ELECTRICITY DEMAND ANALYSIS AND FORECASTING – THE TRADITION IS QUESTIONED !

N. Vijayamohanan Pillai

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Centre for Development Studies
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This paper is part of a larger study, under the co-ordinatorship of Dr. K.P. Kannan at the Centre for Development Studies, Thiruvananthapuram, on the problems of power sector in India, with special reference to Kerala. I am thankful to Dr. K. P. Kannan for the support and rapport to doubt the treadability of beaten tracks; to Dr. Chandan Mukherjee, Dr. D. Narayana, Dr. Indrani Chakraborty and others at the Centre for Development Studies for comments when the paper was presented in a seminar; and to Rju for forgiving my absences

ABSTRACT

The present paper seeks to cast scepticism on the validity and value of the results of all earlier studies in India on energy demand analysis and forecasting based on time series regression, on three grounds. (i) As these studies did not care for model adequacy diagnostic checking, indispensably required to verify the empirical validity of the residual whiteness assumptions underlying the very model, their results might be misleading. This criticism in fact applies to all regression analysis in general. (ii) As the time series regression approach of these studies did not account for possible non-stationarity (i.e., unit root integratedness) in the series, their significant results might be just the misleading result of spurious regression. They also failed to benefit from an analytical framework for a meaningful long-run equilibrium and short-run 'causality' in a cointegrating space of error correction. (iii) These studies, by adopting a methodology suitable to a developed power system in advanced economies, sought to correlate the less correlatables in the context of an underdeveloped power system in a less developed economy. All explanations of association of electricity consumption in a hopeless situation of chronic shortage and unreliability with its generally accepted 'causatives' (as in the developed systems) of population, per capita income, average revenue, etc., all in their aggregate time series, might not hold much water here.

Our empirical results prove our secepticism at least in the context of Kerala power system. We find that the cost of dispensing with model adequacy diagnosis before accepting and interpreting the seemingly significant results is very high. We find that all the variables generally recognised for electricity demand analysis are non-stationary, I(1). We find that all the possible combinations of these I(1) variables fail to be explained in a cointegrating space and even their stationary growth rates remain unrelated in the Granger-'causality' sense.

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Key words: India, Kerala, demand analysis, forecasting, non-stationarity,

"Puranam ityeva na sadhu sarvam;
Na capi kavyam navam ity avadyam.
Santah pariksyanyatarad bhajante;
Mudah parapratyayaneya budhih."[1]
- Kalidasa (Malavikagnimitra I, 2).

1. Introduction

Electricity has become a vital input to the wellbeing of any society and the demand for it from an ever-expanding set of diverse needs is growing at an increasing rate. This in turn places increasing demands on scarce resources of capital investment, material means, and man-power. Forecasting of electricity consumption needs has thus become a significant element of utmost necessity of the planning exercise in the power sector. More specifically, the advent of the 'energy crisis' has made crucial the need for accurate projection of electricity demand.

A large number of studies have come up in India too, toeing the same methodology as applied elsewhere. These studies, however, are analytically insufficient and methodologically unsound. Their results are doubtful to the extent of their failure to fulfil model adequacy diagnostic checking[2] . Their conclusions are even more questionable on account of their methodological failure to allow for the possible persistence of unit root shock in the time series data used; their seemingly significant results might be only an indication of spurious regression. Again, they failed to take advantage of an integrated analytical framework for long-run equilibrium and short-run ‘causality’[3] in a cointegrating space of error correction. Moreover, to the extent that the very foundation of demand analysis that links energy consumption to socio-economic ‘causal’ variables is shattered in the face of long-run power shortage and unreliability, that render demand just supply-constrained, these econometric demand analysis lose their relevance. In this light, their pedantic attempt to correlate the less correlatables is of little empirical significance.

In what follows we empirically prove, in the context of Kerala power system, our scepticism on all earlier works on energy demand analysis and forecasting. The paper is divided into four sections. The following section is a brief theoretical discussion, introducing the most common models for forecasting and demand analysis, the important tests for model adequacy, the unit root problem and the related topics. In the third section are presented our empirical results and the last one concludes the paper with some broad suggestions.

2. Theoretical Discussion

Forecasting Models

The forecasting methods used for electricity demand in general may be divided into *formalised* and *non-formalised* methods.

Non-formalised methods such as some variants of *Delphi* (‘jury of executive opinion’) method are in general used for forecasts for more distant periods of time during which some changes in the structure of the power sector must be considered.

In the case of the formalised forecasting methods, two approaches may be distinguished in their scope:

i) an input-output approach in which we try to penetrate the internal structure, and to examine the internal and external linkages of the observed object and to explain its response to input impulses; and

ii) a statistical approach in which the object is treated as a 'black box' whose internal workings are unknown.

More common are the statistical approaches that take the object as a 'black box' and try to explain its mechanism on the basis of the interconnections of the individual elements of the observed path of the system. Here the analysis of *extrapolation* (or *non*-'*causal'* methods) and one-dimensional or multi-dimensional *regressions* (or '*causal'* methods) are used. The latter seek to explain the behaviour of the variables and its 'determination' in a relationship framework, while the former non-'causal' methods are solely concerned with forecasting.

Extrapolation methods, based on the assumption that the past patterns repeat in the future, thus utilise time series data to identify past pattern in the observations and then to project it into the future. Past patterns in time series data are recognised in two ways – one is based on the trend of the series, i.e., the general movement of the series in a particular direction. In such trend extrapolation, the general behaviour of the variable over time (as presented in the time series data) is determined and is then projected into the future. Thus time is the argument of trend functions. In the second method of extrapolation, viz., auto-regressive model, one or more previous values of the observations themselves are the arguments; the order of the function is determined by the number of previous observations used as arguments.

The extrapolation of energy demand may in general be carried out using a number of mathematical functions such as:

i) linear trend : $y_t = \alpha + \beta t;$ (1)

ii) parabola (second degree) trend : $y_t = \alpha + \beta t + \gamma t^2;$ (2)

iii) geometric (compound) trend : $y_t = \alpha (1 + \beta) t;$ (3)

iv) exponential trend : $y_t = \alpha e^{\beta t};$ (4)

v) k-transformation trend : $y_t = (\alpha + \beta t)^{1/k};$ (5)

vi) Growth curves; and

vii) (First order) auto-regressive model : $y_t = \alpha + \beta y_{t-1}.$ (6)

A variation of the previous model is the logarithmic auto-regressive model:

viii) Logarithmic auto-regressive model : $\log y_t = \alpha + \beta \log y_{t-1.}$ (7)

Growth curves include logistic function and Gompertz function.

a) Logistic function : $y_t = L / (1 + \alpha e^{-\beta t});$ (8)

and

b) Gompertz function : $y_t = L \exp(-\alpha e^{-\beta t});$ (9)

where L is the prescribed upper limit, and 'α' and 'β' are the parameters to be estimated. L, α, $\beta > 0$.

In linear extrapolation, the variable to be forecast, $y_{t,}$ is linearly plotted against time (t), and the resulting plot is extrapolated into reasonable future time spans. The parameter 'β' gives the rate of change (slope) of the line, and dividing the rate of change coefficient by the average value of y_t gives an average (arithmetic) growth rate per time unit. While in a linear trend the rate of change is constant, in a second degree polynomial (parabola), it varies linearly with time as '$\beta + 2\gamma t$', 'γ' giving the acceleration coefficient. In geometric trend extrapolation, the logarithm of y_t is plotted against time and these linear semi-log plots are then projected into the future. The geometric (compound) growth rate is obtained by subtracting one from the anti-logarithm of (β) the coefficient of time (t). In extrapolation using exponential trend, the natural logarithm of y_t is plotted against time. These linear semi-log plots are then extrapolated into the future to make forecasts. In this case, the parameter 'β' directly gives the (exponential) growth rate of y_t. For analysis, we consider only the exponential trend model in its linear semi-log form, but not the geometric trend model. In k -transformation trend method, y_t values are transformed using an appropriate power coefficient 'k' lying between zero and unity. (If $k = 1$, we get a linear trend.) The growth rate of this function is obtained by dividing the 'β' coefficient by the product of 'k' and the linear trend, '$\alpha + \beta t$'.

Growth curves are used to predict the time path of a variable for which there is a limit. The curves trace the time path of the variable in an 'S'-form; and range from zero at '$t = -\infty$' to the upper limit, L, at '$t = +\infty$'. These curves, for example in the case of demand for durable goods, explain cumulative market penetration (i.e., the percentage of consumers possessing the durable goods), y_t, as a function of time, subject to a saturation level. The *logistic* function can be transformed into

$\log[y_t/(L - y_t)] = -\log\alpha + \beta t$, and the *Gompertz* curve into

$\log[\log(L/y_t)] = \log\alpha - \beta t$.

Given the value of L, the function can be evaluated on a time series and the parameters estimated. The Gompertz curve, however, is not symmetrical, while the logistic one is. With the Gompertz curve, the growth in the variable in the initial stages is comparatively faster than with the logistic curve.

In the *first-order autoregressive* [AR(1)] models, y_t is forecast on the basis of a weighted value of the previous observation, y_{t-1}. A variant of this model is the *logarithmic* (log-linear) autoregressive model. In these models one has the option of setting the intercept term $(\alpha) = 0$;

then ‘β’ in the simple autoregressive model represents the rate of change of the series y_t, and in the logarithmic model, the compounded rate of growth of the series. If $\alpha \neq 0$, and $\beta = 1$, then the projection will increase by the same absolute amount each time period (a random walk with drift). If, on the other hand, $\alpha = 0$, and $\beta = 1$, we have the naïve ‘no change’ model (driftless random walk), giving the best prediction of y_t in its previous value. Both linear and compounded extrapolations based on these two autoregressive models are commonly used as a simple means of forecasting. Note that these models involve regression with a lagged dependent variable. If the additive error process is serially correlated, the coefficient estimates will be inconsistent.

Another extrapolation method based on previous values is *moving average* model. Here, for example, from a monthly time series, the forecast for the next month may be obtained by the simple average of the values over the last 12 months. Instead of assigning equal weights to all the 12 values (such as 1/12 in the above case), it is usual that recent values are weighted more heavily as more recent values of y_t play a greater role than earlier values. This method constitutes *exponentially weighted moving average* model.

In any given case, such regression functions need not be equally convenient. A judicial selection of an appropriate model in the given objective condition is all the more significant. For instance, in the case of electricity consumption, numerous analyses have revealed that three very different time intervals can be defined for the long-run development of individual countries. The first corresponds to low values of energy consumption per capita and is marked by a considerable variation in annual increments. After having reached a certain value of the per capita consumption, the development becomes steadier and its trend begins to conform to an exponential pattern. Annual increments stabilise and assume a normal distribution. Having achieved a certain development level, the growth gradually slows down, requiring functions with decreasing annual increments for extrapolations (Lencz 1977: 85).

Simple extrapolation of historical growth rates had presented reasonably accurate results for decades (Tyrrell 1974). In fact, the post-World War II demand for electricity in the United States had been recognised to have a consistent exponential growth (uniformly in all the sectors: residential, commercial and industrial) and this is a well documented phenomenon (Tansil and Moyers 1974). Later on, however, it was felt questionable whether these trends would remain unchanged in the future, whether the simple extrapolation technique would provide accurate predictions of the future, in the face of the changes observed to occur in many of the underlying economic factors. This scepticism was well-confirmed by the findings of Chapman, Tyrrell and Mount (1972) who explained electricity demand growth as an econometric function of four ‘causal’ factors: population, per capita personal income and the prices of electricity and natural gas, and compared electricity demand projections obtained from this model with the extrapolated estimates of the government and industry.

This pioneer econometric model has since been refined to reflect more accurately the behaviour of each class of electricity consumers, by, say, incorporating price of electric appliances as an additional argument, formulating variable elasticity model (e.g., to account for spatial heterogeneity), instead of constant elasticity one, and by employing more consistent estimation techniques (e.g., instrument variable estimation versus the familiar ordinary least squares). Such demand analysis has facilitated to estimate the ‘effect’ of a variable on electricity demand in terms of elasticity measures; if the model is specified in logarithms, the coefficient of an argument directly gives the demand elasticity with respect to that variable.

To account for the dynamic characteristic of demand, a lagged dependent variable is usually used as a regressor in the log-linear model with a partial adjustment mechanism (Koyck distributed lag with geometrically declining weights). This specification facilitates to distinguish between short run and long run elasticities. Thus while the coefficient of the price variable in this model represents the short run price elasticity of demand, the long run price elasticity is obtained by dividing the short run coefficient by one less the coefficient of the lagged dependent variable used as a regressor, i.e., by the rate of adjustment. However, the presence of the lagged dependent variable, as already noted, makes the ordinary least squares (OLS) estimator inconsistent due to the possible correlation between the lagged endogenous variable and the random variable, as well as the serial correlation among the successive values of the latter. Hence the significance of instrument variable estimation.

It should be pointed out that the use of such models is connected with the prognosis of the independent variables. This in turn may involve macro-econometric modelling[4] .

A classical survey of the studies on the demand for electricity (in the U. S.) was given by Taylor (1975) in The *Bell Journal of Economics*, and it was later on updated and extended to natural gas, heating fuels, diesel and aviation fuels, coal, and gasoline (Taylor 1977). In summarising the empirical results on the demand for electricity in his survey paper in 1975, Taylor concluded:

(a) The price elasticity of demand for electricity, for all classes of consumers, is much larger in the long run than in the short run.

(b) This holds for the income elasticity of demand.

(c) The long run price elasticity of demand is indicated to be elastic.

(d) The evidence on the magnitude of the long run income elasticity is much more mixed. Estimates range from 0 to 2, and clearly depend on the type of model employed.

Power Consumption Forecasting in India

At the all-India level, forecasts of electricity requirement and demand are made by the Planning Commission and by the Annual Electric Power Surveys (APS) convened by the Ministry of Energy, the Central Electricity Authority (CEA) being the Secretariat to the APS. The two bodies do have extensive discussion and this usually leads to a reconciliation of results. Still, subtle differences exist between the methodologies employed by them.

The Planning Commission estimates electricity demand as part of its macro-economic analysis for all the sectors of the economy. Industrial power demand is estimated for a selected set of 'major' (i.e., very power intensive) industries by applying consumption norms to production targets. The rest of the industrial sector is assumed to consume some proportion of the power consumption of these major industries. Railway and irrigation requirements are also projected, based on targets and consumption norms. For all other sectors – domestic, commercial, public lighting, water works, and miscellaneous – power consumption is estimated using trend extrapolations or regression analysis that relates sectoral growth rates to electricity requirements. The Planning Commission also uses input-output model to check the consistency of the macro level estimates.

On the other hand, the projection by the APS of power consumption of the industry starts with a detailed survey of major industries (that demand 1 MW or more of power) on their estimated requirements. For all other sectors, almost the same methods are used by the APS as by the Planning Commission, many of the coefficients of output-electricity relationship being identical. However, the APS relies more on trend extrapolation than on 'causal' demand analysis; further, the APS exercises are carried out first State-wise, then region-wise and finally at the aggregate national level. In fact, the APS State-wise forecasts form the basis for power requirement estimates of the SEBs and State governments. The APS position is of immense significance for the States, since the State level power sector investment programmes are attuned to these forecasts and stand to influence the case for Central Plan assistance.

The APS, while providing disaggregated data, unlike the Planning Commission, suffers from its length of preparation and the considerable cost involved in organising a detailed survey of so many units throughout India. Furthermore, it has been found that the APS may often be upwardly biased. The APS forecasts exceed the demand met by between 20 and 80 per cent, and the divergence generally increases in the later years, as might be expected. Thus the energy consumption forecasts for Kerala by the successive APS since the 12th APS, for 1994 are in the order of 12466, 9328, 9409, and 8567 million units (MU) respectively (by the 12th, 13th, 14th, and 15th, the latest, APS). It should, however, be pointed out that it does no good to compare these forecasts with the actual demand met (about 7027.7 MU of energy internally sold) in Kerala, fraught with severe power cuts and load shedding. One way to account for such upward divergence is to regard it as reflecting the unsuppressed demand more faithfully than the realised demand.

No econometric study of electricity demand had dealt with the decreasing block pricing in a completely satisfactory way, and the estimates of price (as also income) elasticities probably contained biases of indeterminate sign and magnitude as a consequence. Taylor's suggestions (1975) to deal with this problem were two-fold:

(a) Multi part tariffs require the inclusion of marginal price and intramarginal expenditure as arguments in the demand function, and

(b) The prices employed should be derived from actual rate schedules.

All the studies (in the US) had used either ex post average prices or prices derived from *Typical Electric Bills*, an annual publication of the US Federal Power Commission. In response to Taylor's suggestions, most of the studies since then have utilised 'the wisdom of employing electricity prices from actual rate schedules'. Several studies have also sought to improve modelling of the dynamics of electricity demand through inclusion of stocks of electricity consuming appliances in the demand function, and also the possibilities of inter-fuel substitution. Some other studies have utilised date on individual households, small geographical areas, or the area served by a utility, in a bid to utilise a data set of higher quality than that provided by data at the state, or national level, as well as to avoid (or at least reduce) aggregation bias in estimates of price and income elasticities.

Demand Forecasts for Kerala

Demand projections for Kerala based on the 12th, 13th, 14th and 15th APS results are in consideration now in the State. A steady decrease in the peak demand/energy consumption requirements is discernible in each of these forecasts that is attributed to some restrictions and revisions in the trends relative to the base year, (reflecting the increasing quanta of suppressed demand due to lack of generation capability). The State has accepted the 14th APS as 'more dependable' (Government of Kerala, Report of the Steering Committee on Energy and Power, Ninth Five Year Plan, 1997-2002, State Planning Board, Thiruvananthapuram, Feb., 1997, p. 12); whereas the Balanandan Committee (to study the development of electricity in Kerala) finds the 15th APS 'as the better estimates for future planning' (Report, Feb., 1997, p.37). Considering the divergences in these forecasts of the APS for Kerala (as shown above, for example, for 1994), the State Planning Board constituted a working group to study the demand forecasts for Kerala. The committee used a log-linear model and growth rates of 4.72, 10, and 15 per cent for the HT and EHT industries to arrive at three different demand projections. The domestic demand projections in all these exercises were based on the growth of population as per the Census report. For the other sectors, the projections were made based on the trends (using semi-log scale). It should be noted that the energy demand forecast for 1994 by the Committee is only 8945 MU.

International Energy Initiative (IEI), Bangalore, has put forward a Development Focused End-Use Oriented, Service directed methodology (DEFENDUS) for estimating demand and supply of energy in an energy system, and an exercise based on this has been done for the KSEB. This methodology, with its twin focus of developed living standard and improved end-use efficiency, seeks to estimate demand for a particular energy source/carrier in a given year based on two variables – the number of energy users and their actual energy requirement in any base year as well as the expected changes in the subsequent years. The total energy demand is then equal to the aggregate demand of all the categories of users for every end-use.

Model Adequacy Diagnosis

In addition to the usual parameter significance tests, demand analysis and forecasting models are evaluated for their simulation potential also. The simulation error measures, signifying the deviation of the simulated variable from its actual time path, which we consider in this study are the Theil inequality coefficient (TIC) and its 3 components.

TIC is a very useful simulation statistic related to root mean square error (RMSE), which is the square root of the mean of the squared deviations between the simulated and the actual values, and applied to the evaluation of historical simulations or ex post forecasts. It is given by the ratio of the RMSE to the sum of the square roots of the mean squared values of the simulated and the actual data series, such that it will always fall between 0 and 1. If TIC = 0, the simulated and the actual series coincide for all t and there is a perfect fit. If TIC = 1, on the other hand, the predictive performance of the model is the worst. The TIC is decomposed into 3 components, bias proportion (BP), variance proportion (VP), and covariance proportion (CP), with BP + VP + CP = 1. The BP is an indication of systematic error, since it measures the extent to which the mean values of the simulated and actual series deviate from each other. Whatever be the value of the TIC, we would hope to obtain a BP much closer to zero for a good fit. The VP indicates the ability of the model to replicate the degree of variability in the variable under study. If VP is large, it means that the actual series has fluctuated considerably while the simulated series shows little fluctuation, or vice versa, which is quite undesirable. We would hope to see minimum variability between the two. The CP measures the unsystematic error, i.e., it represents the remaining error after deviations from average values and average variabilities have been accounted for. Since it is unreasonable to expect simulations perfectly correlated with actual series, this component of error is less problematic. In fact, it is generally accepted that for any value of TIC > 0, the ideal distribution of inequality over the 3 components is BP = VP = 0, and CP = 1.

An important stage, however, that is to *precede* hypothesis testing in forecast modelling is model adequacy diagnostic checking, one of the three concerns in this paper. The fitted model is said to be adequate if it explains the data set adequately, i.e., if the residual does not contain (or conceal) any ‘explainable non-randomness’ left from the (‘explained’) model. It is assumed that the error term in the model is a normally distributed white noise[5] (with zero mean, constant (finite) variance, no serial (auto) correlation and no (cross) correlation with the explanatory variables). Since the ordinary least squares (OLS) estimators are linear functions of the error term, (under its normality assumption) they themselves are normally distributed. This normality assumption is essential for deriving the probability (sampling) distributions of the OLS estimators and facilitates hypothesis testing, using t and F statistics, which follow t and F distributions only under normality assumption, in finite samples. Hence a diagnostic checking on normality assumption must be carried out *before* proceeding with hypothesis (significance) tests. The normality test we report here is described in Doornik and Hansen (1994); it tests whether the skewness and kurtosis of the OLS residuals correspond to those of a normal distribution. A reasonably high probability (p-) value, associated with a small test statistic value, indicates non-rejection of the normality assumption. It should also be noted here that the mean of the OLS residuals is zero by construction when an intercept is included in the model.

The no serial correlation assumption may be tested by checking whether the residual autocorrelation coefficients are statistically zero compared with standard deviation limits. Alternatively, we can test the joint hypothesis that all the autocorrelation coefficients (for a given lag) are statistically zero, using the residual correlogram ('portmanteau') statistic, viz., Ljung-Box (1978) statistic[6]. Too large a value of the 'portmanteau' statistic can be viewed as evidence *against* model adequacy, or conversely, a large p-value *confirms* model adequacy. However, as residual autocorrelations are biased towards zero, when lagged dependent variable is included as regressor in the model, this (as well as Durbin-Watson, DW) statistic is not reliable. The correct procedure in such conditions is to use Lagrange Multiplier (LM) test as residual correlogram; the F-form LM test, suggested by Harvey (1981), is the recommended diagnostic test of no residual autocorrelation. Durbin h test for first-order serial correlation is a LM test. It should also be noted that a low DW statistic need not be due to autoregressive errors, warranting correction for first-order autoregression[7] (AR(1)). Mis-specifications in time series data can also induce serious serial correlation among the residuals, to be reflected in low DW statistic. The RESET (Regression Specification Test, due to Ramsey 1969) tests the null of no functional form mis-specification, which would be rejected if the test statistic is too high.

In addition to these, the assumption of no-heteroscedastic errors should also be checked, using, say, White's (1980) general heteroscedasticity (F-) test; a small p-value (associated with large F-value) rejects the null of no heteroscedasticity in errors. Often the observed serial correlation in errors may be due to what is called autoregressive conditional heteroscedasticity (ARCH) effect, that makes the residual variance at time t depend on past squared disturbances (Engle 1982). Hence it is advisable that one test for the ARCH effect too before accepting the routine statistics at face value. We can also test for the instability of the parameters in the model through a joint (F-) statistic, large values of which reveal parameter non-constancy and indicate a fragile model with some structural breaks (Hansen 1992). Note that the indicated significance is valid only in the absence of non-stationary regressors.

Unit Root Problem

This is the second of our concerns.

From a theoretical point of view, a time series is a particular realisation (i.e., a sample) of a stochastic process. If the underlying stochastic process that generates the series can be assumed to have finite parameters and to be invariant with respect to time, then the process (as well as its realised series) is said to be stationary. This simply means that the mean, variance and autocovariances of the series are all constants. In this case, i.e., if the process is stationary, the time series can be described by a simple algebraic model. If, on the other hand, the characteristics of the stochastic process change over time (i.e., is non-stationary), it is not possible to model the process in terms of an equation with fixed coefficients, estimated from past data.

For an instance, consider the process given by the first order autoregressive, AR(1), model with $\alpha = 0$,

$$y_t = \rho y_{t-1} + u_t, \tag{10}$$

where u_t is a white noise and ρ is the root of (10). If $|\rho| < 1$, the process is dynamically stable (i.e., stationary) and if $|\rho| > 1$, it is dynamically explosive (i.e., non-stationary). If the process has a unit root, i.e., if $|\rho| = 1$, the process never dampens down nor explodes. In this case, y_t can be represented, through successive substitution and assuming that the initial value (of y_t at $t = 0$) $y_0 = 0$, in terms of the cumulation of all the past shocks: $y_t = u_t + u_{t-1} + .. = \Sigma u_i$ for $i = 1, 2, \ldots, t$; thus the behaviour of y_t is determined solely by the cumulation (from past to the present) of random shocks. That is the shock persists and the process is non-stationary[8]. Thus unit root problem refers to non-stationarity problem of economic time series. In this case, the process has a zero mean (that is, its trend, Σu_i for $i = 1, 2, \ldots, t$; is stochastic, that cannot be predicted perfectly), but its variance and autocovariances increase infinitely with time[9].

With a unit root, the above process in (10) is called a random walk (without drift), in recognition of the similarity of the evolution of y_t to the random stagger of a drunk. Thus the change in y_t, i.e., the first difference $\Delta y_t = y_t - y_{t-1}$, is simply a (stationary) white noise (u_t) and is hence independent of past changes. Thus in this case y_t can be made stationary through first-differencing. A series that can be made stationary through differencing is said to belong to difference stationary process (DSP) class.

Adding a constant ($\alpha \neq 0$) to the above simple random walk model yields a random walk with drift, accounting for a deterministic trend also in the series, upward or downward depending on α > or < 0. The process in this case can be written as $\alpha t + \Sigma u_i$ for $i = 1, 2, \ldots, t$, so that the mean, variance and autocovariances of the process are all functions of time. On the other hand, for a stationary (less-than-unit root) process, all these characteristics are constant and this property is made use of in econometric estimation. Remember that the OLS estimator from a regression of y_t on x_t is the ratio of the covariance between y_t and x_t to the variance of x_t. If y_t is a stationary ($|\rho| < 1$) variable and x_t is non-stationary ($|\rho| = 1$), the OLS estimator from the regression of y_t on x_t converges to zero asymptotically, because the variance of x_t, the denominator of the OLS estimator, increases infinitely with time and thus dominates the numerator, the covariance between y_t and x_t. Thus the OLS estimator cannot have an asymptotic distribution. This is the unit root (non-stationarity) problem.

Results from regressions with non-stationary variables can be very much misleading. Granger and Newbold (1974) found that the regression coefficient estimated from two series generated by independent random walk processes was statistically significant, with very high R^2, but very low DW statistic (indicating high autocorrelation in residuals). When the regression was run in first differences of the series, the R^2 was close to zero and the DW statistic close to 2, thus proving that there was no relationship between the series and the significant results obtained earlier was spurious. Hence they suggested that the event $R^2 > DW$ meant 'spurious regression' and the series should therefore be examined for association by running regression in the first differences of the variables. Plosser and Schwert (1978) gave further empirical evidences in favour of first differencing in regression models.

Trend removal via differencing to induce stationarity in non-stationary series is an important stage in autoregressive-integrated-moving average (ARIMA) model building (Box and Jenkins 1976). If a series requires differencing k times to be stationary, the series is said to be integrated of order k, denoted by I(k). In the earlier example of random walk model (10), y_t is I(1) variable, while Δy_t is I(0), stationary, variable.

At the same time, detrending has been widely used in regression analyses; residuals obtained from such detrending models, regressing economic time series on time, have been interpreted as cyclical components in the context of business cycle theory[10] . Such models, taking the variables in logarithm have also been used to estimate trend growth rates in historical contexts (Craft et al. 1989 a, b). The question of the choice between differencing and detrending has subsequently led to recognising the differentiation between difference stationary and trend stationary series. A process that is stationary around a deterministic trend is then called a trend-stationary process (TSP, so that the series can be detrended). The model $x_t = \alpha + \beta t + u_t$, with finite mean $(\alpha + \beta t)$, and constant variance (σ_u^2) over the sample period, represents a TSP. The mean, though a function of time, is perfectly predictable given the values of time and the parameters α and β, and represents a deterministic trend of the non-stationary x_t. On the other hand, the driftless random walk model, $y_t = y_{t-1} + u_t$, with a zero mean and a time-varying variance, represents a DSP (as Δy_t is stationary). It has a stochastic trend, incorporating all the past shocks (Σu_i for $i = 1, 2, \ldots, t$, which is hardly predictable) that have persistent effect on the level of y_t. For a random walk with drift, there is a deterministic trend (αt) also, buried in the noise component[11] .

Thus it becomes essential to identify the true nature of a non-stationary series i.e., whether it belongs to TSP class (described by deterministic trend) or to DSP class (integrated processes described by stochastic trend and also a deterministic trend, if $\alpha \neq 0$). In regressions with TS series, inclusion of a time trend in the model will detrend the variables[12] . With DS series, on the other hand, cointegration modelling is required, if feasible. The first step however is to deal with the problem of discrimination between TSP and DSP models.

The first ever attempt at such a model selection was by Nelson and Plosser (1982), though they accomplished it as a (nested) hypothesis testing. They tested the null hypothesis that a time series belongs to DSP class against the alternative that it belongs to TSP class, using the (augmented) Dickey-Fuller unit root tests (Dickey 1976; Fuller 1976; Dickey and Fuller 1979). They started with a TSP model in which the errors are serially correlated (in first order):

$$y_t = \alpha + \beta t + u_t, \text{ and } u_t = \rho u_{t-1} + e_t,$$

where e_t is assumed to be Gaussian white noise. Nesting these two models[13] gives:

$$y_t = \alpha + \beta t + \rho[y_{t-1} - \alpha - \beta (t - 1)] + e_t, \text{ or}$$

$$y_t = \delta + \gamma t + \rho y_{t-1} + e_t, \qquad (11)$$

where $\delta = \alpha (1 - \rho) + \beta\rho$ and $\gamma = \beta (1 - \rho)$. After observing the sample autocorrelation function of the first differences of the series, Nelson and Plosser included in the above model, lagged values of Δy_t as additional regressors to correct possible serial correlations in the errors (as in ADF testing procedure). The null hypothesis to be tested is Ho: $\rho = 1$ (and $\gamma = 0$), against the one-sided alternative $| \rho | < 1$. If the unit root null is rejected, then y_t belongs to the TSP class, otherwise to the DSP class. Note that in this Bhargava formulation of the model, if $\rho = 1$ then $\gamma = 0$, and y_t (under the null) is a random walk with drift (i.e., DSP). However, the usual t-test cannot be used to test the null hypothesis of $\rho = 1$ in the above equation, since under this null, y_t is I(1) and hence the t-statistic does not have an asymptotic distribution. The relevant asymptotic distribution, based on Wiener processes, is known as Dickey-Fuller distribution and Fuller (1976) provides the critical values of these statistics. Nelson and Plosser found that 13 out of 14 US macroeconomic time series they analysed belonged to the DSP class (the exception being the unemployment rate), the autoregressive unit root null having failed to be rejected. The study has been followed by a large number of empirical analyses, with different unit root tests procedures, that have basically confirmed the findings.

In a second model with a constant only (i.e., no trend, $\alpha \neq 0$, $\beta = 0$) in the Bhargave type formulation, we have

$$y_t = \delta + \rho y_{t-1} + e_t, \tag{12}$$

where $\delta = \alpha (1 - \rho)$; if $\rho = 1$, then $\delta = 0$, and (under the null) we have a drftless random walk or DS series. Under the alternative, $| \rho | < 1$, y_t is a stationary series around $\delta/(1 - \rho)$. If the unit root null is not rejected in the first model, we can check for another unit root in the series, by applying the ADF test to the differenced series[14]. Since our inference from the non-rejection of the unit root null in the first model characterises the series as difference stationary with drift, we can use the second model in differences for testing for a second unit root or stationarity. If the null is rejected, then the first-difference series is stationary[15].

Perron (1989), however, demonstrated that structural breaks in the series can lead to biased results in favour of presence of persistence (when in fact there is not). Assuming that the shock (such as the Great Crash of 1929 and the oil price shock of 1973) is exogenous (i.e., known structural break), he proposed a modified DF test for a unit root in the noise function. He considered three different models under the unit root null. The models allowed for an exogenous change i) in the level (intercept) of the series (a 'crash'), ii) in the rate of growth (slope), and iii) in both the intercept and slope of the series. The general model (iii) is given by:

$$y_t = \alpha + \rho y_{t-1} + \beta t + \gamma DT_t + \theta DU_t + \Sigma\delta_i \Delta y_{t-i} + u_t,$$

where $DU_t = 1$ if $t > TB$, 0 otherwise, and

$DT_t = t$ if $t > TB$, 0 otherwise; TB refers to the time of break and the summation is over $i = 1, 2, \ldots, p$.

The variable DU (dummy model) captures the possibility of 'crashes' and DT (spline model[16]), growth changes. Results from a Monte Carlo experiment (Perron 1989) showed that if the magnitude of the shock is significant, one can hardly reject the unit root null, even if the series is stationary with a broken trend and white noise errors (i.e., with no unit root in the noise term). Perron tabulated the critical values for the unit root tests in the presence of structural break, for given values of $\lambda = TB/T$, the ratio of pre-break sample size to total sample size. Applying the modified DF test to the same US macroeconomic series as used by Nelson and Plosser (1982), Perron reached the 'startling conclusion' that most of the series (except three) 'are not characterised by the presence of a unit root and that fluctuations are indeed transitory' (Perron 1989: 1362). This paper has sparked a controversy and his assumption of a known, exogenous break has been severely criticised as raising the problem of pre-testing and data-mining for the choice of the break date. Several methods have since been developed for endogenising the choice of break point into the testing model, and some of the results have reversed Perron's conclusions.

Modelling relationships among non-stationary variables has essentially involved their differencing to induce stationarity. Solving the non-stationarity problem via differencing is, however, equated to *'throwing the baby out with the bath water'*, because differencing results in '*valuable long-run information being lost'*. Most of the economic relationships are stated in theory as long-term relationships between variables in their levels, not in their differences. We need to conserve and utilise in analysis this long-run information contained in the level variables, and at the same time, we have to be on the watch for spurious regression of integrated variables. Both these seemingly irreconcilable objectives could be achieved by means of cointegration mechanism.

The concept of cointegration was introduced by Granger (1981) and Engle and Granger (1987), and is used as a statistical property to describe the long-run behaviour of economic time series. If two series y_t and x_t both are I(1), then in general, any linear combination of them will also be I(1). However, an important property of I(1) variables is that there can be some linear combinations of them that are in fact I(0), i.e., stationary. Thus, a set of integrated time series is cointegrated, if some linear combinations of those (non-stationary) series are stationary.

Let us define u_t as:

$$u_t = y_t - \beta x_t, \tag{13}$$

where both y_t and x_t are I(1). If u_t is I(0), then y_t and x_t are said to be cointegrated, denoted by CI (1, 1). Since both the variables are I(1), they are dominated by 'long wave' components, i.e., they are on the same wave length. But u_t, being I(0), does not have these 'long wave' components as these 'trends' in y_t and x_t cancel out to produce stationary, I(0), u_t (see Griffiths, et al. 1993: 700-702). β is called the *constant of cointegration*[17].

Thus, if two variables are integrated of the same order (having the same 'wave length'), they can be cointegrated. In this light, the regression of these two variables, $y_t = \beta x_t + u_t$ makes sense (is not spurious), because the variables do not tend to drift apart from each other (i.e., they move together) over time. This then implies that there is a long-run equilibrium relationship between them.

Engle and Granger (1987) discuss two simple tests of the null hypothesis that y_t and x_t are not cointegrated, that is the u_t is I(1). The first, Durbin-Watson Cointegrating Regression (DWCR), test is based on the DW statistic from the relationship between y_t and x_t and tests, on the null hypothesis that the residual u_t is I (1), whether DW is significantly different from zero[18] using the critical values provided by Sargan and Bhargava (1983: Table 1). Also, the R^2 value will be very high for cointegrated variables. The second test directly examines residuals through an ADF test for unit root. Thus, given two variables y_t and x_t, if they are indeed I(1) processes, verified through some unit root tests, a simple method of testing whether they are cointegrated is to estimate the 'cointegrating regression':

$$y_t = \alpha + \beta x_t + u_t \,, \tag{14}$$

and then test whether the residual u_t is I(0) or not, using the t-ratio on u_{t-1} from the regression of Δu_t on u_{t-1} and lagged values of Δu_t, in a way analogous to the unit root (ADF) testing discussed earlier. If u_t has no unit root, that is, the linear combination $u_t = y_t - \alpha - \beta x_t$ is I(0), then there exists a cointegrating relationship between y_t and x_t. The DF and ADF tests in this context are known as Engle-Granger (EG) test or Augmented Engle-Granger (AEG) test. Engle and Granger (1987) prefer this latter test as having more stable critical values, though Banerjee, et al. (1986) make a case for DW statistic on the grounds that its distribution is invariant to nuisance parameters such as a constant.

A significant recognition in this context is the model adequacy diagnosis implied in the single-equation residual-based cointegration tests. Remember two (or more) non-stationary variables integrated of the same order can be cointegrated, if the residuals from their linear relationship are a I(0), or stationary, series, i.e., white noise! This is nothing but the model adequacy criterion in regression approach. In this light, residual based cointegration tests can be a final step in model adequacy diagnostic checking.

The residual based single equation methods fail to test for the number of cointegration relationships when there are more than two variables. Hence the use of system methods in vector autoregression (VAR) framework that treats all the variables as endogenous. The most popular system method is the Johansen (or Johansen and Juselius, JJ) method, based on canonical correlations (Johansen 1988; Johansen and Juselius 1990), that provides two likelihood ratio (LR) tests. The first, trace test, tests the null hypothesis that there are at most r $(0 \leq r \leq n)$ cointegrating vectors, or equivalently, $n–r$ unit roots. The second, maximum eigenvalue test, tests the null hypothesis that there are r cointegrating vectors against the alternative of $r+1$ cointegrating vectors. Johansen and Juselius recommend the second test as better. Reimers (1992) argues through a Monte Carlo study of the Johansen LR test that the test statistic be corrected for the number of estimated parameters to obtain satisfactory size properties in small samples. The correction is by replacing T by $T–np$ in the test statistic, where T is the number of observations, n is the number of variables and p is the lag length of the VAR.

If y_t and x_t are both $I(1)$ and cointegrated, then by the Granger Representation Theorem (Engle 1983; Engle and Granger 1987), there exists an ‘error correcting’ data generating mechanism through the 'equilibrium error', u_t. In an error correction model (ECM), the 'equilibrating' error in the previous period, u_{t-1}, captures the adjustment towards the long-run equilibrium. This error correction term (EC), u_{t-1}, is said to 'Granger cause' Δy_t or Δx_t (or both). As u_{t-1} itself is a function of y_{t-1} and x_{t-1}, either x_t is 'Granger caused' by y_{t-1} or y_t by x_{t-1}. That is, the coefficient of EC contains information on whether the past values of the variables 'affect' the current values of the variable under consideration. A significant coefficient implies that past equilibrium errors play some role in 'affecting' the current outcomes. This then implies that there must be some 'Granger causality' between the two series in order to induce them towards equilibrium. The short run dynamics are captured through the individual coefficients of the difference terms. Thus ECM brings together 'Granger causality', concerned with short term forecastability, and cointegration, concerned with long run equilibrium.

3. Analysis

Model Adequacy Diagnostic Checking

We start with an analysis of the time series data on the internal consumption of electricity (in million units, MU) in the Kerala system from 1957-58 to 1998-99 in the framework of the common extrapolation models[19]. We are not considering the growth curves, which are more appropriate for the demand for durable goods with an acceptable market saturation level. Table 1 reports the OLS estimates of the parameters along with other statistics of these models – the four trend extrapolation models (linear, quadratic, k-transformation and semi-log or exponential) and the two first order autoregressive [AR(1)] ones. The 'k-transformation' model has been turned out to be either defined or significant only for the values of k = 0.3, k = 0.4 and k = 0.5, out of a range of values tried; we report only the results for k = 0.5.

All the models appear to have highly significant fit, based on the conventional tests (R^2, F- and t- values), to the immediate satisfaction of an average researcher. The estimated measures of simulation error – TIC and its three components – also offer pleasant results. By these measures, it appears that all the models in general have very good fitting performance, with very low TIC, along with an almost zero BP in most cases and a close to zero VP. In fact, this close correspondence between the actual and the fitted is an indication of non-stationarity of the series (Doornik and Hendry 1997: 33); but an average investigator, unaccounting for this, might be easily misled by the seemingly significant results. Here lies the significance of model adequacy tests.

Now see the danger signal of 'spurious regression' (R^2 > DW) blazing in most of these models, where diagnostic tests for model adequacy fail to recognise them. Thus, although for all the four trend extrapolations, the normality assumption of the residuals cannot be rejected[20], the important stationarity conditions all stand violated. The very low DW statistics for these four models indicate possible positive first-order serial correlation among the residuals that leaves the estimated standard errors unreliable. But this is not the only problem; the LM statistic is highly significant, such that the null of no residual autocorrelation gets rejected with almost certainty in all the four cases[21]. So does the null of no heteroscedasticity in errors for the linear and semi-log models. Thus in these two models, the observed residual autocorrelation may be due to the ARCH effect also[22]. In the k-transformation model too this is so (i.e., the error variance is serially correlated), but at 10 per cent significance level only, while in the quadratic trend model, at 25 per cent level. The joint parameter stability statistic is large enough to reject the null hypothesis of parameter constancy and of a strong model in all these cases; and so is the RESET (F-) statistic such that the null of no functional form mis-specification too is rejected (except the k-transformation model, for which these statistics could not be estimated); the observed autocorrelation can be due to mis-specified functions also.

The effects of first order autoregressive [AR(1)] correction on linear, quadratic and semi-log trend models[23] are also reported in Table 1. The first two models fail to recover in this exercise. The parameter instability persists; the data remain functionally mis-specified, and the residuals come out to be non-normal, serially correlated and heteroscedastic. The semi-log model, on the other hand, has tremendously improved, with no mis-specification. The errors are now statistically normal, serially uncorrelated and homoscedastic; the null hypothesis of joint parameter constancy cannot be rejected. The series appears to be almost stationary after the 'quasi-differencing', involved in the AR(1) correction of the logarithmically transformed series. And the model may pass safely for the next stage of hypothesis testing[24].

The two autoregressive extrapolation models offer opposite behaviour patterns, though very low RESET statistics refute mis-specification in both the cases. Note that the coefficient of the lagged dependent variable used as the regressor in both the cases is almost unity! The residuals from the simple autoregressive equation are distributed highly leptokurtic, such that the normality test fails. The Durbin-h statistic for the simple AR model turns out to be 0.533, which is much less than the normal critical value of 1.645 at 5 per cent significance level, indicating non-rejection of the null of no first order serial correlation. However, the LM test confirms the presence of overall serial correlation in the errors, which are also heteroscedastic, as the White and ARCH tests indicate. The model is also fragile with joint parameter non-constancy. The logarithmic autoregressive model, on the other hand, passes all the tests – the parameters are not unstable; and the residuals are normal, uncorreelated[25], and non-heteroscedastic also.

Having thus proved that unwarranted application of extrapolation models for forecasting without model adequacy tests leads to misleading results, we now turn to examine the general practice of time series econometric analysis of electricity demand. It goes without saying that in the backdrop of a high standard of living, the distinctly evolved influential matrix of socio-economic factors must have a significant say in determining electricity consumption in Kerala – for one thing, consider the spread effect of the 'Gulf boom', blooming the construction sector and the markets for electrical and electronic appliances. Hence the significance of a demand analysis.

In Table 2 we report the results of the econometric analysis of electricity demand (internal consumption) in Kerala for the period 1960-61 to 1998-99. The 'causal' factors considered are the ones usually used in such studies – per capita state income (at 1980-81 prices), number of consumers (in the place of population), and real average revenue (average sales revenue deflated by wholesale price index number for electricity, base: 1981-82; as a proxy for average price). The results are mixed for the two types of models (simple and logarithmic) considered, though all the first four models suffer from parameter instability[26]. Surprisingly, the logarithmic model (Model 2) is haunted by 'spurious regression' effect, which persists even in the presence of a time trend, included to 'detrend' the variables (Model 4). In the simple Model 1, DW test result is inconclusive, but there is no presence of it when a time trend is included (Model 3). Except this one, all the other three models are functionally mis-specified also. Normality and White homoscedasticity assumptions are violated for the simple models (1 and 3) without and with trend, though there is no ARCH effect; and by the LM tests, residuals from all the models are autocorrelated.

A final model (Model 5), including a one-period lagged dependent variable in the logarithmic mould, comes out to be non-fragile with normally distributed and homoscedastic residuals. Note that this is the usually used partial adjustment (short run consumption) model[27], appearing here with appealingly significant R^2 and t-values. However, the large Durbin-h statistic strongly rejects the null of no serial correlation[28]; the LM (F-) test also confirms this. And the no-mis-specification null too remains rejected. Note that the lagged dependent variable in this model, unlike in the above autoregressive cases, has not (as it should have) biased DW towards 2.

The upshot of the whole exercise brings into light an important aspect in model building, in terms of the significant results of the diagnosis for model adequacy of the two extrapolation models: semi-log trend model with AR(1) correction and first-order logarithmic AR model. That important aspect is that both the models involve logarithmic transformation and 'quasi' differencing of the consumption series that could induce to some extent stationarity in the non-stationary series[29]. And this induced stationarity is reflected here through the whiteness of the residuals.

It should be noted that while the above two models pass the diagnosis, its failure marks the multivariate models, which might otherwise pass all hypothesis and simulation significance tests and mislead a researcher.

Our intention of this presentation has been to bring it home that a non-judicious handling of regression techniques (considering only the significance of R^2 and t-values, as also the simulation error measures) for time series analysis/forecasting could be misleading. Most macroeconomic time series being non-stationary, a fixed-coefficients model building endeavour is just undesirable. Successful infusion of stationarity into non-stationary series, however, depends on the right choice of the appropriate method – detrending or differencing. And this in turn depends upon the factual recognition of the true nature of these series; i.e., whether they belong to TSP class or DSP class. In any analysis based on time series, an identification exercise for the series must then precede the model building stage, because of possible problems of misleading results particularly of under-differencing[30] (i.e., modelling a DS series as a TS series). This is a possible problem with trend extrapolation models. For instance, electricity consumption in Kerala being a DS series with a unit root (this will be proved later on), its under-differencing in the above trend models results in misleading results of spurious regression. In this light should we consider the common practice of estimating trend growth rate from semi-log (exponential) trend model. If model adequacy tests are significant after first order AR correction, carried out in view of $R^2 >$ DW, the coefficient of t may be interpreted as the trend growth rate.

In this context we propose another useful model – a partial adjustment (short run) growth rate model, regressing logarithmic consumption on its own first order lagged term and time (Table 1, Model 10). Most of the results from this model are the same as those from the semi-log trend model with AR(1) correction (model 9), such that the two models are equivalent, since the presence of the lagged dependent variable as a regressor has the same quasi-differencing effect (in Model 10) as AR(1) correction (in Model 9); the two parameter estimates are equal (0.798). The advantage of using Model 10 is that it gives a short run growth rate (coefficient of t = 0.0136), a coefficient of long run adjustment (0.798) and a long run growth rate (0.0136/(1 – 0.798) = 0.0676), the same trend growth rate from Model 9.

In line with our interpretation of residual based cointegration test as a model adequacy diagnostic checking, we have applied unit root (DF) tests to the residuals from these three significant models (7, 9 and 10), and found no unit root in the noise functions, thus reconfirming their whiteness[31] . These models are thus adequate. The logarithmic AR(1) model (7) is a random walk with drift; the intercept (0.231) gives the approximate growth over the previous period.

Our linear and quadratic extrapolation models with and without AR(1) correction, as well as the econometric models 3 and 4 (models with time trend) are good illustrations of under-differencing. In the absence of a detailed model adequacy diagnostic checking, the 'high significance' of these models would have fascinated and thus misled an average researcher; and so it has been, unfortunately, in the case of almost all the previous studies on electricity/energy consumption in India.

To start with, Pachauri (1977) and Tyner (1978), through regression technique, have found very strong association between energy consumption and economic development in India, and the latter has gone to the extent of attempting to identify 'causation' between the two. A large number of regression analysis of electricity demand (forecasting models and 'causative' models, using population or number of consumers, per capita state income or domestic product or sectoral income, average sales revenue, etc.) have mushroomed in the luxuriant academic/ professional fields. The Fuel Policy Committee of India (1974), Banerjee (1979), World Bank (1979), Parikh (1981) and Pillai (1981) are some of the forerunners here, in addition to the regular exercises by Planning Commission, CEA and SEBs. All such studies, based on time series regression analysis, not accounting for possible non-stationarity problem in the data series, invite scepticism about the validity and value of their empirical results. Almost none of these studies has surprisingly cared for even model adequacy diagnosis! In this light, all these studies might be just spurious regression. They might also suffer from having inconsistent and less efficient OLS parameter estimates by using non-stationary variables in levels outside the cointegrating space (Engle and Granger 1987). Hence our methodological scepticism about the significant results of correlation or 'causality' found in such studies.

Unit Root Tests and Cointegration Analysis

We now therefore turn to the starting point of our time series analysis, viz., the identification stage: finding out whether our series belong to TSP or DSP class. The series we analyse are: (internal) electricity consumption (C in MU) in Kerala, number of consumers (N), average price (revenue) (AR, paise per unit) (all during 1957-58 to 1998-99) and per capita State income (PCI, in constant Rs., during 1960-61 to 1998-99). All the variables are in logarithms; logarithmic transformation is expected to reduce the effects of a time-varying variance in a series and make it stationary[32] (Holden, et al. 1990: 64).

Following Nelson and Plosser (1982), we base upon the Bhargava-type formulation of two ADF test models, our conclusion and interpretation of the unit root test results under the null and alternative hypothesis – one with a trend (including constant) and the other with a constant only. In the ADF test model, the specification of the lag length assumes that the residual (u_t) is white noise. Hence the optimum lag length (2 for C and PCI and 3 for N and AR in levels and 1 for all in differences) is selected so as to achieve empirical white noise residuals[33], satisfying normality, stationarity and homoscedasticity assumptions (Table 3). The selected lag was favoured by Akaike information criterion also. The univariate ADF unit root test results are reported in Table 4.

The DW-statistic for the level of a variable (y_t) is a simple indicator of its integrated property, and therefore we also report the DW-statistics for the concerned level variables. If y_t is a random walk (with or without drift), DW will be close to zero, and if it is white noise, DW will be around two[34] . The DW-statistics obtained of the levels of (the logs of) C, N, and PCI are close to zero and that of AR is also small, indicating the integratedness of these variables. The univariate ADF test results also show that the unit root null cannot be rejected in all the cases – that is, all the series we consider do belong to (drifting) DSP class. We further check for another unit root in the series. The DW-statistics for the first-differences of (the logs of) C and AR are around two, suggestive of their whiteness, but those for N and PCI are small, giving some signs of integratedness. The ADF tests, however, fail to find any more unit root, and hence we maintain that all these series are I(1), not I (2).

Is this inference influenced by the effects on the ADF test statistic of structural change in the series? To find out whether any significant structural change has tended to taint the test statistic in favour of non-rejection of the unit root null in each case, we apply Perron's (1989) unit root test in the presence of structural breaks. Graphical analyses[35] identify three possible breaks of 'crashes' (and subsequent 'growth rises') in the time series of electricity consumption in 1983-84, 1987-88 and in 1996-97, and a 'growth leap' in the series of customers' number in 1979-80 and in the series of per capita income in 1985-86. The average price series appear very much erratic and fail to help us recognise any trend break in its temporal behaviour.

The infamous power famine inflicted on the pure hydro-power system of Kerala by a series of drought since the turn of the 80s in league with the defective capacity expansion planning explains the 'crashes' in the power consumption series. At the same time, demand has been on the rise at an increasing rate reinforced by an ever-growing number of new connections as well as connected load[36] . In 1983-84, consumption fell by about 7.2 per cent over 1981-82, and then rose by 25 per cent in the next year; a fall of 4 per cent in consumption in 1987-88 over 1985-86 was followed by an increase of 21 per cent in the next year, and a fall of 5.3 per cent in 1996-97 over the previous year, by a rise of 10 per cent in 1997-98. The growth in the number of consumers got an accelerated fillip with the commissioning of the Idukki (Stage I) power project in 1976-77, and by 1979-80 the growth trend started to shoot up, but only to lose some momentum during the shortage period. In (constant) per capita income series, an insignificant growth is discernible after 1964-65 for a few years; from 1970-71, the series appears stagnant for about one and a half decade, and then from 1985-86, significant growth pushes the series up forcefully – a manifestation of the 'gulf boom' in a liberalised economic atmosphere.

In the face of such apparent breaks in these series, we subject them to Perron (1989)'s unit root test and the results are presented in Table 5. The optimum lag is identified such as to achieve white noise residuals here also. The coefficients of t, DU and DT in the Perron's unit root test regression models turn out to be insignificant in the case of consumption with break years of 1983-84 and 1987-88. These coefficients are significant for the consumption series with a break in 1996-97 (at 10 per cent level only), for customers' number with break in 1979-80, and for per capita income series with break in 1985-86. However, considering the estimated Perron's test statistic, in no case is it significant even at the 10 per cent level, reconfirming the presence of unit root in these series.

The series thus being integrated of the same order, i.e., I(1), we next turn to check whether the power consumption series has a long-term relationship with other variables under consideration, that is, whether there exists an economically meaningful cointegrating vector (cv) among these variables, using the two commonly used cointegration tests namely, the (Augmented) Engle-Granger (AEG, Engle and Granger 1987) test and Johansen and Juselius (1990) test. Since the cointegration test results are sensitive to the lag length of the VAR model (Hall 1991), optimum lag length for cointegration test is determined on the basis of the residual mis-specification tests of the VAR model. For a lag length of 2, the VAR model residuals have been found to be strictly white noise (Table 3).

As a first step, we compare the CRDW statistic of 0.635, obtained from a logarithmic model[37] of electricity consumption (C) with number of consumers (N), per capita State income (PCI) and average price (AR), with the approximate critical value of 0.641 at 5 per cent significance level, and fail to reject the null of no cointegration among the variables (even though the R^2 is close to unity, which is an indication of cointegration). Next we go to the AEG procedure to examine whether the residuals from this relationship are stationary, I(0). The results up to 2 lags are reported in Table 6. Here too the non-rejection of the null of no cointegration (or of I(1) residuals) persists even at 10 per cent significance level for all the lags up to 2. Hence, for reconfirmation we turn to the JJ method, which provides more robust results when there are more than two variables (Gonzalo 1994). The JJ cointegration test results are given in Table 7, where we use the maximum eigenvalue and trace statistics with small sample correction (Reimers 1992). Starting with the null hypothesis of no cointegartion ($r = 0$) among the variables, we find that both the corrected maximum eigenvalue and trace statistics[38] are well below the respective 95 per cent critical values, further confirming non-rejection of the null of no cointegration among these variables at 5 per cent level of significance; i.e., there are no common stochastic trends and the system contains four unit roots. Hence we conclude that the cointegrating regression is spurious: the regression residual is an I(1) process and there is no equilibrium in the levels of the variables (Phillips 1986). Hence the analysis should now be proceeded with on their differences.

We continue with these testing procedures to see if there exists any significant relationship for C with different possible combinations of the three ‘causal’ variables. Thus, for instance, we consider the logarithmic model of C with N and PCI; the CRDW statistic is 0.618, less than the critical value at 5 per cent significance level; all the AEG test statistics up to lag 2 are also less (in absolute value) than the respective critical values, even at 10 per cent level (Table 6). The JJ test also fails to reject the null of no cointegration among the three variables now considered (Table 7). Continuing with other combinations, we find that there exists statistically no relationship at all for C with any of the three proposed ‘causal’ variables[39] .

Causality in Growth Models

The result that there exists no meaningful cointegrating vector of interest among the variables considered (that any linear combination of these integrated variables still remains integrated) deprives us of taking advantage of a valid error correction representation[40] , and thus analysing the relationship among the variables in their levels, without losing *valuable long run* information. This leaves us with the only option of differencing the set of variables, proved to belong to DSP class, prior to further analysis. Differencing, as already noted above, is recommended for integrated series (Granger and Newbold 1974); taking differences of logarithmic series is approximately equivalent to using rates of growth of the series. Hence the significance of growth rate models, expressing relationship among variables in terms of their growth rates, that is first differences of their logarithms.

All the four I(1) series in our consideration are therefore first-differenced and the resultant stationary series (as proved by ADF tests earlier) of growth rates come in for possible choice as candidates in a growth rate model. This selection is carried out in terms of the significance of the variables (in growth rates) in a temporal lead-lag relationship, to find, through pair-wise Granger-non-'causality' tests, whether the growth in N, AR and PCI are the leading indicators of the growth in C. Remember that capacity expansion planning is based on possible growth in demand from a growing number of consumers in conjunction with price and income. The results are reported in Table 8. In none of the cases we can reject the null hypothesis of pair-wise Granger-non-'causality'. That is, the annual growth rates of electricity consumption are not granger-'caused' by those of any of the three variables, each considered in turn. Similarly, there has been no significant temporal feedback from annual growth rates of electricity consumption to those of any of the other variables considered[41]. Since the Granger-non-'causality' test is very sensitive to the number of lagged terms included in the model, it is recommended that more rather than fewer lags should be used. Hence we have considered lags up to 10, obtaining the same result of non-rejection of the null[42].

The Less Correlatables Dissected

This rather surprising result that none of the three variables considered is eligible to be included in the growth rate model of electricity consumption in Kerala leaves us finally with no further scope for multivariate time series regression analysis of demand, despite the seemingly significant scope for electricity demand analysis in Kerala, having a high standard of living. However, these results do make some sense in an underdeveloped power system like ours, plagued with substantial supply bottlenecks. Our scepticism on applying regression method directly to non-stationary series should also descend upon the common practice of attempting to correlate the less correlatables. Estimating GDP-electricity use elasticity in industrialised countries where electricity service contributes significantly to everyday life has become a standard tool of simple analysis for some obviously general conclusions. However, in a comprehensive international comparative study of bivariate 'causality' between energy use and GNP of five countries, Yu and Choi (1985) found no 'causality' in the US, the UK and Poland, but observed a unidirectional 'causality' from energy consumption to GNP in the Philippines and a reverse 'causality' from GNP to energy consumption in South Korea. Recently, Cheng (1995) detected in a multi-variate framework no 'causality' from energy consumption along with capital to economic growth in the US. In another study (Cheng 1997) for the Latin American countries, he found 'causality' from energy use to economic development in Brazil, but not in Mexico and Venezuela. In a most recent study for India (Cheng 1999; the first of its kind in his knowledge), Cheng found, in a multi-variate model, no 'causality' from energy consumption to economic development, 'which in general is consistent with many previous studies of other countries' (ibid.: 47), but saw a reverse 'causality' from GNP to energy use, using Hsiao's version of the Granger-'causality' method.

We argue, however, that it may be unfair to map such elasticity/ 'causality' methodology on to an alien range in an underdeveloped power system where the contribution of the service of electricity is insignificant. This is so even in the industrial sector in India, where power remains too insignificant an input[43], highly substitutable by capital and/or labour, primarily because of inadequate and unreliable supply, which has become a long-run experience.

The methodology is questionable even in the industrialised sector power demand analysis in a less industrialised region like Kerala, that too with very limited number of electricity-intensive industries. Adoption of this methodology here then amounts to correlating the national/State domestic product or industrial product exclusively with an insignificant input, in violation of the ethics of a consistent and logical analytical exercise, and results in gross specification error. Moreover, there are a large number of small scale and cottage industries that use practically little electricity but together contribute significantly to the industrial product. About 41 per cent of the net State domestic product in 1997-98 that originated in the manufacturing sector in Kerala was contributed by the unregistered firms, most of which use little electricity[44] . It was found in 1994-95 that about 66 per cent of the enterprises in rural India and about 52 per cent in urban India did not use any energy in their manufacturing process (Government of India 1998b : ii). Only 7.9 per cent of the rural firms and 30.4 per cent of the urban firms in India (and 11.9 and 17.7 per cent respectively in Kerala) are reported to have used some electrical energy in their production process in that year (ibid.: 35-36). The contribution of the unorganised manufacturing sector, on the other hand, in terms of gross value added to the national economy in 1994-95 was estimated at Rs. 32,274.89 crores, out of which 41 per cent came from the rural sector; and that to the Kerala State's economy was at Rs. 646.64 crores, with 72.1 per cent from the rural enterprises (ibid.: 57-64).

There is in this respect another aspect also. Kerala experienced one of the worst drought and the consequent power famine in 1983-84, with year-long imposition of 10 to 100 per cent power cut on industries. However, it had surprisingly no negative effect on the growth of industrial output. The contribution of the manufacturing sector to net State domestic product at current prices rose by 5.4 per cent over 1982-83, and that at constant prices showed a marginal increase of 0.2 per cent in the registered manufacturing sector and a fall of 12.3 per cent in the unregistered sector

– this fall in the unregistered sector continued for the following years almost till the turn of the nineties, including normal periods, indicating the influence of some other factors. Though power cut was in force in the three years from 1986-87 to 1988-89, the contribution at constant prices of the manufacturing sector, though declined by 10.5 per cent in 1986-87, shot up in the following years (at 14.4 and 12.8 per cent respectively); at current prices, however, it was steadily on the rise. The registered sector had the very same pattern. The growth trend without a break continued in the following years too. In 1996-97, even 35 to 100 per cent power cut had no adverse effect on manufacturing (both the sectors) contribution (at both constant and current prices).

As already explained, all the earlier studies in India on electricity demand[45] have invariably used as ‘causal’ regressors national/State (per capita) income, average sales revenue and population. The first two variables in aggregate values conceal everything of the characteristics of the units into which the analysis is paradoxically intended to make a look. It goes without saying that the time series regression with these variables, even if valid in a cointegrating space, yields only the macro level elasticities over time. Consumption elasticities in the true sense, i.e., across different income categories and tariff blocks, get suppressed in this aggregation. Moreover, the use of time series data simply ignores the possibility of changes of the intercept (that on an average accounts for the influence of factors other than those considered in the model) and of the slope of the line (that reflects the average intensity of energy consumption with respect to that variable); using dummy variables to account for significant structural changes might result in increasing loss of degrees of freedom. Choice of a suitable deflator also poses problems.

Average sales revenue as a proxy for average price is pregnant with a danger of measurement error as well. Proper estimation of price elasticity of demand requires, (in conformity with the suggestion made by Taylor long back, 1975, 1977), the use of data on actual rate paid by a cross-section of consumers, rather than the aggregate average revenue (to the utility) over time. Average revenue might be an indicator of the supply price in the aggregate, but never a representative of the demand price, the particular price a customer is faced with at a decision making juncture, especially in the context of the block rate tariff system. Average tariff rate might be a better alternative here.

This too in its aggregation, however, conceals an important implication of block rate structure, that makes the price of electricity itself a function of consumption, since in the increasing block rate tariff prevalent in Kerala/India, the price to a customer rises as the volume of consumption increases. This in turn entails a simultaneous equations system for electricity demand and price[46] across customer categories in different blocks of tariff. Temporal effects through changes in intercept and slope can be checked and explained, if pooled time series cross section data are used in this model. Thus a better alternative is electricity demand analysis based on pooled data, subject to appropriate unit root tests. However, such data-base is not at all available in India; and at best we can have only a cross sectional primary survey for study.

Even here the very elasticity of electricity demand is open to serious questioning. The price elasticity of demand loses its relevance in an underdeveloped power system such as ours. Demand for electricity remains largely unresponsive or less responsive to its price as it has almost become a necessity for the basic need of lighting for the habitual customers. In fact some studies have shown that even the domestic customers are willing to pay much higher prices for uninterrupted supply (Upadhyay 1996, 2000). At the same time, energy consumption commands a substantially lower budget share due both to lower unit price and to low consumption level. Thus for example, the share of fuel and power in the total private final consumption expenditure in the domestic market (at current prices) in India in 1997-98 was just 3.29 per cent; and electricity consumption accounted for only 0.68 per cent in the total. In 1980-81 and 1990-91, the share of fuel and power was 4.64 and 4.52 per cent respectively, and that of electricity, 0.40 and 0.62 per cent respectively[47] . The growth in electricity consumption has not been strong enough to facilitate a pronounced rate of substitution for other fuels, especially, the traditional one, kerosene oil. The percentage share of electricity in the private final consumption expenditure on total fuel and power grew from 8.63 per cent in 1980-81 to 20.57 per cent in 1997-98, marking an average annual compound growth rate of 5.24 per cent, while that of kerosene oil fell from 15.22 per cent to 10.5 per cent only over the same period at a decay rate of (-) 2.16 per cent per annum. This in turn suggests a very weak marginal rate of substitution of electricity for kerosene oil (or elasticity) of just about (-) 0.40; i.e., one percentage increase in the share of electricity consumption expenditure could on an average substitute for (or induce a fall of) 0.4 percentage in the share of kerosene oil consumption expenditure. In short, electricity could not yet make an effective inroad upon the economic life in India in general to the extent it should have done.

For a more concrete example, let us consider the case of the connected consumers themselves. The per capita electricity consumption of the connected domestic customers (that made up about 75 per cent of the total customers) in India in 1995-96 was 772.32 units at an average rate of Ps. 95.94 per unit (for 18 State Electricity Boards), thus giving in general an average per capita electricity consumption expenditure of Rs. 740. 97 (or, Rs. 61.75 per month) – only 7.04 per cent of the per capita income (of Rs. 10524.8) of that year. In the case of Kerala State, the electricity consumption per (electrified) domestic consumer in 1997-

98 was 953.72 units at an average rate of Ps. 76.96 per unit, that indicates an average domestic consumption expenditure of Rs. 733.99 (or Rs. 61.66 per month) on electricity. The domestic sector that made up about 75 per cent of the total customers nearly consumed 50 per cent of the electricity sold in Kerala in that year. In general, the consumption of electricity per connected consumer in Kerala in 1997-98 was 1480.71 units at an average rate of Ps. 123.74 per unit, giving an average electricity consumption expenditure of Rs. 1832.16 (or, 152.68 per month) – only 15.35 per cent of the per capita income (of Rs. 11936) of that year. Similarly, as a substantial share of residential and commercial electricity consumption goes to serve the basic need of lighting which is fairly unresponsive to income rather than to more income elastic, luxury end uses, power demand remains less income elastic also to this extent. Moreover, the whole edifice of demand analysis crumbles to dust in an encounter with power cuts and load shedding, that restrict actual consumption to availability rather than to actual requirement which is the long run experience of Kerala.

We thus see that the economic relationship demand is hypothesised to have with (per capita) income and unit price is weak and hence unwarranted in the case of an underdeveloped power system such as in India/Kerala. The same is true for the role of the demographic variable viz., population too in power demand analysis. As annual population figures are only interpolated ones, they might contain a systematic pattern, causing residual serial correlation that might not be there in the original data; using these data thus involves analytical problems. Moreover, since in a less developed power system, electricity connection remains inaccessible to a large section of the population[48], number of consumers, instead of population, must be accepted as a more direct and right determinant. The growth of demand for power is generally assumed to be determined by the growth of number of (connected) consumers and that of intensity of their power consumption (i.e., electricity consumption per customer), as also the interaction between these two factors[49].

Till the turn of the Eighties, Kerala had apparently been a power surplus state, exporting power to neighbouring states. Since the drought year of 1982-83, unprecedented power shortage has become a part of life in the state. Recurring drought coupled with inadequate installed capacity has thus unleashed a reign of power cuts and load shedding, constraining the actual demand down[50]. Reliance on past demand data for forecasting purposes thus becomes grossly erroneous and highly questionable. If some measurement of these shortages is possible to be made, the constrained demand can be adjusted accordingly to arrive at a probable measure of unsuppressed demand, which in turn can be used as data base for forecasting, subject to the unit root constraints (unless it contains any induced pattern). One method is to assume first that when restrictions are imposed on consumers, their level of consumption is held at some fraction of their consumption during an earlier base period. Then the shortfall in supply equal to these percentage restrictions can be found and inflated by a factor that reflects suppressed growth in demand since the base period and the impact of unscheduled load shedding. This in turn can be used to adjust the suppressed demand data (World Bank 1979: 13). Another method uses as demand inflative factor, the fraction of customers affected by load shedding during peak period and thus deprived of chance to contribute to peak period demand. The main problem with all such methods is the non-availability of accurate data and information.

4. Conclusion

The results of the present study signifies that the earlier works both in professional and in academic circles on electricity/energy demand analysis and forecasting, without accounting for non-stationary, integrated, behaviour of the time series they used, must have involved misleading results of spurious regression and of inconsistent and less efficient estimates. That these econometric practices lacked analytical soundness and intellectual integrity is evident in the utter neglect of model adequacy diagnostic checking, the indispensable primary stage in significance evaluation of any regression mapping. Just taking for granted the assumptions underlying a model, without an examination of its empirical significance, using available techniques, amounts to gross negligence, if not sheer gloss. At least these two fundamental flaws, viz., not caring for model adequacy diagnosis and not allowing for non-stationarity in the time series data, detract the whole value from these studies. The examples in the first part of our analysis illustrate the significance of our scepticism on this count.

A third strain in our scepticism about the earlier studies in general relates to their efforts of correlating the less correlatables. In an underdeveloped power system like ours, plagued with long-run constraints of inadequate and unreliable supply, electricity consumption remains an input too insignificant to our economic life to be analysed in the framework of some macroeconometric ‘causality’ models, as is usually done in the context of advanced systems. The second part of our analysis in terms of cointegration and Granger-‘causality’ confirms this at least in the case of Kerala power system. Electricity consumption in the State, coupled with the usually selected ‘causatives’ of number of consumers, per capita income and average price, all being I(1) variables, fails to be explained in a cointegrating space in any combination. All the linear combinations examined turn out to be still non-stationary. Further analysis for identifying some temporal lead-lag relationship (Granger-‘causality’) among them in terms of their annual growth rates, found to be stationary, again draws blank. These two unusual results are a potent pointer to the badly constrained electricity consumption in an underdeveloped system, devoid of its inherent growth mechanism (even from the number of customers itself). The general evolution of the economy may have dragged it up along some of its trend.

Demand forecasting in such contexts becomes highly uncertain. To the extent that the demand forecast has nothing to do with the capacity expansion planning on a bounded budget as well as with the actual materialised capacity additions in the system, the very exercise becomes futile, except as some routine liturgy. The widening gaps between the actual consumption and the forecast levels (even with the revised lower ones of the 15th APS or of the KSEB-State Planning Board), in the last few years in Kerala prove this point. Accurate demand forecasting is relevant as well as essential only in a growing system under an efficient management directed by a government of determined political will. This notwithstanding, forecasts under such circumstances, however, do serve a good purpose of quantifying (through the gap between forecast and the actual) the unsatisfied demand, the extent of the shortage.

All the above results and implications are based on the linearity assumption. However, 'economic theory is often non-linear' (Barnett et al. 2000: 1). Non-linearities are encountered when, for example, capacity constraints restrict generation and disequilibria persist due to rationing, the circumstances very much true for our power system. In the presence of non-linearity, (of, say, structural breaks) tests most often reject parameter constancy, as the results in Tables 1 and 2 indicate. In this paper, however, we have not considered testing for the existence of non-linearity in the data series; yet it adds to our scepticism about the earlier studies in that they did not account for possible non-linearity problem too.

As a corollary to the above implications of our results, it is high time we questioned the inappropriate, pedantic, practice of linear regression mapping for trend extrapolation not only for the unit root problems, but also when similar results can be generated by means of much simpler methods, for example, growth rate based projections[51]. Useful short-term projection can be had from simple annual growth rates (percentage deviation over previous year) of electricity consumption. The method can be modified by accounting for the effect on consumption of possible growth of the direct causatives such as number of consumers and connected load. Below we suggest one of such models:

$$\ln C_t = \varepsilon_{CN}\, r_N + \ln C_{t-1}$$

where $\varepsilon_{CN} = \Delta \ln C/\Delta \ln N$ is the elasticity of consumption (C) with respect to number of consumers (N) or consumption intensity factor and r_N is the growth rate of N. The above relation is in fact an identity only[52]. The model can be modified to include the effect of connected load (of electrical appliances) also by rewriting ε_{CN} as $\varepsilon_{CN} = \varepsilon_{CL}\, \varepsilon_{LN}$, where ε_{CL} is the consumption intensity with respect to connected load and ε_{LN} is the load intensity of the customers. Moreover, the expression resembles the 'explained' part of a random walk with drift.

Consumption intensity of the power customers in general in the State was quite elastic (much more than unity) in normal years. It even went up to more than 2.5 during the two years of 1966-68 when the Board became liberal in giving new connections following the commissioning of the Sabarigiri project, and more than three in 1984-85 and 1988-89 immediately after the 'crashes' of 1982-84 and 1986-88. These years saw great leaps in electricity consumption (the growth rates being between 20 – 33 per cent over the previous year) of a fast-growing number of customers. However, as energy export picked up, the consumption elasticity fell below unity; the 'informal' constraints on internal electricity use, covertly imposed in order to boost export show, continued till the drought year of 1982-83; growth in new connections was also checked during most of these years. Once the export frenzy has subsided, consumption now grows subject only to the combined constraints of inadequate capacity and monsoon failure, eased to some extent by heavy imports. And the consumption elasticity in the recent years has been well above 1.5, the growth in new connections being 6 to 8 per cent.

Using these constrained rates (ε_{CN} = 1.5 and r_N = 0.07), the supply-constrained power consumption in the State in 1999-2000 would be 9952 MU over the previous year's 8960 MU[53]. This implies a maximum demand of 1893 MW at 60 per cent load factor, which, accounting for 18 per cent loss factor (as at present), entails an available capacity of about 2234 MW. The total installed capacity of the State is reported to be about 2343 MW only.

In concluding, we recap that the simple is often safe.

Notes

1 "Everything is not good simply because it is old; no literature should be treated as unworthy simply because it is new. Great men accept the one or the other after due examination. [Only] the fool has his understanding misled by the beliefs of others."

2 In fact this important stage in regression analysis is entirely overlooked and skipped in general. It is just assumed that the residual whiteness assumption is satisfied by the model considered, without empirically verifying for its non-violation, except in some ARIMA modelling.

3 Econometric 'causality' is a contentious term. Can econometrics explain 'causality' (in the sense the word is generally understood), instead of mere 'association' among variables? For example, Edward Leamer and others prefer 'precedence' to 'causality', in the context of Granger-'causality' that explains temporal lead-lag relationship between two variables. On Granger-'causality' Pagan (1989) remarks: '…….it was one of the most unfortunate turnings for econometrics in the last two decades, and it has probably generated more nonsense results…' Hence our use of quotation marks enclosing 'causality'.

4 A number of computer software packages of energy planning models are available at present for energy demand forecasts, such as LEAP (Long range Energy Alternative Planning), BEEAM-TEESE (Brookhaven Energy Economy Assessment model-TERI Economy Simulation and Evaluation), MEDEE-S, ELGEM, etc.

5 A sequence u(t) , $t \geq 0$, is white noise process if it possesses a constant spectral density function. Thus a white noise process is a stationary process which has a zero mean and constant variance and is uncorrelated over time. It is therefore necessarily second-order (i.e., covariance-) stationary, and if u_t is normally distributed, it is strictly stationary as well, since in this case higher-order moments are all functions of the first two. Also see Granger and Newbold, 1977: 51.

6 This corresponds to Box-Pierce Q statistic (Box and Pierce 1970), but with a degrees of freedom correction (Ljung and Box 1978), and has more powerful small sample properties than the Box-Pierce Q statisitic.

7 Hendry and Doornik (1999) remark: "…most tests also have some power to detect other alternatives, so rejecting the null does not entail accepting the alternative, and in many instances, accepting the alternative would be a *non sequitur*" (p.187). "Perhaps the greatest *non sequitur* in the history of econometrics is the assumption that autocorrelated residuals entail autoregressive errors, as is entailed in 'correcting serial correlation using Cochrane-Orcutt'" (p. 131).

8 Remember the solution of a homogeneous first order difference equation $y_t = \rho y_{t-1}$ is given by $y_0 \rho^t$. The time path of the process converges, persists (in oscillation) or diverges (explodes) according as the root $|\rho|$ is less than, equal to or greater than unity.

9 The mean of y_t is $E(y_t) = \Sigma E(u_i) = 0$, variance of y_t is $var(y_t) = \Sigma var(u_i) = t\sigma_u^2$, for i = 1, 2, .., t, and autocovariances for lag k are $cov(y_t y_{t+k}) = E\{\Sigma u_i \Sigma u_{i+k}\} = (t-k)\sigma_u^2$, functions of time.

10 See for references on such modelling, Nelson and Plosser (1982).

11 This is why a random walk with drift can be represented in terms of a simple forecasting model, where the forecasts (trend αt) increase linearly with time and the forecast error variance ($t\sigma_u^2$) increases infinitely.

12 This follows from the classic result of Frisch and Waugh (1933) that including a time trend in a regression is equivalent to first-detrending the variables by regressing them individually on time.

13 This is known as Bhargava type formulation for unit root testing (Bhargava 1986) that can dispense with a number of problems in interpreting the test results. In the original unit root tests developed by Dickey (1976), Fuller (1976) and Dickey and Fuller (1979),

three functional forms of simple autoregression with and without constant or time trend are considered for testing the null $\rho = 1$ against the alternative $|\rho| < 1$:

$$y_t = \alpha + \beta t + \rho y_{t-1} + u_t, \quad (1)$$
$$y_t = \alpha + \rho y_{t-1} + u_t, \quad (2)$$
$$y_t = \rho y_{t-1} + u_t, \quad (3)$$

The parameters in the first two functions have different interpretations under the null and the alternative (Schmidt and Phillips 1992). In (1), under the unit root null, α and β represent coefficients of t and t^2 in a quadratic trend, while under the alternative, they represent the level and the coefficient of t in a linear trend. Similarly in (2), under the null hypothesis α represents the coefficient of t in a linear trend, whereas under the alternative, there is no trend, and y_t is stationary around $\alpha/(1 - \rho)$. Bhargava-type formulation, which implies that $\beta = 0$, if $\rho = 1$ in (1) and $\alpha = 0$ if $\rho = 1$ in (2), does not suffer from such problems.

14 But also see Dickey and Pantula (1987).

15 A trend or constant is included in these models, since most economic variables show a trend in line with the general evolution of the economy.

16 Note that *DT* is in fact an interaction term, the product of the dummy variable (*DU*) and trend (*t*).

17 If there are more than two variables, the set of β values is called the cointegrating vector. In general, if both y_t and x_t are I(d), then they are CI(d, b) if $u_t = y_t - \beta x_t$ is I(d – b), with b > 0.

18 The DW statistic is given by $DW = \Sigma(u_t - u_{t-1})^2/\Sigma u_t^2$, where the estimated residual values are used, and the summations are from 2 to n in the numerator and 1 to n in the denominator. If u_t is I(1), the DW statistic will be close to zero, since the numerator of DW is the sum of squares of (n – 1) white noise terms (as $u_t = u_{t-1} + e_t$), and the denominator is the sum of squares of n terms, each of which, through repeated substitution, can be written as an infinite

number of white noise terms. Hence the test is to see if CRDW is significantly greater than zero. If it exceeds the critical value, then u_t is I(0) and y_t and x_t are cointegrated.

19 Remember the data we use here are the ones actually constrained by power shortages – power cuts and load shedding. It goes without saying that reliance on and use of these data for forecasting purposes just involves high risk of errors of underestimation.

20 As indicated by the high p-values associated with the low normality test statistic values – thus the residuals are distributed with statistically small skewness and excess kurtosis.

21 LM test and White (F-) test are not available for the non-linear k-transformation model; AR(1) correction also is not possible for this model. And for the quadratic model, White (F-) test could not be computed due to near singularity of the matrix.

22 There is a reverse possibility also, residual autocorrelation causing ARCH effect (Engle, Hendry and Trumbull 1985), and this may be due to the difficulty in interpreting results when several tests reject together.

23 AR(1) correction is not possible for the non-linear *k*-transformation model. Also see foot note 7.

24 It should be pointed out, however, that it may not be appropriate to consider again DW statistic for the efficacy of the AR(1) correction; see the note by Kenneth White in his SHAZAM (p. 86).

25 Durbin-h in this case is 0.414, much less than the 5 per cent normal critical value.

26 It should be noted that the indicated significance is only valid in the absence of non-stationary regressors, which is not the case here.

27 Note that all the long-run elasticities implied by the model, if valid, are much less than unity.

28 Remember that these autoregressive errors, in the presence of lagged dependent variable as regressor, leave the OLS estimators inconsistent.

29 It should be noted that the parameter estimate of the logarithmic AR(1) model being close to unity and the residuals being white noise, we have a random walk model with drift. The unit root tests will also prove this.

30 Note that our findings compare well with those of Nelson and Kang (1984) who discuss misleading results resulting from estimating relationships among under-differenced series.

31 Applying unit root (DF) test to the residuals from Model 7, (logarithmic AR(1) model), the t-statistic obtained is –5.741 against the critical value of –3.607 at one per cent significance level, that thus rejects the null of unit root in the noise term. Similarly, for the semi-log trend model (9) with AR(1) correction and the short run consumption model (10), the t-statistic estimated is –5.670 versus the critical value of –3.607 at one per cent level, (same estimate for both the models, as they are equivalent), reconfirming the stationarity of the residuals.

32 Nelson and Plosser (1982: 141) state that 'the tendency of economic time series to exhibit variation that increases in mean and dispersion in proportion to absolute level motivates the transformation to natural logs and the assumption that trends are linear in the transformed data'.

33 The residuals from the models are strictly white noise for these lags with levels and with differences. Note that the unit root null might be rejected for some other lags, since the results of univariate ADF testing are sensitive to the lag length in the regression model for the tests. Hence the significance of a choice of optimum lag length, that is to satisfy the residual whiteness assumption.

34 This DW-statistic for the level of a variable is not to be confused with the cointegrating regression Durbin-Watson (CRDW) statistic of the residuals; see foot note 18.

35 Chow tests for structural stability carried out on the logarithms of the series confirm the following breaks: 1983-84 and 1987-88 in consumption; 1979-80 in number of consumers; and 1985-86 in per capita income. However, since the Chow test is meant for only stationary variables, its results cannot be relied upon in our case, and they are not reported.

36 The so-called 'Gulf boom' of increasing remittances of the non-resident Keralites from the Gulf has triggered an unprecedented growth of the housing sector and encouraged an increasing demand for electricity intensive appliances in Kerala especially since the mid-seventies. Number of houses in the electrified group must also have increased (in absolute terms) as a result of the social security schemes of the government (IRTC and IEI, Exercises for Integrated Resource Planning for Kerala: End-Use Analysis – An Empirical Study: Technical Report I – Electricity, 1996, Chap. 3, p.33). Though the serious power shortage situation has however entailed restrictions on providing new connections since 1982-83, energy consumption intensity in relation to number of customers as well as connected load has been on the increase.

37 See the multivariate econometric model 2.

38 The first row (null of r = 0) maximum eigenvalue and trace statistics are respectively 27.83 and 43.16, and the former is significant, though marginally, at 5 pe rcent level, but the latter is not. Dickey, et al. (1991) recommend the maximum eigenvalue test as more reliable than the trace test especially in small samples. This then suggests that there exists one cointegrating vector (cv) of long-run relationship among the four variables, if we disregard small sample bias. The relationship of interest in our case is that of electricity consumption (C) with other variables. The estimated cv of this relationship (with normalised coefficients representing long-run elasticities) is given by C = 0.734 N – 2.941 AR – 0.474 PCI, where all the variables are in logarithms. In view of the wrong sign of PCI (as well as the very high elasticity of AR against actual experiences), we fail to give a consistent economic meaning to this cv, and conclude against identifying the relationship of

interest. Any other relationship among the variables implied in the existence of a cv is of no interest to us now.

39 In Table 8, in the last model of C with N, note that both the statistics in the second row, Ho: $r \leq 1$, are significant at 5 per cent level. However, since the first row, Ho: $r = 0$, cannot be rejected, we cannot consider the second row. That is, if the first (row) statistic is not significant, then r is selected as zero (Doornik and Hendry 1997: 224-225).

40 Remember that by the Granger Representation Theorem (Granger 1983), if a set of variables are cointegrated, then there exists an error correction representation (and vice versa).

41 Note the null hypothesis that elctricity consumption (C) growth rates do not Granger-'cause' N growth rates can be rejected at 5 and 10 per cent significance levels respectively for lags 4 and 5, and the same is so for AR growth rates at 7 per cent level for lag 3. However, in view of the persistence of non-rejection for all other lags, we cannot consider such isolated results.

42 The results are reported for lags up to 6 for space limitation.

43 For example, in 1995-96, the percentage share of fuels, electricity, and lubricants consumed in the ASI factory sector of India in the value of total inputs was 9.56 per cent only and that in value of products, 7.81 per cent; in Kerala, these were respectively 5.77 and 4.72 per cent only (Government of India 1998a: 85-86). During the 90s (1991-92 to 1997-98), power and fuel expenses of the whole manufacturing sector in India remained at about 6 per cent of the net sales and at about 7.5 per cent of the total production costs (CMIE 1999).

44 The percentage share of the unregistered firms in the manufacturing sector's contribution to net domestic product (at current prices) in India in 1997-98 was 35.4 per cent; in 1970-71, 1980-81 and 1990-91, it was respectively 46.7, 46.3 and 39.1 per cent.

45 An apt example of mechanical adoption and use of econometrics against its grain usual in the academic circles is Pillai (1981)'s Cobb-Douglas production function approach to Kerala's hydro-electric power system, with capital and labor as 'variable' inputs. It is common sense that labor is not at all a variable factor of production in hydro-electric power generation, it being a part of sunk capital.

46 The latter (price) equation need not be confused with the usual supply function; many studies (for example, Halvorsen 1975) assume electricity supply in this context as fixed. However, the unique technical characteristic of electricity that it cannot be stored in its original form and hence must be generated the moment it is demanded stands to do away with the usual demand-supply distinction. This also makes the question of identification irrelevant. The earlier studies in India on electricity demand analysis have ignored the question of identification, as pointed out by Dr. Indrani Chakraborty; no reason is provided as to why the equation estimated as for demand may not be a supply function. It should however be noted that a distinction between demand (= supply) and capacity provision is possible here except in power shortage situations.

47 Government of India, National Accounts Statistics, different issues.

48 Nearly 50 per cent of the households in Kerala (and nearly 60 per cent in the rural areas) remain unelectrified (as per 1991 Census). This problem also haunts the regressor of per capita State income that includes the share of the unelectrified households also.

49 See Pillai (1981: 81 – 82); Henderson (1975) uses sectoral output in the place of number of consumers. Another immediate factor of influence is connected load, the total of the rating (in kilowatts) of all the electricity using appliances installed on a consumer's premises. This also may be considered along with the relevant intensity of energy consumption (electricity consumption per kilowatt (KW) of connected load) and the interaction between

the two. However, number of customers (N) is more immediate and direct than connected load (CL) in determining energy demand, as not only is N in fact the causative of CL, but also a customer may not use all his electric devices simultaneously or continuously; there are times, on the other hand, when *all* the consumers together exert demand pressure on the system. There is yet another significant reason. A growing power system is expected to become more and more electricity intensive in that its CL grows faster than N (so that the electricity intensification factor, i.e., connected load per customer (CL/N), increases over time). Despite the restrictions imposed on providing new connections since 1982-83, the domestic, commercial, and LT industrial consumers in Kerala have behaved in the expected line, becoming more electricity intensive (in terms of appliances installations), but the HT-EHT industry and 'others' (agriculture, public services, licensees, etc.) have not. This surprising tendency of a faster decaying electricity intensity in the State's HT-EHT industrial and agricultural sectors has overshadowed the normal growth in the other sectors and been reflected in the aggregate, the growth of CL trailing behind that of N.

50 Even during the 'surplus' period, it can be seen, the internal consumption was constrained in order to boost the KSEB's export extravaganza.

51 Note that the projections from semi-log (i.e., exponential) trend extrapolation model and simple and logarithmic AR(1) models are in fact (constant) growth rate based ones.

52 This follows since $r_N = \Delta \ln N$. Note that the relation also amounts to one period (compound) growth expression: $C_t = C_{t-1}(1+r)$, where r is the compound growth rate of consumption and $(1+r) = \exp(r_C)$, where $r_C = \Delta \ln C$.

53 These rates imply a consumption growth rate of about 11 per cent; the KSEB anticipates an annual growth rate of 10 per cent in power consumption at present.

Table 1. Estimation Results of the Forecast Models – Period : 1957-58 to 1998-99

1. Linear Trend : Consumption = f (Time)

	Estimate	t-value	Adj R^2	F-value	DW statistic
Constant	-899.54	-3.76	0.895	348.62	0.157
Time	181.02	18.67	Parameter instability : 3.159**		
Stimulation Error Analysis					
	TIC	BP	VP	CP	
	0.099	4.90E-17	0.027	0.973	
Residual Analysis					
Normality (χ^2)	Skewness	Kurtosis	SD		
3.35 (0.1870)	0.681	3.25	752.21		
Autoregression (F)	Heteroscedasticity (F)	ARCH (F)			RESET (F)
30.03	9.11	12.95			18.38
(0)	(0.0006)	(0)			(0)

2. Quadratic Trend: Consumption = f (Time, Time Squared)

	Estimate	t-value	Adj R^2	F-value	DW statistic
Constant	725.61	4.68	0.982	1088.1	0.706
Time	-40.595	-2.44	Parameter instability : 2.371 **		
$Time^2$	5.154	13.75			
Stimulation Error Analysis					
	TIC	BP	VP	CP	
	0.041	8.05E-16	0.004	0.996	
Residual Analysis					
Normality (χ^2)	Skewness	Kurtosis	SD		
0.631(0.7294)	-0.056	3.59	311.11		
Autoregression (F)	Heterosced asticity (F)	ARCH (F)			RESET (F)
10.94	++	1.39			10.70
(0)		(0.2548)			(0.0002)

3. Semi Long Trend: Consumption = f (Time)

	Estimate	t-value	Adj R^2	F-value	DW statistic
Constant	6.082	141.94	0.977	1773.7	0.317
Time	0.073	42.12	Parameter instability :3.437 *		
Stimulation Error Analysis					
	TIC	BP	VP	CP	
	0.0086	2.10E-12	0.0056	0.994	
Residual Analysis					
Normality (χ^2)	Skewness	Kurtosis	SD		
1.44(0.4864)	0.119	2.12	0.135		
Autoregression (F)	Heterosced asticity (F)	ARCH (F)			RESET (F)
10.34	10.14	5.69			13.28
(0)	(0.0003)	(0)			(0)

4. k-kransformation (k=0.5) : Consumption = f (Time)

	Estimate	t-value	Adj R^2	F-value	DW statistic
Constant	7.26	3.67	0.973	1479.5	0.487
Time	1.937	31.53			
Stimulation Error Analysis					
	TIC	BP	VP	CP	
	0.05	0.017	0.0074	0.976	
Residual Analysis					
Normality (χ^2)	Skewness	Kurtosis	SD		
2.08(0.3541)	-0.29	3.92	377.14		
Autoregression (F)	Heterosced asticity (F)	ARCH (F)			RESET (F)
+	+	2.16			+
		(0.0845)			

5. First-order Auto-regressive: C_t =f (One period lagged C_t)

	Estimate	t-value	Adj R^2	F-value	DW statistic
Constant	15.296	0.22	0.987	3087.1	1.837
C_{t-1}	1.068	55.56	Durbin h:	0.533	
			Parameter instability : 1.149*		
Stimulation Error Analysis					
	TIC	BP	VP	CP	
	0.034	1.33E-14	0.003	0.997	
Residual Analysis					
Normality (χ^2)	Skewness	Kurtosis	SD		
17.50(0.0002)	-0.387	6.11	260.94		
Autoregression (F)	Heterosced asticity (F)	ARCH (F)			RESET (F)
7.25	10.82	2.78			0.076
(0.001)	(0.0002)	(0.0355)			(0.9132

6. Logarithmic Auto-regressive: In C_t = f (In C_{t-1})

	Estimate	t-value	Adj R^2	F-value	DW statistic
Constant	0.231	2.24	0.993	5327.46	1.873
InC_{t-1}	0.9799	72.99	Durbin h:	0.414	
			Parameter instability : 0.216		
Stimulation Error Analysis					
	TIC	BP	VP	CP	
	0.005	9.99E-14	0.002	0.998	
Residual Analysis					
Normality (χ^2)	Skewness	Kurtosis	SD		
1.37(0.5039)	0.411	2.64	0.075		
Autoregression (F)	Heterosced asticity (F)	ARCH (F)			RESET (F)
1.45	0.215	0.336			0.369
(0.2322)	(0.8073)	(0.8872)			(0.6936)

7. Linear Trend with AR (1) correction : Consumption = f (Time)

	Estimate	t-value	Adj R^2	F-value	DW statistic
Constant	-1983.66	-0.19	0.987	1510.03	1.810
Time	-100.570	-0.25	Parameter instability : 1.545 *		
AR (1)	1.045	16.40			
Stimulation Error Analysis					
	TIC	BP	VP	CP	
	0.034	4.95E-11	0.003	0.997	
Residual Analysis					
Normality (χ^2)	Skewness	Kurtosis	SD		
14.81(0.006)	-0.334	5.87	260.4		
Autoregression (F)	Heterosced asticity (F)	ARCH (F)			RESET (F)
6.95	8.78	3.64			3.35
(0.0002)	(0.007)	(0.0109)			(0.0457)

8. Quadratic Trend with AR (1) correction: = f (Time, Time Squared)

	Estimate	t-value	Adj R^2	F-value	DW statistic
Constant	1413.96	1.80	0.989	1162.47	1.625
Time	-110.12	-1.55	Parameter instability : 2.185 *		
Time ^{2}	6.65	4.72			
AR (1)	0.709	4.99			
Stimulation Error Analysis					
	TIC	BP	VP	CP	
	0.031	5.60E-13	0.003	0.997	
Residual Analysis					
Normality (χ^2)	Skewness	Kurtosis	SD		
11.34(0.0034)	-0.481	5.39	239.37		
Autoregression (F)	Heterosced asticity (F)	ARCH (F)			RESET (F)
5.76	++	4.99			3.67
(0.0007)		(0.0019)			(0.0350)

9. Semi-long Trend wiht AR (1) correction : In C = f (time)

	Estimate	t-value	Adj R^2	F-value	DW statistic
Constant	6.25	39.54	0.993	2927.36	1.766
Time	0.068	12.82	Parameter instability :0.810		
AR (1)	0.798	9.540			
Stimulation Error Analysis					
	TIC	BP	VP	CP	
	0.004	1.13E-13	0.002	0.998	
Residual Analysis					
Normality (χ^2)	Skewness	Kurtosis	SD		
0.066(0.9674)	0.095	3.05	0.07		
Autoregression (F)	Heterosced asticity (F)	ARCH (F)			RESET (F)
1.36	0.363	0.202			0.091
(0.2655)	(0.6977)	(0.9591)			(0.9132)

10. Partial Adjustment (Short-run Growth Rate) Model : In C_t = f (In $C_{t-1,}$ Time)

	Estimate	t-value	Adj R^2	F-value	DW statistic
Constant	1.31	2.61	0.993	2927.36	1.766
Time	0.0136	2.20	Durbin h : 0.887		
In C_{t-1}	0.798	9.54	Parameter instability :0.810		
Stimulation Error Analysis					
	TIC	BP	VP	CP	
	0.004	1.13E-13	0.002	0.998	
Residual Analysis					
Normality (χ^2)	Skewness	Kurtosis	SD		
0.066(0.9674)	0.095	3.05	0.07		
Autoregression (F)	Heterosced asticity (F)	ARCH (F)			RESET (F)
1.36	1.77	0.202			2.36
(0.2655)	(0.1562)	(0.9591)			(0.1082)

Note:

1. *' and '**' indicate statistical significance at 5 and 1 per cent respectively.
2. + = not available in non-linear least squares
3. ++ = near singular matrix
4. Figures in brackets are the corresponding p-values.
5. C = Electricity Consumption in the State (Million Units)
6. Adj. R-squared = Adjusted R-squared;
7. TIC = Theil inequality coefficient
8. ln = Natural log
9. BP = Bias proportion; VP = Variance proportion
10. CP = Covariance proportion
11. AR(1) = Estimate of first order auto-regression coefficient
12. Parameter instability = Joint (F-) test statistic for parameter constancy
13. ARCH (F) = Autoregressive Conditional Heteroscedasticity (F) statistic (5 lags)
14. RESET (F) = Regression Specification Test (F) statistic

Table 2. Multi-variable Econometric Models – Period: 1960-61 to 1998-99

Model 1. $C_t = (N_t, PCl_t, AR_t)$

	Estimate	t-value	Adj R^2	F-value	DW statistic
Constant	-129.66	-0.23	0.993	1686.1	1.306
N_t	1.175	18.53	Parameter instability : 1.591*		
PCl_t	1.127	4.23			
AR_t	-30.53	-2.30			
Stimulation Error Analysis					
	TIC	BP	VP	CP	
	0.024	1.64E-14	0.002	0.998	
Residual Analysis					
Normality (χ^2)	Skewness	Kurtosis	SD		
14.19 (0.0008)	-1.161	4.83	191.94		
Autoregression (F)	Heteroscedasticity (F)	ARCH (F)			RESET (F)
3.08	2.64	0.443			3.44
(0.0233)	(0.0340)	(08145)			(0.0434)

•

Model 2. In C_t =f (In N_t, In PCl_t, InAR_t)

	Estimate	t-value	Adj R^2	F-value	DW statistic
Constant	0.237	0.27	0.990	1266.21	0.635
In N_t	0.683	29.61	Parameter instability : 2.501*		
In PCl_t	0.539	4.71			
In AR_t	-0.398	-3.26			
Stimulation Error Analysis					
	TIC	BP	VP	CP	
	0.005	1.03E-13	0.002	0.998	
Residual Analysis					
Normality (χ^2)	Skewness	Kurtosis	SD		
1.006 (0.6048)	-0.048	2.22	0.077		
Autoregression (F)	Heteroscedasticity (F)	ARCH (F)			RESET (F)
6.08	0.695	0.791			6.95
(0.0005)	(0.6552)	(0.5652)			(0.0029)

•

Model 3. $C_t = f(N_t, PCl_t, AR_t, Time)$

	Estimate	t-value	Adj R^2	F-value	DW statistic
Constant	-1261.12	-1.92	0.994	1505.83	1.609
N_t	0.876	7.12	Parameter instability : 1.837*		
PCl_t	1.567	5.37			
AR_t	-18.287	-1.41			
Time	30.180	2.76			
Stimulation Error Analysis					
	TIC	BP	VP	CP	
	0.022	7.54E-15	0.001	0.999	
Residual Analysis					
Normality (χ^2)	Skewness	Kurtosis	SD		
232.32 (0.0)	-1.22	5.91	173.47		
Autoregression (F)	Heteroscedasticity (F)	ARCH (F)			RESET (F)
3.44	3.03	1.10			0.457
(0.0147)	(0.0129)	(0.3821)			(0.6373)

•

Model 4. $\ln C_t = f(\ln N_t, \ln PCl_t, \ln AR_t, Time)$

	Estimate	t-value	Adj R^2	F-value	DW statistic
Constant	-4.52	-1.73	0.991	1023.51	0.748
$\ln N_t$	1.040	5.53	Parameter instability : 2.155**		
$\ln PCl_t$	0.916	4.07			
$\ln AR_t$	-0.295	-2.29			
Time	-0.040	-1.92			
Stimulation Error Analysis					
	TIC	BP	VP	CP	
	0.005	2.56E-13	0.002	0.998	
Residual Analysis					
Normality (χ^2)	Skewness	Kurtosis	SD		
0.652 (0.7219)	-0.165	2.46	0.073		
Autoregression (F)	Heteroscedasticity (F)	ARCH (F)			RESET (F)
4.88	0.756	1.05			7.76
(0.0023)	(0.6430)	(0.4115)			(0.0017)

Model 5. In C_t =f (In N_t, In PCl_t, In AR_t In C_{t-1})

	Estimate	t-value	Adj R^2	F-value	DW statistic
Constant	-0.004	-0.01	0.994	1476.77	1.37
In N_t	0.301	3.45	Durbin h: 2.788		
In PCl_t	0.300	2.83	Parameter instability : 1.445		
In AR_t	-0.217	-2.05			
In C_{t-1}	0.537	4.50			
Stimulation Error Analysis					
	TIC	BP	VP	CP	
	0.004	3.69E-13	0.001	0.999	
Residual Analysis					
Normality (χ^2)	Skewness	Kurtosis	SD		
0.1.65 (0.4379)	-0.110	3.26	0.060		
Autoregression (F)	Heterosced asticity (F)	ARCH (F)			RESET (F)
2.77	0.461	0.0004			5.92
(0.0774)	(0.8718)	(0.9833)			(0.0206)

Note:

1. *' and '**' indicate statistical significance at 5 and 1 per cent respectively.
2. C = Electricity Consumption in the State (Million Units)
3. N = Number of Electricity Consumers
4. PCI = Per Capita State Income (at 1980-81 prices)
5. AR = Average Price (Revenue) (at 1981-82 prices)
6. Figures in brackets are the corresponding p-values.

Table 3. Residual Analysis

	(Variables in logarithms)			
	C	N	AR	PCI
1. ADF unit root tests				
- Levels (Model 2)				
Standard Deviation	0.064	0.024	0.088	0.029
Skewness	0.054	0.343	0.427	-0.005
Excess kurtosis	0.292	0.823	-0.298	0.345
Normality (χ^2) p-value	0.4146	0.1323	0.4566	0.2589
Autocorln LM (F) p-value	0.7832	0.3342	0.4446	0.5325
Heteroscedasticity				
White (F) p-value	0.3250	0.4613	0.4303	0.2938
ARCH (F) p-value	0.8302	0.1887	0.3847	0.4882
2. ADF unit root tests				
- Differences (Model 1)				
Standard Deviation	0.072	0.027	0.096	0.030
Skewness	0.518	0.598	0.433	-0.112
Excess kurtosis	0.419	0.271	-0.194	0.070
Normality (χ^2) p-value	0.2827	0.2528	0.4631	0.6039
Autocorln LM (F) p-value	0.6162	0.4216	0.1230	0.2229
Heteroscedasticity				
White (F) p-value	0.7554	0.2437	0.9030	0.7851
ARCH (F) p-value	0.3148	0.3189	0.8155	0.7904
3. VAR Model (for 2 lags)				
Skewness	-0.026	0.317	1.505	-1.122
Excess kurtosis	0.138	1.218	-0.2440	0.053
Normality (χ^2) p-value	0.8099	0.4368	0.4243	0.1075
Autocorln LM (F) p-value	0.3787	0.0892	0.2167	0.8150
Heteroscedasticity				
White (F) p-value	0.3819	0.3996	0.3350	0.9856
ARCH (F) p-value	0.9169	0.4505	0.1594	0.4559
Vector normality χ^2 = 5.189 (0.1744)				
Vector autocorrelation F = 1.315 (0.1744)				
Vector heteroscedasticity F = 0.476 (0.9991)				

Note: Autocorln = Autocorrelation

Figures in brackets are the corresponding p-values.

Table 4. Results of Unit Root Tests

Variables (in log)	DW -Statistic for Variables (in log)	ADF test statistics		Inference
		Model 1 (with constant)	Model 2 (with trend+constant	
I Levels				
1. C	0.0176 (0.632)	-2.146	-2.554	DS with drift
2. N	0.0088 (0.632)	-2.825	-0.381	DS with drift
3. AR	0.919 (0.632)	-2.363	-2.603	DS with drift
4. PCI	0.0378 (0.659)	1.514	-0.038	DS with drift
II First Differences				
1. C	1.727 (0.645)	-5.614**	-6.042**	Stationary
2. N	0.862 (0.645)	-3.459*	-4.957**	Stationary
3. AR	2.199 (0.645)	-7.349**	-7.244**	Stationary
4. PCI	1.292 (0.673)	-3.029*	-3.684*	Stationary

Note:

1. '*' and '**' indicate statistical significance at 5 and 1per cent respectively.
2. Inference for the levels is based on Model 2 and for the differences on Model 1.
3. C = Electricity Consumption in the State (Million Units)
4. N = Number of Electricity Consumers
5. PCI = Per Capita State Income (at 1980-81 prices)
6. AR = Average Price (Revenue) (at 1981-82 prices)
7. Figures in brackets are approximate critical values at 5 per cent significance level (Sargan and Bhargava 1983:Table 1).

Table 5. Perron's Unit Root Test in the Presence of Structural Break

1. Consumption (C_t) Break year: 1983-84; Lags 2; TB/T = 0.61.

	Trend (*t*)	*DU*	*DT*	C_{t-1}	Critical
Estimate	0.0173	-0.197	0.002	-0.257	value 10%
t-value	1.374	-0.472	0.391	-1.837	-3.95
Residual Analysis					
	SD	Skewness	Kurtosis	Normality (χ^2)	
	0.063	0.247	3.216	1.512	(0.4695)
Autoregression (F)		Heteroscedasticity (F)		ARCH (F)	RESET (F)
0.347	(0.7097)	1.487	(0.2123)	0.031(0.8618)	0.010 (0.9206)

1. Consumption (C_t) Break year: 1987-88; Lag 1; TB/T = 0.71.

	Trend (*t*)	*DU*	*DT*	C_{t-1}	Critical
Estimate	0.016	-0.011	5.20E-05	-0.223	value 10%
t-value	1.711	-0.018	0.008	-2.022	-3.86
Residual Analysis					
	SD	Skewness	Kurtosis	Normality (χ^2)	
	0.070	-0.043	3.159	1.223	(0.5427)
Autoregression (F)		Heteroscedasticity (F)		ARCH (F)	RESET (F)
2.385	(0.1083)	0.775	(0.6407)	0.134(0.7172)	0.278 (0.6017)

3. Consumption (C_t) Break year: 1996-97; Lag 1; TB/T = 0.95.

	Trend (*t*)	*DU*	*DT*	C_{t-1}	Critical
Estimate	0.014	-8.792	0.090	-0.208	value 10%
t-value	2.011	-1.742	1.738	-2.191	-3.46
Residual Analysis					
	SD	Skewness	Kurtosis	Normality (χ^2)	
	0.067	0.081	3.554	2.954	(0.2283)
Autoregression (F)		Heteroscedasticity (F)		ARCH (F)	RESET (F)
1.637	(0.2104)	1.066	(0.4211)	0.802(0.3771)	0.315 (0.5783)

4. No. of consumers (N_t) Break year: 1979-80; Lags 5; TB/T = 0.50.

	Trend (t)	DU	DT	C_{t-1}	Critical value 10%
Estimate	0.021	0.708	-0.008	-0.222	
t-value	1.944	2.653	-2.482	-2.411	-3.96
Residual Analysis					
	SD	Skewness	Kurtosis	Normality (χ^2)	
	0.019	0.238	3.977	5.111	(0.0776)
Autoregression (F)		Heteroscedasticity (F)		ARCH (F)	RESET (F)
1.623	(0.2183)	0.431	(0.9312)	0.272(0.6069)	0.119 (0.7331)

5. Per capita income (PCl_t) Break year: 1985-86; Lags 3; TB/T = 0.66.

	Trend (t)	DU	DT	C_{t-1}	Critical value 10%
Estimate	0.0024	-1.901	0.022	-0.467	
t-value	1.64	-3.52	3.60	-3.209	-3.86
Residual Analysis					
	SD	Skewness	Kurtosis	Normality (χ^2)	
	0.022	-0.821	3.664	4.45	(0.1079)
Autoregression (F)		Heteroscedasticity (F)		ARCH (F)	RESET (F)
0.116	(0.8909)	0.375	(0.9555)	0.238(0.6299)	1.893 (0.1806)

Note:

1. Critical values are from Perron (1989 Table VI B).
2. TB/T = ratio of pre-break sample size to total sample size.
3. C = Electricity Consumption in the State (Million Units)
4. N = Number of Electricity Consumers
5. PCI = Per Capita State Income (at 1980-81 prices)
6. Figures in brackets are the corresponding p-values.

Table 6. Cointegration Analysis

Cointegration of C with	CRDW Statistic	Augmented Engle-Granger Test		
		Lag	ADF Statistic	Critical Value (10 %)
1. N, PCI, AR	0.635	0	-2.909	-4.034
	(0.641)	1	-2.381	-4.040
		2	-2.497	-4.046
2. N, PCI	0.618	0	-2.926	-3.618
	(0.661)	1	-2.910	-3.623
		2	-2.785	-3.627
3. N, AR	0.448	0	-1.903	-3.606
	(0.661)	1	-1.678	-3.610
		2	-1.503	-3.614
4. AR, PCI	0.109	0	-1.801	-3.618
	(0.661)	1	-1.256	-3.623
		2	-1.697	-3.627
5. PCI	0.072	0	-1.738	-3.157
	(0.681)	1	-1.125	-3.160
		2	-1.656	-3.164
6. AR	0.072	0	-1.360	-3.149
	(0.681)	1	-1.149	-3.152
		2	-1.305	-3.154
7. N	0.483	0	-2.133	-3.149
	(0.681)	1	-2.421	-3.152
		2	-1.834	-3.154

Note:

1. All variables are in logarithms.
2. CRDW = Cointegrating Regression Durbin-Watson statistic; figures in brackets are approximate critical values at 5 % significance level (Sargan and Bhargava 1983: Table 1).
3. C = Electricity Consumption in the State (Million Units)
4. N = Number of Electricity Consumers
5. PCI = Per Capita State Income (at 1980-81 prices)
6. AR = Average Price (Revenue) (at 1981-82 prices)

Table 7. Johansen and Juselius (J J) Cointegration Tests

1. Variables (in log): C, N, AR, PCI.
   Eigenvalues: 0.529, 0.226, 0.147, 3.8E-06

Null	Maximum Eigenvalue Test			Trace Test		
Ho :	Alternative	Statistic+	95 % CV	Alternative	Statistic+	95 % CV
r = 0	r = 1	21.81	27.1	r ≥ 1	33.83	47.2
r ≤ 1	r = 2	7.42	21.0	r ≥ 2	12.01	29.7
r ≤ 2	r = 3	4.60	14.1	r ≥ 3	4.60	15.4
r ≤ 3	r = 4	0.0001	3.8	r ≥ 4	0.0001	3.8

2. Variables (in log): C, N, PCI.
   Eigenvalues: 0.223, 0.174, 0.0015

Null	Maximum Eigenvalue Test			Trace Test		
Ho :	Alternative	Statistic+	95 % CV	Alternative	Statistic+	95 % CV
r = 0	r = 1	7.83	21.0	r ≥ 1	13.80	29.7
r ≤ 1	r = 2	5.92	14.1	r ≥ 2	5.96	15.4
r ≤ 2	r = 3	0.046	3.8	r ≥ 3	0.046	3.8

3. Variables (in log): C, AR, PCI.
   Eigenvalues: 0.399, 0.137, 2.79E-07

Null	Maximum Eigenvalue Test			Trace Test		
Ho :	Alternative	Statistic+	95 % CV	Alternative	Statistic+	95 % CV
r = 0	r = 1	15.83	21.0	r ≥ 1	20.40	29.7
r ≤ 1	r = 2	4.57	14.1	r ≥ 2	4.57	15.4
r ≤ 2	r = 3	8.6E-06	3.8	r ≥ 3	8.6E-06	3.8

4. Variables (in log): C, N, AR.
   Eigenvalues: 0.351, 0.172, 0.068.

Null	Maximum Eigenvalue Test			Trace Test		
Ho :	Alternative	Statistic+	95 % CV	Alternative	Statistic+	95 % CV
r = 0	r = 1	13.40	21.0	r ≥ 1	21.44	29.7
r ≤ 1	r = 2	5.86	14.1	r ≥ 2	8.04	15.4
r ≤ 2	r = 3	2.18	3.8	r ≥ 3	2.18	3.8

5. Variables (in log): C, AR.
   Eigenvalues: 0.301, 0.026.

Null	Maximum Eigenvalue Test			Trace Test		
Ho :	Alternative	Statistic+	95 % CV	Alternative	Statistic+	95 % CV
r = 0	r = 1	11.83	14.1	r ≥ 1	12.69	15.4
r ≤ 1	r = 2	0.85	3.8	r ≥ 2	0.85	3.8

6. Variables (in log): C, PCI.
Eigenvalues: 0.145, 9.74E-04

Null	Maximum Eigenvalue Test			Trace Test		
Ho :	Alternative	Statistic+	95 % CV	Alternative	Statistic+	95 % CV
$r = 0$	$r = 1$	5.18	14.1	$r \geq 1$	5.21	15.4
$r \leq 1$	$r = 2$	0.032	3.8	$r \geq 2$	0.032	3.8

7. Variables (in log): C, N.
Eigenvalues: 0.169, 0.116

Null	Maximum Eigenvalue Test			Trace Test		
Ho :	Alternative	Statistic+	95 % CV	Alternative	Statistic+	95 % CV
$r = 0$	$r = 1$	6.11	14.1	$r \geq 1$	10.17	15.4
$r \leq 1$	$r = 2$	4.07*	3.8	$r \geq 2$	4.07*	3.8

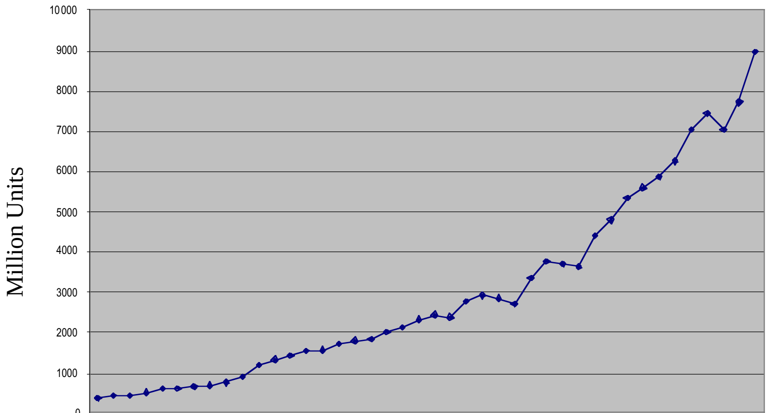
Note: + = Test statistics are with small sample correction.
* = Significant at 5 % level; CV = Critical value.

Table 8. Pair-wise Granger Non-'Causality' Tests

Null Hypothesis	p-values		
1. r (C) is not Granger-'caused' by			
Lags	r(N)	r(PCI)	r(AR)
1	0.975	0.650	0.743
2	0.631	0.939	0.166
3	0.990	0.934	0.350
4	0.962	0.888	0.323
5	0.967	0.864	0.417
6	0.984	0.349	0.577
2. r(C) does not Granger-'cause'			
Lags	r(N)	r(PCI)	r(AR)
1	0.190	0.391	0.234
2	0.270	0.414	0.165
3	0.289	0.803	0.068
4	0.049	0.716	0.158
5	0.096	0.461	0.233
6	0.322	0.154	0.418

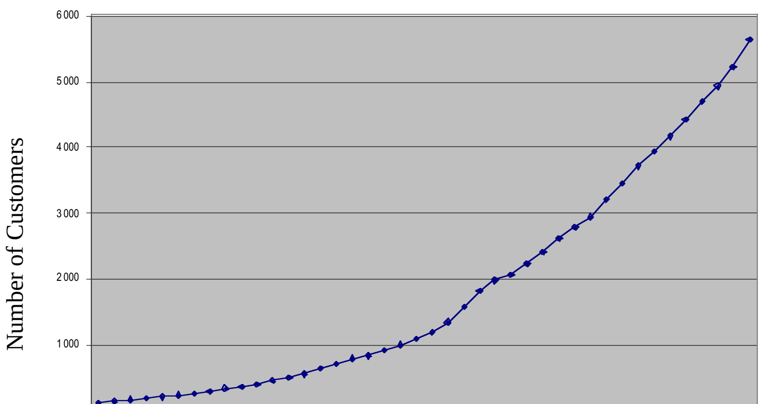
Note: r refers to growth rates (i.e., first differences of logarithmic series)

Electricity Consumption in Kerala



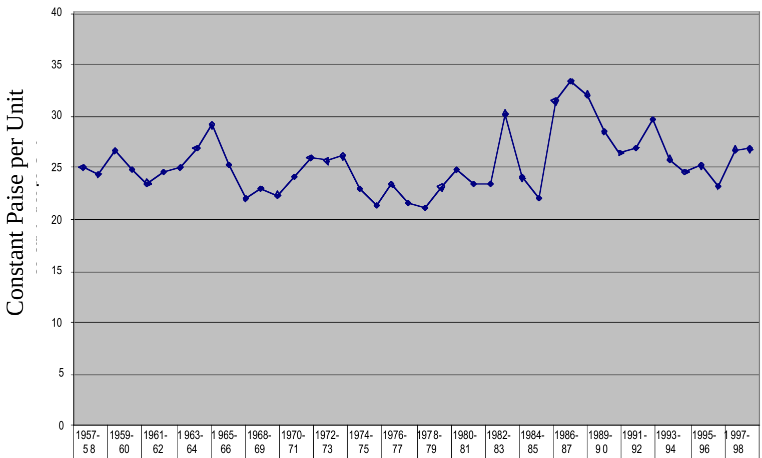
	1957-58	1959-60	1961-62	1964-65	1966-67	1968-69	1970-71	1972-73	1975-76	1977-78	1979-80	1981-82	1984-85	1986-87	1988-89	1990-91	1992-93	1995-96	1997-98
C	363	4233	6182	6826	905	1338	1531	1729	2015	2331	2384	2912	3376	3697	4387	5332	5839	7415	7716

Number of Electricity Consumers in Kerala



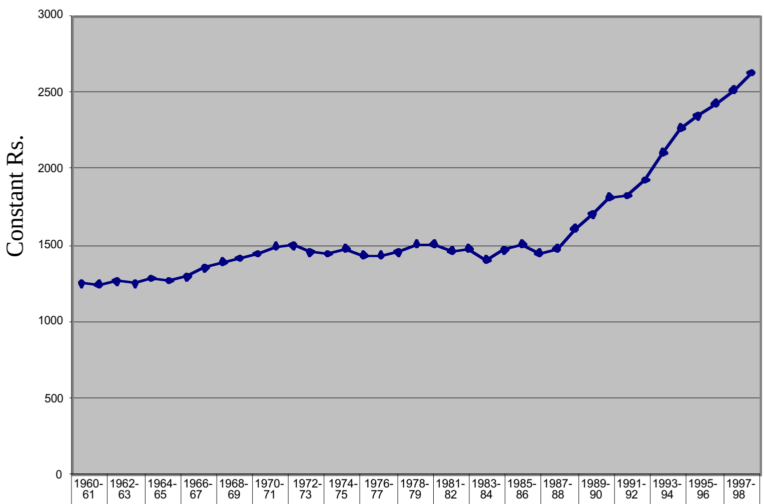
	1957-58	1959-60	1961-62	1963-64	1965-66	1968-69	1970-71	1972-73	1974-75	1976-77	1978-79	1980-81	1982-83	1984-85	1986-87	1989-90	1991-92	1993-94	1995-96	1997-98
N	1062	149.8	1988	242.1	325.1	4397	544	7112	8254	9886	1172	1569	1969	2217	2606	3192	3698	4154	4686	5211

Average Price (Revenue) of Electricity in Kerala (at 1981-82 Prices)



	1957-58	1959-60	1961-62	1963-64	1965-66	1968-69	1970-71	1972-73	1974-75	1976-77	1978-79	1980-81	1982-83	1984-85	1986-87	1989-90	1991-92	1993-94	1995-96	1997-98
RAR	24.93	26.61	23.49	24.93	29.09	22.99	24.13	25.63	22.97	23.34	21.1	24.74	23.48	23.99	31.43	28.46	26.93	25.78	25.13	26.71

Per Capita State Income (at 1980-81 Prices)



	1960-61	1962-63	1964-65	1966-67	1968-69	1970-71	1972-73	1974-75	1976-77	1978-79	1981-82	1983-84	1985-86	1987-88	1989-90	1991-92	1993-94	1995-96	1997-98
PCI	1261	1266	1286	1304	1391	1450	1501	1451	1443	1461	1469	1406	1507	1482	1705	1826	2114	2349	2519

APPENDIX

1. Unit Root Tests

We have seen that the decision as to whether to difference or to detrend a time series before proceeding with further analysis depends upon whether the series is DSP or TSP. This in turn depends, as we know, upon whether the root of the series $\rho = 1$ or $|\rho| < 1$. Hence the significance of unit root tests.

Consider the following model:

$$y_t = \alpha + \beta t + \rho y_{t-1} + u_t, \qquad (1)$$

where u_t is white noise. We consider the following possibilities:

1. When $\beta \neq 0$, $|\rho| < 1$, y_t has a linear trend and hence is a trend-stationary series.
2. When $\beta = 0$, then $y_t = \alpha + \rho y_{t-1} + u_t$. (2)

Here we have two cases:

i) if $|\rho| < 1$, y_t is a stationary series;
ii) if $\rho = 1$, y_t is a difference-stationary series with a drift term.

3. When $\alpha = \beta = 0$, then $y_t = \rho y_{t-1} + u_t$, (3)

The two cases here are:

i) if $|\rho| < 1$, y_t is stationary;
ii) if $\rho = 1$, y_t is a difference-stationary series without drift.

Now subtracting y_{t-1} from (3)

$$\Delta y_t = \gamma y_{t-1} + u_t, \qquad (3.b)$$

where $\gamma = (\rho - 1)$. Now, testing the null hypothesis Ho: $\gamma = 0$, in the usual way is equivalent to testing Ho: $\rho = 1$. Similarly, (1) and (2) can be rewritten as

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + u_t, \qquad (1.b)$$

$$\Delta y_t = \alpha + \gamma y_{t-1} + u_t. \qquad (2.b)$$

Now, in order to find out whether a series y_t has unit root (y_t is a non-stationary, integrated, process), run the regression (3) and find out if $\rho = 1$ statistically, against the one-sided alternative $|\rho| < 1$, or, equivalently, estimate (3.b) and find out if $\gamma = 0$, on the basis of e.g., the t-statistic. Dickey and Fuller (1979), however, show that this statistic does not follow Student's t-distribution, even in the limit as the sample size increases infinitely. The distribution of this statistic is known as (Dickey-Fuller) τ (tau) statistic, to distinguish it from the conventional t-statistic, whose critical values have been tabulated by Dickey and Fuller, and later on extended to a much wider range of sample sizes by MacKinnon (1990), both through Monte Carlo simulations. The numerator of this statistic is skewed to the right, being a $\chi^2(1)$ minus its expectation. Since $\mathrm{Prob}[\chi^2(1) \leq 1] \approx 0.70$, the majority of this statistic outcomes are negative. If the estimated τ–value is sufficiently more negative (i.e., less) than the critical value at the chosen significance level, we reject the null of unit root and accept the hypothesis of stationarity. This test is known as Dickey-Fuller (DF) unit root test.

In deriving the asymptotic distributions, Dickey and Fuller (1979, 1981) assumed that the errors u_t were iid$(0,\sigma^2)$. However, the limiting distributions obtained by them cease to be appropriate when the errors are non-orthogonal (i.e., serially correlated). Dickey and Fuller (1979) and Said and Dickey (1984) modified the DF test by means of AR correction. The new augmented Dickey-Fuller test (ADF) is carried out by estimating an autoregression of (y_t or) Δy_t on its own lags and y_{t-1} using OLS:

$$y_t = \rho y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + u_t ,$$

or

$$\Delta y_t = \gamma y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta y_{t-i} + u_t , \qquad (4)$$

When $\gamma = 0$, $\rho = 1$. The (t-) test statistic for the unit root null follows the same DF distribution (t –statistic) as above, so that the same critical values can be used.

Nelson-Plosser Test for TSP vs. DSP

Nelson-Plosser (1982) approach to unit root testing was a simple method of model selection between TSP ($y_t = \alpha + \beta t + u_t$) and DSP ($\Delta y_t = \alpha + u_t$) models (where u_t is stationary). However, they approached it as a test for a nested hypothesis. To test the hypothesis that a time series belongs to DSP against the alternative that it belongs to TSP, they employed ADF unit root test, starting with the TSP model with first-order autocorrelation in errors:

$$y_t = \alpha + \beta t + u_t; \; u_t = \rho u_{t-1} + e_t, \tag{5}$$

(a Bhargava (1986)-type formulation, in which the linear or quadratic trend problem, discussed above, does not arise).

The nested model is:

$$y_t = \alpha + \beta t + \rho [y_{t-1} - \alpha - \beta(t-1)] + e_t$$

$$= \delta_0 + \delta_1 t + \rho y_{t-1} + e_t, \tag{6}$$

where e_t is iid(0, σ^2) and $\delta_0 = \alpha(1 - \rho) + \rho\beta$ and $\delta_1 = \beta (1 - \rho)$. They included (in (6)) additional regressors Δy_{t-i} to correct the possible serial correlation in the errors, and tested the unit root null Ho: $\rho = 1$ and $\delta_1 = 0$. (Remember that the value of the constant δ_0 will not affect the asymptotic properties of the OLS estimators of ρ and δ_1, if the regression includes time as a regressor (see Frisch and Waugh 1933.) In the above testing procedure, if the unit root null is rejected, y_t belongs to TSP; otherwise, y_t belongs to DSP. They found that 13 of the 14 US macroeconomic time series belonged to DSP.

Other Unit Root Tests

We have seen that significant MA errors require a large number of lagged Δy_t terms as regressors in the ADF test model for AR correction. Since one effective observation is lost for each extra lagged term included, the power of the ADF test is adversely affected. Phillips and Perron's (1988) non-parametric unit root test (PP test) is valid even if the errors are serially correlated and heteroscedastic. However, this test has serious size distortions in finite samples when the data generating process (DGP) has significant negative autocorrelations in first differences (Phillips and Perron 1988; Schwert 1989; De Jong et al. 1992). However, Perron and Ng (1996) suggest some useful modifications of the PP test that solve this problem.

There is a voluminous literature on the theory and practice of unit root tests, as a large number of testing procedures have mushroomed ever since the Nelson-Plosser investigation. See for formal reviews: Fuller (1985), Perron (1988), and Diebold and Nerlove (1990); and for simple expository reviews: Dickey, et al. (1986), and Dolado et al. (1990). With Sims (1988), a Bayesian approach to unit roots testing also has drawn much attention; also see De Jong and Whiteman (1991 a, b), Sims and Uhlig (1991), and Koop (1992). It is interesting to note that there has followed a fierce interchange between Phillips (1991 a, b) and some Bayesian critics, Volume 6 (October – December 1991) of *The Journal of Applied Econometrics* being fully devoted to this debate.

Double Unit Roots Testing

The unit root test procedure we discussed above has been based on the assumption that the series y_t contains at most one unit root, i.e., $y_t \sim I(1)$. If the unit root null is not rejected, it may be necessary to find out whether the series contains a second unit root, i.e., whether y_t is I(2). Remember, I(2) implies that the series be differenced twice to make it stationary. The presence of a second unit root may be tested by estimating the regression of $\Delta^2 y_t$ on a constant, Δy_{t-1}, and the lagged values of $\Delta^2 y_t$, and comparing the 't-ratio' of the coefficient of Δy_{t-1} with the Dickey-Fuller critical values. Alternatively, the presence of two unit roots may be tested jointly by estimating the regression of $\Delta^2 y_t$ on y_{t-1}, Δy_{t-1}, and the lagged values of $\Delta^2 y_t$, and computing the usual F-statistic for testing the joint significance of y_{t-1} and Δy_{t-1}, using the critical values given as $\Phi_1(2)$ by Hasza and Fuller (1979).

However, the first of the above procedures using DF critical values is not justified theoretically, as DF type unit root tests are based on the assumption of *at most* one unit root. If, in fact, there are more than one unit root, the empirical size of such tests is greater than the nominal size, so that the probability of finding any unit root is reduced. Dickey and

Pantula (1987) suggest an alternative sequence of tests in this connection. To test the null hypothesis of unit roots against the alternative of one, estimate the regression of $\Delta^2 y_t$ on a constant and Δy_{t-1}, and then compare the 't-value' of the coefficient of Δy_{t-1} with the τ_μ tables in Fuller (1976). If the null is rejected, then we test the null hypothesis of exactly one unit root against the alternative of none by estimating the regression of $\Delta^2 y_t$ on a constant, y_{t-1}, Δy_{t-1}, and comparing the 't-ratio' of the coefficient of y_{t-1} with the τ_μ distribution.

2. Cointegration

In view of spurious regression with non-stationary variables, the usual conventional time series (Box-Jenkins) analysis of proceeding with suitably *differenced*, stationary, variables has gained much attraction. However, soon this temptation and trend fell under fire; solving the non-stationarity problem via differencing was equated to '*throwing the baby out with the bath water*', because differencing results in '*valuable long-run information being lost*'. Most of the economic relationships are stated in theory as long-term relationships between variables in their levels, not in their differences. We need to conserve and utilise in analysis this long-run information contained in the level variables, and at the same time, we have to be on the watch for spurious regression of integrated variables. Both these seemingly irreconcilable objectives could be achieved by means of *cointegration* mechanism.

In short, if, in a regression relationship between y_t and x_t, one of them is an integrated (stochastic) process (and the other deterministic), we have a case of spurious regression; if both variables are deterministic, the regression results are valid; but if both the variables are integrated processes, then the regression is spurious, *unless the variables are cointegrated.*

Phillips (1986: 321) shows that the usual least squares theory of stationary processes actually holds when the limiting covariance matrix of the model (y_t, x_t) is singular. In this case there exists a linear relationship between y_t and x_t such that the least squares coefficient estimator is consistent. This singularity is in fact a necessary condition for (y_t, x_t) to be cointegrtaed.

The concept of cointegration was introduced by Granger (1981) and Engle and Granger (1987), and is used as a statistical property to describe the long-run behaviour of economic time series.

We have explained earlier that a variable is integrated if it requires differencing to make it stationary. If the (non-stationary) series needs to be differenced d times to be stationary, then the series is said to be I(d). If two series y_t and x_t both are I(1), then in general, any linear combination of them will also be I(1); for example, data on income and consumption over a long period exhibit strong upward trends, and their difference (saving) also shows an upward trend. However, an important property of I(1) variables is that there can be some linear combinations of them that are in fact I(0), i.e., stationary. Thus, a set of integrated time series is cointegrated, if some linear combinations those (non-stationary) series is stationary.

Let us define u_t as:

$$u_t = y_t - \beta x_t, \tag{7}$$

where both y_t and x_t are I(1). If u_t is I(0), then y_t and x_t are said to be cointegrated, denoted by CI(1, 1). Since both the variables are I(1), they are dominated by 'long wave' components, i.e., they are on the same wave length. But u_t, being I(0), does not have these 'long wave' components as these 'trends' in y_t and x_t cancel out to produce stationary, I(0), u_t (see Griffiths, et al. 1993: 700-702). β is called the *constant of cointegration*. (If there are more than two variables, the set of values is called the *cointegrating vector*.) In general, if both y_t and x_t are I(d), then they are CI(d, b) if $u_t = y_t - \beta x_t$ is I(d – b), with b > 0.

Thus, if two variables are integrated of the same order (having the same 'wave length'), they can be cointegrated. In this light, the regression of these two variables, $y_t = \beta x_t + u_t$ makes sense (is not spurious), because the variables do not tend to drift apart from each other (i.e., they move together) over time. This then implies that there is a long-run equilibrium relationship between them.

A long run equilibrium is defined (e.g., in a bivariate case) by the relationship: $y_t = \beta x_t$ or $y_t - \beta x_t = 0$. Thus u_t given above (7) measures the extent to which the system (y_t, x_t) is out of equilibrium and is therefore called the ‘equilibrium error’ (Griffiths, et al. 1993: 701). Hence if both the variables are I(1), then the equilibrium error u_t will be I(0) and it will rarely drift away from long run equilibrium, say, zero, if it has zero mean, moving closely around (often crossing) the zero mean. These ‘crossings’, called ‘*mean-reverting*’ imply that equilibrium will occasionally occur (at least to a close approximation). If, on the other hand, the variables y_t and x_t are not cointegrated, such that $u_t \sim I(1)$, it (equilibrium error) will fluctuate widely with very rare zero-mean crossings, resulting in long-run disequilibrium (Mills 1990: 271).

Cointegration Tests

We have found that a time series is integrated, if it requires differencing to make it stationary, and a set of integrated series is cointegrated, if some linear combination of those non-stationary series is stationary. Thus, given two variables y_t and x_t, if they are indeed I(1) processes, verified through some unit root tests, a simple method of testing whether they are cointegrated is to estimate the ‘cointegrating regression’:

$$y_t = \alpha + \beta x_t + u_t \,, \tag{8}$$

and then test whether the residual u_t is I(0) or not.

Such residual-based procedures were the earliest cointegration tests, and Engle and Granger (1987) discuss two such simple tests of the implied null hypothesis that y_t and x_t are not cointegrated, [i.e., u_t is I(1)]. The first test is based on the DW statistic for (8) and tests, on the null that u_t is I(1), whether DW is significantly greater than zero using the critical values provided by Sargan and Bhargava (1983). Engle and Granger (1987), however, prefer the second test of using the t-ratio on u_{t-1} from the regression of Δu_t on u_{t-1} and lagged values of Δu_t, in a way analogous to the unit root (ADF) testing discussed earlier. The DF and ADF tests in this context are known as Engle-Granger (EG) test or Augmented Engle-Granger (AEG) test.

Engle and Granger (1987) and Engle and Yoo (1987) provide critical values of the appropriate distribution, which we denote τ_u, obtained by Monte Carlo simulations. Phillips and Ouliaris (1990) obtain the limiting asymptotic distribution of τ_u and provide critical values.

Since the asymptotic distributions differ according to different trend variables in cointegrating regression, they provide critical values in three parts, i.e., when the cointegrating regression contains no constant (nor trend), only a constant, and both a constant and a time trend. MacKinnon (1990) provides an approximation formula for computing critical values for all sample sizes, estimated using surface regressions. DF/ADF tests for unit roots and EG/AEG tests for cointegration are now built into several econometric software packages (e.g., MICROTSP 7.0, MICROFIT 3.0, ET, SHAZAM 7.0, etc.).

While Engle and Granger (1987) found the second test to have more stable critical values, Banerjee et al. (1986) preferred the DW statistic as its distribution is invariant to nuisance parameters such as a constant. Engle and Granger (1987) also point out that some seemingly obvious procedures of estimating the cointegrating parameter are inconsistent, e.g., regressing Δy_t on Δx_t and the use of Cochrane-Orcutt or some other serial correlation correction procedure in the cointegrating regression.

These single equation methods, however, cannot give us any indication of the number of cointegration relationships in the system. Hence the significance of system (multiple equation) methods. The most popular system method is the Johansen and Juselius (JJ) tests based on canonical correlations, involving two test statistics (Johansen 1988; Johansen and Juselius 1990). The first (trace test) tests the hypothesis that there are at most r cointegrating vectors, and the second (maximum eigenvalue test) tests the null hypothesis that there are r cointegrating vectors against the hypothesis that there are r+1 cointegrating vectors. Johansen and Juselius (1990) recommend the second test as better.

In the vector autoregression (VAR) model, all the variables are treated as endogenous, so that

$$\mathbf{Y_t} = \pi_i \mathbf{Y_{t-i}} + \mathbf{e_t} \text{ where } e_t \sim \text{iin}(0, \Omega) \text{ for all } i = 1, 2, \ldots, p. \tag{9}$$

When the set of series are I(1), the system can be formulated in terms of first differences in an equilibrium-correction form as (Hendry, Pagan and Sargan 1984; Engle and Granger 1987; Johansen 1988; Banerjee, Dolado, Galbraith and Hendry 1993):

$$\Delta \mathbf{Y_t} = \Sigma \delta_i \Delta Y_{t-i} + \gamma Y_{t-1} + e_t \text{ for all } i = 1, 2, \ldots, p-1. \quad (10)$$

The coefficient matrix γ is called the impact matrix and contains information on the long-run relationships among the variables in the system. When Y_t is I(1), then ΔY_t is I(0) and the system is balanced only if γY_{t-1} also is I(0). If γ has full rank (n), then the vector process Y_t is stationary; and if its rank (r) is equal to zero, γ is a null vector and (10) becomes equivalent to a traditional first-differenced VAR model. However, with the assumption that Y_t is I(1), γ cannot be full rank; and rank $(\gamma) = r < n$. Hence there exist r cointegrting I(0) linear combinations of Y_t. The impact matrix can then be written as $\gamma = \alpha\beta'$, where α and β are (n x r) matrices of rank r and $\beta' Y_t$ comprises r cointegrating stationary relations inducing the I(0) system:

$$\Delta \mathbf{Y_t} = \Sigma \delta_i \Delta \mathbf{Y_{t-i}} + \alpha (\beta' \mathbf{Y_{t-1}}) + \mathbf{e_t} \text{ for all } i = 1, 2, \ldots, p-1.$$

Johansen (1988) and Johansen and Juselius (1990) have derived the likelihood ratio test to determine the cointegrating rank (r) of γ. The null hypothesis that there are at most r (i.e., $0 \le r \le n$) cointegrating vectors (cvs) is tested using the trace test with the statistics:

$$\text{Trace} = -T\,\Sigma \log_e(1 - \lambda_i), \quad \text{for } i = r+1, \ldots, n \text{ and } r = 0, 1, \ldots, n-1,$$

where $\lambda_{r+1}, \lambda_{r+2}, \ldots, \lambda_n$ are the (n - r) smallest eigenvalues. This tests Ho: r cvs against H_1: > r cvs. Thus the first row tests Ho: r = 0 against H_1: r > 0; if this is significant, Ho is rejected and the next row is considered. Thus the rank (r) is chosen as the last significant statistic, or as zero if the first is not significant.

The likelihood ratio test statistic for the null hypothesis of r cointegrating vectors against the alternative of r+1 cointegrating vectors is the maximum eigenvalues using

$\lambda_{max} = -T \log_e(1 - \lambda_{r+1})$. This tests Ho: r cvs against H_1: r + 1 cvs. Thus the first row tests Ho: r = 0 against H_1: r = 1; if this is significant, Ho is rejected and the next row is considered.

The distributions of these statistics are functionals of vector Brownian motion and their critical values are tabulated by, *inter alia*, Johansen (1988) and Johansen and Juselius (1990). There is a potential problem with the size of these test statistics in small samples, that is, the JJ procedure tends to over-reject the null when it is true (Reimers 1992). Hence a small-sample correction is applied to these statistics, replacing T by T- np, where T is the number of observations, n is the number of variables and p is the lag length of the VAR.The JJ procedure is now programmed as specific commands in MICROFIT, PC-GIVE, E-VIEWS, and has a separate software package CATS in RATS.

3. Granger Causality

Consider the following equations:

$$Y_t = \Sigma\alpha_i Y_{t-i} + \Sigma\beta_i x_{t-i} + e_{1t}, \tag{11}$$

$$x_t = \Sigma\gamma_i Y_{t-i} + \Sigma\delta_i x_{t-i} + e_{2t}, \tag{12}$$

where the summations are for some lag length k, and e_{1t} and e_{2t} are independently distributed white noises.

(11) hypothesises that the current value of y is related to past values of y itself and those of x, while (12) postulates a similar behaviour for x.

We have the following implications:

i) *x does not 'Granger-cause' y* if, and only if, $\beta_i \equiv 0$, for all i, as a group. Thus the *measure of linear feedback* from x to y is zero (Geweke 1982). That is, the past values of x do not help to predict y. In this case, y is exogenous with respect to x (Engle et al. 1983).

ii) Similarly, *y does not 'Granger-cause' x,* if, and only if, $\gamma_i \equiv 0$ for all i as a group; the measure of linear feedback from y to x is zero. That is, the past values of y fail to help predict x. Here x is exogenous with respect to y. If the lagged terms have significant non-zero coefficients, then there is 'causality' or feedback in both directions.

The 'Granger non-causality' may be tested by estimating the general (unrestricted) model (11) [or (12)], and comparing the residual sum of squares from it with that from the restricted model without the lagged x values in (11) [or lagged y values in (12)] by means of an F-test.

Though 'Granger causality' is concerned with short run forecastability, while cointegration, with long run equilibrium, the two (different) concepts can be brought together in an error correction model (ECM). Suppose y_t and x_t are both I(1) series and they are cointegrated such that $u_t = y_t - \beta x_t$ is I(0). As we have seen earlier, this cointegrtaed system can be written in terms of ECM as:

$$\Delta y_t = -\delta_1 u_{t-1} + \text{lagged } \{\Delta y_t , \Delta x_t\} + \theta(L)\varepsilon_{1t}, \qquad (13)$$

$$\Delta x_t = -\delta_2 u_{t-1} + \text{lagged } \{\Delta y_t , \Delta x_t\} + \theta(L)\varepsilon_{2t}, \qquad (14)$$

where $\theta(L)\varepsilon_{1t}$ and $\theta(L)\varepsilon_{2t}$ are finite order moving averages and one of δ_1, $\delta_2 \neq 0$. In the ECM, the error correction term (EC), u_{t-1}, 'Granger causes' Δy_t or Δx_t (or both). As u_{t-1} itself is a function of y_{t-1} and x_{t-1}, either x_t is 'Granger caused' by y_{t-1} or y_t by x_{t-1}. That is, the coefficient of EC contains information on whether the past values of the variables 'affect' the current values of the variable under consideration. A significant coefficient implies that past equilibrium errors play a role in 'affecting' the current outcomes. This then implies that there must be some 'Granger causality' between the two series in order to induce them towards equilibrium. The short run dynamics are captured through the individual coefficients of the difference terms.

Though popularly known as Granger (non-) 'causality' test (Granger 1969), it was first suggested by Wiener (Wiener 1956), and is often referred to more properly as Wiener-Granger 'causality' test. This model has prompted a great deal of debate among economists (for example, Zellner 1979) and even philosophers (for example, Holland 1986).

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