MPRA
Munich Personal RePEc Archive

Electricity Demand Analysis Using Cointegration and ARIMA Modelling: A case study of Turkey

Erdogdu, Erkan
Energy Market Regulatory Authority, Republic of Turkey

2007

Electricity Demand Analysis Using Cointegration and ARIMA Modelling: A case study of Turkey

Erkan Erdogdu[a,b,*]

[a]*Energy Market Regulatory Authority, Ziyabey Cad. No:19 06520 Balgat/ANKARA TURKEY*

Abstract

In the early 2000s, the Republic of Turkey has initiated an ambitious reform program in her electricity market, which requires privatization, liberalization as well as a radical restructuring. The most controversial reason behind, or justification for, recent reforms has been the rapid electricity demand growth; that is to say, the whole reform process has been a part of the endeavors to avoid so-called "energy crisis". Using cointegration analysis and ARIMA modeling, the present article focuses on this issue by both providing an electricity demand estimation and forecast, and comparing the results with official projections. The study concludes, first, that consumers' respond to price and income changes is quite limited and therefore there is a need for

---

[*] Corresponding author. Tel.: +90-312-2872560
E-mail: erkan@erdogdu.net
URL: http://erkan.erdogdu.net/english

[b] The author is working as an Energy Expert in Energy Market Regulatory Authority of the Republic of Turkey. The present article is a part of the dissertation submitted by the author in fulfillment of the requirements for the award of the degree "MSc in Energy Economics and Policy". In October 2005, the author is awarded an "MSc with distinction" by the Department of Economics, University of Surrey (UK). The views, findings and conclusions expressed in this article are entirely those of the author and do not represent in any way the views of any institution he is affiliated with.

economic regulation in Turkish electricity market; and second, that the current official electricity demand projections highly overestimate the electricity demand, which may endanger the development of both a coherent energy policy in general and a healthy electricity market in particular.

Keywords: *Turkish electricity demand, cointegration, ARIMA modelling*

1. Introduction

The Republic of Turkey (hereafter Turkey) has initiated a major reform program of her energy market. The reform program entails privatization, liberalization as well as a radical restructuring of the whole energy sector, especially electricity industry. Also, an autonomous regulatory body, Energy Market Regulatory Authority (EMRA), was created to set up and maintain a financially strong, stable, transparent and competitive energy market.

The most controversial reason behind, or justification for, recent reforms has been the endeavor to avoid so-called “energy crisis”. Therefore, the present article focuses on the electricity demand in Turkey by presenting an electricity demand estimation and forecast. Besides, the econometric analysis here contributes to extremely limited literature in Turkish energy studies.

The article is organized as follows. The next section presents a literature review in energy demand studies. Section three concentrates on the scope of the study. Section four specifies the study methodology. Section five provides an overview of data used in the estimation and forecasting process. In section six, study results are presented; followed by evaluation of these results in section seven. The last section concludes.

2. Literature Review

The experiences of the 1970s and 1980s led to a blast in the number of energy demand studies, a trend that has been to some extent revitalized by the emergence of worries about the emissions of greenhouse gases from the combustion of fossil fuels. Therefore, since the early 1970s, various studies of energy demand have been undertaken using various estimation methods[1]. In most of these studies the purpose has been to measure the impact of economic activity and energy prices on energy demand, i.e. estimating income[2] and price[3] elasticities, which are of the utmost importance to forecasting energy demand. The evidence shows long-run income elasticities about unity, or slightly above, and the price elasticity is typically found to be rather small (Bentzen and Engsted, 1993).

In most cases, energy demand studies have adopted two different types of modeling; namely, "reduced form model" and "structural form model". The former is a double-log linear demand model under which energy demand is assumed to be a direct linear function of energy price and real income.

[1] Since economic theory and a priori knowledge indicates that the demand for energy in general depends on price and income, most of the studies in this area have been concentrated on these two variables as the major determinants of energy demand.
[2] The income elasticity of energy demand is defined as the percentage change in energy demand given a 1% change in income holding all else constant. This measure provides an indication of how demand will change as income changes.
[3] The price elasticity of energy demand is defined as the percentage change in energy demand given a 1% change in price holding all else constant. This measure calculates the influence of energy price on energy demand.

Kouris (1981), Drollas (1984) and Stewart (1991) have employed this model in their studies. Moreover, Dahl and Sterner (1991) report that more than sixty published studies applied the reduced form model. On the other hand, the second model is a disaggregated demand model based on the idea that the demand for energy is derived demand; that is, energy is not demanded for its own sake rather for the services it provides such as lighting, heating and power. It separates energy demand into several number of demand equations and treats it as an indirect, rather than direct, function of energy price and real income. Pindyck (1979) provides a detailed discussion of the structural form model. Although structural form model has various advantages over reduced form model from an economic point of view, its widespread utilization has been limited by the fact that it requires a large number of variables compared to the reduced form model.

Another model for energy demand estimation, namely “irreversibility and price decomposition model”, was first proposed by Wolffram (1971) and developed by Traill et al. (1978). Originally, it was based on the assumption that the response to price reductions would be less than that to price increases. This model was further improved by Dargay (1992) and Gately (1992), who introduced three-way price decomposition to isolate the effects on demand of price decrease, price increase below and above the historic maximum. Some of the work using this method includes that of Dargay and Gately (1995a, 1995b), Haas and Schipper (1998), Ryan and Plourde (2002), just to mention a few. However, it is important to note that most of the studies that applied this method could not find evidence of irreversibility.

Despite the relative popularity of the above methods, the long time span covered by these studies raises serious concerns about the validity of the fixed coefficients assumption in the electricity demand equation employed by these methods. This assumption in a double-log functional form of demand simply implies constant elasticities for the entire sample period under study. This feature of the model is indeed questionable in light of the changes that could have taken place in the economy over such a long period of time affecting the demand for electricity[4]. Therefore, it is argued that if data is collected over a relatively long time period to estimate an electricity demand function, the possibility that the parameters in the regression may not be constant should be considered. Furthermore; previous methods, in general, utilize time series data to estimate energy demand but they do not analyze the data to establish its properties and therefore they implicitly assume the data to be stationary, meaning that their means and variances do not systematically vary over time. However, this attractive data feature is lacking in most cases. Engle and Granger (1987) have developed a technique, popularly known as “cointegration and error correction method” (ECM), for analyzing time series properties and estimating elasticities based on this analysis, which enables full analysis of the properties of the relevant data before actual estimation. In their study, Engle and Granger have devised a model estimation procedure and recommended a number of tests, among which the most notable and commonly used is the Augmented Dickey-Fuller (ADF) test. Subsequent improvements related to this approach have been in the form of inclusion of more specific energy-related variables in the model and the development of new methods to identify cointegrating relationships,

[4] See Hass and Schipper (1998) for further discussion of the issue.

amongst which the Autoregressive Distributed Lag Model (ARDL) and the Johansen Maximum Likelihood Model (JML) – as outlined in Johansen (1988) – are especially popular.

Since the late 1980s, especially cointegration analysis has become the standard component of all studies of energy demand; and most scholars have done their data analysis based on cointegration. The popularity and widespread use of the cointegration originate from the fact that it justifies the use of data on non-stationary variables to estimate coefficients as long as the variables are cointegrated; that is, they have a long-run equilibrium relationship. Actually, this is also the basic reason for the use of cointegration technique in this study. The papers written in this area include that of Engle et al. (1989); Hunt and Manning (1989), Hunt and Lynk (1992), Bentzen and Engsted (1993, 2001), Fouquet et al. (1993), Hunt and Witt (1995); and Beenstock and Goldin (1999).

As for the history of energy demand projection in Turkey; although some efforts for the application of mathematical modeling to simulate the Turkish energy system were made during the late 1970s, the official use of such methods in energy planning and national policy making by the Ministry of Energy and Natural Resources (MENR) was realized only after 1984. The forecasts made before 1984 were simply based on various best fit curves developed by the State Planning Organization (SPO) and MENR. The year 1984 has been a milestone for energy planning and estimation of future energy demands in Turkey since, in that year, the World Bank recommended

MENR use the simulation model MAED[5] (Model for Analysis of Energy Demand) and WASP III (Wicn Automatic System Planning), which were originally developed by the IAEA (International Atomic Energy Agency) for determination of the general energy and electricity demands respectively. Besides, the energy demand model called EFOM-12 C Mark I that was developed by the Commission of the European Communities in 1984 was applied to Turkey. Furthermore, Kouris' correlation models were also applied for forecasting the primary and secondary energy demands in Turkey. Moreover, the BALANCE and IMPACT models were used in the context of ENPEP (Energy and Power Evaluation Program) for the long term supply and demand projections. Finally, State Institute of Statistics (SIS) and SPO have developed some mathematical models (Ediger and Tatlidil, 2002).

Since 1984, the Ministry (MENR) prepares energy production and demand projections in accordance with the growth targets given by SPO. Projections are made taking into account various factors including development, industrialization, urbanization, technology, conservation and so on. The figures are revised each year in the light of the performance over the past year (Ceylan and Ozturk, 2004). Unfortunately, the official forecasts have consistently predicted much higher values than the consumption actually occurred.

[5] The MAED is a detailed simulation model for evaluating the energy demand implications (in the medium and long term) of a scenario describing a hypothesized evolution of the economic activities and of the lifestyle of the population. It requires a number of data inputs from various sectors to simulate the energy demand for the desired years.

3. Scope of Study

One of the objectives of this article is to estimate a model of electricity demand in Turkey with a view to obtaining short and long run estimates of price and income elasticities. Also, an electricity demand forecast constitutes another aim of the article.

The model to be employed in demand estimation is a dynamic version of reduced form model, namely “partial adjustment model”. Also, a cointegration analysis is carried out to analyze the properties of the data. Furthermore, an annual electricity demand forecast is developed and presented based on autoregressive integrated moving average (ARIMA) modelling.

4. Theoretical and Methodological Framework

4.1. Cointegration Analysis

4.1.1. Stationarity and Unit Root Problem

Time series data consists of observations, which are considered as realizations of random variables that can be described by some stochastic process. The concept of “stationarity” is related with the properties of this stochastic process. In this paper, the concept of “weak stationary” is adopted; meaning that the data is assumed to be stationary if the means, variances and covariances of the series are independent of time, rather than the entire distribution.

Nonstationarity can originate from various sources but the most important one is the presence of so-called “unit roots”. Consider the AR(1) process below:

$$Y_t = \theta Y_{t-1} + \varepsilon_t \tag{1}$$

where ε_t denotes a serially uncorrelated white noise error term with a mean of zero and a constant variance. If $\theta = 1$, equation (1) becomes a random walk without drift model. If θ is in fact 1, we face what is known as the unit root problem, that is, a situation of nonstationarity. The name ”unit root”[6] is due to the fact that $\theta = 1$. If, however, $|\theta| \leq 1$, then the time series Y_t is stationary. The stationarity of time series is so important because correlation could persist in nonstationary time series even if the sample is very large and may result in what is called spurious (or nonsense) regression, as showed by Yule (1926). Granger and Newbold (1974) argue that it is a good rule of thumb to suspect that the estimated regression is spurious if R^2 is greater than Durbin-Watson d value; that is $R^2 > d$.

As easily be concluded from equation (1), the unit root problem can be solved, or stationarity can be achieved, by differencing and this can be indicative of the order of integration in the series. The basic idea behind cointegration is that if a linear combination of nonstationary $I(1)$ variables is stationary; that is $I(0)$, then the variables are said to be cointegrated. So to speak, the linear combination cancels out the stochastic trends in the two $I(1)$ series and, as a result, the regression would be meaningful; that is, not

[6] The terms ‘nonstationarity’, ‘random walk’, and ‘unit root’ can be treated as synonymous.

spurious[7]. As Granger (1986, p 226) notes, “A test for cointegration can thus be thought of as a pre-test to avoid ‘spurious regression' situations”. Therefore, it is vital to specify whether each variable in the model is stationary or not in order to examine a possible cointegrating relationship between them. The established way to do so is to apply a formal unit root test in each series.

4.1.2. The Augmented Dickey-Fuller (ADF) Test

We know that if $\theta = 1$; that is, in the case of unit root, the equation (1) becomes a random walk model without drift, which we know is a nonstationary process. The basic idea behind the unit root test of stationary is to simply regress Y_t on its (one-period) lagged value Y_{t-1} and find out if the estimated θ is statically equal to 1 or not.

For theoretical reasons, equation (1) is manipulated by subtracting Y_{t-1} from both sides to obtain:

$$Y_t - Y_{t-1} = (\theta - 1)Y_{t-1} + \varepsilon_t \tag{2}$$

which can be written as:

$$\Delta Y_t = \delta Y_{t-1} + \varepsilon_t \tag{3}$$

where $\delta = (\theta - 1)$ and Δ, as usual, is the first difference operator. So, in practice, instead of estimating equation (2), we estimate equation (3) and test the null hypothesis that $\delta = 0$. If $\delta = 0$, then $\theta = 1$, meaning that we have a

[7] As mentioned before, a regression of *I(1)* variables that are not cointegrated produces spurious regression, and the results obtained have no interpretation.

unit root problem and time series under consideration is nonstationary. The only question is which test to use to find out whether the estimated coefficient of Y_{t-1} in equation (3) is zero or not. Unfortunately, under the null hypothesis that $\delta = 0$ (i.e., $\theta = 1$), the t value of the estimated coefficient of Y_{t-1} does not follow *t* distribution even in large samples; that is, it does not have an asymptotic normal distribution. Dickey and Fuller (1979) have shown that under the null hypothesis that $\delta = 0$, the estimated *t* value of the coefficient of Y_{t-1} in equation (3) follows the τ (tau) statistic. These authors have also computed the critical values of the τ (tau) statistic. In literature tau statistic or test is known as the Dickey-Fuller (DF) test, in honor of its discoverers.

In conducting DF test, it is assumed that the error term ε_t is uncorrelated. However, in practice the error term in DF test usually shows evidence of serial correlation. To solve this problem, Dickey and Fuller have developed a test, known as the augmented Dickey-Fuller (ADF) test. In ADF test, the lags of the first difference are included in the regression in order to make the error term ε_t white noise and, therefore, the regression is presented in the following form:

$$\Delta Y_t = \delta Y_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta Y_{t-i} + \varepsilon_t \tag{4}$$

To be more specific, we may also include an intercept and a time trend t, after which our model becomes:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta Y_{t-i} + \varepsilon_t \tag{5}$$

The DF and ADF tests are similar since they have the same asymptotic distribution. In literature, although there exist numerous unit root tests, the most notable and commonly used one is ADF test and, therefore, it is used in this study.

4.1.3. Cointegration Tests

On the basis of the theory that $I(1)$ variables may have a cointegrating relationship; it is crucial to test for the existence of such a relationship. This article considers two most commonly used tests of cointegration; namely Augmented Engle-Granger (AEG) test and cointegrating regression Durbin-Watson (CRDW) test.

4.1.3.1. Augmented Engle-Granger (AEG) Test

We have warned that the regression of a nonstationary time series on other nonstationary time series may produce a spurious regression. If we subject our time series data individually to unit root analysis and find that they are all $I(1)$; that is, they contain a unit root; there is a possibility that our regression can still be meaningful (i.e., not spurious) provided that the variables are cointegrated. In order to find out whether they are cointegrated or not, we simply carry out our original regression and subject our error term to unit root analysis. If it is stationary; that is, $I(0)$, it means that our variables are cointegrated and have a long-term, or equilibrium, relationship between them. In short, provided that the residuals from our regression are $I(0)$ or stationary, the conventional regression methodology is applicable to data involving nonstationary time series.

Augmented Engle-Granger test (or, AEG test) is based on the idea described above. We simply estimate our original regression, obtain the residuals and carry out the ADF test. In literature, such a regression is called “cointegrating regression” and the parameters are known as “cointegrating parameters”. However, since the estimated residuals are based on the estimated cointegrating parameters, the ADF critical values are not appropriate. Engle and Granger (1987) have calculated appropriate values and therefore the ADF test in the present context is known as Augmented Engle-Granger test.

4.1.3.2. Cointegrating Regression Durbin-Watson (CRDW) Test

An alternative method of testing for cointegration is the CRDW test, whose critical values were first provided by Sargan and Bhargava (1983). In CRDW, the Durbin-Watson statistic d obtained from the cointegrating regression is used; but here the null hypothesis[8] is that d=0, rather than the standard d=2. The 1 percent critical value to test the hypothesis that the true d=0 is 0.511. Thus, if the computed d value is smaller than 0.511, we reject the null hypothesis of cointegration at the 1% level. Otherwise, we fail to reject the null, meaning that the variables in the model are cointegrated and there is a long-term, or equilibrium, relationship between the variables.

[8] We know that $d \approx 2(1-\hat{\rho})$, so if there is to be a unit root, the estimated ρ is about 1, which implies that d is about zero.

4.2. Partial Adjustment Model

In line with economic theory and a priori knowledge, this study starts with a single equation demand model expressed in linear logarithmic form linking the quantity of per capita electricity demand to real energy price and real income per capita.

The simplest model can be written as:

$$\ln E_t = \alpha + \beta_1 \ln P_t + \beta_2 \ln Y_t + u_t \qquad (6)$$

where E_t is per capita demand for electricity, P_t is the real price of electricity, Y_t is real income per capita, u_t is the error term, the subscript t represents time, α is intercept term; and finally β_1 and β_2 are the estimators of the price and income elasticities of demand respectively.

This simple "static" model (6) does not make a distinction between short and long run elasticities. Therefore, instead of this static one, a dynamic version of reduced form model, called "partial adjustment model", is used in this study to capture short-run and long run reactions separately. The partial adjustment model assumes that electricity demand cannot immediately respond to the change in electricity price and real income; but gradually converges toward the long run equilibrium. Suppose that E'_t is the desired or equilibrium electricity demand that is not observable directly but given by:

$$\ln E'_t = \alpha + \beta_1 \ln P_t + \beta_2 \ln Y_t + u_t \qquad (7)$$

and the adjustment to the equilibrium demand level is assumed to be in the form of

$$\ln E_t - \ln E_{t-1} = \delta(\ln E'_t - \ln E_{t-1}) \tag{8}$$

where δ indicates the speed of adjustment ($\delta > 0$). Substituting equation (7) into equation (8) gives:

$$\ln E_t - \ln E_{t-1} = \delta(\alpha + \beta_1 \ln P_t + \beta_2 \ln Y_t + u_t - \ln E_{t-1})$$
$$\ln E_t = \delta\alpha + \delta\beta_1 \ln P_t + \delta\beta_2 \ln Y_t + \delta u_t - \delta \ln E_{t-1} + \ln E_{t-1}$$

$$\ln E_t = \delta\alpha + \delta\beta_1 \ln P_t + \delta\beta_2 \ln Y_t + (1-\delta)\ln E_{t-1} + \delta u_t \tag{9}$$

where $\delta\beta_1$ and $\delta\beta_2$ are the short-run price and income elasticities respectively. The long-run price and income elasticities are given by β_1 and β_2 correspondingly. Since the error term δu_t is serially uncorrelated, consistent estimates of α, β_1, β_2 and δ can be obtained by OLS (Ordinary Least Squares).

4.3. Autoregressive Integrated Moving Average Modelling

The publication authored by Box and Jenkins (1978) ushered in a new generation of forecasting tools, technically known as the ARIMA methodology[9], which emphasizes on analyzing the probabilistic, or stochastic, properties of economic time series on their own rather than constructing single or simultaneous equation models. ARIMA models allow

[9] For a detailed discussion of ARIMA modelling, see Chapter 22 of Gujarati (2004, p 835).

each variable to be explained by its own past, or lagged, values and stochastic error terms.

If we have to difference a time series *d* times to make it stationary and apply the ARMA(p,q) model to it, we say the original time series is ARIMA(*p,d,q*). The important point to note in ARIMA modelling is that we must have either a stationary time series or a time series that becomes stationary after one or more differencing to be able to use it.

ARIMA methodology consists of four steps; namely, identification, estimation, diagnostic checking and, of course, forecasting. First of all, in the first step, we need to identify appropriate values of our model; that is, *p*, *d* and *q*. The chief tools in identification are the autocorrelation function (ACF), the partial autocorrelation function (PACF), and the resulting correlogram, which is simply the plots of ACF and PACF against the lag length.

The ACF at lag *k*, denoted by ρ_k, is defined as

$$\rho_k = \frac{\gamma_k}{\gamma_0} \tag{10}$$

where γ_k is the covariance at lag k, γ_0 is the variance. Since both covariance and variance are measured in the same units, ρ_k is a unitless, or pure, number; and lies between -1 and +1.

In time series data the main reason of correlation between Y_t and Y_{t-k} originates from the correlations they have with intervening lags; that is, Y_{t-1},

Y_{t-2}, … , Y_{t-k+1}. The partial correlation measures the correlation between observations that are *k* time periods apart after controlling for correlations at intermediate lags; that is, it removes the influence of these intervening variables. In other words, partial autocorrelation is the correlation between Y_t and Y_{t-k} after removing the effect of intermediate Y's.

If we find out, as a result of visual inspection of correlogram and/or formal unit root tests, that our data is nonstationary; we need to make it stationary by differencing until nonstationary fades away. Then, based on the stationary data after differencing and its correlogram, we identify the appropriate values of our model; that is, p, d and q.

In the second step; that is, estimation, the model based on the results from the first step is constructed and estimated, which is followed by diagnostic checking in the third step. To check whether the model is a reasonable fit to the data or not, we collect residuals from the estimation in previous step and check whether any of the autocorrelations and partial correlations of the residuals is individually statistically significant or not. If they are not statistically significant, then it means that the residuals are purely random and there is no need to look for another ARIMA model. In the final step, forecasting is carried out based on the constructed and checked ARIMA model.

5. Overview of Data

The data used in the estimation process is quarterly time series data on real electricity prices, real GDP per capita and net electricity consumption per capita for the period 1984-2004, a total of 84 observations. The data is obtained from the “International Energy Agency” (IEA), the “Organisation for Economic Co-operation and Development” (OECD), the “International Monetary Fund” (IMF) and some national institutions of Turkey; namely, the “State Institute of Statistics” (SIS), the “Turkish Electricity Transmission Company” (TEIAS), Undersecretariat of Treasury and State Planning Organization (SPO).

Since the data on net electricity consumption, population and GDP is not available quarterly, the annual series on these data are converted into quarterly data by linear interpolation so as to make use of them together with quarterly data on electricity prices. Specification of data and their sources are summarized in Appendix A.

Since one of the main aims of this study is to get elasticities of electricity demand, the series were transformed into natural logarithms so that direct estimates of elasticities can be obtained[10]. Graphs below show time series plots of natural logarithms of real electricity prices (LP), real GDP per capita (LY) and real net electricity consumption per capita (LE).

[10] The use of log-log specification only provides us with constant elasticities; however, elasticities may also be estimated from linear functions (or other specifications) that are not constant.

[“image1.bmp” goes here]

Figure 1. Time Series Plots of Natural Logarithms of LP, LY and LE

A close look at the graphs reveals that there are trends in the variables with the exception of LP, which fluctuates within an interval. Visual inspection of the plotted data also indicates that LY and LE have non-constant means and non-constant variances; that is, they seem to be non-stationary.

6. Presentation of Study Results

6.1. Partial Adjustment Model

Using quarterly data discussed in the previous section, the reduced form model is estimated[11]. Equation (6) is estimated as follows:

$$\ln E_t = -5.12 - 1.17 \ln P_t + 1.18 \ln Y_t \qquad (11)$$

In this model, p-values of α, β_1 and β_2 are all within acceptable range and the null hypothesis that one of these coefficients is zero can be rejected at the 2% significance level. As for “goodness-of-fit” measures, “R-squared” and “Adjusted R-squared” values are about 0.38 and 0.36 respectively; which cannot be regarded as high enough for an appropriate model.

[11] Unless otherwise stated, all estimation throughout the study is carried out by EViews 5.1, the Windows-based forecasting and econometric analysis package.

As to serial correlation, Durbin-Watson statistic in our estimation output is very close to 0.14, indicating the existence of serial correlation in the residuals. The p-value of the F-statistics is almost zero; so we can reject the null hypothesis that all slope coefficients in the regression are zero.

Although the coefficients of price and income have correct signs[12], econometric indicators imply that this equation may be misspecified. Therefore, the lagged dependent variable, $\ln E_{t-1}$, is added in the right-hand-side of the equation (6) so as to obtain partial adjustment model in equation (9), estimation of which gives the following result.

$$\ln E_t = -0.04 - 0.01 \ln P_t + 0.01 \ln Y_t + 0.99 \ln E_{t-1} \tag{12}$$

This new model is clearly better than the first one. First of all, the coefficients of price and income have still correct signs. Second, p-values of all coefficients, with the exception of intercept term, are within acceptable range and they are significant at 2% significance level[13]. Third, "R-squared" and "Adjusted R-squared" measures in this model are about 1, meaning that the regression fits almost perfectly. Finally, p-value of the F-statistics is still zero.

Based on this model, the estimated short-run and long-run elasticities of demand are as follows[14]:

---

[12] The economic theory states that there is an inverse relationship between demand and price; and a positive relation exists between demand and income.

[13] However, the p-value of the intercept term (0.44) is so high that we cannot reject the zero null hypotheses even at the 40% significance level!

[14] Relying on the notation in equation (9), estimated parameters are as follows:

$\delta\alpha = -0.041010 \quad \delta\beta_1 = -0.012257 \quad \delta\beta_2 = 0.014779 \quad (1-\delta) = 0.986500$

From above, it is obvious that $\delta = 0.0135$ and, therefore, $\beta_1 = -0.9079$ and $\beta_2 = 1.0947$.

Table 1. Elasticities of Demand for Electricity in Turkey, based on Conventional Partial Adjustment Model

	Short-run	**Long-run**
Price Elasticity	-0.0123	-0.9079
Income Elasticity	0.0148	1.0947

There seems to be a substantial difference between short-run and long-run elasticities of demand because, in this model, the speed of adjustment to the long-run equilibrium demand level is so close to 0 ($\delta = 0.0135$). The other, and probably more striking, outcome from this model is the fact that although short-run elasticities are extremely low, less than 0.02; the long-run response to both price and income changes is exceptionally high. For instance, according to this model, if real income doubles (or, increases by 100%) in Turkey, the demand for electricity increases by 109% in the long run. Similarly, if real price of electricity declines by 100%, the demand increases by 91% in the long run.

There is, however, a possibility that the OLS results may be misleading due to inappropriate standard errors because of the presence of heteroskedasticity. In order to test whether error terms are heteroskedastic or not, White heteroskedasticity test (without cross terms) is carried out. The probability value of 0.146 in this test indicates that they are not jointly significant even at 10% significance level; meaning that error terms are not heteroskedastic in our model.

We need also to test for serial correlation. Breusch-Godfrey Serial Correlation LM Test is applied. The (effectively) zero probability value in this test strongly indicates the presence of serial correlation in the residuals. In the presence of serial correlation, the OLS estimators are still unbiased as well as consistent and asymptotically normally distributed, but they are no longer efficient, meaning that standard errors are estimated in the wrong way and, therefore, usual confidence intervals and hypotheses tests are unreliable. Moreover, usually, the finding of autocorrelation is also an indication that the model is misspecified. Newey and West (1987) proposed a general covariance estimator that is consistent in the presence of both heteroskedasticity and autocorrelation. Thanks to Newey-West procedure[15], we can still use OLS but correct the standard errors for autocorrelation. However, when we correct the standard errors for autocorrelation, p-values of all coefficients become insignificant even at 10% significance level, supporting the previous indication that the model is misspecified.

Since it is obvious that conventional partial adjustment model is not the appropriate one in our case; after experimenting with various functional forms, the model below is specified and estimated.

$$\ln E_t = \phi_0 + \phi_1 \ln P_t + \phi_2 \ln Y_t + \phi_3 \ln P_{t-2} + \phi_4 t + \phi_5 \ln E_{t-2} + \varepsilon_t \qquad (13)$$

where $\ln E_{t-2}$ and $\ln P_{t-2}$ are the second lag of natural logarithms of demand and real price respectively; and t is a trend that increases by one for each observation[16].

[15] It is important to point out that the Newey-West procedure is strictly speaking valid in large samples and may not be appropriate in small ones. Since we have 84 observations, our sample may be regarded as reasonably large.
[16] The base period for the trend is the 29th observation, the 1st quarter of 1991; which has the lowest figure for real electricity price for the period 1984-1998. The trend in our model starts from -180 for the 1th quarter of 1984, then increases by one in each period; and at the end,

This last model is obviously the best one. The coefficients of price and income have correct signs. P-values of all coefficients, without exception, are significant at 5% significance level. "R-squared" and "Adjusted R-squared" measures indicate that the regression fits almost perfectly. P-value of the F-statistics is zero. White heteroskedasticity test (without cross terms) and Breusch-Godfrey Serial Correlation LM Test are carried out once more for the new model and the results indicate that we have no heteroskedasticity in our model but there exists serial correlation in the residuals. In order to correct the standard errors for autocorrelation, the model is re-estimated by OLS with Newey-West procedure and it is seen that all coefficients are still significant at 5% significance level.

Although all econometric indicators support the appropriateness of this model, a formal test for functional form, namely Ramsey's RESET test, is also carried out to make sure that our specification is correct. This test does not indicate a specification problem in our model at the 5% level of significance. That is, the model appears to be free from misspecification.

Based on these results, it seems that we need to respecify reduced form model for Turkish case. First of all, we need to readjust the desired or equilibrium electricity demand level (E'_t) in partial adjustment model as follows:

$$\ln E'_t = \alpha + \beta_1 \ln P_t + \beta_2 \ln Y_t + \beta_3 \ln P_{t-2} + \beta_4 t + u_t \qquad (14)$$

4[th] quarter of 2004, becomes -97. The time trend introduced here may be regarded as a proxy for technical progress.

Second, based on the model represented by equation (13), it is clear that partial adjustment process in Turkey operates as follows:

$$\ln E_t - \ln E_{t-2} = \delta(\ln E'_t - \ln E_{t-2}) \quad (15)$$

Substituting equation (14) into equation (15) and rearranging gives:

$$\ln E_t = \delta\alpha + \delta\beta_1 \ln P_t + \delta\beta_2 \ln Y_t + \delta\beta_3 \ln P_{t-2} + \delta\beta_4 t + (1-\delta)\ln E_{t-2} + \delta u_t \quad (16)$$

In order to simplify notation, equation (16) can be rewritten as:

$$\ln E_t = \phi_0 + \phi_1 \ln P_t + \phi_2 \ln Y_t + \phi_3 \ln P_{t-2} + \phi_4 t + \phi_5 \ln E_{t-2} + \varepsilon_t \quad (17)$$

where $\phi_0 = \delta\alpha$, $\phi_1 = \delta\beta_1$, $\phi_2 = \delta\beta_2$, $\phi_3 = \delta\beta_3$, $\phi_4 = \delta\beta_4$, $\phi_5 = (1-\delta)$ and $\varepsilon_t = \delta u_t$. In equation (17)[17], ϕ_1 and ϕ_2 are the short-run price and income elasticities respectively. The long-run price and income elasticities are given by β_1 and β_2 correspondingly. Therefore, based on our estimation results given below, the short-run and long-run elasticities of demand for electricity in Turkey are as follows[18]:

$$\ln E_t = 0.653 - 0.041 \ln P_t + 0.057 \ln Y_t + 0.017 \ln P_{t-2} + 0.002t + 0.862 \ln E_{t-2} \quad (18)$$

[17] Please note that equations (17) and (13) are identical.

[18] Relying on the notation in equation (17), elasticities are obtained as follows:

$$\phi_1 = \delta\beta_1 = -0.041 \quad \phi_2 = \delta\beta_2 = 0.057 \quad (1-\delta) = 0.862$$

From above, it is obvious that $\delta = 0.138$ and, therefore, $\beta_1 = -0.297$ and $\beta_2 = 0.414$.

Table 2. Elasticities of Demand for Electricity in Turkey, based on Readjusted Partial Adjustment Model

	Short-run	Long-run
Price Elasticity	-0.041	-0.297
Income Elasticity	0.057	0.414

Now, there seems to be less difference between short-run and long-run elasticities of demand because, in this new model, the speed of adjustment to the long-run equilibrium demand level ($\delta = 0.138$) is much higher, meaning that now it takes demand less time to reach long run equilibrium. Furthermore, it is clear that the long run demand is relatively elastic compared to short run demand. Moreover, the level of income has more effect on demand than that of prices. As also suggested by economic theory, the demand is most responsive to income changes in the long run. According to this model, in Turkey, if real income increases by 100%, electricity demand increases by 41% in the long-run.

6.2. Cointegration Analysis

As indicated before, since it is critical to find out whether the results obtained from our model are meaningful (i.e., not spurious) or not, let me apply formal unit root tests in each series to test the reliability of our estimates.

6.2.1. The Augmented Dickey-Fuller (ADF) Test

The established standard procedure for cointegration analysis is to start with unit root tests on the time series data being analyzed. The augmented

Dickey-Fuller (ADF) test is used to test for the presence of unit roots and establish the order of integration of the variables in the model. The table below shows the results of the unit root tests[19] from estimation of equation (5). The null hypothesis of the test is that there is a unit root against the alternative one that there is no unit root in the variables.

Table 3. Summary of ADF Tests for Unit Roots in the Variables (in level form with a trend and intercept)

Variable	ADF Test Statistic	Results
LNE	-1.008983	Fail to reject the null
LNP	-2.627504	Fail to reject the null
LNY	-2.614160	Fail to reject the null

Note: The ADF statistic at 5% significance is -3.466248.

The ADF statistics for the natural logarithms of electricity demand (LNE), real electricity prices (LNP) and real income (LNY) are all insignificant at 5 percent level of significance, which leads to non-rejection of the null hypothesis that there is a unit root problem in the variables. Based on ADF test, it is obvious that the variables are non-stationary.

As mentioned previously, differencing has the effect of making the variables stationary. The table below summarizes the results of unit root tests for the differenced variables.

[19] Since equation (17) implies that the electricity demand in time t is affected by the second lag of the variables; two lags have been used in ADF unit root tests.

Table 4. Summary of ADF Tests for Unit Roots in the Variables (in 1st difference form with a trend and intercept)

Variable	ADF Test Statistic	Results
Δ LNE	-4.569026	Reject the null
Δ LNP	-13.98314	Reject the null
Δ LNY	-38.88917	Reject the null

Note: The ADF statistic at 5% significance is -3.466966.

The ADF statistics for the first difference variables are all significant at 5 percent level of significance, which leads to rejection of the null hypothesis that there is a unit root problem in the variables. Based on ADF test, it is apparent that the first difference variables are stationary, which implies that the variables are integrated of order one, $I(1)$.

6.2.2. Cointegration Tests

6.2.2.1. Augmented Engle-Granger (AEG) Test

The residuals from the estimation of equation (17) were used to test for the existence of cointegrating relationship between the variables. The null hypothesis is that the residuals have a unit root problem against the alternative that the variables cointegrate. The result of AEG test[20] is presented in the table below.

[20] The test is carried out by Microfit 4.1.

Table 5. Summary of AEG Test Output for Equation (17)

Variable	ADF Test Statistic	Result
Residuals	-5.3643	Reject the null

Note: 95% critical value for the Dickey-Fuller statistic is -4.9387.

It is clear that absolute value of ADF test statistic is more than the critical value, meaning that the null hypothesis is rejected. To reject the null hypothesis implies that the residuals have not a unit root problem; i.e., they are stationary. It can therefore be concluded that, based on the AEG method, the variables are cointegrated.

6.2.2.2. Cointegrating Regression Durbin-Watson Test

Since cointegration is very crucial to the reliability of estimated parameters, a second test, namely CRDW test, was carried out to make sure that the variables in this study are definitely cointegrated. The Durbin-Watson statistic for the regression represented by equation (17) is 0.559, which is above the 1% critical value of 0.511. Therefore, we fail to reject the null hypothesis of cointegration at the 1% level, which reinforces the finding on the basis of the AEG test.

To sum up, our conclusion based on both the AEG and CRDW tests is that the variables LNE, LNP and LNY are cointegrated. Although they individually exhibit random walks, there seems to be a stable long-run relationship between them; they do not wander away from each other in the long-run.

Based on these results, we may conclude that the appropriate model for Turkish electricity demand is the one represented in equation (17) and that our estimates are reliable; that is, not spurious.

6.3. Electricity Demand Forecast for Turkey: 2005-2014

6.3.1. Data and Methodology

Before starting the forecast, it is important to make some points clear. First of all, data used here is annual data covering the period 1923[21]-2004, a total of 82 observations. Also, unlike previous section, the data here is not converted into natural logarithms and, therefore, the unit is GWh.

In literature, there are five main approaches to economic forecasting based on time series data; namely, (1) exponential smoothing methods, (2) single-equation regression models, (3) simultaneous-equation regression models, (4) autoregressive integrated moving average models (ARIMA), and (5) vector autoregression. Although still used in some areas, the first group of models is now supplanted by the other four methods; therefore, we don't use them in this study. Taking into account rather low estimates of elasticities obtained in previous section[22], it seems better not to include price and income variables in the forecasting process and "let the demand data speak for itself", which is the main philosophy behind ARIMA modelling. Since the second, third and the fifth group of models require the inclusion of price,

[21] The Republic of Turkey was founded in 1923.
[22] Low elasticities imply that responsiveness of demand to price and income changes is rather limited, meaning that a forecast linking price and income to consumption may not produce healthy results.

income and some other variables in the forecasting process; they are also not used here. In short, this section develops an electricity demand forecast for Turkey based on ARIMA modelling.

6.3.2. Development of the Model

As mentioned before, ARIMA modelling consists of four steps. In the first step, namely identification step, we need to identify the appropriate parameters in our model, that is, ARIMA(*p,d,q*). The figure below provides us with the correlogram up to 40 lags, or the plots of ACF and PACF against the lag length of 40.

[“image2.bmp” goes here]

Figure 2. The Correlogram of Turkish Electricity Consumption Data up to 40 lags

The column labeled AC and PAC are the sample autocorrelation function and the sample partial autocorrelation function respectively. Also the diagrams of AC and PAC are provided on the left. The solid and dashed vertical lines in the diagram represent the zero axis and 95% confidence interval respectively. From this figure, two facts stand out: First, the autocorrelation coefficient starts at a very high value at lag 1 (0.937) and declines very slowly; and ACF up to 16 lags are individually statistically significant different from zero as they are all outside the 95% confidence bounds. Second, after the first lag, the PACF drops dramatically, and all PACFs after lag 1 are statistically insignificant. These two facts strongly support the idea that the electricity consumption time series is nonstationary. It may be nonstationary in mean or variance, or both.

Since the data is nonstationary, we have to make it stationary. The figures below show the correlograms of the first and second differenced data up to 40 lags.

[“image3.bmp” goes here]

Figure 3. The Correlogram of the First-Differenced Data up to 40 lags

[“image4.bmp” goes here]

Figure 4. The Correlogram of the Second-Differenced Data up to 40 lags

We still observe a trend in the first-differenced consumption time series but this trend disappears in the second-differenced one, perhaps suggesting that the second-differenced data is stationary. A formal application of the ADF unit root test shows that that is indeed the case.

In Figure 4, we have a much different pattern of ACF and PACF. The ACFs at lags 1, 3 and 4; and PACFs at 1, 2, 4, 6 and 13 seem statistically different from zero. But at all other lags, they are not statistically different from zero. If the partial correlation coefficient were significant only at lag 1, we could have identified this as an AR(1) model. Let us therefore assume that the process that generated the second-differenced consumption is at most an AR(13) process. Since from the partial correlogram we know that only the AR terms at lag 1, 2, 4, 6 and 13 are significant, we only need to include these AR terms in our model. Therefore at the end of the first step we may conclude that the original time series is ARIMA(13,2,0); that is, the second differenced stationary data can be modeled as an ARMA(13,0) process.

The second step in ARIMA modelling is estimation. Let E_t^* denote the second-differenced data. Then, in line with the conclusion in the first step, our model is:

$$E_t^* = \delta + \alpha_1 E_{t-1}^* + \alpha_2 E_{t-2}^* + \alpha_4 E_{t-4}^* + \alpha_6 E_{t-6}^* + \alpha_{13} E_{t-13}^* + u_t \qquad (19)$$

Using EViews, we obtained the following estimates:

$$E_t^* = 275.93 - 0.56E_{t-1}^* - 0.44E_{t-2}^* - 0.62E_{t-4}^* - 0.56E_{t-6}^* + 0.54E_{t-13}^* \quad (20)$$

In the third step; that is, diagnostic checking, we obtain residuals from (20) and get the ACF and PACF of these residuals up to lag 40 in order to check that the model represented by equation (20) is a reasonable fit to the data. The estimated ACF and PACF are shown below.

[“image5.bmp” goes here]

Figure 5. The Correlogram of the Residuals from Equation (20)

As can be seen in Figure 5, none of the autocorrelations and partial correlations is individually statistically significant. In other words, the correlograms of both autocorrelation and partial autocorrelation give the impression that the residuals estimated from regression (20) are purely random. Hence, there is not any need to look for another ARIMA model.

The final step is forecasting. However, we need to integrate the second-differenced series to obtain the forecast of consumption rather than its changes. We know that the following formula integrates data from second-differenced form into level form.

$$E_t^* = E_t - 2E_{t-1} + E_{t-2} \tag{21}$$

If we transform all variables in equation (19) based on this formula and rearrange it, our model becomes:

$$\begin{aligned} E_t \;=\; & \delta + (2+\alpha_1)E_{t-1} + (\alpha_2 - 2\alpha_1 - 1)E_{t-2} + (\alpha_1 - 2\alpha_2)E_{t-3} \\ & + (\alpha_2 + \alpha_4)E_{t-4} - 2\alpha_4 E_{t-5} + (\alpha_4 + \alpha_6)E_{t-6} - 2\alpha_6 E_{t-7} \\ & + \alpha_6 E_{t-8} + \alpha_{13}E_{t-13} - 2\alpha_{13}E_{t-14} + \alpha_{13}E_{t-15} + u_t \end{aligned} \tag{22}$$

The values of δ, α_1, α_2, α_4, α_6 and α_{13} are already known from the estimated regression (20) and u_t is assumed to be zero, which enables us to convert equation (22) into equation (23). Using equation (23), we may easily obtain the forecast values for the period 2005-2014.

$$\begin{aligned} E_t \;=\; & 275.93 + 1.44E_{t-1} - 0.32E_{t-2} + 0.32E_{t-3} - 1.06E_{t-4} \\ & + 1.23E_{t-5} - 1.17E_{t-6} + 1.11E_{t-7} - 0.56E_{t-8} \\ & + 0.54E_{t-13} - 1.08E_{t-14} + 0.54E_{t-15} \end{aligned} \tag{23}$$

6.3.3. Validation

Before presenting the results, it is useful to validate the present model with observed data. In order to do this, electricity demand is calculated by equation (23) supposing that present year is 1999; that is, five years observed data is used for validation. As can be seen in the table below, the results from ARIMA model deviates from the observed data 2.2% on average, which may definitely be regarded as within the acceptable range.

Table 6. Validation of ARIMA Modelling

Year	Forecasted Net Electricity Consumption (GWh)	Annual % Change	Index (1999=100)	Actual Net Electricity Consumption (GWh)	Annual % Change	Index (1999=100)	Absolute Value of Deviation	Deviation as a Percentage of Actual Consumption
2000	98,788	8.3	108	98,296	7.8	108	492	0.5
2001	101,167	2.4	111	97,070	-1.2	106	4,097	4.2
2002	105,143	3.9	115	102,948	6.1	113	2,195	2.1
2003	111,053	5.6	122	111,766	8.6	123	713	0.6
2004	112,466	1.3	123	116,561	4.3	128	4,095	3.5

Note: Average deviation as a % of actual consumption is ***2.2***

6.3.4. Presentation of the Results

By using equation (23), net electricity demand forecasts are obtained for Turkey up to the year 2014. As given below, the results from ARIMA modelling clearly indicate that average annual percentage increase in electricity consumption will be 3.3% during the following decade.

Table 7. Demand Forecast for Turkey, 2005-2014

Year	Forecasted Net Electricity Consumption (GWh)	Annual % Change	Index (2004=100)
2005	129,311	10.9	111
2006	132,631	2.6	114
2007	138,134	4.1	119
2008	146,365	6.0	126
2009	145,144	-0.8	125
2010	155,667	7.3	134
2011	156,010	0.2	134
2012	158,150	1.4	136
2013	169,210	7.0	145
2014	160,090	-5.4	**137**

*Note: Average annual % change is **3.3***

7. Evaluation of Study Results

As a result of estimation and forecasting procedure outlined above, the results given in Table 2 and Table 7 are obtained. Having obtained both the elasticities of electricity demand in Turkey and forecasted values for this demand, let me interpret the results and compare them with the official estimates that are available from TEIAS (2005c).

The estimated elasticities indicate that the price and income elasticities of electricity demand in Turkey are quite low, meaning that there is definitely a need for economic regulation in Turkish electricity market. Otherwise, since consumers do not react much especially to price increases, the firms with monopoly power (or those in oligopolistic market structure) may abuse their power to extract “monopoly rent”.

As to forecasted net electricity consumption values, it is obvious that there exists an electricity demand growth in Turkey; and in the following decade (i.e., 2005-2014), based on ARIMA modelling, we may argue that the demand will continue to increase at an annual average rate of 3.3% and will turn out to be 160,090 GWh in 2014, corresponding to a 37% increase compared to 2004 demand level.

As for comparison of our results with official demand projections, the official projections are available from TEIAS (2005c) and provided below. However, the official forecasts are for gross demand; and, therefore, they need to be converted into net consumption for a meaningful comparison. The details of this conversion are provided in Appendix B and the result is presented in the table below. Also, official estimates are based on two different scenarios and therefore formulated in two different ways. Average annual percentage increase in net electricity consumption is 8.2% in Scenario 1; and 6.3% in Scenario 2.

Table 8. Official Projections for Electricity Demand

Year	Official Projections for Gross Electricity Consumption (GWh)		Average Total Int. Cons. and Net. Losses as a % of Gross Cons.	Official Projections for Net Electricity Consumption (GWh)		Annual % Change in Net Electricity Consumption		Index (2004=100)	
	Scenario 1	Scenario 2		Scenario 1	Scenario 2	Scenario 1	Scenario 2	Scenario 1	Scenario 2
2005	159,650	159,650	22.3	124,048	124,048	6.4	6.4	106	106
2006	176,401	169,517	22.3	137,064	131,715	10.5	6.2	118	113
2007	190,700	180,248	22.3	148,174	140,053	8.1	6.3	127	120
2008	206,400	191,677	22.3	160,373	148,933	8.2	6.3	138	128
2009	223,500	203,827	22.3	173,660	158,374	8.3	6.3	149	136
2010	242,021	216,747	22.3	188,050	168,412	8.3	6.3	161	144
2011	262,000	230,399	22.3	203,574	179,020	8.3	6.3	175	154
2012	283,501	244,951	22.3	220,280	190,327	8.2	6.3	189	163
2013	306,100	260,401	22.3	237,840	202,332	8.0	6.3	204	174
2014	330,301	276,799	22.3	256,644	215,073	7.9	6.3	**220**	**185**

*Note: Average annual % change in net electricity consumption is **8.2** for Scenario 1; and **6.3** for Scenario 2*

The table below compares the results from ARIMA modelling with official projections based on two different scenarios.

Table 9. The Comparison of ARIMA Results with Official Projections

Year	Official Projections for Net Electricity Consumption (GWh)		Forecasted Net Elec. Cons. based on ARIMA Modelling (GWh)	Difference		Difference as a % of Forecasts based on ARIMA Modelling	
	Scenario 1	Scenario 2		Scenario 1	Scenario 2	Scenario 1	Scenario 2
2005	124,048	124,048	129,311	-5,263	-5,263	4	4
2006	137,064	131,715	132,631	4,433	-916	3	1
2007	148,174	140,053	138,134	10,040	1,919	7	1
2008	160,373	148,933	146,365	14,008	2,568	10	2
2009	173,660	158,374	145,144	28,516	13,230	20	9
2010	188,050	168,412	155,667	32,383	12,745	21	8
2011	203,574	179,020	156,010	47,564	23,010	30	15
2012	220,280	190,327	158,150	62,130	32,177	39	20
2013	237,840	202,332	169,210	68,630	33,122	41	20
2014	256,644	215,073	160,090	96,554	54,983	**60**	**34**

The most outstanding outcome from the comparison is the fact that there is a substantial difference between official projections and forecasts based on ARIMA modelling. If we suppose that ARIMA results are valid; for 2014, Scenario 1 and 2 inflate electricity demand by 60% and 34% respectively. To put it in a different way, if we take electricity demand in 2004 as 100 units; ARIMA modelling suggests that the demand will turn out to be 137 units in 2014, while official projections imply that it will turn out to be either 220 or 185 units depending on the scenario adopted.

There exist two important points to keep in mind while evaluating (and perhaps using) these results. First of all, forecasting, especially in energy demand, is considered more an art than a science; therefore, some variations are to be expected depending on the model’s underlying assumption(s). Like all other models, ARIMA modelling is based on some assumption(s) and, of course, there is a direct link between the accuracy of the forecast and the validity of the underlying assumption(s). The main assumption behind ARIMA modelling is that the already existing trends in electricity consumption will more or less repeat themselves in the future. Despite the fact that this is a widely used, essential and reasonable assumption; some unanticipated events may also occur and it is always very difficult, if not impossible, to foresee such "unexpected" events that have a potential to completely change the electricity demand trend in Turkey reducing the precision of the forecasts presented here. Second, due to nature of ARIMA modelling and the low elasticities obtained, present study has only employed net total consumption data for forecasting. There is an apparent need for further work with more variables that will examine the demand of different sectors (e.g., industry, households etc.) separately, which is not only essential for policy formulation in Turkey but also will make more detailed and accurate understanding of the trends possible.

Ozturk et al. (2005) conclude that official total electricity demand projection for the period of 1996–2001 overestimated demand by 36% either due to inappropriateness of the model used or in order to justify the construction of new electric power plants to use excess amount of natural gas. In line with this conclusion; in this study, we find that the official net electricity consumption projection for 2014 again overestimates demand at least by 34% compared to the forecasted values based on ARIMA modelling.

8. Conclusion

The main objectives of this article have been, first, to estimate short and long run price and income elasticities of electricity demand in Turkey; and, second, to forecast future growth in this demand using ARIMA modelling and compare the results with official projections.

In the course of study, elasticities are obtained and it is found out that they are quite low, implying that consumers' respond to price and income changes is quite limited; and, therefore, there is a need for economic regulation in Turkish electricity market. Then, an ARIMA model is developed and used to forecast future net electricity consumption in Turkey. Based on forecasts obtained, it is clear that the current official projections highly overestimate the electricity demand in Turkey.

Developing countries like Turkey should plan very carefully about their energy demand for critical periods, such as economic crises that frequently hit them. For instance, economic crisis hit Turkey three times in the last decade, once in 1994 and the others in 2000 and 2001. During these periods, energy consumption shows fluctuations and presents a decreasing trend. After the economic crises, the energy consumption recovers and shows about the same trend as before the economic crises. Therefore, official energy projections should be formulated in such a way that possible crises are taken into account. Moreover, all related bodies in Turkey should take necessary steps to find out the reasons for apparently misleading demand forecasts in electricity market; and develop accurate demand projections. In this context; the market regulator, EMRA, is especially responsible for development of healthy forecasts, which is one of the most important determinants in the success of recent energy market reforms in Turkey. Future energy consumption in Turkey have consistently been predicted much higher values than actually occurred. It should be kept in mind that it is almost impossible to create a well-functioning electricity market under these conditions. In addition; while developing forecasts, the emphasis should be on the development and use of appropriate data and econometric techniques which are open to debate, rather than some computer packages for demand estimation provided by various international organizations or, even worse, the methods in which the demand is determined as a result of a bargaining process among various public bodies.

It is believed that the elasticities, forecasts and the comments presented in this paper would be helpful to policy makers in Turkey for future energy policy planning.

Acknowledgements

I would like to thank my supervisor, **Joanne Evans** (Lecturer in Economics, University of Surrey, UK), for all her helpful comments and continuous encouragement during the writing of the dissertation on which this paper is constructed. I would also like to thank **Lester C. Hunt** (Professor of Energy Economics, University of Surrey, UK); **Paul Appleby** (BP plc, UK); **Gürcan Gülen** (Senior Energy Economist, University of Texas, USA) and **David Hawdon** (Senior Lecturer in Economics, University of Surrey, UK) for priceless comments on the final draft. I am also grateful to the British Government through the **Foreign and Commonwealth Office** for awarding me the British Chevening Scholarship that financed my studies in the UK. I also extend my thanks to the **British Council** for excellent administration of the scholarship. Besides, I am indebted to the Turkish Government through the **Energy Market Regulatory Authority** both for granting me a study leave to undertake my academic work in the UK and for the financial support towards my studies there.

I would also like to thank **anonymous referees** for their very helpful comments on an earlier draft of the paper. The author is, of course, responsible for all errors and omissions.

References

Beenstock, M., Goldin, E., 1999. The demand for electricity in Israel. Energy Economics, 21:2, 168-183.

Bentzen, J., Engsted, T., 1993. Short- and long-run elasticities in energy demand: A cointegration approach. Energy Economics, 15:1, 9-16.

Bentzen, J., Engsted, T., 2001. A revival of the autoregressive distributed lag model in estimating energy demand relationships. Energy, 26:1, 45-55.

Box, G.P.E., Jenkins, G.M., 1978. Time Series Analysis: Forecasting and Control, Holden Day: San Francisco.

Ceylan, H., Ozturk, H.K., 2004. Estimating Energy Demand of Turkey based on Economic Indicators Using Genetic Algorithm Approach. Energy Conversion and Management, 45, 2525–2537.

Dahl, C., Sterner, T., 1991. Analysing gasoline demand elasticities: a survey. Energy Economics, 13:3, 203-210.

Dargay, J.M., 1992. The Irreversible Effects of High Oil Prices: Empirical Evidence for the Demand for Motor Fuels in France, Germany, and the UK, in: David Hawdon (Ed.), Energy Demand: Evidence and Expectations, Surrey University Press: London.

Dargay, J.M., Gately, D., 1995a. The Response of World Energy and Oil Demand to Income Growth and Changes in Oil Prices. Annual Review of Energy and the Environment, 20, 145-178.

Dargay, J.M., Gately, D., 1995b. The imperfect price reversibility of non-transport oil demand in the OECD. Energy Economics, 17:1, 59-71.

Dickey, D.A., Fuller, W.A., 1979. Distribution of the Estimators for Autoregressive Time Series With a Unit Root. Journal of the American Statistical Association, 74:366, 427-431.

Drollas, L.P., 1984. The demand for gasoline: Further evidence. Energy Economics, 6:1, pp 71-82.

Ediger, V.S., Tatlidil, H., 2002. Forecasting the primary energy demand in Turkey and analysis of cyclic patterns. Energy Conversion and Management, 43, 473-487.

Engle, R.F., Granger, C.W.J., 1987. Co-Integration and Error Correction: Representation, Estimation, and Testing. Econometrica, 55:2, 251-276.

Engle, R.F., Granger, C.W.J., Hallman, J.J., 1989. Merging short-and long-run forecasts: An application of seasonal cointegration to monthly electricity sales forecasting. Journal of Econometrics, 40:1, 45-62.

Fouquet, R., Hawdon, D., Pearson, P., Robinson, C., Stevens, P., 1993. The SEEC United Kingdom Energy Demand Forecast, Surrey Energy Economics Centre (SEEC): Occasional Paper 1, Department of Economics, University of Surrey, Guildford, UK.

Gately, D., 1992. Imperfect price-reversibility of U.S. gasoline demand: asymmetric responses to price increases and declines. Energy Journal, 13:4, 179-207.

Granger, C.W.J., 1986. Developments in the Study of Cointegrated Economic Variables. Oxford Bulletin of Economics & Statistics, 48:3, 213-228.

Granger, C.W.J., Newbold, P., 1974. Spurious regressions in econometrics. Journal of Econometrics, 2:2, 111-120.

Gujarati, D.N., 2004. Basic Econometrics. Fourth Edition. New York: McGraw-Hill/Irwin.

Haas, R., Schipper, L., 1998. Residential energy demand in OECD-countries and the role of irreversible efficiency improvements. Energy Economics, 20:4, 421-442.

Hunt, L.C., Lynk, E.L., 1992. Industrial Energy Demand in the UK: A Cointegration Approach, in: David Hawdon (Ed.), Energy Demand: Evidence and Expectations, Surrey University Press: London.

Hunt, L.C., Manning, D.N., 1989. Energy Price- and Income-Elasticities of Demand: Some Estimates for the UK using the Cointegration Procedure. Scottish Journal of Political Economy, 36:2, 183-193.

Hunt, L.C., Witt, R., 1995. An Analysis of UK Energy Demand Using Multivariate Cointegration. Surrey Energy Economics Centre (SEEC): Discussion Paper No: 86; Department of Economics, University of Surrey, Guildford, UK.

IEA (International Energy Agency), 2002. Energy Balances of OECD Countries, Paris, France.

IEA (International Energy Agency), 2004. Energy Balances of OECD Countries 2001-2002, Paris, France.

IEA (International Energy Agency), 2005. Energy Prices and Taxes, accessed from http://www.sourceoecd.org on 20.06.2005 at 20:43.

IMF (International Monetary Fund), 2005. World Economic Outlook Database, April 2004, accessed from http://www.imf.org/external/pubs/ft/weo/2004/01/data/index.htm on 27.06.2005 at 17:28.

Johansen, S., 1988. Statistical analysis of cointegration vectors. Journal of Economic Dynamics and Control, 12:2-3, 231-254.

Kouris, G., 1981. Elasticities - science or fiction?. Energy Economics, 3:2, 66-126.

Newey, W.K., West, K.D., 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica, 55:3, 703-708.

Ozturk, H.K., Ceylan, H., Canyurt, O.E., Hepbasli, A., 2005. Electricity estimation using genetic algorithm approach: a case study of Turkey. Energy, 30:7, 1003-1012.

Pindyck, R.S., 1979. The Structure of World Energy Demand, Mass.: M.I.T. Press: Cambridge.

Ryan, D.L., Plourde, A., 2002. Smaller and smaller? The price responsiveness of nontransport oil demand. The Quarterly Review of Economics and Finance, 42:2, 285-317.

Sargan, J.D., Bhargava, A., 1983. Testing Residuals from Least Squares Regression for Being Generated by the Gaussian Random Walk. Econometrica, 51:1, 153-174.

SIS, 2005a. Enerji Istatistikleri Haber Bultenleri (Energy Statistics News Bulletins), accessed from http://www.die.gov.tr/TURKISH/SONIST/ENERJI/enerji.html on 24.06.2005 at 19:42.

SIS, 2005b. Population by Census Year, accessed from http://www.die.gov.tr/IstTablolar/04nf023t.xls on 20.06.2005 at 23:09.

SIS, 2005c. Kullanim Yerlerine Gore IV. Donem Elektrik Tuketimi, 2003-2004 (Electricity Consumption by Sectors, the 4th Quarter of 2004), accessed from http://www.die.gov.tr/TURKISH/SONIST/ENERJI/t4-23032005.xls on 21.06.2005 at 00:14.

SPO, 2005. Gross Domestic Product (By Expenditures), accessed from http://ekutup.dpt.gov.tr/teg/2005/04/tii.7.xls on 29.06.2005 at 12:27.

Stewart, J., 1991. Econometrics, Philip Allan: Hemel Hempstead.

TEIAS, 2005a. Annual Development of Installed Capacity, Gross Generation, Supply and Net Consumption In Turkey (1975 - 2003), accessed from http://www.teias.gov.tr/istatistik/30.xls on 20.06.2005 at 20:19.

TEIAS, 2005b. Annual Development of Installed Capacity Gross Generation and Net Consumption in Turkey and Per Capita (1923-1974), accessed from http://www.teias.gov.tr/istatistik/29.xls on 13.07.2005 at 12:03.

TEIAS, 2005c. Talep Gelisimi (Demand Development), accessed from http://www.teias.gov.tr/apkuretim/talepgelisim.htm on 17.02.2006 at 20:15.

TEIAS, 2005d. Annual Development of Electricity Generation, Consumption and Losses in Turkey (1970-2003), accessed from http://www.teias.gov.tr/istatistik/31-32(kayıplar).xls on 17.07.2005 at 14:00.

Traill, B., Colman, D., Young, T., 1978. Estimating Irreversible Supply Functions. The American Journal of Agricultural Economics, 60:3, 528-531.

Undersecretariat of Treasury, 2005. Gross Domestic Product by Expenditures (At Current Prices), accessed from http://www.hazine.gov.tr/yayin/hazineistatistikleri/1-4A.xls on 29.06.2005 at 12:16.

Wolffram, R., 1971. Positivistic Measures of Aggregate Supply Elasticities: Some New Approaches-Some Critical Notes. The American Journal of Agricultural Economics, 53:2, 356-359.

Yule, G.U., 1926. Why do we Sometimes get Nonsense-Correlations between Time-Series?--A Study in Sampling and the Nature of Time-Series. Journal of the Royal Statistical Society, 89:1, 1-63.

Appendices

Appendix A: Specification of Data

Real Electricity Prices

The quarterly data on *electricity prices for industry and households* is collected from IEA (2005). All prices are electricity end-use prices in New Turkish Lira (YTL) per kilowatt hour (kWh). The annual data on *electricity consumption by industry and households* is taken from IEA (2002) for 1984-2000 and IEA (2004) for 2001-2002. Moreover, the data for the period from the first quarter of 2003 to the last quarter of 2004 is collected from SIS (2005a). The data from SIS is in GWh; however, the original data from IEA is measured in ktoe. To get a single unit, the data from IEA is converted into GWh using the simple equality 1 ktoe = 11.63 GWh. Finally, the data on *annual percentage change in inflation* is taken from IMF (2005).

A single time series data on real electricity prices in Turkey is not directly obtainable. Therefore, it is calculated using available data. First of all a weighted average price is computed using the existing data on electricity prices for industry/households and electricity consumption by industry/households. Then, an inflation index is also computed using the data on annual percentage change in inflation assuming 2004 as the base year; that is 2004=1. Finally, real electricity prices are obtained by dividing weighted average price for each period by inflation index for the related year.

Real Income

A single time series data on real income (or real GDP per capita) is also not directly available. Therefore, it is calculated by using available data on population, GDP per capita at current prices and annual percentage change in inflation. The annual time series data on Turkish *population* is collected from SIS (2005b). It is measured in thousand people. In Turkey, censuses are carried out once in every five years. The figures for years without a census are official estimates by SIS. The annual time series data on Turkish *gross domestic product (GDP) per capita* at current prices in YTL is obtained from the Undersecretariat of Treasury (2005) for 1984-2003 and from SPO (2005) for 2004.

To get real income, GDP per capita at current prices is calculated and the figures are converted into real prices by using the inflation index computed in the previous step. At the end, real GDP per capita at 2004 prices is obtained in YTL.

Electricity Demand

Electricity demand (or net electricity consumption per capita) is not directly accessible, so once more the data is worked out. The annual data on *net* *electricity consumption*[23] is collected from TEIAS (2005a) for 1984-2003 and from SIS (2005c) for 2004. All figures are measured in GWh. These figures are converted into kWh and then divided by population figures to get net electricity consumption per capita in kWh.

In forecasting section, besides annual net electricity consumption data from TEIAS (2005a), additional data from TEIAS (2005b) is also used. Furthermore, the data to be used in this section is annual data for 1923-2004 period, rather than quarterly data from 1984 to 2004.

Appendix B: The Process of Conversion of Official Electricity Gross Demand Projections into Net Electricity Consumption Figures

The relationship between various technical terms used to express electricity demand is shown below. Please note that network losses include both transmission and distribution losses; and internal consumption refers to electricity consumed by power plants for the purposes of heating, pumping, traction, lighting and so on.

<table>
<tr><td></td><td></td><td>Internal Consumption</td><td rowspan="4"><u>Gross Demand</u>
=
Gross Supply</td><td>Import-Export</td><td></td></tr>
<tr><td rowspan="2"><u>Net Consumption</u></td><td>Import-Export</td><td rowspan="3">Net Supply</td><td rowspan="3">Gross Generation</td><td>Internal Consumption</td></tr>
<tr><td rowspan="2">Gross Consumption</td><td rowspan="2">Net Generation</td></tr>
<tr><td>Network Losses</td></tr>
</table>

The table below shows the data on gross demand, internal consumption and network losses for the latest available 10-year period (i.e., 1994-2003); and, as can be seen in the table, during this period, internal consumption and network losses accounted for 22.3% of gross demand on average.

[23] Net electricity consumption is calculated by subtracting network loses from total supply.

Table 10. The data on gross demand, internal consumption and network losses for 1994-2003

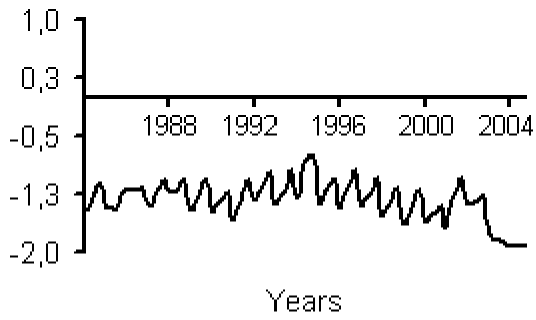
	Gross Demand *(GWh)* (a)	**Internal Consumption** *(GWh)* (b)	**Internal Cons. as a % of Gross Demand**	**Network Losses** *(GWh)* (c)	**Network Losses as a % of Gross Demand**	**Total** *(GWh)* (d=b+c)	**The Total as a % of Gross Demand**
1994	77,783.0	4,539.1	5.8	11,843.0	15.2	16,382.1	21.1
1995	85,551.5	4,388.8	5.1	13,768.8	16.1	18,157.6	21.2
1996	94,788.6	4,777.3	5.0	15,854.8	16.7	20,632.1	21.8
1997	105,517.1	5,050.2	4.8	18,581.9	17.6	23,632.1	22.4
1998	114,022.7	5,523.2	4.8	20,794.9	18.2	26,318.1	23.1
1999	118,484.9	5,738.0	4.8	21,545.0	18.2	27,283.0	23.0
2000	128,275.6	6,224.0	4.9	23,755.9	18.5	29,979.9	23.4
2001	126,871.3	6,472.6	5.1	23,328.7	18.4	29,801.3	23.5
2002	132,552.6	5,672.7	4.3	23,931.9	18.1	29,604.6	22.3
2003	141,150.9	5,332.2	3.8	24,052.7	17.0	29,384.9	20.8
		Annual Average:	*4.8*		*17.4*		***22.3***

Source: TEIAS (2005a,d)

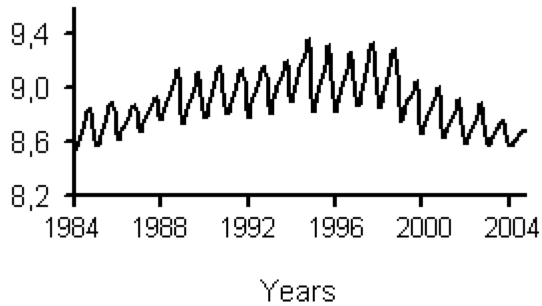
Assuming that internal consumption and network losses continue to account for 22.3% of gross demand on average during the period 2005-2014, Table 8 is prepared.

Image1.bmp

LP



LY



LE

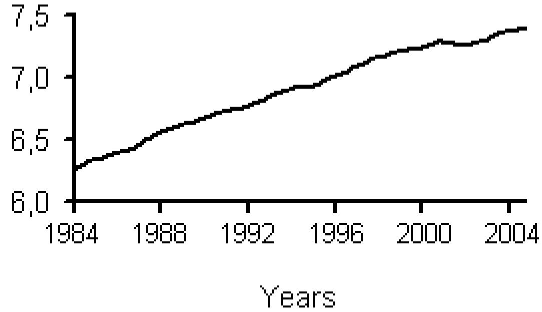


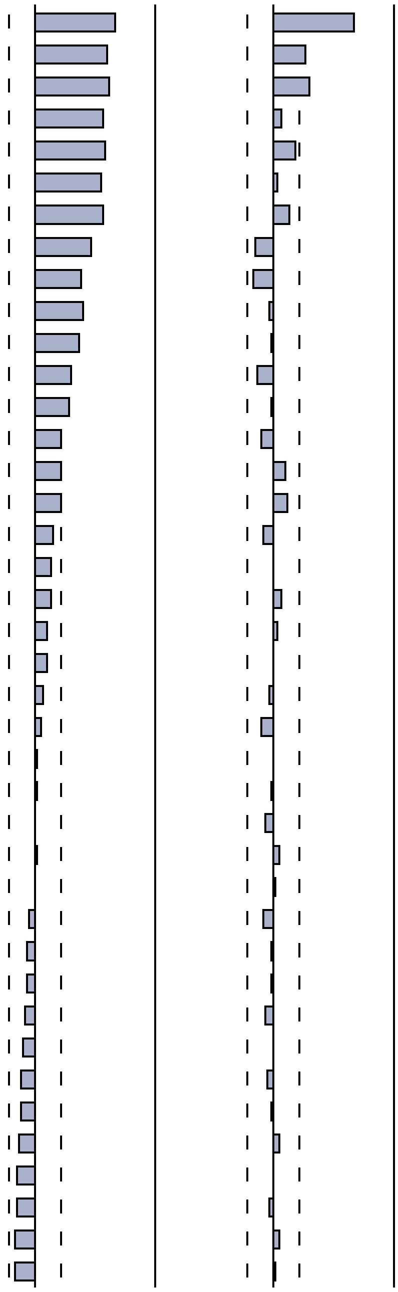
Image2.bmp

Sample: 1923 2004
Included observations: 82

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.937	0.937	74.580	0.000
		2	0.873	-0.029	140.27	0.000
		3	0.816	0.013	198.37	0.000
		4	0.761	-0.013	249.54	0.000
		5	0.700	-0.079	293.38	0.000
		6	0.643	-0.003	330.83	0.000
		7	0.585	-0.041	362.30	0.000
		8	0.530	-0.014	388.49	0.000
		9	0.481	0.012	410.31	0.000
		10	0.436	0.004	428.52	0.000
		11	0.395	0.006	443.69	0.000
		12	0.354	-0.033	456.03	0.000
		13	0.316	-0.001	466.02	0.000
		14	0.281	-0.006	474.04	0.000
		15	0.247	-0.023	480.33	0.000
		16	0.215	-0.005	485.18	0.000
		17	0.185	-0.013	488.82	0.000
		18	0.157	-0.008	491.49	0.000
		19	0.133	0.008	493.41	0.000
		20	0.110	-0.012	494.75	0.000
		21	0.087	-0.011	495.61	0.000
		22	0.068	-0.002	496.14	0.000
		23	0.048	-0.024	496.40	0.000
		24	0.028	-0.013	496.49	0.000
		25	0.010	-0.014	496.51	0.000
		26	-0.009	-0.021	496.52	0.000
		27	-0.028	-0.019	496.61	0.000
		28	-0.047	-0.020	496.89	0.000
		29	-0.064	-0.009	497.43	0.000
		30	-0.079	-0.001	498.26	0.000
		31	-0.092	-0.002	499.41	0.000
		32	-0.105	-0.013	500.92	0.000
		33	-0.117	-0.014	502.85	0.000
		34	-0.128	-0.010	505.19	0.000
		35	-0.138	-0.013	507.98	0.000
		36	-0.148	-0.015	511.24	0.000
		37	-0.157	-0.011	514.99	0.000
		38	-0.165	-0.013	519.26	0.000
		39	-0.173	-0.013	524.07	0.000
		40	-0.181	-0.012	529.43	0.000

Image3.bmp

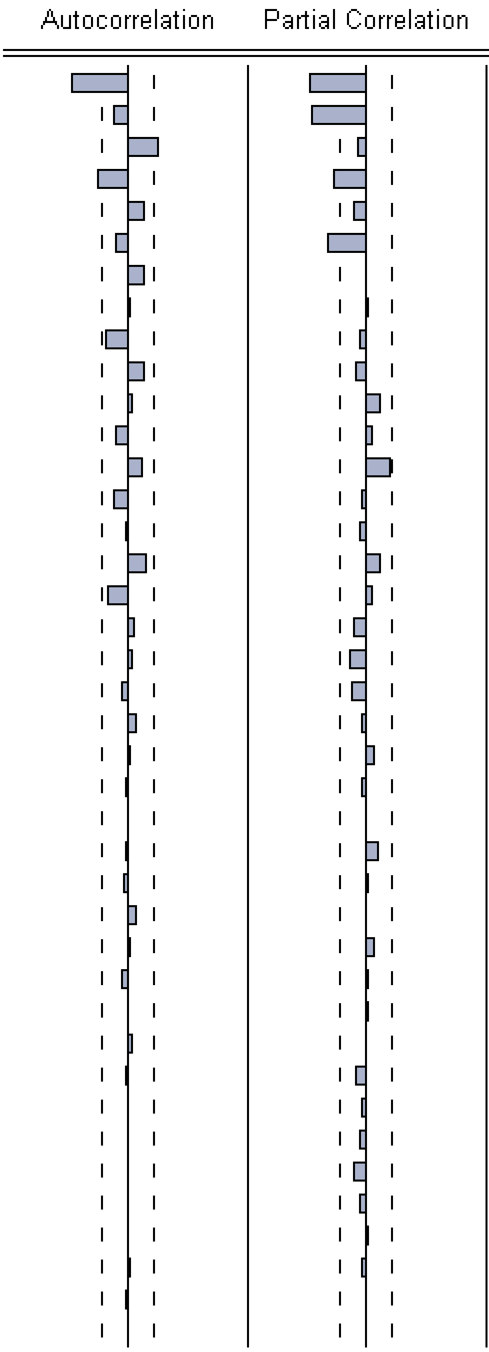
Sample: 1923 2004
Included observations: 81



	AC	PAC	Q-Stat	Prob
1	0.691	0.691	40.090	0.000
2	0.623	0.280	73.170	0.000
3	0.653	0.310	109.91	0.000
4	0.592	0.072	140.50	0.000
5	0.611	0.186	173.55	0.000
6	0.580	0.038	203.76	0.000
7	0.589	0.136	235.24	0.000
8	0.495	-0.160	257.84	0.000
9	0.403	-0.180	272.98	0.000
10	0.421	-0.033	289.78	0.000
11	0.390	-0.014	304.40	0.000
12	0.311	-0.142	313.79	0.000
13	0.298	-0.019	322.60	0.000
14	0.235	-0.100	328.14	0.000
15	0.231	0.104	333.56	0.000
16	0.236	0.119	339.31	0.000
17	0.149	-0.084	341.64	0.000
18	0.147	0.006	343.95	0.000
19	0.133	0.075	345.87	0.000
20	0.106	0.037	347.12	0.000
21	0.101	0.001	348.26	0.000
22	0.079	-0.032	348.98	0.000
23	0.045	-0.109	349.21	0.000
24	0.022	-0.001	349.27	0.000
25	0.008	-0.015	349.28	0.000
26	0.008	-0.065	349.29	0.000
27	0.022	0.057	349.35	0.000
28	-0.007	0.014	349.35	0.000
29	-0.053	-0.087	349.72	0.000
30	-0.070	-0.015	350.37	0.000
31	-0.073	-0.024	351.08	0.000
32	-0.095	-0.066	352.31	0.000
33	-0.108	0.007	353.94	0.000
34	-0.119	-0.051	355.97	0.000
35	-0.130	-0.010	358.45	0.000
36	-0.143	0.056	361.51	0.000
37	-0.153	0.001	365.09	0.000
38	-0.160	-0.031	369.09	0.000
39	-0.172	0.042	373.84	0.000
40	-0.175	0.009	378.88	0.000

Image4.bmp

Sample: 1923 2004
Included observations: 80



	AC	PAC	Q-Stat	Prob
1	-0.481	-0.481	19.185	0.000
2	-0.122	-0.459	20.439	0.000
3	0.266	-0.067	26.449	0.000
4	-0.269	-0.279	32.683	0.000
5	0.141	-0.101	34.410	0.000
6	-0.104	-0.325	35.377	0.000
7	0.143	0.004	37.207	0.000
8	0.012	0.019	37.219	0.000
9	-0.181	-0.052	40.240	0.000
10	0.144	-0.097	42.179	0.000
11	0.034	0.123	42.289	0.000
12	-0.109	0.057	43.439	0.000
13	0.122	0.213	44.904	0.000
14	-0.122	-0.028	46.389	0.000
15	-0.013	-0.055	46.405	0.000
16	0.163	0.118	49.126	0.000
17	-0.170	0.054	52.134	0.000
18	0.050	-0.106	52.397	0.000
19	0.028	-0.138	52.483	0.000
20	-0.055	-0.116	52.811	0.000
21	0.063	-0.041	53.250	0.000
22	0.010	0.072	53.261	0.000
23	-0.021	-0.039	53.310	0.000
24	-0.003	0.008	53.311	0.001
25	-0.023	0.104	53.374	0.001
26	-0.030	0.009	53.484	0.001
27	0.060	0.002	53.924	0.002
28	0.017	0.080	53.961	0.002
29	-0.043	0.018	54.195	0.003
30	-0.006	0.011	54.200	0.004
31	0.031	0.003	54.329	0.006
32	-0.020	-0.092	54.385	0.008
33	0.001	-0.029	54.385	0.011
34	0.004	-0.057	54.387	0.015
35	0.000	-0.100	54.387	0.019
36	-0.003	-0.046	54.388	0.025
37	-0.005	0.010	54.392	0.032
38	0.011	-0.033	54.410	0.041
39	-0.017	0.003	54.455	0.051
40	0.008	-0.007	54.464	0.063

Image5.bmp

Sample: 1923 2004
Included observations: 67

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.034	0.034	0.0827	0.774
		2	-0.156	-0.157	1.8092	0.405
		3	-0.047	-0.036	1.9683	0.579
		4	-0.168	-0.195	4.0469	0.400
		5	-0.076	-0.083	4.4761	0.483
		6	0.154	0.101	6.2740	0.393
		7	0.175	0.139	8.6420	0.279
		8	-0.155	-0.171	10.536	0.229
		9	0.132	0.194	11.918	0.218
		10	-0.027	-0.048	11.975	0.287
		11	0.097	0.249	12.750	0.310
		12	0.143	0.086	14.464	0.272
		13	-0.128	-0.105	15.866	0.256
		14	-0.088	-0.009	16.542	0.281
		15	0.051	0.114	16.770	0.333
		16	0.108	0.073	17.826	0.334
		17	-0.006	0.015	17.829	0.400
		18	0.036	-0.121	17.950	0.459
		19	-0.039	0.037	18.096	0.516
		20	0.063	0.190	18.488	0.555
		21	0.101	0.048	19.516	0.552
		22	0.024	-0.009	19.574	0.610
		23	0.002	-0.047	19.574	0.667
		24	-0.066	0.025	20.039	0.695
		25	-0.105	-0.008	21.262	0.678
		26	-0.073	-0.148	21.867	0.696
		27	0.070	-0.118	22.440	0.715
		28	0.023	-0.036	22.502	0.758
		29	-0.007	-0.019	22.508	0.799
		30	-0.024	-0.068	22.583	0.832
		31	0.013	-0.072	22.604	0.863
		32	-0.026	-0.111	22.694	0.888
		33	-0.010	0.048	22.708	0.911
		34	-0.003	0.005	22.709	0.930
		35	-0.018	-0.003	22.757	0.945
		36	-0.010	-0.062	22.772	0.958
		37	-0.022	0.005	22.850	0.967
		38	-0.014	0.008	22.880	0.975
		39	-0.025	-0.000	22.986	0.981
		40	-0.006	-0.075	22.992	0.986