Estimating Consumption Function

With & Without Unit Root Testing Time Series

Properties

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CERTIFICATE

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I Lubna Bano hereby state that my MPhil thesis titled "Estimating Consumption Function with & without Unit Root Testing Times Series Properties" is my own work and has not been submitted previously by me for taking any degree from Pakistan Institute of Development Economics or anywhere else in the country/world.

At any time if my statement is found to be incorrect even after my Graduation the university has the right to withdraw my MPhil degree.

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Lubna Bano

This dissertation is dedicated to

My Parents, My Beloved Brothers &

Sister.

(For their endless Love, support, Prayers

and encouragement)

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Abbreviations	Complete Name
UR	Unit Root
RMSE	Root Mean Square Error
ARDL	Auto Regressive Distributed Lag
VAR	Vector Auto Regressive
GDP	Gross Domestic Product
GNP	Gross National Product
UK	United Kingdom
ECM	Error Correction Model
EG	Engle and Granger
EY	Engle and Yoo
JJ	Johansen and Juselius
PO	Phillips and Ouliaris
GH	Gregory and Hansen
ADF	Augmented Dickey Fuller Test
I(0)	Integrated of order zero
I(1)	Integrated of order one
LCU	Local Currency Unit

ABSTRACT

Unit root and cointegration literature is based on the idea that integrated variables lead to spurious regression and spurious regression can be avoided by cointegration analysis but Granger *et a*l. (2001) found that spurious regression can also occur in stationary series, implying that unit root and cointegration analysis are not much helpful to avoid spurious regression. In addition to that there are size and power problem associated with unit root testing. On the other hand there are methods to model time series without unit root and cointegration analysis. If we take the objective of forecasting, how do methods using with unit root and methods avoiding unit root perform? So far there is no answer to this question. The objective of this study is to evaluate performance of four methods of modelling time series of which two methods are based on unit root and cointegration analysis (i.e. Engel and Granger two-step process and Johansen and Juselius maximum likelihood approach) and two methods which do not require unit root and cointegration analysis root (i.e. ARDL bound test and vector auto regressive). The performance of four methods is compared on the basis of forecasting ability on real data. ARDL bound test proved to be the most efficient estimation method with least chance of spurious regression and optimal forecasting. Based on these estimation result, this study concludes that ARDL bound test is most powerful for testing long run relationship and also for the forecast.

CHAPTER 1

INTRODUCTION

1.1 Background

Spurious regression has a long history and is scrutinized by Yule (1926). This phenomenon occurs when pair of theoretically independent series come up with statistically significant results. The spurious regression prevails owing to strong temporal properties and the series are seemingly found to be associated according to standard inference in least square regression (Granger *et al.*, 1998). According to Granger and Newbold (1974) the nonstationarity of time series is the main cause of spurious regression. While (Nelson and Plosser, 1982) taken together in their experiment that most of economic series are having unit root. Both the studies imply that, there is huge probability of spurious regression in time series analysis.

Unit root and co-integrated analysis was developed to deal with the problem of spurious regression due to nonstationarity of time series. Engel and Granger (1987) introduced the remedy of spurious by using the concept of cointegration. According to them, two non-stationary time series are cointegrated if their linear combination is stationary and in this case the regression is not spurious. Later on the researchers commonly employed unit root and cointegration procedures to deal with the problem of spurious regression in non-stationary time series.

The rapid development has been observed in the past three decades in unit root and cointegration literature. An enormous number of tools have been developed but the reliability of these procedures is equally doubtful .There is no tool which is not suffering in size and power problems in case of small samples (Maddala and Kim, 1998). Besides this, all these procedures require some decision of prior specification e.g. drift and trend, lag length, structural stability, and distribution of error term. These prior specification decisions make these procedures more complex and the cumulative probability of the type I and II errors makes the results of these procedures unreliable. According to Rehman and Zaman (2008) the performance of unit root tests is unreliable owing to misspecification of the model and observational equivalence.

There is ample of studies which are considering that the only reason of spurious regression is nonstationarity and they frequently employed unit root and cointegration as a remedy to this problem. However, (Granger *et a*l., 2001) find that spurious regression can occur between two stationary series. If this is the case, then the massive number of unit root and cointegration tools will fail to cure this problem.

One alternative is to make use of methods which do not require unit root testing such as Autoregressive Distributed Lag Bound test (Pesaran *et al.*, 2001) and Vector Autoregressive (Sims, 1980). However, there is no documented evidence that how the alternate procedures will work in comparison with unit root and cointegration analysis. One difficulty in the comparison arises as to what criteria should be adopted for comparison of two different type of procedures. This can be answered by comparing the forecast performance of methods that require unit root testing with those methods which do not have such requirement. This study makes comparison of the techniques of modelling time series data with and without unit root on the basis of forecasting for real data.

The performance of the four methods is illustrated on the consumption function data. Normally, one does not know about nature of relationship between two macroeconomics series. However in case of consumption and income, one can predict the nature of relationship with greater level of confidence. The consumption and income of same country should have long run relationship and there is no economic theory to deny this fact and empirical studies also support this. Regression of consumption on income of same country makes the case of genuine regression.

1.2 Objective of the study

The purpose of this study is to compare performance of procedure for the estimation of consumption function with and without unit root for real data on the basis of forecasting. These methods include Engel and Granger, Johansen and Juselius, Autoregressive Distributed Lag Bound test and Vector Autoregressive.

1.3 Motivation of the study

The time series data often produce spurious regression and most common method to avoid spurious regression is unit root and cointegration analysis. Cointegration analysis is applicable when series are nonstationary. However it is found by (Granger *et a*l., 2001) that spurious result can also happen in stationary series as well. Thus, cointegration analysis cannot provide solution to spurious regression. There are alternative ways of modelling time series but it is not known that how these methods work. So in this study we will compare the methods with unit root which are Engel and Granger and, Johasnsen and Juselius and without unit root are ARDL bound test and Vector auto regression on the basis of their forecast performance. For this purpose, real world data will be used.

1.4 Significance of the study

As discussed unit root and cointegration analysis cannot provide sufficient safeguard from spurious regression if they are stationary and we do not know how alternative methods perform. This study will provide guidance which procedure is performing better to model time series.

1.5 Organization of the study

This study is consists of five chapters: introduction, objective of the study, significance of the study are provided in Chapter 1, Chapter 2 provides the literature review. Chapter 3 concentrates on econometric methodology. Chapter 4 result and discussion and the final chapter contain summary conclusion and recommendation.

CHAPTER 2

LITERATURE REVIEW

The problem of spurious regression has been investigated broadly in literature, following is a review of some studies .Literature review is organized as follows.

2.1 The Challenge of Spurious Regression

Spurious regression was initially detected by Yule (1926). This phenomena occurs when pair of independent series come up with significant results. The spurious regression prevails owing to strong temporal properties and the series are found apparently to be associated according to standard inference in least square regression (Granger *et al.,* 1998). Yule detected it through the result of proportion of Church of England marriages to all marriages and rate of mortality during the time period of 1866-1911. Their correlation was 0.95 whereas there was no sound theoretical foundation, connecting the two variables indicating spurious regression.

Up until 1974, spurious regression problem was considered to be a consequence of omitted variables only. Interestingly, Granger and Newbold (1974) discovered that nonstationary time series is another cause of spurious regression.

2.2 Experiments of Granger and Newbold's (1974)

Granger and Newbold (1974) performed an experiment and showed that the estimated results of two independent nonstationary time series turns out to be highly significant. They developed autoregressive series of independent variables such as, X_t and Y_t. Both X_t and Y_t are depend on their own lag values.

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

$$X_t = X_{t-1} + u_t$$

Then they regressed dependent variables on each other like X_t on Y_t and Y_t on X_t..

$$Y_t = \alpha + \beta_1 X_t + \varepsilon_t$$

$$X_t = \alpha + \beta_1 Y_t + u_t$$

The estimated results of these two regression were highly significant even there is no missing variable. Therefore this is a case of spurious regression due to non-stationary variables. This experiments implies spurious regression can occur due to unit root.

2.3 Nelson and Plosser's investigation (1982)

Nelson and Plosser (1982) studied the macroeconomic time series of United States of America. They employed Dickey Fuller test to detect unit root various time series. Among 14 series, 12 variables were found to be nonstationary. Presence of nonstationarity in such a large number of major macroeconomics series and the earlier result of Granger Newbold which imply that nonstationarity leads to spurious regression.

2.4 Renowned illustration of spurious regression

Yule detected spurious regression through the result of proportion of Church of England marriages to all marriages and rate of mortality during the time period of 1866-1911. Their correlation was 0.95 whereas there was no sound theoretical foundation, connecting the two variables indicating spurious regression.

In 1980 Hendry presented a spurious correlation via rainfall in UK and Price level. In 1982 Plosser and Schwert claimed that regression between two non-stationary series without taking difference provide nonsense result. Statistically significant relationship was found between two dissimilar series. Thus probability of spurious regression is very high when series are nonstationary. Roger and Jupp (2006) provided example of positive spurious relationship between stork nesting and human baby birth in the arrangement of spring, in reality both variables were related to a third variable i.e. weather. Both independent variables had relation with the weather, because regression did not cater for the missing variable and result were spurious. Hofer et al. (2004) also stated that spurious correlation is by the reason of absence of statistical information.

2.5 Post Nelson and Plosser development and Concept of Cointegration

One significant advancement in Post Nelson and Plosser literature was the concept of cointegration. It can be summed up in following steps: Suppose X_t and Y_t are two I (1) series and if $Z_t = aX_t + bY_t \sim I(0)$. We then check for the stationarity of the residuals, if Z_t is I (0) then we conclude that the given two series are co-integrated. However, if Z_t is I (1), we fail to provide evidence for cointegration. The concept was Introduce by Engle Granger in 1987.

2.6 Tests of Cointegration

From above literature it is evident that working with non-stationary time series data can lead to spurious regression, the solution therefore is differencing the data before further analysis. However, taking difference can lead to loss of long run information. To account for this, cointegration techniques are employed since they provide results about short run while retaining the long run information too. Cointegration tests have many classification and two important classification are residual based tests and system based tests.

2.6.1 Residual Based Tests

These tests make sure following kind of organization; first is to estimate a static regression, next is to obtain the residual from static regression and then apply unit root test for residual series. These test comprise Engle and Granger (1987), Engle and Yoo (1987) and Philips and Ouliaris (1990). It is evidence from Engel and Granger (1986) that each co-integrating relationship has an ECM. Which is typically called the Granger representation theorem. Consequently, for the structure with non-stationary I (1) series, Engel and Granger anticipated a process for testing cointegration and to build ECM. Which is actually known as Engel and Granger two-step process. It is evidenced that in the existence of cointegration relationship, OLS provides reliable estimates for all the parameters (Stock, 1987). ADF test correct critical values found Engle and Yoo (1987). In Engle Granger cointegration test, it is supposed that only one cointegration relationship exist among the series. When we have more than two series it does not provide the accurate number of long run relationship between variables. Engle and Yoo (1991) recommend a three-step estimation method to control for two main shortcoming of the classical Engle and Granger two-step process.

2.6.2 System based Test

System based test are based on multiple equation as an alternative to single equation. These tests contain JJ, ARDL bound test, etc. JJ is first test and it accomplished more than one critical values. Similarly, this test does not involve contrast of endogenous and exogenous series. Johansen and Juselius (1992) proposed a test that allows to find out more than on co-integrated vector. EG single equation pay no attention to short run change whereas JJ studies focus on short run change. JJ test empowers to regulate more than one co-integrating vector. Charemza and Deadman (1993) diagnose in the context of statistical properties that JJ test is powerful as related to EG.

Trace Statistics are used in Johansen (1988) and maximum Eigenvalues (ME) are used in JJ (1990) for the estimation in case there is long run relationship among series. ME value gives consistent results as compare to TS. Regardless of its theoretical benefits and superiority, the Johansen estimating procedure is, in practice, also subject to some deficiencies. First, given the small sample size, the method cannot be known as suitable one since the point estimates attained for cointegrating vector may not be mostly meaningful. Second, some added problems happen if we do not have a limited cointegrating vector. Phillips and Loretan (1991) favors for the use of equation-by-equation method of the single-equation ECM and possibility is not presented in complete systems-methods such as the Johansen method.

2.7 Spurious Regressions with Stationary Series and Implication

Granger *et a*l. (2001) found that stationary series have spurious regression. Generating two series $X_t = \theta_1 + \beta_1 X_{t-1} + \varepsilon_{xt}$ and $Y_t = \theta_2 + \beta_2 Y_{t-1} + \varepsilon_{yt}$ where $|\theta_1| < 1 \mathit{and} |\theta_2| < 1$, then results will be significant. The series are stationary so conventional understanding is that when there is stationary series there is no spurious regression but they found huge probability of spurious regression. This means that unit root and cointegration are not sufficient to prevent spurious regression.

They find that spurious regression can occur between two stationary series. If this is the case, then the huge number of unit root and cointegration tools will fail to cure this problem.

2.8 Solution without Unit Root

The single equation ARDL technique was proposed by Pesaran et al. (1996) and Pesaran (1997) as a better substitute for Engle and Granger. It can be used regardless of the order of integration of the data whether it is I (0), I (1) or mixture of both. However, ARDL model does not provide appropriate long run information in the presence of an I(2) variable in the model. Therefore, unit root testing is undertaken to eliminate the presence of any such series and to ensure that all the variables have order I (0) and I (1). If a co-integrating vector is detected, the model is re-parameterized to ECM which provides results of both short run and long run dynamics. In such case, ARDL can distinguish between dependent and independent variables. The underlying assumption for ARDL is that there is only exists a single reduced form equation relation among the variables. The ARDL technique assumes that only a single reduced form equation relationship exists between the dependent variable and the 10 exogenous variables (Pesaran, Smith, and Shin, 2001). Davidson et al. (1978) modelled UK consumption function by using ARDL technique. Since missing variables is a significant reason of spurious regression, Ghouse et al (2018) suggested that ARDL could account for such problems.

Ohanian (1988) finds whether the use of non-stationary data in VAR can result in spurious result. Simulation base study conducted and VAR can be applied without unit root. VAR's with integrated regressors is to recognize the number of unit roots in the variables. Phillips and Toda (1993) have done the analytical study of spurious regression effects of unit root on VAR. They conclude that there is no need of unit root testing. Toda and Yamamoto (1995) anticipated a simple method to test economic hypothesis articulated as restrictions on the parameters of VAR models without pretests for a unit root(s) and a co-integrating rank(s).

2.9 Literature Gap

Granger *et al*. (2001) found that spurious regression can exist in I(0) series and cointegration cannot provide solution . This means, that the cointegration analysis and solution avoiding cointegration both are at par with respect to avoiding spurious regression. Spurious regression can exist in stationary series. Unit root and cointegration cannot insure avoidance of spurious regression. Unit root and cointegration procedures are very complex. There are lots of orbitrary choices of deterministic part, structural breaks and lag length. All these things make unit root unreliable. There are other potential solution such as ARDL and VAR. How do these methods perform? Comparison of these techniques with each other, no existing study addresses this question.

CHAPTER 3

METHODOLOGY AND DATA

In this chapter we will discuss methods which we have been employed in this study. We have selected four methods to compare. Two of the methods required unit root and cointegration analysis, whereas other two do not require unit root to model consumption function as shown in figure 3.1.

- Firstly we will discuss the details of four estimation methods.
- Secondly how these methods compare in terms of forecasting.
- Thirdly we discuss data to be used.

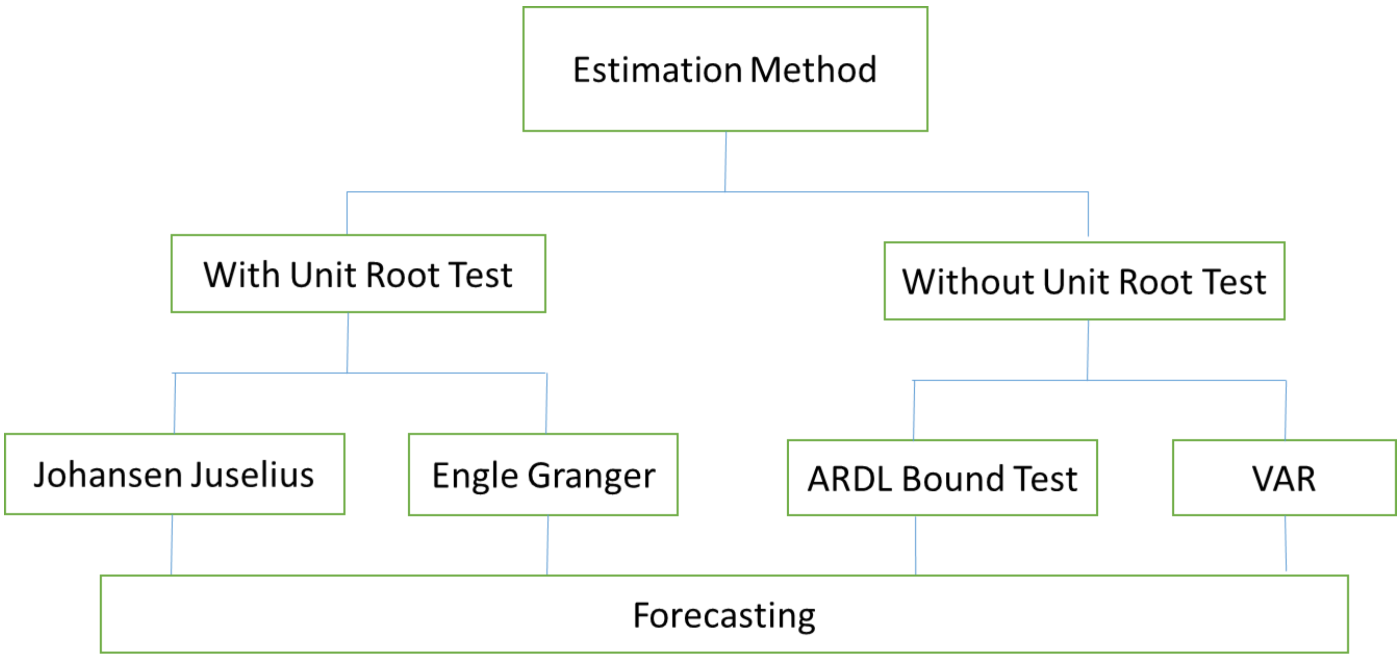

Figure 3.1: Methodology

3.1 Unit root test

Financial and economic time series show non-stationary behavior in the mean. Unit root tests can be used to check the fluctuation around the mean, if trend is present in the series then should take first differenced or regressed on deterministic functions of time to reduce stationarity. Non stationary data change their mean and variance over time and can give spurious result. The most popular class of unit root tests is ADF test.

3.1.1 Augmented Dickey Fuller (ADF) Test

Augmented Dickey Fuller (ADF) test introduced by Dickey and Fuller in (1979) which is broadly used for detection of the order of integration I(d) of the series. General form of ADF test is given below:

$$Y_t = \alpha + \phi Y_{t-1} + \varepsilon_t \quad , \quad H_0 : \phi = 1 \ , H_1 : \phi < 1 \qquad ...(3.1)$$

$$\Delta Y_t = \alpha + \rho Y_{t-1} + \varepsilon_t \quad , \quad H_0 : \rho = 0 \ , \ H_1 : \rho < 0 \qquad ...(3.2)$$

Where, Y_t indicates the time series variable and time period is denoted by t and first difference indicated by Δ . α Indicates the drift and root of equation is ϕ. First difference equation roots is indicated by ρ .

In this present study ADF test will be applied to find whether there is unit root or not in any specific data set, involving drift term. Optimal lag selection criteria is used for annual data.

3.1.2 Engle and Granger

EG test of cointegration was introduced by Engle and Granger in 1987. It is one of the most widely use method to estimate cointegration relationship. And is commonly known as Engel and Granger two step method of cointegration. First step is to check whether the series is stationary. If they both series are of integrated of order one then next step is to estimate the equation.

$$Y_t = \alpha + \beta X_t + \varepsilon_t \qquad ...(3.3)$$

Where X_t is independent and Y_t is independent and ε_t is the error term. In the next step we test the null hypothesis of no cointegration on the residual series. For cointegration Engel Granger preferred ADF test.

$$\Delta\varepsilon_t = \rho\varepsilon_t + b_1\Delta\varepsilon_{t-1} + ...+ b_p\Delta\varepsilon_{t-p} + \mu_t \qquad \ldots (3.4)$$

Where ε_t is the residual from equation form (3.3). The hypothesis that $\rho = 0$ is tested under the critical value of student t distribution. Rejection of null hypothesis of no cointegration suggest that the series are co-integrated and that long-term relationship exists between them. In presence of cointegration relationship, long-run estimates of model are given by the above estimated regression equation 3.3 and 3.4.

Furthermore, it is assumed that there is only one cointegration relation among the series. The long-term relationship among C_t and Y_t indicates that if there linear association $\varepsilon_t = C_t - \beta Y_t$ is I(0) then cointegration exist. The ε_t tested for unit root by any Augmented Dickey Fuller test.

3.1.3 Johansen Cointegration

The Johansen (1988) and Johansen and Juselius (1990) maximum likelihood approach is one of the dynamic and typically used methodology for cointegration analysis to deal with econometric modeling of non-stationary series. Johansen (1988) suggested the maximum likelihood process to estimate the co-integrated vectors.

The model of cointegration is denoted through ECM. The long run relationship among cointegration and error correction mechanism (ECM) is showed in the Granger representation theorem (Engle and Granger, 1987). The VAR is illustrated as;

$$X_t = \mu_t + A_1X_{t-1} + A_2X_{t-2} + ...+ A_kX_{t-k} + \phi D_t + \varepsilon_t \qquad \ldots(3.5)$$

Where X_t is vector of variables contain in the model. The above equation can be written as,

$$\Delta X_t = \mu_t + \Pi X_{t-1} + \Gamma_1 \Delta X_{t-1} + \Gamma_2 \Delta X_{t-2} + \ldots\ldots + \Gamma_{k-1} \Delta X_{t-(k-1)} + \Phi D_t + \varepsilon_t \qquad \ldots(3.6)$$

Where

$$\Pi = \sum_{i=1}^{k} \alpha_i - 1$$

And

$$\Gamma_j = \sum_{j=i}^{k-1} \alpha_j$$

For the existence of cointegration at least one non zero row exist in Π. i.e. 0 < (Π)< k. Johansen and Juselius (1990) maximum likelihood procedure of cointegration for the measurement of the rank Π matrix used the maximum eigen values and trace test. The null hypothesis stated that there exist “r” or less co-integrated vector.

$$H_0(r): rank(\Pi) \leq r$$
$$H_1(r): rank(\Pi) > r$$

The existence of cointegration is checked through test statistics.

Trace Test:

$$\lambda_{trace} = -T \sum_{i=r+1}^{n} \ln(1 - \widehat{\lambda}_t)$$

$\widehat{\lambda}$ is the eigenvalues of Π matrix arranged in decreasing order show that $\widehat{\lambda}_1 > \widehat{\lambda}_2 > \ldots. > \widehat{\lambda}_k$. Maximum eigen values null and alternative hypothesis is

$$H_0(r): Rank(\Pi) = r$$
$$H_1(r+1): Rank(\Pi) = r + 1$$

Test statistics for maximum eigenvalues is

$$\lambda_{\max} = -T \times \ln(1 - \widehat{\lambda}_{r+1})$$

Cointegration exists when null is rejected.

3.2 Methods Avoiding Cointegration Analysis

Several techniques come under the umbrella of avoiding cointegration analysis for example co-breaking, state space and modified R many more. The two important methods avoiding cointegration are ARDL bound test and vector auto regression (VAR).

3.2.1 Autoregressive Distributed Lag (ARDL) Bound Test

Autoregressive Distributed Lag (ARDL) bound test of long run was initially established by Pesaran et al (2001). The purpose of using this technique is to check if the variables have long run relationship or not. ARDL Bound test used is to check the effect of many independent variables on a dependent variable in short run as well as long run. For small data set ARDL bound test is relevant. At same time ARDL Bound test estimates the long run and short run coefficient through OLS process for the analysis of cointegration among variables.

ARDL bound test is flexible model for the analysis of order of integration for the variables. Where JJ cointegration technique requires pre-testing of the variables for unit root, ARDL has no such requirement. It provides appropriate and unbiased results regardless of the order of integration of the variables whether they are all I(0), I(1) or have mixed order. Further, along with the long run estimates, the short run estimates can be studied by using the unrestricted error correction model (UECM). In contrast to other techniques the following advantages of ARDL can be listed:

- It does not require same integration order for all variables.
- For finite sample size, ARDL is more effective than other estimation techniques.

- It provides unbiased long run estimates.[1]

We started with most general ARDL (1, 1) model. Which can be written as follows.

ARDL (1, 1)

$$Y_t = \beta_0 + \beta_1 x_t + \beta_2 x_{t-1} + \beta_3 Y_{t-1} + \varepsilon_t \quad \text{... (3.7)}$$

$$\Delta Y_t = \beta_0 + \sum_{i=1}^{n} \beta_{1i} \Delta y_{t-i} + \sum_{i=0}^{n} \beta_{2i} \Delta x_{1t-i} + r_0 Y_{t-1} + r_1 x_{1t-1} + \varepsilon_t \quad \text{... (3.8)}$$

Where Y_t is dependent variable and x_t is independent variable. In equation (3.8) r_0 *and* r_1 are the long run coefficients and $\beta_{1,}$ and β_2 are short run coefficients. Following two hypothesis will be tested to check the cointegration between variables. ε_t is normally distributed with zero mean and constant variance $(0, \sigma^2)$. Restriction applied on (3.8) to check the following hypothesis .

$H_0 : (r_0, r_1) = 0$ (Coefficients of lag independent variable and lag dependent variable are equal to zero)

$H_1 : (r_0, r_1) \neq 0$ (Coefficients of lag independent variable and lag dependent variable are not equal to zero)

The F-test has two critical values, the lower bound and upper bound. If the calculated value lies above the upper bound then will reject the null hypothesis and conclude that there is long run relationship between the variables. If the calculated value lies below the lower bound then will accept the null hypothesis and concludes that long run relationship does not exist between the variables. If the calculated value lies between the upper and lower bound then will concludes that results are inconclusive.

[1] (Belloumi, 2014)

3.2.2 Vector Auto regressions (VARs)

VAR are multivariate linear time series models design to capture the joint dynamics of multiple time series .VARs treat each endogenous variable in the system as a function of its lagged values of all endogenous variables. VARs offers simple and flexible alternative to the traditional multiple equation models.

"At first glance VAR’s appear to be straight forward multivariate generalization of univariate autoregressive models .At second sight ,they turn out to be one of the key empirical tools in modern macroeconomics”. (Del Negro and Schorfheide, 2011)

The main advantage of VAR is that it does not require to differentiate variables as pure endogenous or exogenous because it treats all variables as endogenous. Each variable has its separate equation with lagged values of all regressors in the system as the independent variables. Making the whole system of equations works better in depicting the data is compound dynamic properties (Managi, 2011). Owing to the large number of coefficients which apparently lack statistical implications, the estimates are not directly interpretable. One way to extract meaningful implications is via Granger causality testing. Granger causality tests whether the lagged variables in each equation helps in explaining the current values of other variables.

VAR estimates can also be used to analyze the dynamics of any exogenous shock in the endogenous variables on other variables in the system using impulse response function (IRF) and Variance decomposition analysis. The IRF particularly tests and traces out the impact of shock/innovation in one variable on the current and future realizations of other variables. However, presence of serial correlation in VAR residuals makes interpreting the impulse responses difficult. Thus, orthogonalized IRFs by making use of Cholesky decomposition are used which requires ordering of variables in the system. In orthogonalization, only the explicit series has contemporaneous correlation. Thus, shocks in the first variable will have contemporaneous impact on rest of the variables but shocks in others will not have any impact on it. Similarly, the second variable will have contemporaneous impact on rest of the variables (excluding first) but shocks in others will not have any impact on it, and so on. Nevertheless, finding the appropriate order for variables is difficult and the resultant IRFs might not be robust for variable ordering in VAR.

Following is the system of equations for VAR model for two variables consumption and income:

$$C_t = \beta_0 + \beta_{11} C_{t-1} + \beta_{12} Y_{t-1} + \varepsilon_{ct} \qquad ...(3.9)$$
$$Y_t = \beta_0 + \beta_{21} C_{t-1} + \beta_{22} Y_{t-1} + \varepsilon_{yt} \qquad ...(3.10)$$

According to assumption C_t and Y_t are stationary ε_{yt} and ε_{ct} are independently and identically distributed respectively ε_{yt} and ε_{ct} are uncorrelated that is IID. First order vector autoregressive represented by Equation (3.7) and (3.8) and the maximum lag length is one. This simple model consist of two variable and first order VAR two variable first order VAR is helpful for explaining the multivariate higher order structure.

Equation (3.7) and (3.8) cannot be estimated by OLS since C_t has an indirect contemporaneous effect on Y_t and Y_t has an indirect contemporaneous effect on C_t. The OLS estimates would suffer from simultaneous equation bias since the regressors and the error terms would be correlated. Fortunately .it is possible to transfer the system of equations into a more usable from .using matrix algebra, we can write the system in the compact form.

$$\begin{bmatrix} C_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \beta_{10} \\ \beta_{20} \end{bmatrix} + \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \gamma_{22} \end{bmatrix} \begin{bmatrix} C_{t-1} \\ Y_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{Ct} \\ \varepsilon_{zt} \end{bmatrix}$$

$$\text{Or} \quad x_t = \Gamma_0 + \Gamma_1 x_{t-1} + \varepsilon_t$$

Where,

$$x_t = \begin{bmatrix} C_t \\ Y_t \end{bmatrix}, \quad \Gamma_0 = \begin{bmatrix} \beta_{10} \\ \beta_{20} \end{bmatrix}, \ \Gamma_1 = \begin{bmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{bmatrix}, \ \varepsilon_t = \begin{bmatrix} \varepsilon_{ct} \\ \varepsilon_{Zt} \end{bmatrix}$$

3.3 Forecast Based Comparison between Techniques

In the analysis of forecasting we have two series each having n observation. Estimation will be done using n-k observations while forecast will be made for the k time period[2]. Then we take difference between forecast value and actual value and calculate Root Mean Square Error (RMSE) Process of forecasting is same for all the four techniques. Comparison is made on the bases of RMSE from all four estimations. The technique with minimum RMSE will be considered best among all.

3.4 Source of Data

The time frame for the study is from 1970 to 2016. The initial sample of countries was whole world, however due to unavailability of the data sample size reduce to 59 countries. Real data of consumption and GDP and source of the data world development indicator. The variables are consumption and GDP (constant LCU).

[2] n= 47 and k=3

CHAPTER 4

RESULT AND DISCUSSION

Econometrics techniques estimated result are discuss and explain in this chapter. Estimation established on the methodology that is given in the preceding chapter. Further this chapter involved discussion based on the result estimated using real data of consumption and GDP. In section 4.1 Augment Dickey Fuller test, Engle Granger and Johansen and Juselius cointegration results are discussed. In section 4.2 ARDL Bound test results are discussed. Section 4.3 is related to the result of Vector Autoregression. In section 4.4 forecast based performance of all the above mentioned techniques are compared.

4.1 ADF Unit Root Test

Augmented dickey fuller test is used for checking whether the series is I(0) or I(1).I(0) means series is stationary at level while I(1) means series is stationary at 1st difference. To avoid the problem of I(2) we apply ADF unit root on series. We applied the ADF test of unit root on consumption and GDP series separately including intercept of all countries. Some countries results are shown in table 4.1.

Table 4.1 Results of ADF unit root test

Country Name	ADF (Consumption)	ADF (GDP)	Country Name	ADF (Consumption)	ADF (GDP)
Algeria	-3.017 *	-3.590*	**Japan**	-5.603 *	-5.080*
Australia	-5.519	-6.214	**Kenya**	-4.572	-5.437
Austria	-3.766	-3.169*	**Korea, Rep.**	-5.056	-5.437
Bangladesh	-13.604	-6.493	**Luxembourg**	-4.465	-5.137
Belgium	-5.525 *	-6.240	**Madagascar**	-12.279	-7.118
Benin	-6.943	-6.802	**Malaysia**	-6.458	-5.609
Brazil	-6.059	-4.309*	**Mauritania**	-4.47	-7.626
Burkina Faso	-6.743	-7.473	**Mexico**	-6.495*	-4.879
Canada	-3.059	-4.744	**Morocco**	-4.096	-3.821
Chile	-6.246	-4.869	**Netherlands**	-5.099	-4.048
Colombia	-8.595	-4.666	**Nicaragua**	-5.705	-5.068
Congo	-6.935	-2.666	**Norway**	-5.225*	-3.178
Cost Rica	-3.605	-3.767	**Pakistan**	-8.367	-4.794
Cuba	-4.167	-3.716	**Panama**	-5.981	-4.339
Denmark	-4.894	-5.477	**Peru**	-4.921	-4.174
Dominican Republic	-5.88	-5.073	**Philippines**	-4.086	-3.655
Ecuador	-5.108	-4.031	**Portugal**	-7.038*	-3.953
Finland	-7.722 *	-4.021	**Senegal**	-5.457	-7.977
France	-9.682 *	-4.558	**Singapore**	-6.976	-2.981*
Gabon	-6.028	-4.884	**South Africa**	-3.274	-4.677
Germany	-3.926 *	-5.526	**Sri Lanka**	-10.158	-5.597
Greece	-3.775	-3.759	**Sudan**	-5.506	-4.579
Guatemala	-3.549	-3.022	**Sweden**	-3.496	-5.253
Honduras	-5.518	-5.176	**Togo**	-6.782	-6.834
Hong Kong	-4.827 *	-3.892*	**Trinidad**	-5.757	-3.044
Iceland	-3.643 *	-4.513	**UK**	-3.939	-4.571
India	-4.467	-6.01	**US**	-3.526	-4.836
Indonesia	-7.844	-4.808	**Uruguay**	-6.877	-3.576
Iran	-4.853*	-0.606	**Venezuela**	-7.551	-5.055
Ireland	-3.347	-4.399			
Critical values of ADF at 5% is -2.926 I(0) , -2.928 I(1).* Integrated of order 0					

There are few countries having both the series are I(0) as shown in the Table 4.1 Algeria consumption and GDP both are I(0) , Japan ,Hong Kong and China are also one of them. And some of the countries only consumption series are I(0) and some of the countries only GDP series is I(0).

4.1.1 Engle and Granger test for cointegration

This test consist of following rules.

1) Make secure that series are I (1) and run the equation

$$C_t = \beta_0 + \beta_1 y_t + \varepsilon_t \qquad \text{...(4.1)}$$

Where consumption is denoted by C_t and GDP is denoted by y_t .

2) We obtain residual from equation (4.1) and then check for their stationarity. Cointegration exist when residual are I (0). Original or genuine relationship would be valid if regression is run between consumption and GDP of same country.

Engle and Granger procedure is applied to testify whether this approach is able to investigate the probability of spurious regression and analysis was undertaken for all 59 countries. These results are shown in Table 4.1. Firstly we performed unit root test for both consumption and GDP of all countries and whether these series are integrated of order one results are noted in Table 4.1.

From the Table 4.1 it is shown that consumption and GDP are integrated of order one for all countries. Next, we apply cointegration. Following the Table 4.3 we have measure the ADF values for the residuals of these all countries. And reported their probability values in the Table 4.2.

Following table shows the results from EG cointegration.

4.2 Results of EG test for cointegration

Country Name	P value.	Country Name	P value.
Algeria	0.0041	**Japan**	0.6809
Australia	0.1461	**Kenya**	0.0433
Austria	0.0155	**Korea, Rep.**	0.4716
Bangladesh	0.0019	**Luxembourg**	0.0122
Belgium	0.058	**Madagascar**	0.4328
Benin	0.0478	**Malaysia**	0.4844
Brazil	0.2089	**Mauritania**	0.2695
Burkina Faso	0.0816	**Mexico**	0.2164
Canada	0.0929	**Morocco**	0.2527
Chile	0.8661	**Netherlands**	0.2731
Colombia	0.0566	**Nicaragua**	0.2677
Congo	0.2411	**Norway**	0.0118
Cost Rica	0.0272	**Pakistan**	0.0867
Cuba	0.4597	**Panama**	0.0341
Denmark	0.2503	**Peru**	0.3983
Dominican Republic	0.0344	**Philippines**	0.0038
Ecuador	0.3628	**Portugal**	0.2854
Finland	0.2555	**Senegal**	0.0206
France	0.2562	**Singapore**	0.2002
Gabon	0.2331	**South Africa**	0.3255
Germany	0.0593	**Sri Lanka**	0.0478
Greece	0.2105	**Sudan**	0.1144
Guatemala	0.0763	**Sweden**	0.1894
Honduras	0.3202	**Togo**	0.0751
Hong Kong	0.0894	**Trinidad**	0.1634
Iceland	0.7979	**United Kingdom**	0.2542
India	0.2159	**United States**	0.0213
Indonesia	0.1265	**Uruguay**	0.234
Iran	0.0013	**Venezuela**	0.1884
Ireland	0.1358		
5% criteria of Probability			

Table 4.2 gives us the result about existence of cointegration by the values of probabilities. To testify the hypothesis we randomly select few countries from Table 4.2 which are Pakistan, Colombia, United States and Brazil. Probability value for Pakistan, Colombia and Brazil are 0.0867, 0.056 and 0.2089 and these values are greater than 5% which show insignificant results accepting the null hypothesis and

probability value of United States is 0.0213 which is less the 5 % and shows significant result rejecting the null hypothesis.

Correspondingly, Null hypothesis and alternative hypothesis of EG test is there is no cointegration and there is cointegration so following this hypothesis out of 59 there is 15 countries shows that there is cointegration and 44 countries shows that there is no cointegration accepting the null hypothesis.

4.1.2 Johansen and Juselius Cointegration

For implementation of Johansen and Juselius test for cointegration series must be I (1). So in the very first step we are checking the stationarity of series and in the second step we apply Johasnsen cointegration test to examine the long run relationship between two series. For understating we took four countries randomly. Null hypothesis and alternative hypothesis of Johansen test is there is no cointegration and there is cointegration.

$$H_0 : r = 0$$
$$H_1 : r \geq 1$$

Results are given in the Table 4.3.

Table 4.3 Results of JJ Test for Cointegration

Country Name	P value of Trace Test	Country Name	P value of Trace Test
Algeria	0.0062	**Japan**	0.0024
Australia	0.2226	**Kenya**	0.4071
Austria	0.0010	**Korea, Rep.**	0.0828
Bangladesh	0.0010	**Luxembourg**	0.0348
Belgium	0.0010	**Madagascar**	0.1281
Benin	0.3437	**Malaysia**	0.6224
Brazil	0.0060	**Mauritania**	0.9293
Burkina Faso	0.2467	**Mexico**	0.0010
Canada	0.0010	**Morocco**	0.6719
Chile	0.1280	**Netherlands**	0.0012
Colombia	0.6442	**Nicaragua**	0.7691
Congo	0.0744	**Norway**	0.0010
Cost Rica	0.0039	**Pakistan**	0.4580
Cuba	0.6009	**Panama**	0.0123
Denmark	0.2141	**Peru**	0.6416
Dominican Republic	0.3453	**Philippines**	0.5272
Ecuador	0.0701	**Portugal**	0.0010
Finland	0.0010	**Senegal**	0.4244
France	0.0010	**Singapore**	0.0342
Gabon	0.1280	**South Africa**	0.0089
Germany	0.0010	**Sri Lanka**	0.1042
Greece	0.0010	**Sudan**	0.2218
Guatemala	0.1888	**Sweden**	0.0376
Honduras	0.8184	**Togo**	0.5872
Hong Kong	0.0010	**Trinidad**	0.0328
Iceland	0.0010	**United Kingdom**	0.2434
India	0.0289	**United States**	0.1951
Indonesia	0.1566	**Uruguay**	0.7153
Iran	0.0010	**Venezuela**	0.6465
Ireland	0.0010	**5% criteria of probability**	

To testify the hypothesis we randomly select few countries from Table 4.3 which are Pakistan, Colombia, United States and Brazil. Since P value for Pakistan Colombia and United States are greater than 5%, we fail to reject the H_0. Whereas for Brazil, the P value is less than 5% implying presence of cointegration. In the above table for Pakistan, Colombia and United States we cannot reject the null hypothesis but for Brazil we reject the null hypothesis Pakistan, Colombia and United States values are greater than 5% and Brazil probability value is less value than 5%.

Correspondingly 27 out of 59 countries have probability less than 5%. Signifying the presence of cointegration.

4.1.3 Power of Test Based on Cointegration Analysis

In power based test of cointegration we will show the empirical power of the Engle Granger and Johansen and Juselius.

Table 4.4 Empirical Power for Cointegration Analysis

	Engle Granger	Johansen Juselius
Relationship	**16%**	**45%**
No Relationship	**74%**	**55%**

The empirical power is 74% for Engle Granger and 55% is for Johansen and Juselius. Empirical power is when they showed no relationship.

4.2 Results of Techniques Avoiding Cointegration Analysis

In this results of the methods which avoid cointegration analysis are given. These techniques are ARDL bound test and VAR and their Empirical power is also discussed in the end.

4.2.1 Autoregressive Distributed Lag (ARDL) Bound Test

For implementation of bound test we estimate equation 4.2 in which we regress consumption of same country on its GDP and then apply restriction on its long run coefficients and calculate the bound test as follows in Table 4.4 and their significance value for 10 %, 5% and 1% are given below in the Table 4.4 with their lower and upper bound.

$$C_t = \beta_0 + \beta_1 C_{t-1} + \beta_2 Y_t + \beta_3 Y_{t-1} + \varepsilon_t \quad ..(4.2)$$

Where C_t is denotes the consumption, C_{t-1} is lag of consumption and Y_t denotes the GDP and Y_{t-1} is the lag of GDP.

Table 4.5 Results of Bound Test

Country Name	**F statistics**	**Country Name**	**F statistics**
Algeria	8.682	**Japan**	66.649
Australia	13.627	**Kenya**	15.057
Austria	20.044	**Korea, Rep.**	22.902
Bangladesh	5.697	**Luxembourg**	62.573
Belgium	76.988	**Madagascar**	4.037
Benin	3.965	**Malaysia**	2.741
Brazil	1.656	**Mauritania**	0.543
Burkina Faso	8.097	**Mexico**	15.449
Canada	19.917	**Morocco**	1.769
Chile	2.494	**Netherlands**	18.394
Colombia	13.712	**Nicaragua**	3.103
Congo	1.690	**Norway**	92.664
Cost Rica	23.978	**Pakistan**	7.699
Cuba	2.902	**Panama**	13.131
Denmark	20.623	**Peru**	0.893
Dominican Republic	5.537	**Philippines**	2.331
Ecuador	0.854	**Portugal**	16.906
Finland	71.312	**Senegal**	10.490
France	60.443	**Singapore**	25.293
Gabon	2.332	**South Africa**	37.103
Germany	25.278	**Sri Lanka**	6.037
Greece	18.663	**Sudan**	5.554
Guatemala	18.450	**Sweden**	25.473
Honduras	5.117	**Togo**	3.148
Hong Kong	52.862	**Trinidad**	6.911
Iceland	61.283	**United Kingdom**	24.502
India	30.962	**United States**	9.655
Indonesia	1.967	**Uruguay**	1.975
Iran	11.711	**Venezuela**	2.140
Ireland	20.683		

Critical Values of ARDL Bound Test		
Size	**Upper Bound**	**Lower Bound**
10%	3.51	3.02
5%	4.16	3.62
1%	5.58	4.94

To testify that cointegration exist we randomly select four countries which are Pakistan, Brazil, Colombia and United States. F statistics for Pakistan is 7.699 which is above than lower and upper bound for all the significance values so we conclude that cointegration exist and there is a long run relationship. For Brazil value of F statistics is 1.656 which is lower than the lower bound for all the significance so we conclude that cointegration does not exist. Next Colombia F statistics value is 13.712 which also above then upper bounds so concluding that there is long run relationship exist. For United States F statistics value is 9.655 which is greater than the upper bounds there is also long run relationship exist.

There is 37 countries out of 59 and their values of F statistics are above than lower and upper bound so there is long run relationship exist and 11 countries values are less than the lower bound so there is no long run relationship. So remaining 11 countries values of F statistics are lies between the lower and upper bound so we are inconclusive about long run relationship.

4.2.2 Vector Autoregressive

For implementation of VAR firstly we regress both equation 4.3 and 4.4 and in the next step we apply Granger Causality test and noted their result in the Table 4.6.

$$C_t = \beta_0 + \beta_1 C_{t-1} + \beta_2 Y_{t-1} + \varepsilon_{ct} \quad \text{...(4.3)}$$

$$Y_t = \beta_0 + \beta_1 C_{t-1} + \beta_2 Y_{t-1} + \varepsilon_{yt} \quad \text{...(4.4)}$$

Where $\hat{C}_t$ denotes the consumption and $\hat{Y}_t$ denotes the GDP

Table 4.6 Results of Granger Causality Test

Granger Causality	P value	Granger Causality	P value
$GDP_{ALG} \nrightarrow Con_{ALG}$ $Con_{ALG} \nrightarrow GDP_{ALG}$	0.0630 0.0346	$GDP_{JAP} \nrightarrow Con_{JAP}$ $Con_{JAP} \nrightarrow GDP_{JAP}$	0.6133 0.7454
$GDP_{AUS} \nrightarrow Con_{AUS}$ $Con_{AUS} \nrightarrow GDP_{AUS}$	0.1074 0.2326	$GDP_{KEN} \nrightarrow Con_{KEN}$ $Con_{KEN} \nrightarrow GDP_{KEN}$	0.2317 0.4072
$GDP_{BAN} \nrightarrow Con_{BAN}$ $Con_{BAN} \nrightarrow GDP_{BAN}$	0.2309 0.0032	$GDP_{LUX} \nrightarrow Con_{LUX}$ $Con_{LUX} \nrightarrow GDP_{LUX}$	0.2005 0.1462
$GDP_{BEl} \nrightarrow Con_{BEL}$ $Con_{BEL} \nrightarrow GDP_{BEL}$	0.0001 0.3065	$GDP_{MAD} \nrightarrow Con_{MAD}$ $Con_{MAD} \nrightarrow GDP_{MAD}$	0.0114 0.7504
$GDP_{BEN} \nrightarrow Con_{BEN}$ $Con_{BEN} \nrightarrow GDP_{BEN}$	0.0053 0.8237	$GDP_{MAL} \nrightarrow Con_{MAL}$ $Con_{MAL} \nrightarrow GDP_{MAL}$	0.2531 0.7117
$GDP_{BRZ} \nrightarrow Con_{BRZ}$ $Con_{BRZ} \nrightarrow GDP_{BRZ}$	0.0950 0.7177	$GDP_{MAU} \nrightarrow Con_{MAU}$ $Con_{MAU} \nrightarrow GDP_{MAU}$	0.9146 0.4356
$GDP_{BUR} \nrightarrow Con_{BUR}$ $Con_{BUR} \nrightarrow GDP_{BUR}$	0.0141 0.8600	$GDP_{MEX} \nrightarrow Con_{MEX}$ $Con_{MEX} \nrightarrow GDP_{MEX}$	0.0291 0.3798
$GDP_{CAN} \nrightarrow Con_{CAN}$ $Con_{CAN} \nrightarrow GDP_{CAN}$	0.0006 0.1085	$GDP_{MOR} \nrightarrow Con_{MOR}$ $Con_{MOR} \nrightarrow GDP_{MOR}$	0.3571 0.9375
$GDP_{CHI} \nrightarrow Con_{CHI}$ $Con_{CHI} \nrightarrow GDP_{CHI}$	0.0574 0.1165	$GDP_{NET} \nrightarrow Con_{NET}$ $Con_{NET} \nrightarrow GDP_{NET}$	0.0008 0.1577
$GDP_{COL} \nrightarrow Con_{COL}$ $Con_{COL} \nrightarrow GDP_{COL}$	0.0525 0.7186	$GDP_{NIC} \nrightarrow Con_{NIC}$ $Con_{NIC} \nrightarrow GDP_{NIC}$	0.2030 0.7248
$GDP_{CON} \nrightarrow Con_{CON}$ $Con_{CON} \nrightarrow GDP_{CON}$	0.5228 0.0044	$GDP_{NOR} \nrightarrow Con_{NOR}$ $Con_{NOR} \nrightarrow GDP_{NOR}$	0.3556 0.2237
$GDP_{CR} \nrightarrow Con_{CR}$ $Con_{CR} \nrightarrow GDP_{CR}$	0.3413 0.0145	$GDP_{PAK} \nrightarrow Con_{PAK}$ $Con_{PAK} \nrightarrow GDP_{PAK}$	0.0164 0.8503
$GDP_{CUB} \nrightarrow Con_{CUB}$ $Con_{CUB} \nrightarrow GDP_{CUB}$	0.3016 0.3493	$GDP_{PAN} \nrightarrow Con_{PAN}$ $Con_{PAN} \nrightarrow GDP_{PAN}$	0.0002 0.0103
$GDP_{DEN} \nrightarrow Con_{DEN}$ $Con_{DEN} \nrightarrow GDP_{DEN}$	0.0845 0.8665	$GDP_{PER} \nrightarrow Con_{PER}$ $Con_{PER} \nrightarrow GDP_{PER}$	0.0157 0.1050
$GDP_{DOR} \nrightarrow Con_{DOR}$ $Con_{DOR} \nrightarrow GDP_{DOR}$	0.0053 0.4996	$GDP_{PHI} \nrightarrow Con_{PHI}$ $Con_{PHI} \nrightarrow GDP_{PHI}$	0.1136 0.6085
$GDP_{ECU} \nrightarrow Con_{ECU}$ $Con_{ECU} \nrightarrow GDP_{EUC}$	0.0717 0.0403	$GDP_{POR} \nrightarrow Con_{POR}$ $Con_{POR} \nrightarrow GDP_{POR}$	0.4433 0.4471
$GDP_{FIN} \nrightarrow Con_{FiN}$ $Con_{FIN} \nrightarrow GDP_{FIN}$	0.0144 0.9441	$GDP_{SEN} \nrightarrow Con_{SEN}$ $Con_{SEN} \nrightarrow GDP_{SEN}$	0.0156 0.9781
$GDP_{FRA} \nrightarrow Con_{FRA}$ $Con_{FRA} \nrightarrow GDP_{FRA}$	0.0103 0.9709	$GDP_{SIN} \nrightarrow Con_{SIN}$ $Con_{SIN} \nrightarrow GDP_{SIN}$	0.0132 0.8220
$GDP_{GAB} \nrightarrow Con_{GAB}$ $Con_{GAB} \nrightarrow GDP_{GAB}$	0.2581 0.8746	$GDP_{SOU} \nrightarrow Con_{SOU}$ $Con_{SOU} \nrightarrow GDP_{SOU}$	0.0002 0.0728
$GDP_{GER} \nrightarrow Con_{GER}$ $Con_{GER} \nrightarrow GDP_{GER}$	0.002 0.7624	$GDP_{SRI} \nrightarrow Con_{SRI}$ $Con_{SRI} \nrightarrow GDP_{SRI}$	0.0030 0.7977
$GDP_{GRE} \nrightarrow Con_{GRE}$ $Con_{GRE} \nrightarrow GDP_{GRE}$	0.0005 0.0949	$GDP_{SUD} \nrightarrow Con_{SUD}$ $Con_{SUD} \nrightarrow GDP_{SUD}$	0.0027 0.7763

Granger Causality	P value	Granger Causality	P value
$GDP_{GUA} \nrightarrow Con_{GUA}$ **$Con_{GUA} \nrightarrow GDP_{GUA}$**	0.0021 0.2218	**$GDP_{SWE} \nrightarrow Con_{SWE}$** **$Con_{SWE} \nrightarrow GDP_{SWE}$**	0.0353 0.7504
$GDP_{HON} \nrightarrow Con_{HON}$ **$Con_{HON} \nrightarrow GDP_{HON}$**	0.1730 0.2971	**$GDP_{TOG} \nrightarrow Con_{TOG}$** **$Con_{TOG} \nrightarrow GDP_{TOG}$**	0.0441 0.4358
$GDP_{HOG} \nrightarrow Con_{HOG}$ **$Con_{HOG} \nrightarrow GDP_{HOG}$**	0.1236 0.5288	**$GDP_{TRI} \nrightarrow Con_{TRI}$** **$Con_{TRI} \nrightarrow GDP_{TRI}$**	0.0491 0.0515
$GDP_{ICE} \nrightarrow Con_{ICE}$ **$Con_{ICE} \nrightarrow GDP_{ICE}$**	0.0902 0.4325	**$GDP_{UK} \nrightarrow Con_{UK}$** **$Con_{UK} \nrightarrow GDP_{UK}$**	0.0079 0.3492
$GDP_{IND} \nrightarrow Con_{IND}$ **$Con_{IND} \nrightarrow GDP_{IND}$**	0.0909 0.2738	**$GDP_{US} \nrightarrow Con_{US}$** **$Con_{US} \nrightarrow GDP_{US}$**	0.0317 0.4709
$GDP_{INO} \nrightarrow Con_{INO}$ **$Con_{INO} \nrightarrow GDP_{INO}$**	0.4573 0.0910	**$GDP_{URU} \nrightarrow Con_{URU}$** **$Con_{URU} \nrightarrow GDP_{URU}$**	0.0400 0.5795
$GDP_{IRA} \nrightarrow Con_{IRA}$ **$Con_{IRA} \nrightarrow GDP_{IRA}$**	0.0347 0.0091	**$GDP_{VEN} \nrightarrow Con_{VEN}$** **$Con_{VEN} \nrightarrow GDP_{VEN}$**	0.5140 0.1632
$GDP_{IRE} \nrightarrow Con_{IRE}$ **$Con_{IRE} \nrightarrow GDP_{IRE}$**	0.0006 0.0220		
$\nrightarrow$ **Does not Granger Cause** **5% criteria of probability**			

To testify the null and alternative hypothesis we randomly taken four countries Pakistan, Brazil, Colombia and United states. For Pakistan the null hypothesis GDP does not Granger Cause consumption is rejected as its value is 0.0164 which is less than 5% of probability and for Brazil the null hypothesis the null hypothesis GDP does not Granger Cause consumption is accepted as its value is 0.0950 which is greater than 5% of probability. For Colombia the null hypothesis GDP does not Granger Cause consumption is accepted as its value is 0.0525 which is greater than 5% of probability. Next country is United States the null hypothesis GDP does not Granger Cause consumption is rejected as its value 0.0317 which is less than 5% of probability. There are 31 countries out of 59 accepting the null hypothesis which is GDP does not Granger Cause consumption as their probabilities are greater than 5% and 28 countries rejected the null hypothesis which is consumption does not Granger Cause GDP their values are less than 5%.

4.2.3 Power of test based on Methods avoiding Cointegration Analysis

In power based test of avoiding cointegration analysis we will show the empirical power of the ARDL bound test and Vector autoregressive.

Table 4.7 Empirical Power for Methods Avoiding Cointegration Analysis

	ARDL bound test	VAR
Relationship	**62%**	**52%**
No Relationship	**19%**	**48%**
For ARDL: 19% Results are inconclusive.		

The empirical power is 19% for ARDL bound test and 48% is for VAR. Empirical power is when they showed no relationship.

4.3 Forecast Performance of Modelling Techniques

Comparison is made on the basis of Root Means Square Error of All the techniques which required and did not required pre testing of unit root. Results are shown in the Table 4.8.

4.3.1 ARDL Bound Test

In this method we regress consumption on GDP using consumption lag term and GDP lag term. We have 47 observation which starts from 1970 to 2016 but in this analysis we take 44 observation for the time period of 2013 and estimate the equations.

After estimation of equation 4.2 next step is related to forecasting. Forecasting will be based on 44 observation. Calculating the value of year 2013 we find next year forecast on using 2013 value and so on for the year 2016. Next step is calculating the forecast error between the forecasted consumption and actual consumption. After calculating the forecast error we find sum of square. Results for 59 countries are given below in Table 4.8.

4.3.2 Vector Autoregressive

In this method first we regress consumption on its GDP, and GDP on consumption involving its first lag termes. We have 47 observation starting from 1970 to 2016 but in this analysis we take 44 observation for the time period of 2013 and estimate the equation 4.3 and 4.4 following equations.

After estimation of these equation we forecast next year value using 4.3 and 4.4 equation. It means we find 2014 value of consumption and GDP using 2013 actual value and for the next 2015 value we will put 2014 estimated value and repeat this process for 2016 as well. So next we will find error between estimated $\hat{C}_t$ and C_t, and between $\hat{Y}_t$ and Y_t. After calculating error for both equation we find their root means square error for the purpose of comparison with other techniques. Results are given for the 59 countries are shown in the Table 4.8.

4.3.3 Engle and Granger

For the purpose of forecasting we first estimate the equation 4.1 in which we regress consumption on its GDP as we have 47 observation starting from 1970 to 2016 but in this analysis we take 44 observation for the time period of 2013 and estimate the equations.

And then find the root mean square error for the purpose of comparison with other techniques. Results are noted in the Table 4.8.

4.3.4 Johansen and Juselius Cointegration

For the purpose of forecasting firstly we estimate equation 4.5 consumption on its GDP. We have 47 observation but we take 44 observation and for 3 time period we will forecast the values using equation 4.5. Next step we will calculate root means square error for the purpose of comparison with other techniques and results are shown in Table 4.8.

$$C_t = \beta_0 + \beta_1 C_{t-1} + \beta_2 Y_{t-1} + \varepsilon_t \quad ...(4.5)$$

Where $\hat{C}_t$ consumption and C_{t-1} is lag of consumption and Y_{t-1} is the lag of GDP.

Table 4.8 Comparison of All Four Techniques

Country Name	**RMSE ARDL**	**RMSE VAR**	**RMSE EG**	**RMSE JJ**
Algeria	0.03306	1.13730	0.06921	0.85653
Australia	0.01476	0.01389	0.15810	0.70846
Austria	0.00877	0.00964	0.01580	0.41432
Bangladesh	0.04690	0.10545	0.26332	1.38260
Belgium	0.00141	0.00783	0.00518	0.33828
Benin	0.17873	4.75768	0.16222	1.04250L
Brazil	0.01187	0.05537	0.05775	0.60091
Burkina Faso	0.11776	0.08640	0.10903	1.33560
Canada	0.00748	0.03155	0.01016	0.39357
Chile	0.06341	0.06370	0.21873	0.75191
Colombia	0.05993	0.04872	0.08989	1.35300
Congo	0.33601	0.45177	1.32720	1.16450
Cost Rica	0.04070	0.03103	0.05624	0.58582
Cuba	0.05924	0.02855	0.13302	0.58363
Denmark	0.01565L	0.02046	0.05588	0.36936
Dominican Republic	0.09040	0.04662	0.17871	1.06630
Ecuador	0.09397	0.10367	0.19949	0.89020
Finland	0.01295	0.01052	0.02704	0.37110
France	0.00812	0.04566	0.00187	0.43447
Gabon	0.12885	0.04544	0.12773	0.86056
Germany	0.04632	0.05363	0.03964	0.37618
Greece	0.01296	0.01299	0.02519	0.19001
Guatemala	0.03341	0.04537	0.05134	1.06400
Honduras	0.01595	0.04411	0.01856	0.81326
Hong Kong	0.00436	0.01042	0.07029	0.86011
Iceland	0.02959	0.00929	0.18599	0.61800
India	0.06206	0.23194	0.13418	1.37800
Indonesia	0.03107	0.02794	0.03705	1.18260
Iran	0.01114	0.02339	0.08594	0.20188
Ireland	0.04964	0.01959	0.16636	0.43676
Japan	0.00327	0.00785	0.09407	0.53705
Kenya	0.05277	0.08437	0.08342	1.06830

Country Name	RMSE ARDL	RMSE VAR	RMSE EG	RMSE JJ
Korea, Rep.	0.07026	0.01958	0.23780	1.10010
Luxembourg	0.01386	0.01018	0.00976	0.81101
Madagascar	0.08707	0.07182	0.13166	0.27171
Malaysia	0.01404	0.01270	0.15122	1.42530
Mauritania	0.01170	0.03247	0.30972	0.66343
Mexico	0.00939	0.01961	0.09437	0.55034
Morocco	0.08181	0.07774	0.15752	0.60865
Netherlands	0.01745	1.36520	0.02986	0.52173
Nicaragua	0.01602	0.04803	0.27561	0.76770
Norway	0.02252	0.03115	0.04350	0.60623
Pakistan	0.07972	0.38061	0.14663	1.20450
Panama	0.07429	0.05835	0.04434	0.73742
Peru	0.10117	0.06453	0.17525	0.88927
Philippines	0.06649	0.11405	0.09899	0.81812
Portugal	0.02561	1.52046	0.05077	0.49916
Senegal	0.01967	0.03121	0.03682	0.59404
Singapore	0.03443	0.03537	0.04259	1.36320
South Africa	0.04486	0.07291	0.05184	0.69358
Sri Lanka	0.02758	0.03638	0.10290	1.13710
Sudan	0.14573	0.15237	0.26787	1.29510
Sweden	0.03147	0.03333	0.03759	0.30709
Togo	0.19697	0.21242	0.42787	0.87126
Trinidad	0.10798	0.08480	0.01306	0.52565
United Kingdom	0.01390	0.02066	0.05640	0.38954
United States	0.03307	0.02527	0.06343	0.29526
Uruguay	0.00987	0.01890	0.02297	0.50597
Venezuela	0.07090	0.08053	0.21592	0.99911

As Table 4.8 shows the RMSE of all the four techniques. RMSE of ARDL are less as compare to other three techniques. So ARDL is best among all the other three techniques. As ARDL gives best results and this techniques have more advantages as compare to other. It estimates the short run and long run coefficients through OLS process. ARDL is flexible model for the analysis of order of integration. It does not required pre-testing of unit root testing.

CHAPTER 5

SUMMARY, CONCLUSION AND RECOMMENDATION

The first part of the chapter is summary and conclusion of study. Then recommendations are given in the end of the chapter.

5.1 Summary and Conclusion

The purpose of this study was to compare several techniques of time series analysis on the basis of their forecast performance. For this purpose techniques were categorized under two heads, techniques that required pre testing i.e. unit root analysis and techniques that did not required such pre testing. EG and JJ were considered under the first heading with ADF test for unit root analysis whereas ARDL bound test and VAR were considered under the second heading. Modeling was done on income and consumption data of 59 countries individually.

Firstly ADF was applied. ADF unit root test result showed that out of 59 data of only 4 countries was stationary at level, 11 countries had mixed results i.e. stationary at level and stationary at first difference some of the countries only consumption series is stationary at level and stationary at first difference and some of the countries GDP series is stationary at level and stationary at first difference. While the rest of the countries had data stationary at first difference[3].

After making the data stationary, next step was to apply the two cointegration tests as stationarity of the series is necessary part for cointegration test. Both EG and JJ were applied. Both the methods were compared on the basis of probability of detection of cointegration. Results showed that out of 59, JJ detected cointegration in 27 countries while EG detected for 15 countries[4]. Thus signifying the efficiency of JJ over EG

[3] Results are reported in table 4.1

[4] Results are reported in Table 4.2 and 4.3 respectively.

technique. The empirical power table is also given in which EG empirical power is 74% and JJ empirical power is 45%[5].

Next analysis is carried out for the techniques which did not required pre testing of unit root which are ARDL bound test and VAR. Firstly ARDL bound test in which their F statistics are calculated and compared with 10%, 5% and 1% significance of their upper and lower bounds. There are 37 countries out of 59 which shows there is long run relationship exist and 11 countries shows that there is no long run relationship and 11 countries results are inconclusive[6]. Next is VAR in which Granger Causality test are applied and 31 countries shows that GDP does not granger cause consumption and 28 countries shows that GDP does granger cause consumption[7]. Power based test avoiding cointegration are also given and the empirical power is 19% for ARDL bound test and empirical power is 45% for the VAR[8].

Consequently next important part is the forecast performance of modelling techniques. These four methods were compared on the basis of their RMSE. ARDL bound test RMSE is less than that other four techniques[9]. ARDL bound test provide better result as compare to other four techniques.

5.2 Recommendations

We have done the analysis of with unit root and without unit root. The technique which performed better with unit root analysis is JJ and in the analysis of without unit root ARDL bound test performs better. So recommendation is that ARDL bound test should be used for forecasting as it provides less RMSE as compare to other three techniques and it did not required pre testing of unit root.

[5] Result of power based cointegration analysis in Table 4.4
[6] Result are reported in Table 4.5.
[7] Result are reported in Table 4.6.
[8] Result of power based avoiding cointegration analysis 4.7
[9] Result are reported in Table 4.8.

REFERENCES

Atiq-ur-Rehman, A. U. R., & Zaman, A. (2008). Model specification, observational equivalence and performance of unit root tests.

Belloumi, M. (2014). The relationship between trade, FDI and economic growth in Tunisia: An application of the autoregressive distributed lag model. *Economic Systems*, *38*(2), 269-287.

Charemza, W. W., & Deadman, D. F. (1997). New directions in econometric practice. *Books*.

Cribari-Neto, F.(1996). On time series econometrics. *Quarterly Review of Economics and Finance,* 36, 37-60,

Davidson, J. E. (1978). Econometric Modelling of the Aggregate Time-Series Relationship between Consumers' Expenditure and Income in the United Kingdom. *Economic Journal*, *88*(352), 661-692.

Del Negro, M., Schorfheide, F., Smets, F., & Wouters, R. (2007). On the fit of new Keynesian models. *Journal of Business & Economic Statistics*, *25*(2), 123-143.

Dickey, D. A. (1976). Estimation and hypothesis testing in non-stationary time series.

Dickey, D.A. & W.A. Fuller (1981). Likelihood Ratio Statistics for Autoregressive

Enders, W., & Granger, C. W. J. (1998). Unit-root tests and asymmetric adjustment with an example using the term structure of interest rates. *Journal of Business & Economic Statistics*, *16*(3), 304-311

Engle, R. and Yoo Sam (1991). Forecasting and Testing in Co-integrated Systems, In Engle and Granger (eds.), Long Run Economic Relationships. Readings in Cointegration, *Oxford University Press, New York*, 237-67.

Engle, R. F., & Granger, C. W. (1987). Cointegration and error correction: representation, estimation, and testing. Econometrica: journal of the Econometric Society, 251-276.

Engle, R. F., & Yoo, B. S. (1987). Forecasting and testing in co-integrated systems. *Journal of econometrics*, *35*(1), 143-159.

Fatai, K., Oxley, L., & Scrimgeour, F. G. (2003). Modeling and forecasting the demand for electricity in New Zealand: a comparison of alternative approaches. *The energy journal*, 75-102.

Ghouse, G., Khan, S. A., & Rehman, A. U. (2018). ARDL model as a remedy for spurious regression: problems, performance and prospectus (No. 83973). University Library of Munich, Germany.

Granger IV, C. W., Hyung, N., & Jeon, Y. (2001). Spurious regressions with stationary series. *Applied Economics*, *33*(7), 899-904.

Granger, C.W.J. & P. Newbold (1974). Spurious Regressions in Econometrics, *Journal of Econometrics*, *2,* 111−120

Gregory, A. W., & Hansen, B. E. (1996). Residual-based tests for cointegration in models with regime shifts. Journal of econometrics, 70(1), 99-126.

Hendry, D. F. (1980). Econometrics-alchemy or science?. *Economica*, 387-406.

Hendry, D. F., Pagan, A. R., & Sargan, J. D. (1984). Dynamic specification. Handbook of econometrics, 2, 1023-1100.

Höfer, Thomas; Hildegard Przyrembel; Silvia Verleger (2004). New evidence for the Theory of the Stork. *Paediatric and Perinatal Epidemiology. 18 (1):* 18–22.

Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration—with applications to the demand for money. *Oxford Bulletin of Economics and statistics*, *52*(2), 169-210.

Johansen, S., Mosconi, R., & Nielsen, B. (2000). Cointegration analysis in the presence of structural breaks in the deterministic trend. The Econometrics Journal, 3(2), 216-249.

Kumar, S., Managi, S., & Matsuda, A. (2012). Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. *Energy Economics*, *34*(1), 215-226.

Maddala, G. S., & Kim, I. M. (1998). *Unit roots, cointegration, and structural change* (No. 4). Cambridge university press.

McCallum, B. T. (2010). Is the spurious regression problem spurious? Economics Letters, 107(3), 321-323.

Nelson, C. R., & Plosser, C. R. (1982). Trends and random walks in macroeconmic time series: some evidence and implications. *Journal of monetary economics*, *10*(2), 139-162.

Nkoro, E., & Uko, A. K. (2016). Autoregressive Distributed Lag (ARDL) cointegration technique: application and interpretation. *Journal of Statistical and Econometric Methods*, *5*(4), 63-91.

Noriega, A. E., & Ventosa-Santaularia, D. (2011). A Simple Test for Spurious Regressions (No. 2011-05).

Ohanian, L. E. (1988). The spurious effects of unit roots on vector autoregressions: A Monte Carlo study. *Journal of Econometrics*, *39*(3), 251-266.

Olatayo, T. O., Adeogun, A. W., & Lawal, G. O. (2012). Cointegration approach to the spurious regression model.

Perman, R. (1991). Cointegration: an introduction to the literature. Journal of Economic Studies, 18(3), 3-30.

Pesaran, M. H., Shin, Y., & Smith, R. J. (1996). Testing for the' Existence of a Long-run Relationship' (No. 9622). *Faculty of Economics, University of Cambridge.*

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of applied econometrics*, *16*(3), 289-326.

Phillips, P. C. (1986). Understanding spurious regressions in econometrics. Journal of econometrics, 33(3), 311-340.

Phillips, P. C., & Ouliaris, S. (1990). Asymptotic properties of residual based tests for cointegration. *Econometrica*, *58*(1), 165-193.

Plosser, C. I., & Schwert, G. W. (1978). Money, income, and sunspots: measuring economic relationships and the effects of differencing. *Journal of Monetary Economics, 4(4),* 637-660.

Rehman, A. (2011). Impact of Model Specification Decisions on Unit Root Tests. *International Econometric Review (IER)*, *3*(2), 22-33.

Reimers, H. E. (1992). Comparisons of tests for multivariate cointegration. Statistical papers, 33(1), 335-359.

Sapsford, Roger; Jupp, Victor, eds. (2006). Data Collection and Analysis. Sage. ISBN

Shin, Y. (1994). A residual-based test of the null of cointegration against the alternative of no cointegration. Econometric theory, 10(1), 91-115.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: journal of the Econometric Society*, 1-48.

Ssekuma, R. (2011). A study of cointegrating models with applications (Doctoral dissertation).

Stock, J. H. (1987). Asymptotic properties of least squares estimators of cointegrating vectors. *Econometrica: Journal of the Econometric Society*, 1035-1056.

Time Series with a Unit Root, *Econometrica*, *49*, 1057−1052.

Toda, H. Y., & Phillips, P. C. (1993). The spurious effect of unit roots on vector autoregressions: an analytical study. *Journal of Econometrics*, *59*(3), 229-255.

Toda, H. Y., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of econometrics*, *66*(1-2), 225-250.

Yule, G. U. (1926). Why do we sometimes get nonsense-correlations between Time-Series? --a study in sampling and the nature of time-series. Journal of the royal statistical society, 89(1), 1-63