ANALYSIS OF GAS PRICES FOR TURKEY FROM 2003-2011

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ABSTRACT

ANALYSIS OF GAS PRICES FOR TURKEY FROM 2003-2011

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This study aimed to construct a forecasting model for gas prices in Turkey using Univariate time series analysis. The best model was developed after assessing the forecasting performances for both Seasonal Autoregressive Integrated Moving Average (SARIMA) model and Exponential Smoothing (ES) model. Firstly, we fitted different combinations of both ARIMA and SARIMA models (from which the best model was chosen) by using the monthly oil prices from January 2003 to December 2011. The ES model was automatically fitted next for forecasting performance comparison purposes. We then extracted the forecasted monthly values for 2012 for both models and compared their forecast performances. The ARIMA (1,1,0) model gave the best fit for the gas price series for Turkey. The results depicted that the ARIMA model forecasts work effectively and reliably, and is a useful tool for forecasting future Turkish gas prices. It can be used by governments, investors and other gas users to predict and address negative impacts that gas shocks creates.

KEY WORDS: Univariate time series, Gas prices, Forecasting, Accuracy measures, Box-Jenkins Approach, ARIMA, SARIMA and Exponential Smoothing (ES) models.

ÖZ

TÜRKİYE BENZİN FİYATLARININ 2003-2011 YILLARI ARASINDAKİ ANALİZİ

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Yüksek Lisans, İstatistik Bölümü

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Bu çalışmanın amacı, tek değişkenli zaman serileri kullanarak Türkiye benzin fiyatı tahmin modeli oluşturmaktır. En iyi model, Otoregresif Tamamlanmış Hareketli Ortalama (OTHO) ve üssel Düzleştirme (ÜD) tahmin modellerinin başarımlarını karşılaştırarak geliştirildi. Öncelikle, 2003 Ocak ayından 2011 Aralık ayına uzanan süre içerisinde elde edilen aylık benzin fiyatlarından oluşan verilerin modellenmesi için, OTHO modelinin farklı kombinasyonlarını inceledik. Ardından tahmin performanslarını karşılaştırmak için ÜD modelini kurduk. Daha sonra, her iki modeli de kullanarak, 2012 yılı tahminlerini elde ettik ve tahmin performanslarını karşılaştırdık. OTHO(1,1,0) modelinin Türkiye benzin fiyatları serisi için en uygun model olduğu ortaya çıktı. Sonuçlar, OTHO modelinin etkin ve güvenilir tahminler yaptığını ve Türkiye benzin fiyatları serisinin tahmininde kullanılabileceğini gösterdi.

To Walyomu's family...

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ABBREVIATIONS

ACF	Autocorrelation Functions
PACF	Partial Autocorrelation Functions
AR	Autoregressive
MA	Moving Average
ARIMA	Autoregressive Integrated Moving Average
AIC	Akaike Information Criterion
BIC	Bayes Information Criterion
GDP	Gross domestic product
SARIMA	Seasonal Autoregressive Integrated Moving Average
UBJ	Univariate Box-Jenkins
ES	Exponential smoothing
SES	Simple exponential Smoothing
SMA	Simple moving average
US	United States
NOPI	Net Oil Price Increase
GARCH	General autoregressive conditional heteroscedasticity
TGARCH	Threshold Generalized Autoregressive Conditional heteroscedasticity
EGARCH	Exponential Generalized Autoregressive Conditional
VAR	Vector Autoregressive
VECM	Vector Error Correction Model
ME	Mean Error
MSE	Mean square Error

SSE	Sum of Squares Error
RMSE	Root Mean Squared Error
MPE	Mean Percentage Error
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MAD	Mean Absolute Deviation
ADF	Augmented Dickey Fuller
KPSS	Kwiatkowski, Phillips, Schmidt and Shin
TS	Time Series

CHAPTER 1

INTRODUCTION

Gas price is a vital economic development indicators directing all the economies in the world. According to Brahim Fezzani and Dilyara Nartova (2011), global gas production is approximately close to 37%. The gas price changes are linked with major developments and are always considered as a cause for inflation and recessions in the world economy. The rise in gas prices both in 1974 and 1979 were crucial impacts in producing a retardation in the world economy during the period in which inflation was rising. The previous rises in gas prices have led concern although they have not been on such a large scale as in the 1970's where we also live in a smaller inflation world, and many think that gas price surges could change this. A slight change in gas prices can lead to either positive or negative effect on most of the economic indicators. The impacts of gas prices on the economy differ from country to country. That is, for the gas importing economies, gas price rise and economic development are expected to be negatively related while all other factors remaining constant, the behavior is expected be positive for gas exporting economies. In other words, the economic significance of gas comes not only from the sheer size of the market, but also from the crucial, almost strategic, role it plays in the economies of both gas-exporting and gas-importing economies. The gas prices take the revenues to gas-exporting countries in a large amount of which, gas exports stand above 20% of its gross domestic product (GDP)

(Narmit Shama, 1998). On the other hand, effects of gas imports have a significant impacts on the development initiatives of the developing economies. The energy price changes are always seen as leading to adverse macroeconomic impacts on total product and employment worldwide. This behaviour of gas price changes, to a certain extent, impacts the economic growth of a country. For example, the study by Scerri and Reut (2009), claims that shocks in gas prices have also impact on the estimated budget. The estimates of revenue from taxation change in favour of gas generating companies whereas it would depicts a decrease on the consumer side. In addition to that, the nature of profit allocation also varies across industrial sector and also the household expenditure would give varying pattern with changes in gas prices. Turkey, being one of the developing and gas-importing countries in the world, with 68% of total primary energy consumption reported in 2002 and gas standing at 40% of her primary energy consumption in 2002 (state planning organisation, 2004) is thought to be affected by these changes in gas prices. In other words, the variations in gas prices are expected to have significant impacts on its economy as well. Researchers have employed different linear and nonlinear methodology to capture the magnitude and direction of the gas price-macroeconomy relationship but have mostly limited their studies to advanced economies. In this study, a Univariate time series technique is employed for the analysis and fitting of the model for a developing economy of Turkey. Specifically a non-seasonal and Seasonal Autoregressive Integrated Moving Average (SARIMA) model are used. We use the Autoregressive Integrated Moving Average (ARIMA) models because of some reasons. According to Pankratz (1983), Box-Jenkins technique gave the appropriate prediction which accounted for 74% of the series that he examined in his research using this approach. The technique has three major advantages over its other existing related methods. Firstly, the ideas related with these Univariate Box-Jenkins (UBJ) models are obtained from a fundamental class of probability concepts and mathematical statistics. However, some of the historical popular univariate methods are generated using a unique approach. The second reason is that ARIMA models come from a family of models instead of a single model. Box and Jenkins came up with appropriate procedures (to be discussed in the methodology section) that help the analysts to select at least one appropriate models out of a given combinations of possible models within this family. Thirdly, the ARIMA or SARIMA model gives the minimum univariate forecast errors. That is, no other standard univariate series model can produce lower mean squared forecast error of the forecasts. Thus, because of these highlighted abilities of the model over the others, we decided to employ the method. Another method used in this study is the Exponential smoothing (ES) method. It is used to statistically model time series data for smoothing purpose or prediction. The aim of using this method is to minimize irregularities in time series data set. That is, it provides a true picture behind the behavior of the series. The technique also gives an effective means of forecasting future values of the time series. It is preferred over the other simple moving average forecast because its model is fit automatically. It also places relatively more weight on the recent observations to changes occurring in the recent past than its counterparts. The ES model also uses a smoothing parameter which is continuous variable, so it can easily be optimized by using this parameter algorithm to minimize the mean square error encountered within the series under investigation. However, despite of all the above mentioned advantages it has over the others, it also suffers from drawbacks. For instance, the smoothing parameters of these fitted models do not undergo statistical significance checks and diagnostic tests for their parameters as well as adequacy. Because of this, ES models are considered statistically as ad hoc models. Thus, this study aims to achieve three main objectives as listed below;

- To Model the monthly gas prices for Turkey's economy.
- To make forecasts and assess the performance of the tools employed in this analysis. The best model will then be chosen based on these results.
- To contribute to the literature of gas price modeling within the country as well as helping the investors and policy makers execute their businesses and government plans more effectively.

Modeling gas price is a very important issue for both policymakers and agents in financial markets. In fact, the study sees relevant and timely in view of the limited empirical analysis on the modeling of gas prices for Turkey's economy. The findings will guide the decision makers in coming up with economic growth energy sector policies that favour both individual and public owned investments. To the best of my knowledge, there is no study that have been carried out on Turkey that models gas prices on its economy using this approach. The remaining chapters of this study are structured as follows: Chapter 2 presents the related literature review survey. Chapter 3 presents methodology used. Chapter 4 introduces the data description, source and analysis. Finally, Chapter 5 presents the conclusion and future research.

CHAPTER 2

LITERATURE REVIEW

The gas product has a key role to play in the economic growth of the world. This has attracted the attention of many scholars to examine the correlation between economic growth and oil price shocks and modeling of the latter variable. In doing so, a great number of technical literature review have been carried out on the subject in question. However, the literature on modeling of gas prices is still scarce. Some of the literature reviews being mentioned in the different studies are as follows;

The fluctuation of oil prices was investigated in comparison with volatility of other commodities by a number of authors Pindyck (1999) and Regnier (2007). For example, Pindyck (1999) investigated oil, coal, and natural gas over a long horizon and found that oil depicted the highest degree of volatility. In a more general perspective, Regnier (2007) proves that gas price change is somehow high compared to the changes of other goods. Huang et al. (1996) analyses the relationship between the oil price volatility and stock prices. They find that daily changes in oil price volatility do affect the daily stock prices of oil companies, but there is a minimum impact on the broad stock market.

On the other hand, some researchers have studied that the correlation between oil prices and inflations are time-varying. For instance, in considering the way-through from gas changes to core inflation, Hooker (2002) singles out a structural variation in the correlation at 1981Q1 (quarter 1) based on the series from 1962-2000. He notes that, monetary policy did not itself become less accommodative of gas volatility, but may have enhanced the creation of a situation where inflation is invisible to price changes in general. Similarly, Roubini and Setser (2004) illustrate that the effects of inflation as a result of changes in gas prices was high in the 70s, pointing out that any policy reaction aimed at increasing gas prices bases on a combination of influences like the size of inflation anticipated, the general inflation size and the amount of household leverage. Others, such as Barsky and Kilian (2004), claim that the impact is not large and that gas changes only is not enough to detect the US stagflation that occurred in the 1970s.

Hamilton (1983, 1996, 2005, 2009) has shown analytical evidence proposing that gas price changes have been part of the major causes of recessions in the U.S. Hooker (1999) re-examined the gas price-inflation relationship in a Philips-curve framework. His findings reveal that since 1980, gas price fluctuation appeared to be affecting inflation mainly through their contribution in the price index, with minimum or no pass-through into core measures. However, gas price changes enhanced significantly to core inflation before 1980.

Malik (2007) studied the effect of increased gas prices on economic growth with other macroeconomic variables such as deficit spending, public debt, expected inflation and investment spending for Pakistan's economy. The finding reveals a nonlinear relationship within the gas prices and economic development. That is, the rise in gas prices is necessary for economic development but after threshold level it tends to impact the country adversely. Similarly, using panel Pedroni's cointegration methodology, Parida and Sahoo (2007) examined whether export caused hypothesis for four south Asian countries (India, Sri lanka, Pakistan and Bangladesh) for the period of 1980-2002. The hypothesis test was based on manufacturing exports together with other indicators such as human capital and capital formation. The results indicate that there is a long run growth relationship between export and GDP.

Rasche and Tatom (1981), Darby (1982), Burbidge and Harrison (1984), and Gisser and Goodwin (1986) studied the economic significance of gas price shocks on the macroeconomy for the gas importing countries. Their studies based on neoclassical theory, found a negative linear correlation between gas prices and main activity for the gas importing countries. On the other hand, Hamilton's (1983) research found a robust correlation between gas price rises and resulting economic downturns for majority of the post-World War II recessions in the US economy. In another important study, Hamilton (1996) uses Net Oil Price Increase (NOPI) to assess whether there is a linear relationship between GDP growth and gas prices. His study results reveal that there is no statistical evidence between the two variables in question for the smaller sample period of 1973 to 1973. However, a significant statistical evidence for the whole sample covering the periods 1948 to 1994 is reported.

Using a two research design step process (that is, obtaining cointegration and causality as the first and second steps, respectively), Amano and Van Norden (1998) obtain a significant cointergration between gas prices and exchange rates for Germany, US and Japan in their examination of whether gas price leads real changes in the real exchange rates for the three countries mentioned in their study. On the other hand, no significant evidence of the reverse is obtained for the causality. That is, no empirical evidence is reported that real exchange rate leads to volatilities in gas prices. In a related study and methodological approach, Chaudhuri and Daniel (1998) reported the same findings for 16 OECD countries as Amano and Van Norden (1998) did. That is, they find that there is cointegration between gas prices and exchange rates and that variations in the US dollar real exchange rate are due to changes in the real price of gas. Meanwhile, the same conclusion is reached at when other approaches are utilized. For example, Akram (2004) uses equilibrium corrections model technique in assessing whether there is a nonlinear relationship between gas prices and Norwegian exchange rate. The study reveals that changes in the gas price leads to a significant non-linear negative variation in the exchange rates for the country. Another differing study approach based on both supply and demand variables to determine the real exchange rate is carried out by Bergvall (2004). In his study, he applies intertemporal optimizing model and variance decomposition to depict that terms-of-trade shocks are the most influential for Denmark and Norway while demand shocks are the most influential for Sweden and Finland. In addition, the author also reports that as the gas prices increase, the exchange rates for Finland, Denmark and Sweden decrease. Meanwhile, the exchange rates for Norway appreciate since it is an oil exporting country.

In most early studies, standard deviation of price differences is mainly applied as a tool of volatility of goods prices (Ferderer, 1996; Fleming and Ostdiek, 1999). On the other hand, in the recent studies dealing with volatility measuring and modeling have significantly increased with more sophisticated techniques. These include the general conditional heteroskedastic models (GARCH) and their modifications such as Threshold Generalized Autoregressive Conditional heteroscedasticity (TGARCH) and Exponential Generalized Autoregressive Conditional heteroscedasticity (EGARCH). In another recent study, Jimenez-Rodriguez and Sanchez (2004) analyzed the empirical impacts of gas price changes on the main economic activities for seven selected OECD economies, Norway and the Euro area at large. They applied a vector autoregressive (VAR) method using both linear and nonlinear models. The study finds that oil price rises have a bigger impact on gross domestic product (GDP) growth than gas price falls. The study also reveals that for the gas importing country, the increase in the gas prices have a significant non positive effects on its economic activities. In contrast for the gas exporting economies, the impact is uncertain. In another similar study done by Eltony and Al-Awadi (2001), a linear gas price changes is reported as crucial in explaining the changes in macroeconomic variables in Kuwait. Their findings depict the significance of gas price shocks in government expenditures, which are the main determinant for the country's economic activity.

Raguindin and Reyes (2005) assessed the impacts of oil price shocks on Philippine's economy from 1981 to 2003. Their research findings response functions for the linear transformation of gas prices suggest that gas price change causes delayed decrease in the real GDP of the Philippines. However, when a non-linear VAR model is used, a reduction in the oil price plays a greater role for the changes in each variable compared to oil price rise.

Anashasy et al. (2005) studied the impacts of gas price changes on Venezuela's economic performance for the years 1950 to 2001. The study used a general to a particular modeling (VAR and Vector Error Correction Model) approach to examine the correlation between gas prices, governmental revenues, governmental consumption spending, GDP and investment. The findings of their study revealed two significant long run relations which are consistent with economic growth and fiscal balance and that the relationship is vital not only for the long run performance but even for the short term changes as well.

Berument and Ceylan (2005) investigated how gas price changes impacts the output growth for the chosen sample of gas importing and gas exporting economies from the Middle East and North Africa. In their study, a structural VAR model is applied based on explicitly world gas prices and the actual GDP for the period 1960 to 2003. Their study findings suggests a positive and statistically significant effect of the world gas price on the GDP of Algeria, Iran, Jordan, Iraq, Kuwait, Oman, Qatar, Syria, Tunisia and United Arab Emirates. On the other hand, no significant impact on oil price shock was found for Egypt, Lebanon, Bahrain, morocco and Yemen. In another similar study on the impacts of gas price changes on inflation, output, real exchange rate and money supply in Nigeria, was done by Olomola and Adejumo (2006). They used VAR technique in the analysis of the quarterly data from 1970 to 2003. The results of their study revealed that gas price changes have no significant effect on both output and inflation. However, the changes are found to have a significant influence in determining the real exchange rate and long run money supply. They (authors) deduced that this could end up squeezing the trade sector. Narayan, Narayan et al. (2008), on the other hand, examined the relationship between oil prices and the Fijian dollar-US dollar exchange rate using daily data for the period of 2000-2006 via GARCH and EGARCH model. The main result of their study suggests that an increase in oil prices causes an appreciation of the Fijian dollar. Another study on oil price shocks in a global perspective done by Rasmussen, Tobias N. and Augustin Roitman (2011), examined the relationship between the cyclical component of gas prices and the cyclical components of GDP, imports, and exports. The findings indicate that these relationships have, worldwide, always been non negative and rising for the past 40 years. This shows that periods corresponding to increased gas prices have generally coincided with good times for the world economy, more so in the recent years. On the other hand, to assess the effect of high gas price changes on economic activity, the study focus on the 12 episodes since 1970 in which gas prices reached three-year highs. The findings show no evidence as well of a widespread contemporaneous negative impact on economic output across gas-importing economies, but instead value and volume rises in both imports and exports.

Edelstein and Kilian (2007), Herrera and Pesavento (2007) and Blanchard and Gali (2007), find a decreased effect of oil price shocks on real GDP and inflation over time for the US economy. Baumeister and Peersman (2008), on the other hand, have indicated that such comparisons over time are seriously affected since the global oil market has been characterized by another remarkable structural variation since the mid-eighties.

Other researchers investigated whether there is a long-run correlation between gas price changes and real exchange rates. For instance, Chen and Chen (2007), investigated the long-run equilibrium relationship between real gas prices and real exchange rates using monthly data for the G7 economies during 1972M1, 2005M10. The finding of their investigation is that a co-integrating relationship exist between actual gas prices and real exchange rates. Similarly, Lardic and Mignon (2006) examine the long-run equilibrium relationship between gas prices and GDP in twelve European countries using quarterly series. The results of their findings show that the relationship between gas price and GDP is asymmetric. That is, increasing gas prices retard aggregate economic activity more than decreasing gas prices stimulate it. Their findings also show that, while the standard co-integration between the variables is rejected, there is asymmetric co-integration between gas prices and GDP in most of the European countries.

CHAPTER 3

METHODOLOGY

In this section, the methodology used in this thesis is presented. We briefly introduce the main models applied to model gas price series, discuss their main properties, some of their modifications and statistical tools applied to time series modeling.

3.1 Univariate Time Series Model

3.1.1 Autoregressive Integrated Moving Average (ARIMA) Model

Developing an ARIMA model requires an appropriate sample size. Box and Jenkins proposed that at least 50 data points of the series should be the smallest sample size to be used. Some analysts hardly use a smaller sample size and they usually interpret the results with caution. On the other hand, a large sample size is suitable and needed while dealing with seasonal series. Box-Jenkins technique gave better predictions corresponding to 74% of the series examined in the study done by Pankratz (1983).

Many regular ARIMA model consists of three parts namely; p, d, and q. Here p is the number of the autoregressive parameters, d is the number of differencing parameters and q is the number of moving average parameters. A generalized ARIMA model takes the structure (Bruce et al, 2005; and John and David, 2003):

$$Y_t = C + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots \varphi_p Y_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_p a_{t-q} \quad (1)$$

where;

t: is the period, Y_t : is the number of observed series for each period

φ_i : for i = 1, 2,...,*p* are the AR parameters

θ_j : for j = 1, 2,...,*q* are the MA parameters

a_t : is the change term at period *t*

We can obtain the parameters φ_i and θ_j - for a constant values of *p* and *q*, in the expression (2) below after identifying the model.

$$\hat{Y}_t = \mu + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots \varphi_p Y_{t-pt} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_p a_{t-q} \quad (2)$$

There are two stages of identifying a possible Box-Jenkins model. The first is converting the data when due into a stationary series and secondly, obtaining the possible fit by looking at the nature or behaviour of the Autocorrelations (ACF) and Partial Autocorrelations (PACF). A stationary time series is where there is no trend existing in the series. That is, it fluctuates around non varying mean. Box and Jenkins propose the number of lag to be at most (n/4) autocorrelations. The autocorrelation coefficient measures the correlation between a given combination of series and lagged series of observed series. The autocorrelation between Y_t and Y_{t+k} measures the correlation between pair (Y_1, Y_{t+1}), (Y_2, Y_{2+k}),.., (Y_n, Y_{n+k})

Also, the sample autocorrelation coefficient r_k which is an estimate of ρ_k is given as follows

$$r_k = \frac{\sum(Y_t - \bar{Y})(Y_{t+k} - \bar{Y})}{\sum(Y_t - \bar{Y})^2} \qquad (3)$$

with

Y_t: The value of stationary gas prices series

Y_{t+k} : The value of gas price for *k* period ahead of *t*.

$\bar{Y}$: The mean of stationary time series

The approximated PACF and ACF are used to select at least one possible models for series under investigation. The idea of partial autocorrelation analysis is that we want to measure how $\hat{Y}_t$ and $\hat{Y}_{t+k}$ are related. The appropriate partial autocorrelation estimate is given by equation

$$\hat{\varphi}_{11} = r_1$$

$$\hat{\varphi}_{kk} = \frac{\boldsymbol{r_k} - \sum_{\boldsymbol{j=1}}^{\boldsymbol{k-1}} \hat{\varphi}_{k-1,j} r_{k-j}}{\boldsymbol{1} - \sum_{\boldsymbol{j=1}}^{\boldsymbol{k-1}} \hat{\varphi}_{k-1,j} r_j} \qquad k = 2,3,... \qquad (4)$$

$$\hat{\varphi}_{kk} = \hat{\varphi}_{k-1,j} - \hat{\varphi}_{kk}\hat{\varphi}_{k-1,k-j} \qquad (5)$$

Where, *k* = 3, 4,..; j = 1,2,..,k-1

3.1.2 Seasonal ARIMA Model

The shape of the ACF and PACF in a seasonal model can be determined. That is, the multiplicative seasonal ARIMA model (p,d,q)x$(P,D,Q)_S$ is generalized and taken as an extension of the ARIMA technique to the series in which patterns repeat seasonally over time. Here, the parameters (p,d,q) denote non-seasonal part while $(P,D,Q)_S$ represent the seasonal part. s denotes the seasonal period, which is 12 for monthly data set in our study (i.e. s = 12). After obtaining a stationary series, the ACF cuts off quickly. It is then possible to select possible model by analyzing the behaviour of both ACF and PACF. For a combined model, both acf and pacf decays exponentially after lags p and q. If we consider our time series to be generated according to

$$Y_t = e_t - \Theta e_{t-12}, \qquad (6)$$

then we can obtain

$$\text{Cov}(Y_t, Y_{t-1}) = \text{Cov}(e_t - \Theta e_{t-12}, e_{t-1} - \Theta e_{t-13}) \qquad (7)$$

$$= 0.$$

However that

$$\text{Cov}(Y_t, Y_{t-12}) = \text{Cov}(e_t - \Theta e_{t-12}, e_{t-12} - \Theta e_{t-24}) \qquad (8)$$

$$= -\Theta \boldsymbol{\sigma}_e^2$$

This kind of series becomes stationary and with a white noise at lag 12.

When we Generalize the expressions noted before in section 3.1.1, we can now define a seasonal MA(Q) model of order Q with seasonal period *s* by

$$Y_t = e_t - \Theta_1 e_{t-s} - \Theta_2 e_{t-2s} - \cdots - \Theta_Q e_{t-Qs} \tag{9}$$

with seasonal MA characteristic polynomial

$$\Theta(x) = 1 - \Theta_1 x^s - \Theta_2 x^{2s} - \cdots - \Theta_Q x^{Qs}. \tag{10}$$

It is evident that such a series is always stationary and that the ACF will be nonzero only at the seasonal lags of *s*, 2*s*, 3*s*,...,Q*s*. Specifically,

$$\rho_{ks} = \frac{-\Theta_k + \Theta_1\Theta_{k+1} + \Theta_2\Theta_{k+2} + \cdots + +\Theta_{Q-k}\Theta_Q}{1 + \Theta_1^2 + \Theta_2^2 + \cdots + \Theta_Q^2} \tag{11}$$

for *k* =1,2,...,Q

A model is invertible, if the roots of $\Theta(x) = 0$ all are greater than 1 in absolute value.

We can also define the seasonal AR(*p*) model of order *p* and seasonal period *s* by

$$Y_t = \phi_1 Y_{t-s} + \phi_2 Y_{t-2s} + \cdots + \phi_p Y_{t-ps} + e_t \tag{12}$$

with seasonal characteristic polynomial

$$\phi(x) = 1 - \phi_1 x^s - \phi_2 x^{2s} - \cdots - \phi_p x^{ps} \tag{13}$$

In this case, e_t is independent of $Y_{t-1,}Y_{t-2,}$...,and, for stationarity, the roots of $\phi(x)$= 0 have to be greater than 1 in absolute value. It is important to note that equation (12) is a special case for AR(*p*) model of order *p* = *ps* with nonzero ϕ-coefficients only at the seasonal lags *s*, 2*s*, 3*s*,...,*ps*.

3.1.3 Multiplicative Seasonal ARIMA models

Multiplicative seasonality is a case where the size of the seasonal fluctuations deviates based on the general series level. It is obtained by mixing the seasonal and nonseasonal ARIMA models. The resulting model is said to be parsimonious and contains autocorrelation for seasonal lags and also for low lags neighboring the series. Alternatively, the generalized multiplicative seasonal ARMA (p,q)x(P,Q)$_s$ model with seasonal period *s* is defined as a model with AR characteristic polynomial $\phi(x)\Phi(x)$ and MA characteristic polynomial $\theta(x)\Theta(x)$, where

$$\left.\begin{aligned}\phi(x) &= 1-\phi_1 x - \phi_2 x^2 - \cdots - \phi_p x^p \\ \Phi(x) &= 1-\Phi_1 x^s - \Phi_2 x^{2s} - \cdots - \Phi_p x^{ps}\end{aligned}\right\} \qquad (14)$$

and

$$\left.\begin{aligned}\theta(x) &= 1-\theta_1 x - \theta_2 x^2 - \cdots - \theta_q x^q \\ \Theta(x) &= 1-\Theta_1 x^s - \Theta_2 x^{2s} - \cdots - \Theta_Q x^{Qs}\end{aligned}\right\} \qquad (15)$$

3.1.4 Nonstationary Seasonal ARIMA models

The most needed measure in modeling nonstationary seasonal processes is the seasonal difference. This seasonal difference whose period is s for { Y_t} is denoted by $\Delta_s Y_t$ and given as

$$\Delta_s Y_t = Y_t - Y_{t-s} \tag{16}$$

Defining a nonstationary seasonal model

A series Y_t is said to be a multiplicative seasonal ARIMA model with regular orders *p*,*d*, and *q*, seasonal orders *P*,*D*, and *Q*, and seasonal period *s* if the differenced series

$$W_t = \Delta^d \Delta_s^D Y_t \tag{17}$$

Satisfies an ARIMA(*p*,*q*)x(*P*,*Q*)$_s$ model with seasonal period *s*. Then we say that {Y_t} is an ARIMA(*p*,*d*,*q*)x(*P*,*D*,*Q*)$_s$ model with seasonal period *s*. These kind of models are large and flexible from which selection of the best model for a specific series can be done. It is said to be statistically adequate to fit various series using these models and they usually have small number of parameters. Hence, in this thesis, we shall employ the models to analyze the data set.

3.2 Model Estimation

Box and Jenkins suggest a practical four-step procedure for determining the model. The four-step UBJ procedure is given as follows:

Step 1: Pre-requisite Transformation

If the series display futures that violates the stationarity assumption, then it is important to transform the series first in order to satisfy the stationarity assumption. Once the appropriate transformation is applied and autocorrelation function seem to be nonstationary, then differencing should be taken. In this study, the prerequisite test for stationarity and seasonality of the series was carried out in which a first regular difference (*d*) as well as natural logarithm (*ln*) transformation was taken. This power was suggested by Box-Cox transformation. After obtaining the stationarity of the series, both ACF and PACF of the stationary series are used to determine the order p and q of the ARIMA model.

Step 2: Identification

At this point, we now have six parameters *p*, *d*, *q*, *P*, *D* and *Q* to identify the likely model. The identification is done in two stages. The first stage is to identify a combination of *d* and *D* required to produce stationarity. For the seasonal data set, the autocorrelogram will have spikes at the seasonal frequency. For example, monthly series have high autocorrelations at lags 12, 24, 36, 48 and so on in that order.

Examining these will indicate the need for seasonal differencing. In case there is need for seasonal differencing, then the autocorrelogram has to be re-estimated for the seasonally differenced series. Identification of *d* is done in similar way to the nonseasonal case. An extension of the Dickey-Fuller tests due to Hylleberg, Engle, Granger and Yoo (see Canova & Hansen, 1995; Hylleberg et al, 1990; Beaulieu & Miron, 1993) exists and may be used. The second stage is that after selecting *d* and *D*, we tentatively identify *p*, *q*, and *Q* from the ACF and PACF functions as mentioned in

Step 1 (pre-requisite transformation). P and Q are identified by looking at the correlation and partial autocorrelation at lags s, 2s, 3s,....(multiples of the seasonal frequency). Meanwhile, in identifying p and q we ignore the seasonal spikes and proceed as in the nonseasonal case.

$(0, d, 2)\text{x}(0, D, 2)_s$

$(1, d, 1)\text{x}(1, D, 1)_s$

Step 3: Estimation and selection of the model

At the Estimation step, we obtain precise estimates of the coefficients of the model chosen at the identification step. We fit this model to the available data series to obtain estimates of ϕ1 and C in equation (1). After estimation, the best model is selected by use of information criteria. In this criteria, different competing models of a given series may be ranked according to their values of a chosen information criterion. These criterion include;

- AIC – Akaike information criterion

AIC: This is a measure of the goodness-of-fit for the fitted model:

$$AIC = -2log(L) + 2k \qquad (18)$$

where L denotes the maximized value of the likelihood function for the estimated model, k represents the number of parameters in the statistical model. The component 2k is a penalty for large number parameters in the model. A model with the smallest value of the AIC is better than the others.

BIC – Bayes information criterion

BIC is a criterion for model selection among a class of parametric models. It is given as

$$\text{BIC} = -2\log(L) + k\log(\text{n}), \qquad (19)$$

where L is the maximized value of the likelihood function for the estimated model, k is the number of the parameters in the model, n is the sample size. For any two estimated models, the model with the lowest value of BIC is preferred over the other.

This step gives some warning signals regarding the appropriateness of the model. In particular, if the estimated coefficients fail to meet all the conditions, then we reject the model.

Step 4: Model diagnosis

After selecting our model, and having estimated its parameters, the adequacy of the fitted model is assessed by examining if the errors are statistically adequate. That is, if the residuals are white noise; we accept the model, else we reject and go back to Step 1 and remodel until the appropriate fit is found. The outputs at this stage can depict how we can improve on our model. R has the function tsdiag ( ), which gives a diagnostic plot of the estimated model. There are a number of diagnostic measures available for ensuring that the ARIMA model is statistically adequate. The first measure is to first plot the standardized residuals. This must indicate that residuals are stationary. That is, they (residuals) should have zero mean with no autocorrelation. The second check is to simply plot the autocorrelogram of the residuals of the fitted model. The nature of the residuals of the model should resemble a white noise process if the model is appropriately specified. That is, a plot of autocorrelation should immediately die out from one lag on. In that case, any significant autocorrelations may results in model specification. Thirdly, a statistically adequate model should have random shocks, e_t that are statistically independent. The residual autocorrelations r_k (k = 1, 2, ...,l) have to be uncorrelated and normally distributed as N(0, 1/n). The selected model will be examined for autocorrelation in residuals. Generally, it is testing the null hypothesis, that there is no residual autocorrelation, against the alternative hypothesis where there is at least one nonzero autocorrelation. That is,

$H_0 : r_k = 0$ and k = 1, 2, 3, ..., K

$H_0 : r_k \neq 0$ for at least one k = 1, 2, 3, ..., K

To ensure these assumptions, one can adopt a diagnostic chi-square test, known as the Ljung-Box test, on the autocorrelations of the residuals in order to test for adequacy in the model. This test statistic is given as,

$$Q^* = n(n+2)\sum_{k=1}^{k}(n-k)^{-1}\, r_k^2(\hat{a}) \sim \mathcal{X}_{l-m}^2 \qquad (20)$$

where n is the number of the observation used to fit the model and l is the number of autocorrelations included in the test. Also, $r_l^2(\hat{a})$ is the squared sample autocorrelation.

The Q^* statistic approximately follows the chi-squared distribution. Thus, if Q^* is large, and statistically significant from zero, reject the null hypothesis; hence, it indicates that the residuals of the estimated model are autocorrelated.

The fourth tool is that the analyst must check whether the standardized residuals are normally distributed, based on the third and fourth moments, by measuring the difference of the skewness and kurtosis of the series with those from the normal distribution.

3.3. Forecasts for the models

The main goal of constructing a model for a time series is to make future predictions for a given series. It also plays a significant role in assessing the forecasts accuracy. In this section, two methods are used in forecasting. That is, ARIMA or SARIMA and Exponential smoothing methods. The analysis were carried out in R.

3.3.1 ARIMA forecasts

The ultimate test of an ARIMA model is its power or ability to forecast with the use of functions mentioned above. In order to obtain a forecast with a minimal errors, there are seven futures of a good ARIMA model taken into account (Prankratz, 1983). First, a good model is parsimonious. That is, it has the smallest number of coefficients which explain the data set. This provides a strong orientation in the model building. Secondly, a good autoregressive (AR) model must be stationary. That is, the time series should have a constant mean and variance. Thirdly, the moving average (MA) of the model should be invertible. Fourth, a good model should have high quality estimates of its coefficients (AR and MA). That is, the coefficients must be statistically significant and different from zero. Fifth , the residuals of a good model should be independent. Sixth, a good model should be normally distributed. Having obtained the appropriate fitted model, the results of the forecast errors will be determined and examined. Lastly, good fitted model has sufficiently optimal forecast errors, which satisfactorily forecasts the future and fit the past series normally as well. That is, it gives acceptable forecast results.

From the existing theory of the series up to time t, namely, Y_1, Y_2, ...,Y_{t-1},Y_t, we can forecast the value of Y_{t+h} that will happen *h* time units ahead. In this case, time *t* is the forecast origin and *h* is the lead time forecast. This forecast is denoted and estimated as

$$\hat{Y}_t(l) = \mathrm{E}(Y_{t+h}|Y_1, Y_2, ...,Y_t) \tag{21}$$

3.3.1.1 Measuring the Forecast accuracy for SARIMA model

Some goodness-of-fit measures are obtained using accuracy ( ) code in R. These measures of forecast accuracy are based on the differences between predicted values of the dependent variable at time *t* and the actual value of the dependent variable at the same period (time *t*). There are number of forecasting accuracy measures, some of which are based on an average of the errors between the actual and predicted values at time *t*. The forecasting error is represented as:

$$e_t(h) = Y_{t+h} - \hat{Y}_t(h) \tag{22}$$

$$= a_{t+1} + \psi_1 a_{t+(-1} + ... + \psi_{(-1} a_{t+1}$$

$$= \sum_{h=0}^{i-1} \psi_i \, a_{n+(-i}$$

The expectation of the forecast is zero i.e.., $\mathrm{E}(e_t(h))$ = 0 and this means that the prediction is unbiased.

The Variance of the forecast error is obtained as

$$\mathrm{Var}(e_t(h)) = Var(\sum_{i=0}^{i-1} \psi_i \, a_{n+(-i)}) = \sigma_a^2 \sum_{i=0}^{i-1} \psi_i^2 \tag{23}$$

Measuring Forecasting accuracy

A fundamental challenge while predicting is how to determine prediction error and appropriate technique for a series under study. The term accuracy refer to how best the model fits a given series, Makridakis and wheelwright (1989). All the forecast accuracy measures used, are obtained as follows;

- Mean error

$$\boldsymbol{ME = \frac{1}{n}\sum_{i=1}^{n} e_t} \quad (24)$$

- Mean Square Error

$$\text{MSE} = \frac{1}{n}\sum_{t=1}^{n}(\hat{Y}_t - Y_t)^2 \quad (25)$$

- Root Mean Square Error

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\hat{Y}_t - Y_t)^2} \quad (26)$$

- Mean percentage Error

$$\text{MPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{(\hat{Y}_t - Y_t)}{\hat{Y}_t} x100 \quad (27)$$

- Mean Absolute Error

$$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n}|(\hat{Y}_t - Y_t)| \quad (28)$$

- Mean Absolute Percentage Error is also calculated as

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\frac{|(\hat{Y}_t - Y_t)|}{\hat{Y}_t}x100 \qquad (29)$$

where n stands for the retained out-of-sample observations for the forecast appraisal. MAPE is sometimes preferred measure than MSE as it gives less error. However, it is less preferable to RMSE.

3.3.1.2. Exponential Smoothing method and Prediction

The term exponential originates from the fact that weights decay exponentially. It is extended to the "Holt-Winters"-procedure so as to handle series containing both trend and seasonal irregularities. Because of this, three smoothing parameters are needed. These are alpha (α for the level), beta (β for the trend) and gamma (γ for the seasonal variations). The ts-library in R contains the function Holt-Winters (y, alpha, beta and gamma), which enables the analysis to follow the Holt-Winters steps for a given series y. At this point, the three parameters can be identified with the optional α, β and γ. Specific terms are eliminated by considering the corresponding value of the parameter as zero. For example, the seasonal term is removed by taking gamma as zero. Similarly, the smoothing parameters are obtained automatically. Exponential smoothing is a powerful forecasting tool which is characterized by its simplicity and nonparametric properties. According to Hyndman et al. (2002) and Hyndman et al. (2005b) have shown that all exponential smoothing methods (including non-linear methods) are optimal forecasts from innovations state space. Exponential smoothing techniques were originally classified by pegels' (1969) taxonomy. This method was later extended by Gardner (1985), modified by Hyndman et al. (2002), and extended again by Taylor (2003), giving a total of fifteen methods as shown in table 3.1 (below).

Table 3. 1 Exponential smoothing methods

	Seasonal Component		
Trend Component	N (None)	A	M (Additive) (Multiplicative)
N (None)	N,N	N,A	N,M
A (Additive)	A,N	A,A	A,M
A_d (Additive damped)	A_d,N	A_d,A	A_d,M
M (Multiplicative)	M,N		M,A
M_d (Multiplicative	M,M		
damped)	M_d,N		M_d,A
	M_d,M		

When a time series Y_t is decomposed, it is then split up into four non-observed components. A certain relation is assumed between these four components. The decomposition is either of the additive type (A) or the multiplicative type (M)[2].

The multiplicative model is defined by:

$$Y_t = T_t \text{ x } C_t \text{ x } S_t \text{ x } I_t \,. \qquad (30)$$

and the additive model is defined as

$$Y_t = T_t + C_t + S_t + I_t \, . \qquad (31)$$

where;

T is the trend, C is the cycle, S is the seasonal component and I is the irregular component.

The two models differ in that, in the additive model (A), the seasonal variation is independent of the absolute level of the time series, but it takes approximately the same magnitude each time. While in the multiplicative model, the seasonal variation takes the same relative magnitude each time. This means that the seasonal variation equals a certain percentage of the level of the time series. The amplitude of the seasonal factor changes with the level of the time series.

Some of these methods in the above Table 3.1 are well known under other names. For instance, cell (N,N) explains the simple exponential smoothing (SES) method, cell (A,N) describes Holt's linear method, and cell (A_d,N) describes the damped trend method. The additive Holt-Winters' method is given by cell (A,A) and the multiplicative Holt-Winters' method is given by cell (A,M). The remaining cells correspond to less commonly used but analogous methods. The simplest exponential smoothing method is the single smoothing (SES) method where only one parameter needs to be estimated. Holt's method uses two different parameters and allows forecasting for series with trend. Holt-Winters' method involves three smoothing parameters to smooth the data, the trend, and the seasonal index. In this study, we use exponential smoothing (SES) method described in subsection 3.3.2 that follows. It entirely relies upon only the past history of the series as in the question.

3.3.2 Exponential Smoothing method

The exponential smoothing method is applied to minimize or smooth random behaviors existing a given series. It provides a true characteristics of the series. The technique can as well give appropriate ways of forecasting future values. ES is a well-known method which estimates smoothed series. It allocates exponentially reducing weights for the earlier series. The predicted value is generated by the following equation:

$$F_{t+1} = \alpha y_t + (1-\alpha)F_t \qquad (32)$$

where

F_{t+1}= forecast for the next period

α = smoothing factor (constant)

y_t = observed value of series in period t

F_t = old forecast for period t

The forecast F_{t+1} is based on weighting the most recent observations y_t with a weight α and weighting the most recent forecast F_t with a weight of $1-\alpha$.

If we expand equation (32), then we shall have the following

$$F_{t+1} = \alpha y_t + (1-\alpha)F_t$$

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

$$= \alpha y_t + \alpha(1-\alpha)y_{t-1} + (1-\alpha)^2 F_{t-1}$$

If this substitution process is repeated by replacing F_{t-1} by its components and so on, then the result is

$$F_{t+1} = \alpha y_t + \alpha(1-\alpha)y_{t-1} + \alpha(1-\alpha)^2 y_{t-2} + \alpha(1-\alpha)^3 y_{t-3} + \ldots + \alpha(1-\alpha)^{t-1} y_t \quad (33)$$

Here, F_{t+1} is the weighted moving average of all previous series. The exponential smoothing equation can be rewritten as follows:

$$F_{t+1} = F_t + \alpha(y_t - F_t) \quad (34)$$

Exponential smoothing forecast (F_{t+1}) is the old forecast (F_t) plus an adjustment for the error ($e_t = y_t - F_t$) that occurred in the last forecast. The value of smoothing constant α must be between 0 and 1. This means that α cannot be equal to 0 or 1. On the other hand, if stable predictions with smoothed random variation is desired, then a small value of α is used. Similarly, if a rapid response to real change in the pattern of observations is desired, a large value of α is appropriate. Thus, to estimate α, forecasts are computed for α equal to 0.1, 0.2, 0.3, ..., 0.9. Values of α near one have less of a smoothing impact and allocates higher weight to recent changes in the observed series, while values of α near zero have more smoothing impact and are less responsive to recent changes. It is important to know that there is no formally correct criterion for selecting α. However, statistician's judgment is applied to select the best factor. Alternatively, a statistical procedure may be adopted to minimize the size of alpha. For example, the method of least squares might be used to determine the value of alpha for which the sum of the quantities is minimized. The sum of squared forecast error is computed for each of the α level. The mean square error (MSE) is computed as in equation (25) or simply given as

$$\text{MSE} = \frac{SSE}{n-1} \tag{35}$$

where $\text{SSE} = \sum_{t=1}^{n} e_t^2$

The value of α with the smallest MSE is chosen for use in producing the best future forecasts. Other performance measures that can be used include MAD (Mean Absolute deviation) – measures the accuracy of fitted time series value. It expresses accuracy in the same units as data, which helps conceptualize the amount of error. MAPE (Mean Absolute Percent Error) – measures the accuracy of the fitted time series values. It expresses accuracy as a percentage. For all the three measures, smaller values generally indicate a better fitting model.

CHAPTER 4

EMPIRICAL ANALYSIS

This chapter covers the empirical modeling of Turkish oil prices. There are three basic reasons which play active roles in selecting this univariate variable. First, considerable shocks in gas prices always have great effect on the economy. For instance, most US post World War II recessions were triggered by sharp increases in crude oil prices, (Hamilton, 1983). Scerri and Reut (2009) document that changes in oil prices have impacts on budgetary estimates. Rasche and Tatom (1981), Darby (1982), Burbidge and Harrison (1984), and Gisser and Goodwin (1986) discuss the economic importance of gas price shocks on the macroeconomy for the oil importing countries. They report a negative linear relationship between oil prices and real activity for these countries. Furthermore, Pindyck (1999) demonstrates that large oil price changes increase uncertainty about the future of prices and thus leads to delays in business investments. Second, these Turkish series under investigation have not been studied before by using Univariate time series methodology. Observing this fact has triggered our interest to model this variable. Lastly, the oil price shocks play an important role for pricing derivatives and financial tools. Hence, modeling gas prices in order to analyze its behaviour is a crucial issue for both policy makers and agents in the financial markets. For the first step of the empirical analysis, a time series plot, Box-Cox power transformation, first order regular differencing and unit root tests for stationarity were considered. These tests included Kwiatkowski, Phillips, Schmidt and Shin (KPSS) (Kwiatkowski, Phillips et al., 1992) and Augmented Dickey Fuller (ADF) (Dickey and Fuller,1979). According to the results, KPSS or ADF are constructed for the series which provided significant empirical evidence for stationarity of the ARIMA model. ARIMA model was performed by using the methodology suggested by Box and Jenkins (1970). In order to obtain the appropriate or best model, we also constructed ACF and PACF plots to determine the possible models. Akaike information Criteria (AIC) (Akaike, 1974) and significance of parameters of the estimated models are examined for comparison purposes. Finally, diagnostic checks for zero mean, uncorrelated error terms, Normality and homoscedasticity tests are performed for the fitted model. To detect the residual correlations, the Box-Ljung test (1978) and Box-pierce test (1970) are employed. For the normality test, we use both well-known Jargque-Bera (1980) and Shapiro-Wilk normality tests. On the other hand, Breusch-Pagan (1979) test is used to detect the presence of homoscedasticity. The exponential smoothing models are also fitted automatically using the automatic smoothing code and the best one is selected based on the value of α with the smallest RMSE and ME. Other measures that can be used in the selection of the best model are MAD, MAPE and LAD. All these measures mentioned here, are familiar in the literature. Makridakis (1993) pointed out that MAPE may not be appropriate in certain situation, such as budgeting, where the average percentage errors may not properly summarize accounting results and profits. Accuracy measures based on mean square error (MSE) criterion, especially MSE itself, have been used widely for long time in evaluating forecasts for single series. In fact, Carbone and Armstrong (1982) found that RMSE had the most preferred measure of forecast accuracy. These are used to determine which of the values of α being considered have the lowest value of the selected performance measure. This chapter is divided into five sections as shown in Figure 1, below. The first section covers the data source and description part. It mainly shows the visual analysis and statistical descriptions of the series. The second section gives the results from the unit root tests. These results cover the standard unit root tests. The third section deals with model identification and estimation. The fourth subsection assesses the diagnostic checks for the fitted model and finally, section five gives the forecasts for both SARIMA and ES models.

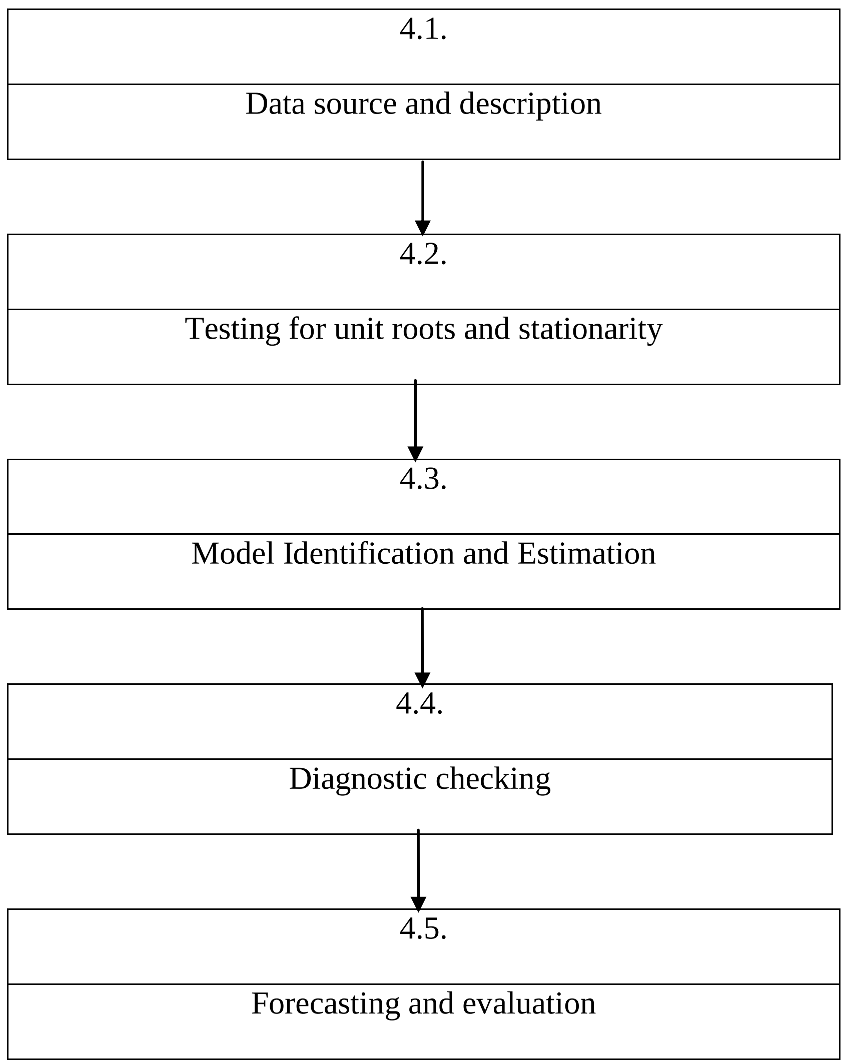

Figure 1: SARIMA modelling procedure

4.1. Data source and description

The data set was extracted from Turkish Statistical Institute. All the series are monthly gas prices data set from January 2003 to December 2011. Petrol series were considered. The statistical tool used in this study to analyze the data set is R. To obtain the general overview for the data set, we first plot the time series (Ts) plot of the original data set to assess the nature and behaviour of the series. According to Figure 2 below, the series shows that there is a possibility of stochastic trend to be existing in the gas price series. The process mean is not constant. The process variance does not indicate presence of heteroscedasticity and seasonality is not visible.

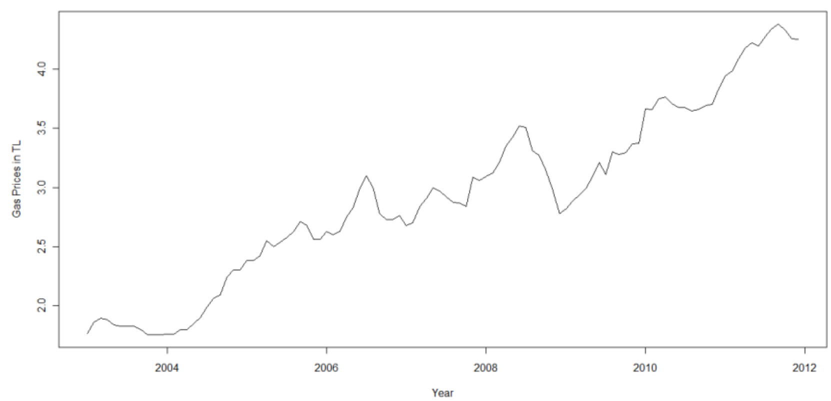

Figure 2: Time series plot of the gas prices in Turkey from January 2003 to December 2011

As next step of the analysis, a Box-Cox transformation is used to find out whether there is need for transformation of the series. The results from the Box-Cox transformation graph in Figure 3 below, indicate that $\hat{\lambda} = 0.002$. This is very close to zero and taking natural logarithm (*ln*) render to be an ideal step in the analysis.

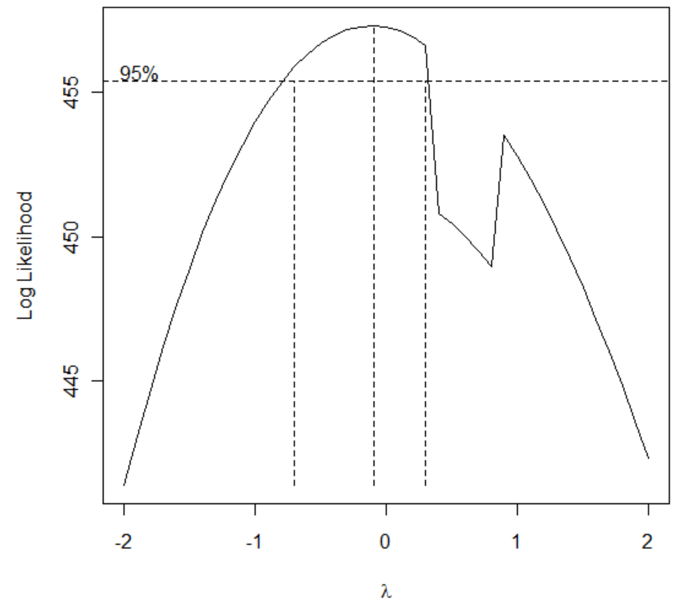

Figure 3. Box-Cox transformation plot

After taking the suggested transformation above, the transformed Ts plot in Figure 4 below seem to be depicting a stationary process. We can use the KPSS test to assess whether there is level stationary or trend in the series. We can do this by using KPSS tests in section 4.2, that follows.

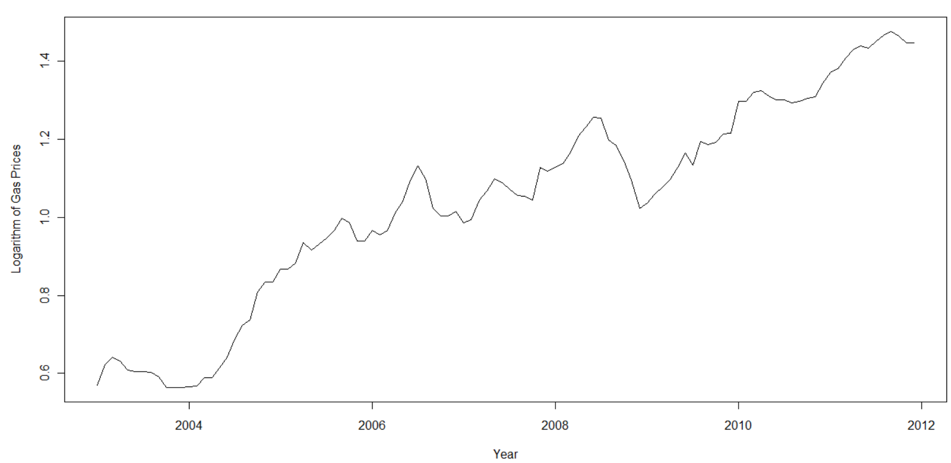

Figure 4. Time series plot of the transformed series

4.2 Phillips-Perron Unit Root Test and Visual Results

This section is divided into two subsections according to the types of unit root tests used in modeling the gas prices as described below. Subsection one presents the results observed from the standard unit root tests for stationarity and trend presence. These tests include Augmented Dickey Fuller (ADF) test and Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test. On the other hand, subsection two uses visual plots (ACF and PACF) to reveal the nature and behaviour of the series. The two detection criteria in both subsections are applied on the transformed series of the model as well as for the differenced one when taken. The motive here is to ascertain whether stationarity is attained after transformation or it can only be obtained after differencing. The examination on these issues follows in the next subsections.

4.2.1. Results from the unit root tests for the transformed series

After taking the proposed transformation, two unit root tests are employed to describe the nature of the data set. These two tests are KPSS and ADF. The KPSS test is used in two ways. Firstly, it is used to test the null hypothesis that the series is level stationary against the alternative that it is nonstationary. Secondly, it is applied to test the null hypothesis that there is trend stationary against the alternative that there is difference stationary series. In the first test, the results obtained show that KPSS Level = 3.3282, Truncation lag parameter = 2, p-value = 0.01. According to these results, the series is nonstationary since the p-value is less than the significance level (0.05). In the second use of this test, the results indicate that KPSS Trend = 0.3435, truncation lag parameter = 2 and p-value = 0.01. Here the p-value is reported to be less than the significance level meaning that we reject H_0 and conclude that the series is difference stationary. It means that there is a stochastic trend in the model. As a result of this, it is necessary to apply the ADF test for further investigation on the above findings. When the test is applied, the results of the output are reported to be; Dickey-Fuller = -11.8602, Lag order = 4 and p-value = 0.4287. Since the p-value is greater than the significance level (0.05), we fail to reject H_0 and conclude that the series is not stationary. By looking at the two different tests; namely stationary and unit root tests, we can say that the series is difference stationary. This can also be investigated graphically in subsection 4.2.2 that follows.

4.2.2. ACF and PACF plots for the transformed series

The ACF plot in Figure 5 below exhibits slow exponential decay behaviour. This could be an indicator of non-stationary process. On the other hand, the PACF plot in the same figure has all its spikes insignificant except one at lag-1.

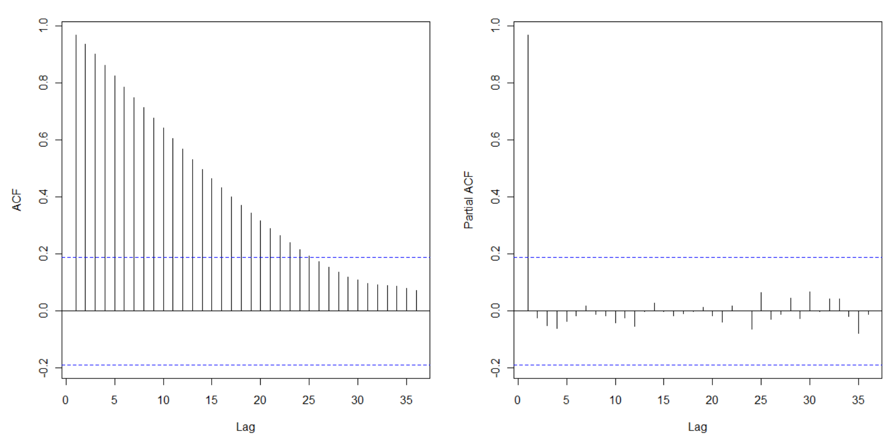

Figure 5: ACF and PACF plot of the transformed series

By looking at the results reported and observed from the two subsections (4.2.1 & 4.2.2) above, we conclude that the series is difference stationary. This means that we should take the first order regular difference. The results of taking this action are reported in section 4.2.3 below.

4.2.3. Results from time series plot for the differenced model

After differencing, the trend seem to be removed from the series and the process mean looks to be constant as shown in Figure 6 below. This means that the series is stationary after first order regular difference is taken on the gas series. However, to ascertain this finding, we need to carry out more analysis before estimating the parameters. That is, we need to carry out the same tests and visual plots applied above to confirm whether there is stationary in the series after differencing.

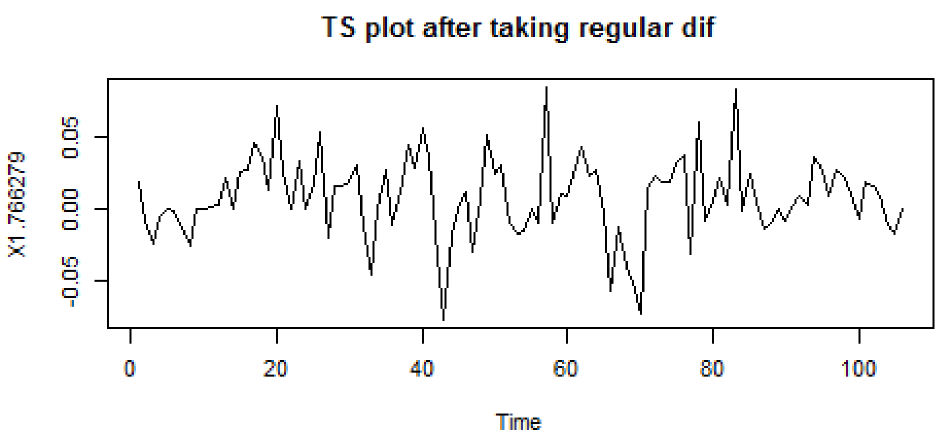

Figure 6. Time series plot of the transformed and differenced series

4.2.4. Results from Unit Root Test after differencing

After taking the first order regular difference, the results from both KPSS and ADF tests suggest that the model is stationary now. That is, in the KPSS test we are testing the null hypothesis that the series is level stationary against the alternative that it is not stationary. The results show that KPSS Level = 0.0576, Truncation lag parameter = 2 and p-value = 0.1. Based on these results, we fail to reject H_0 that the series are level stationary since its p-values is greater than the significance level. On the other hand, in the ADF test for the null hypothesis that the model is not stationary against the alternative that it is stationary, show that; Dickey-Fuller = -82.1174, Lag order = 4 and p-value = 0.01. This means we reject H_0 and conclude that the series is stationary. The two tests are in agreement with visual observation in the differenced TS plot in Figure 6, above. We can thus say that taking the first order regular difference is enough to make the process stationary. A further visual look at the ACF and PACF plots in Figure 7 below justifies our findings. That is, from the ACF plot, there are two significant spikes. Two significant spikes at lag-1 and at lag-6 are seen. This is the sign of MA(2) process. On the other hand, when we look at the PACF plot, there are two significant spikes at lag-1 and the second one at lag-12. This is a sign of AR(3) and AR(12) process.

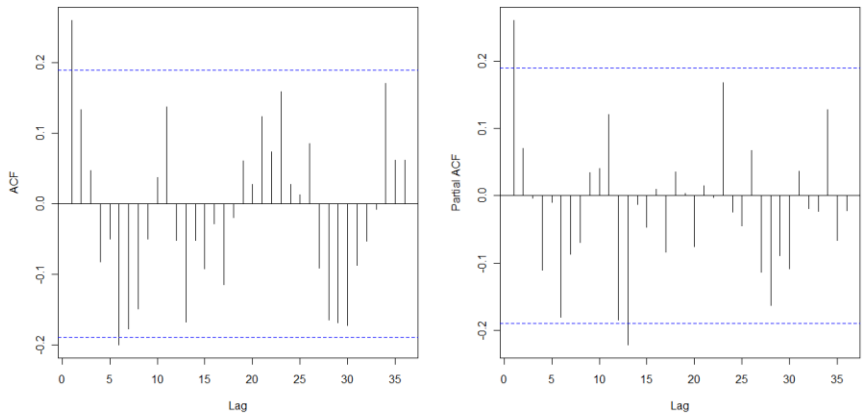

Figure 7. Acf & pacf plots of the transformed and differenced series

From Figure 7 above, we can summarize the observations for *p*, *d*, *q* and *P*, *D*, *Q* as follows:

- Two significant spikes at lag-2 and lag-8 in the ACF plot. Our MA order is 2 (*Q*=2).
- Cut off after lag 3 in ACF. Our MA order, *q*=2
- Lag *p*=6
- One regular difference was taken meaning that *d*=1
- One seasonal difference, *D*=0
- Monthly data, *s*=12

Thus, we can suggest our possible models for the series as SARIMA(1,1,1)(1,0,0)[12], SARIMA(1,1,0)(1,0,0)[12], SARIMA(0,1,1)(1,0,0)[12], ARIMA(1,1,1), ARIMA(1,1,0), ARIMA(0,1,1), ARIMA(1,1,6), ARIMA(0,1,6).

4.3. Model Identification and Estimation

This section is divided into two subsections. First subsection 4.3.1, discusses the model estimation and selection for ARIMA or SARIMA model, and subsection 4.3.2 deals with the estimation of the ES model.

4.3.1 SARIMA and ARIMA Model Estimation and Selection

After the model has been identified, we use conditional-sum-of-squares to determine the starting values of the parameters, then do the maximum likelihood estimate for the suggested models. The process for choosing these models depends on choosing the model with the smallest AIC and BIC. The models are given in Table 4.1 below with their corresponding values of AIC and BIC.

Table 4.1: Final output for the top five SARIMA and ARIMA models

Model	AIC	BIC
SARIMA(1,1,1)$(1,0,0)_{12}$	-459.86	-449.17
(SARIMA1,1,0)$(1,0,0)_{12}$	-460.56	-452.54
SARIMA(0,1,1)$(1,0,0)_{12}$	-458.06	-450.04
ARIMA(0,1,1)	-460.05	-460.05
ARIMA(1,1,0)	-462.55	-462.55
ARIMA(1,1,6)	-456.52	-435.14

Among those suggested possible models, comparing their AIC and BIC as shown in Table 4.1 above, the appropriate model is found to be ARIMA(1,1,0) with its AIC = -462.55. From our fitted model, using the method of maximum likelihood, the estimated parameters (AR1) of the model with its corresponding standard error (s.e.) are given as 0.3221 and 0.0925, respectively. Also $\hat{\sigma}^2$=0.0007613. Based on these results, we conclude that all the coefficients of the ARIMA(1,1,0) model are significantly different from zero and the estimated values satisfy the stability condition. Meanwhile, in time series modeling, the selection of the best model fit to the data is directly related to whether residuals analysis is performed well. One of the assumptions of ARIMA model is that, for a good model, the residuals must follow a white noise process. That is, the residuals have zero mean, constant variance and also uncorrelated. Details of the assumptions are discussed under section 4.4 (diagnostic checks) in this chapter.

4.3.2 Exponential smoothing Model Estimation and Selection

The Exponential smoothing method is used to fit the model as per the procedures discussed in Chapter 3, subsections 3.3.2. The present note gives an interesting Exponential Modeling fit of the gas prices of Turkey. The fit is found to be well enough with a smoothing factor of $\hat{\alpha}$ = 0.9999 as shown below.

This model will be used together with ARIMA model in forecasting and then their results will be compared.

Exponential Smoothing

ETS(M,Ad,N)

Smoothing parameters:

alpha = 0.9999

beta = 0.3157

phi = 0.8

sigma: 0.0275

AIC	AICc	BIC
-36.87265	-36.28441	-23.46199

4.4. Diagnostic checks for the model

In this section, we deal with a rigorous assessment of the diagnostic tests for the selected ARIMA model. The fitted model from the Exponential smoothing method will not be assessed here. It will be assessed at the forecasting stage. Thus, only ARIMA model will be checked in this section. A number of diagnostic tools have been availed for ensuring that the model is statistically adequate. All these tools have been discussed in Chapter 3, section 3.2., step4. This section will be divided according to diagnostic checks as follows;

4.4.1 Checking for zero mean and white noise

From Figure 8 below, we can say that the residuals are stationary. That is, they approximately have zero mean. This is in line with the first assumption made in step 4 of section 3.2. On the other hand, all the spikes seem to be insignificant for both ACF and PACF. Only one spike in the PACF plot is slightly observed as above the white noise band at lag 12. However, if neglected, then we can say that we have a white noise process.

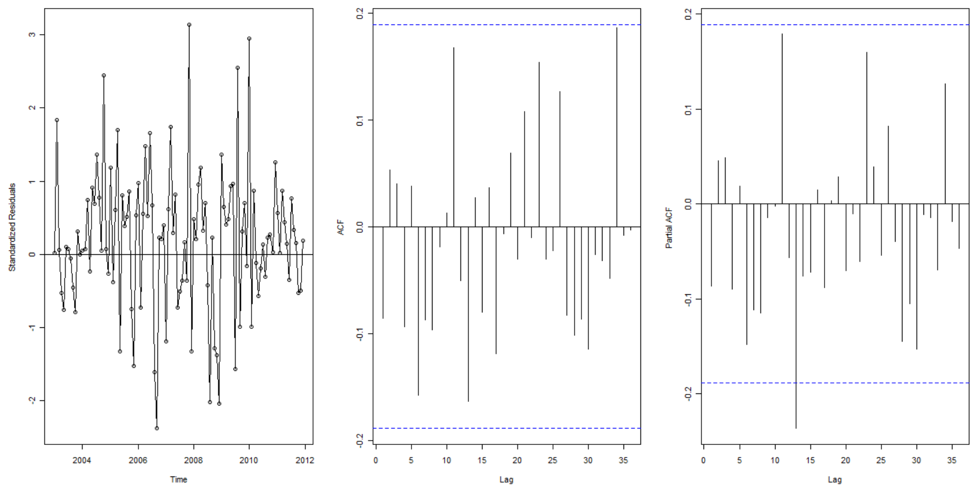

Figure 8: Plot of standardized residuals, ACF and PACF plots of standardized residuals

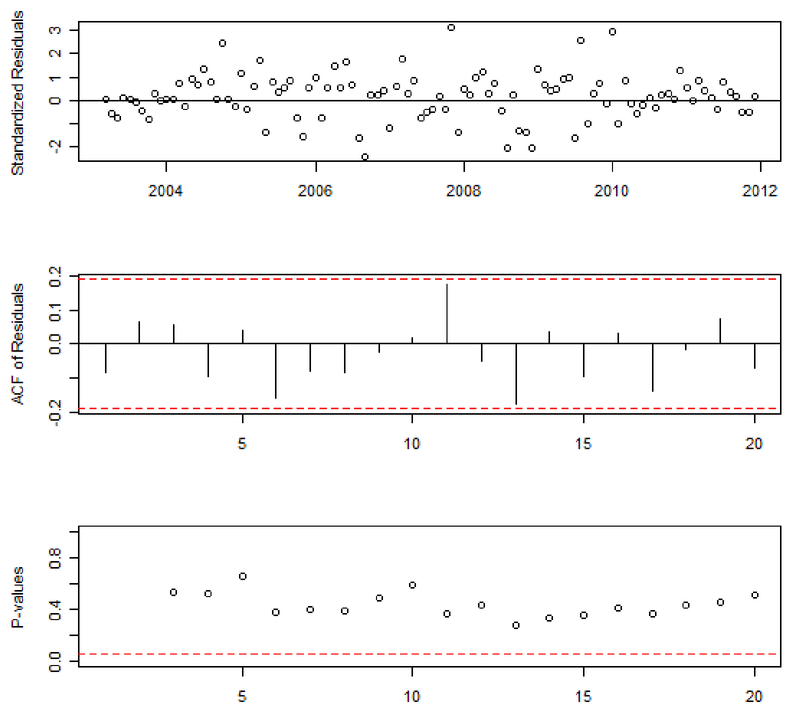

Figure 9: Diagnostic plots of standardized residuals

In Figure 9 above, all the residuals lie between -2 and +3 bands while the second plot of ACF depicts a white noise process. In the third plot of the p-value shows lack of correlation between its lags.

4.4.2. Testing for Uncorrelated error terms

In this section, we use two tests. The first test is the Box-Ljung test and the second test is the Box-Pierce test. The results from the first test are reported as χ-squared = 15.4648, df = 15 and p-value = 0.4185 while those from the second test are χ-squared = 13.9235, df = 15 and p-value = 0.5313. According to these results, the p-values are greater than the alpha level. We thus, fail to H_0 which means that there is no serial correlation. This is in line with the findings observed from p-value plot in Figure 9 above.

4.4.3. Testing for Normality of errors

From the QQ-plot and histogram of residuals below (Figure 10), we can say that the residuals come from a normal distribution. The data points are spread out near straight line although there are some points which depart from this line. We should analyze the test results for normality assumption in a more robust way.

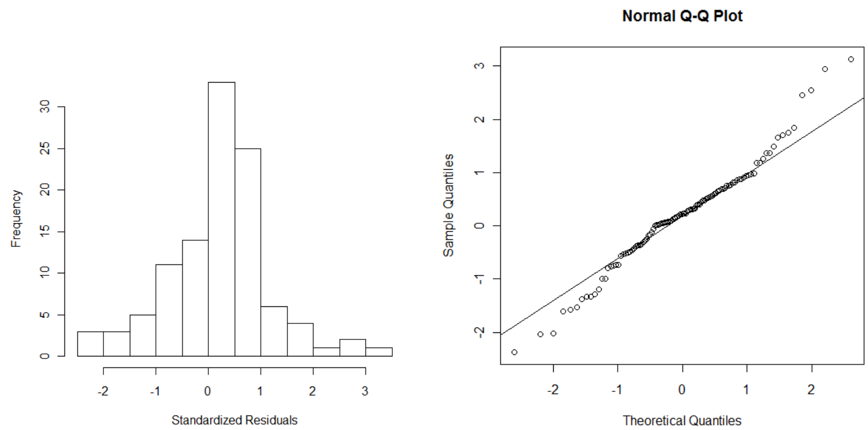

Figure 10: Histogram and QQ plot of standardized residuals

We can use two known tests to further investigate the normality assumption. These two tests are Jargue Berra test and Shapiro-Wilk normality test. They are both employed to test the null hypothesis that the error terms are normally distributed against the alternative that the error terms are not normally distributed. The results from the analysis reports Jargue Bera test as χ-squared = 4.0718, df = 2, p-value = 0.1306 while those for Shapiro-Wilk test as W = 0.9772, p-value = 0.06017. According to these results, the p-values from each test are greater than the alpha value. We thus fail to reject H_0 which means that the error terms are normally distributed.

4.4.4. Testing for homoscedasticity of the residuals

From the ACF and PACF plots in Figure 11 below, the squared residuals lie within the 95% White Noise bands except at high lags where one spike in each plot are seen as significant. However, we can ignore it, each plot has one above the limits each at lag 26 but this can be ignored and conclude that there is no heteroscedasticity.

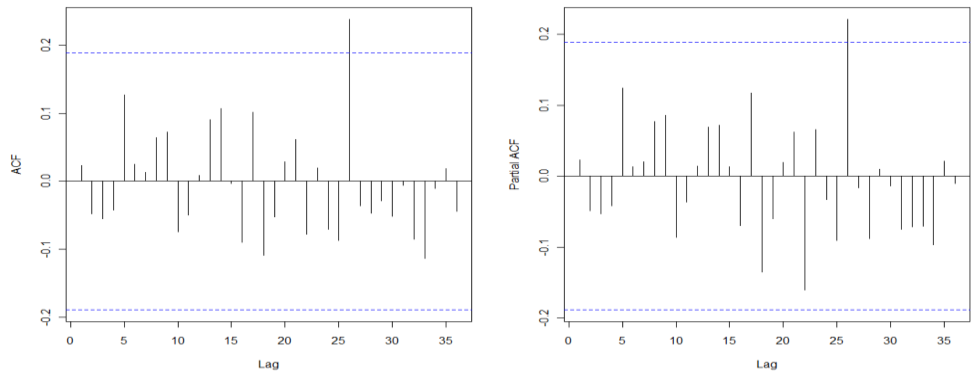

Figure 11: ACF and PACF plots of squared standardized residuals

4.5. Forecasts

In this section, two forecast estimates and forecast accuracy will be made as mentioned in Section 3.3 for the two methods employed in the analysis and their results will be compared in order to assess their forecasting performances. The first forecast are obtained from the ARIMA fitted model and the second one are made using the exponential smoothing model. These forecast estimates and measures of accuracy are computed by employing formulae 24-29 as given in Chapter 3, under Section 3.3.

In Figure 12 below, the red line is the plot of the original values and the black dots are the estimated values. When we look at the position of the dotted black lines, we can conclude that our model is suitable for our data because they are very close to each other. In order to make forecast check, we forecasted monthly gas prices for 2012. Table 4.2 presents the model forecasts and the corresponding standard errors. However, these forecasts are not of the original form of the series under analysis. They are for transformed and we need to retransform these forecasts in order to return to origin values by simply taking the exponential of the forecasted values. The results are presented in Table 4.3 below. On the other hand Table 4.4 below, reports the results for the accuracy measure for the ARIMA model. These results will be used in assessing the appropriate fitted model by comparing them. The model which will have the minimum values will stand to be the best.

4.5.1 ARIMA Forecasts

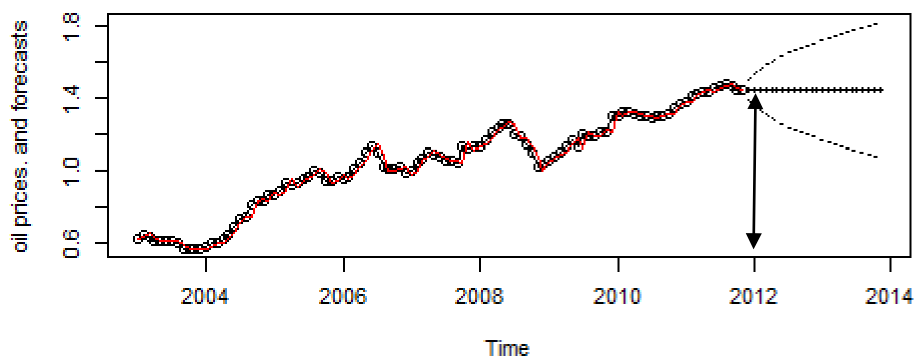

Figure 12. Plot of the estimated and forecasted values

Table 4.2. ARIMA Forecasts and their standard errors per month (in 2012)

Month	$pred	$se	Months	$pred	$se
Jan	1.447	0.045	Jul	1.448	0.107
Feb	1.447	0.059	Aug	1.447	0.114
Mar	1.448	0.071	Sep	1.447	0.121
Apr	1.447	0.081	Oct	1.447	0.127
May	1.447	0.091	Nov	1.447	0.133
Jun	1.447	0.099	Dec	1.447	0.139

Table 4.3. Forecast results of ARIMA after Retransformation

Month	Forecasts	Month	Forecasts
Jan	4.250518	Jul	4.250412
Feb	4.250445	Aug	4.250412
Mar	4.250422	Sep	4.250412
Apr	4.250415	Oct	4.250412
May	4.250413	Nov	4.250412
Jun	4.250412	Dec	4.250412

Table 4.4 Measure of goodness-of-fit for the ARIMA model

ME	RMSE	MAE	MPE	MAPE	MASE
0.0053	0.0272	0.0206	0.5224	2.038	0.954

4.5.2 Exponential Smoothing Forecasts

Table 4.5. Predicted values by ES

Month	Point forecast	Lo80	Hi80	Lo95	Hi95
Jan	4.238759	4.089465	4.388052	4.010434	4.467084
Feb	4.228567	3.951015	4.506118	3.804088	4.653045
Mar	4.220413	3.837416	4.603411	3.634669	4.806158
Apr	4.213890	3.734745	4.693036	3.481101	4.946680
May	4.208672	3.639524	4.777820	3.338236	5.079109
Jun	4.204498	3.550261	4.858734	3.203930	5.205065
Jul	4.201158	3.466091	4.936224	3.076971	5.325345
Aug	4.198486	3.386403	5.010569	2956512	5.440460
Sep	4.196349	3.310712	5.081985	2.841885	5.550812
Oct	4.194639	3.238611	5.150667	2.732520	5.656757
Nov	4.193271	3.169744	5.216797	2.627922	5.758619
Dec	4.192176	3.103800	5.280552	2.527649	5.856703

Table 4.5 above, displays the results of the forecasted gas prices obtained by the smoothing method. The predicted value results (point forecasts) seem to be close to those obtained by ARIMA model in Table 4.3.

4.5.2.1 Exponential Smoothing Forecasts

Figure 13 depicts the predicted and forecasted values using automatic exponential smoothing model obtained in subsection 4.3.2.

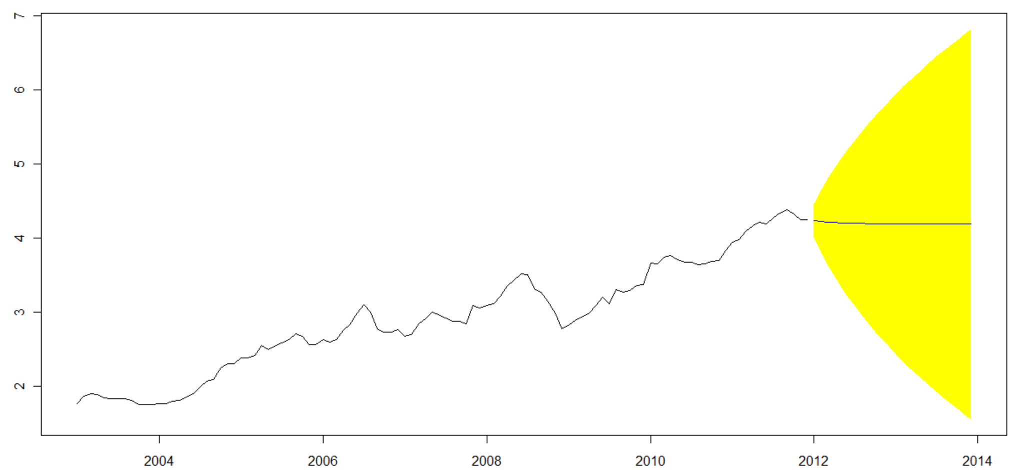

Figure 13. Plot of predicted and forecasted values using ES

Measuring the goodness-of-fit for the exponential model

Table 4.6 shows the results for the goodness of fit for the exponential smoothing model. The ME and RMSE are reported to be 0.008 and 0.0809 respectively.

Table 4.6. Measure of goodness-of-fit for ES model

ME	RMSE	MAE	MPE	MAPE	MASE
0.008	0.0809	0.0598	0.2937	2.0536	0.9431

4.6 Comparison of ARIMA and ES forecasts

Table 4.7. Forecasts of gas prices (in Turkey) for 2012 using ARIMA and ES models

Months	Original gas prices	ARIMA	ES
Jan	4.3657	4.250518	4.238759
Feb	4.3953	4.250445	4.228567
Mar	4.5639	4.250422	4.220413
Apr	4.6789	4.250415	4.213890
May	4.3547	4.250413	4.208672
Jun	4.2383	4.250412	4.204498
Jul	4.3085	4.250412	4.201158
Aug	4.4861	4.250412	4.198486
Sep	4.6023	4.250412	4.196349
Oct	4.8053	4.250412	4.194639
Nov		4.250412	4.193271
Dec		4.250412	4.192176

Table 4.7 presents the forecasts obtained using the two best models from each approach. The results from the ES seem to be close to those of ARIMA model. This means that simple methods like exponential smoothing sometimes give as good results as a complex model like ARIMA. They all give results which are close to the original series. However, the ARIMA model sees to be better in closeness to the original gas price series. We can also look at the accuracy measures for both methods in Table 4.8 below and assess their forecasting performances. Here the results obtained by the ARIMA and ES forecasting models for monthly gas prices in Turkey are compared with respect to

RMSE. From this table (Table 4.8) , it indicates that the ARIMA model is the best to forecast the future values, because it has the minimum measures of forecasting errors for RMSE which is used in our study. This measure is chosen since it is preferred over the others according to Carbone and Armstrong (1982). It is believed to produce more reliable results and it is widely used to choose the best forecasting models.

Table 4.8. Accuracy measures for both SARIMA and ES Forecasts

Methods/measures	ME	RMSE	MAE	MPE	MAPE	MASE
ARIMA	0.0053	**0.0272**	0.0206	0.5224	2.0383	0.9537
ES	0.0088	**0.0809**	0.0598	0.2937	2.0536	0.9431

CHAPTER 5

CONCLUSION AND FUTURE RESEARCH

This research study- is an attempt to choose the most appropriate model among the various estimated combinations of the Univariate time series models. That is, ARIMA model as well as ES models which pose high power for forecasting Turkish gas prices. We have come up with procedure guideline for ARIMA modeling which includes the following steps: data source and description; testing for unit roots and stationarity; model identification and estimation; diagnostic checks, and finally forecasting ability. The traditional Box-Jenkins and ES approaches were mainly employed in the analysis and forecasting of the future values. Specifically, ARIMA and ES methods are used since time series can be expressed in terms of historical data (AR part) plus present and lagged values of a 'white noise' error term (MA part). The main goal of this research was to determine the most appropriate model among these two for the purpose of forecasting in the real world circumstances, holding the cost of model construction. A general procedure for Univariate forecasting is to undergo all the testing stages of ARIMA process. These models are theoretically justified and they can give deviating results from those of the alternative approaches like multivariate modeling. This study is based on the monthly gas price data, which has been used to determine the various possible estimated ARIMA and ES models from which the best ones were selected. The forecasts from the two methods are reported to give results which are slightly deviated from each. In other words, the simple methods like ES sometimes give results as good as a complex model like ARIMA. The results from the two methods are close to the original series. However, the ARIMA was reported to be better in closeness to the original gas price series. Also, based on the accuracy measures, the ARIMA model was reported to have better forecasts than the ES since it has the minimum measures of forecasting errors for RMSE which is used in our study. Therefore, we can conclude that the forecasting of the Turkish monthly gas prices with ARIMA (1,1,0) is more efficient than the ES method.

The main contribution of this research is in evaluating the forecast performance of the various time series models used in a comprehensive and systematic way. Empirical results in this study will also pave the way for future research. The limitations of this study is that model is very effective in the short term forecasts than in the long run forecast. Also other external factors (such as demand and supply, government regulations, natural disasters) may have influenced the monthly variations in the gas prices other than its internal structure. As a further study, we suggest that analysis with explanatory variables, with linear and nonlinear models should be investigated to explore other factors that could be affecting gas prices. Causality analysis may give the factors affecting the gas prices in Turkey.

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