

Percentage in parentheses[3]. Average installed capacity in square brackets.

5.10: Correlation of Efficiency Scores

The final set of results presented here is on the correlation of the efficiency scores between the two broad methodologies. Full translog, Hick's neutral and Cobb-Douglas scores were obtained from stochastic estimation, while technical efficiency (TE) and scale efficiency scores (SE) were derived from DEA.

Table 8: Correlation Table

Pearson Correlation	*TRANSLOG*	*Hicks-Neutral*	*Cobb-Douglas*	*TE (DEA)*	*SE*
TRANSLOG	1.000	.987*	.950*	.396*	.464*
Hicks-Neutral	.987*	1.000	.913*	.438*	.509*
Cobb-Douglas	.950*	.913*	1.000	.383*	.515*
TE (DEA)	.396*	.438*	.383*	1.000	.381*
SE	.464*	.509*	.515*	.381*	1.000

* Correlation is significant at the 0.01 level (1-tailed).

It is clear from Table 8 that within-methodology scores have much higher regression coefficients than between-methodology scores. The correlation coefficients of scores between

[3] The values in parentheses are the percentage of number of units in a given category to the sub-total in that category.

DEA and SFA are about 50% or less. This indicates that the two methodologies may yield different results. And a word of caution is important, in comparing efficiency across a sample of heterogeneous DMUs.

6. Conclusions

Before concluding this paper, two points need mentioning:

1. There is one major problem faced by small and isolated island economies. While electric generating utilities in non-islands can relax the constraint of smallness by interconnection, isolated islands may not easily achieve this. Jersey, Guernsey and Isle of Man, in our sample have successfully interconnected to a mainland grid and import a considerable proportion of what they distribute. These 3 interconnected islands have a mean technical efficiency (VRS TE) score of 0.395 while isolated islands' mean score is 0.356. The capacity utilisation factor for interconnected islands is 36.5% and it is 34.4% for isolated ones. The former islands can also better manage peaking demands more effectively and the 2.1% better capacity utilisation has allowed an efficiency gain of 3.65%.
2. The mean efficiency scores for the non-islands are 0.6533 using SFA and 0.2254 using (VRS) DEA. There are 3 islands whose technical efficiency scores exceed 0.6533 (mean of non-islands): Grenada, Montserrat and St Lucia. The same 3 countries are on the frontier using DEA. There are only 7 US DMUs on the DEA frontier.

Our analyses of a panel data of 137 utilities over a 7-year period suggest that there are identifiable technical inefficiencies in electricity generation. This in turn opens up an important avenue for the implementation of incentive regulation. Both DEA and SFA-generated technical efficiency scores show that capacity utilisation factor is unanimously the most important variable that explains efficiency differences between islands and non-islands.

Considering the impact of isolation (versus interconnection), it is found that technical efficiency scores tend to be higher with interconnection. Interconnected islands have indicated higher technical and scale efficiency. There tends to be a general agreement between the various methodologies as to the impact of interconnection on efficiency. This does not imply that islands should necessarily have to interconnect, but that in a benchmarking exercise involving both interconnected and isolated islands, this ‘environmental variable’ should effectively be accounted for, before a given DMU is subjected to a given regulatory regime.

Dynamic DEA analyses indicate that pure technical efficiency change (technical efficiency change using a VRS technology) was significantly lower for islands (negative) and especially for the interconnected ones. This indicates that islands found it relatively harder to catch up to the efficient frontier. It also indicates that interconnection of a small island generating utility to an inter-continental grid may in the long run reduce the incentives on resource use and may lead to lower gains technical efficiency. This points to one important caution as to the benefits of interconnection: that while interconnection provides benefits in terms of improved efficiency they still need to use diligence in the use of their existing assets. Interconnection itself is a frontier shift for islands (and isolated systems) but there is no guarantee that they will thrive to reach the new frontier at all.

Our final conclusion is that there is ample reason to believe that small islands can be effectively compared with non-islands. At this juncture it would be wise to suggest that contrary to the theoretical literature in yardstick regulation, which requires that DMUs should be benchmarked on a like-to-like basis, our analyses show that this condition may be by-passed so long as all necessary differences between DMUs are fully accounted for. There is, thus, reason to believe that after adjusting for scale, capacity utilisation and interconnection, small island electricity generators could effectively be benchmarked against non-island electricity generators. These results would legitimise the recent European Union (EU) pressures for investments in interconnection capacity. Our analysis can be extended to empirically investigate EU’s claim that interconnection will ease the injection of competition and improve efficiency of ESIs.

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APPENDIX 1: Sources of Data on Islands

Country	Source of Data
Anguilla	Carilec
Antigua	Carilec
Barbados	Carilec; BL&P Annual Reports and Accounts
Belize	Carilec
Bermuda	Carilec
BVI	Carilec
Cayman	Carilec
Dominica	Carilec, (DOMLEC) Annual Reports and Accounts

Martinique	Carilec, Management Reports
Guadeloupe	Carilec, Management Reports
Grenada	Carilec, Management Reports, and (Grenlec) Annual Reports and Accounts
Jamaica	Carilec, Management Reports, (JPSCo) Annual Reports and Accounts and Statistical Review
Montserrat	Carilec, (MONLEC) Annual Reports and Accounts
St_Lucia	Carilec, (Lucelec) Management Reports and Annual Reports
St_Vincent	Carilec
Trinidad	Carilec, Financial Review and (T&TEC) Annual Reports and Accounts
USVI	Carilec
Reunion	EDF-Reunion, Resultats, Bulletin Annuel, Revue des Statistiques
Jersey	Management Reports, (JEC) Annual Reports and Accounts
Guernsey	Billets D'Etats, (GEC) Annual Reports and Accounts
Mauritius	(CEB) Annual Reports and Accounts
Madagascar	Annual Reports
Gibraltar	Personal Communication; Government of Gibraltar: Estimates
Hawaii	FERC, UDI
Malta	(ENEMALTA) Annual Reports and Accounts
IOM	Annual Reports and Accounts
Cyprus	EAC, Annual Reports and Accounts

APPENDIX 2: Hicks' Neutral Technical Change (HNTC)

The rate of technical change is defined as:

$T(x,t) = \frac{\partial \ln f(x,t)}{\partial t}$ where, x is a vector of inputs and t is time. If the technology is homothetic in x, then $y = f(x,t) = H\left[f^{*}(x,t)\right]$ where, $f*(x,t)$ is linearly homogenous in x.

For this technology to be consistent with Hicks neutrality, $f*(x,t)$ must also be consistent with Hicks neutrality since the fact that

$$\frac{\partial f(x,t)}{\partial x_i} = \frac{\partial H}{\partial f^{*}} \times \frac{\partial f^{*}}{\partial x_i} \text{ implies that } \frac{\partial}{\partial t} \times \frac{\partial f(x,t)/\partial x_i}{\partial f(x,t)/\partial x_j} = \frac{\partial}{\partial t} \times \frac{\partial f^{*}(x,t)/\partial x_i}{\partial f^{*}(x,t)/\partial x_j} = 0 .$$

For more details on Hick's neutrality, see for example Chambers (1994).

APPENDIX 3: Input Elasticities

The estimation of translog production function may entail the use of a large number of inputs which can make it difficult to determine the production structure of the industry, and in appraising the economic plausibility of results. Estimating some more interpretable statistics, such as input elasticities and the rate of technical progress (for panel data) becomes handy. The elasticity of scale (κ) can be estimated from the sum of the marginal elasticities of output with regard to each input η_i, such that[4]

[4] Based on a production function of the type:

$$\kappa(x) = \sum_{i=1}^{n} \frac{\partial \ln y}{\partial \ln x_i} = \sum_{i}^{n} \eta_i \qquad (1a)$$

where

$$\eta_i = \frac{\partial \ln y}{\partial \ln x_i} = \alpha_i + \sum_j \beta_{ij} \ln x_j + \delta_i t \qquad (2a)$$

κ is not only DMU-specific, but also varies over time unless the production function is homogenous of degree one. Equation (1a) follows from the definition of the elasticity of scale as a directional elasticity of the production function. We can also calculate the rate of technical progress (*RTP*) using the following formula:

$$RTP = \frac{\partial lny}{\partial lnt} = \gamma_t + \gamma_{tt} t + \sum_j \delta_j ln\, x_j \qquad (3a)$$

Technical progress is neutral if $\delta_j = 0, j = 1,\ldots,n$, otherwise there is technical bias.

$\ln y = \alpha_0 + \alpha' \ln x + \frac{1}{2} \ln x' B \ln x + \gamma_t t + \frac{1}{2} \gamma_{tt} t^2 + \delta' \ln xt + \varepsilon$

where α and δ are n x 1 vectors and B is an n x n symmetric matrix of parameters.