MODELLING MONTHLY NON FOOD COMPONENT OF THE COLOMBO CONSUMER PRICE INDEX (CCPI) USING VECTOR AUTO REGRESSIVE (VAR) APPROACH

S.T. Tharaka Warapitiya

(128960 A)

Dissertation submitted in partial fulfillment of the requirements of the Degree of Master of Science in Business Statistics

Department of Mathematics

Faculty of Engineering

University of Moratuwa

Sri Lanka

May 2016

DECLARATION OF THE CANDIDATE

Hereby I state and declare that this Msc project report is a product of my own and without the participation of any other person or authority. The references made in here have been acknowledged appropriately and with appreciation. The sources of data and external information to the dissertation and the research have been acknowledged appropriately. Any form of substance in this research has never been submitted for any other degree, anywhere else. I hereby give my consent for making this available by photocopy for inter-library uses and for the title and summary of the dissertation to be made available for use of other institutes of learning.

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S.T. Tharaka Warapitiya

(128960 A)

24 May 2016

DECLARATION OF THE SUPERVISOR

I have supervised and accepted this thesis for the submission of the degree.

Signature: Date:

Prof. T S G Peiris
Professor in Applied Statistics
Department of Mathematics
Faculty of Engineering
University of Moratuwa

ACKNOWLEDGEMENT

First I must thank to Prof. T S G Peiris, Professor in Applied Statistics and Head of the Department of Mathematics, Faculty of Engineering, University of Moratuwa for conducting this Master Degree in Business Statistics which provides a vast knowledge in the statistics field. I believe that this course has made a distinguished path of my academic and employment career. I also recognized that the course which I followed has given me satisfactory fulfillment in statistics work in the department of Census and Statistics, my current working place.

In the first place I would like to my gratitude to Prof. T. S. G. Peiris, Professor in Applied Statistics for his supervision, advice and guidance from the very early stage of this thesis as well as giving me very invaluable experiences throughout the work.

I wish to express my sincere thanks to the former Director General of the Department of Census and Statistics, Mr. D. C. A. Gunewardhane and all of the staff of my office, those who helped and support to me in various ways to complete this course without any disturbance.

I gratefully acknowledge to the lectures that involved in lecturing in this course and all other officers in the Department of Mathematics, Faculty of Engineering who helped me to finish this course successfully.

Abstract

This study attempts to model the non food component of monthly Colombo Consumer Price Index (CCPI) in Sri Lanka using multivariate generalization of the univariate ARIMA model known as vector auto regressive (VAR) modeling approach. The data used are monthly series of Colombo Consume Price Index from year 2008 to 2015 and corresponding monthly series of data related to non food items. The structure of model is a linear function of past lags of itself and past lag of the other variables. All series were stationary for the corresponding first difference of log series and confirmed that the existence of long run dynamic relationship among all variables. The significant variables identified are clothing and footwear, housing water electricity gas and fuel, health, education, furnishing, communication, transport, recreation and culture and miscellaneous goods and services. These non food sub categories in the CCPI can be forecast using the developed model. The results would be useful when analyzing the key indicators in the economic sphere. Furthermore, the results of this study emphasize the need to put in place a stable macroeconomic policy environment to maintain price stability, since low inflation would enhance economic growth.

Keywords: Consumer Price Index, Co-integration, Granger causality, Inflation, Vector Error Correction, Vector Auto Regression

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LIST OF ABBREVIATION

Abbreviation	Description
ADF	Augmented Dicky Fuller
CCPI	Colombo Consumer Price Index
CPI	Consumer Price Index
C_F	Clothing and Footwear
Commu	Communication
Edu	Education
Furn	Furnisher
H_W_E_G	Housing_Water_Electricity_Gas and Fuel
HH	House Hold
HIES	House hold Income and Expenditure Survey
M_G_S	Miscellaneous Goods and Services
N_F	Non Food
PCE	Personal Consumption Expenditure
R_C	Recreation and Culture
RMSE	Root Mean Square Error
Trans	Transport
VEC	Vector Error Correction

CHAPTER 1

Introduction

1.1 Background of the study

Index is a statistical indicator that provides a representation of a value for a given system. In an economic environment these measures often act as barometers for markets/industries and Benchmarks against which financial and economic performance is measured. A consumers' Price Index measures changes in the cost of a fixed quantity of consumer commodities and services. It seeks to answer the question of a typical consumer ; "If I buy a given quantity of commodities and services today and compare it with what I would have spent for the same quantity a month (or an year) ago , how much will the cost have changed ? Will it has fallen or risen ?" CPI can be also identified as the minimal expenditure required for buying a unit of consumption. (Department of Census and Statistics, 2012 Technical notes).

1.2 Method of Calculating the Index CCPI

There are three established formulae which could ultimately give an index number of price namely, Paasche, Laspeyres and Fisher. Practically it is always wiser and more meaningful to use the Laspeyres which has fixed base year price index (Department of Census and Statistics,2012 Technical notes).

Colombo Consumer Price Index (CCPI) is given by

$$CCPI_t = \frac{\sum \mathrm{W_t} \times \left[\frac{\mathrm{Pt}}{\mathrm{P0}}\right] \times 100}{\sum \mathrm{W_t}} \quad \ldots\ldots\ldots\ldots \text{(1)}$$

Where;

P_t = Price of commodity i in the current period t

P_o = Price of the commodity i in the reference period

W_i = Weight associated with commodity i n the current period t

Price multiplied by quantity represents the expenditure value of the item. This value is considered for current year (or reference period) and base year (or corresponding previous period) as well for each consuming item. Summation will represents the total expenditure for/ value of basket of consumer items.

In the recent history human consumption pattern (consequently their expenditure pattern as well) has been changing rapidly all over the world. The Sri Lankan scenario as a developing country illustrates overwhelming changes proportionate to its development capacity and spent much on meals (for food items). After the renaissance of the Europe with the industrial revolution and modernization of the society, the earnings improved and their consumption pattern has been sophisticated. As the leisure time is available for an average person, their expenditure on non food items rather than on food items emerged as their social and cultural needs are expanding (with his cultural – civilized life condition). In our pre- history the man spent much time for producing his meal and satisfied with that only. When measuring multi dimension conditions of society, we look into non food consumption pattern and its quality level. Hence it can be said that the Consumer Price Index is a measure of prices by which the repercussions on the consumption of a society is associated.

1.3 Colombo Consumer Price Index (CCPI)

Department of Census and Statistics is responsible for the compilation of CCPI which is the official cost of living index. It is also used to adjust the wage payments for (both government and private sector) employees. CCPI is represented by several sub groups of commodities (both goods and services), namely Food and non alcoholic beverages , Housing-fuel-electricity-gas-water, Transport, Clothes and leather wear, Education, Health, Communication, Furnisher/Household durables, Recreation and culture, Other miscellaneous expenses. Current base year for compilation of CCPI is 2006/2007. When compiling this index, the weights assigned to each sub group are determined according to the ratios or proportionately to expenses out of total household expenses. For example, weight on food and non alcoholic beverage group is determined by the expenditure share on that category out of total household expense from the Household Income and Expenditure survey 2006/2007 (HIES 2006/2007). Hence, according to the latest survey information those weights would be revised repeatedly. This survey is conducted once in every three years. Consequently the process of revision of base year for this index is resumed soon after the latest (2012/2013) HIES information is released.

1.4 Inflation, the Main output from CCPI

Inflation is the change in consumer price index (CPI). Inflation is one of the most frequently used terms in economic discussions, yet the concept is variously misconstrued. Inflation is the rate of increase of the general price level. It is measured in terms of changes in price indices. Such an index would indicate the relative cost of a specified basket of goods and services over time, compared with the cost of such basket of goods and services during a particular (base) year. The annual average inflation rate is based on the average index value during a given year as compared with the previous year for the same period. In Sri Lanka there are several price indices calculated by the Central Bank of Sri Lanka and the Department of Census and Statistics. Few main indices are Colombo Consumer Price Index (CCPI) which is the key index quoted for inflation reporting. The inflation rate for the current year (X_t) is computed as follows.

$$X_t = \frac{(Y_t - Y_{t-1})}{Y_t} \times 100 \qquad \ldots\ldots\ldots\ldots \quad (2)$$

Where

X_t = Inflation rate in current year t,

Y_t = Colombo consumer price index in current year t and

Y_{t-1} = Colombo consumer price index in previous year t-1

In the definition of inflation, two key words must be borne in mind. First, is aggregate or general, which implies the rise in prices that constitutes inflation must cover the entire basket of goods in the economy as distinct from an isolated rise in the prices of a single commodity or group of commodities? The implication here is that changes in the individual prices or any combination of the prices cannot be considered as the occurrence of inflation. However, a situation may arise such that a change in an individual price could cause the other prices to rise. This again does not signal inflation unless the price adjustment in the basket is such that the aggregate price level is induced to rise. Second, the rise in the aggregate level of price must be continuous for inflation to be said to have occurred. (Department of Census and Statistics, 2012 Technical notes).

1.5 Value of one Index point

Consumption expenditure of an average household (per month) based on survey year 2006/2007 was Rs. 27,972.11 .This value was the equivalent to 100 which was the base year index. Hence the value of one index point was 279.72. (27,972.11 divided by 100). That value (value of index point) for the previous base year 2002 was Rs. 179.96. Which was derived by the Consumption expenditure of an average household (per month) based on survey year 2002 was Rs. 17,996.

Market basket: In 2002 this basket contains 83 sub classes (334 consumer items - both goods and services) and this number was further grown up to 95 sub classes (373 consumer items) in 2006/2007 survey year. (Department of Census and Statistics, 2012 Technical notes).

Table 1.1: Description of Base Weights for CCPI

Sub Group	*Value (Rs).*	*Percentage share*
GRAND TOTAL	*27,972.11*	*100.0 %*
Food and Non Alcoholic Beverages	*11,476.50*	*41.03*
Meals bought from outside	*1,634.63*	*5.84*
Clothing and Footwear	*879.53*	*3.14*
Housing, Water, Electricity, Gas & Fuel	*6,635.95*	*23.72*
Furnishing, H/H equipment & Maintenance	*1,005.89*	*3.60*
Health	*884.42*	*3.16*
Transport	*3,430.49*	*12.26*
Communication	*1,329.27*	*4.75*
Recreation and Culture	*419.27*	*1.50*
Education	*1,102.05*	*3.94*
Miscellaneous (Personal care/Insurance/Jewellary)	*808.74*	*2.89*

H/H – House Hold

Source ; http://www.statistics.gov.lk

Price Collection Centres from which retail prices of consumer items (both goods and services) are collected weekly basis. Fourteen price collection centres in and around Colombo are identified as follows; Pettah, Maradana, Wellawatta, Dematagoda, Grandpass, Borella, Kirulapone, Dehiwala, Mt.Laviniya, Kotte, Nugegoda, Kolonnawa, and Special Economic Centres namely Narahenpita and Ratmalana.

1.6 Sub categories of CCPI:

Main categories on which the consumer items grouped into can be identified as bellow:

Food group

Food and non alcoholic beverages

Non Food group

Clothing and footwear

Housing, water, electricity, gas and fuel

Furnishing

Health

Transport

Communication

Recreation and Culture

Education

Miscellaneous goods and services (Personal care/Insurance/Jewellary)

Out of these sub groups the following sub groups following nine sub categories of non food category were selected for the study.

1.7 Variables Selected for the Study:

Sub categories of Colombo Consumer Price Index (CCPI) non food component

1. Clothing and footwear
2. Housing, water, electricity, gas and fuel
3. Health
4. Transport
5. Communication
6. Recreation & Culture
7. Education
8. Furnishing
9. Miscellaneous goods and services

1.8 Significance of the study

Various studies have been conducted from time to time in Sri Lanka and rest of the world as described in literature review on forecasting CPI and on inflation dynamics. Thus expected output is would be more beneficial implementing fiscal, monetary policies and taking decisions regarding the price stability or keeping the inflation rate within one digit level by the policy makers in government and other stakeholder. CCPI and GDP (Gross Domestic Product) deflator generally seem to be same in pattern. But these two have few differences. GDP deflator represents the price inflation/deflation for the total output of domestic economic activities of a country, while CCPI represents the inflation/deflation of pre-determined basket of consuming items (goods & services) of an average household/family in the country. Anyhow it can be said that GDP deflator and CCPI may have a close association in pattern. Hence one indicator can provide a good picture about the behavior of the other indicator. Apart from direct uses and applications of CCPI, this can give an idea about the whole inflation of the total economy. So one can have a cross check the reliability of GDP forecasts with CCPI forecasts generated in this project. So results come out of this project will also help in utilizing on forecasting the GDP with a very strong proxy through CCPI. When GDP is increasing there is a higher possibility of avoiding the demand pull inflation and cost push inflation. Further it is observed that seasonally adjusted GDP shows a negative and statistically significant effect on Sri Lankan inflation.

1.9 Objectives of the study:

In view of the above, the objectives of this study are;

- To identify whether there exists a long run association among variables
- To model non food component of CCPI

1.10 Organization of Thesis

There are five chapters in this study. Chapter one is an introduction which contains the background, measures of Colombo Consumer Price Index, importance of the study, objectives of the study, and organization of the thesis. Chapter two presents the literature review regarding forecasts of consumer price index and its impact. In Chapter three the materials and methodology that will be used are described and Chapter four delivers the results and discussions. Chapter five comprises of the conclusions, recommendations and suggestions..

CHAPTER 2

Literature Review

2.1 Introduction

The past studies related to forecasting Consumer Price Index and related work are reviewed.

2.2 Related Studies in Sri Lanka

Udani and Jayasundara (2013) claimed that inflation is the rise of the general level of prices of goods and services regarding with the consumption structure of the society. It is represented as the change of CCPI. It can be forecast both by econometric tools and by time series tools. Using time series modeling with the past data only where econometric tools concern the impacts, repercussions of other reasons as well, make the policy makers to come across with much more things. When time series ARIMA(1,1,1) approach model fitted to annual CCPI changes (inflation) from 1953 to 2001, the fitted value and actual values were almost similar. Actual figures were within both upper limits and lower limits. Econometric approach by fitting co-integration equation and VECM for annual rates of inflation for the period of 1977 to 2004 the co-integration equation gave a long-run relationship of inflation.

Kodikara and Cooray (2011) analysed the Value Added Tax (VAT) with CCPI in Sri Lanka. This was reported as the first study ever done on this regard. This was an important analysis focusing on finding the determinants of both VAT and CCPI and their forecasts as well. Data were from year 2004 to 2010 on monthly basis. VAT has been affecting on consumer goods and services as the VAT is borne by the final consumer. This study focused on whether there exists a relationship among VAT and CCPI and to fit a suitable model to forecast monthly VAT revenue in Sri Lanka. VECM was formulated in this regard. It was proved that the changes in CCPI (or simply the inflation) considerably affected by the VAT. It was found that CCPI is influential on VAT as well.

Deshappriya (2014) identified inflation dynamics and its determinants during the period 1983 – 2010. VECM and Johanson co-integration test were employed to find the existence of long-run equilibrium together with short-run relationship. The study reveals that broad money supply, rice price and GDP considerably account for inflation in Sri Lanka. Nevertheless GDP does not affect considerably on inflation during the short-run.

2.3 Related Studies in other countries

Worrell (1985) emphasized the role of structural influences and cost push inflation. Recent studies found that monetary disequilibrium and exchange rate changes are significant in describing the pattern/behavior of prices. Inter dependency of money stock and inflation takes place via monetary transmission. Economic agents' ambition is to hold less money than the availability of money stock.

SNB (2006) developed a model for Swiss inflation, using VAR models. Accuracy of forecasting can be improved by combining multiple forecasts. By diversifying the effect, improvement can be achieved. If individual forecast errors (from different models) are not correlated perfectly, the forecast variance of a combination (of forecasts) is smaller than the average forecast variance (of individual forecasts). In the case of VAR models this improvement of forecasting by combining multiple forecasts is important. VAR models have been increasingly applied in macroeconomic studies over the recent past. United States is the leading country, employing this model especially in Federal Reserve (Central Bank of USA) and Bank of England for economic trend forecasting.

Wayne (1998) developed a model Using VAR to understand and predict the inflation in Jamaica the variables taken into consideration were monthly observations of CPI, exchange rate, interest rate on government treasury bills, imported inflation, and a proxy for GDP. The model exhibited greater predictive accuracy compared with other models. The importance of shocks and underlying process was identified in this study. The study observed those interrelations among variables and forecasted inflation by employing VAR as expected.

Moser (1995) has observed that Consumer Price Index was seasonal when Nigerian CPI Data was analyzed using a multiplicative seasonal ARIMA model was fitted to the series (Time Series Analysis on Nigerian Consumer Price Index (CPI) data). A visual inspection of actual and the fitted time plot revealed a close agreement between the two. The time plot of the original series of Nigerian CPI clearly depicts a positive trend. Seasonal differencing of the series produces a series with minor trend. Seasonality was not very evident. Non seasonal differencing yields a series with no trend and no clear seasonality.

Hikaru and Tomek (2000) developed different empirical models of expectations result from nominal and various deflated series that have distinct Time series properties produced varying estimates of supply-response & measures of price risk. The foregoing is illustrated by annual grain prices, monthly milk prices and milk supply analysis. Annual prices of corn and soybean, for example appear to vary around a constant mean. But when deflated by general price indices like CPI, are auto correlated around declining deterministic trend or show a stochastic trend. The question of an appropriate deflator also occurs in price risk. The management of risk appears in portfolio problems, which involve in probability distributions of prices of commodities potential components of the portfolio. Risk variables may be used in supply equations for commodities. Risk is measured by unconditional variance of normal prices. Theoretically risk involves (due to) deviations from expected price. But there should be a definition for expectations. Expectations can be viewed as forecasts from an underlying economic model and models of commodity prices.

Ramirez (2000) developed a dynamic factor model to generate sample forecasts for the inflation in Mexico. A set of 54 macroeconomic series and 243 CPI sub components from 1988 to 2008 were taken into consideration. His results indicated (i) Factor models outperformed the benchmark autoregressive model at horizons of one, two, four & six quarters, (ii) Using disaggregated price data improves forecasting performance and (iii) The factors were related to key variables in the economy such as output growth and inflation. Many economic decisions, made by policy makers, companies/firms, investors are generally based on inflation forecasts. The accuracy of those forecasts can have important repercussions in the economy. Economists have literally thousands of macroeconomic series from different sources (including aggregated levels of series) with or without seasonal and other adjustments. This allows and makes it possible to use time series in forecasting macroeconomic variables like inflation (in an informative and accurate way). But when an empirical study is done using a statistical tool like Vector Auto Regressive, it would typically be limited to less than 10 variables due to computation burden. This study summarizes the information (of large number of series) into a few predictors of the inflation. The assumption in this framework was that a fewer number of unobserved factors were the driving force of the considering series. Instead of a large number of explanatory variables, a few common factors allowed us to come up with forecasts. Forecasting performances were evaluated with stimulation exercise of out of sample information. Factor forecasts were also compared with a benchmark autoregressive model. [It was earlier found that using more data to estimate factors is not necessarily better for forecasting]. That suggests the need to evaluate the role of adding CPI components on forecasting performance.

Inoue and Kilian (2005) discussed how Useful is Bagging in Forecasting Economic Time series. Bagging is a statistical method designed to reduce the out-of-sample prediction mean square error of forecast models selected by unstable decision rules such as pre tests. The term bagging is short for Boot Strap aggregation. Bagging involves fitting the unrestricted model including all potential predictors to the original sample, generating a large number of boot strap re-samples from this approximation of the data. By averaging across re-samples, bagging removes the instability of the decision rule. Forecasts generated using only one of economic variables tend to be unreliable and unstable. On the other hand, including all economic variables is thought to lead to over-fitting and poor out-of-sample forecast accuracy. In this study the usefulness of bagging methods in forecasting economic time series from linear multiple regression models was examined. Forecasting methods allow the user to extract relevant information from large set of potentially relevant predictors. Since there is no universally agreed upon measure of real economic performance, 26 potential predictors, that could be expected to be correlated with real economic activity were considered here. Monthly data of variables were provided by Federal Reserve Bank of United States. All predictor data were standardized. This empirical analysis illustrates that large reductions in the prediction/ forecast mean square error were possible relative to existing methods, a result that was also suggested by the asymptotic analysis of some styled linear multiple regression examples.

Yousif Alrkeb and Alhashiimy (2011) analyzed growth in the economy in Qatar. Growth rates of GDP were 34 %, 13% and 15 % in 2006, 2007 and 2008 respectively. Consequently prices level had been increased rapidly as a result of expansion of construction sector. This affected the prices level in Qatar. This study was intended to perform a comprehensive time series for CPI in Qatar. Quarterly data was obtained for the period of 2002 – 2009. Ratio transformation technique was used to obtain a stationary time series. Analysis indicated that ARIMA model was more adequate in forecasting. Since ARIMA requires a stationary set of data (and the original data is violating this requirement) a transformation was used. When the traditional difference transformation was used the third differenced yield a stationary sets. ARIMA was used for two different sets of data and both provided forecasts more accurate than double exponential smoothing model.

Koopman and Ooms (2011) developed an Auto regressive models (Structural time series models) the following empirical results were taken with respect to GDP growth and CPI inflation.(Forecasting Macroeconomic Time series using unobserved components models) Economic policy makers need/require reliable forecasts in an uncertain economic environment. On the other hand economists prefer to use models which describe dynamic economic relations between GDP and inflation (value change of CPI). Here this project focused on the unobserved component of a univariate time series. In this project long term developments in the economy were characterized by trend component. Mid term dynamics were characterized by cyclic component. To determine whether a time series model predicts better than benchmark, significance tests of the improvements in the root mean square error and mean absolute error statistics were obtained. It was found; with constant trend Auto regressive (2) cycle was the best forecasting method. But time varying structured time series models did not produce more accurate forecasts in general.

Zhang, Wengang and Xu (2013) tried to make short term trend forecasts. Data from January 1995 to September 2008, total of 165 data using the front of 161 data to establish the ARMA model. As the ARMA is applicable to stationary series the stationary test on CPI sequence was carried out before establishing the model. With the result the series being stationary ACF and PACF functions were made use of to determine the order of the model. ARMA(1,1) model shows that the relative error was (relatively) small between the forecast value and the real value of the CPI sequence; the effect of the model was quite well. But with increase in the forecast period, the relative error of the model forecast was also increasing. Hence the short term forecast of the ARMA model was still relatively ideal.

Stock and Watson (1998, revised 1999) investigated forecasts of inflation at the 12 month horizon in United States. Inflation forecasts produced by the Phillips curve generally had been more accurate than forecasts based on macro economic variables. This study re-assessed the use of the Phillips curve for forecasting price inflation. It mainly focused on (1) has the Phillips curve been stable (2) the Phillips curve is conventionally specified in terms of employment , but at a conceptual level other measures of economic activity could be used instead. Do these alternative Phillips curve provide better forecasts of inflation than the unemployment rate Phillips curve. (3) These variables are of cause, a smaller subset of other macro economic variables that are potentially useful for forecasting inflation. Personal Consumption Expenditure (PCE) inflation forecasts were more accurate than CPI forecasts ; over the entire sample period the RMSE for the PCE was approximately 25 % smaller than for the CPI. Forecast errors were smaller in the second half of the forecast period (1984-1996) than in the first half (1970-1983); the RMSE drops by over 40 % for both inflation measures.

Bedia and Pieretti (2008) studied CPI dynamics in a small open economy: A structural Time Series model was used for Luxembourg to examine the relationship between the CPI and its theoretical explanatory variables to treat unobserved components or effects (such as trend, cyclical effect, seasonal effect & irregular effect) of CPI. Theoretically CPI is negatively related with labour productivity; but positively to nominal wages. Small open economies like Luxembourg show CPI is negatively related to labour productivity as expected. Additionally unit labour cost thoroughly explains the CPI.

2.4 Summary

The review on the relevant studies from Sri Lankan and rest of the world provided strong base for the present study. The review also helped in identifying the research models that has been used in similar studies, identifying different variables used by them as proxies to represent CCPI and also to identify the most appropriate methodology to be used in this type of empirical research. Mostly used methodology for such studies was Johansen's Co-integration method with a Vector Error Correction model (VECM) approach in VAR.

CHAPTER 3

Materials and Methods

3.1.1 Introduction

This chapter briefly discusses how research problem has been developed into a model that can be investigated using statistical analysis and statistical methods.

3.1.2 Secondary Data

Secondary Data set was collected from Colombo Consumer Price Index (CCPI) compiled and released by the Department of Census and Statistics (DCS) in monthly basis. Retail prices of consumer items -about 373 items-(both goods and services) are collected by Department field officers from selected markets in and around the Colombo throughout four weeks of every month (average of three days a week). Possibly in every rebasing stage, (around once in five years time) the number of consumer items would be changed / revised. From year 2008 to 2015 monthly CCPI figures (for Non Food Categories) are treated for the analysis. Food and non alcoholic beverages category was exempted in this analysis.

Both CCPI and GDP (Implicit) Deflator reflect [Implicit deflator is derived when GDP value at current prices deflated by the GDP value at base year prices] current economic situation of a country. Inflation could be forecasted by monitoring the Consumer Price Index (CPI). In Sri Lankan case this CPI is named as or defined as Colombo Consumer Price Index (CCPI) by the DCS.

3.1.3 Defining Variables of non food category

Endogenous variables of (non food category of) CCPI

Clothing & Footwear: Expenses on clothing items for elders/ladies/babies, towels/bed sheets, footwear, umbrellas, repair expenses, bags, headwear etc.

Housing, water, electricity, gas and other fuel: Included expenses on House rent/ (own occupied dwellings/residence also valued), expenses for water (for drinking and other purposes), Electricity, Solar power, Kerosene oil, Firewood, L.P. gas, Dry cell batteries and etc.

Health : Included expenses on Toothpaste, tooth brushes, perfumes, face cream, hair oil, shaving, hair dressing /cutting, private medical practices, laboratory expenses, purchasing of medical/pharmaceutical products, spectacles etc.

Transport : Included expenses on train, bus, van, taxi, three wheeler, school service transport, ships & airline, petrol, lubricants, tyres /tubes, license/insurance and vehicle maintenance costs etc.

Communication: Expenses on postal, telephone and internet

Cultural activities & Recreation: Expenses on Cinemas / dramas / video films, books/newspapers / magazines, excursions / pilgrims, art / music / dancing, sports, pets, aquariums etc.

Furnishing : Household sanitary expenses and expenditure on household durables

Education : Expenses on Exercise books, stationary, school facility fees, private school fees, tuition fees, boarding fees, higher education/vocational education fees, montessori fees.

Miscellaneous goods and services : Other non consumptive expenses on social activities, payments for debts insurance , income tax, windfall expenses like weddings, funerals, gifts, random household expenses and litigation.

3.1.4 Gross Domestic Product

Is defined as the value addition due to all economic (economically valued) activities within given time period (a year/ a quarter) within an economic boundary. Economic activities are classified according to internationally recognized standards. Value addition due to economic activities (by human involvement) using material inputs/other intermediate inputs is calculated with the guidance and definitions provided by the internationally recognized manual called System of National Accounts (SNA).

3.1.5 GDP Implicit Deflator

$$GDP(\text{Implicit})\,\text{deflator} = \frac{GDP\text{ at Current Prices}}{\text{GDP at Constant Prices}}\,X\,100 \quad ....(3)$$

3.1.6 GDP at Current Prices

GDP is quarterly and annually estimated at current prices in which the price inflation in the economy is included. But these estimates with price impact could not be used for measuring the growth in the economy or for comparing with another country.

3.1.7 GDP at Constant Prices

To measure the growth of the economy, the price impact on the Value Addition should be removed to measure the actual contribution by economic activities. Hence Value Addition is calculated with constant (base year) prices. Currently the base year is 2010.

3.1.8 Advantages and limits of VAR model

To obtain more accurate progress VAR's are better than simple or general linear statistical model. Because endogenous and explanatory variables are believed to interact which should be included as part of the economic system. It can be proposed that VAR models are closer to economic reality.

When comparing the components simultaneously model may be more parsimonious. Then more accurate forecasting is possible due to the extended information set. But as we expect to capture the dynamics of the system (modeled) the greater the number of parameters (to be estimated) fewer the degree of freedom. That is a limit of VAR model.

3.2 Methodology

Various economic variables may depend, in one way or another, on each other. Thus a uni-variate time series approach might not be appropriate if we aspire to capture interactions between different variables. Although each and every series of variables could be modeled independently by univariate approach, to analyze potential interactions among group of series (variables) multivariate time series approach can be exercised.

3.2.1 Vector Auto Regressive Model

This economic model is often used to capture the linear interdependencies among multiple time series. It allows more than one evolving variable; each variable has an equation explaining its evolution based on its own lags and the lags of the other model variable (Peiris,2012).

This is an extension of uni-variate auto regressive model to dynamic multivariate time series. This is especially useful for describing the dynamic behavior of economic or financial time series and forecasting. In addition to data description and forecasting VAR model is also used for structural inference and policy analysis (VAR models for Multivariate time series p.383-384).

Vector Auto Regressive model in Time Series analysis would be applied to forecast CCPI and Johanson Co-Integration Analysis is applied to check whether a long run relationship is existing among variables.

3.2.2 Mathematical representation of VAR

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \ldots\ldots\ldots + A_p y_{t-p} + Bx_t + e_t \quad \ldots\ldots\ldots (4)$$

VAR is generally used to analyze the impact of random disturbances on the system (variables) and to forecast for interrelated variables of time series. For example suppose two interrelated variables U and V are jointly considered by VAR. Assume VAR containing with two lagged values can be written as;

$U_t = a_{11}U_{t-1} + a_{12}V_{t-1} + b_{11} U_{t-2} + b_{12} V_{t-2} + C_1 + e_{1t}$ …….. *(5)*

$V_t = a_{21}U_{t-1} + a_{22}V_{t-1} + b_{11} U_{t-2} + b_{21} V_{t-2} + C_2 + e_{2t}$ …….. *(6)*

Where a_{ij} and b_{ij} are to be estimated. (Peiris.,2012)

3.2.3 Test for stationary (Unit Root Test)

Stationarity is a key requirement for external validity of Time series regression. It describes whether the history is relevant. A time series is said to be stationary if it's probability distribution does not change over time. Joint distribution of a time series does not depend on starting point of the time series. (Peiris, 2012)

3.2.4 Augmented Dicky-Fuller (AD-F) Test

The Dicky-Fuller test is used to test whether a unit root is present in an Auto Regressive model. Augmented Dickey–Fuller test is an augmented version of the Dickey–Fuller test for a larger and more complicated set of time series models. AD-F test is equivalent to test whether a series follows a random walk without a drift ($y_t = ø_t y_{t-1} + e_t$) or a random walk with a drift ($y_t = ø_0 + ø_1 y_{t-1} + e_t$)

The hypothesis test under AD-F is H_0: ø > 1 vs H_1: ø < 1 (Peiris, 2012)

3.2.5 Phillips–Perron Test

Phillips–Perron test is a unit root test. That is, it is used in time series analysis to test the null hypothesis ø =0 that a time series is integrated of order 1. It builds on the Dickey–Fuller test of the null hypothesis in $y_t = ø_t y_{t-1} + e_t$, here is the first difference operator. Like the augmented Dickey–Fuller test, the Phillips–Perron test addresses the issue that the process generating data for y_t might have a higher order of autocorrelation than is admitted in the test equation - making y_t endogenous and thus invalidating the Dickey–Fuller t-test. Whilst the augmented Dickey–Fuller test addresses this issue by introducing lags of Δy_t as regressors in the test equation, the Phillips–Perron test makes a non-parametric correction to the t-test statistic. The test is robust with respect to unspecified autocorrelation and heteroscedasticity in the disturbance process of the test equation (Phillips and Perron, 1988).

3.2.6 Co integration Test

Order of integration [I(d)] is a summary statistic for a time series. It reports the minimum number of differences required to obtain a covariance stationary series. If two or more time series are individually integrated but some linear combination of them has a lower order of integration then the series are said to be co integrated. If X and Y series following a random walk; testing the hypothesis that there is a statistically significant connection between variables could be done by testing for the existence of a co integrated combination of two series (Peiris, T.S.G.,2012, Lecture Notes). Although VAR modeling traditionally assumes stationarity of all series, it is not generally recommended to difference non-stationary components individually, as such a step may destroy important dynamic information. The most critical issue is co-integration. In short, when there is co-integration, co-integrated models should be used for forecasting. When there is no co-integration, series with an integrated appearance should be differenced. Co-integration is said to exist in a vector time series y_t when some of the components are individually first-order integrated (I(1)) while the remaining components may be stationary, and there is a linear combination of components that can be expressed by a vector β such that $\beta_0 y$ is stationary (I(0)). Co-integration is non-trivial when β has non-zero entries at the integrated components. Apart from this CI(1,1) co-integration, which reduces integration order from one to zero, higher-order co-integration can be defined but its practical applicability is reduced and examples for applications are rare. Note that there are slightly different definitions of CI(1,1) co-integration in the literature but that the above definition is the most convenient for multivariate VAR modeling. The issues at stake can be best motivated by considering a VAR system that possibly contains some integrated and some stationary components. (Multivariate Forecasting Methods, http://www. google.com)

3.2.7 Pair wise Granger Causality Test

Causality can be described as the relationship between cause and effect. Basically the term “ Causality” suggests a cause and effect relationship between two sets of variables. Say Y and X recent advances in graphical models and the logic of causation have given rise to new ways in which scientists analyze cause- effect relationship (Pearl, 2012).One of the main uses of VAR models is forecasting. The structure of VAR model provides information about variables’ forecasting ability for other variables. If a set of variables (Y) is found to be helpful for predicting another variable (or set of variables) (say X) then Y is said to Granger Cause X; otherwise it is said to fail to Granger Cause X (VAR models for Multivariate time series p.370-381). One good feature of the VAR model is that it allows us to test for directional causality. The causality tests give an indicator about the ability of one variable to predict the other variable. If there are two variables, x_t and y_t, each affect the other with distributed lag, the relationship between these two variables can be captured by using the VAR model. Four possible relationships can be identified in this model; (*a*) x_t causes y_t (*b*) y_t causes x_t (*c*) there is a bidirectional causality, and (*d*) two variables are independent. Granger (1969), developed a test to examine the causality. The test defines causality as follows: a variable y_t is said to be granger cause x_t , if x_t can be predicted with greater accuracy by using past values of the y_t variable rather than by not using such past values, all other terms remain unchanged (Engle, and Granger, 1987).

3.2.8 Normality Test (Jarque-Bera Test)

The Jarque-Bera Test statistic measures the difference of the skewness and kurtosis of the series with those from the normal distribution.

Test statistic: H_0 : Data series is normal Vs H_1 : Data series is not normal

Skewness, $g_1 = \Sigma (y_i - \tilde{y})^3 / ns^3$ kurtosis, $g_2 = \{\Sigma (y_i - \tilde{y})^4 / ns^4\} - 3$

$$JB = \frac{ng1^2}{6} + \frac{ng2^2}{24} \sim \chi^2 \text{ under } H_0 \quad \text{........} (7)$$

Economic or finance theories suggest the existence of long run equilibrium relationships among non stationary time series variables. (Peiris, 2012)

3.2.9 Test of Serial Correlation (LM test)

Reports the multivariate LM test statistics for residuals serial correlation up to the specified order. The test statistics for lag order *h* is computed by running an auxiliary regression of the residuals U_t on the original right-hand regressors and the lagged residuals U_{t-h} , where the missing first *h* values of U_{t-h} are filled with zeros. (Sims, 1980)

3.2.10 White Heteroskedasticity Test

These tests are the extension of White's (1980) test to systems of equations as discussed by Kelejian (1982) and Doornik (1995). The test regression is run by regressing each cross product of the residuals on the cross product of the regressor and testing the joint significance of the of the regression. (Sims, 1980)

3.2.11 Wald Test

Whenever a relationship within or between data items can be expressed as a statistical model with parameters to be estimated from a sample, the Wald test can be used to test the true value of the parameter based on the sample estimate.(Gail, Mitchell H. ,1996).

3.2.12 Vector Error Correction Model (VECM)

An error correction model is a dynamical system with the characteristics that the deviation of the current state from its long-run relationship will be fed into its short-run dynamics. This is not a model that corrects the error in another model. Error Correction Models (ECMs) are a category of multiple time series models that directly estimate the speed at which a dependent variable Y returns to equilibrium after a change in an independent variable X. ECMs are a theoretically-driven approach useful for estimating both short term and long term effects of one time series on another (Engle, and Granger, 1987). This is generally developed, if the variables are co-integrated after Johansen co-integration test. This is known as restricted vector autoregressive (VAR) model. (Peiris, T.S.G,2012).

CHAPTER 4

Results and Discussions

4.1 Exploratory Analysis

The important descriptive statistics for CCPI(Non Food) and it's nine sub categories and their distribution were obtained for empirical investigation.

Table 4.1.1 : Descriptive Statistics of sub categories of CCPI (Non Food)

variable	N	Range	Minimum	Maximum	Mean
Non Food	96	56.23	109.37	165.6	142.878
Clothing and Footwear	96	96.52	108.88	205.4	151.471
Communication	96	11.81	82.19	94.0	89.969
Education	96	49.37	104.83	154.2	135.340
Furnishing	96	59.45	109.15	168.6	138.100
Health	96	198.16	120.74	318.9	236.608
Housing Water Electricity & Gas	96	45.95	110.35	156.3	131.389
Recreation and Culture	96	56.10	111.40	167.5	140.001
Transportation	96	82.61	116.89	199.5	165.405
Miscellaneous goods & Services	96	49.86	106.04	155.9	134.097

Table 4.1.2: Temporal Variability of sub categories of CCPI (Non Food)

variable	N	Std. Error	Variance	**Skewness**	**Kurtosis**
Non Food	96	1.74816	293.382	-0.148	-1.442
Clothing and Footwear	96	2.77914	741.466	0.133	-0.942
Communication	96	0.36188	12.572	-1.048	0.354
Education	96	1.27567	156.224	-1.056	0.056
Furnishing	96	1.64556	259.955	0.090	-0.862
Health	96	4.86767	2274.647	-0.378	-0.152
Housing Water Electricity & Gas	96	1.53311	225.64	0.395	-1.151
Recreation and Culture	96	1.53707	226.808	-0.161	-0.925
Transportation	96	2.55453	626.461	-0.118	-1.498
Miscellaneous goods & Services	96	1.31631	166.337	-0.098	-0.781

According to the table 4.1.1 and 4.1.2, highest mean and variance were recorded in health. Lowest mean and variance were recorded in communication among all other variables. Expenses on postal and communication purposes have been declining. That causes the index for that component shows this distinction.

4.2 Change in index point of sub categories of CCPI (Non Food)

For the co-integration analysis it is necessary to test whether all series are stationary. Time series plot for the Non food, clothing and footwear, housing_water_electricity_gas, health, transport, communication, recreation and culture, education, furnishing and miscellaneous goods and services are shown in Figures 4.1 - 4.10 respectively.

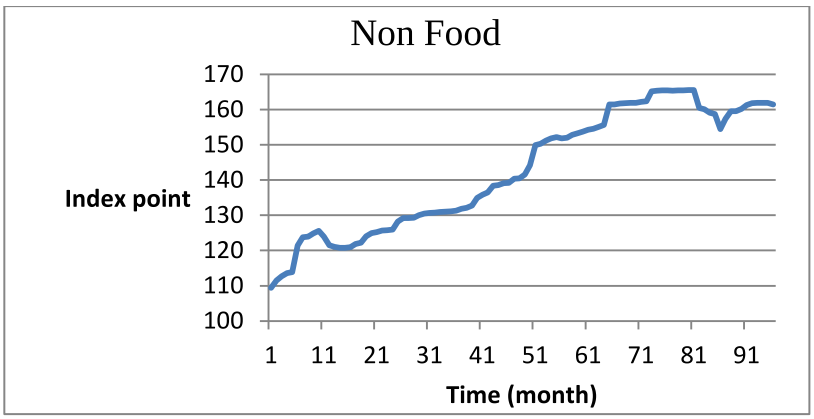


Figure 4.1: Trend of Increase in CCPI(Non food) 2008 – 2015

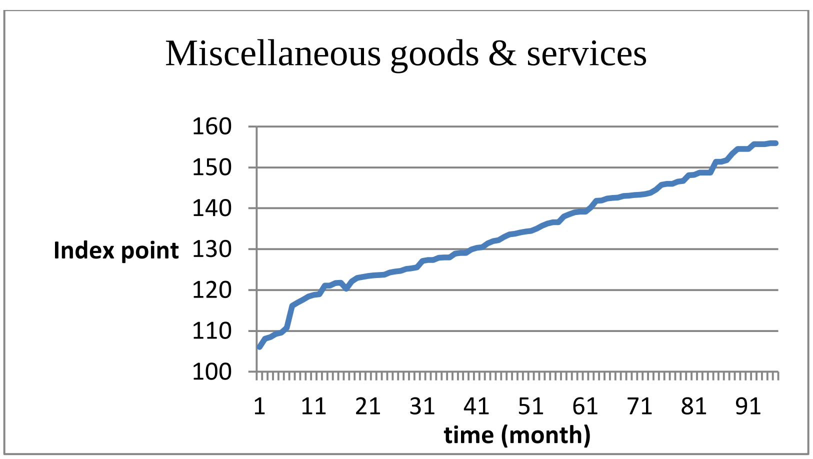


Figure 4.2: Trend in miscellaneous goods and services 2008 - 2015

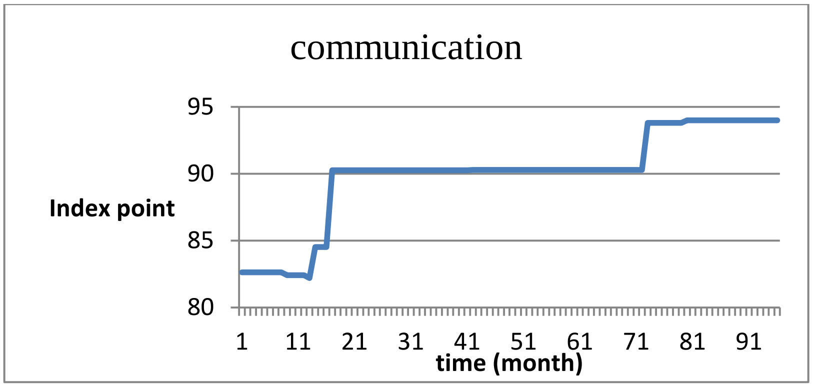


Figure 4.3: Trend in communication 2008 – 2015

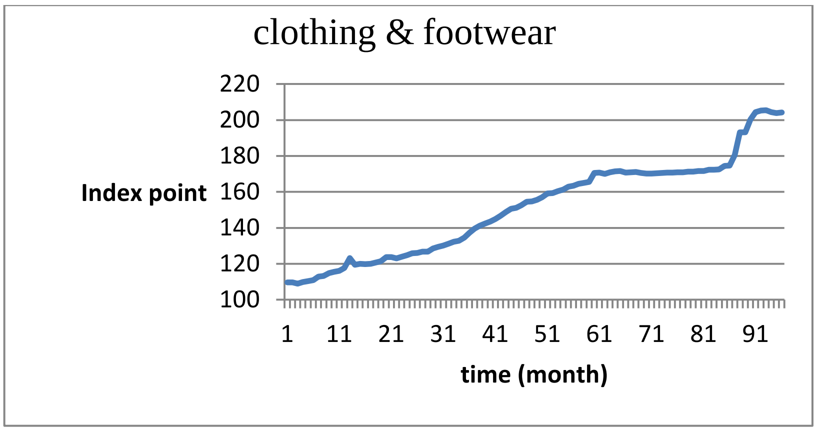


Figure 4.4: Trend in clothing and footwear 2008 – 2015

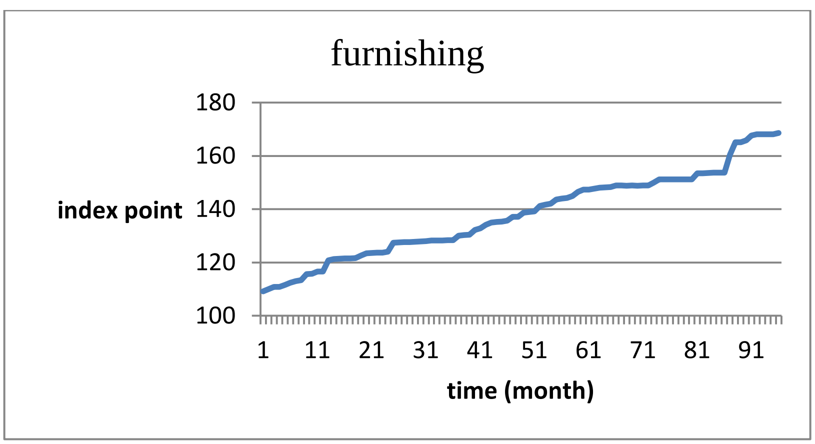


Figure 4.5: Trend in furnishing 2008 - 2015

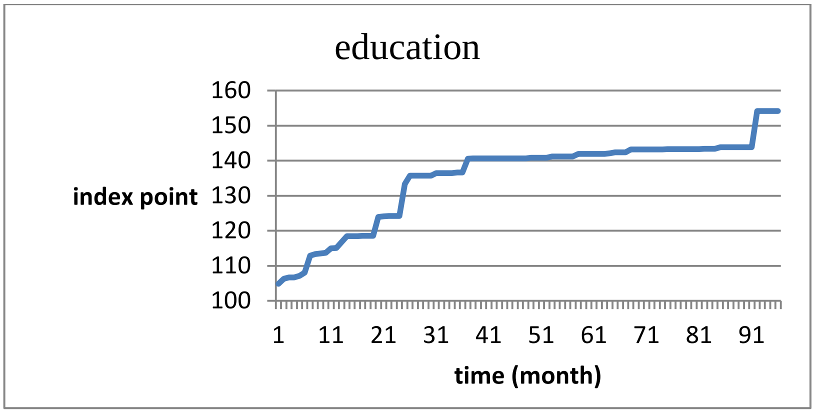


Figure 4.6: Trend in education 2008 - 2015

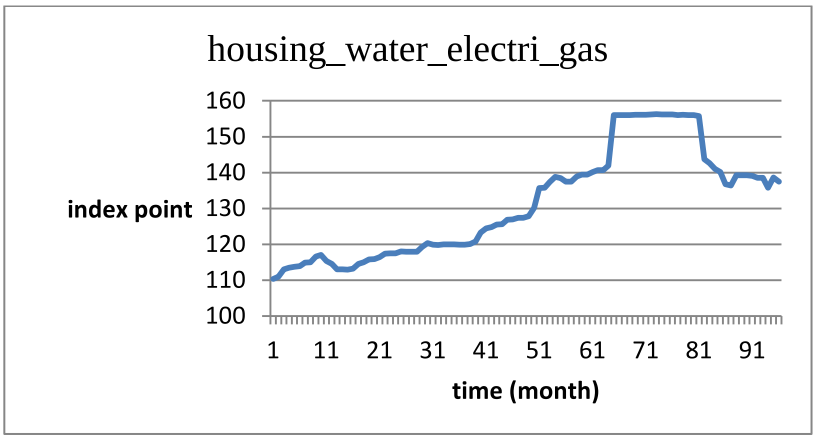


Figure 4.7: Trend in housing_water_electricity-gas 2008 – 2015

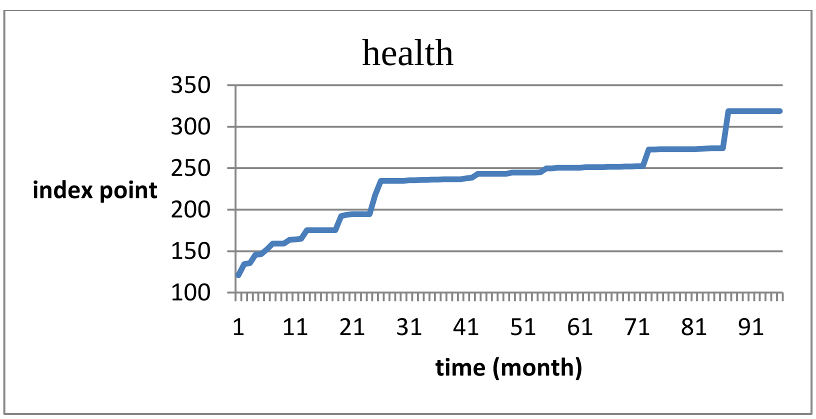


Figure 4.8: Trend in health 2008 - 2015

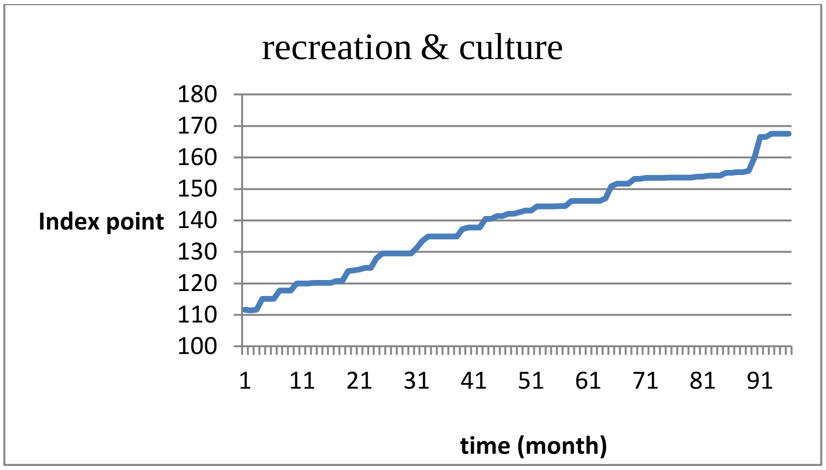


Figure 4.9: Trend in recreation and culture 2008 - 2015

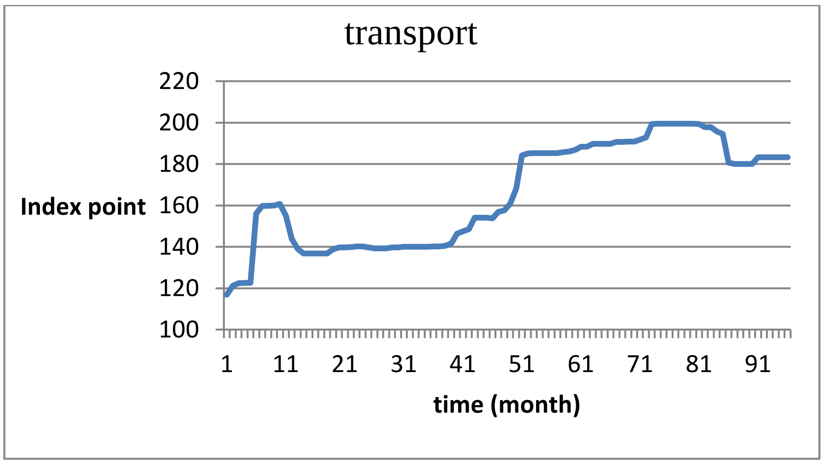


Figure 4.10: Trend in transport 2008 – 2015

As can be seen in the above figures clothing and footwear, furnishing, health, communication, recreation and culture, education and miscellaneous goods and services series have upward trend, (describe upward trend in the index) while the indices for housing, water electricity and gas and transport show some fluctuations. It seems that they are non stationary.

Table 4.2 : Correlation between Non Food and its sub components

Variable		N_F	C_F	COMMU	EDU	FURN	HEALTH
N_F	Pearson correlation	1.000	0.936	0.775	0.850	0.941	0.870
	P-Value		0.000	0.000	0.000	0.000	0.000
C_F	Pearson correlation	0.936	1.000	0.788	0.875	0.991	0.932
	P-Value	0.000		0.000	0.000	0.000	0.000
COMMU	Pearson correlation	0.775	0.788	1.000	0.876	0.834	0.900
	P-Value	0.000	0.000		0.000	0.000	0.000
EDU	Pearson correlation	0.850	0.875	0.876	1.000	0.884	0.947
	P-Value	0.000	0.000	0.000		0.000	0.000
FURN	Pearson correlation	0.941	0.991	0.834	0.884	1.000	0.953
	P-Value	0.000	0.000	0.000	0.000		0.000
HEALTH	Pearson correlation	0.870	0.932	0.900	0.947	0.953	1.000
	P-Value	0.000	0.000	0.000	0.000	0.000	
H_W_E_G	Pearson correlation	0..952	0.812	0.653	0.720	0.814	0.712
	P-Value	0.000	0.000	0.000	0.000	0.000	0.000
R_C	Pearson correlation	0.954	0.982	0.844	0.924	0.983	0.955
	P-Value	0.000	0.000	0.000	0.000	0.000	0.000
TRANS	Pearson correlation	0.951	0.834	0.609	.6960	.832	0.714
	P-Value	0.000	0.000	0.000	0.000	0.000	0.000
M_G_S	Pearson correlation	0.949	0.974	0.852	0.890	0.990	0.951
	P-Value	0.000	0.000	0.000	0.000	0.000	0.000

Variable		H_W_E_G	R_C	TRANS	M_G_S
N_F	Pearson correlation	0.932	0.954	0.931	0.949
	P-Value	0.000	0.000	0.000	0.000
C_F	Pearson correlation	0.812	0.982	0.834	0.974
	P-Value	0.000	0.000	0.000	0.000
COMMU	Pearson correlation	0.653	0.844	0.609	0.852
	P-Value	0.000	0.000	0.000	0.000
EDU	Pearson correlation	0.720	0.924	0.696	0.890
	P-Value	0.000	0.000	0.000	0.000
FURN	Pearson correlation	0.814	0.983	0.832	0.990
	P-Value	0.000	0.000	0.000	0.000
HEALTH	Pearson correlation	0.712	0.955	0.714	0.951
	P-Value	0.000	0.000	0.000	0.000
H_W_E_G	Pearson correlation	1.000	0.842	0.928	0.826
	P-Value		0.000	0.000	0.000
R_C	Pearson correlation	0.842	1.000	0.840	0.982
	P-Value	0.000		0.000	0.000
TRANS	Pearson correlation	0.928	0.840	1.000	0.848
	P-Value	0.000	0.000		0.000
M_G_S	Pearson correlation	0.826	0.982	0.848	1.000
	P-Value	0.000	0.000	0.000	

According to the table 4.2, all variables are significantly correlated with each other ($p<0.05$). All correlations are positive and greater than 0.60.

4.3 Check for Stationary

For Granger Causality test, it is necessary that all series should be stationary at the same level. Thus the original series, log series and 1st differences of the series were checked for stationarity. Results are shown in Tables from 4.3 to 4.8.

Table 4.3 : Results of the Augmented Dicky_ Fuller Unit Root Test for original data Series

Series	**Test Statistic of Augmented Dicky_ Fuller**	**P-Value**
CCPI (NON FOOD)	-1.100731	0.9230
CLOTHING & FOOTWEAR	-3.146615	0.9996
HOUSE_ELECTRICITY_ GAS_WATER_FUEL	-0.584638	0.9775
EDUCATION	-2.132463	0.5210
HEALTH	-2.782117	0.2076
RECREATION & CULTURE	-3.057254	0.1228
TRANSPORT	-1.965795	0.6120
FURNISHING	-2.513540	0.3211
MISCELLANEOUS GOODS & SERVICES	-4.218247	0.0062
COMMUNICATION	-2.020505	0.5825

Table 4.4 : Results of the Phillips-Perron Unit Root Test for original data Series

Series	Test Statistic of Phillips-Perron	P-Value
CCPI (NON FOOD)	1.856611	0.3514
CLOTHING & FOOTWEAR	0.354618	0.9800
HOUSE_ELECTRICITY_ GAS_WATER_FUEL	-1.367382	0.5951
EDUCATION	-2.260616	0.1869
HEALTH	-1.847118	0.3559
RECREATION & CULTURE	-0.537049	0.8781
TRANSPORT	-1.843336	0.3577
FURNISHING	-0.043653	0.9515
MISCELLANEOUS GOODS & SERVICES	-1.995998	0.2882
COMMUNICATION	-1.786866	0.3849

Results indicate that the null hypothesis cannot be rejected for the data series of the CCPI sub category variables as the respective p values are higher than 0.05. Thus it can be concluded that all series are not stationary at the original form.

Table 4.5 : Results of the Phillips-Perron Unit Root Test for Log Series of variables

Series	Test Statistic of Phillips-Perron	P-Value
LCCPI (NON FOOD)	-2.232978	0.1962
LCLOTHS & FOOTWEAR	-0.277388	0.9232
LHOUSE_ELECTRICITY_ GAS_WATER_FUEL	-1.428317	0.5653
LEDUCATION	-2.841611	0.0563
LHEALTH	-3.561034	0.0084
LRECREATION & CULTURE	-1.206414	0.6692
LTRANSPORT	-2.078975	0.2536
LFURNISHING	-0.874359	0.7924
LMISCELLANEOUS GOODS & SERVICES	-2.874096	0.0522
LCOMMUNICATION	-1.829797	0.3641

Table 4.6 : Results of the Augmented Dicky_ Fuller Unit Root Test for Log Series of variables

Series	Test Statistic of Augmented Dicky_ Fuller	P-Value
LCCPI (NON FOOD)	-1.372377	0.8629
LCLOTHS & FOOTWEAR	-1.545832	0.8066
LHOUSE_ELECTRICITY_ GAS_WATER_FUEL	-0.480400	0.9829
LEDUCATION	-2.275118	0.4430
LHEALTH	-3.868996	0.0171
LRECREATION & CULTURE	-2.923023	0.1602
LTRANSPORT	-2.200130	0.4837
LFURNISHING	-2.537401	0.3099
LMISCELLANEOUS GOODS & SERVICES	-4.845227	0.0008
LCOMMUNICATION	-2.000445	0.5934

As discussed for Table 4.5 and 4.6, results indicate that the null hypothesis cannot be rejected for the log series of the CCPI sub category variables as the respective *p* values are very much higher. Thus log series are also not stationary. Therefore data were transformed to log to reduce the heteroskedascify of the series and the first difference of the log series were considered for stationarity.

Table 4.7 : Results of the Phillips-Perron Unit Root Test for 1st Difference Series of Log of variables

Series	Test Statistic of Phillips-Perron	P-Value
DL CCPI (NON FOOD)	-8.004157	0.0000
DL CLOTHS & FOOTWEAR	-8.862712	0.0000
DL HOUSE_ELECTRICITY_ GAS_WATER_FUEL	-8.539189	0.0000
DL EDUCATION	-9.321523	0.0000
DL HEALTH	-9.880744	0.0000
DL RECREATION & CULTURE	-8.819989	0.0000
DL TRANSPORT	-7.923405	0.0000
DL FURNISHING	-8.616379	0.0000
DLMISCELLANEOUS GOODS & SERVICES	-9.636044	0.0000
DL COMMUNICATION	-10.01332	0.0000

Results in Table 4.7 indicate that the null hypothesis can be rejected for the 1st differenced series of log series of all the variables as the respective *p* values are less than the significance levels α = 0.01, 0.05 and 0.1. On the other hand it can be said that higher the negative value of test statistic, stronger the rejection of the hypothesis. Therefore it can be concluded that the 1st Difference of all log series are stationary.

Table 4.8: Results of the Augmented Dicky_ Fuller Unit Root Test for 1st Difference Series of Log Series

Series	Test Statistic of Augmented Dicky_Fuller test	P-Value
DL CCPI (NON FOOD)	-8.008642	0.0000
DL CLOTHS & FOOTWEAR	-8.663649	0.0000
DL HOUSE_ELECTRICITY_ GAS_WATER_FUEL	-8.527443	0.0000
DL EDUCATION	-9.309842	0.0000
DL HEALTH	-9.850471	0.0000
DL RECREATION & CULTURE	-8.840536	0.0000
DL TRANSPORT	-7.923405	0.0000
DL FURNISHING	-8.652140	0.0000
DLMISCELLANEOUS GOODS & SERVICES	-7.179318	0.0000
DL COMMUNICATION	-10.01235	0.0000

Results in Augmented Dicky Fuller test confirm that the 1st Difference of log series are stationary (which means joined distribution function is un-effected by shifting time axis forward or backward) by rejecting the null hypothesis (as it was mentioned earlier, higher the negative value of test statistic, the stronger the rejection of the hypothesis) and thus all are considered as I(1) level.

4.4 Estimation of Long - Run Equation

Since the variables are integrated of the same order I(1) it is required to estimate the long-run equilibrium relationship between these series. For this purpose, the simple regression was carried out taking LN_F (log of Non Food) as the response variable and other variables as explanatory variables. Summary result of the model and residuals are shown in Table 4.9 below.

Table 4.9: Results of the Estimated Simple Linear Regression model

Variable	**Co-efficient**	**P-value**
Dependent Variable: LN_F		
LM_G_S	-0.003665	0.7815
LH_W_E_G	0.357899	0.0000
LHealth	0.086173	0.0000
LFurnisher	0.110726	0.0000
LEducation	0.033089	0.0000
LCommunication	0.033902	0.0006
LC_F	0.038680	0.0000
LR_C	0.087082	0.0000
LTransport	0.038293	0.0000
C	0.062360	0.1375
R-Squared	0.999898	
Adjusted R-Square	0.999888	
DW Statistic	1.169839	
Sum squared residual	0.000144	
S.E. of regression	0.001293	
F-statistic	93960.83	

The results confirm that eight parameters (LHealth ,LEducation, LH_W_E_G, LFurnisher, LCommunication, LC_F, LR_C and LTransport) are statistically significant at 1% level. It can be seen that the R-squared and adjusted R-squared of the model are very high (0.999898, 0.999888) Furthermore Durbin-Watson statistic is not close to two (1.169839) confirming errors are not randomly distributed. Thus it can be concluded there is no possible evidence of the spurious regression.

4.5 Selection of Optimal Lag Length

A major requirement in conducting Johansen co-integration tests and estimation of a VECM system is the choice of an optimal lag length. In this study, the optimal lag length choice was made by examining the lag structure in an unrestricted VAR using lag order selection criteria. Minimum value of Akaike Information Criterion(AIC), Schwarz Information Criterion(SIC) and Hannan-Quinnin Information Criterion(HQ) had been considered to select the optimal lag length.

Table 4.10: VAR Lag Order Selection Criteria

Lag	AIC	SC	HQ
0	-49.95382	-49.67420	-49.84111
1	-68.99439	-65.91855*	-67.75461
2	-68.62476	-62.75269	-66.25790
3	-69.07334	-60.40506	-65.57941
4	-69.30189	-57.83738	-64.68087
5	-69.90691	-55.64618	-64.15882
6	-71.57462	-54.51767	-64.69945
7	-76.96343*	-57.11026	-68.96119*

Results in Table 4.10 indicate that minimum value of Akaike Information Criterion(AIC), and Hannan-Quinnin Information Criterion(HQ) (Peiris, T.S.G.,2012, Lecture Notes on Time series) indicators were obtained at Lag 7. Therefore it can be concluded that the optimal lag order is 7 for Johansen co-integration model. However, to apply Johansen co-integration test, variables should be non stationary at level and to be stationary at the first differences of each series.

4.6 Tests for Causality between Series

The next step of analysis is to test for causality between inflation and it's determinants in the long run. According to the results of VAR lag order selection criteria (Table. 4.10), it was decided to use lag length 7 for the Granger Causality test. The results (which do not Granger cause) are shown below in Table 4.11.

Table 4.11: Pair wise Granger Causality Test

Null Hypothesis	F-Statistic	Probability	Decision
DLC_F does not Granger Cause DLCOMMU	2.73618	0.0140	Rejected
DLC_F does not Granger Cause DLEDU	3.97157	0.0010	Rejected
DLHWEG does not Granger Cause DLC_F	2.31778	0.0343	Rejected
DLM_G_S does not Granger Cause DLC_F	2.51804	0.0224	Rejected
DLHEALTH does not Granger Cause DLEDU	2.18644	0.0452	Rejected
DLM_G_S does not Granger Cause DLEDU	4.00312	0.0009	Rejected
DLHWEG does not Granger Cause DLFURN	2.20545	0.0434	Rejected
DLM_G_S does not Granger Cause DLFURN	4.08226	0.0008	Rejected
DLFURN does not Granger Cause DLR_C	2.96342	0.0086	Rejected
DLTRANS does not Granger Cause DLFURN	3.05577	0.0071	Rejected
DLHWEG does not Granger Cause DLHEALTH	2.52481	0.0221	Rejected
DLHEALTH does not Granger Cause DLR_C	2.22687	0.0415	Rejected
DLTRANS does not Granger Cause DLHEALTH	2.88391	0.0102	Rejected
DLM_G_S does not Granger Cause DLR_C	3.46820	0.0029	Rejected

4.7 Estimation of the Johansen Co-integration Model

Since the variables are integrated of order one to test for co-integration, Johansen Co integration test was applied at the predetermined lag length to estimate the long run equilibrium relationship among the variables. In this test, maximum Eigen value statistics and trace statistics were compared to the corresponding critical values. Co-integration test for log transformation series are shown in Table 4.12 and Table 4.13.

Table 4.12 : **Unrestricted Co-integration Rank Test (Trace) for Log transformed Series**

Unrestricted Co-integration Rank Test				
Number of Co-integrating equation	Trace test			
	Eigen Value	Statistic	Critical Value (5%)	P-Value
None *	0.555875	298.7386	239.2354	0.0000
At most 1 *	0.428148	222.4435	197.3709	0.0015
At most 2 *	0.408663	169.9093	159.5297	0.0120
At most 3	0.323746	120.5247	125.6154	0.0981
At most 4	0.248481	83.75315	95.75366	0.2504
At most 5	0.204521	56.90126	69.81889	0.3426
At most 6	0.185407	35.39305	47.85613	0.4274
At most 7	0.093084	16.11673	29.79707	0.7040
At most 8	0.071095	6.932409	15.49471	0.5855
At most 9	0.000000	0.000016	3.841466	0.9991

Table 4.13 Unrestricted Co-integration Rank Test (Maximum Eigen Value) For Log transformed series

Unrestricted Co-integration Rank Test				
Number of Co-integrating equation	Maximum Eigen value test			
	Eigen Value	Statistic	Critical Value (5%)	P-Value
None *	0.555875	76.29503	64.50472	0.0000
At most 1	0.428148	52.53421	58.43354	0.1698
At most 2	0.408663	49.38463	52.36261	0.0979
At most 3	0.323746	36.77156	46.23142	0.3531
At most 4	0.248481	26.85189	40.07757	0.6434
At most 5	0.204521	21.50821	33.87687	0.6456
At most 6	0.185407	19.27632	27.58434	0.3934
At most 7	0.093084	9.184317	21.13162	0.8173
At most 8	0.071095	6.932393	14.26460	0.4972
At most 9	0.000000	0.000016	3.841466	0.9991

Results in Table 4.12 indicate that trace statistics are greater than critical value at 5% level only for the 1^{st} three Eigen values. Confirming H_0 is rejected at 5% significant level. Thus there is no co-integration among the series. However according to results in maximum Eigen test (Table 4.13) only the 1^{st} Eigen value test statistic is significant at 5% level, indicates that there exists a long run relationship among the variables. Hence it can be concluded that both series do not move together.

Table 4.14 : Unrestricted Co-integration Rank Test (Trace) for original Series

Unrestricted Co-integration Rank Test				
Number of Co-integrating equation	Trace test			
	Eigen Value	Statistic	Critical Value (5%)	P-Value
None *	0.640722	326.7633	239.2354	0.0000
At most 1 *	0.521053	230.5394	197.3709	0.0004
At most 2 *	0.387910	161.3399	159.5297	0.0397
At most 3	0.292900	115.1975	125.6154	0.1808
At most 4	0.244832	82.61872	95.75366	0.2825
At most 5	0.212877	56.22214	69.81889	0.3691
At most 6	0.164345	33.72132	47.85613	0.5171
At most 7	0.111175	16.84458	29.79707	0.6515
At most 8	0.059080	5.766166	15.49471	0.7230
At most 9	0.000445	0.041852	3.841466	0.8379

Table 4.15 : **Unrestricted Co-integration Rank Test for original Series**

Unrestricted Co-integration Rank Test				
Number of Co-integrating equation	Maximum Eigen value test			
	Eigen Value	Statistic	Critical Value (5%)	P-Value
None *	0.640722	96.22389	64.50472	0.0000
At most 1 *	0.521053	69.19950	58.43354	0.0032
At most 2	0.387910	46.14234	52.36261	0.1884
At most 3	0.292900	32.57882	46.23142	0.6194
At most 4	0.244832	26.39658	40.07757	0.6752
At most 5	0.212877	22.50082	33.87687	0.5689
At most 6	0.164345	16.87674	27.58434	0.5906
At most 7	0.111175	11.07841	21.13162	0.6398
At most 8	0.059080	5.724315	14.26460	0.6488
At most 9	0.000445	0.041852	3.841466	0.8379

The trace statistics are greater than the critical value at 5% significance level (p-value < 0.05) up to at most 2 and maximum Eigen value statistics are greater than the critical value at 5% significance level (p-value < 0.05) up to at most 1. Therefore, trace statistics confirm co-integrating equations at 5% level of significance and maximum Eigen value statistics test also indicate co-integrating equations at 5% level of significance. This indicates that there exists a long run relationship among the series and thus vector error correction model (VECM) can be explored.

4.8 Determination of Vector Error Correction Model

Since the variables are co-integrated, restricted VAR model known as vector error correction model (VECM) was applied to determine the short run relationship among series. Results are shown in Table 4.16.

Table 4.16: Co-integrating Results for Error Correction Model

Co-integrating Eq:	CointEq1
LN_F(-1)	1.000000
LC_F(-1)	0.410893
	(1.07531)
	[5.45607]
LCOMMU(-1)	-0.204519
	(0.07103)
	[-2.87948]
LEDU(-1)	-0.160577
	(0.06697)
	[-2.39785]
LFURN(-1)	-1.012829
	(0.14365)
	[-7.05043]
LHEALTH(-1)	0.143403
	(0.04347)
	[3.29926]
LH_W_E_G(-1)	-0.361199
	(0.03077)
	[-11.7390]
LM_G_S(-1)	0.633660
	(0.11432)
	[5.54291]
LR_C(-1)	-0.701045
	(0.10879)
	[-6.44414]
LTRANS(-1)	-0.214856
	(0.02204)
	[-9.74683]
C	2.113452

Coefficient estimated of the VEC model is presented in Table 4.17. Table 4.17 contains the detail of the co-integration vector which is derived by normalizing the CCPI(Non_Food). The long run equation is given as follows:

LN_F(-1) = 2.113452 + 0.410893*LC_F(-1) - 0.204519*LCOMMU(-1) - 0.160577*LEDU(-1) - 1.012829*LFURN(-1) + 0.143403*LHEALTH(-1) - 0.361199*LH_W_E_G(-1) + 0.633660*LM_G_S(-1) - 0.701045*LR_C(-1) - 0.214856* LTRANS(-1) …….. *(8)*

Table 4.17: Coefficients of the Error Correction Terms

Error Correction:	D(LN_F)	D(LC_F)	D(LCOMMU)	D(LEDU)	D(LFURN)	D(LHEALTH)	D(LHWEG)	D(LM_G_S)	D(LR_C)	D(LTRANS)
CointEq1	-0.151575	0.448058	-0.03582	-0.105655	0.175050	-0.846142	0.252887	-0.020633	0.136004	-0.870448
	(0.12986)	(0.12169)	(0.10076)	(0.11658)	(0.08434)	(0.29479)	(0.17851)	(0.06109)	(0.09483)	(0.34932)
	[-1.16723]	[3.68188]	[-0.35548]	[-0.90626]	[2.07557]	[-2.87031]	[1.41663]	[-0.33776]	[1.43417]	[-2.49184]
D(LN_F(-1))	0.669025	0.081826	-0.284305	-0.784751	-0.333466	0.242425	2.114618	-0.030748	0.292904	1.493960
	(0.99434)	(0.93181)	(0.77156)	(0.89269)	(0.64579)	(2.25724)	(1.36689)	(0.46776)	(0.72613)	(2.67477)
	[0.67284]	[0.08781]	[-0.36848]	[-0.87909]	[-0.51637]	[0.10740]	[1.54702]	[-0.06573]	[0.40338]	[0.55854]
D(LC_F(-1))	0.090138	-0.200543	0.029524	0.114018	0.026169	0.153039	-0.094141	0.030171	-0.002118	0.382532
	(0.15638)	(0.14654)	(0.12134)	(0.14039)	(0.10156)	(0.35499)	(0.21497)	(0.07356)	(0.11420)	(0.42066)
	[0.57641]	[-1.36848]	[0.24331]	[0.81214]	[0.25766]	[0.43110]	[-0.43793]	[0.41013]	[-0.01855]	[0.90937]
D(LCOMMU (-1))	-0.145134	-0.106884	-0.018663	-0.053568	-0.00579	-0.295312	-0.179411	0.137449	-0.079604	-0.291854
	(0.15976)	(0.14971)	(0.12396)	(0.14343)	(0.10376)	(0.36266)	(0.21961)	(0.07515)	(0.11666)	(0.42975)
	[-0.90847]	[-0.71394]	[-0.15055]	[-0.37349]	[-0.05581]	[-0.81429]	[-0.81694]	[1.82892]	[-0.68233]	[-0.67913]
D(LEDU(-1))	-0.061565	-0.102725	-0.013418	0.065939	-0.059202	0.051205	-0.097981	-0.033252	-0.009871	-0.227844

Table 4.17: Coefficients of the Error Correction Terms (conti.)

Error Correction:	D(LN_F)	D(LC_F)	D(LCOMMU)	D(LEDU)	D(LFURN)	D(LHEALTH)	D(LHWEG)	D(LM_G_S)	D(LR_C)	D(LTRANS)
D(LFURN(-1))	-0.09367	0.080474	0.116387	0.271334	-0.076959	0.280713	-0.544953	0.094357	-0.066672	0.108137
	(0.24924)	(0.23356)	(0.19340)	(0.22376)	(0.16187)	(0.56579)	(0.34262)	(0.11725)	(0.18201)	(0.67044)
	[-0.37583]	[0.34455]	[0.60181]	[1.21263]	[-0.47544]	[0.49615]	[-1.59055]	[0.80478]	[-0.36631]	[0.16129]
D(LHEALTH(-1))	-0.031543	0.152360	0.020320	0.061203	0.131174	-0.075082	-0.053802	-0.004579	-0.056024	-0.263403
	(0.10151)	(0.09513)	(0.07877)	(0.09114)	(0.06593)	(0.23045)	(0.13955)	(0.04775)	(0.07413)	(0.27307)
	[-0.31073]	[1.60157]	[0.25796]	[0.67155]	[1.98959]	[-0.32581]	[-0.38554]	[-0.09589]	[-0.75572]	[-0.96458]
D(LHWEG(-1))	-0.179868	-0.083588	0.093549	0.102057	0.112856	-0.183246	-0.636259	-0.034559	-0.091152	-0.377467
	(0.36307)	(0.34024)	(0.28173)	(0.32596)	(0.23580)	(0.82421)	(0.49911)	(0.17080)	(0.26514)	(0.97667)
	[-0.49540]	[-0.24567]	[0.33205]	[0.31310]	[0.47860]	[-0.22233]	[-1.27479]	[-0.20234]	[-0.34379]	[-0.38649]
D(LM_G_S(-1))	-0.204076	-0.54901	0.041809	-0.234683	-0.128672	0.247727	-0.323574	0.027822	-0.076434	-0.199347
	(0.22606)	(0.21185)	(0.17541)	(0.20295)	(0.14682)	(0.51318)	(0.31076)	(0.10635)	(0.16509)	(0.60811)
	[-0.90274]	[-2.59154]	[0.23834]	[-1.15634]	[-0.87640]	[0.48273]	[-1.04122]	[0.26162]	[-0.46300]	[-0.32782]
D(LR_C(-1))	-0.08087	0.067778	-0.075128	0.825269	0.056082	0.010977	-0.161999	-0.027897	0.092026	-0.392943
	(0.15817)	(0.14822)	(0.12273)	(0.14200)	(0.10273)	(0.35906)	(0.21743)	(0.07441)	(0.11551)	(0.42548)
	[-0.51129]	[0.45727]	[-0.61213]	[5.81174]	[0.54594]	[0.03057]	[-0.74505]	[-0.37493]	[0.79672]	[-0.92354]
D(LTRANS(-1))	-0.096614	-0.021615	0.055222	0.312349	0.038355	-0.16561	-0.447545	0.120015	-0.003839	-0.190018
	(0.24740)	(0.23184)	(0.19197)	(0.22211)	(0.16068)	(0.56162)	(0.34010)	(0.11638)	(0.18067)	(0.66551)
	[-0.39052]	[-0.09323]	[0.28766]	[1.40629]	[0.23871]	[-0.29488]	[-1.31594]	[1.03121]	[-0.02125]	[-0.28552]
C	0.003848	0.008486	0.001361	6.18E-05	0.004838	0.007021	0.003498	0.002902	0.004321	0.003539
	(0.00171)	(0.00161)	(0.00133)	(0.00154)	(0.00111)	(0.00389)	(0.00236)	(0.00081)	(0.00125)	(0.00461)
	[2.24438]	[5.28130]	[1.02297]	[0.04016]	[4.34434]	[1.80396]	[1.48400]	[3.59827]	[3.45107]	[0.76734]

Table 4.18 contains the coefficients of the error correction terms (cointEq1) for the co-integration vector. These coefficients are called the adjustment coefficients. This measures the short-run adjustments of the deviations of the endogenous variables from their long- run values. Thus, using the error correction term as another independent variable in the restricted VAR model, the following Vector Error Correction Model can be recommended.

LN_F(-1) = -0.151575*(LN_F(-1) + 0.410893*LC_F(-1) - 0.204519*LCOMMU(-1) - 0.160577*LEDU(-1) - 1.012829*LFURN(-1) + 0.143403*LHEALTH(-1) - 0.361199*LH_W_E_G(-1) + 0.633660*LM_G_S(-1) - 0.701045*LR_C(-1) - 0.214856* LTRANS(-1)) + 2.113452 + 0.669025*D(LN_F(-1))+0.090138*D(LC_F(-1))-0.145134*D(LCOMMU(-1))-0.061565*D(LEDU(-1))-0.09367*D(LFURN(-1))-0.031543*D(LHEALTH(-1))-0.1798668*D(LHWEG(-1))-0.204076*D(LM_G_S(-1))-0.08087*D(LR_C(-1))-0.096614*D(LTRANS(-1)) +.003848.... *(9)*

4.9 Check Long Run and Short Run Causality

LN_F(-1) = C(1)*(LN_F(-1) + 0.410893*LC_F(-1) - 0.204519*LCOMMU(-1) - 0.160577*LEDU(-1) - 1.012829*LFURN(-1) + 0.143403*LHEALTH(-1) - 0.361199*LH_W_E_G(-1) + 0.633660*LM_G_S(-1) - 0.701045*LR_C(-1) - 0.214856* LTRANS(-1))+ C(2)* D(LN_F(-1)) + C(3)*D(LC_F(-1)) + C(4)*D(LCOMMU(-1)) + C(5)*D(LEDU(-1)) + C(6)*D(LFURN(-1)) + C(7)*D(LHEALTH(-1))+C(8)*D(LH_W_E_G(-1))+C(9)*D(LM_G_S(-1))+C(10)*D(LR_C(-1)) +C(11)*D(LTRANS(-1))+C(12) ……… *(10)*

Table 4.18: Error Correction Terms to Determine Long Run Causality

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.151575	0.129858	-1.167230	0.2465
C(2)	0.669025	0.994337	0.672835	0.5029
C(3)	0.090138	0.156378	0.576411	0.5659
C(4)	-0.145134	0.159757	-0.908472	0.3663
C(5)	-0.061565	0.126317	-0.487382	0.6273
C(6)	-0.093670	0.249235	-0.375831	0.7080
C(7)	-0.031543	0.101515	-0.310728	0.7568
C(8)	-0.204076	0.226062	-0.902741	0.3693
C(9)	-0.080870	0.158170	-0.511286	0.6105
C(10)	-0.096614	0.247400	-0.390518	0.6972
C(11)	-0.179868	0.363073	-0.495404	0.6216
C(12)	0.003848	0.001715	2.244377	0.0275

According to the results in table 4.18 there is no long run causality on dependent variable.

Table 4.19: Error Correction Terms to Determine Short Run Causality (Wald Test)

Test Statistics	Value	Probability
F-statistic	0.893850	0.5426
Chi-square	8.938497	0.5380

A result of Table 4.19 indicates that both test statistics are not significant (P value > 0.05) and thus H_0 is not rejected. It means all the coefficients of independent variables jointly not influence in dependant variable. There is no short run causality on dependant variable.

4.10 Model Checking

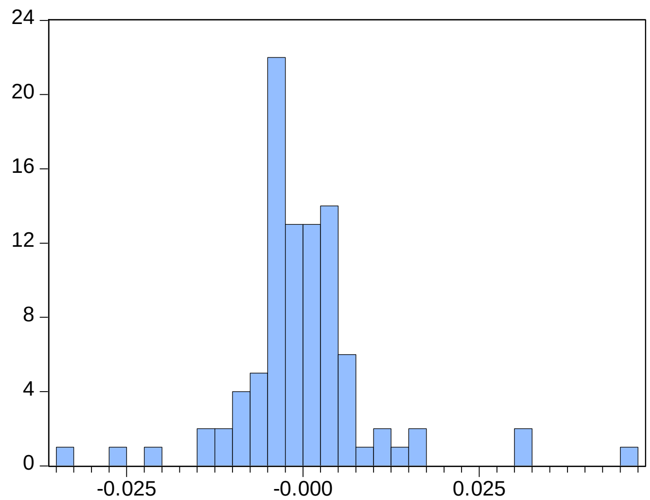
In order to ascertain whether the model provides an appropriate representation, a test for misspecification should be performed.

Table 4.20: Test of Residual Autocorrelation

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |. |	. |. |	1	0.005	0.005	0.0022	0.963
. |. |	. |. |	2	0.004	0.003	0.0034	0.998
. |. |	. |. |	3	-0.048	-0.048	0.2337	0.972
. |. |	. |. |	4	0.065	0.066	0.6525	0.957
**|. |	**|. |	5	-0.255	-0.257	7.1791	0.208
**|. |	**|. |	6	-0.214	-0.224	11.808	0.066
. |* |	. |* |	7	0.091	0.107	12.662	0.081
. |* |	. |* |	8	0.093	0.077	13.559	0.094
. |. |	. |. |	9	-0.031	-0.026	13.659	0.135
. |. |	. |. |	10	0.060	0.034	14.047	0.171

Table 4.20 presents the results of the Correlogram Q-statistic test for VEC model residual serial correlation. These tests are used to test for the overall significance of the

residual autocorrelations. Both results suggest that there is no obvious residual autocorrelation problem up to lag 2 because all p-values are larger than the 0.05 level of significance.



Series: Residuals	
Sample 4 96	
Observations 93	
Mean	1.36e-17
Median	-0.001091
Maximum	0.046175
Minimum	-0.033631
Std. Dev.	0.010057
Skewness	1.112361
Kurtosis	9.523061
Jarque-Bera	184.0614
Probability	0.000000

Figure 4.11: Normality Test

A result of Figure 4.11 implied that Jarque-Bera value is 184.0614 and the corresponding P value is 0.0000 less than 0.05; Confirming that residuals are not normally distributed at 5% level.

Table 4.21: Test of Serial Correlation

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	3.776408	Probability	0.000406
Obs*R-squared	32.34048	Probability	0.000351

Result of Table 4.21, indicate that P value is less than 5%, indicating that H_0 is rejected. Thus it can conclude that this model has any serial correlation.

Table 4.22: ARCH LM Test

ARCH Test:

F-statistic	0.408210	Probability	0.938572
Obs*R-squared	4.448455	Probability	0.924858

Results of Table 4.22 in implied that fitted model does not have any ARCH effect since P value is 0.75%.

Table 4.23: White Heteroscedasticity Test

White Heteroscedasticity Test

F-statistic	3.085196	Probability	0.000072
Obs*R-squared	64.88158	Probability	0.005739

Results of table 4.23, indicates that residuals are heteroscedasticity ($p < 0.05$).

4.11 Summary

Over the time period considered, all ten series showed an increasing pattern and as results of all series are non stationary. Unit root tests also confirmed that all series are non stationary at level, but stationary at first difference, at 5% significant level. In order to develop a VAR (either resticted or unresticted) model, the unit root tests (ADF and Phillips-Perron tests), identification of the number of lags and co-integration analyses were carried out. The Johansen co-integration test suggests that there are three co-integration vectors, which describes the long run short run relationship CCPI(Non Food) and its' endogenous variables. The appropriate number of lag identified was seven. Since the series are cointegrated, Granger causality test is applied to explore the long run relationships using unresticted vector error correction model. Granger causality test indicates that relationship exists among CCPI(Non_Food) and its' endogenous variables.

CHAPTER 5

Conclusions Recommendations and Suggestions

5.1 Conclusions

The aim of this study is to generate a multivariate time series model for CCPI (non food) and its sub components which can be used to forecast the CCPI (non food) in Sri Lanka. Prediction of CCPI in a given country helps to outline relevant policy measures which can be used to forecast the index for Sri Lanka. Monthly series of nine non food categories from 2008 to 2015 namely clothing and footwear, housing _ water_ electricity _gas and fuel, health, education, furnishing, communication, transport, recreation and culture and miscellaneous goods and services are treated in this study. As the series are cointegrated, restricted vector autoregressive model (VAR) was developed. The model and all the parameters in the model were significant at least 10% level. The residuals of the fitted model were white noise. Furthermore it was found that causality is running from non food to its sub categories and there are one way causal relationships among these sub categories. The long run equation is given as follows:

LN_F(-1) = 2.113452 + 0.410893*LC_F(-1) - 0.204519*LCOMMU(-1) – 0.160577*LEDU(-1) - 1.012829*LFURN(-1) + 0.143403*LHEALTH(-1) - 0.361199*LH_W_E_G(-1) + 0.633660*LM_G_S(-1) - 0.701045*LR_C(-1) - 0.214856* LTRANS(-1)

The results also reveal that there is a stable CCPI (non food) function in the long run in Sri Lanka and indicates the reliability of forecasting CCPI (non food) using its sub components mentioned above as key determinants. Results derived in this study have more practical implications for government policy planners, researchers and academic in the field of study.

5.2 Recommendations

- It is recommended to carry out such studies more often.
- This model can be used to forecast GDP implicit deflator.
- This study emphasize the need to put in place a stable macroeconomic policy environment relating to these variables in an effort to maintain price stability, for enhancing social well being in Sri Lanka.

5.3 Suggestions

- Personal Consumption Expenditure (PCE) is a significant indicator in the field of econometrics. PCE can be identified as the value of total consumption by the people within the economic boundary of a nation for a given period. When aggregating PCE it is assumed that all consumer items are included and valued. It can be recommended that series of PCE and CCPI could have a strong association and possibly one series could be used as a proxy to forecast or to identify the behavior of the other series.

- Results come out of this project will also help in utilizing on forecasting the GDP with a very strong proxy through CCPI. When GDP is increasing there is a higher possibility of avoiding the demand pull inflation and cost push inflation.

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