MODELLING AND FORECASTING THE CRUDE OIL DEMAND IN SRI LANKA: AN ECONOMETRIC APPROACH

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DECLARATION

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ABSTRACT

This study examines the effect of economic variables, Gross Domestic Product (GDP), Foreign Direct Investment (FDI), Population and Oil Price on oil consumption in Sri Lanka using an Error Correction Model. Yearly data of oil consumption, Gross Domestic Product (GDP), Foreign Direct Investment (FDI), Sri Lankan population and crude oil price during the period 1988 – 2013 were used in the analysis. All the data have been obtained by the online data sources of World Bank and United States energy information administration. This research involves estimating the elasticity of Gross Domestic Product (GDP), Foreign Direct Investment (FDI), Sri Lankan population and crude oil price on crude oil consumption in Sri Lanka.

Unit root test confirmed that series are not stationary in its levels but they are stationary in first difference. Therefore the study uses the Engle-Ganger cointegation method to create a dynamic short run model. Also Chow - break point test was used to test the significance of a structural break down in the data set and the dummy variable was significant in allowing for the structural change.

The Vector Error Correction (VEC) model finds that Gross Domestic Product (GDP), Foreign Direct Investment (FDI), population and oil price are determinants of the oil demand. It shows that in the long run only FDI increases the overall oil demand while GDP and population increase the oil demand in the short run.

By using the selected model, oil demand was forecasted and the Mean Absolute Percentage Error (MAPE) of the fitted model was found less than 5 percent. Therefore the fitted model is recommended as the suitable model to forecast oil demand. As the crude oil storage is a common problem in Sri Lanka, forecasting oil demand can be used to find the solutions for the challenges in the petroleum sector.

Key words: Petroleum Sector, Demand, Sri Lanka, Crude oil

Table of Contents

List of Figures

List of Tables

List of Abbreviations

Abbreviation	**Description**
ADF	Augmented Dicky Fuller
AR	Auto Regressive
ARIMA	Auto Regressive Integrated Moving Average
ARMA	Auto Regressive Moving Average
CEB	Ceylon Electricity Board
CON	Consumption
CPC	Ceylon Petroleum Corporation
df	degrees of freedom
FDI	Foreign Direct Investment
GDP	Gross Domestic Product
GDP(E)	Gross Domestic Product by expenditure approach
GDP(I)	Gross Domestic Product by the total Income generated
GDP(P)	Gross Domestic Product by production approach
iid	independent and identically distributed
LIOC	Lanka Indian Oil Corporation
LNCON	Logged values of oil consumption
LNFDI	Logged values of Foreign Direct Investment
LNGDP	Logged values of Gross Domestic Product
LNOILPRICE	Logged values of oil price
LNPOP	Logged values of population
MA	Moving Average
MAPE	Mean Absolute Percentage Error
Mbd	Million barrels per day
Mn	Millions

MSE	Mean Squared Error
OECD	Organization for Economic Corporation and Development
OLS	Ordinary Least Squares
POP	Population
RSS	Residual Sum of Squares
USD	Unites States Dollar
VAR	Vector Auto Regressive
VEC	Vector Error Correction
VECM	Vector Error Correction Model

CHAPTER 1

INTRODUCTION

1.1 Introduction

Crude oil is considered as an unrefined oil product composed of organic compound which consists of different organic materials. Crude oil is used to refine usable products like hydrocarbon, solvents, gasoline, kerosene, diesel and various kinds of petrochemicals. It is an unrenewable resource, which implies that it cannot be replaced naturally at the speed of consumption. Hence it is considered as a limited resource.

Global crude oil demand is around 90 million barrels per day (Mbd), from that 50% is consumed by the countries who are members of Organization for Economic Corporation and Development (OECD) (Samaratunga, 2014). Sri Lanka's crude oil consumption is very small compared with the world demand. Sri Lanka has been an importer of crude oil for a long time and the country spends 24% of the import price on it. The Ceylon Petroleum Corporation (CPC) has been a monopoly supplier of fossil oil to the native market. However, Lanka Indian Oil Corporation (LIOC) was added to the market to form a duopoly within the fossil oil product distribution in 2003. Many subsectors of fossil oil business are liberalized since the 90s to make a competitive surrounding within the business. Emerging trends within the business indicate that the control of the country's petroleum business is a crucial space of concern. As seen in several different countries, transport sector is that the largest shopper of oil in Sri Lanka.

Sri Lanka is importing refined products since many years for domestic consumption. Hence the demand of the petroleum products is increasing in both volume and value terms. Ceylon Petroleum Corporation (CPC) was ready to meet the overall fossil oil product demand of the country through its solely plant within the nineteen seventies. As the emerging need of crude oil demand, now Sri Lanka depends on foreign refined product sources because the provide capability of the Ceylon Petroleum Corporation's (CPC) plant remained as a constant. In 2011 local petroleum demand was 4200 million (Mn) liters per year and from that only one third is provided by local refined imported crude oil. The remaining amount is imported as refined products. In the past, majority of the fuel oil consists with kerosene, among that 40% was petrol and two third of that was provided by the refinery. But the contribution of the refinery to satisfy the local market demand has come down over the years apart from kerosene. Hence the rise of domestic demand has primarily met from the foreign product. Consequently, the country is spending a large amount of money for importing crude oil products. From 2009- 2011 the petroleum bill has more than doubled. After late 90s the global trend shows that there is a rise of prices on long term basis in crude oil, indicating the rise of worldwide consumption of crude oil and limits of global production (Samaratunga, 2014). If the trend keeps on continuing like this, we have to arrange a considerable proportion of resources to import crude oil.

Considering the industry, government rating policy for the business has been consistent since 2005 within the country, which frequent price changes of the international market has been abandoned. It should get into consideration that, there has been an upward movement of long run international costs of crude oil with short term fluctuations. Although with a wait and in tandem with international changes, Sri Lanka also adjust its value structure of crude oil and it has been the case of all oil importing countries. Hence Sri Lanka is considered as a value taker within the oil market as its demand represents a tiny quantum compared to the worldwide demand. As a practice all these prices have been adjusted together.

From 1960s crude oil distribution and pricing have been operated by the government. Even today the government has a bigger extent in deciding the prices of crude oil but with the duopolistic market structure which was established in 2003 Lanka Indian Oil Corporation (LIOC) has the authority to change the prices in response to the changes in the international market and based on company's international requirements in several petroleum products. Since Ceylon Petroleum Corporation (CPC) has the largest market share still Sri Lanka has a significant control over pricing.

As we are facing with difficulties in managing Ceylon Petroleum Corporation (CPC), fuel oil for electricity generation has been recognized as a major challenge throughout the last few years. Unless there is a structural amendment within the electricity generation program, Sri Lanka needs to still work on oil based power generation to fulfill the rising demand. In this regard, current oil provide arrangements between Ceylon Petroleum Corporation (CPC) and Ceylon Electricity Board (CEB) have to be reviewed during a manner to make sure efficiencies of Ceylon Petroleum Corporation (CPC).

Refinery based domestic supplies, require both the infusion of modern refining technologies and up scaling of the capacity of the refinery to meet the country's demand. Otherwise we have to use imported refined products to satisfy a larger proportion of the demand.

1.1.1 Challenges of Sri Lanka's Petroleum Industry

Currently Sri Lanka is facing for several challenges in petroleum industry. Among them uncertainty of supply due to current tension in the middle east and diversification of the resources due to technological issues are main concerns. The recent crude oil crisis in Sri Lanka is also attributed to the limited supply of crude oil. Although we have a duopoly market for crude oil in Sri Lanka, both are import dependent to a lager extent. Hence the challenges remain the same as the overall demand for crude oil is rapidly increasing.

As in 2011 petroleum accounts for 24% of import bill and 45% of exports. Hence more resources will be required for imports in absolute and relative terms in future (Samaratunga, 2014).

As it is an emerging need to get an idea about the future crude oil demand and also its determinants, the objective of this study is to explore several important factors that cause for Sri Lankan crude oil demand. Also this study aims to forecast the crude oil demand using a suitable model. Hence this thesis comprises a long run and short run models using data from 1988 – 2013. This will have significant policy implications on planning the future Sri Lankan economy and oil demand in Sri Lanka.

1.2 Determinants of Crude Oil Demand in Sri Lanka

The current literature suggests that aggregate oil consumption is determined by factors such as prices, income, and the economic structure of the country (Howard et al., 1993, cited in Narayan and Smyth, 2007). The crude oil demand model used in this study is based on the general energy demand model, which is specified as a function of price of crude oil, Gross Domestic Product (GDP) and other macroeconomics control variables (Ozcan 2015; Marbuah, 2014). Hence the crude oil demand is expressed as a function of oil price, Gross Domestic Product (GDP), Sri Lankan population and Foreign Direct Investment (FDI).

1.2.1 Crude oil Consumption

The oil demand will be measured by the consumption of crude oil in Sri Lanka. The figures for oil consumption are published in both thousand barrels daily or in million tons per annum. This study has considered annual data to coincide with the rest of the annual data.

1.2.2 Gross Domestic Product (GDP)

GDP stands for gross domestic product. Gross Domestic Product is a measure of the economic output of a country. Hence as it increases there is a high tendency to obtain a rise in the oil demand. Gross Domestic Product is usually defined as the total market value of goods and services produced within a given period after deducting the cost of goods and services used up in the process of production, but before allowances for depreciation. Most countries compile estimates of their Gross Domestic Product (GDP) based on guidelines from the United Nations. Although there are three different ways to calculate Gross Domestic Product (GDP), same result can be obtained by any method.

1.2.3 Gross Domestic Product by expenditure approach (GDP (E))

This is calculated using the expenditure approach by taking the sum of expenditures on household consumption, government consumption, gross fixed capital expenditure, changes in inventories and net exports. Net exports are exports minus imports. This method is the most used measure of GDP.

1.2.4 Gross Domestic Product by the total Income generated (GDP (I))

This is calculated using the income approach. It is derived as the sum of factor incomes, consumption of fixed capital (depreciation) and taxes less subsidies on production and imports. Factor incomes include wages, salaries and other compensation of employees plus gross operating surplus, or profit of private companies and other entities. In theory, this approach measures the income received by all producers in the country.

1.2.5 Gross Domestic Product by production approach (GDP (P))

This is calculated using the production approach. It is derived as the sum of gross value added for each industry, at basic prices, plus taxes less subsidies on products. Industries are sectors of the economy such as agriculture, mining and manufacturing. Basic values mean the amounts received by producers, including the value of any subsidies on products, but before any taxes on products.

Gross Domestic Product by production approach **(**GDP (P)) has been considered in this study as it measures the market value of all goods and services produced. Since the values are not adjusted for inflation, nominal GDP has been considered.

1.2.6 Population

As for the biological definition of the population, it is all the organisms of the same group or species, which live in a particular geographical area. As the population grows, all the human needs will tend to grow. The Population Division of the United Nations predicts, in 2050 the global population will grow by over 2 billion more people than are alive today. Using these predictions the world’s two main energy agencies, the International Energy Agency (IEA) and the Energy Information Administration (EIA), then extrapolate past and current trends in energy consumption, and forecast how much energy we will need in the future. Hence population growth determines the energy consumption forecasts.

1.2.7 Oil Price

Oil prices change daily because they are controlled by traders who bid on oil futures contracts in the market. The U.S. government and the members of the Organization of Petroleum Exporting Countries are the other entities who can affect the traders' bidding decisions. They do not control the prices because traders actually set them in the markets. Current oil supply, future supply and oil demand are the main factors that commodities traders look at when developing the bids that create oil prices. Hence oil price can be used as a determinant of oil demand.

1.2.8 Foreign Direct Investment (FDI)

Foreign Direct Investment (FDI) is defined as an investment made by a company or an individual in a foreign country. In many countries, attracting investment has become the sum of the total of industrial policy. As for the reports of Central Bank of Si Lanka, Sri Lanka's Foreign Direct Investment (FDI) has increased by 394.9 million dollars in June 2017, compared with an increase of 114.4 million dollars in the previous quarter. The petroleum industry depends on multinational corporations which possess huge capital and high technology and the main channel for this firm's expansion strategy is Foreign Direct Investment (FDI).

For developing countries, growth of Foreign Direct Investment (FDI) provides the access to foreign technology, management skills and marketing networks. It enhances the country's domestic capital for exports, facilitating in transfer of technology and new products and services for exports, providing linkages with new and large global markets. Also it helps in training workforce in improving their both technical and management capabilities. Hence it can also be considered as a determinant of oil demand as it is an indicator of the economic growth of a country.

1.3 Objective of the study

Despite the fact that Sri Lanka has achieved a substantial rate of economic growth over the past decades, it remains far from optimal regarding some of its macroeconomic indicators. During this period, the trend of crude oil demand in Sri Lanka has been highly volatile and increased. This has been a major problem all over the country as the crude oil storage is not sufficient to satisfy the emerging needs. The objective of this study is to explore several important factors that cause for Sri Lankan crude oil demand. Therefore this research mainly focuses on to find a relationship between crude oil demand and some of the economic variables like population, oil price, Gross Domestic Product (GDP) and Foreign Direct Investment (FDI). Also this study aims to forecast the crude oil demand using a suitable model.

1.4 Data for the study

All the data have been collected using online resources of World Bank and United States Energy Information Administration. The sample period for this study is 1988 through 2013. The software employed in this research is EViews 8.0.

Oil Consumption in Sri Lanka, Gross Domestic Product (GDP), Foreign Direct Investment (FDI), Crude Oil Price and Sri Lankan Population are the variables used in this study. The log form of the variables have been used for this study. Problems can occur in the interpretation of variables and using the log form of the variables will enable the reader to understand the coefficients easily. It should be cautioned that this is restricting elasticities to be constant over the sample period. However this will ensure consistent analysis of the parameters.

1.5 Chapter Outline

The first chapter gives an introduction to the study. It provides information about crude oil industry of Sri Lanka and its challenges. Further chapter one includes the determinants of oil demand in Sri Lanka such as Gross Domestic Product (GDP), Foreign Direct Investment (FDI), Crude Oil Price and Sri Lankan Population.

The second chapter consists of the literature review. Hence it showcases several attempts that have been taken to analyze the crude oil demand in globally and locally.

The third chapter comprises the methodology, theory and techniques which have been applied to the data analysis. The forth chapter consists the analysis of finding the relationship between oil demand and other determinants using the Vector Error Correction Model (VECM). Chapter five elaborates the summary of findings and conclusions of the study. References are also provided at the end of the thesis.

CHAPTER 2

LITERATURE REVIEW

Tarak Nath et al. (2014) has conducted a research on dynamic relationships between oil price shocks and Indian stock market. In this study researchers have used Johansen's cointegration test, vector error correction model (VECM), Granger causality test, impulse response functions (IRFs) and variance decompositions (VDCs) test to find out the long-run and short-run relationship between the data which have been collected from January 2001 to March 2013. The analysis of the study shows that Indian stock markets and crude oil prices are strongly exogenous. Also they have shown that positive shock in oil price has a positive impact on Indian stock markets in short run.

Vidyarthi, Harishankar (2015) shows the C for a panel of five South Asian economies, namely India, Pakistan, Bangladesh, Sri Lanka and Nepal over the period from 1971 to 2010 within a multivariate framework. It also shows that 1 per cent increase in energy consumption per capita increases the gross domestic product (GDP) per capita by 0.8424 per cent for the panel. Pedroni cointegration and Granger causality test based on panel vector error correction model have been used throughout the research.

A study has conducted by Zhuo Li and Hui Zhao (2011) on the structural origins of international crude oil price fluctuation. Findings shows that four kinds of structural shocks derived from the generalized supply and demand analysis are the essential determinants of crude oil prices fluctuation. Supply side shocks which are known as the exogenous geopolitical ones and other oil supply shocks have little influence. At the same time the aggregate demand shock and the oil market specific demand shock which are considered as the demand side shocks have prominent effects. It is raised that the mismatch comes from the ignorance of the finer decomposition of demand side factors. To decompose those demand side factors further, the US dollar liquidity was added into the model. The results show that the impact of US dollar liquidity on the fluctuation of oil prices cannot be ignored. The argument that ascribes the soaring international crude oil price to China's economic growth lacks theoretical and empirical evidence.

According to the study conducted by Dilip Kumar and S. Maheswaran, (2013) on “Correlation transmission between crude oil and Indian markets", the is better able to capture time-dynamics in comparison to other models, based on which the researchers find evidence of return and volatility spillover effects from the crude oil market to the Indian industrial sectors. Also the study discovers that the conditional correlations between the crude oil market and the Indian industrial sectors change dynamically over time and that they reach their highest values during the period of the global financial crisis (2008-2009).

Perman et al. (1999) show that, outputs from organizations involved in the extraction of oil are satisfying the demands of both households and industry. The model used for this study’s analysis should therefore represent both of these groups. Chan and Lee (1996) use the Engle Granger two stage cointegration method to determine overall Chinese energy demand and source much of their data from the China Statistical Yearbook. They use four variables: energy consumption, gross national income, price of energy, and a variable for structural variation representing the share of heavy industry in the national income. Their study concludes that the share of heavy industry’s output in the national income is a significant variable in determining demand. Income and price were found to have long run inelastic effects of 0.706 and 20.908 on the consumption of energy, respectively. Population was found to be insignificant contradicting a later paper by Crompton and Wu. Crompton and Wu (2005) forecast energy demand for China up to 2010, and predict that energy consumption will grow at a rate of 3.8 percent per year until at least 2010, slightly slower than the previous decade. This is thought to be caused by “further structural changes in the Chinese economy and that subsequently some energy intensive sectors in the economy are expected to decline” (Crompton and Wu, 2005, p. 206). They also predict that oil will be increasingly important at the expense of coal production, due to the change in policy for cleaner fuels. Only four variables are considered by Crompton and Wu: energy consumption, real prices of energy, population, and real GDP. Population is assumed to capture residential demand for energy, and real GDP is thought to capture the energy consumption in domestic production.

Indeed, Perman et al. (1999, p. 40) state that "Human population growth, in conjunction with pressures for higher standards of living increases the demands for agricultural land, energy and water resources." Other studies have looked at factors in the Chinese economy that do not seem to be covered in present models and may mean structural changes in demand. Advancement of technology can improve the efficiency of current processes. With respect to oil, transport efficiency improvements have been modelled by He et al. (2005), showing that considerable savings in oil consumption in the road transport sector could be made by the introduction of more advanced and efficient technologies. They use a simple model, multiplying the vehicle population, average miles travelled, fuel density and the inverse of fuel economy, for several different vehicle types. They suggest that Chinese vehicle fuel economy is 10-15 percent behind that of Europe and 20-25 percent behind Japan. The low-improvement scenario assumes China will catch up with developed countries current consumption efficiency levels by 2008, whereas the high-improvement scenario suggests that Chinese vehicles will catch up with developed countries new efficiency levels by 2008. Their model shows that under low- and high-improvement scenarios, "road transport's oil demand will be 308 and 278 million tons, respectively, resulting in 55 and 85 million tons of oil saved a year" (He et al., 2005, p. 1504). This saving is more than the total oil consumption by Chinese road transport in 2002. If no improvements are made on fuel economy, China will demand around 360 million tons of oil just to satisfy its vehicle population. They observe that past predictions on vehicle growth have generally underestimated the actual figure and warn the reader that their study may also underestimate the future vehicle population.

Jens Hölscher et al. (2008) have used the Engle-Granger two-stage cointegration method to create a dynamic short-run model to discover the determinants of Chinese oil demand and to build a short- and long-run model. They find that only vehicle numbers and real GDP are determinants of the demand in the short-run. It also shows that there is a fairly slow adjustment from the short-run to the long-run model.

Considering Sri Lankan context, R.H.S. Samaratunga (2014) has stated his ideas on the petroleum industry of Sri Lanka. He has shown the organizational and policy challenges in the industry. One of his key points is that with the emerging demand we have to spend more money for importing crude oil. Even though many reports have been written on petroleum industry so far, no study was conducted in Sri Lanka to assess the oil demand.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This study examines the effect of economic variables Goss Domestic Product (GDP), Foreign Direct Investment (FDI), Population and Oil Price on oil consumption in Sri Lanka using an Error Correction Model. Yearly data of oil consumption, Gross Domestic Product (GDP), Foreign Direct Investment (FDI), Sri Lankan population and crude oil price during the period 1988 – 2013 were used in the analysis. All the data have been obtained by the online data sources of World Bank and United States energy information administration. This research involves estimating the elasticity of Gross Domestic Price (GDP), Foreign Direct Investment (FDI), Si Lankan population and crude oil price on crude oil consumption in Sri Lanka. Several statistical methods and econometric tests were carried out in order to meet the objectives of this research. Further, to test the stationary condition on all the time series variables unit root test was used. Also Chow - break point test was used to test the significance of a structural beak down in the data set. Finally residual analysis was carried out to check the validity of the selected model. This study employs the econometric technique of Vector Error Correction Modeling (VECM) and multiple regression methodology to estimate more specific relationship between oil consumption and its determinants.

3.2 Procedure of analysis

In this study Gross Domestic Product (GDP), Foreign Direct Investment (FDI), Sri Lankan population and crude oil price were used to find out the effect on Sri Lankan oil demand. Since problems can occur in the interpretation of variables when they are different units, the log form of the variables have been used for this study.

The oil demand was measured by the consumption of crude oil. Time series plots of each variable show that all the variables are not stationary at levels as they are trending upward series with fluctuations. The stationary condition of the first difference series was checked using the Augmented - Dickey Fuller test.

Chow - break point test was used to test the significance of a structural break down in the data set. Hence a dummy variable was used to indicate the structural break down. Cointegration was checked with the use of Trace statistic test. The Vector Error Correction Methodology was used to find a model for Sri Lankan crude oil consumption.

Then the stationary condition of the error term of the Vector Error Correction Model was checked using the Augmented - Dickey Fuller unit root test and a residual analysis was carried out to check the validity of the model. Stability of the coefficients of the model is checked by Cusum test. Impulse response function was used to study the dynamic effects of shocks of macroeconomic variables on oil demand. Variance decomposition method was used to evaluate dynamic interactions and strength of casual relations among variables in the system. All the outputs of the research is obtained with the use of EViews software.

3.3 Sample

The sample period for this study is 1988 through 2013. The following variables were used in the analysis.

Oil Consumption in Sri Lanka

Gross Domestic Product (GDP)

Foreign Direct Investment (FDI)

Crude Oil Price

Sri Lankan Population

3.3.1 Variables and Operationalization of Variables

Table 3. 1: Variables and Operationalization of Variables

VARIABLE	INDICATOR	MEASREMENT
Oil Consumption	Crude oil consumption of Sri Lanka as mentioned in United States Energy Information Administration.	Thousand Barrels per year
Gross Domestic Product (GDP)	Nominal GDP values of Sri Lanka as mentioned in the World Bank national accounts data were used.	GDP is measured using current US dollars annually.
Foreign Direct Investment (FDI)	FDI values of Sri Lanka as mentioned in the World Bank national accounts data were used.	FDI is measured using current US dollars annually.
Crude Oil Price	Brent, Dubai and West Texas Intermediate crude oil are considered as main three types of crude oil around the world. Hence the average spot price of these was used for the analysis. As monthly data were available in world bank records, annual data points were calculated by taking the average of	Crude oil price was measured using current US dollars per barrel.

	monthly values.	
Sri Lankan Population	Values of Sri Lankan population as mentioned in the World Bank national accounts data were used.	Population was measured annually.

3.4 Time series

A time series is a sequence of data points, measured typically at successive time points. Time series analysis comprises methods that attempt to understand such time series, often either to understand the underlying context of the data points, or to make predictions. Forecasting using a time-series analysis consists of the use of a model to forecast future events based on known past events. An example in education is the prediction of the number of students who will take a test at an administration based on the numbers from the previous administrations of the test. A time-series model generally reflects the fact that observations close together in time will be more closely related than observations further apart. Three broad classes of time-series models of practical importance are the autoregressive (AR) models, the integrated (I) models, and the moving average (MA) models. There are models, such as the autoregressive moving average (ARMA) and autoregressive integrated moving average (ARIMA) that are combinations of the above three.

3.4.1 Autoregressive (AR) models

In a multiple regression model, we forecast the variable of interest using a linear combination of predictors. In an autoregressive model, we forecast the variable of interest using a linear combination of past values of the variable. The term autoregressive indicates that it is a regression of the variable against itself.

Thus an autoregressive model of order p can be written as

$$y_t = c + \emptyset_1 y_{t-1} + \emptyset_2 y_{t-2} + \cdots \emptyset_p y_{t-p} + e_t$$

where c is a constant and e_t is white noise random error with zero mean and constant variance. $\emptyset_1, \emptyset_2, \dots \emptyset_p$ are considered as model parameters. This is like a multiple regression but with lagged values of y_t as predictors. We refer to this as an AR(p) model.

3.4.2 Moving Average (MA) models

Rather than use past values of the forecast variable in a regression, a moving average model uses past forecast errors in a regression-like model.

$$y_t = c + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots \theta_q e_{t-q}$$

where e_t is white noise random error with zero mean and constant variance. $\theta_1, \theta_2, \dots \theta_q$ are considered as model parameters. We refer to this as an MA(q) model. Each value of y_t can be thought of as a weighted moving average of the past few forecast errors.

3.4.3 Autoregressive Moving Average (ARMA) models

Autoregressive Moving Average **(**ARMA) models are known as forecasting models or processes in which both autoregressive terms and moving average terms are applied. The use of ARMA models was popularized by Box and Jenkins. Although both AR and MA models were previously known and used, Box and Jenkins provided a systematic approach for modeling both AR and MA terms in the model. ARMA models are also commonly known as Box-Jenkins models or ARIMA models. ARMA models assume that the data are stationary, i.e. the data have constant location and scale. ARMA models can also incorporate seasonal terms (and seasonal differencing). ARMA models typically require fairly long series.

ARMA(p,q) model is defined as,

$$X_t = c + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \cdots + \emptyset_p X_{t-p} + e_t + \theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_{1q} e_{t-q}$$

where . $c, \theta_1, \theta_2, \dots \theta_q$ and $\emptyset_1, \emptyset_2, \dots \emptyset_p$ are model parameters. e_t is white noise random error with zero mean and constant variance.

3.4.4 Autoregressive Integrated Moving Average (ARIMA) models

ARIMA models can be used to build an adequate model for a time series using three steps, identification, estimation and diagnostic checking. The autoregressive (AR) component in ARIMA is designated as p, the integrated (I) component as d, and moving average (MA) as q. The autoregressive component represents the lingering effect of previous observations. The integrated component represents trends, including seasonality and moving average component represents lingering effect of previous random errors. To fit an ARIMA model to a time series, the order of each model component must be selected.

ARIMA(p,d,q) model is defined as,

$$\left(1-\sum_{i=1}^{p}\emptyset_i L^i\right)(1-L)^d X_t = \left(1+\sum_{i=1}^{q}\theta_i L^i\right)\varepsilon_t$$

where L is the lag operator, $\emptyset_i$ are the parameters of the autoregressive part of the model, θ_i are the parameters of the moving average part and the ε_t are error terms. The error terms ε_t are generally assumed to be white noise with zero mean constant variance.

3.5 Stationary Condition of a Time Series

A Time Series is stationary if it has the following conditions:

1. Constant mean for all t

2. Constant variance for all t

3. The autocovariance function between X_{t1} and X_{t2} only depend on the interval t_1 and t_2.

where t represents the time index.

3.6 Unit Root Test

Many economic and financial time series exhibit trending behavior or non-stationary in the mean. Leading examples are exchange rates and the levels of macroeconomic aggregates like real Gross Domestic Product (GDP).

In statistics a unit root test, tests whether a time series variable is non stationary using an autoregressive model. A well-known test that is valid for large samples is the Augmented - Dickey Fuller test. The optimal finite sample test for a unit root in autoregressive models were developed by John Denis Sargan and Alok Bhargawa. Another similar test is the Philips – Perron test. These tests use the existence of a unit root as the null hypothesis.

H_o: Time series is non stationary

H_a: Time series is stationary

3.6.1 Augmented Dickey Fuller (ADF) test

Augmented Dickey Fuller test is used to test the stationary condition of a time series.

For an example a simple AR (1) model is,

$$y_t = \rho y_{t-1} + u_t \qquad -1 < \rho < 1$$

where y_t is the variable of interest, t is the time index, ρ is a coefficient and u_t is the error term. A unit root is present if ρ = 1. The model would be non-stationary in this case.

Alternatively, the model can be formulated as,

$$\Delta y_t = (\rho - 1)y_{t-1} + u_t = \delta y_{t-1} + u_t$$

where Δ is the first difference operator. (i.e $y_t - y_{t-1}$) and $\delta = \rho - 1$

In this case the unit root hypothesis translates into

$$H_o: \delta = 0 \quad \text{Vs} \quad H_a: \delta < 0$$

The Dickey-Fuller (DF) test is simply the t test for H_o.

$$\hat{\tau} = \frac{\hat{\rho} - 1}{SE(\hat{\rho})}$$

Where $\hat{\rho}$ is the estimator of ρ and $SE(\hat{\rho})$is the standard error of $\hat{\rho}$. The asymptotic distribution of $\hat{\tau}$ is not normal. The distribution depends on the deterministic components. In the simple case, the 5% critical value (one-sided) is -1.95 and not -1.65.

If the process Δy_t is stationary, y_t is denoted as a difference stationary process. If Δy_t is stationary while y_t is not, y_t is called integrated of first order, I(1). A process is integrated of order d, I(d), if it contains d unit roots. On the other hand a stationary process is called an I(0) process.

The important task is to determine the most appropriate form of the trend in the data. If the data set contains a trend then some form of trend removal is required.

The most common trend removal or de-tending procedures are first differencing and time – trend regression. First differencing is appropriate for I(1) time series and time-trending regression is appropriate for trend stationary I(0) time series. Unit root tests can be used to determine whether the trending data should be first differenced or regressed on the deterministic functions of time to render the data stationary. Moreover economic and financial theories often suggest the existence of long run equilibrium relationships among non-stationary time series variables. If these variables are I(1), then cointegration techniques can be used to model these long run relations. Hence pre-testing for unit roots is often the first step in the cointegration modelling. In this study ADF test has been used to test the stationary condition of the time series.

3.7 Cointegration

In generally most of the economic variables are non-stationary – I(1) variables. Hence, any equilibrium theories that involve these variables require the existence of a combination of the variables to be stationary. Otherwise, any deviation from equilibrium will not be temporary

There are some rules concerning linear combination of integrated series. If x_t and y_t are two time series,

- $x_t \sim I(0) \Rightarrow a + bx_t \sim I(0)$
  $x_t \sim I(1) \Rightarrow a + bx_t \sim I(1)$
- $x_t \sim I(0)\ and y_t \sim I(0)\ \Rightarrow ax_t + by_t \sim I(0)$
- $x_t \sim I(0)\ and y_t \sim I(1)\ \Rightarrow ax_t + by_t \sim I(1)$
- $x_t \sim I(1)\ and y_t \sim I(1)\ \Rightarrow ax_t + by_t \sim I(1)$

But under certain conditions the linear combination may be I(0). x and y are cointegrated when there is a stationary equilibrium relationship.

i.e .$z_t = \ ax_t + by_t \sim I(0)$

Adding or subtracting a constant from a cointegrating equation does not alter its properties.

The components of a (k×1) vector, y_t , are said to be cointegrated of order d, b, denoted, y_t~CI(d, b), if all the components of the vector y_t are I(d), that is, they need d differences to induce stationary condition, and there exists a vector β (≠ 0)so that $z_t = \beta^{'y_t} \sim I(d-b)$. The vector β is called the cointegrating vector. Usually we consider the case with d=b=1.

This is an important result as any arbitrary linear combination of I(1) series will be I(1) (unless the series are cointegrated). Cointegrating combinations are "equilibria". Hence it is important to be able to discover and model these relationships. An alternative approach to the analysis of "long-run" (equilibrium) relationship would be to analyze the relationships between the differences of the series, i.e. among I(0) series. However, this approach is only concerned with short-run movements, while it throws useful long-run information.

3.7.1 Testing Cointegration

Johansen test is used to test the cointegration by examining the number of independent linear combinations (k) for an m time series variables set that yields a stationary process. Trace test has been used in this analysis which is one of the forms of Johansen test.

3.7.2 Trace test

The trace test examines the number of linear combinations (i.e. K) to be equal to a given value K_0 (where $K_0 = 0,1,2 \ldots$) , and the alternative hypothesis for K to be greater than K_0

$$H_0: K = K_0$$

$$H_0: K > K_0$$

To test for the existence of cointegration using the trace test, we set $K_0 = 0$ (no cointegration), and examine whether the null hypothesis can be rejected. If this is the case, then we conclude there is at least one cointegration relationship.

In this case, we need to reject the null hypothesis to establish the presence of cointegration between the variables.

3.8 Cointegrating Regressions and Granger Representation Theorem

If a set of variables are cointegrated, then there exists a valid error correction representation of the data, and vice versa. If y and x are both I(1) and have a long run relationship, there must be some force which pulls the equilibrium error back to zero. Engle and Granger (1987, Econometrica) recommend a two-step procedure for cointegration analysis.

(i) Estimate the long-run (equilibrium) equation:

$$y_t = \delta_0 + \delta_1 x_t + u_t \qquad (1)$$

The ordinary least square (OLS) residuals from (1) are a measure of disequilibrium:

$$\hat{u}_t = y_t - (\hat{\delta}_0 + \hat{\delta}_1 x_t)$$

A test of cointegration is a test of whether $\hat{u}_t$ is stationary. This is determined by ADF tests on the residuals, with the MacKinnon (1991) critical values adjusted for the number of variables (which MacKinnon denotes as n). If cointegration holds, the OLS estimator of (1) is said to be super-consistent. Hence as $t \to \infty$ there is no need to include I(0) variables in the cointegrating equation. Also the t-ratios from equation (1) are not interpretable, as it is a long-run equation, and therefore will have serial correlation (due to misspecified dynamics) as well as omitted variable problems, and as such the distribution of the t-ratio is not known.

The traditional diagnostic tests from (1) are unimportant as the only important question is the stationary condition or otherwise of the residuals.

(ii) Second step: estimate the Error Correction Model

$$\Delta y_t = \sum_{j=1} \emptyset_j \Delta y_{t-j} + \sum_{h=0} \theta_h \Delta x_{t-h} + \alpha\, \hat{u}_{t-1} + \epsilon_t$$

by OLS as this equation has only I(0) variables, standard hypothesis testing using t ratios and diagnostic testing of the error term is appropriate. The adjustment coefficient α must be negative.

Special case:

$$\Delta y_t = \emptyset_0 + \emptyset_1 \Delta y_{t-1} + \theta_1 \Delta x_{t-1} + \alpha(y_{t-1} - \hat{\delta}_0 - \hat{\delta}_1 x_{t-1}) + \epsilon_t$$

Error correction model (ECM) describes how y and x behave in the short run consistent with a long run cointegrating relationship.

3.9 Estimation of a time series model

When a model is estimated using time series variables, the first thing that need to make sure is that either all-time series variables in the model are stationary or they are cointegrated, which means that they are integrated of the same order and errors are stationary. In this scenario the model defines a long run equilibrium relationship among the cointegrated variables. Therefore a cointegration test generally takes two steps. The first step is to conduct a unit root test on each variable to find the order of integration. If all variables are integrated in the same order, the second step is to estimate the model which is also called the cointegration equation and test whether the residuals of the model are stationary.

3.10 Estimating Error Correction Model (ECM)

According to the Granger representation theorem, when variables are cointegrated, there must also be an error correction model (ECM) that describes the short run dynamics or adjustments of the cointegrated variables towards their equilibrium values. ECM consists of one period lagged cointegrating equation and the lagged first differences of the endogenous variables.

More generally, in the regression model,

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki} + e_i$$

If there exists a relationship between a set of variables, $Y_i,\ X_{1i},\ X_{2i}, \ldots, X_{ki}$ the error terms can be thought of as measuring the deviation between the components of this model.

$$e_i = Y_i - (\beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki})$$

In the short run the divergence between the components fluctuate, but if the model is genuinely correct there will be a limit to the divergence. Hence although the time series are non-stationary, e_i will be stationary. When two or more non-stationary time series are linked in such a way, it is known as the time series are cointegrated. If there are more than two variables in the model, it is possible to have multiple cointegrating relationships.

To test for cointegration , it is necessary to evaluate whether the error correction term is a stationary process. Therefore, the notion of cointegration, which was given a formal treatment in Engle and Granger, makes regression involving I(1) variables potentially meaningful.

3.10.1 Vector Error Correction Model (VEC Model)

Engle and Granger (1987) point out that a linear combination of two or more non stationary series may be stationary. The stationary combination may be interpreted as the cointegration, or equilibrium relationship between the variables. For example, if the consumption and income are cointegrated, then there exists a long run relationship between them. However, if they are not cointegrated, then consumption might drift above or below income in the long run, implying that consumers either spend too much or increase saving.

A Vector Error Correction Model (VECM) is a restricted Vector Auto Regression (VAR) model. The Vector Error Correction specification restricts the long run behavior of the endogenous variables to converge to their long run equilibrium relationships and allow the short run dynamics.

The VAR model is a general framework used to describe the dynamic interrelationship among stationary variables. So, the first step in time-series analysis should be to determine whether the levels of the data are stationary. If not, take the first differences of the series and should try again. Usually, if the levels of the time series data are not stationary, the first differences will be.

If the time series are not stationary then the VAR framework needs to be modified to allow consistent estimate of the relationships among the series. The Vector Error Correction (VEC) model is just a special case of the VAR for variables that are stationary in their differences (i.e. I(1)). The Vector Error Correction Model can also take into account any cointegrating relationships among the variables.

Suppose x_t and y_t are I(1) and cointegrated. Then $\in_t$ is I(0) in the cointegrating equation

$$y_t = \alpha + \beta x_t + \in_t$$

These equations often are interpreted as long-run or equilibrium relationships between x_t and y_t. A researcher will also be interested in the short-run dynamics - the way that x_t and $y_t$fluctuate around this long-run relationship, as in a business cycle. This is done by estimating an error correction model, which contains first differences of x_t and y_t , their lags, and an error correction term. An Error Correction Model is

$$\Delta y_t = \mu + \gamma_1 \Delta y_{t-1} + \cdots + \gamma_p \Delta y_{t-p} + \omega_1 \Delta x_{t-1} + \cdots + \omega_r \Delta x_{t-r} + \lambda EC_{t-1} + u_t$$

where $\mu, \gamma_i, \omega_j, \lambda$ are the parameters of the model and $EC_{t-1} = y_t - (a + bx_t)$, the error correction term, is the lagged OLS residual from the cointegrating equation. Normally λ is expected to be negative. Then λEC_{t-1} represents a force pulling y_t toward its long-run relationship, being negative when $EC_{t-1} > 0$, and positive when $EC_{t-1} < 0$. u_t is the random error. The cointegrating equation and ECM can be shown to follow from a single dynamic regression model in levels when y_t and x_t are cointegrated.

3.11 Lag Selection criteria

The following informational measures are used to select the appropriate lag length of the Vector Error Correction Model (VECM).

- Akaike (AIC)
- Schwarz (SIC)
- Hannan–Quinn information criterion (HQC)

We choose the lag length of the Vector Error Correction Model (VECM) in levels that minimize the information criteria.

3.11 Model Selection Criteria

There are several measures that have been used to choose among competing models and/ or to compare models for forecasting purposes. They are,

1. R^2
2. Adjusted R^2
3. Akaike information criterion (AIC),
4. Schwarz information criterions (SIC),
5. Mallow's Cp criterion
6. Standard error

All these measures aim at minimizing the residual sum of squares (RSS) (or increasing the R^2 value). However, except for the first criteria (2), (3), (4) and (5) impose a penalty for including an increasingly large number of regressors. Thus there is a tradeoff between goodness of fit of the model and its complexity (as judged by number of regressors).

3.11.1 Akaike Information Criterion (AIC)

The idea of imposing a penalty for adding parameters to the model has been carried further in the Akaike Information Criterion (AIC) criterion, which is defined as:

$$AIC(k) = -2(\log likelihood) + 2k$$

where k is the number of parameters (including the intercept).

Akaike Information Criterion (AIC) criterion imposes a harsher penalty than adjusted R^2 for adding more parameters. In comparing two or more models, the model with the lowest value of AIC is preferred. One advantage of AIC is that it is useful for not only in-sample but also out-of sample forecasting performance of a regression model. Also, it is useful for both nested and non-nested models.

3.11.2 Schwarz Information Criterion (SIC)

Schwarz Information Criterion (SIC) is a criterion for model selection among a class of parametric models with different number of parameters. Choosing a model to optimize SIC is a form of regularization.

When estimating model parameters using maximum likelihood estimation, it is possible to increase the likelihood by adding additional parameters, which may result in over fitting. The SIC resolves this problem by introducing a penalty term for the number of parameters in the model. This penalty for additional parameters is stronger than that of the Akaike Information Criterion. Further, SIC has widely used for model identification in time series and linear regression.

$$SIC(k) = -2L_k + kln(n)$$

where n is the sample size, L_k is the maximized log-likelihood of the model and k is the number of parameters in the model.

3.11.3 Hannan Quinn information criterion (HQC)

Hannan Quinn information criterion (HQC) is an alternative model selection criteria to Akaike information criterion (AIC) and Bayesian information criterion (BIC). HQC is expressed as

$$\mathrm{HQC} = -2L_{max} + 2\mathrm{k}\ln(\ln(\mathrm{n}))$$

where L_{max} is the log-likelihood, k is the number of parameters, and *n* is the number of observations.

3.11.4 Mallows C_p Criterion

Consider a model consisting of k regressors, including the intercept. Suppose that we have only choose p regressors (p≤ k) and obtain the regression sum of squares (RSS) from the regression using these p regressors. Let ESS denote the residual sum of squares using the p regressors. C.P Mallows has developed the following criterion for model selection, known as the Cp criterion:

$$C_p = \left(\frac{ESS}{S^2}\right) - (n - 2p)$$

here n is the number of observations and S^2 is the residual mean square after regressing on the complete set of p regressors and can be estimated by mean square error (MSE).

In choosing a model according to the C_p criterion, we would look for a model that has a low C_p value, about equal to p. In other words, following the principle of parsimony, we choose a model with p regressors (p < k) that gives a fairly good fit to the data.

3.12 Residual Analysis

In order to check the validity of the selected model, a residual analysis should be carried out. If all the assumptions of the residuals are satisfied the selected model is considered as a good fit for the data set.

3.13 Heteroscedasticity

The possible existence of heteroscedasticity is a major concern in the application of regression analysis, including the analysis of variance, because the presence of heteroscedasticity can invalidate statistical tests of significance that assume the effect and residual (error) variances are uncorrelated and normally distributed.

Heteroskedasticity is where there is a non-constant error term and is one of the Gauss-Markov assumptions. Whereas when we have homoskedasticity, or constant variance of the error term, the estimator is still best linear unbiased estimator.

The consequences of using OLS in the presence of heteroskedasticity is that although the estimator is still unbiased, it is no longer best, as it doesn't have the minimum variance. This means the standard errors will be underestimated and the T-statistics and F-statistics will be inaccurate. It is caused by a number of factors, but the main cause is when the variables have substantially different values for each observation. For instance GDP will suffer from heteroskedasticity, if we include large countries such as the USA and small countries such as Cuba. In this case it may be better to use GDP per person. Heteroskedasticity tends to affect cross-sectional data more than time series.

3.13.1 ARCH Test for Heteroscedasticity

Engle's ARCH test is used to test the Heteroscedasticity among the residuals of a given model. The null hypothesis of the test is that a series of residuals (r_t) exhibits no conditional heteroscedasticity (ARCH effects), against the alternative that an ARCH(L) model describes the series.

H_0: residuals (r_t) exhibits no heteroscedasticity (variance of the error term (σ^2) is a constant)

H_1: residuals (r_t) exhibits heteroscedasticity (variance of the error term (σ^2) is not a constant)

The ARCH(L) model has the following form:

$$r_t^2 = a_0 + a_1 r_{2t-1+\cdots+} a_L r_{2t-L} + e_t \qquad (1)$$

where r_t denotes the residuals and e_t denotes the random error. Also a_j s are parameters of the model where there is at least one $a_j \neq 0, j = 0 \ldots L$

The test statistic is the Lagrange multiplier statistic;

$$TR^2 \sim \chi_L^2$$

where: T is the sample size and R^2 is the coefficient of determination from fitting the ARCH(L) model for a number of lags (L) via regression.

Under the null hypothesis, the asymptotic distribution of the test statistic is chi-square with L degrees of freedom.

To test the null hypothesis that there is no ARCH up to order L in the residuals, we run the regression denoted by equation (1). Then the R^2 value has to be calculated and then the test statistic value can be obtained by multiplying the R^2 value by sample size. The null hypothesis can be rejected if the calculated value of the test statistic is greater than the chi square critical value

3.14 LM test for Serial Correlation

This test is an alternative to the Q-statistics for testing serial correlation. The test belongs to the class of asymptotic (large sample) tests known as Lagrange multiplier (LM) tests.

H_0: No serial correlation up to lag order p, where p is a pre-specified integer.

H_1: There is serial correlation up to lag order p, where p is a pre-specified integer.

The test statistic for this test is computed by an auxiliary regression as follows. First, suppose we have estimated the regression;

$$y_t = \beta x_t + \epsilon_t$$

where β are the estimated coefficients and ϵ_t are the errors. The test statistic for lag order p is based on the auxiliary regression for the residuals $\epsilon_t = y_t - \beta x_t$

This is a regression of the residuals on the original regressors X and lagged residuals up to order p. To test the hypothesis we use the Breusch-Godfrey LM test statistic.

$$n * R^2 \sim \chi^2_{df}$$

This is computed as the number of observations, times the R^2 from the auxiliary regression. Under quite general conditions, the LM test statistic has a chi square distribution with degrees of freedom equals to p.

3.15 Normality test for residuals

H_0: Residuals follow a normal distribution

H_1: Residuals do not follow a normal distribution

The normality test of residuals is expressed as a P value. That is if the fitted model is correct and all scatter around the model follows a Gaussian population, what is the probability of obtaining data whose residuals deviate from a Gaussian distribution. If the P value is large, then the residuals pass the normality test. If the P value is small, the residuals fail the normality test and we have evidence that your data do not follow one of the assumptions of the regression.

3.16 Chow Break-point Test

In order to check whether there is a significant structural break down in the data set, chow beak-point test has been carried out.

H_0: There is no break point in the data set

H_1: There is no break point in the data set

As the first step a regression for the entire data set should be run and regression sum of squares should be collected. Then we need to run separate regressions on each half of the data set and regression sum of squares should be collected for the two regressions. After calculating the chow statistic which is having a F distribution, test can be performed in order to check whether we have enough evidence to reject the null hypothesis.

$$CHOW = \frac{(RSS_p - (RSS_1 + RSS_2))/k}{(RSS_1 + RSS_2)/(N_1 + N_2 - 2k)} \sim F_{(p,\ N_1+N_2-2k)}$$

where RSS_p = Regression sum of squares of pooled regression

RSS_1 = Regression sum of squares of the regression line before break

RSS_2 = Regression sum of squares of the regression line after break

K = Number of independent variables

N_1 = Number of data points considered before break

N_2 = Number of data points considered after break

p = Number of parameters in the pooled regression

After calculating the above test statistic, the F-critical value from the F-table has to be calculated. The null hypothesis can be rejected if the calculated F-value falls into the rejection region (i.e. if the calculated F-value is greater than the F-critical value).

3.17 CUSUM test

Visual examination of the graphs of the recursive parameter estimates can be useful in evaluating the stability of the model. It would be useful to have a formal statistical test that we could apply to test the null hypothesis of model stability. The CUSUM test, which is based on the residuals from the recursive estimates, provides such a test.

First we calculate a statistic, called the CUSUM statistic, for each t. Under the null hypothesis, the statistic is drawn from a distribution, called the CUSUM distribution (t is the time index). If, the calculated CUSUM statistics appear to be too large to have been drawn from the CUSUM distribution, we reject the null hypothesis (of model stability).

H_0: Fitted model is stable

H_1: Fitted model is unstable

Let $e_{t+1,t}$ denotes the one-step-ahead forecast error associated with forecasting T_{t+1} based on the model fitted for over the sample period ending in period t. These are called the recursive residuals.

$$e_{t+1,t} = T_{t+1} - T_{t+1,t}$$
$$= Y_{t+1} - [\, \hat{\alpha}_{0,t} + \hat{\alpha}_{1,t}(t+1) + \cdots + \hat{\alpha}_{s,t}(t+)^{s} + \hat{\varphi}_{1,t}Y_t + \cdots + \hat{\varphi}_{p,t}Y_{t-p+1}]$$

where the t subscripts on the estimated parameters refers to the fact that they were estimated based on a sample whose last observation was in period t.

Let $\sigma_{1,t}$ denotes the standard error of the one-step ahead forecast of Y formed at time t, i.e,

$$\sigma_{1,t} = \sqrt{var(\, e_{t+1,t})}$$

The standardized recursive residuals, $w_{t+1,t}$ are defined as,

$$w_{t+1,t} = e_{t+1,t}/\sigma_{1,t}$$

where $w_{t+1,t} \sim i.i.d\ N(0,1)$.

There will be a set of standardized recursive residuals for each sample. The CUSUM (cumulative sum) statistics are defined according to:

$$CUSUM_t = \sum_{i=k}^{t} w_{i+1}\, , i$$

for t = k, k+1,…,T-1, where k = 2p+s+1 is the minimum sample size for which we can fit the model.

Under the null hypothesis, the $CUSUM_t$statistic is drawn from a CUSUM(t-k) distribution. The CUSUM(t-k) distribution is a symmetric distribution centered at 0. Its dispersion increases as t-k increases. We reject the null hypothesis at the 5% significance level if CUSUM_t is below the 2.5-percentile or above the 97.5-percentile of the CUSUM(t-k) distribution.

3.18 t test

t test is used to check the significance of the regression coefficients obtained from long run and short run models. In this test, a statistic based on the t distribution is used to test the two-sided hypothesis that the true slope, β_1, equals to 0. The statements for the hypothesis test are expressed as:

$$H_0: \beta_1 = 0$$

$$H_1: \beta_1 \neq 0$$

The test statistic used for this test is:

$$T_0 = \frac{\hat{\beta}_1}{se(\hat{\beta}_1)}$$

The test statistic, T_0, follows a t distribution with (n-2) degrees of freedom, where n is the total number of observations. The null hypothesis, H_0, is accepted if the calculated value of the test statistic is such that:

$$-t_{\frac{\alpha}{2},n-2} < T_0 < t_{\frac{\alpha}{2},n-2}$$

where $-t_{\frac{\alpha}{2},n-2}$ and $t_{\frac{\alpha}{2},n-2}$ are the critical values for the two-sided hypothesis. $t_{\frac{\alpha}{2},n-2}$ is the percentile of the t distribution corresponding to a cumulative probability of $(1 - \alpha/2)$ and α is the significance level.

3.19 Variance Decomposition and Impulse Response Function Analysis

Variance decompositions serve as a tool for evaluating the dynamic interactions and strength of casual relations among variables in the system. It is used to analyze how much of a change in a variable is due to its own shock and how much due to shocks to other variables. Impulse Response Function analysis is a graphical method to study the dynamic effects of shocks of macroeconomic variables on the selected response variable.

CHAPTER 4

ANALYSIS

4.1 Descriptive Analysis

The sample period for this study is 1988 through 2013. In this section a descriptive analysis of the variables has been carried out using time series plots. Since problems can occur in the interpretation of variables the log form of the variables have been used for this study.

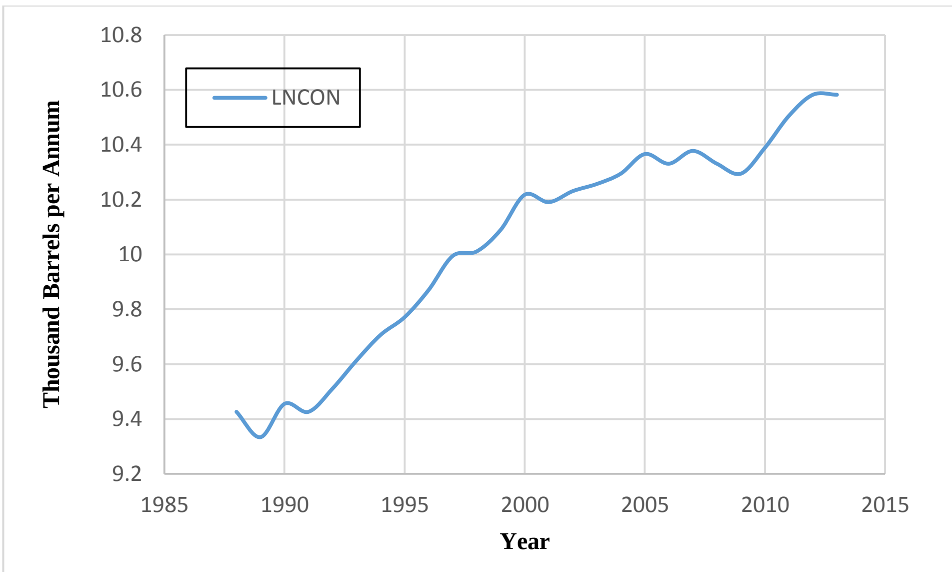

Figure 4. 1: Annual consumption of oil in Sri Lanka

The consumption of crude oil in Sri Lanka has been used to measure the oil demand. As it can be seen in figure 4.1 oil consumption is measured using thousand barrels per annum. The consumption of oil has seen a steady increase since 1988. Also a slight fall can be seen in the years 2001 and 2006. There is a huge decline in the consumption of oil in the period of 2008 – 2009 and this may due to end of civil war in Sri Lanka after 26 years of military campaign.

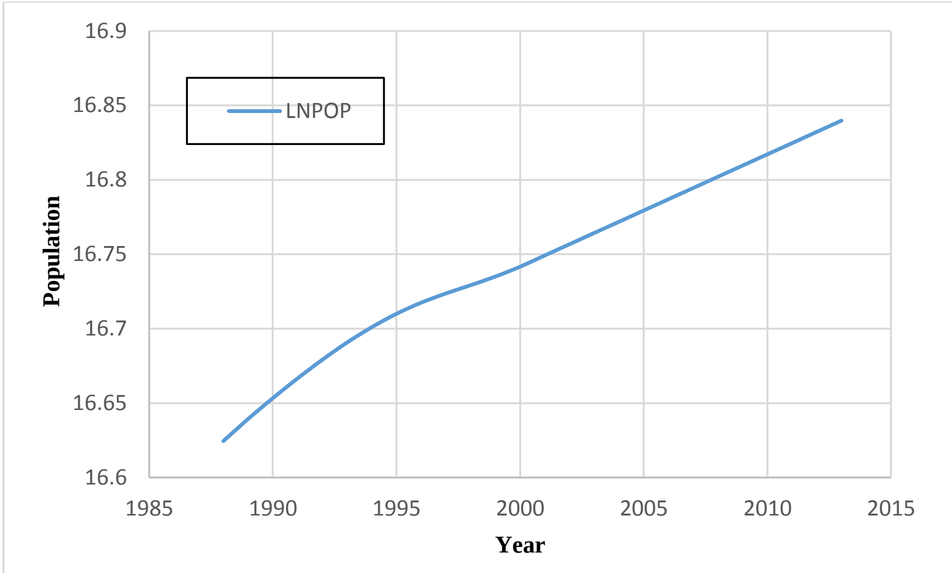

Figure 4. 2: Sri Lankan Population

According to figure 4.2 there is an increasing trend in Sri Lankan population throughout the period.

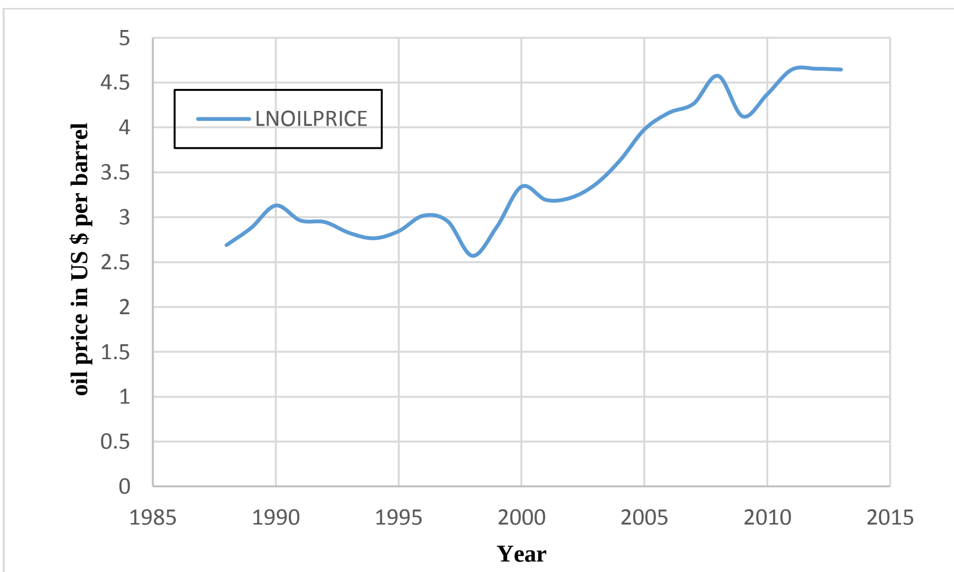

Figure 4. 3: Crude oil price

Figure 4.3 shows that the oil price is having an increasing trend from 1988 to 2013. There is a significant drop in oil price in 2009. This was almost entirely due to a collapse in demand for crude oil during the global financial crisis.

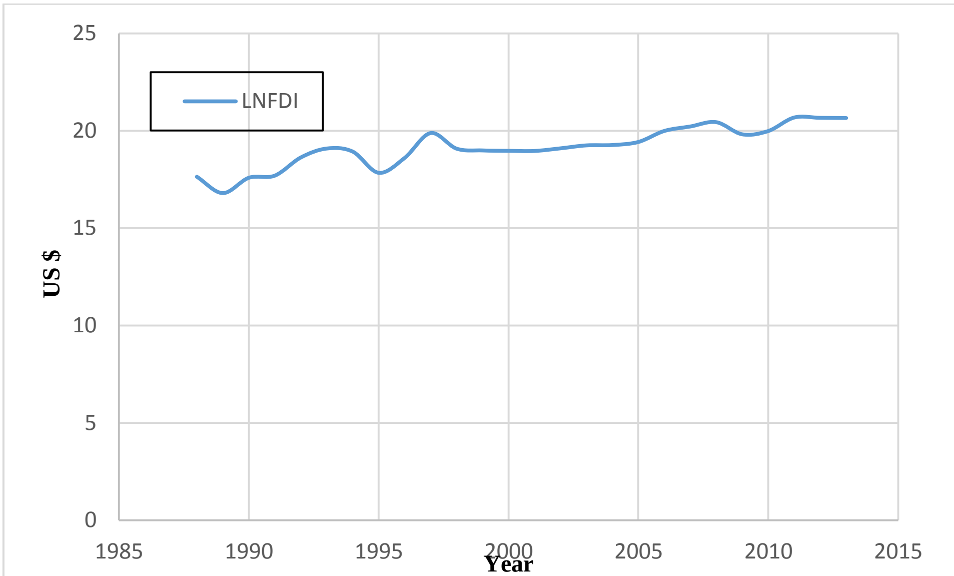

Figure 4. 4: Foreign Direct Investment

Figure 4.4 shows that there is a huge drop in Foreign Direct Investments from 1994 to 1995. Afterwards also there is no rapid growth. As it can be seen in the graph there is another decline in 2009. This may due to the biggest interruption of civil war for attracting foreign investments. Since average Foreign Direct Investment in Sri Lanka is 20 USD million in the second quarter of 2001 with a record as it is the lowest after the year 2000, graph also shows the lowest value in the year 2001 during that period.

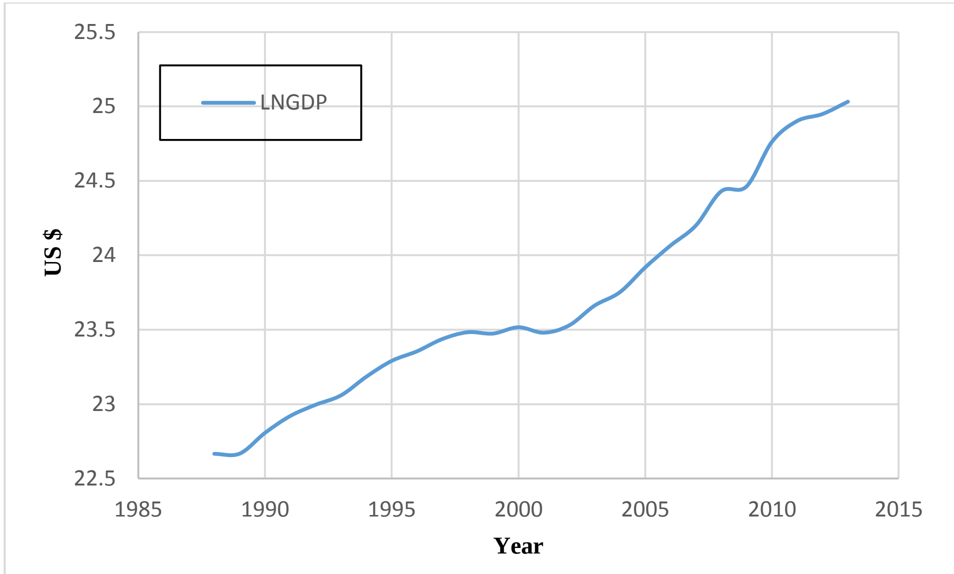

Figure 4. 5: Gross Domestic Product

According to the figure 4.5, there has been small ups and down in GDP, most remarkably in 2009. Throughout the considerable period GDP is having an upward trend as the general tendency.

4.2 Augmented Dickey Fuller tests on variables to check the stationary condition

Augmented Dickey Fuller (ADF) test is used to find out whether the time series variables are stationary. First the log values of all the variables are used to check the stationary condition. Since all the variables are not stationary, first difference values were used to check the stationary condition.

Table 4. 1: Augmented Dickey Fuller test for log values of consumption

Null Hypothesis: LNCON has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.802440	0.8011
Test critical values:	1% level	-3.724070	
	5% level	-2.986225	
	10% level	-2.632604	

*MacKinnon (1996) one-sided p-values.

As it can be seen in table 4.1, the p value of ADF test is greater than 0.05. Hence we do not have enough evidence to reject the null hypothesis of the ADF test. Therefore we can conclude that the log values of consumption are not stationary.

Table 4. 2: Augmented Dickey Fuller test for log values of FDI

Null Hypothesis: LNFDI has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.202924	0.6550
Test critical values:	1% level	-3.752946	
	5% level	-2.998064	
	10% level	-2.638752	

*MacKinnon (1996) one-sided p-values.

According to table 4.2, the p value of ADF test is greater than 0.05. Hence we do not have enough evidence to reject the null hypothesis of the ADF test. Therefore we can conclude that the log values of the variable Foreign Direct Investment (FDI) are not stationary.

Table 4. 3: Augmented Dickey Fuller test for log values of GDP

Null Hypothesis: LNGDP has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.348890	0.9981
Test critical values:	1% level	-3.724070	
	5% level	-2.986225	
	10% level	-2.632604	

*MacKinnon (1996) one-sided p-values.

Table 4.3 shows that the p value of ADF test is greater than 0.05. Hence we can conclude that the log values of the variable Gross Domestic Product (GDP) are not stationary.

Table 4. 4: Augmented Dickey Fuller test for log values of Oil Price

Null Hypothesis: LNOILPRICE has a unit root

Exogenous: Constant

Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.302531	0.9113
Test critical values:	1% level	-3.724070	
	5% level	-2.986225	

	10% level	-2.632604

*MacKinnon (1996) one-sided p-values.

As it can be seen in table 4.4, the p value of ADF test is greater than 0.05. Hence we do not have enough evidence to reject the null hypothesis of the ADF test. Therefore we can conclude that the log values of the variable oil price are not stationary.

Table 4. 5: Augmented Dickey Fuller test for log values of Population

Null Hypothesis: LNPOP has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.987396	0.7400
Test critical values:	1% level	-3.752946	
	5% level	-2.998064	
	10% level	-2.638752	

*MacKinnon (1996) one-sided p-values.

According to table 4.2, the p value of ADF test is greater than 0.05. Hence we do not have enough evidence to reject the null hypothesis of the ADF test. Therefore we can conclude that the log values of the variable Foreign Direct Investment (FDI) are not stationary.

Table 4. 6: Augmented Dickey Fuller test for the first difference of log values of Consumption

Null Hypothesis: D(LNCON) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.760107	0.0001
Test critical values:	1% level	-3.737853	
	5% level	-2.991878	
	10% level	-2.635542	

*MacKinnon (1996) one-sided p-values.

Table 4.6 shows that the p value of ADF test is less than 0.05. Hence we can reject the null hypothesis of the ADF test. Therefore we can conclude that the first difference of the log values of the variable consumption is stationary.

Table 4. 7: Augmented Dickey Fuller test for the first difference of log values of FDI

Null Hypothesis: D(LNFDI) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.991209	0.0064
Test critical values:	1% level	-3.788030	
	5% level	-3.012363	
	10% level	-2.646119	

*MacKinnon (1996) one-sided p-values.

Table 4.7 shows that the p value of ADF test is less than 0.05. Hence we can reject the null hypothesis of the ADF test. Therefore we can conclude that the first difference of the log values of the variable Foreign Direct Investment (FDI) is stationary.

Table 4. 8: Augmented Dickey Fuller test for the first difference of log values of GDP

Null Hypothesis: D(LNGDP) has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.292683	0.0028
Test critical values:	1% level	-3.737853	
	5% level	-2.991878	
	10% level	-2.635542	

*MacKinnon (1996) one-sided p-values.

According to table 4.8 p value of ADF test is less than 0.05. Hence we can reject the null hypothesis of the ADF test. Therefore we can conclude that the first difference of the log values of the variable Gross Domestic Product (GDP) is stationary.

Table 4. 9: Augmented Dickey Fuller test for the first difference of log values of population

Null Hypothesis: D(LNPOP) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.957545	0.00542
Test critical values:	1% level	-3.752946	
	5% level	-2.998064	
	10% level	-2.638752	

*MacKinnon (1996) one-sided p-values.

As it can be seen table 4.9 the p value of ADF test is less than 0.05. Hence we can reject the null hypothesis of the ADF test. Therefore we can conclude that the first difference of the log values population is stationary.

Table 4. 10: Augmented Dickey Fuller test for the first difference of log values of Oil Price

Null Hypothesis: D(LNOILPRICE) has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.720441	0.0011
Test critical values:	1% level	-3.752946	
	5% level	-2.998064	
	10% level	-2.638752	

*MacKinnon (1996) one-sided p-values.

According to table 4.10 p values of the ADF test is less than 0.05. Hence we can reject the null hypothesis of the ADF test at 0.05 level of significance. Therefore the first difference of the log values of oil price is stationary.

4.3 Chow breakpoint test to test the structural breaks

According to the results of the ADF tests all the variables are not stationary before applying the differencing concept. Hence the Engle – Granger two step estimator was used in the analysis. As it can be seen in figure 4.1, there is a break in the oil consumption from the year 2008 to 2009. In order to test the significance of the structural break chow breakpoint test is used.

Table 4. 11: Chow breakpoint test using the selected variables for the model

Chow Breakpoint Test: 22
Null Hypothesis: No breaks at specified breakpoints
Varying regressors: All equation variables
Equation Sample: 2 26

F-statistic	4.897459	Prob. F(5,15)	0.0074
Log likelihood ratio	24.19822	Prob. Chi-Square(5)	0.0002
Wald Statistic	24.48729	Prob. Chi-Square(5)	0.0002

As the p value of the Chow breakpoint test is less than 0.05, we reject the null hypothesis at 5% level of significance. Hence the data set contains a structural break at the 22^{nd} data point.

4.4 Testing for Cointegration

ADF test shows that all the variables are stationary in their first difference. Hence it indicates the existence of a cointegrating relationship between the variables. Therefore Trace test is used to test whether there exists a cointegrating relationship between the variables.

Table 4. 12: Cointegration test Results

Date: 11/23/17 Time: 14:20
Sample (adjusted): 3 26
Included observations: 24 after adjustments
Trend assumption: Linear deterministic trend
Series: LNCON LNFDI LNGDP LNPOP LNOILPRICE
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.929030	127.5967	69.81889	0.0000
At most 1 *	0.805442	64.10492	47.85613	0.0008
At most 2	0.412280	24.81626	29.79707	0.1681
At most 3	0.267806	12.06014	15.49471	0.1541
At most 4 *	0.173698	4.579087	3.841466	0.0324

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.929030	63.49182	33.87687	0.0000
At most 1 *	0.805442	39.28866	27.58434	0.0010
At most 2	0.412280	12.75613	21.13162	0.4749
At most 3	0.267806	7.481050	14.26460	0.4339
At most 4 *	0.173698	4.579087	3.841466	0.0324

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

According to the results of table 4.12, trace test indicates that there are two cointegration equations between log values of Consumption, Gross Domestic Product (GDP), Foreign Direct Investment (FDI), Oil Price and Population at 5% level of significance. Hence we can conclude that a Vector Error Correction model can be used to model the relationship between these variables.

4.5 Engle- Granger estimator for Sri Lankan oil demand

As for the results of trace test there exists a cointegration relationship among variables. Hence Engle Granger approach was used to fit a Vector Error Correction model for the data set in order to find the determinants of Sri Lankan oil demand.

As the first step Vector Error Correction models were estimated with appropriate number of lags.

Table 4. 13: Vector Error Correction model for Sri Lankan oil demand up to lag 1

Vector Error Correction Estimates
Date: 11/29/17 Time: 16:32
Sample (adjusted): 3 26
Included observations: 24 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	CointEq2			
LNCON(-1)	1.000000	0.000000			
LNFDI(-1)	0.000000	1.000000			
LNGDP(-1)	-1.115634	3.023796			
	(0.11975)	(0.86638)			
	[-9.31647]	[3.49014]			
LNPOP(-1)	-6.805764	-7.455268			
	(1.08856)	(7.87574)			
	[-6.25209]	[-0.94661]			
LNOILPRICE(-1)	1.032864	-3.916814			
	(0.07631)	(0.55213)			
	[13.5345]	[-7.09401]			
C	126.7457	47.67044			
Error Correction:	D(LNCON)	D(LNFDI)	D(LNGDP)	D(LNPOP)	D(LNOILPRICE)
CointEq1	-0.506850	-4.901164	-0.203278	0.001840	-1.335292

	(0.05948)	(0.87877)	(0.17735)	(0.00135)	(0.46939)
	[-8.52185]	[-5.57730]	[-1.14620]	[1.36506]	[-2.84471]
CointEq2	-0.047457	-1.207364	-0.097144	0.000210	-0.271976
	(0.01346)	(0.19887)	(0.04014)	(0.00031)	(0.10623)
	[-3.52576]	[-6.07098]	[-2.42037]	[0.68838]	[-2.56029]
D(LNCON(-1))	-0.591575	-0.695527	0.220886	-0.000432	-0.375424
	(0.11582)	(1.71126)	(0.34536)	(0.00262)	(0.91407)
	[-5.10766]	[-0.40644]	[0.63958]	[-0.16469]	[-0.41072]
D(LNFDI(-1))	0.062771	0.513928	0.016194	-0.000262	-0.055665
	(0.01296)	(0.19147)	(0.03864)	(0.00029)	(0.10228)
	[4.84372]	[2.68405]	[0.41907]	[-0.89275]	[-0.54427]
D(LNGDP(-1))	-0.320174	-2.603386	0.051984	-0.001511	-0.391514
	(0.08022)	(1.18524)	(0.23920)	(0.00182)	(0.63310)
	[-3.99124]	[-2.19650]	[0.21732]	[-0.83130]	[-0.61841]
D(LNPOP(-1))	19.97319	3.283147	-10.62764	0.804888	-16.23504
	(2.73489)	(40.4081)	(8.15501)	(0.06198)	(21.5839)
	[7.30312]	[0.08125]	[-1.30320]	[12.9865]	[-0.75218]
D(LNOILPRICE(-1))	0.201533	0.505189	-0.216855	0.000362	0.214981
	(0.03492)	(0.51600)	(0.10414)	(0.00079)	(0.27562)
	[5.77066]	[0.97905]	[-2.08240]	[0.45788]	[0.77999]
C	-0.173734	-1.014187	0.132154	0.002173	-0.160786
	(0.02828)	(0.41780)	(0.08432)	(0.00064)	(0.22317)
	[-6.14392]	[-2.42745]	[1.56732]	[3.39098]	[-0.72047]
DUMMY	0.110398	1.669168	0.073863	-0.000782	0.529935
	(0.02186)	(0.32295)	(0.06518)	(0.00050)	(0.17250)
	[5.05075]	[5.16852]	[1.13328]	[-1.57962]	[3.07204]
R-squared	0.901522	0.756816	0.460130	0.968535	0.617441
Adj. R-squared	0.849000	0.627119	0.172199	0.951754	0.413410
Sum sq. resids	0.007289	1.591287	0.064813	3.74E-06	0.454018
S.E. equation	0.022044	0.325708	0.065733	0.000500	0.173977
F-statistic	17.16479	5.835227	1.598058	57.71554	3.026207
Log likelihood	63.13818	-1.492398	36.91714	154.0274	13.55753
Akaike AIC	-4.511515	0.874367	-2.326429	-12.08561	-0.379794
Schwarz SC	-4.069745	1.316137	-1.884659	-11.64384	0.061976
Mean dependent	0.052006	0.160634	0.098511	0.008352	0.073489
S.D. dependent	0.056730	0.533388	0.072247	0.002274	0.227156

Determinant resid covariance (dof adj.)	1.47E-16
Determinant resid covariance	1.40E-17
Log likelihood	295.3799
Akaike information criterion	-20.03166
Schwarz criterion	-17.33195

As the chow breakpoint test showed that there was a structural breakdown, a dummy variable was used to fit the Vector Error Correction model. All the variables of this model are satisfying the I(1) condition.

Table 4. 14: Vector Error Correction model for Sri Lankan oil demand up to lag 2

Vector Error Correction Estimates
Date: 01/03/18 Time: 17:47
Sample (adjusted): 4 26
Included observations: 23 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1	CointEq2			
LNCON(-1)	1.000000	0.000000			
LNFDI(-1)	0.000000	1.000000			
LNGDP(-1)	1.655375	-4.476418			
	(0.35958)	(2.04477)			
	[4.60368]	[-2.18920]			
LNOILPRICE(-1)	-0.853309	0.790021			
	(0.27305)	(1.55273)			
	[-3.12509]	[0.50879]			
LNPOP(-1)	-18.85770	51.02676			
	(1.81787)	(10.3375)			
	[-10.3735]	[4.93609]			
C	269.4893	-770.4985			
Error Correction:	**D(LNCON)**	**D(LNFDI)**	**D(LNGDP)**	**D(LNOILPRICE)**	**D(LNPOP)**
CointEq1	-0.109099	-6.921338	-0.222624	0.518755	0.001312
	(0.17152)	(2.32123)	(0.21621)	(0.80585)	(0.00108)
	[-0.63607]	[-2.98176]	[-1.02968]	[0.64374]	[1.21704]
CointEq2	-0.024538	-1.515386	0.018332	0.162096	-0.000119
	(0.03680)	(0.49805)	(0.04639)	(0.17291)	(0.00023)
	[-0.66677]	[-3.04263]	[0.39518]	[0.93748]	[-0.51586]
D(LNCON(-1))	0.238485	10.68054	0.702586	0.879202	-0.003982
	(0.32649)	(4.41852)	(0.41156)	(1.53396)	(0.00205)
	[0.73045]	[2.41722]	[1.70715]	[0.57316]	[-1.94079]
D(LNCON(-2))	0.524395	6.787535	-0.286617	-0.752486	-0.005871
	(0.23167)	(3.13528)	(0.29203)	(1.08846)	(0.00146)
	[2.26353]	[2.16489]	[-0.98146]	[-0.69133]	[-4.03253]
D(LNFDI(-1))	0.018687	0.363789	-0.041433	-0.266866	0.000145
	(0.02039)	(0.27591)	(0.02570)	(0.09579)	(0.00013)

	[0.91662]	[1.31851]	[-1.61223]	[-2.78606]	[1.13175]
D(LNFDI(-2))	-0.061303	-0.164196	-0.046405	-0.197019	0.000567
	(0.02589)	(0.35037)	(0.03263)	(0.12164)	(0.00016)
	[-2.36785]	[-0.46863]	[-1.42194]	[-1.61973]	[3.48462]
D(LNGDP(-1))	-0.037016	0.058359	0.146327	1.237400	-0.000556
	(0.17865)	(2.41772)	(0.22519)	(0.83935)	(0.00112)
	[-0.20720]	[0.02414]	[0.64978]	[1.47424]	[-0.49522]
D(LNGDP(-2))	0.473701	2.220515	0.204124	2.002410	0.000324
	(0.13903)	(1.88151)	(0.17525)	(0.65319)	(0.00087)
	[3.40725]	[1.18018]	[1.16476]	[3.06557]	[0.37122]
D(LNOILPRICE(-1))	-0.208948	-3.298777	-0.311298	-0.459584	0.001731
	(0.09115)	(1.23362)	(0.11490)	(0.42827)	(0.00057)
	[-2.29225]	[-2.67406]	[-2.70922]	[-1.07312]	[3.02258]
D(LNOILPRICE(-2))	-0.236581	-2.252394	-0.031102	-0.288782	0.000489
	(0.07133)	(0.96533)	(0.08991)	(0.33513)	(0.00045)
	[-3.31674]	[-2.33330]	[-0.34591]	[-0.86171]	[1.09110]
D(LNPOP(-1))	23.32239	18.64938	-14.66088	236.2670	1.595431
	(21.4824)	(290.728)	(27.0793)	(100.931)	(0.13500)
	[1.08565]	[0.06415]	[-0.54140]	[2.34088]	[11.8177]
D(LNPOP(-2))	-30.50686	-614.2924	14.53639	-192.5151	-0.720317
	(21.8586)	(295.820)	(27.5537)	(102.699)	(0.13737)
	[-1.39564]	[-2.07657]	[0.52757]	[-1.87456]	[-5.24368]
C	0.054157	4.270163	0.033735	-0.800546	0.001372
	(0.13610)	(1.84191)	(0.17156)	(0.63945)	(0.00086)
	[0.39792]	[2.31834]	[0.19664]	[-1.25194]	[1.60358]
DUMMY	0.033206	0.433806	0.051284	0.461666	-0.000172
	(0.02728)	(0.36916)	(0.03438)	(0.12816)	(0.00017)
	[1.21733]	[1.17512]	[1.49148]	[3.60229]	[-1.00414]
R-squared	0.860722	0.713076	0.870925	0.816283	0.995586
Adj. R-squared	0.659542	0.298630	0.684484	0.550914	0.989211
Sum sq. resids	0.009610	1.760150	0.015270	0.212140	3.80E-07
S.E. equation	0.032677	0.442235	0.041191	0.153529	0.000205
F-statistic	4.278366	1.720553	4.671304	3.076032	156.1640
Log likelihood	56.83910	-3.079491	51.51370	21.25344	173.4418
Akaike AIC	-3.725140	1.485173	-3.262061	-0.630734	-13.86451
Schwarz SC	-3.033969	2.176344	-2.570891	0.060437	-13.17333
Mean dependent	0.048991	0.133413	0.096733	0.065866	0.008108
S.D. dependent	0.056004	0.528056	0.073332	0.229100	0.001977

Determinant resid covariance (dof adj.)	4.65E-18
Determinant resid covariance	4.27E-20
Log likelihood	349.7258
Akaike information criterion	-23.45442
Schwarz criterion	-19.50487

As the chow breakpoint test showed that there was a structural breakdown, a dummy variable was used to fit the Vector Error Correction model. According to table 4.14 all the variables of this model are satisfying the I(1) condition.

Table 4. 15: Lag selection criterion values

Lag length	Adj. R-squared	Akaike (AIC)	Schwarz Criterion (SC)	Standard Error
1	**0.849**	**-4.511515**	**-4.069745**	**0.022044**
2	0.659542	-3.72514	-3.033969	0.032677

According to table 4.15 lag 1 gives the values that minimize the Akaike Information Criterion, Schwarz Criterion and Standard Error. Also lag 1 model gives the maximum value for adjusted R squared. Hence Vector Error Correction model was fitted by considering up to lag 1 of all endogenous variables.

Table 4. 16: Significance of the coefficients of the VECM using lag 1

Dependent Variable: D(LNCON)
Method: Least Squares
Date: 11/30/17 Time: 14:03
Sample (adjusted): 3 26
Included observations: 24 after adjustments
D(LNCON) = C(1)*(LNCON(-1) - 1.11563358287*LNGDP(-1) - 6.80576412931*LNPOP(-1) + 1.03286420496*LNOILPRICE(-1) + 126.745741569) + C(2)*(LNFDI(-1) + 3.02379581871*LNGDP(-1) - 7.45526834643*LNPOP(-1) - 3.91681398669*LNOILPRICE(-1) + 47.6704440648) + C(3)*D(LNCON(-1)) + C(4)*D(LNFDI(-1)) + C(5) *D(LNGDP(-1)) + C(6)*D(LNPOP(-1)) + C(7)*D(LNOILPRICE(-1)) + C(8) + C(9)*DUMMY

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.506850	0.059477	-8.521846	0.0000
C(2)	-0.047457	0.013460	-3.525756	0.0031
C(3)	-0.591575	0.115821	-5.107665	0.0001
C(4)	0.062771	0.012959	4.843718	0.0002
C(5)	-0.320174	0.080219	-3.991242	0.0012
C(6)	19.97319	2.734885	7.303119	0.0000
C(7)	0.201533	0.034924	5.770664	0.0000
C(8)	-0.173734	0.028277	-6.143920	0.0000
C(9)	0.110398	0.021858	5.050750	0.0001

R-squared	0.901522	Mean dependent var	0.052006
Adjusted R-squared	0.849000	S.D. dependent var	0.056730
S.E. of regression	0.022044	Akaike info criterion	-4.511515
Sum squared resid	0.007289	Schwarz criterion	-4.069745
Log likelihood	63.13818	Hannan-Quinn criter.	-4.394313
F-statistic	17.16479	Durbin-Watson stat	1.714811
Prob(F-statistic)	0.000003		

As it can be seen in table 4.16, C1 and C2 are the long run coefficients where C3 – C9 are short run coefficients of Consumption, Foreign Direct Investment (FDI), Gross Domestic Product (GDP), Population and Oil Price respectively. FDI, GDP, Oil Price and Population are regressed with consumption and it seems that all the variables are statistically significant at 95 percent confidence interval since p-value of these variables are less than 5 percent. The coefficients of FDI, Population and Oil Price are positive while the coefficient of GDP is negative. The Negative coefficient explains that GDP is having an adverse effect to the oil demand. The positive coefficients of FDI, Population and Oil Price indicate that increasing the value of these variables has a positive effect on oil demand.

Magnitude of population coefficient indicates that when there is an increase in population by 1 percent, the oil demand increased by 19.97 percent. According to the results, changes in population creates highest extended fluctuation in oil demand. Even though FDI and Oil Price are statistically significant on the model, 1 percent increase in FDI will tend to increase the oil demand by 0.06 percent while 1 percent increase in oil price tend to increase the oil demand by 0.2 percent. For one unit increase in GDP, oil demand will tend to drop by only 0.32 percent.

R^2 and adjusted R^2 of the model is 90 percent and 84 percent respectively. That means 84 percent of the variations in oil demand is explained by FDI, GDP, Population and Oil Price. -0.51 and -0.05 are the error correction terms applied in the model to check the effect of variables on oil demand. This shows the speed at which adjustment occurs in the long term equilibrium. Since both values are negative and significant at 95 percent significant level, it indicates that 0.51 percent of previous disequilibrium in long run will be corrected in short run in the first equilibrium relationship while 0.05 percent of previous disequilibrium in long run will be corrected in short run by the second equilibrium relationship. According to the second equilibrium relationship, even though there is an adjustment to the equilibrium, it is slow as only 4.7 percent of the equilibrium has been corrected.

4.6 Impulse Response Function Analysis

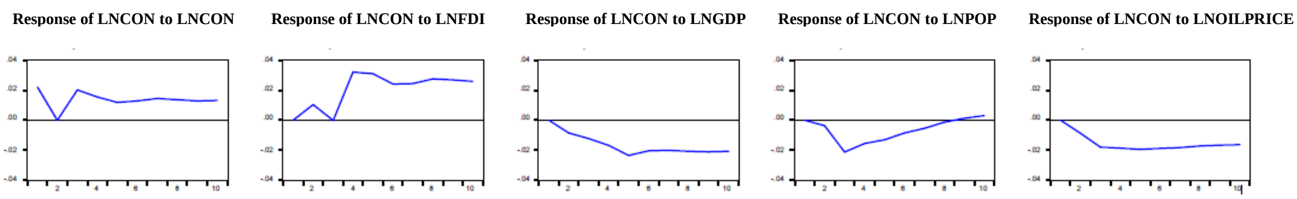

Figure 4. 6: Impulse Response Function

The impulse response function shows that when oil consumption has a positive shock Foreign Direct Investment (FDI) goes up and then again it goes down. From the third year it is increasing and after the fifth year it seems to be steady. Impulse response function also shows that consumption of oil has a negative respond to Gross Domestic Product (GDP) and oil price. Consumption of oil responds negatively to population but from the 10th year it has a positive response.

4.7 Variance Decompositions

Table 4. 17: Variance Decomposition of Oil Demand

Period	S.E.	LNCON	LNFDI	LNGDP	LNPOP	LNOILPRICE
1	0.022044	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.027558	63.99330	14.26846	9.677846	1.825875	10.23452
3	0.045922	42.49715	5.142014	10.73176	22.49813	19.13095
4	0.065330	26.61656	26.73525	12.06626	16.82464	17.75729
5	0.080579	19.69353	32.43079	16.52145	13.74706	17.60717
6	0.089987	17.82904	33.18837	18.50866	11.94351	18.53043
7	0.098420	17.07400	33.93398	19.72275	10.29700	18.97227
8	0.106689	16.16231	35.62095	20.63801	8.781209	18.79752
9	0.114056	15.41708	36.72855	21.54159	7.695846	18.61694
10	0.120729	14.96034	37.39280	22.23204	6.929081	18.48574

Results in table 4.17 shows that oil demand (LNCON) is relatively less exogenous in relation to the shocks of macroeconomic variables in the short run because if considering only two years, the oil demand or the consumption of oil (LNCON) is the most important variable to account for its own innovation, which is nearly 64%. Contribution of Foreign Direct Investment (FDI), Gross Domestic Product (GDP), population and oil price to the forecast error variance is 14.26%, 9.68%, 1.82% and 10.23% respectively.

At the end of the 10th year, only 14.96% of variance of consumption is explained by its own shock. Foreign Direct Investment (FDI), Gross Domestic Product (GDP) and population are the next most important variables to be considered in explaining the forecast error variance, which accounts 37.39%, 22.23% and 18.48% impact on consumption of oil respectively. This implies that Foreign Direct Investment (FDI), Gross Domestic Product (GDP) and population prove to be the most significant factors that explain the movement in oil demand in the long run.

4.8: Diagnostic check for the residuals of the selected model

4.8.1 Normality assumption

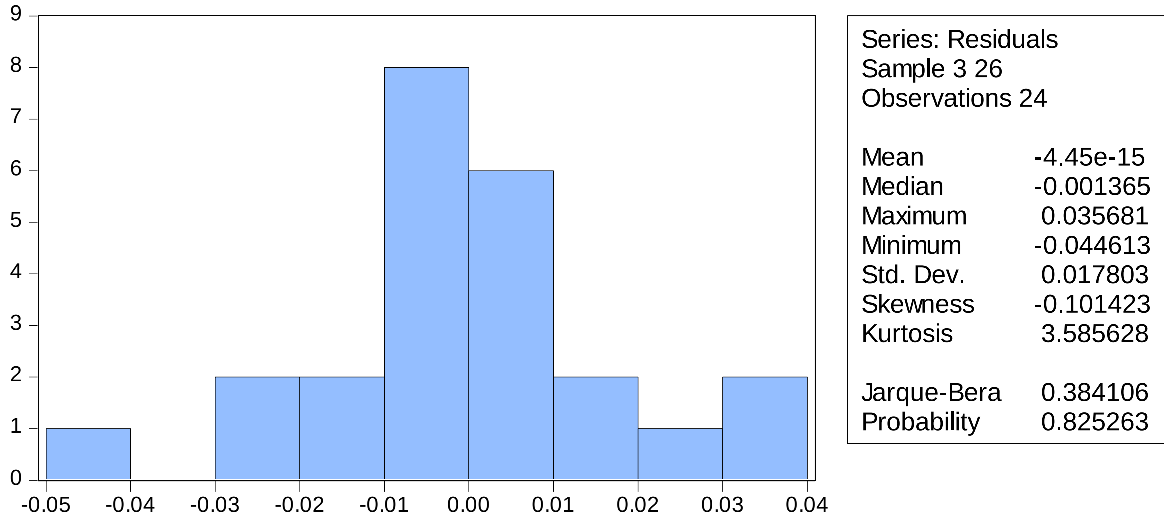

Figure 4. 7: Histogram for the residuals of VECM model

As it can be seen in figure 4.7, residuals of the Vector Error Correction model are normally distributed at 0.05 level of significance.

4.8.2 Serial Correlation

Table 4. 18: Breusch-Godfrey Serial Correlation LM Test

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.000667	Prob. F(1,14)	0.9798
Obs*R-squared	0.001143	Prob. Chi-Square(1)	0.9730

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 11/30/17 Time: 08:38
Sample: 3 26
Included observations: 24
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	2.88E-05	0.061573	0.000467	0.9996
C(2)	1.91E-05	0.013952	0.001367	0.9989
C(3)	-0.000780	0.123630	-0.006309	0.9951
C(4)	3.84E-05	0.013496	0.002844	0.9978
C(5)	-0.000576	0.085981	-0.006704	0.9947
C(6)	0.003245	2.833595	0.001145	0.9991
C(7)	0.000137	0.036538	0.003761	0.9971
C(8)	4.99E-05	0.029333	0.001701	0.9987
C(9)	-2.30E-05	0.022642	-0.001017	0.9992
RESID(-1)	0.008901	0.344676	0.025824	0.9798

R-squared	0.000048	Mean dependent var	-4.45E-15
Adjusted R-squared	-0.642779	S.D. dependent var	0.017803
S.E. of regression	0.022818	Akaike info criterion	-4.428229
Sum squared resid	0.007289	Schwarz criterion	-3.937374
Log likelihood	63.13875	Hannan-Quinn criter.	-4.298005
F-statistic	7.41E-05	Durbin-Watson stat	1.719984
Prob(F-statistic)	1.000000		

According to table 4.18 p value of the LM test is greater than 0.05, which indicates that there is no serial correlation among the residuals of the VECM model.

4.8.3 Heteroscedasticity

Table 4. 18: ARCH test to check Heteroscedasticity of the residuals

Heteroskedasticity Test: ARCH

F-statistic	0.359142	Prob. F(1,21)	0.5554
Obs*R-squared	0.386732	Prob. Chi-Square(1)	0.5340

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 11/30/17 Time: 08:39
Sample (adjusted): 4 26
Included observations: 23 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000359	0.000129	2.791989	0.0109
RESID^2(-1)	-0.185405	0.309378	-0.599284	0.5554

R-squared	0.016814	Mean dependent var	0.000316
Adjusted R-squared	-0.030004	S.D. dependent var	0.000506
S.E. of regression	0.000514	Akaike info criterion	-12.22722
Sum squared resid	5.54E-06	Schwarz criterion	-12.12848
Log likelihood	142.6130	Hannan-Quinn criter.	-12.20239
F-statistic	0.359142	Durbin-Watson stat	1.549032
Prob(F-statistic)	0.555394		

As it can be seen in table 4.19 p value of the ARCH test is greater than 0.05, which indicates that there is no heteroscedasticity among the residuals of the VECM model.

4.8.4 Stationary Condition

Table 4. 19: Unit Root test

Null Hypothesis: RESIDUALS has a unit root

Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=5)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.685488	0.0000
Test critical values:	1% level	-3.788030	
	5% level	-3.012363	
	10% level	-2.646119	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESIDUALS)
Method: Least Squares
Date: 11/30/17 Time: 14:03
Sample (adjusted): 6 26
Included observations: 21 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESIDUALS(-1)	-2.754350	0.411989	-6.685488	0.0000
D(RESIDUALS(-1))	1.386514	0.289479	4.789690	0.0002
D(RESIDUALS(-2))	0.805911	0.210540	3.827825	0.0013
C	0.003701	0.003031	1.220967	0.2388

R-squared	0.752871	Mean dependent var	-0.001689
Adjusted R-squared	0.709260	S.D. dependent var	0.024860
S.E. of regression	0.013405	Akaike info criterion	-5.616764
Sum squared resid	0.003055	Schwarz criterion	-5.417808
Log likelihood	62.97603	Hannan-Quinn criter.	-5.573586
F-statistic	17.26332	Durbin-Watson stat	2.252834
Prob(F-statistic)	0.000021		

As the p value of the unit root test is less than 0.05, we can conclude that the residuals are stationary. Hence a cointegration relationship exists between variables and the long run model parameters are consistent and highly efficient.

4.8.5 Significance of the parameters using Cusum test

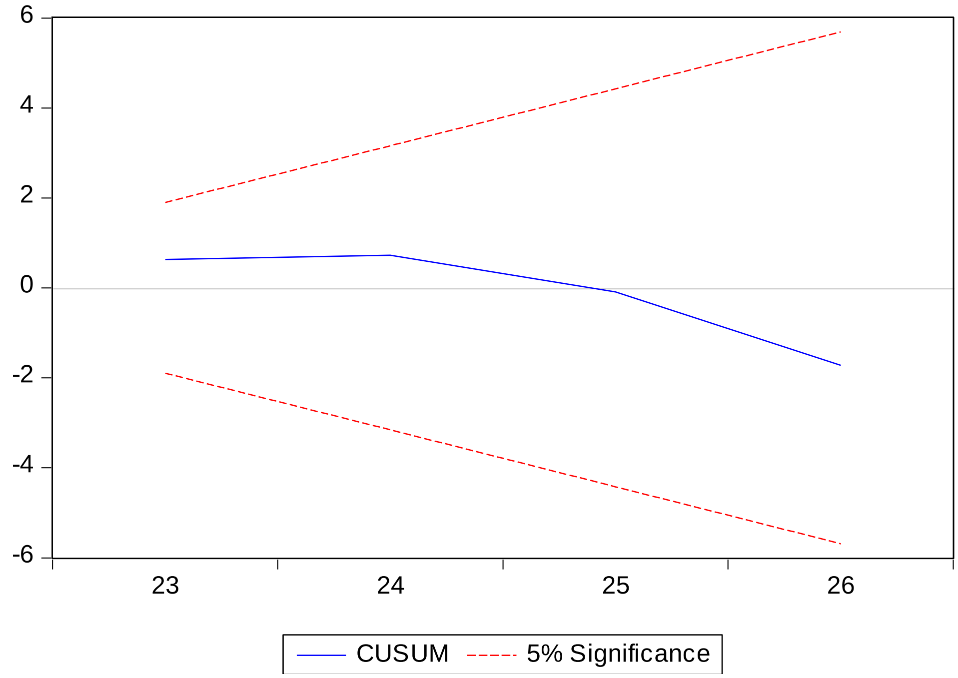

Figure 4. 8: Plot of recursive residuals

As it can be seen in figure 4.8 recursive residuals have been distributed between the 5% significance level. Hence the test clearly indicates stability of the parameters of the equation during the sample period.

4.9 VECM model for the Sri Lankan Oil Demand

$$
\begin{aligned}
D(lncon_t) = & -0.51(lncon_{t-1} - 1.12 * lnGDP_{t-1} - 6.8 * lnpop_{t-1} + 1.03 \\
& * lnOilPrice_{t-1} + 126.74) \\
& - 0.05(lnFDI_{t-1} + 3.02 * lnGDP_{t-1} - 7.46 * lnpop_{t-1} - 3.92 \\
& * lnOilPrice_{t-1} + 47.67) - 0.6 * D(lncon_{t-1}) + 0.06 * D(lnFDI_{t-1}) \\
& - 0.32 * D(lnGDP_{t-1}) + 19.97 * D(lnpop_{t-1}) + 0.2 \\
& * D(lnOilPrice_{t-1}) - 0.17 + 0.11 * dummy
\end{aligned}
$$

4.9.1 Modified Final Equation

The final equation was obtained by simplifying the selected model.

$$
\begin{aligned}
(lncon_t) = & -0.1(lncon_{t-1}) + 0.6(lncon_{t-2}) + 0.13 * lnGDP_{t-1} + 0.32 * \\
& lnGDP_{t-2} - 19.97 * \\
& lnpop_{t-2} + 23.81 * lnpop_{t-1} - 0.13 * lnOilPrice_{t-1} - 0.2 * \\
& lnOilPrice_{t-2} + 0.01 * lnFDI_{t-1} - 0.06 * lnFDI_{t-2} + 67.19 - 0.11 * \\
& dummy
\end{aligned}
$$

4.9.2 Mean Absolute Error Forecasted Values for Sri Lankan Oil Demand

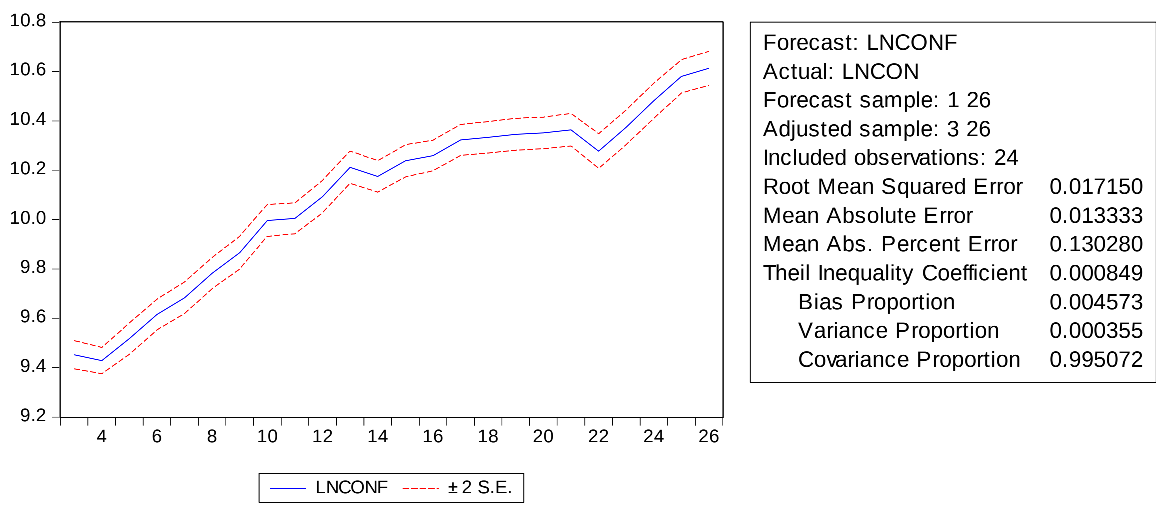

Figure 4. 9: Forecast Values of Sri Lankan Oil Demand

Table 4. 21: Forecasts Vs. Actual Values of ln(Oil Demand)

Year	Forecasted Value	Actual Value
2010	11.03	10.38
2011	11.13	10.50
2012	11.27	10.58

According to table 4.21 forecasted values of Sri Lankan oil demand is very close to the actual value. Further, as it can be seen in figure 4.9 MAPE (Mean Absolute Percentage Error) is less than 5%, verifying that the forecasts give quite approximate values to the actual figures.

4.10 Factors which affect for long run equilibrium of Sri Lankan oil demand

Table 4. 22: Significance of the long run coefficients

Variable	**Long run equilibrium 1**		**Long run equilibrium 2**	
	t statistic	Critical value (5%)	t statistic	Critical value (5%)
$lnGDP_{t-1}$	-9.31647*	1.729	3.49014	1.729
$lnpop_{t-1}$	-6.25209*	1.729	-0.94661*	1.729
$lnOilPrice_{t-1}$	13.5345	1.729	-7.09401*	1.729
$lnFDI_{t-1}$	0*	1.729	1*	1.729

Notes: * 5 percent significance level

As it can be seen in table 4.13 there are two long run equilibriums. Also all the variables are in differenced log form (excluding the dummy variable). As for the first equilibrium relationship, GDP and Population have significant negative inelastic effects on demand for oil. Whereas inelastic effects of oil price and FDI are insignificant.

As for the second equilibrium relationship, Population and Oil Price have negative inelastic effects on demand for oil. Whereas inelastic effect of GDP is insignificant and FDI has a unitary positive inelasticity effect.

4.11 Summary of the analysis

.-0.51 and -0.04 are the error correction terms applied in the model to check the effect of variables on oil demand. This shows the speed at which adjustment occurs in the long term equilibrium. Since both values are negative and significant at 95 percent significant level, it indicates that 0.51 percent of previous disequilibrium in long run will be corrected in short run in the first equilibrium relationship while 0.04 percent of previous disequilibrium in long run will be corrected in short run by the second equilibrium relationship. Since the error correction terms are relatively small there is a slow adjustment to the long run equilibrium. Identifying a demand for oil is a long process, hence although there is a long run relationship, it may take several periods to adjust to its equilibrium.

In both long run and short run models, GDP has a negative inelastic towards the demand. For 1 percent rise in GDP, there is -1.11 percent adjustment in the long run and -0.32 percent adjustment in the short run.

According to the long run model, FDI has unitary inelastic effect and as for the short run model, for 1 percent rise in FDI there is 0.06 percent rise in the demand which indicates a positive inelasticity effect on demand for oil.

Also when population increases by one unit demand increases by nearly 20 units as for the short run model. In the long run population has a negative inelastic effect.

For 1 percent rise in oil price there is a 0.20 percent increment in demand for oil in the short run. In the long run for 1 percent increment there is -3.92 percent adjustment.

According to variance decomposition, oil demand (LNCON) is relatively less exogenous in relation to the shocks of macroeconomic variables in the short run while Foreign Direct Investment (FDI), Gross Domestic Product (GDP) and population prove to be the most significant factors that explain the movement in oil demand in the long run.

CHAPTER 5

CONCLUSIONS

FDI has a huge impact on oil demand in the long run. It has a unitary elastic effect in the long run and FDI has a small effect in increasing the overall demand for oil in the short run, with one percent rise in FDI there is only 0.06 increment in demand. FDI is a long term strategic investment by multinational companies and it may take many years to have an influence in the country's oil demand. Hence it is unsurprising to have a small effect in the short run.

Crude oil price has a huge effect in reducing oil demand in the long run, with one percent increase in oil price there is 3.9 percent reduction in overall demand. In the short run oil demand will increase by 0.2 percent when price increase by one percent. It seems to be that when the oil price remain increased for a long period people and the industry may find alternatives to cut down the expenses by buying less amount of oil.

In the short run one percent rise in population is estimated to have 19 percent increment in oil demand and in the long run there is a reduction, with one percent rise in population there is 7 percent reduction in overall oil demand. Although population is a significant factor in the short run, there may be other factors which have more effect on oil demand. For example, even though the population increases, if the price of the oil is high the demand will reduce in the long run.

In both long run and short run models for one percent increment in GDP, it is estimated to have a 1.11 percent and 0.32 percent reduction in the oil demand respectively. Sri Lanka's GDP mainly depends on tourism, tea export, apparel, textile, rice production and other agricultural products. These industries mainly depending on electricity and over the years proportion of electricity production by coal and hydo has increased while the proportion of electricity produced by oil has reduced significantly. Hence the industrialization in Sri Lanka which has increased the GDP has reduced the oil demand in both short run and long run.

According to variance decomposition, oil demand (LNCON) is relatively less exogenous in relation to the shocks of macroeconomic variables in the short run because if considering only two years, the oil demand or the consumption of oil (LNCON) is the most important variable to account for its own innovation, which is nearly 64%. Contribution of Foreign Direct Investment (FDI), Gross Domestic Product (GDP), Population and Oil Price to the forecast error variance is 14.26%, 9.68%, 1.82% and 10.23% respectively.

At the end of the period, only 14.96% of variance of consumption is explained by its own shock. Foreign Direct Investment (FDI), Gross Domestic Product (GDP) and population are the next most important variables to be considered in explaining the forecast error variance, which accounts 37.39%, 22.23% and 18.48% impact on consumption of oil respectively. This implies that Foreign Direct Investment (FDI), Gross Domestic Product (GDP) and population prove to be the most significant factors that explain the movement in oil demand in the long run.

CHAPTER 6

RECOMMANDATIONS

This study has been used data from 1988 to 2013, in order to find a model to predict the Sri Lankan oil demand. Gross Domestic Product (GDP), Foreign Direct Investment (FDI), population and oil price have been identified as the determinants of the Sri Lankan oil demand. However the results of the study are tentative and are subjected to some improvement. Inclusion of more variables might help in explaining more of the variation in oil demand.

Considering global studies, it is expected Gross Domestic Product (GDP) to show positive impact on oil demand but results of analysis indicates relationship is negative among variables. This may be because the data set is different and also in other studies energy consumption has been considered as a whole, not just oil. This study has used the nominal GDP values, hence more precise conclusions can be made by adjusting the GDP values for inflation.

Since all the parameters in the fitted model are significant, model can be developed by adding variables like vehicle population in Sri Lanka. The dummy variables significantly increase the power of a given model. The research was limited to a small data set which is available for this study, and has prevented the testing of more lagged values or dummy variables that could be of interest for future work.

Even though the policy implications are frighteningly clear all over the world, Sri Lankan oil demand is rising at a rate that will be difficult to sustain. The world's refineries are trying to fullfill the need as far as possible to take the advantage of high oil prices, which continue to rise. Sri Lanka will demand more oil from overseas but it is unclear whether there will be enough oil available to meet this demand.

It seems that heavy investment into other energy sources will be needed to satisfy Sri Lankan oil demand. Hence studies can be conducted to find alternative energy sources for crude oil.

So far the oil price assumed to be determined by the government but it will not be compatible with the global economy once the oil price climbs to unsustainable levels. The political economy implications of this perspective lie beyond the scope of this study.

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