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ABSTRACT

This study estimates electricity demand functions for Sri Lanka using six econometric techniques. It shows that the preferred specifications differ somewhat and there is a wide range in the long-run price and income elasticities with the estimated long-run income elasticity ranging from 1.0 to 2.0 and the long run price elasticity from 0 to –0.06. There is also a wide range of estimates of the speed with which consumers would adjust to any disequilibrium, although the estimated impact income elasticities tended to be more in agreement ranging from 1.8 to 2.0. Furthermore, the estimated effect of the underlying energy demand trend varies between the different techniques; ranging from being positive to zero to predominantly negative. Despite these differences the forecasts generated from the six models up until 2025 do not differ significantly. Thus on one hand it is encouraging that the Sri Lanka electricity authorities can have some faith in econometrically estimated models used for forecasting. However, by the end of the forecast period in 2025 there is a variation of around 452MW in the base forecast peak demand; which, in relative terms for a small electricity generation system like Sri Lanka's, represents a considerable difference.

JEL Classification: Q48, Q41

Key Words: Developing Countries, Electricity Demand Estimation, Sri Lanka

Electricity Demand for Sri Lanka: A Time Series Analysis

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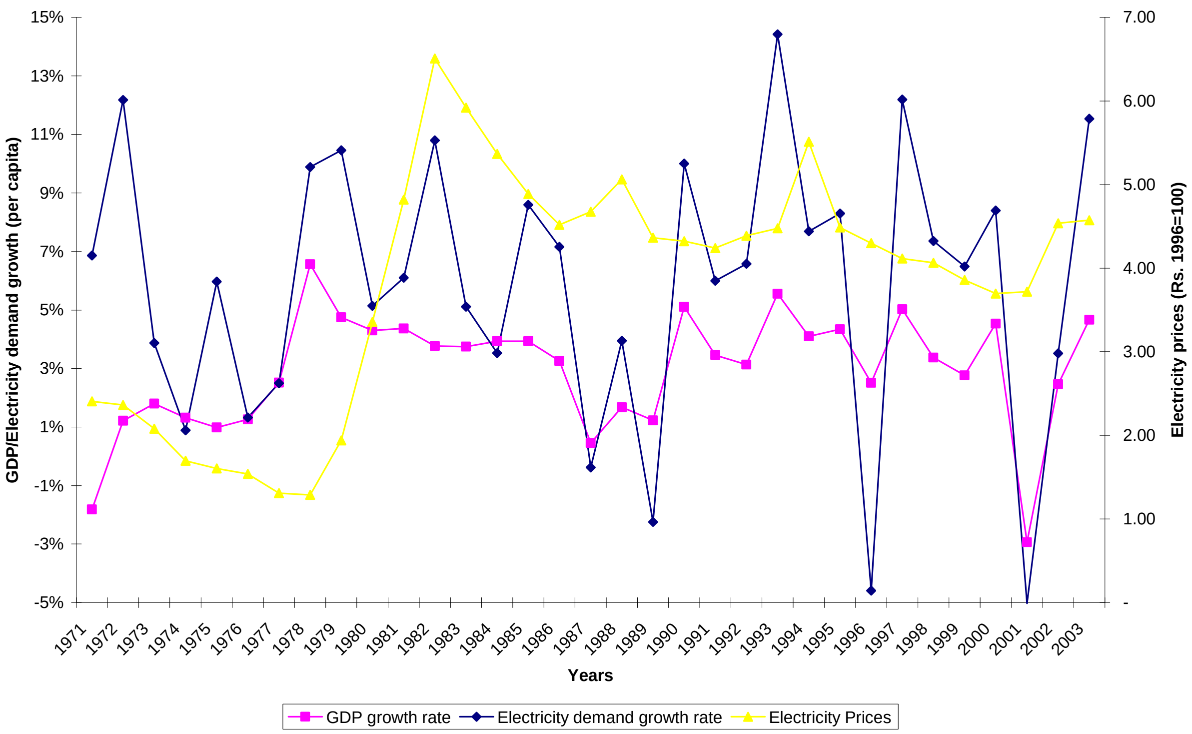
1 INTRODUCTION

With an electricity demand of 322 kWh per capita per year in 2003 Sri Lanka's electricity demand has been growing at an average of 6.8% per year from 1986 to 2003 while the peak demand increased on average by 6.3% per annum from 540MW to 1516 MW. The electricity demand growth, GDP (Gross Domestic Product) growth and electricity price variation for Sri Lanka for the period 1971 to 2003 are shown in Figure 1.

Figure 1
Variation of GDP Growth, Electricity Demand Growth, and Electricity Prices



This illustrates the relatively moderate Sri Lankan GDP growth (averaging 3.5% per annum from 1978 to 2003), but despite this, Sri Lanka's per capita electricity consumption is still somewhat lower than that of its neighbours India and Pakistan although both countries have experienced much lower per capita income levels.[1] Although these economies are not directly comparable with the Sri Lankan economy, they are the closest geographical neighbours to Sri Lanka with some direct cultural and trade links.

In 2003 about 68% of Sri Lankan households were connected to the electricity grid with household electricity consumption accounting for about 35% of total electricity consumption, and household and industrial sector consumption combined accounting for about 65% of the total 6,209 GWh [2]. Further details about the institutional background of the Sri Lankan Electricity Supply Industry (ESI) may be found in Amarawickrama and Hunt (2005) [3] (hereafter AH). Building on AH, this paper focuses on estimating and analysing Sri Lankan electricity demand that is the basis for forecasts of future demand up to 2025.

Previous statistical analysis of Sri Lankan electricity demand is extremely limited. As far is known there are only four previous attempts to analyse Sri Lankan electricity demand.

An early attempt was by Jayatissa (1994) [4] who estimated a number of models for both the Sri Lankan residential and industrial sectors, given that combined these two sectors accounted for about 60% of total electricity demand in 1992. Using pooled cross section-time series data of 178 household consumers from January 1993 to December 1993 and

[1] According to Athalage et al In 1996 [1] the per capita energy consumption of Sri Lanka was about 60% lower than that of India and Pakistan.

monthly time series data from February 1980 to October 1993 Jayatissa estimated a model for the Sri Lankan residential sector using Ordinary Least Squares (OLS).[2] Consequently, Jayatissa generated a number of different elasticity estimates, but concluded that for both data sets household demand for electricity in Sri Lanka is generally neither income nor price elastic in both the short and long run. For the industrial sector Jayatissa primarily used annual data for the period 1971-1992 and again estimated a number of electricity demand models using OLS and concluded that in general industrial demand was neither output nor price elastic in the short or long run.[3]

Using annual data for the period 1960-1998 Hope and Morimoto (2004) [5] investigated the causal relationship between electricity supply and GDP using Granger causality analysis and concluded that changes in electricity supply have a significant impact on change in real GDP in Sri Lanka and therefore every MWh increase in electricity supply will contribute to an extra output of around US$ 1120-1740.

Using annual data for the period 1971-2001, AH estimated an electricity demand function using the Engle and Granger two-step methodology and found the estimated long run income elasticity to be 1.1 and the estimated long run price elasticity to be -0.003. This was used as the basis for an indicative forecast for electricity demand as part of their analysis of proposed electricity industry reforms for Sri Lanka.

[2] Although it should be noted that Jayatissa did experiment with a number of alternative estimation approaches, including correcting for serial correlation (Cochrane-Orcutt procedure, Hildruth-Lu procedure, etc.) and Instrumental variables.

[3] Jayatissa also used a monthly micro data set for 80 individual consumers from the industrial sector but this did not include individual firms' output for the individual consumers since this was not available. Consequently, the estimated models were poorly defined.

Finally, the generation planning branch of the Ceylon Electricity Board (CEB)[4] provide electricity demand forecasts of Sri Lankan electricity demand, but the exact methodology is not detailed.

Accurate and reliable energy demand forecasts are vital to a capital constrained developing country where the capability for the import and export of electricity is severely limited both in the present and the near future.[5] Sri Lanka, which is an island, does not have any sub sea cables from main subcontinent and, at the time of writing, there are no plans to build one given the political unrest in the north of Sri Lanka. This study therefore explores this issue by investigating how different time-series estimation methods perform in terms of modelling past electricity demand, estimating the key income and price elasticities, and hence forecasting future electricity consumption in the context of the Sri Lankan ESI. This allows for the different forecast electricity demand using these different econometric techniques to be compared indicating if the policy decisions might vary according to the chosen econometric method.

The next Section of the paper therefore discusses the different methods analyzed. Section 3 presents and explains the estimation results, with the forecasts of electricity demand for Sri Lanka up to 2025 from the different models presented and compared in Section 4. Section 5 summarizes and concludes the study.

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[4] The electricity utility in Sri Lanka, which generates transmits and supplies for around 80% of Sri Lankan Electricity users.

[5] Wijayathunga et al, 2001 [6].

2 METHODOLOGY

2.1 Electricity Demand Function

It is assumed that there exists for Sri Lanka a simple long-run equilibrium relationship between electricity consumption, economic activity and the real electricity price characterized by:

$$E = f\,(Y, P, \mu) \qquad (1)^{6}$$

where: E = per capita electricity demand;

Y = per capita GDP;

P = the real electricity price; and

μ = the underlying energy demand trend (UEDT).[7]

In order to econometrically estimate equation (1) the conventional log-linear specification is assumed for the long-run equilibrium Sri Lankan electricity demand function as follows:

$$e_t = \beta_1 y_t + \beta_2 p_t + \mu_t + \varepsilon_t \qquad (2)^{8}$$

where: $e_t = Ln\ (E_t)$;

$y_t = Ln\ (Y_t)$;

$p_t = Ln\ (P_t)$.

β_1 = the long-run income elasticity of electricity demand;

β_2 = the long-run price elasticity of electricity demand; and

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[6] This is the standard 'demand' specification used by many previous demand studies. AH did explore whether there was a role for the additional variables 'average annual temperature' and 'rainfall', but they were never found to be significant and so they have not been included in the analysis here.

[7] Exact definitions and sources of the data are given as we explain them below.

[8] This constant elasticity demand function is standard in energy demand estimation, favoured for its simplicity, straightforward interpretation and limited data requirements and, according Pesaran et al. (1998) [7] it generally outperforms more complex specifications.

ε_t = a random error term.

In the most general specification the UEDT is stochastic (μ_t), however this can only be estimated via the Structural Time Series Model (see below) whereas for the cointegration methods the trend in the general model is deterministic and hence collapses to $\beta_0 + \beta_3 t$ so that the most general equation (with a deterministic trend) becomes:

$$e_t = \beta_0 + \beta_1 y_t + \beta_2 p_t + \beta_3 t + \varepsilon_t \qquad (3)$$

where: β_3 = the annual rate of change in the (linear) UEDT.

The relationships specified in equations (2) and (3) are consistent with a number of previous studies of energy demand in general and electricity demand in particular, but it could be argued that these actually represent supply relationships. However, given the nature of electricity production and supply in Sri Lanka this is unlikely to be the case. Over the estimation period the ESI in Sri Lanka was (and remains at the time of writing) a largely government owned and run vertically integrated monopoly, with the government setting prices (and supply during periods of output constraints); consequently, equations (2) and (3) may be regarded as demand relationships. This framework is therefore used to estimate appropriate equations for Sri Lankan electricity demand and hence produce suitable forecasting equations using a variety of cointegration methods as follows:

- Static Engle and Granger method (Static EG)
- Dynamic Engle and Granger method (Dynamic EG)
- Fully Modified Ordinary Least Squares method (FMOLS)
- Pesaran, Shin and Smith method (PSS)

- Johansen method (Johansen)

In addition the alternative approach advocated by Harvey (1989 & 1997) [8, 9] is also adopted:

- Structured Time Series Method (STSM)

The various approaches are now introduced and briefly explained.

2.2 Unit root tests

For most of the cointegration techniques the time series properties of the individual variables need to be investigated. In particular it needs to be determined whether the variables are stationary in levels and therefore integrated of order zero, I(0) or are non stationary and hence have a unit root and hence require differencing to achieve stationarity and are therefore integrated of order d, I(d) where d is the number of time the variable needs differencing to achieve stationarity. This is required since modelling with non-stationary variables can result in spurious relationships, whereas a combination of non-stationary variables can, in certain circumstances, result in cointegration and hence an appropriate relationship (see below).

To test for the presence of a unit root the most commonly used test is the Augmented Dickey-Fuller (ADF) test which involves estimating a form of the following equation by OLS:

$$\Delta x_t = \gamma_0 + \gamma_1 t + \phi x_{t-1} + \varphi_1 \Delta x_{t-1} + \ldots + \varphi_q \Delta x_{t-q} + \varepsilon_t \qquad (4)$$

where Δ is the difference operator.

The t-statistic for the estimated coefficient ϕ in equation (4) is the ADF statistic. However the ADF does not have a conventional student-t distribution, instead the ADF must be compared with specific tables such as those in MacKinnon (1996) [10]. Equation (4) involves the most general specification with q lags. The results below for e_t, y_t, and p_t are therefore obtained by starting with q equal to four[9] and then systematically omitting insignificant variables (lags, constant, and/or trend) ensuring that there is no serial correlation in the residuals. Once the preferred equation has been obtained in this way, using a combination of the software PCGive 10.4 and Eviews 5.0, the t-statistic gives the ADF statistics in the results section below. This therefore gives an indication of the time series properties of the individual variable, but if the variables are found to be non-stationary in levels a similar procedure is undertaken to test the variables in first differences Δe_t, Δy_t, and Δp_t. If, as is the case below, the variables are found to be stationary in first differences (that is the variables in levels, e_t, y_t, and p_t, are I(1) in that they need to be differenced once to achieve stationarity) then this allows progression to the cointegration techniques discussed below.

2.3 Estimation of the long-run cointegrating relationships

2.3.1 Engle-Granger two step method (Static EG)

If all the variables are found to be I(1) then Engle and Granger (1987) [12] have shown that a long-run relationship such as equation (3) may be estimated by OLS and if the resulting residuals are stationary, I(0), then the variables e, y and p are said to co-integrate; hence the estimated equation may be regarded as a valid long-run equilibrium

[9] The choice of lag length is somewhat arbitrary, however given the sample size the choice of q=4 is seen as a prudent lag length to begin the testing down procedure. Furthermore, the formulae suggested by Schwert (1989, p. 151) [11] would suggest that given the sample size used here q should be set at 3, which is within the framework used here.

cointegrating vector. The ADF test outlined above (omitting the constant and the trend) is used to conduct the test. These are computed using a combination of the software PCGive 10.4 and Eviews 5.0.

It has been shown by Engle and Granger (1987) [12], that this approach produces a consistent estimate of the long-run steady state relationship between the variables due to the ‘superconsistency’ property of the OLS estimator. However, it is not possible to conduct conventional inference such as t-tests since the lack of any dynamics renders the standard-errors and t-statistics biased and misleading. Thus a major drawback with this technique is the need just to take the estimated coefficients and long-run elasticities as given without being able to confirm whether they are significantly different from zero or not. This is an issue addressed below in some of the alternative cointegration techniques.

This has summarized the first of the Engle-Granger two step procedure. The second step involves using the information from the estimated long-run equation in a short-run dynamic equation. This is explained in more detail below following the introduction of all the long-run cointegration methods since the short-run methodology is applied consistently across all the different techniques and hence discussed after the methods to estimate the long run relationships have been introduced first.

2.3.2 Dynamic Engle-Granger method (Dynamic EG)

As discussed above the Static EG method produces a consistent estimate of the long-run steady state relationship between the variables due to the ‘superconsistency’ property of the OLS estimator. However, in finite samples these estimates will be biased and Banerjee *et al.* (1993) [13] and Inder (1993) [14] have shown that the bias could often be substantial.

An alternative is therefore used to estimate an over-parameterised dynamic model and derive the long-run parameters by solving the estimated Auto Regressive Distributed Lag (ARDL) since this reduces any bias, giving precise estimates of the long-run parameters. Moreover, Inder (1993) [14] has shown that this procedure provides valid t-tests and hence tests of significance on the long-run parameters may be undertaken. In addition, it is possible to carry out a unit root test of no cointegration since the sum of the coefficients on the distributed lag of e_t must be less than one for the dynamic model to converge to a long-run solution. Therefore dividing this sum by the sum of the associated standard errors gives the PcGive unit root test, which is a t-type test that can be compared against critical values given in Banerjee *et al.* (1993) [13].[10]

Hence an ARDL version of equation (3) is estimated using PCGive 10.4 with a lag of 4 on all the variables and the implicit long-run coefficients and associated t-statistics derived accordingly; with the equation also tested to ensure it does not suffer from any serial correlation and non-normality. Furthermore, given the long-run coefficients have valid t-statistics, variables found to be insignificant in the long-run are eliminated from the estimated equation.

2.3.3 Fully modified ordinary least squares method (FMOLS)

The FMOLS method is a semi-parametric approach developed by Philips and Hansen (1990) [16] for the estimation of a single cointegrating relationship with a combination of I(1) variables; such as equation (3). It makes appropriate corrections to circumvent the inference problems with the Static EG method discussed above, hence t-tests for the

[10] This explanation relies heavily on Harris and Sollis (2003, pp. 89 - 90) [15].

estimated long-run coefficients are valid. The software package Microfit 4.0 is used to estimate various versions of equation (3) with a two year lag. In addition to specifying the lag, two further choices are made: firstly, whether any of the variables included are I(1) with or without drift (which is determined by the ADF tests discussed above); secondly the type of weights used for the correction.

2.3.4 Pesaran, Shin and Smith method (PSS)

Pesaran, Shin and Smith (2001) [17] developed a method to test the existence of level relationship between a dependent variable and regressors where there is an uncertainty as to whether the regressors are trend stationary or first difference stationary. The first stage involves testing for the existence of an acceptable cointegrating vector and the second stage the estimation of the vector and the associated long-run elasticities; both of which are done using the software package Microfit 4.0.

To test for the existence of an acceptable cointegrating vector PSS developed the 'Bounds Test'. For the application undertaken here it involves the estimation of the following equation:

$$\Delta e_t = a_0 + a_t t + \sum_{i=1}^{j} b_i \Delta e_{t-i} + \sum_{i=1}^{j} d_i \Delta y_{t-i} + \sum_{i=1}^{j} f_i \Delta p_{t-i} + \tau_e e_{t-1} + \tau_y y_{t-1} + \tau_p p_{t-1} \qquad (5)$$

and testing the null hypothesis of 'non-existence of the long run relationship' defined by $\tau_e = \tau_y = \tau_p = 0$. The calculated F-statistic from the restriction does not have a standard distribution but contains 'bounds' depending upon whether the variables are I(0) or

I(1).[11,12] If the null is rejected for equation (5) then it suggests that there is a long run relationship between *e*, *y* and *p* and that *y* and *p* may be regarded as the 'forcing variables'.

If the existence of a long-run cointegrating vector is established the second stage of the PSS technique involves the estimation of the long-run relationship in a similar way to the dynamic EG outlined above. However, although it is possible to stipulate the number of lags, Microfit 4.0 allows for a systematic selection of the appropriate number of lags based upon various information criteria.[13]

2.3.5 Johansen method (Johansen)

The Johansen (1988) [19] approach estimates cointegrating relationships between non-stationary variables using a maximum likelihood procedure. This technique tests for the number of distinct cointegrating vectors in a multivariate setting and estimates the parameters of these cointegrating relationships. For the application here, this consists of the following three-dimensional vector autoregressive model:

$$\mathbf{X}_t = \mathbf{A}_1\mathbf{X}_{t-1} + \ldots + \mathbf{A}_k\mathbf{X}_{t-k} + \boldsymbol{\varepsilon}_t\,, \qquad t = 1,\ldots\ldots\ldots,T, \tag{6}$$

where $\mathbf{X}_t = [e, y, p]_t$ as defined above, $\mathbf{X}_t$ are fixed and $\boldsymbol{\varepsilon}_t \sim \mathrm{IN}(0, \boldsymbol{\Sigma})$. Equation (6) can be re-written in error correction form as:

[11] Note that the intercept and/or trend may also be omitted (i.e. a_0 and/or a_t set equal to zero) which require different tabulated values.
[12] Hence there is no real need to test the time series properties of the variables prior to testing for cointegration, however, the cointegration test can result in inconclusive results thus requiring more information about the variables properties.

$$\Delta \mathbf{X}_t = \mathbf{\Gamma}_1 \Delta \mathbf{X}_{t-1} + \ldots + \mathbf{\Gamma}_{k-1} \Delta \mathbf{X}_{t-k+1} + \mathbf{\Pi} \mathbf{X}_{t-k} + \boldsymbol{\varepsilon}_t , \qquad t = 1,........,T, \qquad (7)$$

If the data $\{\mathbf{X}_t\}$are integrated of order one, I(1), then $\Delta\{\mathbf{X}_t\}$ is I(0) and the reduced form model (2) is balanced only if $\mathbf{\Pi X}_{t-k}$ is I(0). Thus, matrix $\mathbf{\Pi}$ has to be of reduced rank:

$$\Pi = \alpha\beta' , \qquad (8)$$

where β may be interpreted as the $m \times n$ matrix of cointegrating vectors and α is the m x n matrix of loading weights.

Given the unit root tests suggest that e, p and y are I(1) (see below) they are entered as endogenous variables in the unrestricted VAR (Vector Auto Regression) equation (6) with a lag length of two years, using PcGive 10.4 and Eviews 5. This produces both the Maximum Eigen and the Trace statistics to test for the number of cointegrating vectors. Once this has been determined it is imposed on the system to produce the cointegrating vector(s) and associated statistics given below in the results section.

2.4 Estimation of the short-run dynamic equations for the various cointegration methods

As indicated above, the estimated cointegrating vectors represent the long-run equilibrium relationships, so that the difference from the 'predicted' values and the actual values of e_t represent the annual disequilibrium errors or the error correction term, EC_t, as follows:

[13] Once the long-run cointegrating vector has been identified and estimated the short-run dynamic equation may also be estimated in Microfit 4.0 [18]. However, for consistency this is done in PCGive 10.4 along with

$$EC_t = e_t - \hat{\beta}_0 - \hat{\beta}_1 y_t - \hat{\beta}_2 p_t - \hat{\beta}_3 t \qquad (9)^{14}$$

Given the tests for cointegration, EC_t will be I(0) and is therefore included in a short-run dynamic equation with the original variables *e*, *y,* and *p* in first difference, which given the unit root testing can be regarded as I(0) – hence avoiding the spurious regression problem. The general specification is therefore given by:

$$\Delta e_t = \alpha_0 + \alpha_1 \Delta e_{t-1} + .. + \alpha_4 \Delta e_{t-3} + \alpha_5 \Delta y_t + .. + \alpha_9 \Delta y_{t-3} + \alpha_{10} \Delta p_t + .. + \alpha_{14} \Delta p_{t-3} + \alpha_{12} EC_{t-1} + \varepsilon_t \qquad (10)$$

The preferred equation is found by selecting a restricted model by testing down from the over-parameterized model of equation (10) that satisfies parameter restrictions without violating a range of diagnostic tests using PcGive 10.4 and Eviews 5. In particular, the equation residuals are tested for the presence of non-normality, serial correlation, heteroscedasticity and instability. In addition, intervention dummy variables are also included for certain time periods such as severe power shortages experienced due to droughts in 1996.

2.4.1 Structural time series modelling method (STSM)

The STSM differs in a number of ways from the cointegration approaches discussed above. In particular, the order of integration of the individual variables is not crucial, it allows for an unobservable stochastic trend and the short-run and long-run effects are

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all other short-run equations (see below).

[14] Note this is the most general specification, whereas in the actual results not all variables are included (see the results section below for details) and due to this and different estimates of the β's the EC_t terms will be different for each cointegration technique.

estimated via one equation, hence a dynamic version of equation (2) for Sri Lankan electricity demand is specified as follows:

$$e_t = \mu_t + \delta_1 e_{t-1} + \ldots + \delta_4 e_{t-4} + \delta_5 y_t + \ldots + \delta_9 y_{t-4} + \delta_{10} p_t + \ldots + \delta_{14} p_{t-4} + \varepsilon_t \qquad (11)$$

Where μ_t is assumed to have the following stochastic process:

$$\mu_t = \mu_{t-1} + \pi_{t-1} + \eta_t \ , \qquad \eta_t \sim NID(0, \sigma_\eta^2) \qquad (12)$$

$$\pi_t = \pi_{t-1} + \varsigma_t \ , \qquad \xi_t \sim NID(0, \sigma_\xi^2)\,. \qquad (13)$$

Equation (12) represents the *level* of the trend driven by the white noise disturbance term, η_t and equation (13) represents the *slope* of the trend driven by the white noise disturbance term ξ_t. The shape of the underlying trend is determined by σ_ξ^2 and σ_η^2, known as the hyperparameters.[15] Its most restrictive form occurs when both σ_ξ^2 and σ_η^2 are zero and the model converts to the traditional deterministic trend model similar to equation (3).

The estimated equation consists of equation (11) with (12) and (13). All the disturbance terms are assumed to be independent and mutually uncorrelated with each other. As seen above, the hyperparameters σ_η^2, σ_ξ^2, and σ_ε^2 have an important role to play and govern the basic properties of the model. The hyperparameters, along with the other parameters of the model are estimated by a combination of maximum likelihood and the Kalman filter. The optimal estimate of the trend over the whole sample period is further calculated by the smoothing algorithm of the Kalman filter. For model evaluation, equation residuals are estimated (which are estimates of the equation disturbance term, similar to those from ordinary regression) plus a set of auxiliary residuals. The auxiliary residuals include smoothed estimates of the equation disturbance (known as the irregular residuals), the smoothed estimates of the level disturbances (known as the level residuals) and smoothed estimates of the slope disturbances (known as the slope residuals).[16] The software package STAMP 6.3 (Koopman *et al.*, 2004 [20]) is used to estimate the model.

3 ESTIMATION RESULTS

3.1 Data

Data used in the estimation consists of annual data over the period 1970 – 2003 inclusive.[17] Electricity consumption data for Sri Lanka were taken from the MOPE (Ministry of Power and Energy) data base[18] for 1970 – 2000 and from the Statistical Digest, CEB [21] and the Central Bank of Sri Lanka Annual Reports (CBSLAR) thereafter. These were divided by the population data taken from CBSLAR 2005 (Special Statistical Appendix), to give per capita consumption, E_t. Data for GDP at 1996 prices were again taken from the Special Statistical Appendix of the CBSL AR, 2003 and divided by population data to give the variable Y_t. Data for the average nominal electricity price per unit were taken from the MOPE data base for 1970 – 2000 and from the Statistical Digest, CEB and the Central Bank of Sri Lanka Annual Report thereafter. These were deflated by the GDP deflator taken from Special Statistical Appendix to give P_t. Since electricity users in different sectors are normally faced with different tariffs it is arguably advisable to estimate demand

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[15] σ_ε^2 is also a hyperparameter

[16] In practice the level and slope residuals are only estimated if the level and slope components are present in the model, i.e. η_t and/or ξ_t are non-zero.

[17] It would have been interesting had the estimation been done on monthly data instead of annual data, but no reliable monthly data for the period of 1970-2003 is available to the authors.

relationships for the domestic, industrial, commercial and other sectors separately. However for simplicity the average electricity tariff has been utilised; nevertheless it is appreciated that sector wise estimation might be more appropriate in certain circumstances.

3.2 Unit root tests

The calculated ADF statistics from testing the time series properties of the variables are given in Table 1. It can be seen that for *e*, *y*, and *p* the null hypothesis of a unit root cannot be rejected indicating that all three variables are non-stationary in levels. Consequently, the ADF statistics from testing the time series properties of the first differences of these variables are also given in Table 1 and it can be seen that for Δe, Δy, and Δp the null hypothesis of a unit root is rejected indicating that *e*, *y*, and *p* are stationary in first differences; that is integrated of order one, I(1).

Table 1: Unit Root Test results

Variable	ADF Test
e_t	-3.07 {c, t, 0}
y_t	-2.81 {c, t, 1}
p_t	-2.15 {c, 0, 1}
Δe_t	-5.95* {c, 0, 0}
Δy_t	-5.15* {c, 0, 0}
Δp_t	-3.00* {0, 0, 0}

[18] Data Base on Energy, Sri Lanka, 2001, on CD-ROM from MOPE, Sri Lanka. This is similar to EIA data base of energy balances for non OECD (Organisation for Economic Corporation and Development) countries.

NB: {c, t, n} indicates the inclusion of a constant (c), the inclusion of a time trend (t) and the number of lags (n) in the ADF regression and * indicates the rejection of the null hypothesis of a unit root at the 1% level (based upon MacKinnon (1996) [10]).

3.3 Engle-Granger two step method (Static EG)

Given that e, y and p can all be regarded as I(1) the long-run electricity demand relationship can be explored as explained above using the Static EG method. Therefore, initially equation (3) was estimated but the estimated coefficient on p was positive.[19] Therefore two alternative specifications were considered; the first with $\beta_2 = 0$ and the second with $\beta_3 = 0$. Given it is not possible to conduct t-tests on the coefficients, both long-run cointegrating vectors (the first including y, and p, and the second including y, and t as explanatory variables) are given below:

$$e_t = -13.2359 + 1.7636\, y_t - 0.0201\, p_t \qquad t = 1970\text{-}2003 \qquad (14)$$
ADF(0) = – 6.09*[20]

$$e_t = -5.7331 + 0.9900\, y_t + 0.0245\, t \qquad t = 1970\text{-}2003 \qquad (15)$$
ADF(0) = – 4.79*

[19] A positive coefficient for p might indicate that the estimation is picking up a supply relationship rather than demand. However, any interpretation is difficult with the Static EG procedure given that the standard errors and t-statistics are not reliable. However, results from alternative approaches applied below such as the Dynamic EG, FMOLS and PSS, where the standard errors and t-statistics are reliable produce estimates of the coefficient on p that are not significantly different from zero; hence consistent with the decision to drop p from the Static EG approach. Furthermore, the two approaches where the coefficient on p is significantly different from zero (Johansen and STSM, where the standard errors and t-statistics are reliable) find a negative coefficient for p; supporting that assumption that an electricity demand relationship is estimated.
[20] The ADF tests for the residuals from the estimated cointegrating equations are undertaken without a constant or trend so only the number of final lags are indicated (after testing down). Furthermore, similar to Table 1, * indicates the rejection of the null hypothesis of a unit root (so that in this case the residuals are stationary and hence indicates that there is a cointegrating relationship) at the 1% level (based upon MacKinnon (1996) [10]).

Cointegration is accepted for both equations given the significance of the ADF statistics. The estimated long-run price elasticity is -0.02 for the first equation, significantly higher (in absolute terms) than that in AH. The estimated long-run income elasticities differ somewhat ranging from 0.99 to 1.76 compared to 1.11 in AH. The estimated UEDT for the second equation suggests an increase of about 2½% per annum (slightly above that in AH). Therefore, although this is not reflecting any improvements in technical progress or increases in energy efficiency it is not rejected given the arguments by Hunt, et al. (2003) [22]. Instead, it is assumed that it is picking up other exogenous effects that are leading to an increase in electricity consumption – quite possibly one important factor being the increase electrification over the estimation period. The difference to AH resulting from an extra two observations is of some concern; as is the instability across the two estimated equations. In part this is due to the problems of not being able to undertake any proper inference in the first stage of the static EG approach which is addressed in some of the alternative methods considered below. But given the difficulty of deciding between the two estimates both are used in the separate estimation of equation (10) with the two preferred estimated short-run dynamic equations given by:

$$\Delta e_t = \underset{[0.00]}{1.9050}\, \Delta y_t \underset{[0.03]}{- 0.0386}\, D89 \underset{[0.00]}{- 0.0804}\, D96 \underset{[0.00]}{- 0.4133}\, ECaI_{t-1} \quad t = 1974 - 2003 \qquad (16)$$

Where $ECaI_t = e_t + 13.2359 - 1.7636\, y_t + 0.0201\, p_t$

se = 0.017 LMSC(2): F = 1.62[0.22]; ARCH(1): F = 0.59[0.45] Norm: $\chi 2$ = 2.92[0.23] Het: F = 0.39[0.87] HetX: F = 0.38[0.90] Reset: F = 0.00[0.95] Chow $FC_{1998\text{-}2003}$: F=0.32[0.92];

$$\Delta e_t = \underset{[0.00]}{1.8450}\, \Delta y_t \underset{[0.02]}{- 0.0461}\, D89 \underset{[0.00]}{- 0.0793}\, D96 \underset{[0.03]}{- 0.2836}\, ECaII_{t-} \quad t = 1974 - 2003 \qquad (17)$$

Where $ECaII_t = e_t + 5.7331 - 0.9900\, y_t - 0.0245\, t$

se = 0.018 LMSC(2): F = 1.06[0.36]; ARCH(1): F = 1.31[0.26] Norm: $\chi 2$ = 0.44[0.80] Het: F = 0.55[0.76] HetX: F = 0.45[0.86] Reset: F = 0.02[0.89] Chow $FC_{1998\text{-}2003}$: F=0.41[0.86];

Where: D89 = intervention dummy variable for 1989

D96 = intervention dummy variable for 1996

Both equations pass all diagnostic tests but both required intervention dummies for 1989 and 1996 to take account for the restricted demand due to planned power cuts in drought years. All coefficients are statistically significant in both equations with the coefficients on the error correction terms both of the right sign, but with a variation in size; equation (16) suggests that just over 40% of any disequilibrium is adjusted in each year whereas equation (17) suggests over 25%. This compares to just less than 75% in AH. No role could be found for the change in prices (*Δp)* in either equation whereas there is a strong estimated impact income elasticity in both equations of 1.9 and 1.8 respectively; compared to 1.5 in AH. The differences between this estimation and that in AH are due to the different data periods, but also the inclusion of the intervention dummies for 1989 and 1996.

3.4 Dynamic Engle-Granger method (Dynamic EG)

The preferred derived long-run equation for the Dynamic EG method is given by:

$$e_t = \underset{[0.00]}{-\,12.7294} + \underset{[0.00]}{1.7127}\, y_t \qquad t = 1974\text{-}2003 \qquad (18)$$

PCGive Unit Root Test = 2.60 LMSC(2): F = 2.05[0.16]; ARCH(1): F = 0.00[0.98] Norm: $\chi 2$ = 2.87[0.24]

Given inference is possible in the dynamic EG approach; both *p* and *t* are omitted from equation (18) since they were not significantly different from zero at the 10% level in the solved long-run equation. Hence *y* is the only included explanatory variable, giving an estimated long-run income elasticity of 1.71; similar to equation (14) for the static EG method. Furthermore, the actual estimated over parametised equation with lags of four does not suffer from any serial correlation or non-normality problems. However, the PCGive unit root test for cointegration is very low, suggesting that cointegration does not exist.

Despite this equation (18) is still used to derive the error correction term and used to estimate the short-run dynamic equation, and following the testing down procedure, the preferred estimated short-run dynamic equation for the Dynamic EG method is given by:

$$\underset{}{\Delta e_t} = \underset{[0.00]}{1.8167\,\Delta y_t} \underset{[0.02]}{-\,0.0434\,D89} \underset{[0.00]}{-\,0.0756\,D96} \underset{[0.01]}{-\,0.4729\,ECb_{t-1}} \qquad t = 1974 - 2003 \qquad (19)$$

Where $ECb_t = e_t + 12.7294 - 1.7127\,y_t$

se = 0.017 LMSC(2): F = 0.84[0.44]; ARCH(1): F = 0.50[0.49] Norm: $\chi 2$ = 0.70[0.70] Het: F = 0.58[0.74]
HetX: F = 0.48[0.84] Reset: F = 0.04[0.84] Chow $FC_{1998-2003}$: F=0.52[0.78];

Equation (19) passes all diagnostic tests, again with the inclusion of the 1989 and 1996 intervention dummies. All coefficients are statistically significant at the 10% level but again there is no role for Δp and an estimated short-run impact income elasticity of 1.8. The coefficient on the error correction term is significant and of the right sign and reasonable magnitude. This suggests that almost half of any disequilibrium is adjusted for each year; closer to the second Static EG specification.

3.5 Fully modified ordinary least squares method (FMOLS)

When conducting the ADF unit root tests above they all included a constant so that all three variables may be thought of as being I(1) with drift. Consequently for the FMOLS estimation this option was chosen along with a two year lag and the ‘Bartlett weights’.[21] In all models p was not significantly different from zero at the 10% level and hence was omitted from the long-run equation, whereas t was significant and hence included. The estimated long-run cointegrating equation from the FMOLS method is therefore given by:

$$e_t = \underset{[0.00]}{-8.2957} \; \underset{[0.00]}{+1.2546\, y_t} \; \underset{[0.02]}{+0.0153\, t} \qquad t = 1972\text{-}2003 \qquad (20)$$

The estimated long-run income elasticity, at 1.3, is lower than those obtained for the Dynamic EG and Johansen methods but higher than the Static EG estimate. The estimated UEDT effect is an increase of about 1½% per annum, again positive but slightly less than the Static EG method estimate – the only other method where t is included in the preferred specification. This equation is used to derive the error correction term and used to estimate the short-run dynamic equation, and following the testing down procedure, the preferred estimated short-run dynamic equation for the FMOLS method is given by:

$$\Delta e_t = \underset{[0.00]}{1.8287\, \Delta y_t} \; \underset{[0.02]}{-0.0454\, D89} \; \underset{[0.00]}{-0.0757\, D96} \; \underset{[0.02]}{-0.3767\, ECc_{t-1}} \qquad t = 1974 - 2003 \qquad (21)$$

Where $ECc_t = e_t + 8.2957 - 1.2545\, y_t - 0.0153\, t$

Se = 0.018 LMSC(2): F = 0.85[0.44]; ARCH(1): F = 1.44[0.24] Norm: $\chi 2$ = 0.19[0.91] Het: F = 0.61[0.72]
HetX: F = 0.55[0.79] Reset: F = 0.02[0.89] Chow $FC_{1998\text{-}2003}$: F=0.47[0.82];

Similar to most of the short-run dynamic equation (21) passes all diagnostic tests with the two intervention dummies, there is no role for any Δp terms, and the estimated impact income elasticity is 1.8. However, the coefficient on the error correction term suggests that

[21] It is worth noting, however, that changing the lags and/or the weights has no discernable effect on the estimated coefficients and standard errors.

just over a third of any disequilibrium is adjusted for each; above the first Static EG estimate but below the rest.

3.6 Pesaran, Shin and Smith method (PSS)

Finding evidence of a unique cointegrating vector for Sri Lankan electricity demand proved difficult. Although initial results from the PSS Bounds tests suggested that a long run relationship might exist between all three variables *e*, *y*, and *p* whenever the long-run relationship was estimated the price variable (and trend) always proved to be insignificant. Hence the long run analysis was restricted to just *e* and *y* so that a number of different lags were considered for equation (5) (including up to j=4) but dropping the *p* and trend terms. The results from these tests are given in Table 2 and show that for a lag of one year the PSS Bounds test statistic is greater than the upper bound value suggesting that there is a long relationship between *e* and *y* and furthermore *y* may be regarded as the forcing variable. However, for the other lags this is rejected.

Table 2: Bounds test statistics

Lags	e_t
1	6.60
2	2.68
3	1.28
4	0.77

Boundary (3.145, 4.153)[22]

Given the above the ARDL for the second stage of the estimation to restricted the long run relationship to be between *y* and *e* only[23] with the chosen equation being an ARDL (1,1) which when solved yields the LR (Long Run) equation given below.

[22] Taken from Table F, Pesaran and Pesaran (1997, p. 484).
[23] And a constant.

$$e_t = -12.6747 + 1.7069\, y_t \qquad T = 1971\text{-}2003 \qquad (22)$$
$$\quad [0.00] \qquad [0.00]$$

This gives an estimated long run income elasticity of 1.71; very similar to that obtained for equation (14) for the Static EG, the Dynamic EG, and the Johansen approaches. Equation (22) is used to form the error correction series and estimate the short-run dynamic equation, with the preferred specification given as follows:

$$\Delta e_t = 1.8517\, \Delta y_t - 0.0737\, D96 - 0.4701\, ECd_{t-1} \qquad t = 1974 - 2003 \qquad (23)$$
$$\quad [0.00] \qquad [0.00] \qquad [0.01]$$

Where $ECd_t = e_t + 12.6747 - 1.7069\, y_t$

se = 0.019 LMSC(2): F = 0.06[0.94]; ARCH(1): F = 1.19[0.29] Norm: $\chi 2$ = 0.65[0.72] Het: F = 0.60[0.70] HetX: F = 0.48[0.82] Reset: F = 0.23[0.63] Chow $FC_{1998\text{-}2003}$: F=0.55[0.77];

Equation (23) passes all diagnostic tests, but in this case only the 1996 intervention dummy is needed. Again there is no role for Δp but the coefficients for all remaining variables are statistically significant at the 10% level at least. The estimated short-run impact income elasticity is about 1.9 and the coefficient on the error correction term suggests that almost half of any disequilibrium is adjusted for each year, similar to the second specification for the Static EG method and the Dynamic EG method.

3.7 Johansen Method (Johansen)

Table 3 shows the Trace and Maximum Eigenvalue statistics to test for the number of cointegrating equations from a VAR with a two year lag that includes e, y and p but no trend. As explained above, initially a restricted trend was specified but since the coefficient on the trend was always not significantly different from zero at the 10% level it was omitted.

Table 3: Johansen Cointegration Tests *(CV=Cointegrating vectors)

Unrestricted Cointegration Test	Results	
	No of CV*	Test statistic [probability]
Trace Statistic	0	36.85 [0.01]
	At most 1	7.40 [0.54]
	At most 2	0.11 [0.75]
Maximum Eigen Statistic	0	29.45[0.02]
	At most 1	7.30 [0.46]
	At most 2	0.11 [0.75]

NB: *CV=Cointegrating vectors

Table 3 clearly indicates that there is only one cointegrating vector, hence this restriction was imposed and the estimated long-run cointegrating equation given by:

$$e_t = \underset{[0.00]}{+ 1.7433\, y_t} \quad \underset{[0.01]}{- 0.0367\, p_t} \qquad t = 1972\text{-}2003 \qquad (24)$$

As stated above *t* was omitted since it was not significant, however, unlike the dynamic EG, *p* proved to be significantly different from zero, even at the 1% and of the right sign so it is maintained, suggesting a long-run price elasticity of -0.04 – almost double that obtained from equation (14) from the Static EG method. The estimated long-run income elasticity is however similar to equation (14) for the static EG method and the Dynamic EG method.

Equation (24) is therefore used to derive the error correction term and used to estimate the short-run dynamic equation, and following the testing down procedure, the preferred estimated short-run dynamic equation for the Johansen method is given by:

$$\Delta e_t = \underset{[0.01]}{-6.2027} + \underset{[0.00]}{1.8289}\,\Delta y_t \underset{[0.00]}{-0.0746}\,D96 \underset{[0.01]}{-0.4772}\,EC e_{t-1} \qquad t = 1974 - 2003 \qquad (25)$$

Where $ECe_t = e_t - 1.7433\, y_t + 0.0367\, p_t$

se = 0.019 LMSC(2): F = 0.11[0.89]; ARCH(1): F = 1.23[0.28] Norm: $\chi 2$ = 0.10[0.95] Het: F = 0.73[0.61]
HetX: F = 0.58[0.74] Reset: F = 0.21[0.65] Chow $FC_{1998\text{-}2003}$: F=0.34[0.91];

Equation (25) passes all diagnostic tests, but in this case with only the 1996 intervention dummy, All coefficients are statistically significant at the 10% level but yet again there is no role for Δp and an estimated short-run impact income elasticity of 1.8 The coefficient on the error correction term is significant and of the right sign and magnitude – suggesting that almost half of any disequilibrium is adjusted for each year, similar to the second specification for the static EG method and the dynamic EG method.

3.8 Structural time series model method (STSM)

Unlike most of the above, the short-run and long-run are estimated by the same equation with the STSM method. Following the testing down procedure outlined above the preferred equation is given by:

$$e_t = \underset{[0.00]}{1.9578}\, y_t \underset{[0.04]}{-0.0625}\, p_{t-2} \underset{[0.01]}{-0.0446}\, D96 + \underset{[0.01]}{0.0732}\,\mathrm{Lvl82} + \mu_t \qquad t = 1974\text{-}2003 \qquad (26)$$

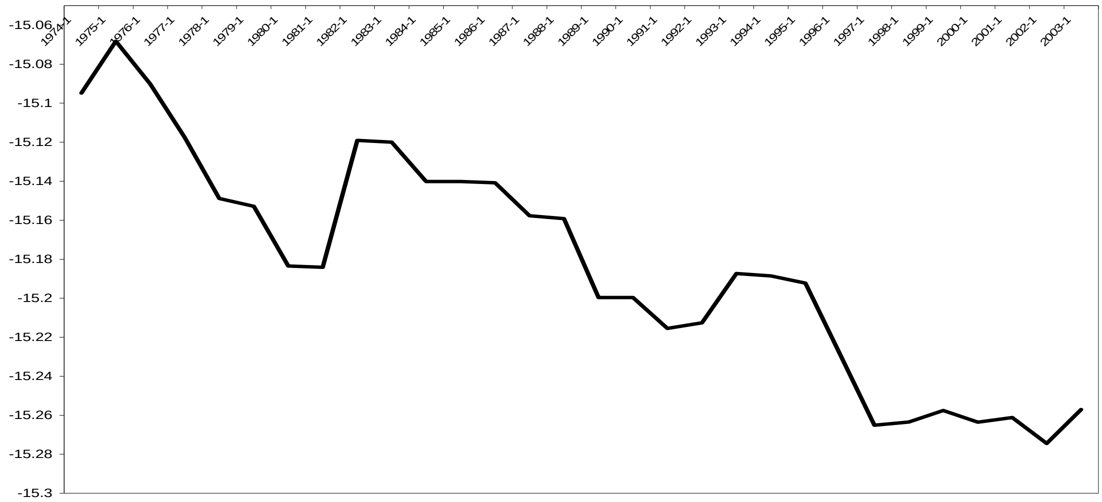
Where $\mu_t = -15.257$ with a slope of –0.0081 at the end of the period.

Se = 0.019 $r_{(1)}$ = 0.10[0.31] $r_{(2)}$ = 0.15[0.22] $R_{(3)}$ = –0.22[0.12] $r_{(4)}$ = $Q_{(10)}$: $\chi 2$ = 5.02[0.76]
Het: F = 0.89[0.56] $Norm_{(Res)}$: $\chi 2$ = 1.62[0.44] $Norm_{(Irr)}$: $\chi 2$ = 0.65[0.73] $Norm_{(Lvl)}$: $\chi 2$ = 0.90[0.64]
$Failure_{(1998)}$: $\chi 2$ = 3.18[0.79]

Where: Lvl82 = level shift dummy variable for 1982

This passes all the diagnostic tests including the additional normality tests for the auxiliary residuals incorporated into the STSM approach but required an intervention dummy variable for 1996 and a level shift dummy for 1982; with estimated long-run income and price elasticities of 1.96 and –0.06 respectively.[24] Interestingly, the estimated stochastic trend shown in Figure 2 is highly non-linear with periods of increases and decreases but over the estimation period clearly falls with a slope of –0.8% p.a. at the end of the period. This is contrary to the positive growth obtained for the second Static EG and FMOLS methods.

Figure 2 Underlying Energy Demand Trend (μ_t)



3.9 Comparison of Long Run Elasticity Estimates

Table 4 summarizes the estimated LR responses from the different methods. It can be seen that the estimated long-run income elasticity ranges from 0.99 for the Static EGII method to 1.96 for the STSM method. For the FMOLS the estimate is somewhat higher than the Static EGII method whereas the Static EGI, Dynamic EG, Johansen and PSS estimates are

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[24] The idea that there is a two year delay in the response of electricity consumption to a change in real electricity prices (as suggested by the estimated equation) is arguably unlikely; despite this result being statistically acceptable. Nevertheless, it is maintained given the prime reason for the estimated equation is to undertake medium to long term forecasts and scenarios, so that the implicit long-run elasticity is the key parameter, not the short run adjustment.

all very similar at about 1.7. The estimated long-run price elasticity ranges from 0 for the Static EGII, Dynamic EG, the PSS and FMOLS methods to –0.06 for the STSM method with the Johansen method giving –0.04 and the Static EGI an estimate of –0.02. Therefore even the largest estimated price elasticity (in absolute terms) would suggest that this has only a very limited effect on the demand for electricity in Sri Lanka. This is not too surprising given non-market driven prices in Sri Lanka as in other developing countries as identified by Dahl (1994) [23].

Table 4: Summary of estimated long-run Sri Lankan electricity demand elasticities and UEDT

	Y	*P*	*UEDT*
Static EGI	+1.76	-0.020	0
Static EGII	+0.99	0	+2.5% p.a.
Dynamic EG	+1.71	0	0
FMOLS	+1.25	0	+1.5% p.a.
PSS	+1.71	0	0
Johansen	+1.74	–0.037	0
STSM	+1.96	–0.063	Stochastic: –0.8% p.a. at the end of the period

For the UEDT component there are mixed results. The trend is omitted in the Static EGI, Dynamic EG, the Johansen and the PSS methods, is positive throughout the period for the Static EGII and FMOLS methods but predominantly negative for the STSM method. For the cointegration methods there is, not surprisingly, a negative relationship between the trend and the estimated long-run income elasticity; where the trend is omitted (or zero) the estimated income elasticity is around 1.7, when the trend is included and estimated at +1.5% p.a. (FMOLS) the income elasticity falls to 1.25 and when the trend is included and estimated at +2.5% p.a. (Static EGII) the income elasticity falls further to just under unity. However this pattern is not maintained by the STSM estimate where the trend is predominantly negative but the income elasticity estimate is the highest. This highlights the fundamental difference between the STSM and the cointegration techniques.

Moreover, it illustrates that when trying to forecast future electricity demand or construct various scenarios a range of techniques should be used where there is no clear statistical rationale for favouring one over another rather than just having a blind faith in just one technique. Hence this is the approach undertaken in the next section.

Before doing this, in addition to comparing the long run elasticity and trend estimates, it is informative to consider the estimated impact elasticities and the estimated speeds of adjustment presented in Table 5.

Table 5: Summary of Impact Elasticities and Adjustment speeds

	Y	**P**	**Proportion of disequilibrium adjusted each year**
Static EGI	+1.91	0	41%
Static EGII	+1.84	0	28%
Dynamic EG	+1.82	0	47%
FMOLS	+1.83	0	38%
PSS	+1.85	0	47%
Johansen	+1.83	0	48%
STSM	+1.96	0	100% but with a two year lag on price

It can be seen that for the cointegration techniques there is a higher degree of consistency across the short-run income (and price) elasticities than for the long-run estimates; which is despite being conditional on the different long-run cointegrating vectors. However, given the structure of the preferred specification for the STSM method the impact elasticity is not only higher than the cointegration approaches it is also identical to the long-run estimate. Furthermore, the estimates for the cointegration models result in what is arguably an odd situation where the short-run impact elasticity is higher than the long-run, whereas *a-priori* the opposite is expected. However, this is not unknown in previous estimates: for example Hunt & Manning (1989) [24] found a similar relationship for the UK aggregate energy demand arguing that this could arise from the inflexibility of the energy-using capital and appliance stock of firms and households so that an increase in income results in an immediate increase in the derived demand for energy in the short-run, but this derived demand reduces in the longer term as more energy efficient machines are installed. This might therefore be the case of the electricity using appliances in Sri Lanka and the efficiency improvement and energy saving programmes implemented over the past years by CEB and other energy sector organisations. Although, it is worth noting that it may be the effect of inadequately modelling the effect of energy efficiency on Sri Lankan electricity demand in the cointegration techniques where the underlying energy demand trend is either omitted or restricted to be constant over the whole estimation period; whereas the STSM attempts to take account of this phenomenon, hence the identical short-run and long-run elasticities.[25] Finally, despite the similar short-run impact elasticities the speeds of adjustment do differ somewhat given the different long-run elasticities and hence error correction terms.

4 FORECASTING RESULTS

4.1 Final forecast equations

For the cointegration techniques the error correction equations are substituted into the short-run dynamic equations and simplified and consolidated to give the equations used for the forecasts. These are shown in Table 6 along with the forecasting equation for the STSM method which is just the estimated equation above, with the trend declining by the estimated slope at the end of the estimation period. These are therefore used to drive the forecasts and scenarios below.

[25] More discussion about this argument can be found in Hunt et al (2003) [25]

Table 6: Summary of forecasting equations

	Constant	e_{t-1}	y_t	y_{t-1}	t_{t-1}	*Slope of* μ_t*	p_{t-1}	p_{t-2}
Static EGI	–5.47	0.59	1.91	-1.18			-0.008	
Static EGII	–1.63	0.72	1.84	-1.56	0.007			
Dynamic EG	–6.02	0.53	1.82	-1.01			-0.020	
FMOLS	–3.13	0.62	1.83	-1.36	0.006			
PSS	–5.96	0.53	1.85	-1.05				
Johansen	–6.20	0.52	1.83	-1.00				
STSM	–15.26*		1.96			-0.008		-0.062

* The constant for the STSM approach refers to the non-linear trend at the end of the estimation and the coefficient of the trend represents the annual growth rate of this trend over the forecast.

4.2 Forecast assumptions

Using the consolidated equations in Table 6, future energy demand was forecast until 2025 for Sri Lanka. In order to drive the forecasts, assumptions are required for real GDP, the real energy price and population growth. The projections for population were taken from the department of census and statistics of Sri Lanka, which gives values for every five years (2006, 2011, 2016 and 2021) with the intervening years linearly interpolated and assuming that in 2021 it reaches steady state. For GDP, three scenarios were conducted; the base case is taken from the GDP projections of DOE/EIA July 2005 [26][26] release as given for other Asian countries except China, India and South Korea; the high growth scenario is 2% more than the base case and the low growth scenario is 2% less than the base case. For the electricity price predictions, the actual values for 2004 and 2005 are taken from CBSLAR (2004 and 2005) [27] [27] with an assumed 30% increase in the real price in 2006 reflecting the 30% real price increase in February 2006,[28], and a further 40%

[26] The growth projections for other Asian countries except China, India and South Korea is given as 5.8% in 2004, 5.1% in 2005 and 4.8 from 2006 to 2015 and 4.3% from 2016 to 2025, Report #: DOE/EIA-0484 (2005) [26]. This can be downloaded from http://tonto.eia.doe.gov/bookshelf/SearchResults.asp?title=&product=0484&submit1=Search

[27] The nominal prices being unchanged from 2003, resulting in a fall in the real price of 8.5% and 8.8% in 2004 and 2005 respectively when deflated by 1996 GDP deflator

[28] www.ceb.lk web site.

increase in 2008, based on the assumption that the proposed reforms will be completed by 2008.[29] Thereafter, the real electricity price is assumed to stay unchanged for 5 years and gradually decline by 2% per annum every year until 2020. A steady price is assumed from 2021 onwards[30].

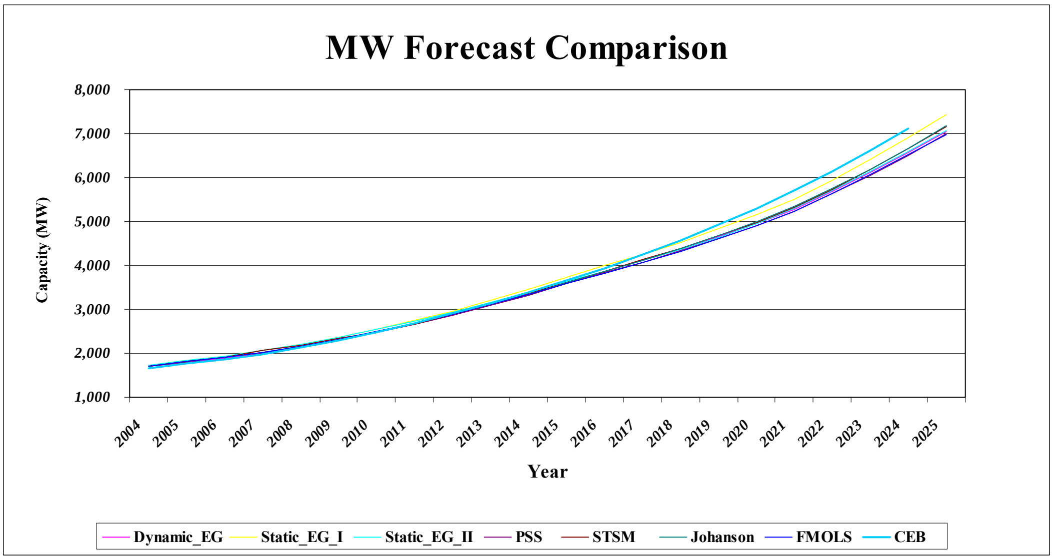
4.3 Forecasts

The base case forecasts are illustrated in Figure 3 and presented in detail in the Appendix. The peak load is calculated by using actual loss levels for 2002 and 2003 and thereafter loss levels as predicted by LTGEP (Long Term Generation Expansion Plan), 2004, CEB [24] and a system LF (Load Factor) of 55%.[31] In addition Table A1 and Table A2 in the Appendix illustrate forecasts up to year 2025 for energy demand (in GWhs – Giga Watt hour) and peak MW (Mega Watt) demand (in MWs). Figure 3 shows that, despite the different estimated long run income elasticities and different trends, the forecasts for peak MW demand using the six different techniques are very similar to each other; however the Static EGI model tends to give a higher forecast than the others. The maximum difference varies from 29 MW in 2004 to 452 MW in 2025. It is noted that the CEB forecasts behave very similar to those given here using the six methods up to 2018 but thereafter the CEB forecasts are notably higher. However, it is hard to judge whether this is just coincidence or not, given that it is not very clear how the CEB forecast has been generated. It would appear that it is by a bottom up engineering approach, which might explain some of the differences post 2018, but it is also not clear what forecast assumptions CEB used in

[29] It is assumed that when the political prices are replaced with MC (Marginal Cost) based prices initially there will be an average price rise of around 40%.
[30] It is appreciated that this assumption rests heavily on the implementation of electricity sector reforms in Sri Lanka and its success subject to a high degree of uncertainty. However, given the very low estimated price effects in the models the effect on the forecast is very small. Hence, the assumed change in price over the forecast does not significantly affect the forecast results.

generating their forecast, which might be the reason for the similarity up to 2018 and the difference thereafter. Either way it is arguably encouraging that there is at least some degree of similarity since, as argued by Adeyemi and Hunt (2007, p. 698) [28], when forecasting future energy demand "it is usually preferable ... to combine both 'top–down and 'bottom–up' techniques"; so a divergence between the two techniques is to be expected, but at the same time a degree of consistency – which is the situation here.

Figure 3: Base case forecasts



The base case (central) forecast is compared to the 'high' and 'low' scenarios in Figure 4 and presented in detail in the Appendix (Table A3). Figure 4 shows that peak demand in the high case scenario is about double the base case and that of the low case scenario is about half of the base case in 2025. This shows the uncertainty of longer term demand forecasts due to the variation of mainly per capita GDP of the country. This makes the planning risk higher for Sri Lankan authorities compared to countries with more stable economic growth rates.

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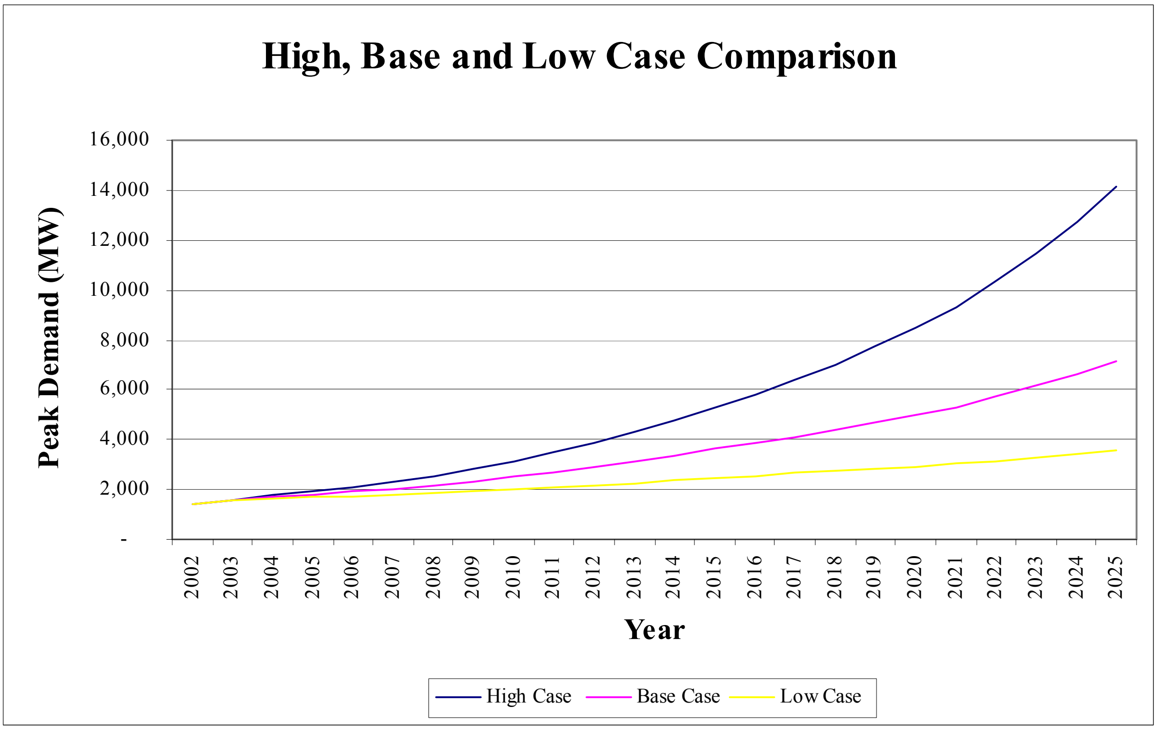
[31] Average LF for 1986-2000 is around 55% as mentioned in AH [3]. This assumption is used by CEB in its LTGEP, 2004 for the prediction of peak MW.

Figure 4: High and low scenarios



5 SUMMARY AND CONCLUSION

This paper has explored the effect of using different econometric estimation techniques to model Sri Lankan electricity demand. It has shown that there is some variation in the estimated results both in terms of the preferred specifications and resultant coefficients. In particular the estimated long-run income elasticity ranges from 1.0 to 2.0 and the estimated long run price elasticity from 0 to –0.06. There is also a wide range of estimates of the speed with which consumers adjust to any disequilibrium, although the estimated impact elasticities tended to be more in agreement; the income elasticity ranging from 1.8 to 2.0 and the price elasticity zero for all estimates. Furthermore, the estimated effect of the underlying energy demand trend varies between the different techniques; ranging from being positive to zero to predominantly negative. This highlights the importance, when attempting to forecast electricity demand or construct various scenarios using a causal econometric relationship, that a range of techniques should be used where there is no clear statistical rationale for favouring one over another rather than just having a blind faith in one technique.

Despite these differences the forecasts from the six different techniques look fairly similar up to 2025 which will be encouraging for the Sri Lanka electricity authorities who can have some faith in the models used for forecasting.[32] However, as shown in Section 4 by the end of the forecast period in 2025 the difference between the base case lowest and highest forecasts amounts to around 452 MW in forecast peak demand; which, considering its current status, for a small electricity generation system like Sri Lanka's with the single largest generation unit size is around 120 MW, represents a fairly considerable difference of about 6%. Hence the chosen econometric work potentially has a significant impact of the policy decisions in the Sri Lankan electricity supply industry in the long run.

In summary, there is a huge uncertainty of the longer term demand forecasts due to the variation of mainly per capita GDP of the country. This makes the planning risk higher for Sri Lankan authorities compared to countries with more consistent economic growth rates.

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[32] This, however, should be seen as a specific result for the Sri Lankan ESI and should not be generalised.

Appendix: High and Low Case Forecast Results

For the high case, the estimation method which gives the highest possible forecast with high case GDP assumptions has been used. For the low case the estimation method which gives the lowest possible forecast with low case GDP assumptions has been used. Similarly for the base case the base case GDP assumptions has been used.

Table A1 and A2 set out base case energy demand forecasts in GWh and base case peak demand in MW. Also a comparison table of low, base and high case peak demand forecasts in MW are given in Table A3.

Table A1: Forecasting for Base case (Energy demand in GWhs)

Year	Dynamic_EG (GWh)	Static_EG_I (GWh)	Static_EG_II (GWh)	PSS (GWh)	STSM (GWh)	Johanson (GWh)	FMOLS (GWh)	CEB (GWh)
2002	5,502	5,502	5,502	5,502	5,502	5,502	5,502	5,502
2003	6,209	6,209	6,209	6,209	6,209	6,209	6,209	6,209
2004	6,700	6,775	6,802	6,688	6,710	6,715	6,760	6,573
2005	7,192	7,323	7,347	7,170	7,259	7,232	7,273	7,032
2006	7,674	7,849	7,854	7,641	7,819	7,746	7,758	7,569
2007	8,249	8,450	8,453	8,210	8,478	8,310	8,338	8,149
2008	8,875	9,105	9,092	8,830	8,991	8,936	8,962	8,804
2009	9,553	9,790	9,774	9,502	9,694	9,565	9,632	9,515
2010	10,285	10,542	10,505	10,228	10,235	10,274	10,351	10,284
2011	11,076	11,362	11,287	11,011	11,037	11,056	11,125	11,112
2012	11,935	12,261	12,133	11,864	11,911	11,917	11,964	12,005
2013	12,862	13,235	13,039	12,783	12,855	12,851	12,864	12,965
2014	13,862	14,289	14,008	13,773	13,874	13,863	13,831	13,995
2015	14,940	15,431	15,048	14,841	14,975	14,962	14,870	15,100
2016	15,963	16,517	16,021	15,851	16,034	16,012	15,846	16,283
2017	16,982	17,597	16,993	16,854	17,076	17,062	16,825	17,556
2018	18,075	18,759	18,064	17,934	18,188	18,190	17,900	18,920
2019	19,246	20,008	19,234	19,090	19,376	19,400	19,066	20,383
2020	20,497	21,346	20,504	20,327	20,645	20,695	20,325	21,949
2021	21,833	22,779	21,875	21,648	22,000	22,080	21,677	23,627
2022	23,495	24,583	23,596	23,302	23,727	23,796	23,366	25,429
2023	25,269	26,508	25,384	25,062	25,557	25,627	25,120	27,361
2024	27,168	28,570	27,254	26,943	27,529	27,590	26,963	29,431
2025	29,205	30,784	29,222	28,958	29,652	29,697	28,913	-

Table A2: Forecasting for Base case (Peak demand in MWs)

Year	Dynamic_EG (peak MW)	Static_EG_I (peak MW)	Static_EG_II (peak MW)	PSS (peak MW)	STSM (peak MW)	Johanson (peak MW)	FMOLS (peak MW)	CEB (peak MW)
2002	1,413	1,413	1,413	1,413	1,413	1,413	1,413	1,413
2003	1,579	1,579	1,579	1,579	1,579	1,579	1,579	1,579
2004	1,700	1,719	1,726	1,697	1,703	1,704	1,715	1,668
2005	1,805	1,838	1,844	1,799	1,822	1,815	1,825	1,765
2006	1,880	1,923	1,925	1,872	1,916	1,898	1,901	1,855
2007	2,010	2,058	2,059	2,000	2,065	2,024	2,031	1,985
2008	2,144	2,200	2,197	2,134	2,173	2,159	2,165	2,127
2009	2,308	2,365	2,362	2,296	2,342	2,311	2,327	2,299
2010	2,485	2,547	2,538	2,471	2,473	2,482	2,501	2,485
2011	2,676	2,745	2,727	2,661	2,667	2,671	2,688	2,685
2012	2,884	2,962	2,932	2,867	2,878	2,879	2,891	2,901
2013	3,108	3,198	3,150	3,089	3,106	3,105	3,108	3,133
2014	3,349	3,453	3,385	3,328	3,352	3,350	3,342	3,382
2015	3,610	3,729	3,636	3,586	3,618	3,615	3,593	3,649
2016	3,857	3,991	3,871	3,830	3,874	3,869	3,829	3,934
2017	4,103	4,252	4,106	4,072	4,126	4,123	4,065	4,242
2018	4,367	4,533	4,365	4,333	4,395	4,395	4,325	4,572
2019	4,650	4,834	4,648	4,613	4,682	4,687	4,607	4,925
2020	4,953	5,158	4,954	4,911	4,988	5,000	4,911	5,303
2021	5,275	5,504	5,285	5,231	5,316	5,335	5,238	5,709
2022	5,677	5,940	5,701	5,630	5,733	5,750	5,646	6,144
2023	6,106	6,405	6,133	6,056	6,175	6,192	6,070	6,611
2024	6,565	6,903	6,585	6,510	6,652	6,666	6,515	7,111
2025	7,057	7,438	7,061	6,997	7,165	7,176	6,986	

Table A3: High, Low and Base Case Forecasts

Year	High Case (peak MW)	Base Case (peak MW)	Low Case (peak MW)
2002	1,413	1,413	1,413
2003	1,579	1,579	1,579
2004	1,770	1,709	1,649
2005	1,950	1,821	1,699
2006	2,103	1,902	1,717
2007	2,323	2,035	1,779
2008	2,551	2,167	1,836
2009	2,829	2,330	1,913
2010	3,128	2,500	1,990
2011	3,472	2,691	2,077
2012	3,856	2,899	2,170
2013	4,283	3,123	2,268
2014	4,758	3,365	2,370
2015	5,286	3,627	2,478
2016	5,823	3,874	2,567
2017	6,387	4,121	2,648
2018	7,012	4,388	2,735
2019	7,703	4,674	2,826
2020	8,466	4,982	2,923
2021	9,308	5,312	3,023
2022	10,345	5,725	3,161
2023	11,484	6,162	3,301
2024	12,740	6,628	3,445
2025	14,128	7,126	3,593

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