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**FOOD PRICE DYNAMICS AND INFLATION IN SRI LANKA**

**BY**
**SELLIAH SIVARAJASINGHAM**

UUM
Universiti Utara Malaysia

**Thesis Submitted to**
**the School of Economics, Finance and Banking,**
**Universiti Utara Malaysia,**
**in Fulfilment of the Requirements for the Degree of Doctor of Philosophy**

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**Kolej Perniagaan**
*(College of Business)*
**Universiti Utara Malaysia**

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|---|---|---|
| Nama Pelajar<br>(Name of Student) | : | Sivarajasingham |
| Tajuk Tesis / Disertasi<br>*(Title of the Thesis / Dissertation)* | : | Food Price Dynamics and Inflation in Sri Lanka |
| Program Pengajian<br>*(Programme of Study)* | : | Doctor of Philosophy |
| Nama Penyelia/Penyelia-penyelia<br>*(Name of Supervisor/Supervisors)* | : | Assoc. Prof. Dr. Shri Dewi Applanaidu<br>Tandatangan |
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## ABSTRACT

Food price contributes the largest share in the general price index in developing countries. Consequently, the nature of food price dynamics, global and domestic food price and volatility transmission influence the general price inflation. The main objective of the study is to examine food price dynamics and inflation in Sri Lanka for the period of 2003M1-2014M12 by focusing on two perspectives: i) long memory of food price inflation and ii) food price transmission. This study attempts to examine specifically (i) the long memory properties of food price dynamics, (ii) the transmission of global food price dynamics to domestic prices, (iii) the transmission of global food price volatility to domestic prices, and (iv) the spillover effects of domestic food prices on overall consumer price. Rescaled range statistic, Geweke and Porter–Hudak statistic, Local Whittle estimator, autoregressive fractional integrated moving average model and fractional integrated generalised autoregressive conditional heteroscedastic model were used to estimate the long memory parameter of the food price series. Cointegration technique, error correction models, Granger causality analysis, and impulse response function analysis (IRF) were employed to investigate the price transmission effects. The long memory analysis shows that all food price and volatility series possess long memory. The cointegration and causality analysis show that the global food price and volatility transmit significantly to the domestic prices. In addition, the results also reveal that the domestic food prices influence positively and significantly the overall consumer price. IRF analysis also shows that there is a positive shock of global food price on the domestic prices which lasts for longer periods. Hence, the policy makers are recommended to take into account food prices in computing core inflation which is used for monetary policy in Sri Lanka.

**Keywords:** food price, inflation, long memory, price transmission, volatility

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# ABSTRAK

Harga makanan menyumbang sebahagian terbesar dalam indeks harga umum di negara-negara membangun. Oleh itu, sifat dinamik harga makanan, harga makanan global dan domestik dan transmisi turun naik mempengaruhi inflasi harga umum. Objektif utama kajian ini adalah untuk mengkaji dinamik harga makanan dan inflasi di Sri Lanka bagi tempoh 2003M1-2014M12 dengan memberi tumpuan kepada dua perspektif iaitu (i) memori jangka panjang inflasi harga makanan, (ii) transmisi harga makanan. Kajian ini bertujuan untuk mengkaji secara khusus (i) sifat-sifat memori jangka panjang dinamik harga makanan, (ii) transmisi dinamik harga makanan global kepada harga domestik, (iii) transmisi turun naik harga makanan global kepada harga domestik, dan (iv) kesan limpahan harga makanan domestik pada harga pengguna secara keseluruhannya. Statistic julat pengkalaan semula, statistik Geweke dan Porter-Hudak, peramal Whittle tempatan, model purata autoregresif pecahan bersepadu bergerak dan model pecahan bersepadu umum autoregresif heteroskedastik bersyarat digunakan untuk menganggar parameter memori jangka panjang siri harga makanan. Teknik kointegrasi, model pembetulan ralat, analisis sebab-akibat Granger dan analisis fungsi tindak balas dorongan (IRF) telah digunakan untuk menyelidik kesan transmisi harga. Analisis memori jangka panjang menunjukkan bahawa semua harga makanan dan turun naik siri memiliki memori jangka panjang. Analisis kointegrasi dan analisis sebab-akibat menunjukkan bahawa harga makanan global dan transmisi turun naik adalah signifikan bagi harga domestik. Di samping itu, keputusan juga menunjukkan bahawa secara keseluruhannya harga makanan domestik mempengaruhi harga pengguna secara positif dan signifikan. Analisis IRF pula menunjukkan bahawa terdapat satu kejutan positif harga makanan global ke atas harga domestik yang berlaku bagi tempoh yang lebih lama. Oleh itu, pembuat dasar disyorkan untuk mengambil kira harga makanan dalam pengukuran rasmi inflasi teras yang digunakan dalam dasar kewangan di Sri Lanka.


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**Kata kunci**: harga makanan, inflasi, memori jangka panjang, transmisi harga, turun naik

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# LIST OF ABBREVIATIONS

| | |
|---|---|
| ACF | Autocorrelation Function |
| AD | Aggregate Demand |
| ADB | Asian Development Bank |
| ADF | Augmented Dickey-Fuller |
| AGARCH | Asymmetric GARCH |
| AIC | Akaike Information Criteria |
| AR | Autoregressive |
| ARCH | Autoregressive Conditional Heteroscedasticity |
| ARFIMA | Autoregressive Fractional Integrated Moving Average |
| ARIMA | Autoregressive Integrated Moving Average |
| ARMA | Autoregressive Moving Average |
| CBSL | Central Bank of Sri Lanka |
| CFPI | Consumer Food Price Index |
| CNFPI | Consumer Non-Food Price Index |
| CII | Core Inflation Index |
| CIRF | Cumulative Impulse Response Function |
| CPI | Consumer Price Index |
| CV | Coefficient of Variation |
| CVINFGFPI | Conditional Variance of Global Food Price Inflation |
| CUSUM | Cumulative Sum |
| DCS | Department of Census and Statistics |
| DM | Domestic Market |
| ECM | Error Correction Model |
| EGARCH` | Exponential Generalized Autoregressive Conditional Heteroscedastic |
| EML | Exact Maximum Likelihood |
| ER | Exchange Rate |
| FAO | Food and Agriculture Organization |
| FER | Food Expenditure Ratio |
| FIGARCH | Fractionally Integrated GARCH |
| FIEGARCH | Fractionally integrated exponential GARCH |
| FIML | Full Information Maximum Likelihood |

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| | |
|---|---|
| GDP | Gross Domestic Product |
| GARCH | Generalized Conditional Heteroscedastic |
| GCT | Granger Causality Test |
| GPH | Geweke and Porter-Hodak |
| GFPI | Global Food Price Index |
| GJR | Glosten, Jaganathan, and Runkle |
| GNP | Gross National Product |
| H | Hurst Exponent |
| HL | Half Life |
| HIES | Household Income and Expenditure Survey |
| HP | Hodrick-Prescott |
| HPT | Horizontal Price Transmission |
| HQIC | Hannan-Quinn Information Criterion |
| IHPT | Indirect Horizontal Price Transmission |
| IGARCH | Integrated GARCH |
| IMF | International Monetary Fund |
| INFCFPI | Inflation of Consumer Food Price Index |
| INFCPI | Inflation of Consumer Price Index |
| INFCNFPI | Inflation of Consumer Non-Food Price Index |
| INFWFPI | Inflation of Wholesale Food Price Index |
| INFWPI | Inflation of Wholesale Price Index |
| INFGFPI | Inflation of Global Food Price Index |
| IP | Inflation Persistence |
| IPI | Implicit Price Index |
| IRF | Impulse Response Function |
| KPSS | Kwiatkowski-Phillips-Schmidt-Shin |
| LAR | Largest Autoregressive Root |
| LCPI | Natural log of Consumer Price Index |
| LCFPI | Natural log of Consumer Food Price Index |
| LCNFPI | Natural log of Consumer Non-Food Price Index |
| LER | Natural log of exchange rate |
| LGFPI | Natural log of global food price |
| LMSV | Long Memory Stochastic Volatility |

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| | |
|---|---|
| LOILP | Natural log of Oil price Index |
| LOP | Law of One Price |
| LM | Lagrangian Multiplier |
| LR | Likelihood Ratio |
| LWE | Local Whittle Estimator |
| LWFPI | Natural log of Wholesale Food Price Index |
| LWPI | Natural log of Wholesale Price Index |
| MLE | Maximum Likelihood Estimation |
| MPL | Modified Profile Likelihood |
| NLS | Nonlinear Least Square |
| OECD | Organization for Economic Co-operation and Development |
| OILP | Oil Price Index |
| OLS | Ordinary Least Squares |
| PCM | Perfect Competitive Market |
| PP | Phillips–Perron |
| PT | Price Transmission |
| R/S | Rescaled Range Statistic |
| SARC | Sum of Autoregressive Coefficients |
| SDE | Spectral Density Estimate |
| SIC | Schwarz Information Criterion |
| SZF | Spectrum at Zero Frequency |
| SSA | Sub-Saharan Africa |
| SV | Stochastic Volatility |
| TGARCH | Threshold GARCH |
| UC | Unobserved Component |
| UK | United Kingdom |
| U.S | United States |
| USD | United States Dollar |
| VAR | Vector Autoregressive |
| VPT | Vertical Price Transmission |
| VR | Variance Ratio |
| VECH | Vector Error Correction Model |

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| | |
|---|---|
| UC | Unobserved component |
| UC-SV | Unobserved Component Stochastic Volatility |
| UNCTAD | United Nations Conference on Trade and Development |
| WFPI | Wholesale Food Price Index |
| WM | World Market |
| WPI | Wholesale Price Index |

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# CHAPTER ONE

# INTRODUCTION

## 1.1 Background of the Study

Price stability is one of the principal economic goals of the central bank in an economy. Potential success in any price stabilization effort depends on understanding the characteristics of the inflation dynamics. The general price dynamics play a prominent role in macroeconomic policy. Price dynamics refers to its behavior over time (Frisch, 1936). According to Luenberger (1979), "The term dynamic refers to the phenomena that produce time-changing patterns, the characteristics of the pattern at one time being interrelated with those at other times".

The general price level is measured by consumer price index (CPI) of all items; goods and services including food in general. The CPI for food (CFPI) is a component of all items CPI. The CFPI measures the changes in the retail prices of food items only. As food expenditure accounts for the larger portion of CPI, food price dynamics play a vital role in general price dynamics. Food prices are the most visible and best published of all elements of the CPI which are commonly used to measure general price inflation (Davidson, Halunga, Lloyd, McCorriston and Morgan, 2012).

The average general price movements and price movements of food commodities have been one of the most crucial economic, political and social issues in a globalized world. Thus, key properties of price dynamics are of interest in micro and macroeconomics, namely i) average price changes (general price inflation dynamics), the variability of price changes (price volatility dynamics), and iii) long memory of price changes. Food price dynamics in the past decades on a global level have been major components of unanticipated increases in the general inflation rate.

The frequent and wide fluctuations of food commodity prices have directly influenced the stability of food prices. Food prices affect an economy or world economy in several ways, such as the cost of living, investment and trade balance. Therefore, food price dynamics can have nontrivial implications on business cycle fluctuations of developing and developed countries. In addition, it has also been observed that dynamics of average and variability of general price in general, and food price in particular in developing countries differ from those in developed countries (Minot, 2011).

South Asian economies are continuously having relatively high fiscal deficits, public debt burdens, more expansionary fiscal policies, and low monetary policy rates. The expenditure on food consumption which is more than one-third of household total expenditure, is the salient feature of developing economies. Food expenditure share in CPI for developing countries is more than 30 percent on average (ADB, 2011). Thus, inflation dynamics in developing countries differ from those in developed countries. Since food expenditure share for most of the developing countries is larger in their household total consumption expenditure compared to developed countries, food price becomes the dominant contributor to general inflation in developing countries than in developed countries.

The common feature of food price dynamics in the world food market has been rising, highly volatile and very persistent dynamics. In the case of developing countries, Walsh (2011) had highlighted that the distinguished characteristics of food price behavior are high level and a high degree of volatility. Global food prices showed sudden increases multiple times and remained very volatile during the period 2007-2012 (Mishra & Roy, 2012). The evolution of food prices over the last decade and the characteristics of various food commodity prices are shown in Figure 1.1. The price index for food items designed by the Food and Agriculture Organization (FAO) is used as a proxy for the world food price level. This food price index is called global food price index, denoted by GFPI. The GFPI is calculated using five commodity price indices of cereals, meat, dairy, vegetable oils, and sugar. All these commodity prices are moving in tandem with an increasing trend and a higher degree of volatility (Figure 1.1). Cereals, dairy, and sugar recorded high increases in particular.

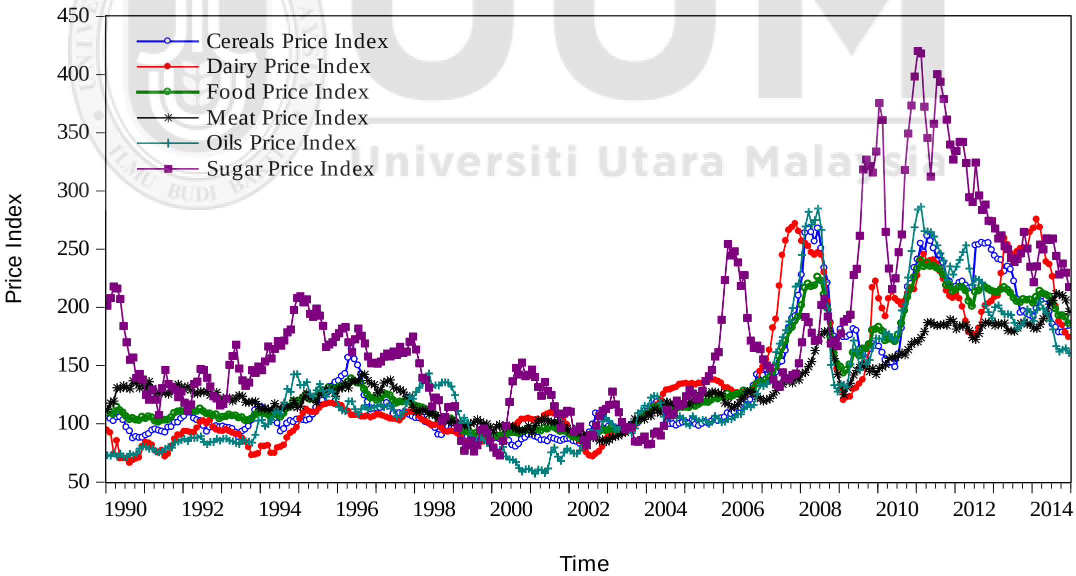


Figure 1.1
*World Commodity Price Dynamics, 1990M1-2014M12*

Since 2003, global food prices started to increase exponentially and had experienced a significant steep growth since the second half of 2007. Food prices in global level are likely to fall somewhat for some time periods, but not to the previous average level.

It seems to be higher than the previous average level. Many researchers concluded that prices of food items are expected to high persistence and more volatile (FAO, IMF & UNCTAD, 2011). In terms of price levels, many medium–long-term projection models suggested that food commodity prices will remain relatively high over the next decade or so.

The layering of multiple drivers of food commodity price dynamics, long memory of the food commodity price series and inflation expectations will keep food prices higher in the coming decades than in the past. There are several explanations for food price increases at the global level in the past. Food price rise may be attributed to multiple and diverse sources of structural and cyclical factors (Gilbert, 2010). These factors can be categorized into two parts; demand driven factors and supply side factors. From demand side: i) increasing world demand for food products due to economic improvements in big developing economies such as India, China, ii) growing production of biofuels and ethanol in the U.S. and Europe, have increased the demand for food products as inputs, iii) there was speculation in futures markets for food commodities, iv) easy monetary policy in the U.S. and v) weakening dollar (depreciating dollar) led to inflationary pressures. The role of the depreciation of the USD was a significant factor for food commodity price rises (Abbott, Hurt & Tyner, 2009). Carrasco and Mukhopadhyay (2012), Timmer (2008), and Headey and Fan (2008) have also highlighted the factors that caused food price rises. Supply-side factors are i) low research and development investments in food commodity sector reduce productivity and production hence supply of food, ii) higher input prices of oil and fertilizers limit the supply of food production, iii) domestic policy interventions such as trade barriers and export restrictions due to higher food prices tighten the world supply of food commodities, and iv) weather shocks such as droughts affects the supply of food.

High and persistent characteristics of food price inflation dynamics are a crucial macroeconomic challenge and may have distressing impacts in developing countries. Food price inflation has a harmful impact on the real income, nutrition and health of the poor consumers. It can also affect the sustainable growth of an economy. Higher food prices affect people in dissimilar economies differently. The impacts of food price inflation tend to be much greater for countries that are net importers of food and has CPI with higher weights of food expenditure. Figure 1.2 shows the impact of rising food prices on CPI inflation in various developed and developing economies.

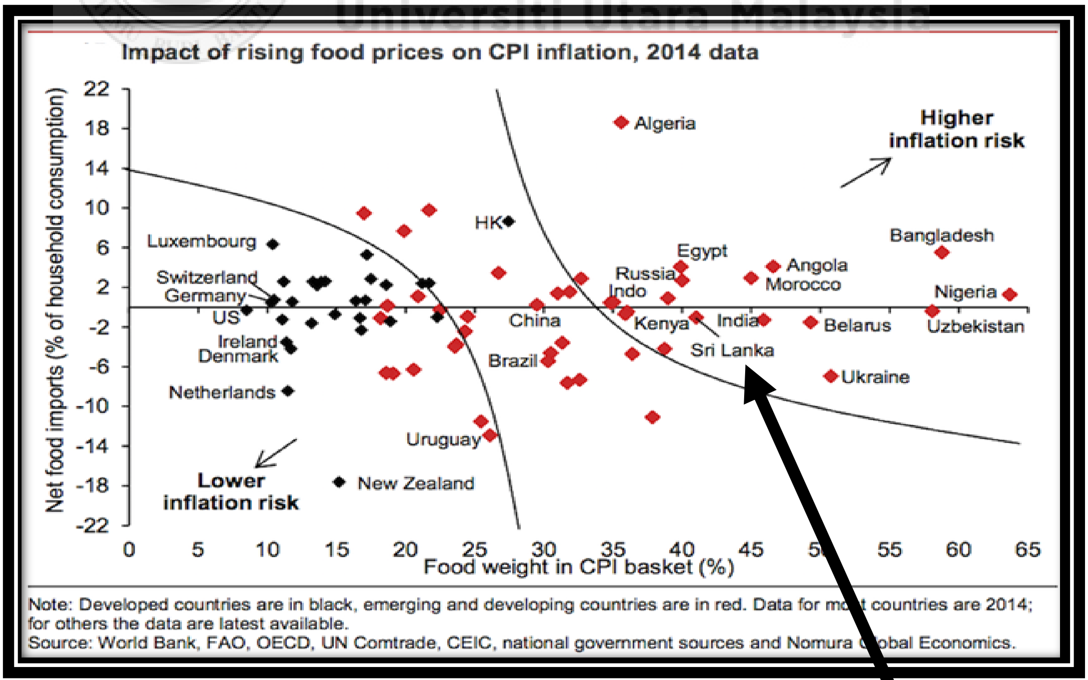


Figure 1.2
*Impact of Rising Food Prices on CPI Inflation, 2014*
Source: Adopted from Nomura (2015)

The impact of food price increases on CPI inflation is substantially larger in developing countries than in developed countries. Apparently, Sri Lanka, in particular, is located in the higher inflation risk area.

Further, global food prices have been one of the most significant sources of domestic headline inflation and food price and its volatility increases in developing countries over the past few years. Domestic food prices move with international food prices closely. These global price movements lead to changes in local headline inflation, local food price inflation and inflation expectations either directly or through second round effects. In every country, the increase in the domestic food price is not only caused by global food price rise, but also crude oil price rise in the world market. Hence, the general inflation around the world increased not only because of global food prices but also domestic food prices since food has a higher share in CPI.

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The combined intertemporal effect that food price, fuel price, and financial crisis had on the world economy was pervasive and was negative. Not only higher prices of food commodities but also higher volatility of food price have a severe impact on the economy. Food prices have been experiencing large volatility in the last decade. Figure 1.1 shows that all commodity prices are volatile. Average price (levels) and price volatility tend to be positively related. Nobel Laureate Friedman (1977) had stated that inflation and uncertainty are positively associated. The high and sustained food price volatility generate considerable uncertainty for market participants such as farmers, consumers, and traders. Specifically, a higher inflation increases the insecurity of investment decisions and distorts the projections of investors and savers.

Thus, food price volatility tends to reduce private investment in development projects with a long–term horizon. Investments are vital for economic growth. Fluctuations in food commodity prices induce fluctuations in real income and pose problems for macroeconomic management. An economy operating under instability will discourage both foreign and domestic investment. World food price volatility and exchange rate volatility can create uncertainty in total expenditure of imports. Foreign exchange savings can be exhausted relatively with food price increase since the price elasticity of import demand for food is low. Food and Nations (2001) report showed that costs of cereal import had led to a substantial increase in the deficit of current account of the balance of payment in some countries that are net importers. According to Gilbert and Morgan (2010), food price volatility may increase the deficits further in the future.

Table 1.1 shows price volatility statistics for selected commodities. Standard deviation (SD) and coefficient of variation (CV) are used to measure the volatility of food price series. CV is a better measure of spread since SD is dependent on the magnitude of the measured values. According to the table, sugar prices are most volatile. Prices of dairy and vegetables are also more volatile compared to meat price series but less than that of sugar price volatility. The volatility of aggregate food price series is relatively lower than that of the individual commodity prices except meat.

Table 1.1
*Volatility Statistics for Selected Food Price Series in the World Market:1990M1-2014M12*

| **Commodities** | **Standard Deviation** | **Coefficient of Variation** |
|---|---|---|
| Cereals | 53.26 | 39 |
| Dairy | 58.43 | 43 |
| Sugar | 76.40 | 43 |
| Vegetable oils | 55.76 | 42 |
| Meat | 30.19 | 23 |

| | | |
|---|---|---|
| Food* | 44.79 | 33 |

Note: Food*: the average of cereals, dairy, meat, vegetable oils, sugar price indices
Source: Author’s calculation based on FAO data.

Persistent food price instability can also have hostile macroeconomic consequences by preventing economic development. It is generally accepted that unanticipated changes in the rate of inflation impose costs on society (Bach & Ando, 1957; Ackley, 1978). In recent decades, food price increases have been major components of unanticipated increases in the general inflation rate. Thus, food price increases have been a basic source of imposed social costs (Lamm, 1979). Food price increases and its volatility are a threat to the economic stability of a country (Bellemare, 2015). It creates macro vulnerabilities. In summary, all consequences of food price and inflation dynamics depend on the memory properties of food price and inflation dynamics and transmission effects.

## 1.2 Food Price Dynamics in Sri Lanka

This section covers the dynamics of food price level, food price inflation and food price inflation volatility in Sri Lanka.

### 1.2.1 Dynamics of Food Prices

Figure 1.3 illustrates the dynamics of consumer and producer food prices and overall consumer prices in Sri Lanka. It is clear that food prices increase expressively since 2003. The CPI and CFPI move together over time. The CFPI has been consistently more volatile and high in magnitude compared to CPI for non-food items (CNFPI).

During the period of 2003M1-2014M12, the CFPI, CNFPI and wholesale food price index (WFPI) increased by 201 percent, 128 percent, and 207 percent respectively.

Figure 1.3 also shows that CNFPI had been higher than CFPI and WFPI before 2007. However, the trend has changed since 2007, where CFPI and WFPI exceeded CNFPI. The gap between food price and nonfood price series has also widened since 2007. Apparently, CFPI and WFPI move in tandem.

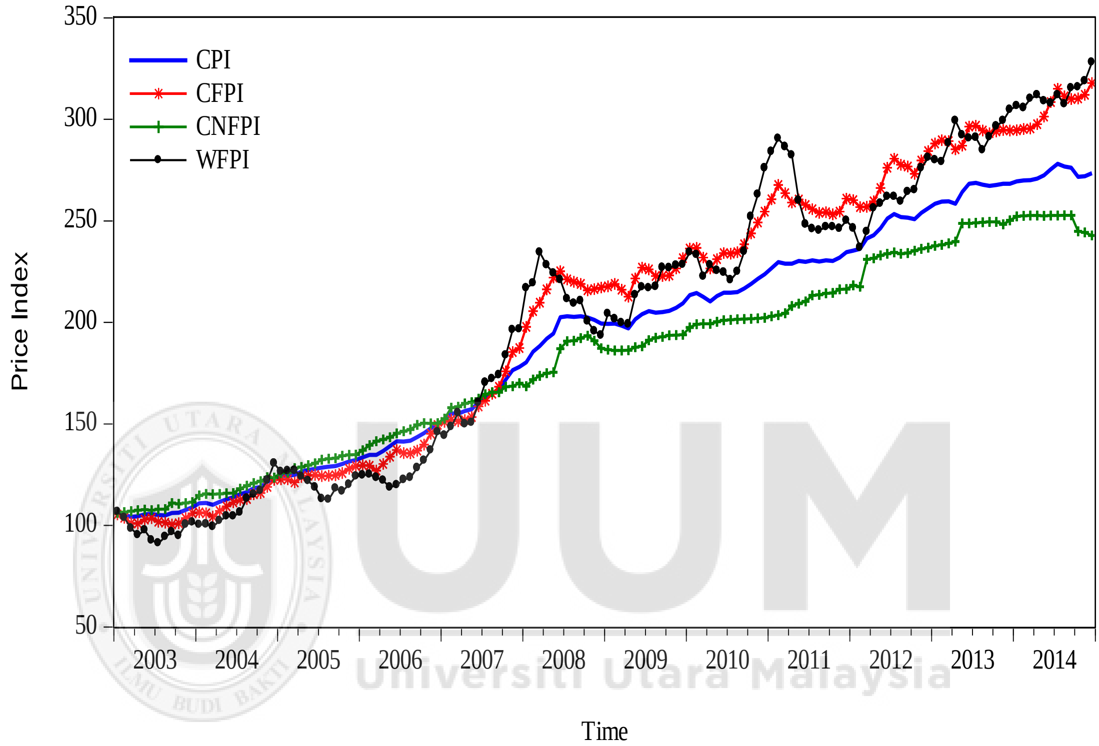


Figure 1.3
*Food and Non-Food Price Behaviour in Sri Lanka, 2003M1-2014M12*

The study period is divided into two; (i) period I is from 2003M1-2007M9, and Period II is from 2007M10-2014M12. An average price and variability of each price index series are reported in Table 1.2. Average price of all price series in Period II is higher than that of all price series in period I. But, the volatility of each price based on SD in period II is higher than that of all price series. Among all these price series, CFPI and WFPI have the higher variability than CNFPI series.

Table 1.2
*Mean and Variability for Selected Price Indices between Periods I and II*

| **Price Indices** | **Period I (2003M2-2007M9)** | | **Period II (2007M10-2014M12)** | |
|---|---|---|---|---|
| | **SD** | **Mean** | **SD** | **Mean** |
| CPI | 18.56 | 128.25 | 29.71 | 230.93 |
| CFPI | 18.86 | 124.78 | 35.00 | 254.87 |
| WFPI | 20.84 | 120.85 | 38.09 | 253.47 |
| CNFPI | 18.45 | 131.29 | 26.55 | 214.30 |
| WPI | 23.96 | 130.98 | 39.19 | 253.47 |
| GFPI | 17.67 | 119.28 | 24.76 | 198.53 |

Note: SD=standard deviation
Source: Author's calculation

### 1.2.2 Dynamics of Food Price Inflation

Dynamics of inflation derived from each CPI, CFPI, WFPI and CNFPI price indices are exhibited in Figure 1.4. Two key characteristics, mean and variability of price inflation for CFPI and CPI dynamics revealed that there may be long memory in mean and variance dynamics of these series. They exhibit time-varying characteristics. In addition, during the study period, the food price inflation derived from CFPI and WFPI is more volatile compared to headline or nonfood price inflation derived from CPI and CNFPI respectively. Food price inflation has been exceeding headline inflation in most of the time periods and food price inflation is more volatile than headline inflation. Food price inflation dynamics exhibit the phenomena of volatility clustering. WFPI has higher variability than CFPI in both periods (Figure 1.4).

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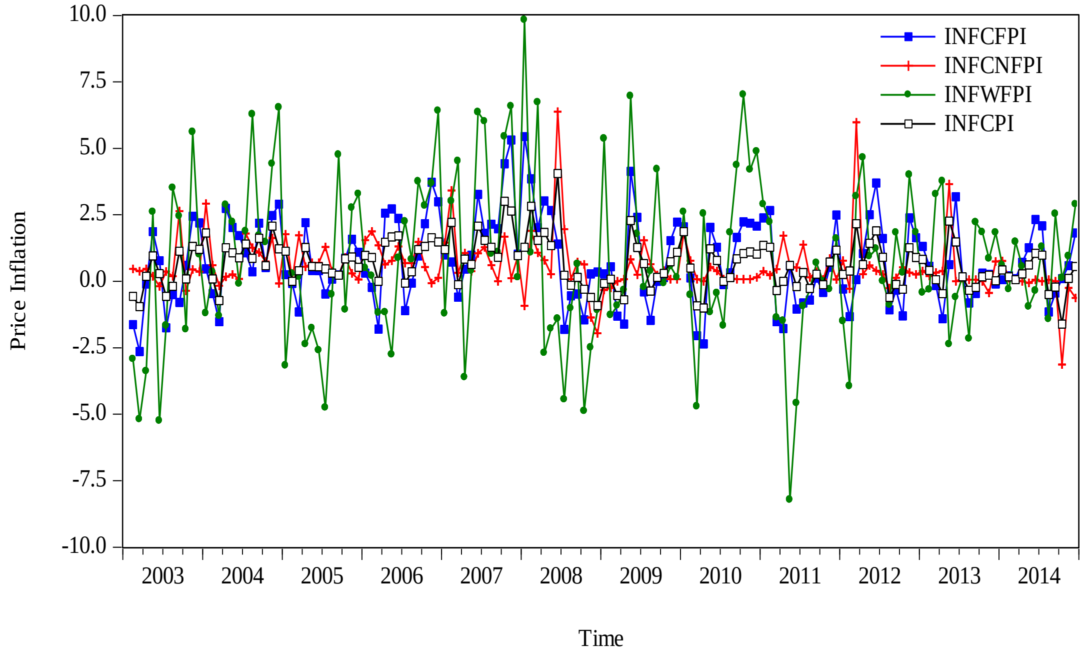


Figure 1.4
*Dynamics of Monthly Inflation of CCPI, CFPI, WFPI CNFPI in Sri Lanka, 2003M1-2014M12*

It is stated that food prices contribute significantly to headline inflation in developing countries. Figure 1.5 exhibits the association between food price inflation and headline inflation in Sri Lanka. The 95 percent confidence ellipse of the variables shows the high and positive degree of association. This implies that food price inflation is positively associated with headline inflation. The Kernel fit line shows positive and linear relationship between these variables.

More explicitly Figure 1.6 shows that the average food inflation is higher in most periods than the average of nonfood price inflation. Therefore, increases in food price will influence general price inflation significantly than nonfood price increases. Mean food price inflation dynamics seems more volatile than that of average nonfood price inflation dynamics.

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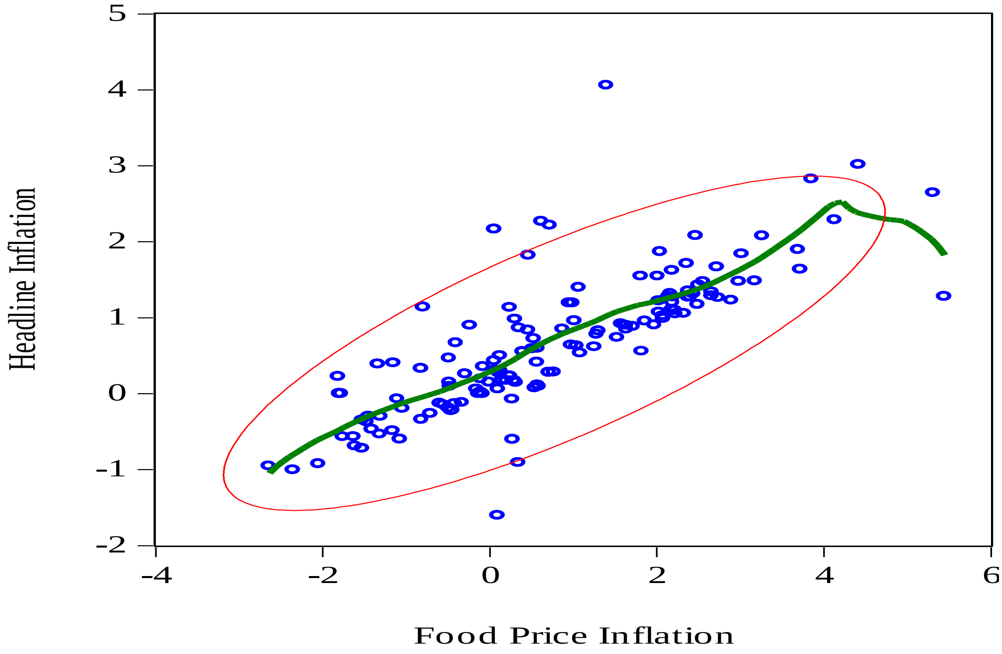


Figure 1.5
*Association between Food Inflation and Headline Inflation*

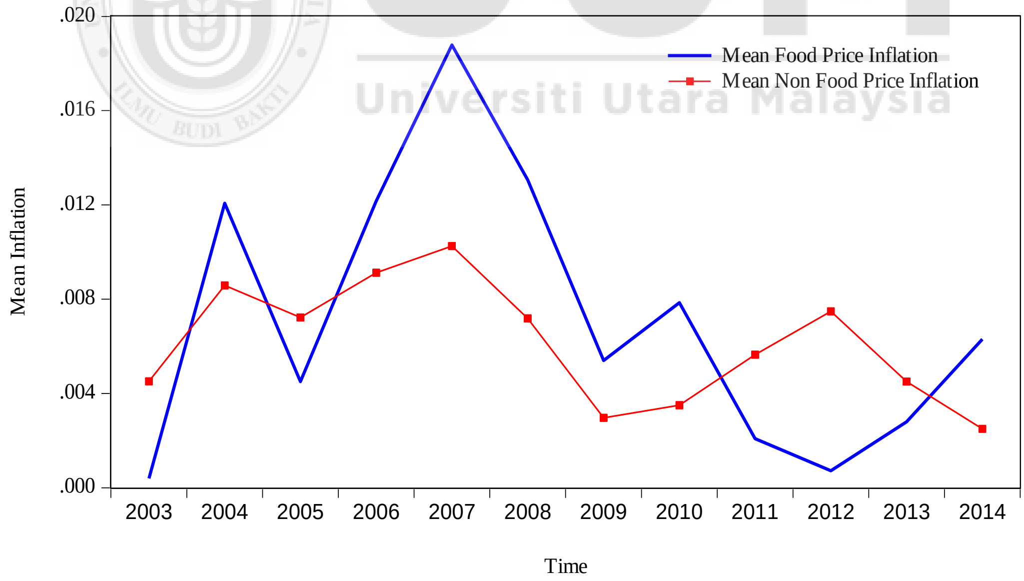


Figure 1.6
*Mean Food Price and Nonfood Price Inflation, 2003-2014*

The contribution of food inflation to headline inflation in Sri Lanka has increased considerably in recent periods (CBSL, 2013).

### 1.2.3 Dynamics of Food Price Inflation Volatility

Volatility phenomena is also an important element to describe food price inflation dynamics. The volatility of food price inflation is proxied by absolute inflation $|\pi|$ and squared inflation ($\pi^2$). Volatility dynamics of food price inflation and nonfood price inflation are compared in Figure 1.7. It is observed that CFPI inflation is more volatile than nonfood price inflation. The average volatility of food price inflation exceeds that of nonfood price inflation in almost all the time periods.

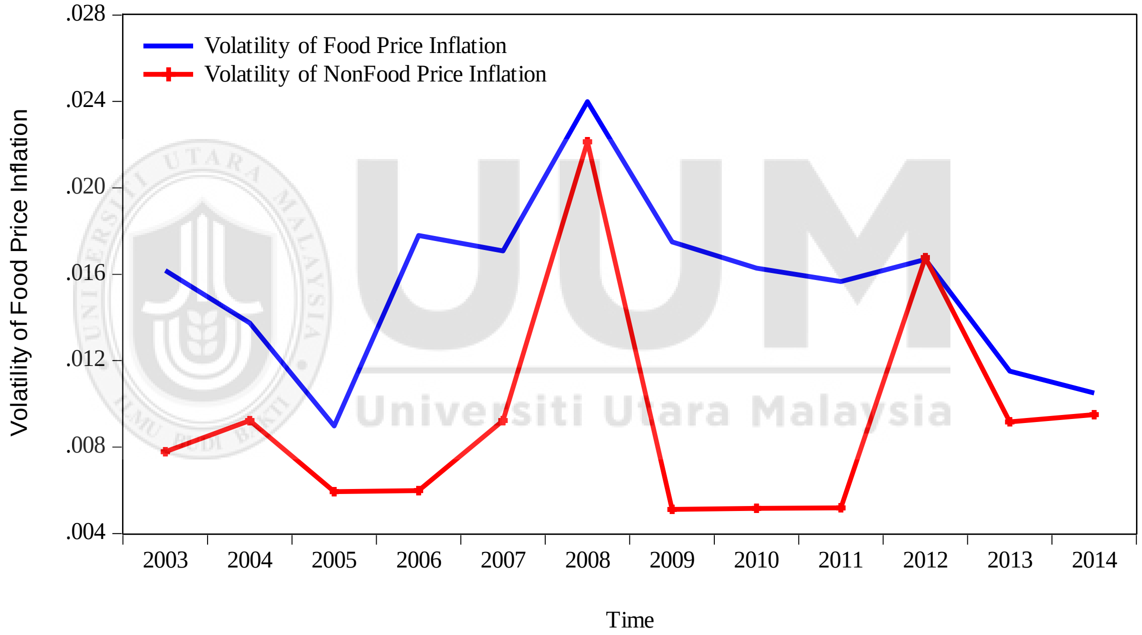


Figure 1.7
*Volatility Dynamics of Price Inflation for Food and Nonfood, Sri Lanka, 2003-2014.*

Further analysis of mean and variance dynamics of food price inflation shows a stylised fact which is exhibited in Figure 1.8. This figure reveals that mean food price inflation is below the variability of food price inflation dynamics. The volatility dominating characteristics imply over-dispersion of food price inflation which is also an important issue to be researched.

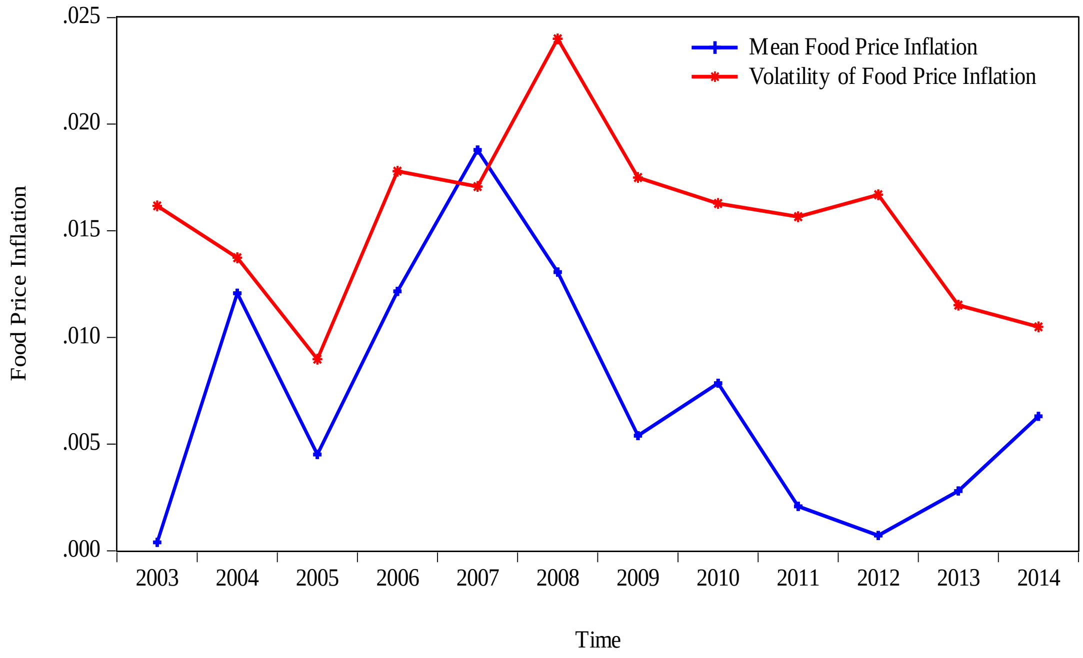


Figure 1.8
*Mean Food Price Inflation and Volatility of Food Price Inflation, 2003M1-2014M12*

The Sri Lankan economy is extremely defenseless to shocks in the international food markets since Sri Lanka depends on imports for more essential food items. In Sri Lanka, approximately 40 percent of total consumer goods imported are food and beverages. Figure 1.9 shows that food import value has been increasing in Sri Lanka which indicates that the dependence of Sri Lanka in the world market has increased.

In the context of imports of Sri Lanka, consumers are price takers in food imports; they have no power to determine the price of food items in the world market as well as in the local market, because locally produced food items also depend on imported raw materials such as fertilizers (CBSL, 2014).

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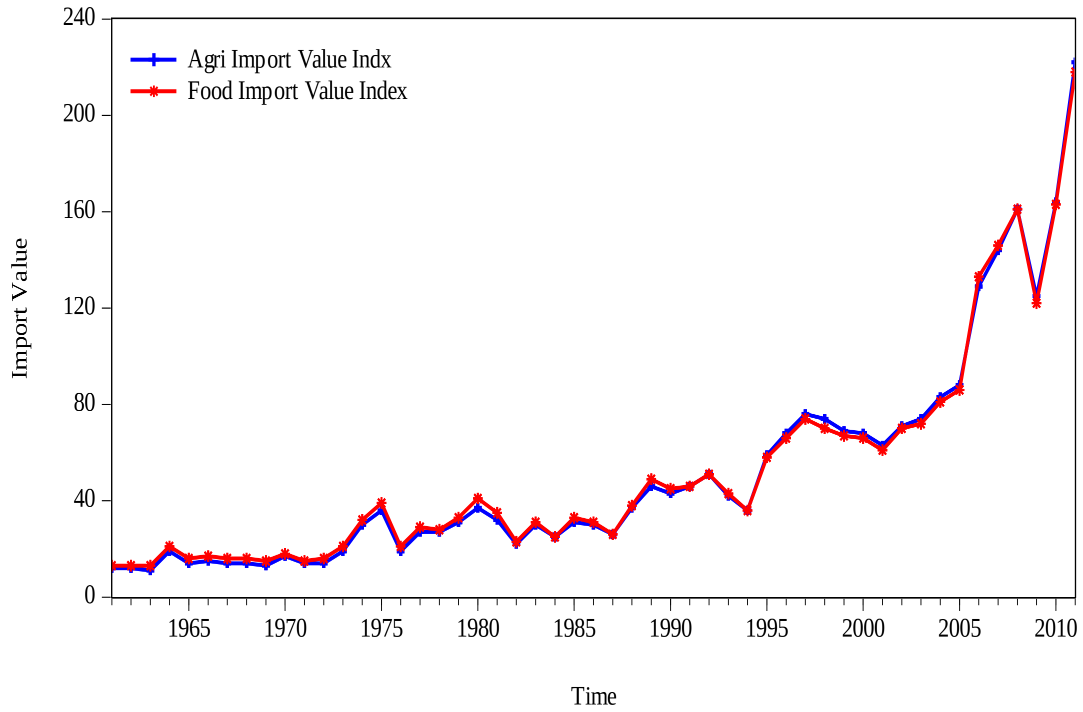


Figure 1.9
*Food Import Value Index, Agriculture Value Index, Sri Lanka 1961-2011*

Thus, global food price plays a significant role in Sri Lanka not only on the average level but also on volatility.

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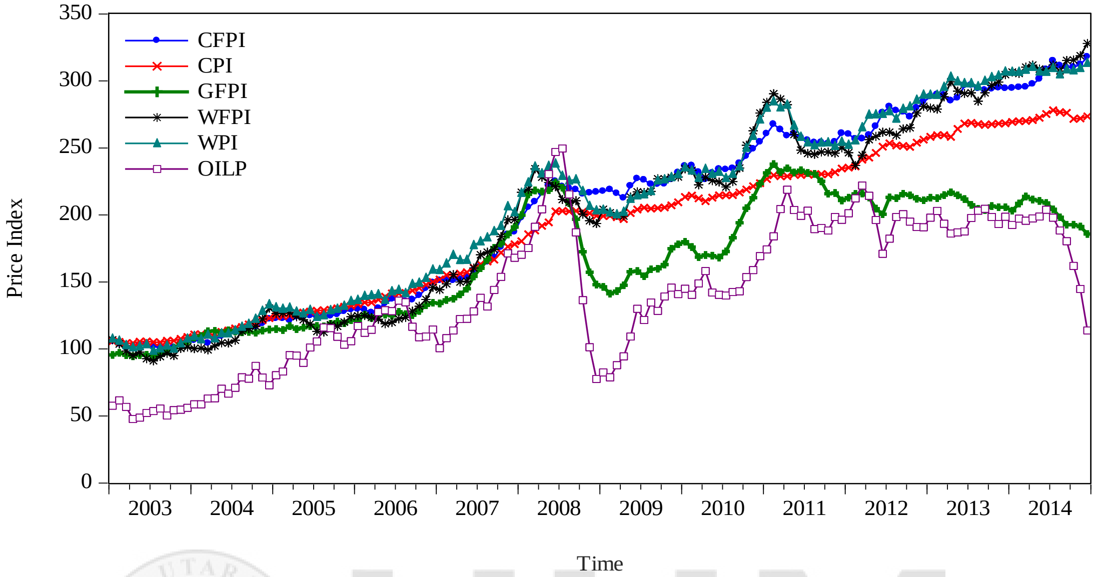
### 1.2.4 Dynamics of Global and Domestic Prices

World price behavior also plays an important role in determining the characteristics of food price and general price inflation dynamics in Sri Lanka. All domestic price series (CPI, CFPI, CNFPI, WPI and WFPI) and GFPI have increasing trends. However, the rate of increase of each food price series varied over the time. For example, during the study period, CPI increased by 158.54 percent. WPI increased by 190.67 percent and GFPI increased by 95 percent. There is a positive relationship between domestic and international food prices. But the degree of variability of each price series varies. Global food price and crude oil price are more volatile and have more structural breaks compared to domestic prices. Figure 1.10 shows the global and domestic price trend behavior.  All price series are interrelated over time and non-stationary and there is asymmetric behavior among these price series.




Note: CPI=Colombo Consumer Price Index, CFPI=Colombo Consumer Food Price Index, GFPI=Global Price Index, WPI=Wholesale Price Index, WFPI=Wholesale Food Price Index

Figure 1.10
*Trends of Global and Domestic Food Prices, 2003M1-2014M12*

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It is also clear that shocks of food prices, both domestic and the world, seem to be more persistent and transmit sturdily into non-food inflation and overall inflation in Sri Lanka. Even global food price transmission also appears to be influencing domestic prices.  Thus, all economic agents-central bank, business people, policy makers, investors, and wage bargaining groups are highly concerned about food price dynamics.  In terms of price level, food price indexes are often argued to be a vital indicator of inflation in emerging countries. Thus, understanding the macro and micro characteristics of food price dynamics is essential for monetary policies.  In addition, understanding the dynamic relationships between food prices and general price inflation is also useful for monetary policies. These findings may highlight the significance of food price dynamics on headline inflation.

## 1.3 Problem Statement

Inflation is a common problem for all the countries in the world. Everyone is affected to some degree by food price inflation in the world. All consequences of general inflation and food price inflation in a country depend on the nature of general price and food price dynamics. Food price dynamics and general price inflation are interrelated. Since 2003, average food prices and volatility of the food prices in the world and Sri Lanka in particular, have been rising exponentially. The increase in the food price and the volatility of the food prices in developing countries leads to an element of uncertainty and has destabilizing consequences on the economy. Thus, high and volatile food price dynamics are becoming a serious problem in developing countries. As Sri Lanka is a small open developing economy, interrelationship between global food price and domestic prices are crucial for this country. Hence, the nature of food price dynamics, international food price transmission, international food price volatility transmission and local food price spillover effects on inflation need to be focused.

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Knowing the nature of food price dynamics is very important for monetary policy makers. It is not explicitly visible to identify whether food price shocks are transitory or permanent, and this makes it difficult to identify whether they are likely to spawn second round effects on nonfood price inflation hence overall (headline) inflation. In the case of Sri Lanka, the pertinent question remains unanswered. The nature of food price dynamics is reflected by properties of the stochastic price distributions of food items. This issue concentrates on the long-range dependence property. The consequences of inflation and measuring inflation depends on the nature of price dynamics. The food expenditure accounts for around 40 percent of CPI. But 50 percent of households spend more than 50 percent of their income on food. Therefore, food price dynamics play an imperative role in overall inflation. Thus, the long memory property of food price dynamic behavior over time is important to construct good policy.

For example, food prices are mostly omitted from the formula of inflation assuming food price changes are transitory in nature. Thus, this issue is related to the measurement of inflation. Core inflation measure was introduced to solve the problem of short-lived noise. Economic theories advocate that monetary policy should ignore temporary price shocks and should only respond to core inflation to avoid unjustified volatility in output as food and energy price inflation is usually assumed to be caused by purely temporary supply-side shocks (Law, 2010). But this assumption does not always hold in the real world. Supply shocks can be structural and can lead to an upward shift in prices. In addition, this assumption may not be true in particular for developing countries as food price changes are driven significantly by demand pressures (Law, 2010). The recurring volatile elements distort the signal of food price dynamics. Further, it is not easy to discriminate food price inflation induced by supply side shocks from that caused by demand pressures in practice. In general, the core inflation measure scientifically under assesses headline inflation when food price inflation has a long memory. Thus, elimination of prices of food items might lead to loss of valuable information dynamics and lead to imprecise measurement of the underlying long run trend inflation. Forecasts of inflation would be downward biased. Memory properties may vary from commodity (say food) to commodity (say nonfood), and country (developed) to country (developing). Therefore, policy makers have to study memory properties of the price dynamics before selecting the measure of inflation. In Sri Lanka, core inflation measure is implemented following the international practice adopted by many countries. If food price inflation has a long memory, then core inflation would mislead the policy makers in Sri Lanka. Accurate measurement is very important to monitor prices effectively in the economy. So the challenge for a central bank is to determine whether food price inflation is transitory or permanent in nature.

Long range dependence is described by the terms, persistence and long memory. How past changes in food prices will stimulate the course of future changes in prices of food and how rapidly policy actions will take effect? This question is necessary for policy makers. To what extent are the theories consistent with the investigational evidence on persistence? These questions are necessary for theorists. Therefore, the issue of the nature of food price inflation dynamics needs to be researched in depth.

The second issue is whether increases in world food prices are transferred to the domestic economy. The spread of world food price increases to national market governs the choice of farmers, traders, consumers and policy planners of a national economy. Ignoring world market food price pass-through effects may lead us to overstate the importance of domestic factors. Sri Lanka is a small open economy and also a dependent economy which is a price taker in the world food commodity markets. Thus, the Sri Lanka's economy is extremely susceptible to shocks in the world food markets.

The third issue is volatility transmission from global market to domestic market. The volatility of food price inflation is another characteristic leading to uncertainty in future food price movements. Increases in volatility of food price have significant destructive consequences in emerging countries or low income countries where a huge portion of total income is spent on food. The volatility of inflation refers to the unpredicted components in the time series process of food price that arises from the recurrence of shocks. Some domestic markets are more interdependent in volatility than in average (mean) price levels with world markets. In practice, average and variability of price distribution tend to be positively related. Therefore, average and variability of international food prices influence national food price and general price level and their volatility. Mundlak and Larson (1992) had found that volatility of commodity prices is the core basis of variability of domestic food prices. As world markets are more integrated, information from one country can affect other markets. The volatility of food price inflation can lead to non-trivial outcomes. It ruins economic stability. It misleads relative prices, leads to misallocation of resources, erodes savings, weakens investment and hinders economic growth. The variability of the food price dynamics makes planning more difficult in an investment plan or household expenditure decision, or government policy plan. The high volatility affects predicting food commodity price movements by increasing standard error. Volatile food prices push small scale farmers and poor consumers into long term poverty traps by reducing their income. Thus, this issue needs to be investigated in depth.

The fourth issue is that domestic food price inflation has a spillover effects on headline inflation. Food expenditure accounts for around 40 percent of CPI that is calculated based on Colombo District in Sri Lanka. In contrast, Household Income and Expenditure Survey (HIES) says that 50 percent of households spend more than

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50 percent of their income on food in Sri Lanka. Therefore, food price inflation may contribute more to general inflation. Thus, this issue also needs to be examined in depth.

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## 1.4 Research Questions

Based on the problem statement, the research questions can be formulated. The main motivation of the study is to respond to the following set of questions:

i. Is food price inflation transitory or permanent in nature in Sri Lanka?

ii. Do increases in global food prices transmit to domestic prices in Sri Lanka?

iii. Does volatility of global food prices pass-through to domestic prices in Sri Lanka? and

iv. Does domestic food price affect headline inflation in Sri Lanka?

In order to answer these research questions, the following research objectives are formulated.

## 1.5 Research Objectives

The general objective of this study is to analyse the food price dynamics and inflation in Sri Lanka. The specific objectives are:

i. to analyse the nature of food price behavior over time in Sri Lanka;

ii. to estimate the pass-through effect of global food price on domestic prices;

iii. to examine the pass-through effect of global food price volatility on domestic prices; and

iv. to study the effects of domestic food prices on headline inflation in Sri Lanka.

## 1.6 Scope of the Study

This study focuses on food price dynamics and inflation in Sri Lanka. Long memory property , price transmission , and price volatility transmission are the main areas of this study and are covered by consumer prices, (CPI, CFPI, CNFPI), producer prices (WFPI, WPI) and global food prices for the period of 2003M1-2014M12.

## 1.7 Significance of the Study

The recent food price dynamics are interest of researchers, academics, politicians, policy makers, funding agents, farmers, wholesalers, processors industry analysts and food market participants and it plays an important roles in the well-being of the people in an economy.

This study contributes to the existing literature in many ways. It provides a comprehensive analysis dealing with the area of statistical memory properties of food price dynamics, memory properties of food price volatility dynamics, world food price transmission in Sri Lanka and world food price volatility transmission. Hence, this study would add to the existing available knowledge in the following ways.

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Firstly, it estimates the long memory parameter for inflation of food prices in Sri Lanka using time domain and frequency domain approaches. Uncovering long memory of food price dynamics can have exciting implications. Knowledge about long memory parameter will assist economists to decide whether price shocks are short lived or long lived. This study examines long memory not only in food price inflation but also in volatility of food price inflation. Hence, this study can give new market information (how long shocks last) by studying memory properties of food inflation. This knowledge may help to improve inflation forecasts. The estimates of memory parameter are useful in order to build an adequate framework for price analysis, in monetary policy formulation, in inflation targeting, welfare programs and the decision making process of economic agents. Further, estimates of means and higher moments (variance, skewness, and kurtosis) dynamics of food price distribution in Sri Lanka will enable economists to understand distributional characteristics of food price dynamics in a comprehensive way.

Secondly, this thesis makes use of the analytical tools and methodologies developed in statistical mechanics and theoretical physics and econometrics, namely econophysics in the field of food price dynamics for Sri Lankan context. Advanced econometric time series techniques such as fractional integration test: Auto regressive fractional moving average (ARFIMA) modeling, the Geweke and Porter-Hudak (GPH) testing methodology and maximum likelihood estimation method are used to study the long memory and hidden features in food price dynamics. Thus, the application of the analytical methods is new in the field of food price analysis. This thesis uses non-parametric, semi-parametric and parametric approaches in order to get robust results. Further, this study uses fractional integration generalized autoregressive conditional heteroscedastic (FIGARCH) models to investigate food price volatility dynamics using Sri Lankan data and global food price data.

Thirdly, the results of this thesis will have important implications for food policy, trade policy, and for the economy as a whole. They may provide useful clues to the government to take appropriate measures in making a macro and micro economic policy decisions. All economic agents; central bank, business men, policy makers, investors, and wage bargaining groups are highly concerned about food price dynamics as more than 50 percent of households spend more than half of their income on food in Sri Lanka. Therefore, the results arising from this study will help to figure

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out the role of food prices in overall inflation as food expenditure accounts more than 40 percent of CPI.

Fourthly, in order to achieve price transmission objectives, the law of one price (LOP) model is used. In this thesis, the LOP theoretical model is modified to include two more variables; dummy variable and crude oil price into the model. Crude oil price is also an important variable that determines food price in Sri Lanka and in the world at large. Dummy variable is used to capture the structural break. The modeling used herein differs from the previous studies.

In addition, the estimated results from global food price transmission will help to understand how foreign food price causes of domestic inflation. The results of volatility transmission of food price inflation will provide useful information for determining the cost of capital, for assessing investment and leverage decisions as it is related to risk.

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Next, food price dynamics in developed countries, many African countries and selected countries except Sri Lanka in Asia are widely researched by Food and Agriculture Organization (FAO), World Bank (WB), the International Monetary Fund (IMF), Asian development bank (ADB). Thus, this study wishes to make a contribution through a case study of Sri Lanka. A closer look at the specific problems and characteristics of an economy would help address the country's problems more effectively. Hence, this thesis will add significantly in various ways to available knowledge.

## 1.8 Organization of the Thesis

The thesis consists of seven chapters that are organized as follows: The present chapter discusses the introduction of the study in which background, statement of the problem, research questions, objectives of the study, and the significance of the study which were briefly discussed. Chapter 2 highlights the salient features of food price dynamics in the Sri Lanka's economy and its background. Chapter 3 reviews the relevant existing theoretical and empirical literature related to price and price volatility dynamics, properties of the food price distributions, and pass-through effects. Chapter 4 reports the conceptual framework and theoretical background of the study. Chapter 5 describes the methodology of this thesis which consists of variable justifications, empirical model, data and the method of analysis. Chapter 6 presents the results and discussion. Chapter 7 concludes with policy recommendations and offers directions for future research.

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# CHAPTER TWO

# BACKGROUND OF SRI LANKAN ECONOMY

## 2.1 Introduction

This chapter describes the background of the Sri Lankan economy in terms of location, population, role of agriculture sector, role of food in consumption expenditure pattern, food price dynamics, general price dynamics, and role of food imports in balance of payments to understand food price dynamics in Sri Lanka and how it has evolved over time.

## 2.2 Location

Sri Lanka is an island situated in the Indian Ocean to the South India, Asia between 5.55-9.50 north latitudes and 79.42-81.53 east longitudes. This island is about 270 miles long and 150 miles wide. Area of Sri Lanka is 65, 610 square kilometers. Sri Lanka has a tropical monsoon climate. Around 15 percent of the territorial land has been used for permanent crops while the arable land area is 14 percent and permanent pastures are seven percent forests and woodlands are 32 percent and the balance 32 percent is for other uses.

In economics perspectives, Sri Lanka is an emerging economy which is a small, open and dependent economy in the South Asian Region. It is a low income food importing country and net food importer.

## 2.3 Population Distribution

The majority of the population in Sri Lanka lives in the rural area. The Household Income Expenditure Survey (DCS, 2012/13) shows that total population size in Sri Lanka was 20.2 million. There is 3.6 million (18 percent) in the urban sector, 15.7 million (78 percent) in the rural sector, and 0.9 million (4 percent) in estate sector. More than 80 percent of the total population lives in rural and estate area in Sri Lanka.

## 2.4 Inflation Measure in Sri Lanka

Colombo Consumer Price Index is used for inflation measure and used as the official cost of living measurement index in Sri Lanka. It is denoted by CPI in this study. The CPI was designed by the Department of Census and Statistics (DCS) using the data collected from the survey that was conducted in the Colombo Municipal Council in the Colombo district of the Western province that is one of the 9 provinces of Sri Lanka (Figure 2.1). Further, it has to be noted that Colombo district is one of the 25 administrative districts in Sri Lanka. This raises a question of whether this CPI will represent the entire Island.

Food is an important element of the cost of living index represented by Colombo Consumer Food Price Index (CPI) in Sri Lanka. According to the CPI, the food component in CPI was 41 percent in 2006. But, if the food share is calculated based on all island, then the statistics differ from the food share calculated from CPI. In the case of the overall Island, expenditure for food of per household's total expenditure accounts for more than 50 percent (DCS, 2013). In addition, a large fragment of the population, generally from the estate and rural sectors in Sri Lanka spends more than half of their total income on food. Figure 2.3 based on DCS statistics show that more

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than 80 percent of the total population lives in rural and estate sectors in Sri Lanka (DCS, 2012/13). Low income families in urban and estate sectors spend more than 60 percent of total expenditure on food. On an overall average, households in Sri Lanka spend more than half of their total income on food items. Large numbers of households are net buyers in terms of staple foods.

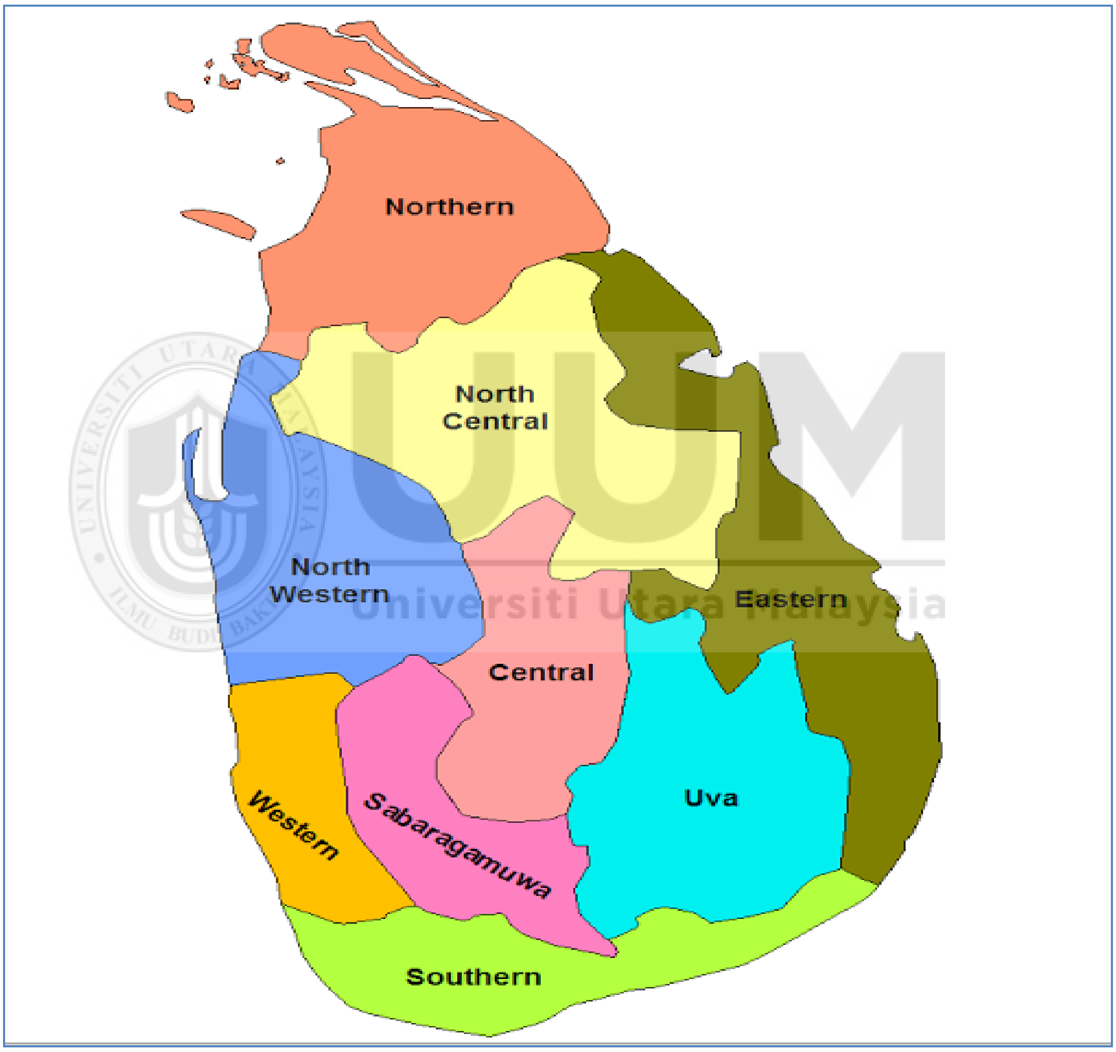


Figure 2.1
*Map of Provinces in Sri Lanka*
Source: DCS, Sri Lanka. 2014

## 2.5 Role of Agriculture in the Sri Lankan Economy

Agriculture sector plays a vital role in the Sri Lankan economy, in terms of employment, agricultural land use, paddy and vegetable production, calorie intake, and contribution to national income. It acts as the mainstay of livelihood for a vast majority of people. The agricultural sector comprises plantation (commercial) agriculture sector and subsistence agriculture sector where paddy is the main crop which covers a large portion of used land along with other food crops such as cereals, fruits, and vegetables. The majority of the population depends on this paddy sector. Paddy production remains as the basis of domestic agriculture during all the periods in Sri Lanka. Food and agriculture sector in Sri Lanka plays an important role in determining food security, food price, employment and balance of payment.

With respect to comparison of sectoral shares in GDP since the 1960s, the relative share of agriculture has declined over time (Figure 2.2). In 1960, the contribution of agriculture to GDP was 37.8 percent and it continuously decreased with slight fluctuations to 12.1 percent of GDP in 2011 to become the relatively least contributor to GDP. Though its involvement to the GDP declined considerably throughout the past three decades, it is the main source of employment for a large number of the workforce in Sri Lanka. Approximately, one third of the total labor force was engaged in agriculture in 2012 (Central Bank of Sri Lanka, 2014 (CBSL, 2014)). Its performance has an important role in household food security, both directly and indirectly. More than 70 percent of the population in the country still makes their livelihood directly or indirectly based on it.

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Most small scale farmers in the agriculture sector have been unable to capitalize on price rises due to a lack of access to markets and key production inputs such as seed, fertilizer, know how, irrigation facilities, land, and credit.

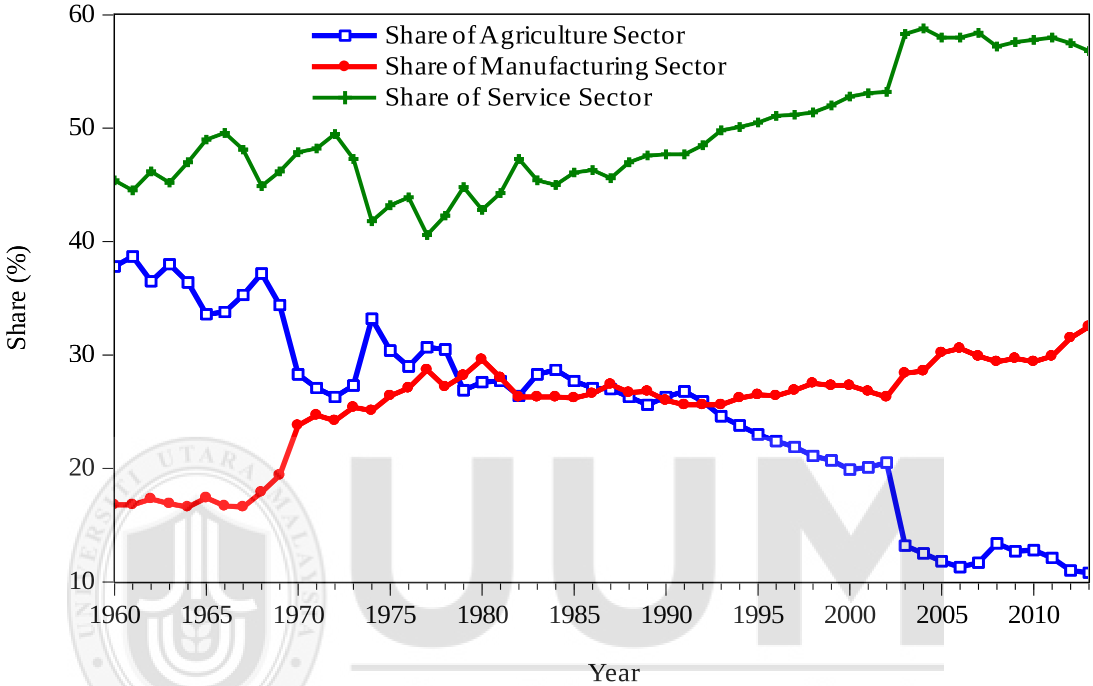


Figure 2.2
*The Trends of Sectoral Share of GDP*

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## 2.6 Food and Household Expenditure in Gross National Expenditure

At the national level, the food expenditure share to private consumption, domestic demand expenditure, and domestic product is 37 percent, 23 percent, and 25 percent, respectively in 2013. These are higher ratios compared to developed countries where food expenditure ratio is 10-16 percent.

The ratio of expenditure on food and drink to total expenditure per household is called the food expenditure ratio (FER). FER is a simple indicator of economic conditions of a society. FER is one of the prime indicators that reflects the living standards of people in a country. It is usually indicated as a percentage. Average monthly expenditure values per household are used to calculate this ratio.

Food expenditure accounts for relatively large weight in the CPI in Asia in particular Sri Lanka (Table 2.1). Thus, food price inflation contributes significantly to headline (general) inflation in Asia.

Table 2.1
*Weights of Food Expenditure in Consumer Price Index in Asia 2010*

| **Economy** | **Share (%)** | **Economy** | **Share (%)** | **Economy** | **Share (%)** |
|---|---|---|---|---|---|
| Bangladesh | 58.84 | Indonesia | 36.20 | Singapore | 22.05 |
| Cambodia | 44.78 | Korea, Republic | 14.04 | Sri Lanka | 45.50 |
| China | 30.20 | Malaysia | 31.40 | Taipei, china | 26.08 |
| Hong Kong | 26.67 | Pakistan | 40.34 | Thailand | 33.01 |
| India | 46.19 | Philippines | 46.58 | Vietnam | 39.93 |

Source: Asian Development Bank, 2011

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The food expenditure part accounted for around 41 percent in 2006 in the CCPI. The CCPI is formulated from Colombo district based survey data. But, it is interesting to see that FER varies among sectors and expenditure deciles.

Table 2.2 shows implicitly that changing FERs over time indicate that living standards in all sectors are improving. However, all sectors have FER more than 30. Expenditure decile analysis shows that FER is higher than 50 for the 50 percent households in all sectors.

Table 2.2
*Food Expenditure Ratio Distributions Among Sectors, 1980/81-2012*

| **Sectors** | **2012** | **2009/10** | **2006/07** | **2002** | **1995/96** | **1990/91** | **1985/86** | **1980/81** |
|---|---|---|---|---|---|---|---|---|
| Sri Lanka | 38 | 41.7 | 37.6 | 43.8 | 54.4 | 59.2 | 57.6 | 65.0 |
| Urban | 31 | 36 | 31.2 | 35.9 | 42.8 | 47.1 | 50.2 | 58.4 |
| Rural | 39 | 44 | 38.7 | 45.3 | 57.0 | 63.9 | 60.7 | 66.8 |
| Estate | 50 | 51 | 55.8 | 60.1 | 69.1 | 69.4 | 61.8 | 71.9 |

Source: DCS, HIES, Sri Lanka, 2012/13

Figure 2.3 shows that FER declines along with income level. This is consistent with Engel's Law. According to the HIES report-2012/13, the group of first expenditure decile (poorest 10 percent) spent more than 60 percent of their expenditure on food and drink on average. The first five expenditure deciles (lower 50 % of households) spent more than 50 percent of their total expenditure on food and drink on average. But the expenditure on food and drink of the richest 10 percent of the households ($10^{th}$ decile group) is only 12.7 percent of their total expenditure. According to HIES-2012/13, based on household monthly expenditure deciles at the national level, the FERs of the first eight expenditure deciles (80 percent) are higher than the countrywide level of FER 37.6 percent. People from rural and estate sector expend more than half of their total expenditure on food. Overall, an average household expends more than half of their total expenditure on food in Sri Lanka.

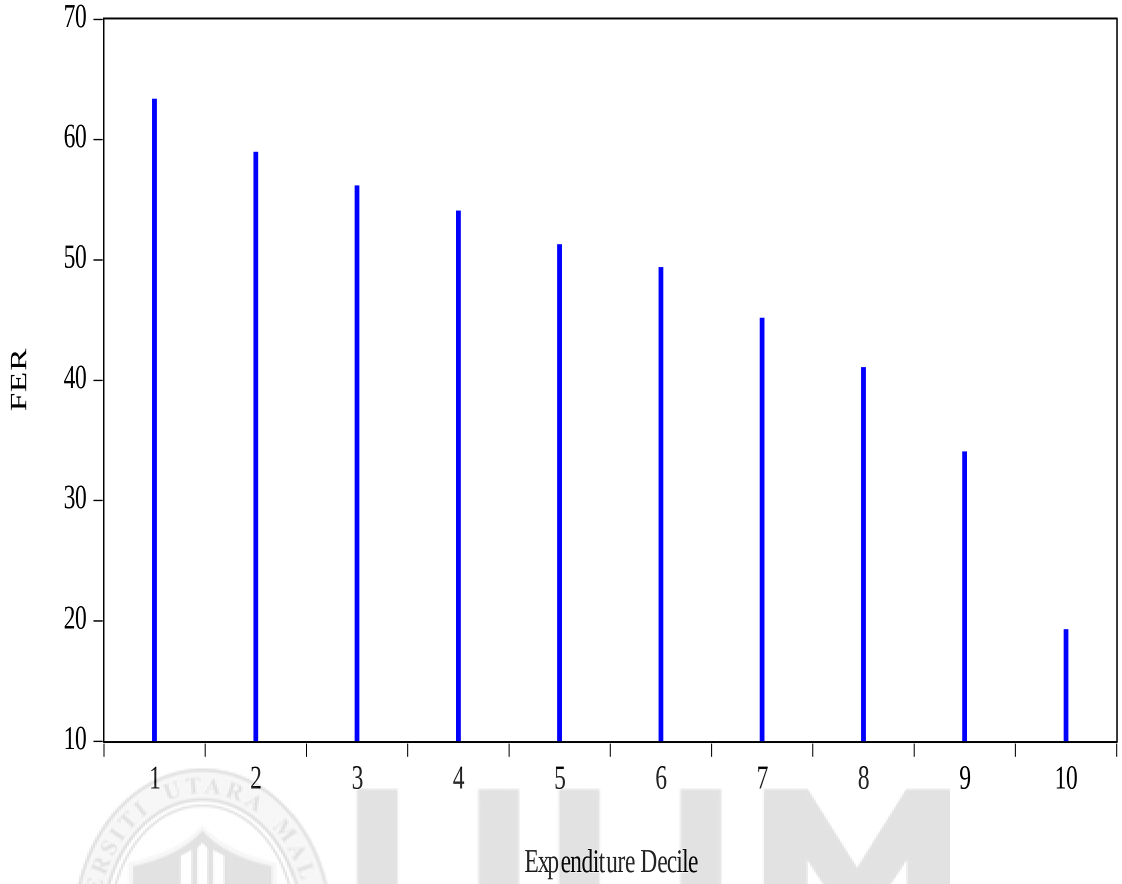


Figure 2.3
*Food Expenditure Ratio distributions-Sri Lanka, 2006/07*

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Table 2.3 shows more information about the food ratio that has been changing over time and its distribution among deciles. It shows that average FER has been decreasing over the period. The overall food ratio for Sri Lanka has been decreasing. It is important to note that overall food ratio for Sri Lanka has been less than 50 percent during the study period. However, 50 percent of households expend more than 50 percent on food. This information is not available in CPI. Income distribution was not taken into account in CPI.  Assuming constant FER for all expenditure deciles may mislead policy makers.

Table 2.3
*Food Expenditure Ratio- Expenditure Decile Wise*

| Expenditure Decile | 2012/13 | 2009/10 | 2006 | 2002 |
|---|---|---|---|---|
| 1 | 63.4 | 67 | 60.8 | 69.4 |
| 2 | 59.0 | 63 | 57.1 | 67.7 |
| 3 | 56.2 | 61 | 56.0 | 65.6 |
| 4 | 54.1 | 59 | 54.3 | 62.2 |
| 5 | 51.3 | 56 | 51.0 | 60.9 |
| 6 | 49.4 | 52 | 47.3 | 57.7 |
| 7 | 45.2 | 48 | 44.2 | 53.1 |
| 8 | 41.1 | 44 | 39.5 | 49.0 |
| 9 | 34.1 | 39 | 33.4 | 40.7 |
| 10 | 19.3 | 24 | 17.9 | 24.1 |
| Sri Lanka | 37.6 | 42 | 35.8 | 43.8 |

Source: DCS, HIES-Sri Lanka, 2012/13

The provincial FERs pattern in Table 2.4 shows that there is unequal development among provinces. Most of them (eight out of nine) have FER more than the national level[37.6]. Only one province, the Western province has less than the national level FER. The other eight provinces have more than the national level of FER.

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Table 2.4
*Food Expenditure Ratio by Provinces in Sri Lanka*

| Provinces | 2012 | 2009/10 | 2006/07 |
|---|---|---|---|
| Western | 30.6 | 35 | 31.8 |
| Central | 41.2 | 45 | 42.7 |
| Southern | 37.8 | 44 | 39.2 |
| Eastern | 44.8 | 57 | 47.2 |
| North Western | 55.0 | 47 | 41.6 |
| North Central | 41.3 | 41 | 35.6 |
| Uva | 41.1 | 47 | 44.2 |
| Sabragamuwa | 41.7 | 46 | 45.2 |
| Northern | 43.2 | 59 | - |
| Sri Lanka | 37.6 | 42 | 37.6 |

Source: DCS, HIES, Sri Lanka, 2012. Average (arithmetic mean) is used

## 2.7 Food Expenditure in Inflation Measure in Sri Lanka

The CPI is the most extensively used and best known indicator of the changes in the cost of living. The CPI index is used to measure changes in the general price level. This index was recognized as the official indicator of inflation in Sri Lanka. This index is used for various policies, particularly monetary policy, and various social and economic impact policies. This index is computed by the DCS, Sri Lanka. The DCS constructed a more comprehensive CPI with base year 2002=100 in 2007. Laspeyre's base weighted price formula was used to calculate CPI index. This index was calculated using urban households of 12 centres: Borella, Dehiwala, Dematagoda, Grandpass, Kolonnawa, Kotte, Kirulapone, Maradana, Nugegoda, Petta, Ratmalana, and Wellawatte, in the Colombo District consisting of 1300 Households from the western province whereas there were nine provinces and twenty five 25 districts in Sri Lanka. The CPI was based on the average household expenditure of the sample from Colombo. Other 24 districts were not counted in the CPI calculation. Figure 2.4 shows the location of the western province that is one of the nine provinces.

Further, another inflation measure called "Core Inflation Index" (CII) was derived from the CPI. This is also calculated by the DCS for the purposes of monetary policy.

The CPI inflation has been affecting economic growth negatively in Sri Lanka during the last time periods. This phenomenon is exhibited in Figure 2.4 which shows that the association between inflation, based on CPI (INFCPI) or GDP deflator (INFLGDP), and economic growth indicates negative relationship for the period of 2000-2013in Sri Lanka.

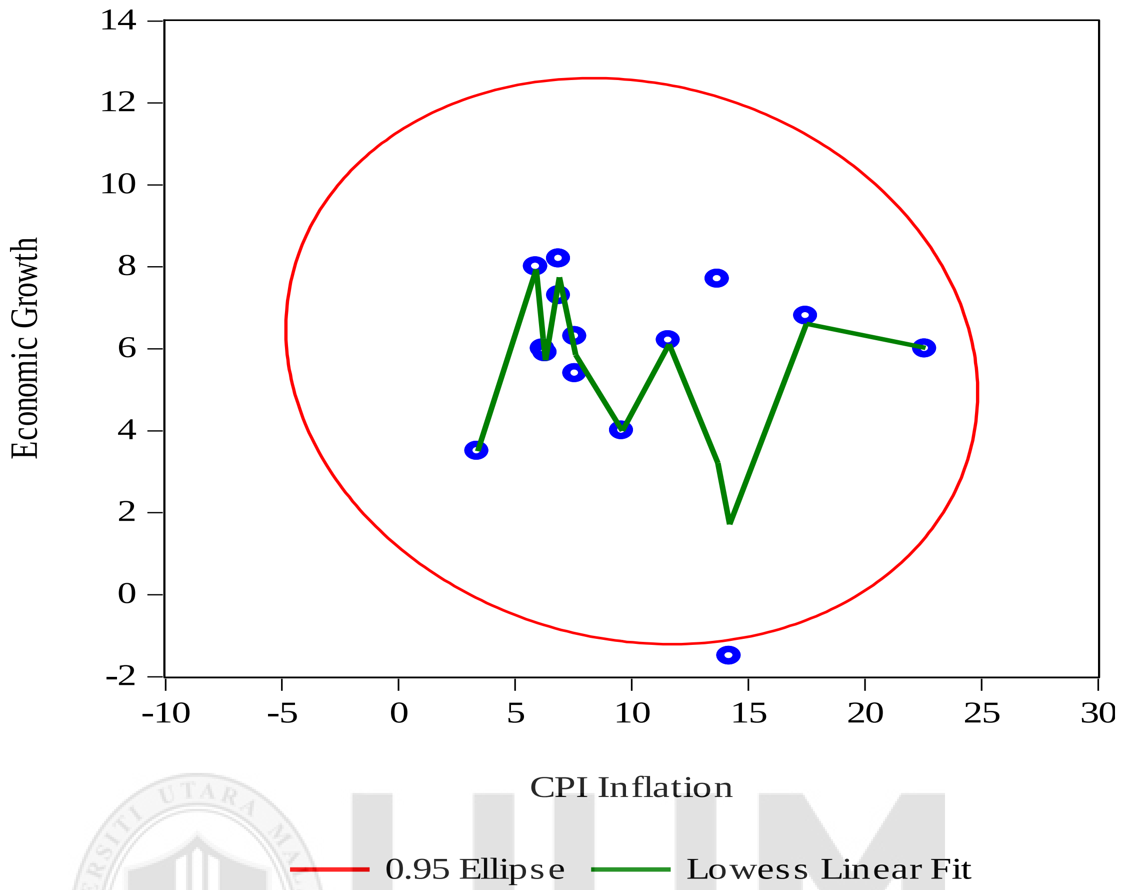


Figure 2.4
*Associations between Inflation and Economic Growth in Sri Lanka, 2000*-2013

Food and beverages components in CPI consist mainly of dairy products, sugar, rice, wheat, and lentils. Food price increases have been major components of the general inflation rate in Sri Lanka. The influence of food prices to general inflation in Sri Lanka has increased considerably in recent periods. Food share in CPI is higher than other categories. The expenditure on food and non-alcoholic beverages accounts for 41 percent in CPI index (Table 2.5). Thus, price increases in the food category contributed largely to the overall increase in inflation.

Table 2.5
*Description of Base Weights for CPI Sub-Groups (Base 2006/07=100)*

| **Sub Groups** | **Percent** |
|---|---|
| Food and Non Alcoholic Beverages | 41.0 |
| Clothing and foot wear | 3.1 |
| Housing water , Electricity, Gas, and other fuels | 23.7 |
| Furnishings, Household Equipment, and Routing Household maintenance | 3.6 |
| Health | 3.2 |
| Transport | 12.3 |
| Communication | 4.8 |
| Recreation and Culture | 1.5 |
| Education | 3.9 |
| Miscellaneous goods and services | 2.9 |

Source: DCS, Sri Lanka, 2012

Figure 2.5 exhibits the behavior of domestic (retail) prices of rice and wheat, sugar and milk powder. It shows that the mean price has increased over time. Prices of milk powder, sugar, and wheat have moved upwardly. Rice, wheat, milk product, sugar domestic retail prices during this study period increased by 250 percent, 413 percent, 315 percent, 310 percent respectively.

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Variability of wheat, sugar, milk and rice prices (measured by the coefficient of variation) during the study period are 57, 44, 41 and 37 percent, respectively. It is important to note here that Sri Lanka depends highly on the world market for sugar, wheat, and milk powder.

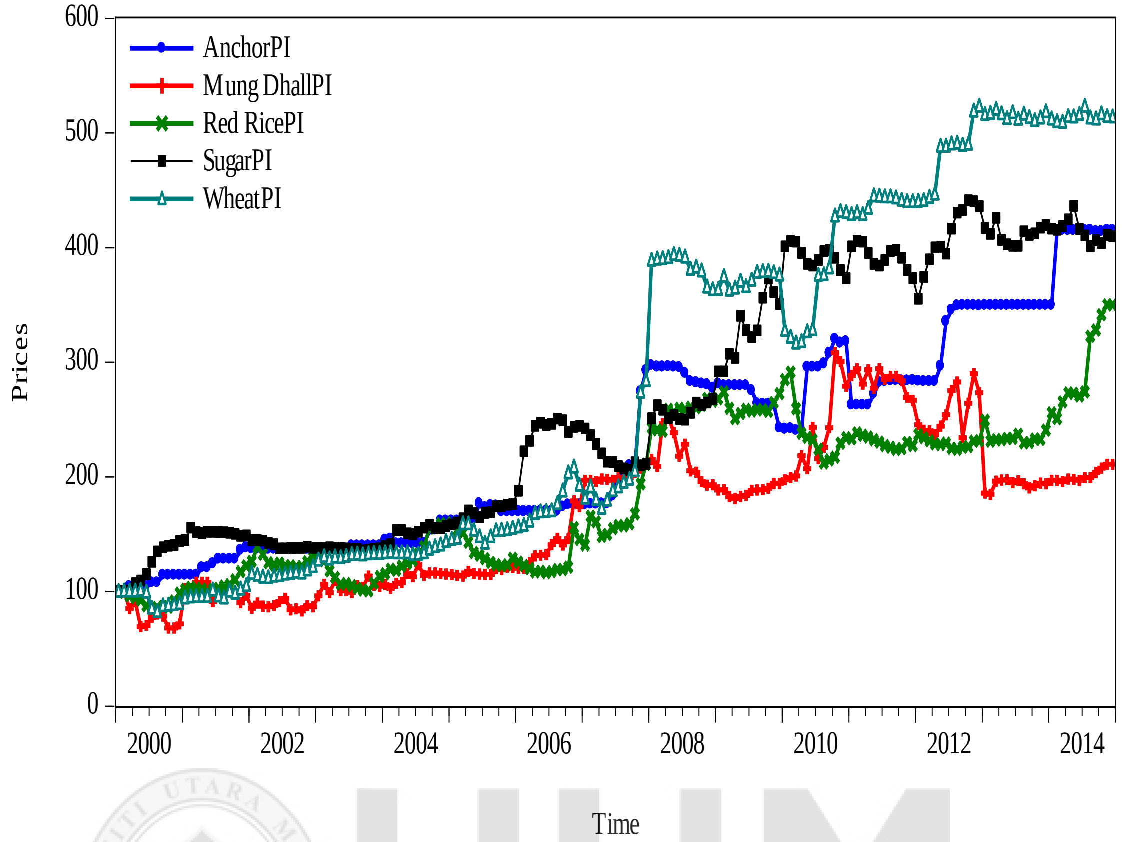


Figure 2.5
*Rice, Sugar, Milk Powder and Wheat Domestic Retail Price Trends in Sri Lanka, 2003M1-2014M12.*

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## 2.8 Food Expenditure Pattern in Sri Lanka

Rice, bread, and wheat flour are the most consumed main food items in Sri Lanka (Table 2.6). Rice, wheat flour, and bread, buns, and hoppers are the major items on which the highest proportions of the total food expenditure are spent. The urban people spent more on the prepared food than the cereals whereas the people from estate sector expends little on prepared food and almost one third of their total food expenditure is for cereals.

Table 2.6

*Average Monthly Household Expenditure (%) of GDP by Major Food Category and Sector in Sri Lanka, 2012*

| **Major Food Category** | **Sri Lanka** | **Urban** | **Rural** | **Estate** |
|---|---|---|---|---|
| Cereals | 16.3 | 12.1 | 16.9 | 27.4 |
| Prepared foods | 11.8 | 17.4 | 10.6 | 5.9 |
| Pulses | 3.4 | 2.7 | 3.5 | 5.0 |
| Vegetables | 7.9 | 6.8 | 8.2 | 8.0 |
| Meat | 4.4 | 6.0 | 4.0 | 4.2 |
| Fish | 9.2 | 11.2 | 9.0 | 3.9 |
| Dried Fish | 4.0 | 2.9 | 4.3 | 2.6 |
| Coconuts | 5.2 | 4.4 | 5.4 | 4.9 |
| Condiments | 8.8 | 7.5 | 9.1 | 9.2 |
| Milk &Milk foods | 9.4 | 10.6 | 9.0 | 9.8 |
| Fats and Oil | 2.3 | 1.7 | 2.4 | 3.2 |
| Sugar, Juggery, Treacle | 3.1 | 2.6 | 3.2 | 3.2 |
| Fruits | 3.3 | 3.6 | 3.3 | 1.9 |
| Other food items | 10.7 | 10.4 | 10.8 | 10.8 |
| All | 100 | 100 | 100 | 100 |

Source: HIES, Sri Lanka, 2012/13

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## 2.9 Food Imports in Sri Lanka

South Asian economies including Sri Lanka are the largest net importers of commodities compared to other developing nations. Sri Lanka is an open economy and it is dependent on imports. There has been a negative trade balance for a long period in Sri Lanka since 1950s. Since 1977, the Sri Lankan economy has become a more liberalized economy. It joined the globalized system. The Sri Lankan economy has had a free float exchange rate system since 2001. It has been a net importer since 1940s and has consequently been affected by the developments in the global food markets. The food security situation in Sri Lanka is still dependent on the world food market. In recent years, it has been highly import-dependent for wheat, sugar and milk products. In Sri Lanka, 25 percent of food is imported including wheat, sugar, pulses and milk products.

As Sri Lanka is an open and dependent economy, Sri Lanka is highly vulnerable to shocks in the international food prices. Further, the food consumption basket has a large portion of imported food components. The imports expenditure for food and beverages is around 50 percent of total expenditure for consumer goods imports for the period 2009-2012. Thus, food expenditure takes on a significant role even in total import expenditure in Sri Lanka. The key food items of imports are sugar, flour, milk and milk products, red-dhal, wheat and maize, big onions, potato, and dried fish. Around 9-12 percent of total imports, expenditure comes from food, beverages, wheat and maize.

Main food items of total imports in Sri Lanka are cereals (rice, wheat) animal source foods (milk, fish); processed food (sugar, edible oil), fruits and vegetables. They are the primary drivers of food price inflation in Sri Lanka. Food imports are around 14 percent of merchandise imports in Sri Lanka. Sri Lanka imports wheat, milk items, fuel, and rice. Fuel imports are around 23 percent of merchandise imports in Sri Lanka. In 2007, Sri Lanka imported food items worth of USD 1.5 billion. The share of food and beverages in total import value had increased from 6.8 percent in 2012 to 7.6 percent in 2013.

Table 2.7 provides data on food imports as a percentage of total imports of consumer goods. Food imports account around 40 percent of total consumption imports which indicates that we depend on the world market for 40 percent of consumption imports.

Table 2.7
*Food Imports Expenditure–Sri Lanka, 2013*

| Year | Value of Food Imports* | Value of Total Imports of Consumer Goods* | Value of Food Imports /Value of Total consumer Goods Imported* (%) | Food imports/ Total Imports (%) |
|---|---|---|---|---|
| 2010 | 1321.6 | 2476.3 | 53 | 9.8 |
| 2014 | 1634.0 | 3853.0 | 42 | 8.4 |

Source: CBSL, Sri Lanka, 2014 (* imports values are in US$ Million)

## 2.10 Conclusion

This chapter provided brief highlights on the background of the Sri Lankan economy, covering the location of Sri Lanka in the world map, population size, the role of agriculture, food expenditure in inflation measure, food expenditure in household expenditure, and food expenditure pattern and food imports.

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# CHAPTER THREE

# REVIEW OF LITERATURE

## 3.1 Introduction

This chapter critically reviews the previous research works that relates to this study. It covers long memory properties of price dynamics, global food price transmission, global food price variability transmission and the relationship between mean and variance of food price dynamics. The review of previous studies helps in identifying the research gaps and advancing analytical methods for the study. In this chapter, theoretical studies related to the issues of this study are reviewed first and then major empirical previous works related to this study were also reviewed.

## 3.2 Review of Theoretical Studies

In this section, the theoretical aspects of the definition of price dynamics, properties of price dynamics price transmission, price inflation and inter temporal relationship between mean and variance of inflation are reviewed.

### 3.2.1 Definition of Price Dynamics and Inflation

Two terms related to this study are price dynamics and inflation. Each of these terms; price dynamic and inflation has multiple definitions. According to Frisch (1936), price dynamics refers to its behavior over time. Collins English dictionary (2014) defines price dynamics as changing price signals that are created by demand and supply forces over time. Taylor (2005) says that prices move as time progresses, they are dynamic. From these definitions, food price dynamics refers to the behavior of food prices over time.

Meanwhile, inflation is defined as a sustained increase in the general price level of goods and services in an economy over a period of time. Economists today use the term "price inflation" to refer to a rise in the price level. Adamson (1996) defines inflation as the rate of increase in the general price level in an economy. Nwankwo (1982) believes that inflation is an excess of demand over supply. However, mathematically, the rate of inflation is defined as percentage changes in the general price level. Price inflation is defined mathematically as $\pi_t = \ln(P_t / P_{t-1}) * 100$, where $P_t$ is the price index at time *t*. Generally, three indices, namely the GDP deflator or implicit price index (IPI), the wholesale price index (WPI), and the consumer price index (CPI) are used to measure inflation in an economy. Inflation dynamics refers to the rate of inflation changes over time, in an economy.

### 3.2.2 Properties of Price Dynamics and Inflation Persistence

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The purpose of this section is to review some of the properties that describe the price dynamics. Price dynamic response to an innovation is an important phenomenon in a macroeconomic analysis. Actually, price dynamics refers to both dynamics of mean (first moment) and variability (second moment) of price distribution. It is influenced by many economic and non-economic factors such as economic and non-economic shocks. The nature of shocks to food prices plays an important role in impacting rising food prices on inflation and food inflation dynamics. In studying food price dynamics, the statistical properties of food price dynamics are of great importance in understanding the underlying features of the price dynamics. Persistence and long memory are important informative properties in understanding the nature of price dynamics. These properties were developed and have also been used in physics, statistical physics, and mathematical finance.

### 3.2.2.1 Inflation Persistence

This section covers the definition of inflation persistence and measurement of inflation persistence. Persistence measures the long run permanent impact of shocks on economic time series. Inflation persistence (IP) is an important statistical property of inflation dynamics. However, economic theory had not explained explicitly the underlying properties of inflation dynamics. IP infers that all variations in inflation are of an undying nature. The literature reveals that there are several definitions of IP. For instance, Batini and Nelson (2001) and Batini (2002) discriminate three categories of persistence as (i) "positive serial correlation"; (ii) "lags between systematic monetary policy actions and their result on inflation"; and (iii) "lagged reactions of inflation to non-systematic policy shocks". However, Nelson and Batini's (2001) definitions were not popular. Meanwhile, Willis (2003) defines IP as the slowness of returning inflation to its baseline after a shock. Marques (2004) defines IP as the time during which inflation converges to a long run equilibrium path after a specific shock. In a different perspective, Angeloni *et al*. (2004) and Margues (2004) defines IP based on the speed of inflation convergence to the equilibrium path. Campbell and Mankiw (1987) defines persistence as continuing for a long time into the future. Therefore, in simple terms, IP refers to the period of shocks hitting inflation. It indicates that the current value of the inflation rate is strongly influenced by its history. In this definition, shocks are referred to as unexpected changes in a variable. The definitions that deal with the idea of "speed" and "convergence" became common (Andrews & Chen, 1994). If the speediness of the response of inflation to a shock is low, inflation is very much persistent while if the speed is high, inflation may not be persistent for a long period. On the other hand, low persistence means that inflation reverts faster while high persistence means inflation falls slowly back to the long term level after a disturbance.

Before IP explicitly emerged, the concept of persistence actually appeared implicitly in economic theory during the 1940s, especially when economists discussed the theory of business cycle. For instance, some economists such as Fellner (1956), Mitchell (1927), Keynes (1936), and Burns and Mitchell (1946) are considered the earliest group of economists who researched business cycles. Based on the ground-breaking empirical work of Burns and Mitchell (1946), business cycles focused on the decomposition of trend component and cyclical component for the U.S. GNP series. The cyclical component is assumed to be transitory in nature and the trend component is viewed as long run movement (permanent). Trend component changes gently and smoothly compared to the cyclical component. Furthermore, Friedman (1957) had decomposed the measured income series into permanent and transitory components, which is similar to trend–cycle decomposition of Mitchell (1927). In fact, Friedman's permanent component reflects the persistence of series to a shock. However, Friedman has not used persistence measure or talked about memory properties. Until the 1960s, researchers modeled economic variables as covariance stationary. In contrast, Box and Jenkins (1976) first proposed the idea of first differencing. They argued that GDP series is not a covariance stationary, but a nonstationary series. In this area, Box and Jenkins identified that the nature of permanent component of a stochastic series differs from the nature of business cycle of the series. Though they have not used persistent concept explicitly, it implicitly implied that the series are autocorrelated and can be stated in another word as persistent. Thus, they started to question that this trend component moves around a deterministic trend or moves around a stochastic trend. Afterward, Beveridge and Nelson (1981) and Nelson and Plosser (1982) emphasized that the trend component is stochastic and not deterministic. Following Nelson and Plosser's work, Campbell and Mankiw (1987) defined a measure of persistence using autoregressive moving (ARMA[1]) approach, denoted the measure by $A(1)$[2], which is the sum of moving average coefficients from finite polynomials in the lag operator. This shows that Beveridge and Nelson considered persistence measure implicitly. However, there are some limitations of $A(1)$ measure of persistence. Further, if $Y_t$ is stationary around a deterministic trend, then the ARMA model is over differenced. This over differencing may induce a unit root in the moving average component. Long auto regressions do not provide an adequate approximation in this case. In addition, it is important to avoid estimation of the ARMA model via quasi-maximum likelihood techniques, since these may not provide good approximations when there is a unit MA root. It is also very sensitive to the order of the fitted ARMA process (Christiano & Eichenbaum, 1990).

Cochrane (1988) criticized Campbell and Mankiw's measure and argued that the estimates of persistence by fitting ARMA or any parametric models with Gaussian maximum likelihood estimation (MLE) would have an upward bias if the fitted model is misspecified. Thus, Cochrane, (1988) proposed another measure of persistence as a ratio of variances based on the ratio of the k period variance to the one period variance, variance ratio (VR)[3] measure, based on the variance of its long differences by a nonparametric approach. It is called limiting variance ratio (VR) and denoted by $V_k$ . Variances are functions of autocorrelation. This is a non-parametric approach that differs from earlier measures that were based on parametric approach. The estimate from this nonparametric method is more stable compared to Wold MA representation estimation *A(L)* parameters. The estimates of parameters *A(L)* are sensitive to change. More generally, both measures, $V_k$ and $A$ (1) are not the same. However, they gave the same conclusion for a stationary and random walk processes.

Meanwhile, Watson (1986) and Clark (1987) proposed another measure for persistence. They proposed that GNP can be the sum of two or more components. These components are not directly observed, but their relative importance and the implications for persistence are inferred from the time series behavior for GNP. Therefore, this model is formulated using unobserved components (UC). The UC model has proved to be useful in analysing permanent and transitory components in GDP. In this UC model, a time series is represented by the sum of two unobserved components, namely stochastic trend and cycle. Beveridge and Nelson (1981) also used this UC approach. They assumed that stochastic trend follows a random walk process and cycle follows a stationary process. Beveridge and Nelson assumed that they are perfectly correlated. Nevertheless Watson and Clark expressed output as the sum of two independent processes. Watson and Clark imposed a restriction on this ARMA model. They yield low persistence on low frequency behavior. Watson and Clark estimated the parameters of the unobserved components model via maximum likelihood and then infer *VR* and *A*(1).

The previous literature shows that IP can be estimated through parametric, non-parametric and unobserved component (UC) model approaches. A parametric approach is a method of measuring IP using parametric models such as autoregressive (AR *(p))* model, ARMA or autoregressive integrated moving average (ARIMA (*p, d,*

$q$)) models. A parametric approach is easy to estimate and interpret. Campbell and Mankiw (1987) used $A$(1) as a measure of persistence. Meanwhile, the other method is the non-parametric approach to measuring IP. It is not based on parametrized families of the probability distributions. The third one is the UC models that is formulated using latent variables. The UCM had been used in applied econometric research and statistical practical applications. This model was first introduced to the econometrics and statistics fields by Harvey (1990). A time series of observations can be seen as the combinations of several unobserved components such as trend, seasonal and cycle components. The fully specified UCM is written as

$$[3.1] \quad y_t = \mu_t + \gamma_t + \psi_t + r_t + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{m} \beta_j x_t + \varepsilon_t$$

where $y_t$ represents the time series to be modeled and forecast, $\mu_t$ the trend component, $\gamma_t$ the seasonal component, $\psi_t$ the cyclical component, $r_t$ the autoregressive component, $\varepsilon_t$ the irregular component. All of these components are assumed to be unobserved and must be estimated given the time series data on $y_t$ and $x_t$.

Economists proposed some parametric approaches to measuring IP to the univariate situation. As summarized by Marques (2004), these measures are the sum of autoregressive coefficients (SARC) in the time domain, the spectrum at zero frequency (SZF) in the frequency domain, the largest autoregressive root (LAR), and the half-life (HL). Andrew and Chen (1994) had discussed the first three measures based on cumulative impulse response function (CIRF) from AR($p$) process. They derived these measures from the simple AR(p) model. Pivetta and Reis (2007) had

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also used SARC, LAR, and HL measures for estimating IP. Specifically, SARC measures IP using lag effects or coefficients that are estimated from AR($p$) model. In mathematical form, it can be shown as $IP^4 = \sum_{i=1}^{n} \hat{\alpha}_i$ where $\alpha_i$ represents the coefficient of $i$ th lag ($i$ = 1, 2, …, $p$). One of several advantages of SARC is simplicity in terms of estimation and interpretation. In addition, as suggested by Campbell and Mankiw (1987), this would be a good measure of IP. However, this method also has some limitations. For example, if some of the coefficients are positive and some are negative, the sum of coefficients may be zero.

The other famous measure of IP is SZF. Mathematically, it is measured by $h(0) = \sigma_\varepsilon^2 / (1-\rho)^2$ for the AR($p$) process, where $\rho$ is the correlation coefficient and $\sigma_\varepsilon^2$ is the variance of the residual ($\varepsilon_t$). If IP changes over time, this measure is not a good estimator. Persistence changes come from changes in $\rho$ and $\sigma_\varepsilon^2$. Thus, it becomes problematic. Comparing to SARC measure, SZF is less preferable. SARC is more preferable because it is more innate and has a small and visibly defined range of potential variation. If the series is integrated order one, $I(1)$ or $\rho = 1$, the CIRF and the SZF cannot be computed[5].

LAR is another measure of IP. LAR is derived from the lag polynomial of AR($p$) model, $L(p) = (1 - \theta_1 L - \theta_2 L^2 - .......... - \theta_p L^p)$. This polynomial can be factored as $L(p) = \{(1-\beta_1 L)..........(1-\beta_{p-1} L)$, where $\beta_i$ are coefficients that are ordered according to their magnitudes. The coefficient of $\beta_1$ is considered as the largest one. In the long run, the consequence of a shock on inflation will be dominated by this largest root. When $\rho = 1$ the series has a unit root and all shocks are permanent. The LAR measurement is effective when $\beta$ is close to the unit root. Other roots that are beyond the unit root are not effective. In practice, if a series has a higher root value, it will display more persistence than one that has a lower value of a root. Stock (2001) had used this measure as a measure of persistence. However, Pivetta and Reis (2001) had criticized this measure by stating that the shape of impulse response function (IRF) depends on other roots as well, not only on the largest one. It is a very poor descriptive measure of IP. However, it has an advantage to calculate asymptotically valid confidence intervals for the IP measure (Stock, 2001).

Finally, HL is another measure of IP. This measure uses an IRF of the estimated AR($p$) models. HL is defined as the number of times for which the consequence of a unit shock to inflation remains above 0.5. In the case of an AR(1) model, $\pi_t = \rho\pi_{t-1} + \varepsilon_t$, HL is computed using the formula of $HL = \frac{\ln(0.5)}{\ln(\rho)}$. This was the extensively used measure of IP in the literature. Pivetta and Reis (2007) had also used the three methods (SARC, LAR, HL) for estimating IP. SARC was widely used in the literature of IP. However, Mankiw and Reis (2001) noted that if IRF is oscillating, it can understate or overstate the persistence of the process. Further, if the series is integrated of order one, $I(1)$ or $\rho = 1$, CIRF and the spectrum at zero frequency, $h(0)$, cannot be computed.

### 3.2.2.2 Long Memory of Inflation

This section focuses on the definition of long memory and measures of long memory. Long memory refers to the extent to which inflation tends to approach slowly its equilibrium level after a shock, rather than instantly. It implies that shocks have long lasting effects and the process contains a lot of time dependence. If persistence continues for a long time into the future, it becomes a long memory of the series. Long memory is defined by an empirical approach (data driven approach) in terms of the persistence which is exhibited by the rate of decay of ACF. There is no explicit economic theory about the long memory of an economic series. But, the theory of long memory from statistical physics is employed to achieve the first objective of this study. The long memory characteristics in a price dynamics can be looked at in two ways. One is on its mean dynamics and the other one is its volatility dynamics.

The phenomenon of long memory has a long history (Newcomb, 1895; Student, 1927; Wilson & Hilferty, 1929; Mosteller & Tukey, 1977). The phenomenon of long memory has been applied in diversified fields; agronomy, astronomy, chemistry, economics, econometrics, engineering, environmental sciences, hydrology, mathematics, physics, and statistics For example, in hydrology, Hurst (1951) discovered an empirical law while studying the Nile river dam.

Mandelbrot (1967, 1971, 1972, 1977, 1983), Mandelbrot and Van Ness (1968) and Mandelbrot and Wallis (1969) led to a new branch of mathematics; “fractals”, and “self-similarity” that was used for long memory theory in many scientific fields such as statistics, hydrology, geology, and economics. Following Mandelbrot’s pioneering work on long memory, it has become a rapidly popular subject and its practical significance has been recognized. Long memory study has become an active topic in financial time series and economics following Mandelbrot’s work.

Recent literature shows that a study of long memory phenomena goes beyond the presence of random walk and unit roots in time series analysis. Diebold and Rudebusch (1991), Lo and MacKinlay (1989) and Sowell (1990) highlighted the low power of the asymptotic unit root type tests and motivated the use of fractional differencing. In the innovative framework of Box and Jenkins (1970), ARIMA($p$,$d$,$q$), they have not accounted for long memory of the time series. The parameter $d$ was limited to be an integer, by way of $d$=0 for stationary series, I(0) or $d$=1 for non-stationary; I(1) series. On the contrary, Granger and Joyeux (1980) and Hosking (1981) emphasized and accounted for long memory. They argued that $d$ need not be an integer, it can be a fraction. In addition, they suggested that the properties of the autocorrelation function depend on the parameter $d$. The nature of the shock effect depends on the value of $d$. Thus, they proposed $d$ to measure long memory of a time series. Hosking (1981) came to the conclusion that fractional differencing parameter ($d$) can account for persistence of a shock in the series explicitly, incorporate both short run and long term correlations in the data, and support in forecasting.

Long memory had been estimated in time domain or frequency domain. The long memory phenomena were investigated by different approaches namely, parametric, semi-parametric and non-parametric estimation methods in the past literature. Long memory features can be captured by the degree of fractional integration ($d$) (Baillie, Bollerslev, & Mikkelsen, 1996; Barkoulas, Labys, & Onochie, 1997; Booth & Tse, 1995; Cheung & Lai, 1995). The literature reveals that long memory of a series is analysed using unit root tests, the Rescaled Range (*R/S)* statistic, Geweke and Porter-

Hudak (GPH) estimator and Autoregressive Fractional Moving Average (ARFIMA) model long memory parameter '*d*'.

Unit root tests can identify whether series have unit root I(1) or not I(0). Examples of unit root tests are the Augmented Dickey–Fuller (ADF) test, the Phillips and Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. However, they are unsuccessful in distinguishing an extremely persistent stationary process from non-stationary processes (Sowell, 1990). Therefore, other test methods are recommended to measure long memory property. Sowell (1990) and Diebold and Rudebusch (1991) showed that the ADF test has low power for fractionally integrated series. The effects of a shock persist forever in a unit root I(1) process.

The R/S statistic of the measures of long memory is derived by the nonparametric approach. Hurst (1951), an English hydrologist, proposed the "*R/S*" or Hurst exponent statistic to measure long memory. Hurst used the coefficient (*H)* as an index for the persistence of the time series. Then, Hurst's statistic was improved by Mandelbrot (1971, 1972, 1975), Mandelbrot and Taqqu (1979) and Mandelbrot and Wallis (1969) in several important ways. This statistic was used as a long memory statistical test in the early period. Granero *et al*. (2008) noted that though this statistic is valid to detect long memory in a series, it is delicate to the length of the series that influenced standard deviation and mean. Lo (1991) has found that standard *R/S* statistic becomes biased and not robust by the short memory effects. Lo (1991) revised standard deviation to solve the effects of short memory using Newey-West correction and derived a modified *R/S* statistic. The reformed *R/S* statistic is more robust than the standard *R/S* statistic (Teverovsky *et al*., 1999). Giraitis *et al*. (2003)

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proposed another statistic called rescaled variance (V/S) test. This statistic has high power in relation to the KPSS statistic.

The other measure of long memory is a fractional differencing test of the semiparametric approach proposed by Geweke and Porter-Hudak (1983). In this test, the long memory is estimated exclusively by the fractional differencing parameter '*d*'. The estimate of this long memory parameter is obtained from a log periodogram regression. The advantage of this measure is that application of the GPH test is simple. The GPH test can increase estimation efficiency compared to the non-parametric R/S test. This estimation method is asymptotically robust to the specifications of the polynomials of $\phi(z)$ and $\theta(z)$. Semi parametric approaches evade the misspecification issue. Nevertheless, the GPH long memory estimator $\hat{d}$ has not proved its reliability and the limiting distribution were obscure. Later, Robinson (1995) proved that the estimator is consistent and asymptotically normal. Agiakloglou and Newbold (1992) argued that it is biased and inefficient when error term, $\varepsilon_t$ is AR (1) or MA(1), and the AR or MA parameter is relatively large. It is a frequency domain regression to estimate fractional "*d*". The GPH method was modified by Kunsch (1986), Robinson (1995), Hurvich and Ray (1995, 2003), Hurvich *et al.* (2005), and Phillips and Shimotsu (2004) to improve consistency and asymptotic normality when $d \geq 0$. However, the GPH method is still used widely.

The third measure, fraction difference parameter *d* of autoregressive fractionally integrated moving average (ARFIMA) model uses a parametric approach. Granger and Joyeux (1980) and Hosking (1981) introduced a parametric model, ARFIMA model[6]. In ARFIMA model, long memory parameter is denoted by '*d*' which is a fractional differencing parameter. The values of '*d*' describe the long memory of the series and dynamic behavior of the series. Statistical significance of the parameter *d* is evidence of long memory. It is used extensively in finance and economics in recent periods. This model is used to capture both long term dynamics and short term dynamics of the series. Various methods of estimating ARFIMA models had been proposed in the literature of Baillie (1996) and Ooms and Doornik, (1999). For example, one method was Sowell's (1992) Exact Maximum Likelihood (EML) method. Even though it is a heavy computational exercise, it is widely used. The presence of nuisance parameters biases EML estimates. To overcome these problems, Ooms and Doornik (1999) proposed Modified Profile Likelihood (MPL) method. It is a nonlinear least square (NLS) estimator of Ooms and Doornik (1999). The parameters $\{\phi, \theta, \mu, d, \sigma_\varepsilon^2\}$ of the ARFIMA models for the given series are estimated by optimizing the likelihood function. The parametric approach has limited flexibility when it comes to model specification. Incorrect specification considerably affects the estimates of the long memory parameter '*d*' (Gil Alana, 2001). The estimation of ARFIMA models is more difficult than the usual ARIMA models with integer '*d*'. However, the MLE method has been popular among researchers and extensively used. Appropriate specification of *p* and *q* is estimated using Akaike information criterion (AIC). The best model has the smallest AIC value. Long memory specifies the evidence of non-linear dependence in the first and second moments.

Memory properties can be estimated for any time series. Not only for mean of the series, but also for variance of the series. In this aspect, estimating memory of volatility series is useful in economic decision making. Volatility refers to unexpected price movements. One of the statistical stylized fact (second moment) of a price dynamics is volatility of price dynamics. Inflation volatility distorts the decision of economic agents (Fischer, 1981). There are large numbers of theoretical literature on volatility phenomena. Mandelbrot (1967, 1971) investigated the time series properties of asset price changes and argued that variance of an economic time series is time varying. However, in the 80's, academics started to realize the importance of modelling variability of a time series. Since then, studies on modeling volatility phenomena have been developed by many researchers. The Autoregressive Conditional Heteroscedastic (ARCH) modeling was introduced by Engle (1982) to measure volatility. However, prior to the Engle's ARCH, there was no proper statistical model employed. Engle (1982) first developed the ARCH model using inflation data series for the U.K. This ARCH model was able to capture the stylized facts such as volatility clustering, the persistence of inflation volatility for the U.K. Following Engle's (1982) seminal paper, ARCH model has been developed in modeling of volatility phenomena. The literature on ARCH has grown in a remarkable style. Engle (1982) used conventional inflation equation with fixed parameters to model inflation volatility. But, it allowed to vary the conditional variance of inflation over time. The ARCH model has increased interest in volatility modeling in financial markets. Various models have been developed over time. For example, Generalized Autoregressive Conditional Heteroscedastic (GARCH) models of Bollerslev (1986), by extending the simple ARCH model. Bollerslev (1986) generalized the ARCH model to the GARCH by including lagged conditional variances as well as lagged squared innovations in the equations explaining conditional movements. Exponential Generalized Autoregressive Conditional Heteroscedastic (EGARCH) models of Nelson (1991), and GJR models of Glosten, Jagannathan, and Runkle (1993),and Threshold Autoregressive Conditional Heteroscedastic (TGARCH) models of Zakoian (1994), arose from this.

Since the introduction of the GARCH model, a large number of extensions of GARCH model were suggested due to the limitations of the standard GARCH model. GARCH model did not account for the leverage effects, and it does not allow for any direct feedback between the conditional variance and the conditional mean. Further, nonnegative conditions are violated in estimated models. The assumption of symmetric response of conditional volatility to positive and negative shocks was another drawback of ARCH and GARCH models. Brunner and Hess (1993) and Fountas *et al.* (2006) criticized the GARCH model saying that inflation volatility behavior was asymmetric. In order to overcome these drawbacks, various models were suggested by researchers. They were the threshold GARCH (TGARCH) models of (GJR) or Glosten, Jagannathan and Runkle (1993), the asymmetric GARCH (AGARCH) model of Engle and Ng (1993), the exponential GARCH (EGARCH) model of Nelson (1991). ARCH and GARCH models account for the non-normalities in the empirical distribution of commodity prices.

Another important and useful feature of the GARCH model is the memory of the conditional volatility process (Baillie *et al*., 1996; Zaffaroni, 2007). The memory of a GARCH model determines how long shocks to the volatility take to dissipate. There are usually two cases discussed in the literature relating to the memory of GARCH, namely the geometric (short) memory, and hyperbolic (long) memory. The stationary ARCH and GARCH models are usually considered to have a short memory as shocks have relatively "less" persistent effects on the conditional volatility. Its memory decays at the exponential rate. For example, if $\{\varepsilon_t\}$ are ARCH (1), then the autocorrelation of $\{\varepsilon_t^2\}$ is $\rho_k = \alpha^k$. This indicates that the decay is unrealistically fast (power law). On the other hand, when $\rho_k = 1$ for all k, there is no decay.

Long memory in volatility denotes a slow decay (hyperbolic rate) in autocorrelation function (ACF) of the squared or log squared returns or conditional variance that are proxies of the volatility of return. Many of the previous work on volatility were in the area of finance. Taylor (1986) contributed first in this regard. He had noticed that ACF of the absolute values of stock returns decays very slowly. Bollerslev *et al.* (1992), Bera and Higgins (1993), Bollerslev *et al.* (1994), Engle (1995), and Gourieroux, (1997) among others focused on the GARCH modelling. Recent literature shows that ARCH and GARCH do not perform well in modelling volatility clustering. GARCH class models worked under additional restrictive assumptions. GARCH models that were widely used in the empirical analysis do not account for long memory in volatility. Short run dynamics or short memory models are modeled by the standard GARCH models. Dacorogna, Muller, Nagler, Olsen and Pictet (1993), Ding, Granger and Engle (1993) and Harvey (1993) argued that squared exchange rate returns have a long memory. In order to account for long memory in volatility, Baillie, Bollerslev, and Mikkelsen (1996) introduced a new model called fractionally integrated GARCH (FIGARCH) model. Long memory parameter of FIGARCH model is estimated by the MLE method. FIGARCH models allow for long memory in the conditional variance. The MLE estimators of the FIGARCH model parameters are consistent with limiting normal distributions. This FIGARCH model can be extended to the other parametric ARCH formulations. For example, FIEGARCH model was extended from EGARCH by Bollerslev and Mikkelsen (1996).

### 3.2.3 Price Transmission

This section reviews the previous theoretical studies related to price transmission. A price transmission (PT) refers to the effect of prices in one market that is transmitted to prices in another market. PT is also termed as pass-through. Transmission elasticity is used to measure the strength of price transmission, calculated as the percentage change in the price in the importing market for a one percentage change in the price in the exporting market place. Price changes are transmitted in two ways; transmission in mean (level) and/or in volatility of price changes between countries. PT is categorized as complete transmission or incomplete transmission based on the magnitude of the transmission. The magnitude of PT is also determined by government policies such as price control, subsidies, and trade barrier.

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#### 3.2.3.1 Mean-Price Transmission

Price theory in economics indicates that flexible prices are responsible for efficient resource allocation and PT incorporates markets vertically or horizontally. Therefore, PT processes need to be investigated. Markets may be either independent or interdependent, depending on the type of economic and technical relationships among the exchanged commodities. Products may be a substitute or complement to each other and this kind of relationship is based on technical aspects.

Price is transmitted along the stages of the supply (marketing) chain. This is called vertical price transmission (VPT), for example, input cost is transmitted into the output price (wheat-flour-bread). There is another economic relationship for the same product exchanged in spatially separated markets. This is horizontal price transmission (HPT). Price is transmitted across spatially separated markets, from origin market to destination market. For example, world food prices are transmitted to national prices in a country. The other type of relationships are chronological linkages between different markets for the same goods. Literature shows that a large number of studies covering spatial (horizontal), vertical (product) PT studies are available. In this section, the relevant theories are reviewed to obtain elements that can be useful in explaining the findings of the empirical analysis carried out in this study.

The perfect competitive market (PCM) model which was expounded by the Neoclassical theory is standard in PT process. However, it has been criticized under many facets. Under the assumption of perfect competitive markets, any price shock in a market should be perfectly transmitted to the related markets given the costs of transportation between markets. In this situation, price trends would have similar patterns and symmetries in both markets. In practice, markets are not perfect. Therefore, the presence of asymmetries is visible in the PT process.

According to Neoclassical theory, factors that explain HPT can be divided into technical and economic factors. Some examples for technical factors are costs of transport, storage commercial facilities and for economic factors, the existence of different demand curves. In practice, the structure of the markets differed from one to another. In this case, arbitrage between markets is possible and allows for asymmetric PT.

Theoretically, the Law of One Price (LOP) says that identical goods should be sold for the same price in two separated markets. This law assumes no transportation costs. When a commodity price in an importing country is regressed on the same commodity price in an exporting country, then slope coefficient is restricted to equal to one and the intercept term is restricted to equal to zero. If these restrictions are not rejected, then LOP exists. However, these tests have been criticized on various grounds. Isard (1977) and Richardson (1978) among others, argued that the assumption is not consistent with practice. Transaction costs need to be incorporated in the model. They found the LOP works when an expectations-augmented model is used. Ardeni (1989) and Baffes (1991) had examined spatial price transmission within the context of the LOP. Ardeni (1989) investigated first on agricultural price transmission using cointegration techniques and found there was world price transmission to domestic economy.

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PT in practice is not consistent with standard economic theory which assumes symmetric PT. However, asymmetric PT can have significant implications for policy planning. Literature shows that there are many studies that were related to agricultural commodities PT. Asymmetry of PT depends on the speed, magnitude or direction of price changes and its value can be positive or negative. If the price in destination market responds more fully or rapidly to an increase in the price in the first market than to a decrease, the asymmetry is denoted as positive asymmetry. If the price in the destination market responds more fully or rapidly to a decrease in price in the first market than to an increase, the asymmetry is denoted as negative asymmetry. The causes of asymmetric PT highlighted in the literature are the presence of non-competitive markets, the existence of adjustment costs, government intervention, and distorted information. Market power is expected to lead to positive asymmetric PT. However, Ward (1982) had found that market power can lead to negative asymmetry, if oligopolists in the markets are unwilling to risk losing market share by increasing prices. Bailey and Brorsen (1989) concluded that it is not clear whether market power can lead to positive or negative asymmetry.

The various estimation techniques for asymmetric PT have been cited in the literature. Farrell (1952) first investigated irreversibility empirically. Nevertheless, in agriculture, Tweeten and Quance (1969) used a dummy variable technique to estimate irreversible supply functions. Wolffram (1971) suggested another method; variable splitting technique. Following these studies, Ward (1982), and Boyd and Brorsen (1988) had also tried to contribute to the methods. In the evolution of estimation methods, von Cramon-Taubadel and Fahlbusch (1998) first employed cointegration techniques to test asymmetric PT. This method was expanded by adding error correction model later by Cramon-Taubadel and Loy (1996), and Cramon-Taubadel (1998).

#### 3.2.3.2 Price Volatility Transmission

Literature shows that GARCH type models, Regime Switching models, Stochastic Volatility models, and cointegration analysis have been used to study volatility interrelationship between markets and volatility transmission. GARCH models have been extensively applied in analyzing relationships between markets, financial markets in particular. Hamao *et al*. (1990) first studied volatility transmission using the univariate GARCH method among international financial markets. Wang et al.

(2002) had also studied volatility transmission using univariate GARCH specification. All of them found volatility transmission effects. Many studies included dummy variables in the mean and variance equations to capture structural effects; eg., Susmel and Engle (1994). Volatility structural breaks were studied by many researchers. Some of them are Diebold (1986), Hamilton and Susmel (1994) and Diebold and Inoue (2001).

Stochastic volatility (SV) models are another method to analyze volatility transmission between markets. The variance of a stochastic process is itself randomly distributed. Taylor (1982) introduced the basic SV model[7]. Taylor revised this SV model again in 1994. Advantages of SV models have been discussed in some of studies, like Harvey *et al*. (1994), Shephard (1996) and Kim *et al*. (1998). The SV model differentiate error in level ( $\varepsilon_t$ ) from error in variance ( $\eta$ ) explicitly. Ghysels *et al*. (1996), Shephard (2005) and Asai *et al*. (2006) focused on stochastic volatility. The main advantages of SV models in contrast to GARCH models are: generalization to the multivariate case is much easier (Harvey *et al*., 1994) and properties of the series can be easily obtained. The studies by Shephard (1996) and Kim *et al*. (1998) had compared SV models with GARCH models in detail.

### 3.2.4 Price Inflation

For the purpose of a survey of the literature of inflation, a pragmatic definition of inflation is employed here. Inflation is a sustained increase in the general or aggregate price level in an economy. It is typically measured by CPI or WPI or GDP deflator.

Until early 1960s, the inflation theory focused on cost push and demand pull factors. Then towards the end of the decades, new perspectives came into the inflation literature. In the 1960's the Phillips curve explanations dominated the discussion. The focus of explanation shifted towards monetarist inflation model (Friedman, 1968, 1970, 1971) at the early 1970s. Then, structural factors came to explain the long run tendency to inflation. For a small open economy, the structural model became popular in the discussion. This model linked the structural productivity gap with global price level changes. The Norwegian and the Scandinavian models that combine the essential elements of the structural explanation of inflation highlight that overall inflation is determined by foreign prices (imported inflation). These models accounted for global inflationary transmission to domestic market.

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### 3.2.5 Intertemporal Relationship between Mean and Variance of Inflation

A profound understanding of the link between the mean rate of inflation and the variability of inflation would help in understanding the price dynamics in depth. In order to understand the previous work in this area, this section concentrates on a number of theories put forth to explain the association between variability of inflation and the average rate of inflation. The positive association between mean and variance of inflation has been extensively documented in the literature; Okun (1971), Logue and Willet (1976), Tylor (1981), Golob (1994) and Rizvi and Naqvi (2009). Since the 1970s, academics have started to give more attention to the relation between inflation and its temporal variance. The theoretical underpinnings of this area have not been rigorously investigated. However, there is ample empirical evidence of this relationship in economic literature.

The hypothesis that higher inflation is related to high inflation uncertainty stated in Okun's (1971) paper became well known by Friedman's (1977) Nobel lecture. Both Okun and Friedman provided an informal argument only. Low variance inflation is associated with low welfare loss. On the other hand high variance inflation is generally related to high welfares losses. High variance inflation contracts the efficiency of intertemporal allocation decisions. Friedman argued that higher inflation lessens the predictability of future inflation. In addition, he found that price inflation Granger- causes inflation uncertainty. This is generally known as Friedman-Ball Hypothesis. Ball (1992) had discussed theoretically why high inflation raises inflation uncertainty using a model of monetary policy. Based on his findings, he theorized that higher inflation rates stimulate inflation uncertainty and concluded that in actual economies, high inflation creates uncertainty whether inflation will rise further.

## 3.3 Review of Empirical Studies

This section reviews empirical studies that are grouped into memory properties, price transmission and price inflation and the inter-temporal relationship between mean and variance of inflation.

### 3.3.1 Memory Properties

This section describes the empirical studies of memory properties by classifying them into persistence and long memory.

#### 3.3.1.1 Persistence

Many researchers have reported on the persistence properties of inflation series. Persistence is much concerned in current policy studies as it is a very informative concept in macroeconomic policy formulation and micro-investment decision making. Persistence reflects the long lasting effects of a shock. Thus, persistence can be used to assess the long term effect of a shock. Literature survey shows that persistence has been investigated in various countries by many researchers in recent periods.

Most of the studies discuss persistence of various macro series for developed countries. Stock and Watson (1986) and Clark (1987) using unobserved components models had found less persistence for U.S. GNP growth data. Campbell and Mankiw (1987) used same variable (GNP) and found no evidence for output fluctuations quickly trend-reverting to long run equilibrium path. They found the earlier studies have not distinguished business cycle from other fluctuations in real GNP. They used unemployment to decompose GNP fluctuations, then concluded that there was no evidence of transitory nature. IP has been extensively analysed for Euro Area countries. The European Central Bank and the 12 National Central Banks of the Euro members examined IP in the Euro-Area and its associate countries. The team that conducted the research was called the Inflation Persistence Network (IPN). The IPN focused on computing and comparing patterns of price setting and IP in the Euro Area.

Some of the other studies of U.S. GNP (developed countries) were Clark (1987), Watson (1986), Stock and Watson (2007), Mishkin (2007), Levin and Piger (2007), Cecchetti and Debelle (2006) and Cogley *et al*. (2009). Campbell and Mankiw (1987) and Cochrane (1988) found long term persistence against the previous studies work on persistence in GNP and criticized the conventional method of persistence. Hence, almost all studies have rejected that output shocks have no permanent effect.

Following these studies, persistence had been used to investigate the other macro variables, such as stock prices, and exchange rates and in other sectors and in other countries. For examples, Pesaran *et al.* (1993) employed the persistence measure for multivariate time series using 10 U.S GNP sectors. They found that most of the sectors were very persistent. Mayadunne *et al.* (1995) examined persistence using the Australian data and compared with the U.S results. Van de Gucht *et al*. (1996) examined persistence using Canadian seven exchange rates of daily frequency. Barsky (1987) had found that inflation was not persistent, close to white noise in the pre-war period but very persistent since the 1960s. This evidence indicates that IP is also time varying. IP was examined in the United States by various researchers. Some of them are Cogley and Sargent (2002), Stock (2001) and Taylor (2000). Stock (2002) found that IP was not changing. Taylor (2000) found that IP was lower (LAR=0.64) for the period of 1982M1-1999M4 than that (LAR=1.02) for 1960M2-

1979M4. Kim *et al*. (2004) found that IP was lower in late 1979. However, these changes were short lived. Therefore, Pivetta and Reis (2007) concluded that IP had been high and approximately not changed between 1947 and 2001. Stock and Watson were consistent with Pivetta and Reis (2007) results. Owyang (2001), Barsky (1987), and Fuhrer and Moore (1995) had also found that U.S inflation was persistent. Using ARFIMA-GARCH model, Baillie, Chung, and Tieslau (1996) also identified that U.S inflation was persistent and mean reversion and heteroscedastic.

There were a few papers on IP in South Africa. Inflation persistence was estimated using ARMA model for South Africa (Rangasamy, 2009, 2011). To estimate persistence, he used inflation deviations from a time varying inflation mean estimated from Hodrick-Prescott (HP) filter. His results show that inflation had been persistent in South Africa. There are a few studies which focused on IP for developing countries, Asia in particular. For example, Gerlach and Tilmann (2012) investigated IP in some Asian countries (except Sri Lanka). They found that inflation targeting influences IP in these countries.

There are a few studies focused on food price dynamics. Findings of Vega and Wynne (2001), Bryan and Cecchetti (1997), Culter (2001) and Bilke and Stracca (2008) showed that food prices were relatively persistent in Euro area. From the Walsh study (2011), based on all three measures of persistence, one can conclude that food inflation had more persistence than nonfood inflation in low income countries. Walsh (2011) found that the HL for food inflation was higher than that of nonfood inflation.

Cecchetti and Moessner (2008) also used SARC to measure persistence. Andrews and Chen (1994), Levin and Piger (2002), Rangasamy (2009) and Clark (2006) had estimated the SARC as 0.9 for the U.S inflation. Andrews and Chen (1994) had recommended the SARC as a best measure of IP.

Nelson and Plosser (1982) found that most of GNP deflators, CPI and money stock exhibit more persistent autocorrelation in first differences. They had also shown that differenced stationary (DS) class of process contains stochastic trends characteristics. Changes to monetary policy, supply push shocks such as oil price changes and wage spirals are able to influence inflation persistence (Balcilar, 2004 & Rangasamy, 2009). Balcilar, Gupta and Jooste (2014) tested the inertial properties of South African inflation using a Markov-Switching ARFIMA model. They found that inflation was more volatile and persistent during high inflation episodes relative to low inflation episodes. They showed that it takes roughly 70 months for 50 percent of the shocks to dissipate in higher inflation periods compared to 10 months in lower inflation periods.

Persistence of shocks in globalized information and computing technology world occupies an important place in macroeconomics. The effects of shocks in world food prices on domestic price dynamics depend on the persistence of the shock. If the price increases are temporary, then food price increases are less likely to affect headline inflation. If the price increases are persistent, then they are more likely to affect headline inflation. Walsh (2011) had shown that LAR for food price inflation was higher than that of nonfood price inflation. Further, he found that food and nonfood inflation series did not have unit roots, but had largest autoregressive roots (LAR). Both measures (SARC and LAR) in his study showed that the persistence of food and nonfood inflation is negatively related with income level. Campbell and Mankiw (1987) used SARC from the MA representation of AR model of GNP.

In the Eurozone, Alvarez *et al.* (2006) investigated the persistence of inflation across components of CPI and compared with similar studies done in the U.S. They found that in both regions, food prices were less persistent than nonfood prices, services in particular. But, across all categories, prices in Europe are more persistent than to prices in the U.S. In this way, they showed that food price dynamics are relatively less important in headline inflation dynamics.

Cecchetti, Hooper, Kasman, Schoenholtz and Watson (2007) investigated inflation dynamics in the U.S. and other G-7 countries using a statistical model. They first assumed that inflation series could be decomposed into transitory and persistent components. In addition, they investigated both the time varying trend and the time varying transitory components dynamics. They also used a UC model with stochastic volatility (UC-SV) based on Stock and Watson (2001, 2007) to characterize inflation dynamics. Stock and Watson (2005) found that UC-SV model performed well for a growth rate of real GDP for the G-7 countries during 1960-2002. Cecchetti *et al*. (2007) employed this model to describe inflation dynamics for G-7 and USA.

To sum up, several studies investigated the persistence issue for developed countries, in particular, inflation, GNP series of the U.S., G-7 countries, and Euro Area. When results of persistence are classified based on variables, the degree of persistence varies according to the variables. Wage, interest rate, oil price, investment, CPI, GDP, consumption, export, import, productivity were accommodated in the persistence analysis in various studies. GDP, consumption, import and export showed the degree of persistence of less than one. Unemployment had around one, whereas, interest rate, oil price, CPI, and M2 showed a value above one.

### 3.3.1.2 Long Memory

Long memory phenomenon had been investigated in the different variable data sets, for different countries for different periods by different researchers; Hurst (1951, 1957), Mandelbrot and Wallis (1969), Mandelbrot and van Ness (1968), Mandelbrot (1972), and Meleod, and Hipel (1978) among others. Hurst (1951) recommended increasing the height of the planned Aswan High Dam for Nile River far beyond conventional forecasts based on his empirical findings in hydrology.

Berger and Mandelbrot's (1963) paper on price fluctuations is now regarded as one of the key pioneer work to Econophysics. Mandelbrot (1971) first studied the effects of long memory in financial markets using Hurst's 'R/S' statistic to identify long memory behavior in asset return data. Since then, several empirical studies such as Greene and Fielitz (1977) have supported Mandelbrot's findings.

Several empirical studies have illustrated the existence of long memory in economic data; Cheung and Lai, (1995) and Baillie, Chung, and Tieslau (1992). A large number of studies such as Klein (1976), Barsky (1987), and Ball, Cecchetti, and Gordon (1990) had examined the properties of long memory for inflation for industrialized countries namely Brazil, Canada, France, Germany, Israel, Italy, Japan, United Kingdom and the United States. The findings from these studies showed that any shock has a permanent impact on inflation. Greene and Fielitz (1977) had shown empirical evidence of long memory in the US stock market returns based on the R/S analysis. The studies of Hassler and Wolters (1995) and Baillie, Chung and Tieslau

(1996) found substantial evidence of the long memory in inflation rates in G7 countries.

The fractionally integrated models were employed to study long range dependence extensively in developed countries. Using U.S inflation data, Backus and Zin (1993) found that fractional difference parameter was statistically significant. Hassler (1993) and Delgado and Robinson (1994) found strong proof of fractionally integrated behavior in the Swiss and Spanish inflation rates, respectively. De Boef and Granato (1997) reviewed that some data are long memory processes but do not have unit roots, especially in the range $0<d<1$. Even though it does not contain a unit root, it does have a long memory, whereby shocks to the series persist for at least 12 months. Hassler and Wolters (1995) have examined inflation rates of five developed countries for the period of 1969 to 1992 and found that inflation series have long memory. They found that the order of integration of the series is significantly different from 1 (one) as well as 0 (zero). Hassler (1993) and Baillie, Bollerslev and Mikkelsen (1996) studied monthly post-World War II CPI inflation in 10 countries and found evidence of long memory with mean-reverting demeanour in all the countries excluding Japan. Skare and Stjepanovic (2013) examined GDP fluctuations in Croatia using fractional integration framework. They found that ARFIMA model performed well and macroeconomic shocks in GDP were highly persistent. GDP did not behave like I(0) or I(1), it behaved more likely fractionally integrated process. Recent applications of the ARFIMA model includes Barros, Caparale, and Gil-Alana (2012), Kovacs, Huzsvai and Balogh (2013) and Balcilar *et al*.(2014).

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The studies of Andesen and Bollerslev (1997), Dacorogna *et al.* (1993), and Labato and Savin (1998) showed that ACF for log squared, squared or absolute returns decay hyperbolic rate indicates long memory. These mean-reverting dependencies were not captured well by ARCH or stochastic volatility models.

However, long memory application had spread to the area of volatility. The empirical results of Engle's ARCH model motivated researchers to the area of volatility. All the parameterizations of ARCH, GARCH, IGARCH and EGARCH confirm persistence in conditional volatilities. For example, the fractionally integrated GARCH (FIGARCH) from Baillie *et al.* (1996), the long memory ARCH model from Ding and Granger (1996), the long memory nonlinear moving average models from Robinson and Zaffaroni (1996), the long memory stochastic models (LMSV) from Breidt, Crato, and de Lima (1998) were employed to investigate long memory features in variance of returns. In general, the literature on the volatility of food price dynamics is scarce compared to the literature on financial markets.

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In the 1990s, academics started to realize the importance of the role of volatility (second moments). The variance of a variable (second moment of a distribution), is necessary to describe a distribution better. Volatile phenomena cannot be explained by average (first moment) measure alone. Since Engle's (1982) innovative ARCH model, ARCH model, and its various generalizations have been applied to numerous and diverse areas of economics for many countries to describe volatility. Engle (1983) found that the variance of U.K. inflation is time varying and with significant ARCH effect. Engle (1983) first studied volatility of U.S inflation using ARCH model and estimated conditional mean and variance of inflation using the U.S inflation time series data. His results showed the presence of volatility clusters. Owyang (2001) also found that U.S inflation volatility appeared in clusters. Kim (1993) tested the ARCH model against an alternative specification and found that ARCH did not perform well. Lucas (1973) and Logue and Willett (1976) estimated unconditional variances of inflation for several countries assuming that variance is not time varying. Lucas (1973) in macroeconomics found that the variance of inflation determined the response of a variable to various shocks. Friedman (1977) had also argued that there is a positive relation between inflation and its volatility.

Bollerslev and Write (2000) analysed the volatility of Yen-U.S. dollar exchange rate using GPH semi parametric approach. They found that the GPH method was suited well for the empirical analysis of long memory volatility dependencies. Stochastic volatility models were widely used in financial economics to characterize time-varying volatilities. However, recently macroeconomists, econometricians started to use these models to describe the evolving variances of inflation and other real variables (see Cogley and Sargent (2002), Primiceri (2005), Sims & Zha (2006), & Stock & Watson (2001, 2007)). Hassler and Wolters (1995) and Baum, Barkoulas and Caglayan (1999). Bos, Franses and Ooms (1999) examined inflation in the G7 countries and found the evidence of long memory.

There were many other studies that also used the GARCH modeling. For example, Bruner and Hess (1993), and Corporal and McKiernan (1997) for US inflation, Joyce (1995), and Kontonikas (2004) for UK inflation, and Grier and Perry (1998) for G7 countries had modelled inflation volatility using the GARCH model. Rizvi and Naqvi (2009) found some evidence from Pakistan that negative inflation shocks had a lesser

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impact compared to positive inflation shocks, and negative inflation reduced the average inflation.

Ghoshray (2011) had examined the extent to which global food price had transmitted to domestic prices in selected Asian developing countries using time series econometric techniques. The sample covered the following countries; Thailand, India, the Philippines, China (PR) and Indonesia. Sri Lanka was not included in the sample. He had used error correction model to examine the transmission effect. The volatility transmission was not examined in this study. Rapsomanikis and Mugera (2011) examined the food price volatility transmission from global markets to developing countries consisting of Ethiopia, India, and Malawi using bivariate ECM. The GARCH model was used to assess volatility transmission. Volatility transmission was significant only in the period of extreme volatility in the world market. Rapsomanikis and Mugera (2011) examined the price transmission from the world food markets to domestic food prices of selected six developing countries using the VECM and GARCH models. They had examined the transmission both in the mean and volatility of price changes. Transmission in the mean denotes the transmission of price changes from the world to domestic prices in terms of levels. Volatility transmission refers to the transmission of variances in the price changes in the world market to domestic markets.

The volatility of food prices seems to be more than that of the manufactured goods in general. In addition, price levels and volatilities tend to be positively associated. Thus, variance dynamics need to be studied. The volatility models are used to investigate variance dynamics of a distribution. In reviewing the studies that cover volatility would be useful for the analysis. Crato and Ray (2000) provided evidence of long memory for future's returns for 17 commodities and five major currencies using the Hurst test, nonparametric LM test, and GPH test. In another study, Jin and Frechette (2004) had also found evidence of long memory in the volatility of agricultural commodity futures.

The new class of fractionally integrated GARCH (FIGARCH) process was introduced by Baillie, Bollerslev and Mikkelsen (1996) to develop a more flexible model for the conditional variance that represents temporal dependencies in financial market volatility. The FIGARCH model captures the long memory of volatility dynamics whereas the GARCH model captures the short run dynamics. The Maximum likelihood estimates of The FIGARCH model parameters are said to be super consistent ($T^{1/2}$-consistent). Baillie, Chung, and Tieslau (1992, 1996) examined long memory of inflation and its volatility for 10 countries using a new method of ARFIMA-GARCH model and found that inflation and inflation volatility series had long memory in most countries. They had used daily Deutsch mark–U.S. dollar exchange rates to test this model. Myers and Song (2007) had found that very slow hyperbolic decay in the autocorrelations and impulse response of agricultural commodity future returns.

In addition, Wei and Leuthold (1998) employed the ARFIMA model for six agricultural future prices (corn, soybeans, wheat, hogs, coffee and sugar) to find out the memory of the price series. They found that only sugar series had long memory and others did not. The limitation of this model was that they employed a combination of ARFIMA mean model and an ARCH variance model. They could have employed ARFIMA model with FIGARCH type model instead of ARCH model. The GARCH type model can capture volatility clustering in the data. In 2012, Chang, McAleer, and Tansuchat (2012) had examined long memory volatility model for 16 agricultural commodity future return series from different futures markets. They had used various classes of fractional GARCH models such as fractionally integrated EGARCH (FIEGARCH), fractionally integrated asymmetric power ARCH (FIAPARCH). The estimated long memory parameter $d$ indicated that most of the agricultural commodity future returns had a long memory. In addition, they found that FIGARCH (1,$d$,1), FIEGARCH (1,$d$,1) models outperformed the GARCH (1,1) and EGARCH(1,1) models.

The estimation methods of long memory were improved in recent periods. Exact maximum likelihood estimation, semi-parametric approach GPH estimation methods are popular in recent studies.

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### 3.3.2 Price Transmission

This section reviews the empirical studies related to PT which cover both mean and volatility transmission.

#### 3.3.2.1 Mean-Price Transmission

Price transmission denotes the transmission of price changes from one market (world market) to the other market (domestic market) in terms of levels. Volatility transmission refers to the transmission of volatility from one market to the other market. In recent years, there have been a large number of studies that have investigated the transmission of world food prices to the domestic economy; Ardeni

(1989) Conforti (2004), Dawe (2008, 2009), Hazell, Jaramillo and Williamson (1990), Imai, Gaiha and Thapa (2008), Jalil and Tamayo Zea (2011), Lee and Park (2013), Minot (2009), Morriset (1998), Mudlak and Larson (1992), Myers (1992), Rapsomanikis (2011), Shawarby and Selim (2012), Van Duyne (1982). Most of them found transmission was incomplete, and some were asymmetric. Penh, Ginting, and Bird (2009) found that there was a complete transmission of international food price inflation to Cambodia via its main trading partners.

Greb, Jamora, Mengel, von Cramon-Taubadel, and Würriehausen (2012) conducted a study to understand the extent and speed of transmission of international cereal price changes to the domestic retail wholesale level in developing countries. Leibtag (2009) found that the global price pass through is more significant for domestic producers than consumers. The food price pass-through differs across countries. For example, Helbling, Mercer-Blackman, Dao, Erbil and Oakes (2008) show that estimates of the pass through in emerging markets are about three times higher than in advanced economies. They noted that degree of transmission from international to domestic price was less than that of domestic price transmission into general inflation. Gelos and Ustyugova (2012) provided recent evidence of high pass through of food inflation to developing and emerging economies as compared to advanced economies and found that pass through effects tends to be larger in emerging and developing countries than in advanced economies. There were also differences in the pass through effects of emerging economies and developing economies. Conforti (2004) examines global price transmission in 16 countries including three Sub-Saharan Africa (SSA), using ECM and had found that transmission effects vary from country to country. In general, the degree of transmission in the SSA countries were relatively

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less than in Asian and Latin American countries. Food prices in developing countries move more closely to the world food prices than in developed countries (Bekkers, Brockmeier, Francois & Yang, 2013). Lee and Park (2013) provided a comprehensive assessment of the international transmission of food price inflation and volatilities as well as the effects of various internal and external factors on domestic food price inflation and volatility using 72 countries from Asia, Latin America, Sub-Saharan Africa, Europe and other countries for the period 2000-2011. However, Sri Lanka was not included in their study. They found that global food price inflation affected the national food markets in all regions with a time lag. The degree of transmission was different according to regions. But volatility spillovers from global to domestic food prices were contemporaneous.

The findings of Protopapadakis and Stoll (1986) were in favour of the long-run LOP. But, Ardeni (1989) tested the stationary properties of the prices and found that the LOP does not hold as a long run relationship by using co-integration test. Baulch (1997), Gradner and Brooks (1994), Ravallion (1986), Sexton, Kling and Carman (1991) and Zanias (1993) have studied price transmission within the context of market integration.

Bekkers, Brockmeier, Francois and Yang (2014) have studied the factors affecting the food price pass-through effects. They found the factors that hinder the pass-through of global price changes. Per capita income was the main determinant. Full transmission of world prices is distorted by government interventions in the form of policies such as import tariffs, quotas, export subsidies, taxes, and exchange rate. These governmental interventions had weakened the link between the world and domestic markets.

Many studies related to price transmission in agricultural commodity markets found evidence of asymmetric pass-through effects. Asymmetric pass-through occurs when price shock is transmitted differently depending on whether the shock is positive or negative. Upward movements in world prices were clearly passed on to domestic prices. However, the declines in world commodity prices were not transmitted to domestic markets especially in small countries like Sri Lanka. Peltzman (2000) showed that asymmetric price transmission is prevalent in the majority of producer and consumer markets. Meyer and Cramon–Taubadel (2004) and Vara and Goodwin (2005) used various econometric techniques to detect asymmetric pass–through in the food price chain. Ferrucci, Jimenez-Rodriguez, and Onorante (2010) analysed the transmission of commodity prices using data from the European Union. They found significant evidence food price pass-through in the Euro Area.

Lucas (1973) first modeled the relationship between mean and variance of inflation and found that stabilization policy was the motivating force for the positive relationship. Phelps (1972) had highlighted that variability of inflation is costly and needs to be accounted for. Logue and Willet (1976) also found a similar positive relationship using OLS regressions. Since then, attention has shifted towards the measurement of the relationship.

Most of the researchers found that global food price significantly contributed to domestic inflation. Eun and Shim (1989) studied the international transmission of stock market movements. This was the pioneer study in international transmission shocks in returns. Davidson, Halunga, Lloyd, McCorriston and Morgan (2011) using VECM found that drivers of UK food inflation are raw food world prices and exchange rate (GDP/USD). Ferrucci, Jimenez-Rodriguez and Onorante (2010) concluded that international commodity price inflation is the main determinant of producer and consumer food price inflation in the Euro area. Dawe (2008), Minot (2011), Imai, Gaiha, and Thapa (2008) investigated the pass-through effect of global food price shocks to domestic prices of developed countries and emerging economies such as in Malawi, Nigeria, India, the Philippines, Peru, Mexico, and Ghana. However, Sri Lanka is not included in their studies.

Conforti (2004) found that world commodity price transmission has been different from country to country. The degree of transmission in the SSA countries was less than in the Asian and Latin American countries. Imai *et al.* (2008) examined the global agricultural commodity price transmission to domestic prices in India and China. They investigated short and medium run adjustment processes using Error Correction Model. They found that the transmission is incomplete in both countries and the degree of transmission is higher in China than in India. Most of the domestic commodity prices co-moved with global commodity prices. Dawe (2008, 2009) had found that international food price transmission was generally incomplete in the Asian countries owing to the real appreciation of their currencies against the USD which neutralized a considerable portion of the global price increases when these commodities were imported into domestic markets.

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A large number of studies had applied various quantitative techniques to investigate spatial price transmission (PT). Most of the studies used time series econometric techniques to test co-movement of the world and domestic prices. In the context of the method of analysis, early empirical studies of PT were based on simple correlation and regression analysis. Researchers used contemporaneous correlation analysis. A high correlation coefficient indicated evidence of co-movement and interpreted as a sign of an efficient market. Another approach was to use a regression analysis on contemporaneous prices. Regression coefficients were used to measure the co-movement of prices. For example, Mundlak and Larson (1992) found very high rates of price transmission by estimating the transmission of world food prices to domestic prices using 58 countries annual price data from the Food and Agriculture Organization (FAO). The static regression approach has been criticized for assuming instantaneous response in each market to changes in other markets. These methods did not account for dynamics and lead-lag relationships (Fackler & Goodwin, 2001). In fact, time lag plays an important role in responding to a price change in one market to another market. A change in world prices may take more than a month to be reflected in domestic variables in the regression analysis (Ravallion, 1986). In the 1980s, these methods were replaced by dynamic regression models (Ravallion, 1986) and Granger causality test (Gupta & Mueller, 1982). Since price data seems often nonstationary, cointegration methods became important in the analytical methods. In recent periods, most of the studies used time series econometric analysis. Co-integration technique, ECM, and Granger causality test have become the standard tools for analyzing spatial market relationships. Ardeni (1989) has published the first study on agricultural commodity price transmission using co-integration technique. Most of the empirical PT work used cointegration methods and, in particular, vector error correction model (VECM). Asymmetric price responses were analyzed using asymmetric ECM developed by  Granger and Lee (1989). Thus, time series econometric techniques can provide useful insights into the issue of price transmission.

Moreover, the PT from food price to nonfood price in the domestic economy is important (Walsh, 2011). Cecchetti and Monessner (2008) found that in many countries headline inflation is not reverting to core inflation to the same degree it did in earlier periods, indicating that food prices may be affecting non-food prices.

In the empirical application of these methods, there had been a large number of studies employing different techniques to measure asymmetric PT. Most of the studies concerned agricultural commodities. Two-third of the studies focused on the U.S. markets. Most of them were from developed countries. Various techniques were used. In recent periods, cointegration and error correction model were employed to study PT and asymmetric PT. Most of the studies had focused on mean price transmission between markets. A few studies attempted to account the volatility of food price transmission.

**3.3.2.2 Volatility-Price Transmission**

Following time series econometrics development, attention moved to volatility dynamics and volatility transmission between markets. For example, volatility transmission was investigated between monetary markets by Engle and Kroner (1995), and Booth, Martikainen, and Tse (1997), among others. Following monetary markets, food markets also came under transmission analysis. Literature shows that standard deviation of a distribution is used to measure volatility.

Mandelbrot (1963, 1967) had observed some stylized facts such as fat tails, time varying variance, and volatility clustering for unconditional distributions of many economic and financial variables. Felipe and Diranzo (2005) had done a survey of reviews of literature on volatility transmission. A large number of studies such as Onour and Sergi (2011), and Du *et al.* (2009) investigated pass through effects of crude oil on global food prices simple bivariate framework analysis. Many studies such as Diebold and Nerlove (1989), Diebold and Nason (1990), Hsieh (1988), Baillie and Myers (1991), and Baillie, Han Myers and Song (2007) examined volatility patterns in various asset return data, including stock returns, and exchange rates, but there are only very few studies such as Jin and Frechette(2004), von Braun and Tadesse (2012), Omotosho and Doguwa (2013) and Gilbert and Morgan (2010) which examined volatility of agricultural commodity and food prices.

Prices of agricultural commodities, food, in particular, are generally more volatile than prices of manufactured consumer goods (nonfood). Recent studies show that researchers started to focus on volatility area in recent time periods. Mudlak and Larson (1992) studied world agricultural commodity price transmission to European countries using the FAO data for the 1968-78 period and found that most of the variation in world agricultural prices are transmitted to domestic prices. In addition, they found that global food price volatility plays a dominant role in the variations of domestic prices. Hazell, Jaramillo and Williamson (1990) using data from 22 developing countries for the period 1961-87, found that the variability in world prices

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has not been fully transmitted to average producer prices due to government interventions; trade restrictions, exchange rate misalignment. It is universally accepted that food prices in developing countries have become more volatile in recent years (Minot, 2012, 2013, 2014).

### 3.3.3 Price Inflation

Inflation definition varies from country to country for monetary policy purposes. Some countries use core inflation instead of headline inflation. Bryan and Cecchetti (1994) suggested a measure of inflation that is based on components of inflation by focusing on which components of inflation maximize the signal to noise ratio. In contrast, Culter (2001) built a different concept of core measure of inflation by emphasizing persistence. She estimated the persistence of inflation for different components of the UK CPI and weighted the components by their relative persistence. From this analysis, she found that seasonal food items had low weights while non-seasonal food items had a high weight. However, both studies focused on persistent trends.

In addition, Cecchetti (2007) had suggested that a core inflation measure can be less effective than headline inflation. Rich and Steindel (2007) went beyond this assessment, by postulating the important characteristics of core inflation similar to the headline inflation. Using four different models for U.S. inflation, they found that the core measure does not perform well as headline inflation. In addition, they found that dynamics of core inflation are roughly similar to headline inflation, but its predictive power was weak.

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Zang and Law (2010) found that demand pressures have played a significant role in China's general price inflation. The analysis was done on macro level data at both national and provincial levels. Results showed that while supply side factors played a role, demand side factors played a more important role in driving up food inflation in China. Based on the results, they concluded that food inflation is not only driven by supply side factors but demand side factors also play an important role in developing countries. Zhang and Law (2008) had also noted that global food prices had a significant impact on China's food prices. But, Zhang and Reed (2008) considered that supply side factors mainly caused inflation than demand side factors in China.

Cecchetti and Moessner (2008) attempted to answer the following questions, i) Is headline inflation reverting to core inflation? ii) How persistent are CPI food and energy price inflation? They say that if food price inflation occurs due to supply shocks, the impact of food price rises on inflation is expected to be more transitory. If headline inflation reverts to core inflation, it would mean that food price rises are transitory. There was some evidence for the U.S.A. (Kiley, 2008). The study of OECD (2005) also found that headline inflation converged to core inflation for the United States, Canada, Japan, the U.K and Euro area. If core inflation reverts to headline inflation, it would indicate that there would be second-round effects from higher food price rise. It is also found that core inflation has not reverted to headline inflation in many countries of the sample. Further, they found that many countries failed to reject the hypothesis that the sum of the autocorrelation coefficients is zero.

### 3.3.4 Intertemporal Relationship between Mean and Variance of Inflation

There are a large number of empirical studies that examined the relationship between mean and variance of inflation. Many empirical studies provide evidence of the positive relationship between mean and variance of inflation. For examples, Okun (1971), Lucas (1973), Logue and Willet (1976), Friedman (1977), Barro (1976), Foster (1978), Taylor (1981), Grier and Perry (1998), Nas and Perry (2000), and Rizvi and Naqvi (2009). Okun (1971) found a positive relationship between mean and variance of inflation across 17 OECD countries for the period 1951-1968. He had found the results based on descriptive statistics of standard deviation and mean of the annual increase in the GNP deflator series for 17 OECD countries. In addition, using descriptive statistics and scatter diagram, Gordon (1971) had shown that the degree of association between mean and variance of inflation was weak but positive. The correlation coefficient for the full period 1951-68 was 0.78. In the piecewise analysis, 0.90 for the period 1951-60, and 0.40 for the period 1960-68. But, Logue and Willet (1976) obtained similar results of Okun (1971) using least square regression for a large sample of 41 countries for the period 1949-1970. They used absolute changes instead of variance to measure the variability of inflation.

Foster (1978) had confirmed the findings of Logue and Willet. Furthermore, Blejer (1979) found a positive relationship between mean and variance of inflation for Latin American countries. Foster (1978) also concluded the positive relationship between inflation and its variability using 23 countries for the period 1950-1975. Foster's work was more realistic than Okun's work since the random walk model was implicit in his study. Since then, researchers have started to analyse the relationship using time series econometric techniques. For example, Ball *et al.* (1990), Cukierman and Wachtel (1979), Cukierman (1983), Taylor (1981), Golob (1994) and Owyang

(2001), among others, provided evidence in support of the Friedman-Ball hypothesis which states that high inflation increases volatility of inflation. Ball *et al.* (1990) said that policy makers face a dilemma in high inflation. Ball *et al*. (1992) provided a theoretical model that attempts to explain inflation and volatility of inflation relationship. Grier and Perry (1998) found that inflation has a significant and positive effect on inflation uncertainty in all G7 countries.

Friedman's (1977) and Ball's (1992) hypothesis says that higher inflation invokes more inflation uncertainty. In contrast, Cukierman and Meltzer's (1986) hypothesis is that higher inflation uncertainty leads to more inflation. Rizvi and Naqvi (2009) found a positive relationship between inflation and inflation uncertainty and inflation Granger-causes inflation uncertainty for Pakistan. In contrast, Holland (1995) and Cukierman–Meltzer (1986) showed some evidence in support of Cukierman and Meltzer's hypothesis that inflation uncertainty induces inflation.

Baillie, Chung, and Tieslau (1992) examined the Friedman hypothesis of the relationship between the variance and mean of inflation. They used a long memory model, namely the ARFIMA-GARCH model using approximate maximum likelihood estimation method to examine the relationship using data from 10 different countries on monthly CPI inflation. They found strong evidence of long memory and mean-reverting behavior. They found evidence in favor of the Friedman hypothesis in high inflation countries. The existing literature had not accounted for broad geographical coverage with updated data. But, Daal, Naka, and Sanchez (2005) examined the relationship between developed and emerging countries and found a positive relationship between 22 countries covering developed and emerging countries including Sri Lanka for the period 1957-2004. They have used Granger-causality test, and asymmetric power GARCH model to examine the relationship and found that inflation Granger-causes inflation uncertainty for almost all of the countries in the sample. The overall findings of Daal, Naka, and Sanchez's study were consistent with the Friedman-Ball hypothesis. It seems that food price inflation is over dispersed implying that variability of the distribution is greater than the expected food price inflation. Variability of inflation has adverse economic consequences than that of average inflation. Therefore, this stylized fact needs to be investigated.

## 3.4 Research Gaps in the Literature

Inflation dynamics have been an area of interest in theoretical and empirical literature in the world. However, food price inflation was not given much attention in the economics literature. Similarly, inflation in South Asia including Sri Lanka had enough attention, but food price inflation had not much attention.

Properties such as persistence and long memory of food price dynamics had not received much attention by researchers in developing countries. Some studies have examined the long memory hypothesis using data from agricultural commodity prices. Kohzadi and Boyd (1995), Barkoulas, Labys and Onochie (1997), Jin and Frechette (2004) and Kovacs, Huszsvai and Balogh (2013) are few examples of them. Stigler and Prakash (2011) have examined time series properties of commodity prices using 24 commodities for developed countries. Most of these researchers concentrated on developed countries, African countries, and big emerging economies.

In addition, none of the studies has focused on the estimation of fractional integration parameter for food price series in developing countries in general and Sri Lanka in particular. Most of the food price dynamics studies used integer difference parameter (*d*=0 or *d*=1) for integration tests to identify the order of integration of the series. Integer integration tests can lead to erroneous inferences. There were no studies investigating the memory properties of food price dynamics in emerging economies, Sri Lanka, in particular, using fractional integration technique. Further, long memory property in first and second conditional moments has not been explored in most of the emerging countries and Sri Lanka until now.

Further, most of the existing literature on the memory of price dynamics was directed to financial asset prices. Very few studies focused on food commodity prices even in developed countries. Considerable attention has been directed to the analysis of fractional dynamics in financial time series data. Relatively, the fractional analysis in food price dynamics is very few compared to financial data series. There is a lack of evidence of I(*d*) behaviour for food inflation rates for developing countries (Kallon, 1994; Moriyama & Naseer, 2009). In addition, there was no rigorous work on the memory of food price dynamics for developing countries.

However, some studies have attempted to study scientifically about food inflation in Asia, namely India, China and the Philippines and their focus have been mainly on its determinants. They have not focused on the nature of food price dynamics, pass-through effects, and volatility dynamics of food price distributions. In the developed world, the importance of food commodity price dynamics is widely agreed however, the role of food price dynamics, area of statistical properties, co-movements, time varying volatility, global food price transmission remain poorly understood in developing economies including Sri Lanka.

There has been no research to date that had directly addressed the issue of food price inflation in Sri Lanka. There were a few studies about world food price transmission to domestic economy for individual Asian countries. There were also a few studies about specific country studies about this issue in South Asia, including Sri Lanka. Jaffri, Asjed, and Bashir (2013) stated that global food and energy inflation had an impact on CPI inflation in Sri Lanka, India, and Bangladesh. Dawe (2008) had studied international cereal price transmission to domestic economies of seven Asian countries that do not include Sri Lanka. Duma (2008) had attempted to study the foreign shocks transmission to domestic inflation in Sri Lanka. He had focused only on the external shocks to inflation in Sri Lanka in his study. His analysis is based on vector autoregression model (VAR) but had not covered volatility, and the long run relationship between the inflation and its determinants. The risk of second round effects from pass- through effects of exchange rate depreciation and energy price increases were highlighted in his study. He has not accounted the pass-through effects of food price increases. According to the available literature, there are no scientific studies attempted to study about world food price transmission to domestic prices in Sri Lanka.

The volatility of inflation is one of the key elements of inflation dynamics. The volatility of inflation has not received much attention in the economic literature. Research on volatility issue in food price dynamics is still scarce in Asian countries. A substantial body of literature examines volatility patterns in various asset return series, including stock returns and exchange rates. However, there exist a small number of studies examining the volatility transmission of food commodity price. For example, Rapsomanikis and Mugera (2011) studied price (mean) transmission and volatility spillovers from the world food markets to food markets in developing countries; rice markets in India and the Philippines, sorghum markets in Nigeria, maize market in Malawi, wheat market in Peru and maize market in Mexico. Food price volatility is still an area in which little empirical attention has been paid in Sri Lanka. There is little systematic, scientific empirical evidence on the long-term evolution of food inflation in Sri Lanka.

There were not much studies on the relationship between mean and variance of inflation, food price inflation in particular in developing countries except for Pakistan that was studied by Khan (2010). However, there were no studies in the context of food price inflation.

There exists no in-depth econometric analysis on dynamic behavior and the statistical properties of food inflation or on food price transmission to domestic prices both in mean and in volatility in Sri Lanka. Hence, this study intends to fill the gap in the literature. There were scarce studies on the relationship between food price inflation and its volatility for developing countries including Sri Lanka. This study extends the literature by studying not only the properties of food price changes in Sri Lanka but also exploring the link between world food prices and domestic prices.

## 3.5 Conclusion

This chapter reviewed the literature on memory properties, transmission of mean and variance of global food price and the relationship between mean and variance of domestic food price dynamics. In the developed world, the importance of food commodity price dynamics is widely agreed, however, the area of memory properties, volatility, global food price transmission, and the relationship between mean and variance of food price dynamics remain poorly understood in Sri Lanka. Literature survey shows that there exists no comprehensive analysis on dynamic behavior of food price changes covering the memory properties of food price dynamics, global price transmission, and global price volatility transmission in Sri Lanka. This study intends to fill this gap in the literature and provide an in-depth analysis. This in-depth empirical analysis of dynamic behavior of food price in Sri Lanka might also provide useful implications for the direction of future research. Therefore, a comprehensive study based on econometric time series analysis would contribute significantly to the available knowledge.

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# CHAPTER FOUR

# THEORETICAL FRAMEWORK

## 4.1 Introduction

This chapter describes the theoretical background of the study. It covers fractional integration, long memory, ARFIMA model and cointegration. The selected theories related to this study are imported from various disciplines such as econophysics, statistical mechanics, econometrics, and economics. It would be useful to the reader in explaining some key concepts and theories prior to understanding the method of analysis in the study. Three theories, namely theory of long memory, the theory of inflation and theory of price transmission related to this study are described in this section.

## 4.2 Theory of Long Memory

This section describes the theoretical foundation of the long memory. Economic theory does not explain the long memory process explicitly. However, economic variables have a long memory which is an important informative property. Long memory models have been used by econometricians since around the 1980s. The long memory theory uses fractional integration and ARFIMA model.

### 4.2.1 Fractional Integration

Fractional integration is the key conceptual framework for describing long memory in stochastic series. In order to explain fractional integration, consider $y_t$ is a stochastic process. It has ARIMA process

[4.1] $$\phi(L)y_t = (1-L)^{-d}\theta(L)u_t$$

where $L$ is lag operator, $\phi(L)$, $\theta(L)$ are lag polynomials of finite orders. All roots of $\phi(L)$ and $\theta(L)$ assumed to lie outside the unit circle, and $u_t$ is white noise. This process is only defined for integer values of *d*. Fractional integration is a generalization of integer integration. In economic time series, they are usually presumed to be integer integrated form of order zero, I(0), or order one, I(1). The intermediate class of fractionally integrated process was ignored. Granger and Joyeux (1980) and Hosking (1981) show that fractional integration order, *d*, need not be an integer. Fractional integration (non-integer orders of integration) defines the function $(1-L)^{-d}$ for non-integer values of the fractional differencing parameter *d*. An operational definition of $(1-L)^{-d}$, fractional differencing operator, can be derived from a power series expansion as stated in Equation [4.2].

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[4.2] $$(1-L)^{-d} = 1 + dL + \frac{1}{2!}d(1+d)L^2 + \frac{1}{3!}d(1+d)(2+d)L^3 + ..........$$

This power series expansion can be stated in terms of the gamma function in equation [4.3]. (Hosking, 1981; Granger & Joyeux, 1980).

[4.3] $$(1-L)^{-d} = 1 + \sum_{j=1}^{\infty}\frac{\Gamma(j+d)}{\Gamma(d)\Gamma(j+1)}L^j$$

where $\Gamma$ is Gamma function and *d* is fractional differencing parameter.

For *d*=0, the process is stationary and the effect of a shock to $u_t$ on $y_{t+j}$ decays geometrically as j increases (short memory). For *d*=1, the process is said to have a unit root, and the effects of a shock to $u_t$ on $y_{t+j}$ persists into the infinite future. A stationary series ($y_t$) has long memory if there is nonzero d $d \in (-0.5, 0.5)$ such that the spectral density obeys a power law, $f(\lambda) \sim k\lambda^{-2d}$ as $\lambda \to 0^+$. The process $y_t$ is stationary and invertible and the effects of a shock $u_t$ on $y_{t+j}$ decay very slowly (hyperbolically) as $j$ increases (long memory). This type of process is called a fractionally integrated process. if $d$=0 we say {$y_t$} has short memory. In this case, $f(0)$ will be positive and finite.

The autocorrelation function (ACF) of this process decays hyperbolically. This rate of decay is much slower than that for the I(0) process while ACF for I(0) process, decays geometrically. For $-0.5 < d < 0$, the process $y_t$ is said to exhibit anti-persistence, autocorrelations of this process are negative, the process has a large portion of its variance explained by very high frequency components. For $0.5 < d < 1$, the process $y_t$ is nonstationary, exhibits long memory but, with infinite variance. Thus, time series properties of a stochastic process, the autocorrelation properties of the series depend on the fractional difference parameter $d$.

In the frequency domain, for $0 < d < 0.5$, a fractionally integrated process has a very large portion of its variance explained by very low–frequency components, the spectral density at frequency zero is infinite. This implies that the series has long memory.

Differencing is a standard practice in time series analysis to achieve stationarity. Suppose that $y_t$ is a series that, when differenced $d$ times, gives the series $\Delta^d y_t$ which has an ARMA representation. Then, $y_t$ is called an integrated series with parameter $d$. It is denoted $y_t \sim I(d)$. Differencing a time series roughens it while summing a time series smoothens it (Haubrich, 1990). A fractional difference between 0 and 1 roughens a series less than does the first difference. Thus, a fractional stochastic series is rougher than a random walk but smoother than white noise. Let $y_t$ follows a random walk; then it can be written as $\Delta y_t = (1-L)^1 y_t = \varepsilon_t$. Granger and Joyeux (1980) and Hosking (1981) generalized this expression as $\Delta y_t = (1-L)^d y_t = \varepsilon_t$. They defined fractional difference using binomial expression (Binomial theorem) as in Equation [4.4]

[4.4] $$\Delta^d = (1-L)^d = \sum_{k=0}^{\infty} (-1)^k \binom{d}{k} (L)^k$$

with the binomial coefficients $\binom{d}{k}$ defined as

$$\binom{d}{k} = \frac{d(d-1)(d-2)..........(d-k+1)}{k!}$$

where $d$ is any real number (differencing parameter), k is a nonnegative integer. When it takes fractional values, it is called fractional difference parameter.

### 4.2.2 Long Memory

Long memory implies that shocks have long lasting effects. In statistical terms, long memory indicates that the ACF decay to zero at a very slow rate, hyperbolic rate. But short memory indicates that ACF decays geometrically.

### 4.2.3 The Long Memory Process

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There are two possible definitions of long memory based on the domains. Definition 1 is based on the time domain, definition 2 is based on the frequency domain.

**Definition 1**: Assume $y_t$ is a discrete stochastic time series process with autocorrelation function $\rho_j$ at lag *j*, then the process possesses long memory if

[4.5] $$\lim_{T \to \infty} \sum_{j=-T}^{T} \left| \rho_j \right| = \infty$$ (is not finite).

Equation [4.5] states that the sum of the absolute autocorrelations is infinite and non-summable (McLeod & Hipel, 1978).

If the limit value is

[4.6] $$\lim_{T \to \infty} \sum_{j=-T}^{T} \left| \rho_j \right| = k$$ (finite)

then the process possesses short memory. Long memory autocorrelation function (ACF) decays very slowly (hyperbolic decay) for a very large period. The autocorrelation function of these series decays asymptotically as a power law of the form $\tau^{-\gamma}$ with $\gamma < 1$. Long memory of a series describes the dynamics of the correlation structure of the time series at long lags. Long memory can exist in mean or variance volatility dynamics. This definition is based on the time domain. An alternative definition is based on spectral density function on the frequency domain.

**Definition 2**: If $y_t$ has absolutely continuous spectral distribution function, its spectral density function denoted by $f(\lambda)$ can be defined as in Equation [ 4.7 ], [4.7] $f(\lambda) = \frac{1}{2\pi} \sum_{j=-\infty}^{\infty} \gamma_j \cos(\lambda j), \quad -\pi < \lambda \leq \pi$

where $\lambda$ is angular frequency, $\pi$ is radian, and $\gamma$ is auto-covariance.

If $f(\lambda)$ increases without limit as angular frequency tends to zero, i.e. $\lim_{\lambda \to 0} f(\lambda) = \infty$, then the series $y_t$ displays the property of long memory.

### 4.2.4 The Autoregressive Fractional Moving Average Model

Auto Regressive Fractionally Integrated Moving Average is abbreviated by ARFIMA. The theoretical foundation of the ARFIMA model is described in this section. ARFIMA model is a parametric model that has a parameter (*d*) to describe long memory. This model is used to estimate long memory in food price behavior in the study.

An ARFIMA model is an ARMA model where the innovations are fractional white noise that may contain long memory. The Autoregressive Fractional Integrated Moving Average (ARFIMA) model is given by Equation 4.8.

[4.8] $\phi(L)(1-L)^d y_t = \theta(L)u_t$

where $u_t \sim niid(o, \sigma_t^2)$, and $\phi(L)$, and $\theta(L)$ are lag polynomials of finite orders. This is only defined for fractional values of *d*. The well-known Box and Jenkins (1976) ARIMA (*p*,*d*,*q*) model is only defined for integer values of '*d*' (0 or 1). It does not explicitly model long term persistence. It is not flexible enough to explain both the short run and long term correlation structure of a series. But fractionally differenced processes are capable of modeling long term persistence. The ARFIMA

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is a generalization of the ARIMA model to non-integer values of *d*, and it allows for the property of long memory in the region $0 < d < 0.5$.

### 4.2.5 Fractional White Noise

Let $y_t$ be discrete time stochastic process. A theoretical long memory model is called a fractional white noise process denoted by *ARFIMA(0,d,0)*. It is represented by Equation [4.9]. This is the infinite–order moving-average representation. Let $y_t$ follow

$$[4.9] \qquad (1-L)^d y_t = \varepsilon_{tt}$$

where $\varepsilon_t$ is a fractional white noise process (innovations) which consists of independent identically distributed random variables with zero mean and variance $\sigma_\varepsilon^2$. *d* is possibly non-integer, the degree of differencing. *L* is the lag operator. The following theorems give some of the basic properties of the process, assuming for convenience that $\sigma_\varepsilon^2 = 1$This model was proposed by Granger and Joyeux (1980) and Hosking (1981).

**Theorem 1**

Let $y_t$ be an *ARFIMA(0,d,0)* process.

i) When $d < 0.5$ $y_t$ is a stationary process and has the infinite moving average representation that is shown by Equation [4.10 ]

[4.10] $$y_t = \varphi(L)\varepsilon_t = \sum_{k=0}^{\infty} \varphi_k \varepsilon_{t-k},$$

where $\varphi_k$ is defined by Equation [4.11].

[4.11] $$\varphi_k = \frac{d(1+d)..........(k+d-1)}{k!} = \frac{(k+d-1)!}{k!(d-1)!} = \frac{\Gamma(k+d)}{\Gamma(k+1)\Gamma(d)}$$

where $\Gamma(.)$ is a Gamma function

As $k \rightarrow \infty$, $\varphi_k \sim k^{d-1}/(d-1)! = \frac{1}{\Gamma(d)}.k^{d-1}.$

ii) When $d > -0.5$, $y_t$ is invertible and has the infinite autoregressive representation that is shown by Equation [4.12]

[4.12] $$\phi(L)y_t = \sum_{0}^{\infty} \phi_k L^k y_t = \sum_{k=0}^{\infty} \phi_k y_{t-k} = \varepsilon_t$$

where $\phi_k$ is given by Equation [4.13].

[4.13] $$\phi_k = \frac{-d(1-d)..........(k-1-d)}{k!} = \frac{(k-d-1)!}{k!(-d-1)!} = \frac{\Gamma(k-d)}{\Gamma(k+1)\Gamma(-d)}$$

As $k \rightarrow \infty$, $\phi_k \sim k^{-d-1}/(-d-1)! = \frac{1}{\Gamma(-d)}.k^{-d-1}.$

When $-0.5 < d < 0.5$, the auto-covariance is given by Equation [4.14].

[4.14] $$\gamma_k = E(y_t, y_{t-k}) = \frac{\Gamma(k+d)\Gamma(1-2d)}{\Gamma(k+1-d)\Gamma(1-d)\Gamma(d)}$$

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and the autocorrelations function of $\gamma_t$ is given by Equation [4.15] , note : $\sigma_\varepsilon^2 = 1$,

[4.15] $$\rho_k = \frac{\gamma_k}{\gamma_0} = \frac{\Gamma(k+d)\Gamma(1-d)}{\Gamma(k-d)\Gamma(d)}$$

As $k \to \infty$, $\rho_k \sim \frac{\Gamma(1-d)}{\Gamma(d)}.k^{2d-1}$.

iii) The spectral density is $s(\omega) = \left(2\sin\frac{1}{2}\omega\right)^{-2d}$ for $0 < \omega \le \pi$ and $s(\omega) \sim^{-2d}$ as $\omega \to 0$.

**Theorem 2.**

Theorem 2 summarizes the properties of an ARFIMA process. Let $\{y_t\}$ be an *ARFIMA(p,d,q)* process. Then

i) $\{y_t\}$ is stationary if $d < 0.5$ and all the roots of the equation $\phi(L) = 0$ lie outside the unit circle.

ii) $\{y_t\}$ is invertible if $d > -0.5$ and all the roots of the equations $\theta(L) = 0$ lie outside the unit circle.

For proof see Hosking (1981) p.171.

If $\{y_t\}$ is stationary and invertible, with spectral density $s(\omega)$ and correlation function $\rho_k$ then

iii) $\lim \omega^{2d} s(\omega)$ exists as $\omega \to 0$, and is finite

iv) $\lim \kappa^{1-2d} \rho_k$ exists as $k \to \infty$, and is finite.



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Flexible and parsimonious way to model short term and long term behavior of time series is by means of ARFIMA. Recall that a time series, y= {$y_1$, $y_2$, ….$y_T$}, follows an ARFIMA(*p*,*d*,*q*) process as

[4.16] $$\phi(L)(1-L)^d y_t = \theta(L)\varepsilon_t$$

where $\varepsilon_t \sim iid(0,\sigma^2)$, L is the lag operator,

$\phi(L) = 1 - \phi_1 L - ...... - \phi_p L^p$, $\theta(L) = 1 + \theta_1 L + ........ + \theta_q L^q$,

and $(1-L)^d$ is the fractional differencing operator defined by

[4.17] $$(1-L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k-d)L^k}{\Gamma(k+1)\Gamma(-d)}$$

where $\Gamma(.)$ is Gamma function, The parameter *d* is allowed to assume any real value. The stochastic process y is both stationary and invertible if all roots of $\phi(L)$ and $\theta(L)$ lie outside the unit circle and $|d|$ <0.5. Long-memory processes are stationary processes whose autocorrelation functions decay more slowly than short-memory processes. Hosking (1981) showed that the autocorrelation, $\rho(.)$, of an ARFIMA process is proportional to $k^{2d-1}$ as $k \to \infty$, [$\rho(k) \propto k^{2d-1}$]. It implies that the autocorrelations of the ARFIMA processes decay hyperbolically to zero as $k \to \infty$. This behavior is contrary to the geometric decay of a stationary ARMA process. Thus, the memory property of a process depends on crucially on the value of *d*.

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When $d$=0, the series is stationary and exhibiting short memory and mean reversion with finite variance. In this case, the effects of a shock in real output are transitory, decaying geometrically depending on the structure defining the series short run dynamics.

When $d$=1, series is integrated of order one, having a unit root, non-stationary, with infinite memory, and non-mean reverting. Effect of a shock in the series is permanent, having a long run effect, forever persistent. If $d$>1, the series is non-stationary, non-mean reverting with infinite memory. Effect of a shock is diverging forever. For $d$<1, the series is mean-reverting, stationary.

When $d$=0, the ARFIMA (0, $d$, 0) process is white noise, with zero correlations and constant spectral density. The process is stationary, short memory and mean reversion with finite variance. The effects of a shock in the process are transitory. ACF decay geometrically to zero.

If $0 < d < 0.5$, $y_t$ process is a fractionally integrated process indicating a stationary process with a long memory, mean reversion, and covariance stationary. Its autocorrelations decay at a hyperbolic rate. It reveals both short and long memory dynamics. The effects of a shock in the process $y_t$ lasts for longer time. It may be expected to be useful in modeling long-term persistence. Its autocorrelations are all positive and decay monotonically and hyperbolically to zero as the lag increases. The spectral density is concentrated at low frequencies: $s(\omega)$ is a decreasing function of $\omega$ and $s(\omega) \to \infty$ as $\omega \to 0$.

The process is non-stationary for $d \geq 0.5$, because it possesses infinite variance (Granger & Joyeux, 1980), however, long range dependence is associated with all nonzero, *d*>0. When $0.5 < d < 1$ the series is no more covariance stationary but mean reverting with infinite variance. Effect of a shock in the series is long lasting and decays at an even slower rate.

For $-0.5 < d < 0, y_t$ the series exhibits negative dependence, stationary, intermediate memory, The sum of absolute values of the process autocorrelations tends to be a constant, so *ARFIMA(0,d,0)* process has a *short memory,* and is 'antipersistent' in the terminology of Mandelbrot(1977, p. 132). The autocorrelations decay monotonically to zero. The spectral density is dominated by high frequency components. $s(\omega)$ is an increasing function of $\omega$ and vanishes at $\omega$=0.

Long memory can be seen by the relatively flat spectral density over higher frequencies. The effects of shocks are very different for long memory and short memory processes. The behavior of the forecast uncertainty for stationary and non-stationary series depends on the amount of memory. The prediction of an economic variable may vary a lot depending on the specification of the stochastic processes in terms of short or long memory (Backus & Zin, 1993). So, the possible econometric evidence of long memory has considerable implications in the field of economics. The ARFIMA model can be used to estimate the parameter *d* which describes the long run memory of the series. The significance of the parameter *d* is evidence of long memory. Appropriate specification of *p* and *q* is estimated using Akaike information criterion (AIC). The best model has the smallest AIC value. If a series exhibits long memory, there is persistent temporal dependence even between distant observations.

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If prices display long memory, they show significant autocorrelation between observations widely separated in time. Long memory models can increase forecasting accuracy and efficiency (Jin & Frechette, 2004). Long memory indicates the evidence of non-linear dependence in the first and second moments.

The cycles of the long memory processes are more irregular than for the short memory processes. The cycles of a long memory series may have tendency. Another feature of the long memory processes is that there seem to be level shifts. The series tend to stay at a high level, then at a lower level etc.

### 4.2.6 Long Memory in Volatility

A weakly stationary process has a long memory if its ACF has a hyperbolic decay to zero. When its ACF decays geometrically to zero it has a short memory. ARCH of Engle, (1982), GARCH of Bollerlev,(1986), IGARCH of Engle and Bollerslev, (1986), and EGARCH of Nelson,(1991) all have a short memory for volatilities. If the ACF of a volatility series decays very slowly to zero, then it has a long memory. FIGARCH($p$,$d$,$q$) model of Baillie, Bollerslev, and Mikkelsen (1996) captures long memory of the volatility phenomena and is given by Equation [4.18]:

[4.18] $$\phi(L)(1-L)^{d}\varepsilon_t^2 = \omega + [1-\beta(L)]v_t$$

where $v_t = \varepsilon_t^2 - \sigma_t^2$. $v_t$ is innovation for the conditional variance, $v_t$ has zero mean and serially correlated. '$d$' is a fraction $0 < d < 1$. Most of the financial literature, for example, Andersen and Bollerslev (1997), and Baillie *et al.* (1996) had suggested that absolute, squared returns are proxies for return volatilities. Some literature shows that conditional variance series are proxy for volatility series. Quasi-

Maximum likelihood estimates of the FIGARCH parameters are claimed to be $T^{0.5}$ consistent with a limiting normal distribution.

## 4.3 Theory of Price Inflation

A sustained increase in the general price level is called price inflation. It is measured by the CPI or the GNP deflator. Basically, the main causes of inflation are excess aggregate demand or cost push factors (supply side factors). There have been various theories that explain inflation. Some of the basic theories are described in this section. Based on these theories, empirical models of food inflation dynamics are formulated.

### 4.3.1 Headline Price Inflation

Headline price inflation is derived from overall CPI. It is defined as log differenced of CPI, ($\pi_t = ln(CPI_t) - ln(CPI_{t-1})$). This is used as a measure of the cost of living in most of the countries. There are few important inflation theories which are described below.

i) **Demand Pull Inflation**

When the level of aggregate demand grows faster than the level of supply, the price will increase. When the economy is at or close to full employment, then an increase in aggregate demand (AD) leads to an increase in the price level. Also, near full employment, workers can get higher wages which increase their purchasing power. AD can increase due to an increase in any of its components of C, I, G, X, M. Hence, import (M) is one element in the AD. Thus food import prices also pass-through to domestic prices.

### ii) Cost-Push Inflation

If the general price level is increasing persistently due to input costs, the price inflation is said to be cost push inflation. When costs of inputs increase, aggregate supply (AS) curve will shift to the left. Hence, the price of the commodity will increase while other factors are held constant. Cost push inflation can be caused by many factors. They are (i) increases in wages and salaries, (ii) increases in the cost of raw materials, (iii) increases in indirect taxes (or reductions in government subsidies). (iv) imported inflation: increases in the price of imported goods (either as finished goods, intermediate or raw materials). An increase in the prices of imported goods will lead to a rise in the general price level in the economy. Imported inflation is attributed to domestic currency depreciation and import good price rise. If the currency of a country depreciates it will lead to inflation as imports will become expensive. As the prices of imports increase, prices of domestic goods using imports as raw materials also increase. Thus price of imports can lead to increase in the general price level. Imported inflation can be caused by exchange rate depreciation and foreign price increases.

### iii) Quantity Theory

The quantity theory assumes that inflation is due to the excess money supply. Monetarists argue that if the money supply rises faster than the rate of growth of national income then there will be inflation. The quantity theory is written in compact form in Equation [4.19]

[4.19] $MV = PT$

$M$ = Money Supply, $V$= Velocity of circulation, $P$= Price Level and $T$ = Transactions.

*T* is measured by National Income. While if *V* and *T* are constant, the increases in money supply will increase the price level proportionally. It has been used in a large number of studies of inflation in developing countries. Though the assumption of this theory does not hold in practice, the money supply "under full employment" and "over the long run," is still considered the major determinant of the price level.

In general, these theories do not explain explicitly the food price inflation. But, demand side factors, cost push factors and import inflation factors explain food price inflation.

### 4.3.2 Theory of Core Inflation

Core inflation is a construct introduced by Gordon (1975) to assess the underlying inflationary pressures in the economy. Core inflation is defined after excluding food and energy of prices from the overall CPI. It is expected that core inflation should capture long run price movements. Overall inflation is calculated from overall CPI and core inflation is calculated from nonfood and non-energy prices. This is called "Ex food and energy" approach. Core inflation provides the persistent component of measured inflation (Blinder, 1997; Roger, 1998). Core inflation is widely used for monetary policy in developed countries. Core inflation has played a vital role in monetary policy for the three decades. Bernanke *et al*.(1999) noted core inflation as :

*"The core CPI is likely to provide a better guide to monetary policy than other indices since it measures the more persistent underlying inflation rather than transitory influences on the price levels".*

Brauer and Wu (1991), Craven and Gausden (1991), and Ganley *et al*. (1991) have stated that the unwanted components (noise) are needed to be removed from CPI. The remaining is a reliable estimate of the core (underlying) inflation process.

There are various approaches to calculating core inflation. For example, moving average, exclusion based methods, trimmed mean, weighted mean, exponential smoothing and some model based approaches such as Quah and Vahey-SVAR model, principal component analysis, Kalman Filter are used. A more common approach is exclusion method which is used in Sri Lanka. In exclusion methods, some components of the CPI such as selected food items, extreme price volatile items, government controlled price items are excluded from the calculation of core inflation. The rationale for exclusion of these items is because they are mostly affected by supply side transitory factors. However, there are criticisms of this method for developing countries in particular.

### 4.3.3 Theory of Inflationary Expectations

Expectations play an important role in an economic agent's decision making. The dynamics of inflation expectations explain the acceleration of inflation. The role of expectations was highlighted in the Phillips curve model and the monetarist model. The concept of expectations are classified into two; namely, i) adaptive expectations and ii) rational expectations.

The adaptive expectation theory is stated in the Equation [4.20]

[4.20] $\pi^e_{t+1} = \pi^e_t + \gamma(\pi_t - \pi^e_t)$ , with $0 < \gamma < 1$

$\pi^e_t$ = expected inflation rate, $\pi^e_{t+1}$ =future expected inflation rate, $\pi_t$ = observed inflation rate. This model of expectation could be stated as in Equation [4.21]

[4.21] $\pi^e_{t+1} = \gamma \sum_{i=0}^{\infty} (1-\gamma)^i \pi_{t-i}$ ,

where $\gamma$ is the weight. This equation states that the expected inflation rate is equal to a weighted sum of the past rates of inflation. The weighting scheme $\gamma \sum_{i=0}^{\infty} (1-\gamma)^i$ expresses the influences of the past inflation rates on the expected inflation for the *t+1* time period. This indicates that the influence of past rates of inflation is discounted (backwards discount). If $\gamma$ is very small, the weights fall hyperbolically and the economic agent has a long memory. If $\gamma$ is close to one, the weights decline geometrically (rapidly) and the agent has a short memory.

The concept of rational expectations criticizes the model of adaptive expectations stating that other sources of information were ignored. Muth (1961) said that there exists all available information and the prediction is possible. The rational expected inflation is unbiased estimators of actual inflation at the starting period. That is stated in Equation [4.22]

[4.22] $\pi^e_t = E(\pi_t \mid X_{t-1})$ ,

where $X_{t-1}$ all parameters and predetermined variables.

[4.23] $\pi_t - \pi^e_t = \pi_t - E(\pi_t \mid X_{t-1}) = \varepsilon_t$

Equation [4.23] indicates that the deviations of the actual inflation from the expected inflation corresponds to a random variable $\varepsilon_t$ .

### 4.3.4 Food Price Inflation: Some Theoretical Issues

Domestic food prices are affected by domestic and foreign factors. World food prices could rise due to increasing demand or decreasing supply on the world market. Increasing input costs (oil prices) could also lead to an increase world food prices. In addition, domestic food prices are determined by domestic demand, supply, cost factors, exchange rate, oil prices (fertilizer) world food price pass through effects and trade barriers. In sum, food price inflation is determined by demand pressures, supply shocks, inertia, global food price, exchange rates. Inertia might capture expectations. Inertia variable is particularly important in food price dynamics.

Domestic food prices affect overall (headline) inflation directly and indirectly. Direct effects of food prices increase occur through changes in the prices of food components in the consumption basket. Thus, direct effects are related to the food expenditure share (weights) in the consumer price index. If a country has higher weight like in developing country, food prices, *ceteris paribus*, will have a larger impact on general inflation. In addition, food price increases affect different income groups differently. For example, food price increases will have negative welfare effects on the poor. Food prices affect general inflation indirectly (second round) through inflationary expectations, wages and the prices of other components in the CPI.

**4.4 Theory of Price Transmission**

Prices transmission occurs from one market in one location to another market in another location. This study involves spatial or horizontal transmission (HPT). Price transmission is also termed as pass-through.

### 4.4.1 Price Theory

Price theory says that equilibrium price of a commodity is determined by its demand and supply forces. Flexible prices are responsible for efficient resources allocation and price transmission integrates markets vertically and horizontally. Asymmetric transmission can have important implications for policy making. Non-competitive market structure, menu costs, government policies, efficient information system, may cause asymmetric transmission.

The theoretical background for the second, third and fourth objectives draws on the Law of One Price (LOP) (Ardeni, 1989). Price changes originating from the foreign sector can be divided into two transmissions mechanisms: one coming from import price in foreign currency terms and the other is price changes (inflation) from exchange rate changes. Both a depreciation of the currency and an increase in import prices are expected to lead to an increase in the domestic price level.

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### 4.4.2 Law of One Price

LOP can be written in its strict form as in Equation [4.24]

[4.24] $P_{i,t}^{d} = ER_t P_{i,t}^{w}$

where *ER* is nominal exchange rate (units of domestic currency per unit of foreign currency: RS/USD), $P^w$ is the world (foreign) price, $P^d$ is the domestic price for specific (*i*) commodity, *t* time period. The mathematical model of [4.24] can be written in statistical model as $P_{i,t}^{d} = ER_t P_{i,t}^{w} e^{u_t}$. This statistical model can be written in natural log form as in Equation [4.25].

[4.25] $$ln P_t^d = \beta_0 + \beta_1 ln P^w + \beta_2 ln ER_t + u_t, \qquad u_t \sim i.i.d(\mu, \sigma^2)$$

*ER* is implicitly assumed an exogenous variable as Sri Lanka is a price taker. $\beta_1$ is the price transmission elasticity as the model is double log (natural) form.

Commodity market arbitrage and purchasing power parity suggest that in the short run, prices of similar products in varied markets might differ. However, arbiters will prevent the various prices from moving too far apart even if the prices are non-stationary.

The fundamental theoretical basis for price transmission is the LOP (Fackler & Goodwin, 2001). The factors which may explain HPT may be divided into technical and economic factors. Technical factors are mainly to be identified in structure and infrastructure costs which should actually determine different price levels in separated markets, but similar price dynamics over time. Economic factors are mainly the existence of spatially different demand curves.

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### 4.4.3 The Economic Model of Price Transmission Notions

Consider two markets WM (world market) and DM (domestic). Given prices for a commodity in two spatially separated markets, say $P_{dt}$ and $P_{wt}$, the LOP and the Enke-Samuelson-Takayam model (Enke, 1951; Samuelson, 1952; Takayama & Judge, 1971), postulate that at all points of time, allowing for transfer costs, *c*, for transporting the commodity from one market (*WM* ) to another,( *DM),* the relationship between prices is denoted in Equation [4.26]:

[4.26] $P_d = P_w + c$ (spatial arbitrage condition)

If a relationship between two prices exists as given in equation [4.26] then the markets are said to be integrated. It is stated as a strong form of LOP. However, this extreme case is unlikely, especially in the short run. At the other end, if the joint distribution of two prices were found to be completely independent, then, one can say there is no market integration and no price transmission. In general, spatial arbitrage is expected to ensure that prices of a commodity will differ by an amount that is at most equal to the transfer costs with the relationship between two prices as given in the inequality shown in Equation [4.27]

[4.27] $P_{d,t} - P_{w,t} \leq c$

Fackler and Goodwin (2001) refer to the Equation [4.27] relationship as the spatial arbitrage condition. This is a weak form of the LOP. Fackler and Goodwin emphasize that the relationship of Equation [4.27] represents an equilibrium condition. Spatial arbitrage will cause the difference between two prices to move towards the transfer costs. This condition comprises the price relationship that lies between two extreme cases of the strong form of the LOP stated in Equation [4.26] and the absence of market integration (independent markets). In practice, markets are imperfect; the two prices may have complex relationships in a non-linear manner, with the incomplete transmission, not instantaneously due to various market characteristics.

For a small country, domestic prices will not have a significant effect on world commodity prices, but world prices can influence domestic prices. In the absence of trade barriers, world food prices establish upper and lower bounds for domestic food prices as

[4.28] $P_w + c \geq P_A \geq P_w - c$

where $P_w$ is the world price, $P_A$ is the wholesale price in the domestic economy. c is the full cost of transportation between the world market and the domestic market. $P_W + c$ is the import parity price, the full cost of importing the commodity from world markets. Similarly, $P_W - c$ is the export parity price, net price of exporting at the world price after deducting transportation costs. It is expected that price transmission to be higher when the domestic price is near the import parity price or when domestic price is near the export parity price. It is also expected that little or no price transmission when the domestic price is well within the bounds set by import parity and export parity prices. When there are policy barriers to international trade, lack of market information, or uncompetitive markets, price transmission is limited.

If two spatially separated market price series ($P_D$, $P_w$) that contain stochastic trends, are integrated of the same order, the prices are said to be cointegrated if,

[4.29] $P_{D,t} - \beta P_{W,t} = u_t$

where $u_t$ is stationary and β is the cointegrating parameter. There is a tendency for them to co-move in the long run according to a linear relationship. In the short run, the prices may drift apart, as shocks in one market may not be instantaneously transmitted to other markets; however, arbitration opportunities ensure that these divergences from the underlying long run equilibrium relationship are transitory and not permanent.

### 4.4.4 Complete and Incomplete Price Transmission

Within this context, complete price transmission between two spatially separated markets is defined as a situation in which changes in price in one market are completely and instantaneously transmitted to the other market. In this case, spatially separated markets are integrated. If price changes are not transmitted (passed-through) instantaneously, but after some time, price transmission is incomplete in the short run but complete in the long run, as implied by spatial arbitrage condition. Price changes at one market may need some time to be transmitted to other markets due to various reasons such as government policies, the number of stages in marketing, corresponding contractual arrangements between economic agents, storage, and inventory holding, transportation problems, processing delay. If traders do not have up-to–date information about prices in other markets, they cannot respond quickly. In practice, it often takes more than one month from the time trader decides to import from overseas to the availability of the imported goods in domestic markets. Thus, the process of spatial arbitrage can be slow. Price differences may persist over time before being corrected. Government interventions may lead to resulting incomplete price transmission. Indirect horizontal price transmission (IHPT) occurs between markets which are linked by way of technical and economic relationships characterizing two products which can be considered as substitutes or complementary. It is believed that co-movement of prices in different markets can be interpreted as a sign of efficient, competitive markets, while the lack of co-movement is an indication of market failures, including lack of information, poor infrastructure, or

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uncompetitive markets. Two aspects of transmission process: i) horizontal price transmission that relates to world prices to the corresponding domestic producer prices for a commodity, ii) Vertical price transmission relates to changes in the raw commodity through to the corresponding retail price.

### 4.4.5 Common Stochastic Trend and Co-integration

Common stochastic trend: Two commodity prices are said to be cointegrated if they share the same (common) stochastic trend. There has to be less number of stochastic trends than the number of variables. For example,

[4.30] $P_{d,t} = w_t + z_{d,t}$ domestic price model

[4.31] $P_{w,t} = w_t + z_{w,t}$ world price model

If there is a relationship between the two prices as $P_{d,t} - \beta P_{wt} = z_t$, and if $z_t$ is stationary, then $P_d$ and $P_w$ are cointegrated. The parameter $\beta$ characterizes the nature of the long run equilibrium relationship between the series.

Cointegration: Even though individual variables may not be stationary, linear combinations of them can be stationary if they are co-integrated (Granger & Newbold, 1974). Thus, the theory of co-integration gives a way to reconcile findings of non-stationarity with the possibility of testing relationship among the levels of variables. Co-integration is referred to as an economic concept of a long run equilibrium relationship.

Let $P_d$, $P_W$ is I(1) nonstationary variables. The linear combination of these variables can be written as $P_{d,t} - \beta P_{w,t} = z_t$, where $z_t$ is a stationary process and the shocks have transitory effects on $z_t$. Then Pd and Pw are cointegrated. When they are cointegrated, it can be defined as $P^*{}_{d,t} = \mu + \beta P_{w,t}$. $P^*_{d,t}$ is the equilibrium value of $P_{d,t}$. $z_t = P_{d,t} - P^*{}_{d,t}$ is the deviation from equilibrium. The equilibrium value does not have inherent tendency for $P_{d,t}$ to move away. Cointegrated variables both wander stochastically, but they never deviate too much from equilibrium.

The definition of cointegration can be extended to more than two variables. In particular, let $Y_t$ be a px1 vector of variables, multivariate processes with components that are integrated of order one. The components of $Y_t$ are co-integrated if and only if there exists a non-degenerate linear combination $\beta' Y_t$ with $\beta \neq 0$, such that $\beta' Y_t$ is stationary, i.e. $\beta' Y_t \sim I(0)$, $\beta$ is the cointegration vector. This stationary linear combination is called the cointegrating equation. When $\beta' Y_t = 0$, variables are in long-run equilibrium. The deviation from long-run equilibrium is called equilibrium error. It is noted as $z_t = \beta' Y_t$. If the equilibrium error process is stationary, the equilibrium is meaningful (Engle & Granger , 1987). The I (1) time series with a long run equilibrium relationship cannot drift too far apart from the equilibrium because economic forces will act to restore the equilibrium relationship. Some normalization assumption is required to uniquely identify $\beta$ in $\beta' Y_t$. A typical normalization is $\beta = (1, -\beta_2, -\beta_3, ... - \beta_n)'$ so that $\beta' Y_t = (Y_{1t} - \beta_2 Y_{2t} - ... \beta_n Y_t) \sim I(0)$. The cointegrating error is stationary and integrated order zero ($u_t \sim I(0)$). In the long run, equilibrium, $u_t$ =0 and the long run equilibrium relationship is $Y_{1t} = \beta_2 Y_{2t} + .... + \beta_n Y_{nt}$ Cointegration implies the existence of long run equilibrium and common stochastic trend.

## 4.5 Volatility Transmission

An Economic theory such as financial theory, consumer theory, frequently suggests that decision makers respond not only to the mean (first moment) but also to higher moments of economic random variables. GARCH models, Regime Switching models, and stochastic volatility models have been applied in the literature in the analysis of volatility transmission. Volatility refers to unexpected price movements. Volatility is an important ingredient in portfolio selection, risk management, and option pricing. The variance, which measures the spread of results, is the average of all of the squared deviations of each outcome from this mean. It represents the directionless variability/dispersion of an economic variable within a given time horizon. The volatility indicates how much and how quickly the price of an asset or commodity changes. It refers to the degree of unpredictable change over time of a certain variable. The volatility concept is important to describe dispersion from expected price.

## 4.6 Conceptual Model–Price Transmission

Based on the literature, the conceptual model was constructed in Figure 4.1. This model describes the transmission of global food price changes to domestic general price inflation. Domestic prices, CPI, CFPI, WPI, WFPI and CNFPI are determined by domestic as well as foreign factors. Among foreign factors, global food price, exchange rate, oil price are important. Oil price, the exchange rate can affect domestic price through global food price as well as domestic supply side factors. Therefore, these two variables are added in the model as explanatory variables. A rise in global food prices would lead to a rise in prices of food and non-food items for domestic consumers. The exchange rate would determine both time and the magnitude of the transmission. The exchange rate can affect domestic prices through expectation, and imports price. Exchange rate depreciation would increase imports price. World oil price can determine world food price as well as local food supply factors. As a result, exchange rate and oil price can also determine domestic prices through global food prices as well as local supply channels. Wholesale prices (producer prices) also influence consumer prices. GFPI passes through WPI, WPI CFPI to CPI. Domestic food prices and domestic nonfood prices also interlinked through inflation expectation. The interrelationship between GFPI and domestic prices are shown in Figure 4.1

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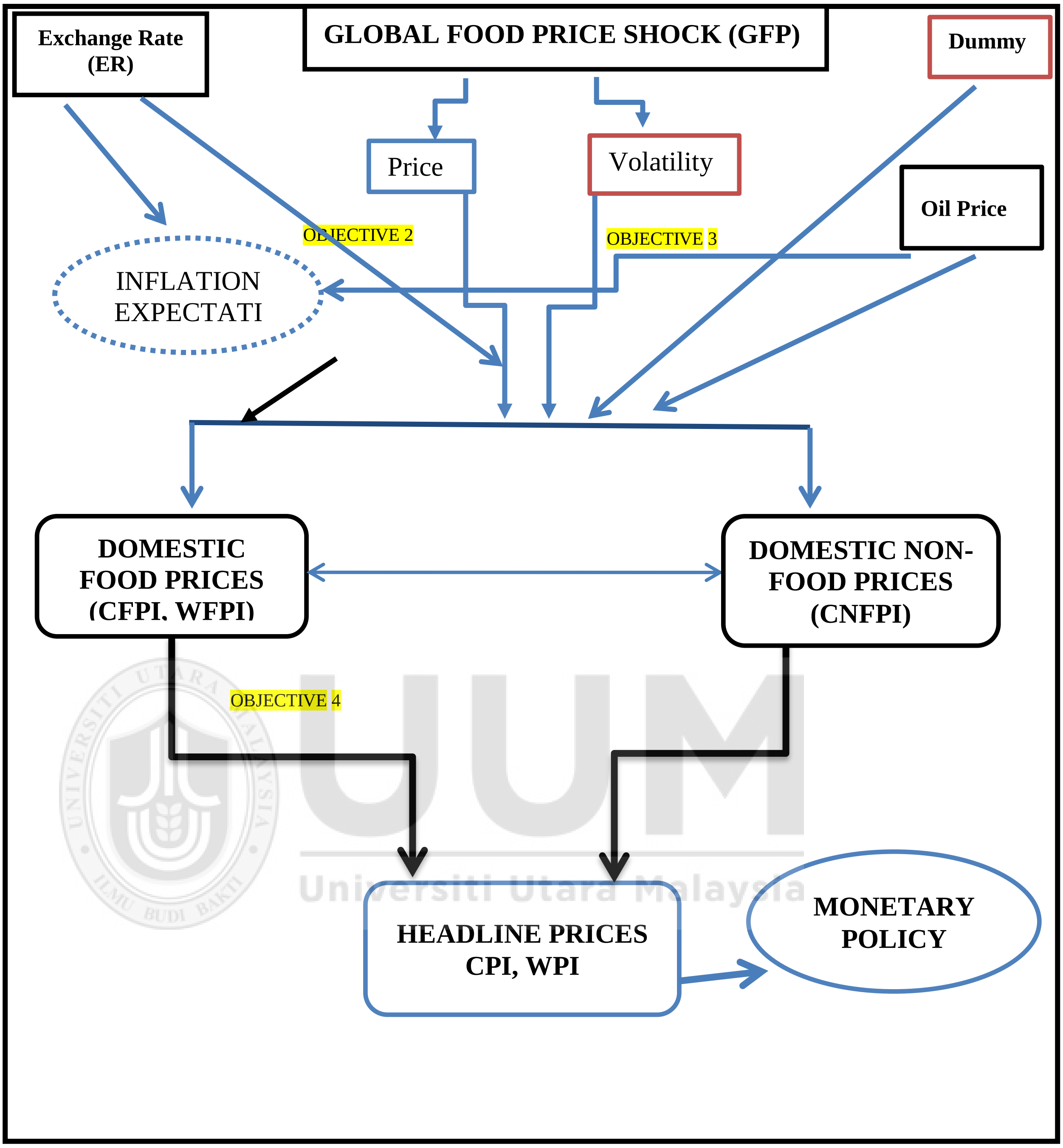


Note: CPI-Colombo Consumer Price Index, CFPI- Colombo Consumer Food Price Index, CNFPI= Colombo nonfood Price Index, WPI=Wholesale Price Index, WFPI-Wholesale Food Price Index, GFPI=Global Food Price Index, ER= Exchange rate

Figure 4.1
*Conceptual Framework of Global Food Price Transmission to Domestic Prices*

# CHAPTER FIVE

# METHODOLOGY

## 5.1 Introduction

This chapter describes models, justification of variables, data and method of analysis that cover the analytical tools used to achieve the objectives of the study. It also describes variable definitions, transformation, and sources of data.

## 5.2 Empirical Model

This section describes the empirical model formulation in the study. In order to achieve the objectives of the study, various models are formulated. For the first objective, ARFIMA and FIGARCH models are used to estimate the long memory parameter. The ARFIMA model is specified in Equation [4.16]. For the second, third and fourth objectives, cointegration regression model based on price transmission LOP theory is used. In order to analyse global food price transmission, a statistical model is formulated based on LOP. The LOP stated in Equation [4.24] is rewritten here in Equation [5.1] for ease of reference;

[5.1] $$P_{i,t}^{d} = ER_t P_{i,t}^{w}$$

where $P_{i,t}^{d}$ is the domestic price, $P_{i,t}^{w}$ is the world price of commodity *(i)* and $ER_t$ is the exchange rate (exogenous). The statistical model of the LOP is rewritten in Equation [5.2] in natural logarithmic form.

[5.2] $ln\,P_t^d = \beta_0 + \beta_1\, ln\,P^w + \beta_2\, ln\,ER_t + u_t\,,$

$\beta_1$ is the price transmission elasticity. In the study, the model given in Equation [5.2] is modified as in Equation [5.3] to study the transmission effects.

[5.3] $LP_t^d = \alpha + \beta LGFPI_t + \theta_1 LER_t + \theta_2 LOILP + \theta_3 D + u_t$

where $u_t \sim IID(\mu, \sigma^2)$ ,and $E(LER_{i,t} u_t) = E(p_t^w u_t) = E(LOILP_t, u_t) = 0$ , $LP^d$, is the log of domestic price, LGFPI is the log of global food price, LER is the log of exchange rate, LOILP is the log of oil price and D is dummy variable introduced to capture structural break. D=1 for 2007-2008 food crisis period, D=0 otherwise.

According to the LOP model, global food price and exchange rate are important. Crude oil price and exchange rate can affect domestic price through global food price as well as domestic supply side factors. In addition, a dummy variable is also added into the model to capture structural breaks.

A rise in global food prices can lead to an increase in domestic food prices or domestic consumer prices in direct and indirect ways. The nominal exchange rate affects domestic prices directly as well as indirectly. A higher nominal exchange rate (depreciation of local currency) directly implies a rise in the prices of food and non-food items for domestic consumers. Hence, the exchange rate would determine both the time and magnitude of the transmission. Further, the exchange rate can affect domestic prices indirectly through the supply side factors. For example, a depreciation of the currency can increase the price of fertilizer. As a result, the exchange rate can also determine domestic prices through global food prices as well as local supply channels. In the same way, higher oil prices also affect domestic prices directly as well as indirectly. World oil price can determine world food prices. It affects domestic prices through transport costs, import prices and cost of production. When comparing the effect of oil price to that of global food price, higher oil prices have a more indirect effect on consumer prices whereas higher food prices have a more direct effect on consumer prices. Considering these factors, the model is formulated to explain the relationship between domestic prices and global food prices.

In order to understand how various domestic prices are affected by GFPI, different empirical models are formulated for each of the domestic prices. Initially, each model is written in the form of mathematical function for each, mean PT and volatility PT in Section 5.2.1 and Section 5.2.2 respectively.

### 5.2.1 Mean Price Transmission

Mean PT refers to the expected price level transmission from the global food markets to the domestic markets. To understand the mean PT effects, various equations, from 5.5 to 5.9 are used separately for each domestic price.

To estimate the transmission effects from the global food price to the domestic consumer price, model [5.4] is used;

[5.4] $CPI = f(GFPI, ER, OILP, D)$

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To estimate the transmission effects from the global food price to the domestic food price, model [5.5] is used;

[5.5] $CFPI = f(GFPI, ER, OILP, D)$

To estimate the transmission effects from the global food price to the domestic consumer nonfood price, model [5.6] is used;

[5.6] $CNFPI = f(GFPI, ER, OILP, D)$

To estimate the transmission effects from the global food price to the domestic wholesale food price, model [5.7] is used;

[5.7] $WFPI = f(GFPI, ER, OILP, D)$

To estimate the transmission effects from the global food price to the domestic wholesale price, model [5.8] is used;

[5.8] $WPI = f(GFPI, ER, OILP, D)$

*D*=Dummy, *D=1* for *2007- 2008, D=0* for otherwise

### 5.2.2 Volatility Price Transmission

Volatility transmission refers to the expected volatility transmission from the global food markets to the domestic prices. The gobal food price inflation volatility is proxied by the conditional variance of global food price inflation derived from the FIGARCH model. The global food price inflation volatility transmission effects are estimated by regression models formulated by Equation 5.9 to Equation 5.13. To estimate the transmission effects of the global food price volatility to domestic CPI, Equation 5.9 is used;

[5.9] $CPI = f(VGFPI, ER, OILP, D)$

To estimate the transmission effects of the global food price volatility to domestic CFPI, Equation [5.10] is used;

[5.10] $CFPI = f(VGFPI, ER, OILP, D)$

To estimate the transmission effects of the global food price volatility to domestic CNFPI, Equation [5.11] is used;

[5.11] $CNPI = f(VGFPI, ER, OILP, D)$

To estimate the transmission effects of the global food price volatility to domestic WFPI, Equation 5.12 is used;

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[5.12] $WFPI = f(VGFPI, ER, OILP, D)$

To estimate the transmission effects of the global food price volatility to domestic WPI, Equation 5.13 is used;

[5.13] $WPI = f(VGFPI, ER, OILP, D)$

where VGFP=Volatility of global food price. In all cases, VGFP is a proxy for volatility of global food price.

### 5.2.3 Transmission of Food Prices to Overall Consumer Price

Domestic food prices are denoted by CFPI and WFPI. In order to achieve the fourth objective of the study, the following empirical models are formulated as given below.

To estimate the transmission effects of CFPI to domestic CPI, Equation [5.14] is used.

[5.14] $CPI = f(CFPI, ER, OILP, D)$

To estimate the transmission effects of WFPI price to domestic CPI, Equation [5.15] is used.

[5.15] $CPI = f(WFPI, ER, OILP, D)$

## 5.3 Justification of Variables

This section briefly describes the variables used in the study which includes Colombo Consumer Price Index for all items (CCPI), Colombo Consumer Price Index for Food and non-Alcoholic Beverages, (CCFPI), Colombo Consumer Price Index for non-food (CCNFPI), Wholesale Price Index (WPI), Wholesale Food Price Index (WFPI), Global Food Price Index (GFPI), and the Exchange rate (RS/ USD). The domestic price level of the Sri Lankan economy is represented by various prices indices, namely CPI, CFPI, CNFPI, WPI, and WFPI. The Colombo Consumer Price Index is the only official consumer price index in Sri Lanka. This study uses all Colombo Consumer Price Indices CCPI, CCFPI and CCNFPI as CPI, CFPI and CNFPI for ease of reference.

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The inflation series of CPI, CFPI, CNFPI, WFPI, WPI and GFPI are denoted by INFCPI, INFCFPI, INFCNFPI, INFWFPI, INFWPI, and INFGFPI respectively.

### 5.3.1 Consumer Price Index

The (Colombo) Consumer Price Index (CPI) is a statistical estimate of consumption expenditure of goods and services. This is the official CPI that has been used as an indicator of the cost of living of the households in Sri Lanka. CPI had been used as the official CPI of Sri Lanka in order to have a single standard measure of inflation in the country.

This index is constructed using the prices of a sample of representative goods and services collected from the Colombo District in Sri Lanka. Prices are collected periodically. CPI has been constructed by the Department of Census and Statistics (DCS), Sri Lanka. This index was computed using the Laspeyre's formula. The base year of CPI was 2002. Its geographical coverage was Colombo District. Its sample size was 1300 households. Price collection centers were 12. The value of one index point was Rs 179.96. First, 10 sub-indices are calculated with different weights, then combined to produce the overall CPI. The CPI weights are based on consumption expenditures from national household income and expenditure surveys of DCS. Their details are as follows: i) food and non-alcoholic beverages (46.7%), ii) clothing and footwear (3.1%), iii) housing, water, electricity, gas, and other fuels (18.3%), iv) furnishing, households equipment and routing household maintenance (3.2%), v) health (4.2%), vi) transport (9.5%), vii) communication (4.4%), viii) recreation and culture (2.2%), ix) education (5.8%), and x) miscellaneous goods and services (2.7%). The annual percentage change in CPI is used as a measure of inflation. Core inflation index is compiled from CPI by the DCS in Sri Lanka to be used for monetary policy purposes. The core inflation assesses the underlying inflationary pressures in the economy. It is a common practice for countries to revise CPI based on the latest Consumer Expenditure Survey in order to reflect changes in the consumption pattern. However, this study converts the 2006 base period (latest) CPI series into 2002 base year using splicing method in order to have the same base period for all data series in the sample. CPI is categorized into two main parts: food price index and nonfood price index.

### 5.3.2 Consumer Food Price Index

The CFPI is the principal indicator of consumer food price changes. CFPI is an average price, a weighted average of prices of various food items. It is defined using food and non-alcoholic beverages. Food category consists of Bread and Cereals, Meat, Fish and Sea food, Milk, Cheese and Eggs, Oil and Fats, Fruits, Vegetables, Sugar, Jam, Honey, Chocolate and Confectionary, and food products. Non Alcoholic beverages consist of Coffee, Tea, Cocoa, Mineral water, Soft drinks Fruit and vegetable juice.

### 5.3.3 Consumer Non-Food Price Index

Consumer Non-Food Price Index (CNFPI) is an average price, a weighted average of prices of various items that consists of Clothing and Foot wear, Housing, Water, Electricity, Gas and Other Fuels, Furnishing Household Equipment and Routine Household Maintenance, Health, Transport, Communication, Recreation and Culture, Education and Miscellaneous Goods and Services.

### 5.3.4 Wholesale Price Index

Wholesale Price Index (WPI) represents the price of a basket of goods at the wholesale stage. WPI refers to a mix of agricultural and industrial goods at various stages of production and distribution, including import duties. The Laspeyres formula is generally used. Goods are traded in this context, between organizations instead of consumers. It is usually considered as representative of producer behavior in the country. WPI comprises as far as possible of all transactions at the first point of bulk sale in the domestic market. Wholesale price index refers to a combination of agricultural and industrial goods at various stages of production and distribution, including import duties. In Sri Lanka, WPI comprises 10 commodity groups. The base year of WPI was 1974. It is used to calculate inflation in some countries like India, USA, and the Philippines.

### 5.3.5 Wholesale Food Price Index

Wholesale Food Price Index (WFPI) is the price of a representative of wholesale food items. It reflects producer's behavior. The WPI for all food items is denoted by WFPI. WFPI is an average price, a weighted average of prices of various food items. Food group has 67.8 % share of WPI.

### 5.3.6 Global Food Price Index

The global food price index (GFPI) is a statistical estimate of consumption expenditure of goods and services in the global context. This is an important independent variable in this study. This has been used as a proxy for the world food prices. GFPI was represented by the Food and Agriculture Organization (FAO) of the United Nations food price index that consists of the average of five commodity group price indices namely, meat price index, dairy price index, cereal price index, vegetable oil price index and sugar price index. It is weighted with the average export shares of each of the groups for 2002-2004. FAO commodity specialists computed this index to represent the international prices of the food commodities. Each sub-index is a weighted average of the price relatives of the commodities included in the group, with the base period price consisting of the averages for the years 2002-2004. GFPI is collected from FAOSTAT online database: http://faostat.fao.org/site/351/default.aspx. GFPI is expected to be positively related to CPI, CFPI, CNFPI, WPI, WFPI in Sri Lanka. The volatility of GFPI is also expected to have a positive relationship with the domestic prices.

### 5.3.7 Volatility of Global Food Price Index

The volatility of a price series is measured by various measures, namely standard deviation/ variance of the series, absolute inflation, squared inflation, and conditional variance generated by the FIGARCH model. In this study, conditional variance generated by the FIGARCH model is used for the volatility of global food price inflation. It is expected to have a positive relationship between the volatility of global food price inflation and domestic prices. The global food price inflation volatility is denoted by CVGFPI.

### 5.3.8 Exchange Rate

Exchange rate (ER) is defined as the rate at which one currency is exchanged for another currency. The value of one currency is stated in another currency. For example, the exchange rate between USD and Sri Lankan rupee is denoted by RS/USD. For the variable of the exchange rate, the RS/USD exchange rate is used in this study. The RS/USD is the key currency in Sri Lanka. Almost all food items in the international market are traded in terms of the USD. All Sri Lankan international trade activities are also traded in USD. In practice, commodity prices are sensitive to exchange rate movements. It is denoted by ER in the study.

Generally, the relationship between exchange rate and domestic prices is expected to be positive. . When an exchange rate depreciates, import prices in domestic currency are increased. Thus, exchange rate also determines the magnitude of PT. The exchange rate of RS/USD is determined by demand and supply forces in the currency market. The data of ER was collected from the Central Bank of Sri Lanka. Abbott *et al* (2008), Abbott, Hurt and Tyner (2011) found that ER was one of the causes for higher food prices.

### 5.3.9 Oil Price Index

Oil prices (OILPI) may determine world food prices in two ways: i). through supply side and ii) through demand side. In the case of supply side, ER can affect food prices directly by shifting the supply curve to the left through the production costs (transport costs and fertilizer cost). In the case of demand side, when crude oil price increases, demand for food increases, because food is used for the use of biofuel feedstocks. In addition, the oil price affects domestic prices in two ways; i) as an input cost variable, ii) through world food prices indirectly. Abbott *et al.* (2008) found that oil price was one of the causes for higher food prices. Baffes (2007) found that the pass-through effects of oil prices into agricultural commodity prices was 17 percent. Mitchell (2008) found that the biofuels demand for food was the largest part of the rise in food prices. Baffes and Haniotis (2010), Write (2011), Hertel and Beckman (2011) had also found that oil price was a significant variable to explain food price dynamics.

### 5.3.10 Dummy Variable

A dummy variable is called an indicator variable or binary variable denoted by *D*. It is a nominal variable and is quantified as 1 or 0. D=1 indicates the presence of an attribute, D=0 indicates the absence of an attribute. For example, D=1 for 2007-2008 food crisis period, D=0 otherwise. It is included to reflect the structural change that occurred during the food crisis.

### 5.3.11 Transformation

All price indices, the exchange rate, and the oil price are transformed into natural logarithmic form for various reasons. First, to stabilize the variability of the series, that is to satisfy constant variance assumption. Second, to bring data closer to a normal distribution; to reduce the relationship between mean and variance, to reduce the influence of outliers, to improve linearity in regression, and to reduce skewness and kurtosis. When analyzing growth measurements, logarithmic transformation is recommended. Growth rates are defined as the log difference of the variables, defined as $Growth = ln(Y_t) - ln(Y_{t-1})$. Growth rates of the variables of CPI, CFPI, CNFPI, WFPI, WPI GFPI, ER, and OILP used in the study are denoted by CPG, CFPG, CNFPG, WFPG, WPG, GFPG, ERG, and OILPG. Further, log transformation is useful to get the elasticity of the response variable directly. The estimated parameters in the global food price transmission model can directly be interpreted as "transmission elasticities" of the domestic prices with respect to GFPI. In addition, the Hodrick-Prescott (HP) filter is also used in this study to separate the trend component and cyclical component of a series. The line graphs and seasonality graphs of the response variables used in the study do not exhibit seasonal features. Therefore, this study has not used seasonal adjustment or dummy for seasonal variation.

## 5.4 Data

This section describes the types of data, study period and sources of data.

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### 5.4.1 Types of Data

This study uses both household expenditure survey data and macro-level data. The Household expenditure survey data are used to derive food expenditure ratio and food expenditure elasticities. Macro-level data (time series) are used for various price indices of Sri Lanka and the world. An ordered sequence of values of price variables at monthly time interval are used in this study. Monthly time series data of domestic aggregate consumer prices (CPI), sub–grouped price indices such as food prices and non-food prices, global food prices, oil price and exchange rate are the macro-level data. The monthly frequency data are used to understand the dynamics of food prices in Sri Lanka.

### 5.4.2 Period of the Data

The data were collected from January 2003 to December 2014. The starting time period, 2003 is selected as food prices started to move upward exponentially in Sri Lanka as well as in the world. The total number of observations was 143.

### 5.4.3 Data Collection

Household expenditure survey data and domestic consumer price indices that represent the consumer behavior are collected from the Department of Census and Statistics (DCS), Sri Lanka. Domestic wholesale price indices that represent producer behavior are collected from the Central Bank Annual Report 2014. Global food price indices are collected from FAOSTAT website: http://faostat.fao.org/site/703/default.aspx#ancor.

## 5.5 Method of Analysis

A variety of econometric analytic methodologies was employed in the study in order to achieve the robustness of the results. Parametric, nonparametric and semi parametric approaches under time and frequency domain were used to achieve the objectives of the study. These techniques were used to describe the first four moments of the food price distribution; its mean, volatility, asymmetry and kurtosis. A special emphasis is given to the first two moments, namely the mean dynamics and variance dynamics of the food price series.

The first objective of the study is to estimate and describe memory properties of food price series. To achieve this objective, the Rescaled Range Statistic (R/S), Geweke and Porter- Hudak (GPH) statistic, and memory parameter '*d*' of ARFIMA and FIGARCH models were used.

The second and third objectives are to estimate the transmission effects of global food prices on domestic prices. the fourth objective is to estimate the spillover effects of domestic food prices on general price. The main analytical tool is cointegration regression analysis. To estimate the transmission effects of global food price changes on domestic prices, the models were formulated for each domestic price based on LOP. A dummy variable is included in the model to capture the structural effects. Thus, the LOP model is modified by adding a dummy variable into the model to capture the structural breaks of 2007-2008 food crisis. In addition, the Granger-causality test (GCT) was used to validate the cointegration results by estimating the causal relationship. The FIGARCH model was used to generate conditional variance series and estimate the long memory parameter of food price volatility dynamics.

### 5.5.1 Descriptive Statistics, Correlation Analysis and Unit Root Tests

Prior to delving into the main task of investigating the objectives, it is useful to do a preliminary analysis to understand the basic features of the variables. For this purpose, descriptive statistics, unit root test, and correlation analysis are employed.

### 5.5.2 Long Memory Tests

To understand and explain food price inflation dynamic behaviour in deep, long memory parameter must be correctly estimated. The first objective of this study is achieved by estimating long memory parameter. In order to estimate long memory parameter, various methods are employed in this study. First, the long memory is detected by visual inspection using autocorrelations function (ACF) and spectral density function (SDF). Correlogram from ACF and periodogram from SDF are derived. By visually inspecting these graphs, one can identify whether the series has a long memory. Then inferential methods are used to detect long memory. This study uses three type inferential methods; nonparametric, semiparametric and parametric approaches. These methods consist of a battery of measures that capture the long memory of food price inflation, namely, unit root tests, the *R/S* Statistic, LWE, GPH estimator and long memory parameter '*d*' of ARFIMA and FIGARCH models. Three food price indices namely, CFPI, WFPI, and GFPI are selected for investigation.

#### 5.5.2.1 Visual Inspection

Long memory of food price series is visually inspected using autocorrelation function (ACF) and spectral density function (SDF).

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**(i) Autocorrelation Function**

One can examine the dynamics of a variable via the autocorrelation function in the time domain. The autocorrelation (ACF) plot is called "autocorrelogram" or "Correlogram". Sample autocorrelations are plotted against lag $\tau$. The autocorrelation function is defined as $ACF(\tau) = \gamma(\tau) = corr(y_t, y_{t-\tau})$. Successive values are correlated in a time series often correlate with each other. Autocorrelation can be detected by using time series plot, lagged scatter plot and autocorrelation function. Positive autocorrelation indicates persistence. The ACF is a preliminary diagnostic tool to detect long memory of a process. Box, Jenkins, and Reinsel (2008) define short memory processes as those whose ACF decay exponentially fast and long memory processes whose ACF decay at the hyperbolic rate.

**(ii) Spectral Density Function**

Alternatively, one can examine dynamics of a variable in the frequency domain via the spectral density function. The spectral density characterizes the frequency content of the signal. Spectral density estimation (SDE) is a technical process of decomposing a complex signal into a simple form. It is a frequency domain representation. SDE describes the information of the relationship between various amounts such as amplitudes, powers, intensities or phases versus frequencies. The periodogram reveals the short term and long term cycles within the period of study. Granger (1966) describes how the spectral shape of an economic variable concentrates spectral mass at low frequencies, declining smoothly as frequencies increases. The series $y_t$ displays long memory if its spectral density, $f_Y$ increases without limit as angular frequency($\omega$) tends to zero, $\lim_{\omega \to 0} f_Y(\omega) = \infty$. The impulse response function dies out at a much slower rate. A convenient way to represent the sequence of auto-co-variances of a covariance stationary process is the application of spectral density. In the frequency domain, the response variable is generated by an infinite number of random components that occur at the angular frequencies $\omega \in [0, \pi]$, measured in radians. The spectral density describes the relative contributions of random components at different frequencies to the variance of the process, with the low-frequency components corresponding to long run effects. If a spectral density (SDF) of a stationary time series {$y_t$} obeys a power law for nonzero *d* and $d \in (-0.5, 0.5)$, that is $f(\omega) \sim c\omega^{-2d}$ as $\omega \to 0^+$, the series has a long memory. The SDF tends to either $\infty$ (if 0<*d*<0.5) or zero (if *d*<0). If *d*=0, the series {$y_t$} has a short memory and SDF $f(0)$ will be positive and finite. For white noise series, the spectrum (SDF) is flat for all frequencies. The long run variance is determined by the SDF at the zero frequency. The periodogram is just a truncated expression of $\hat{f}$. The periodogram measures the amplitude of a time series for all possible frequencies and wavelengths. In a spectral graph, a periodogram is completely dominated by the low frequency components. At the periodogram, long run dependence can be seen by the relatively flat spectral density over higher frequencies.

#### 5.5.2.2 Inferential Tests

**i) Unit Root Test**

Commodity price series have a number of common characteristics that have important implications for sound statistical analysis (Myers, 2006). Therefore, detecting the nature of the trend of a series is very important for analyzing economic time series data before proceeding with the estimation. The existence of stochastic trends (trends which change randomly over time) distorts many of the usual distributional assumptions and implications typical in food price analysis. Thus, great care must be taken in testing for stochastic trends in the econometric analysis in the study.

The conventional unit root tests such as the Augmented Dickey-Fuller (ADF), the Phillips-Perron (PP) tests are not measuring the magnitude of the persistence of the series. They only identify the series are I(0) or I(1). So we use other recently developed models to estimate long memory parameter.

To examine the random walk nature (issue of unit roots) of empirical food price behavior, standard unit root tests; the ADF test (Dickey & Fuller, 1979, 1981) and the PP test (Phillips & Perron, 1988), and the KPSS test (Kwiatkowski–Phillips–Schmidt–Shin (1992)) are implemented on all food price series. The ADF and PP tests are used to test the null hypothesis of the series are non-stationary (I(1), against the alternative that they are stationary I(0). The ADF test method involves estimating the model

[5.14] $$\Delta P_t^f = \alpha_0 + \alpha_1 t + \alpha_2 P_{t-1}^f + \sum_{j=1} \Delta P_{t-j}^f + \varepsilon_t ,$$

and testing the null hypothesis $H_0 : \alpha_2 = 0,$ vs $\mathrm{H}_1 : \alpha_2 < 0$. t is a time trend.

The Phillips-Perron (1988) test involves estimating the model

[5.15] $$r_t = \beta_0 + \beta_1 (t - T/2) + \beta_2 r_{t-1} + v_t$$

and testing the null hypothesis $H_0 : \beta_2 = 1$ vs $\mathrm{H}_1 : \beta_2 < 1$, where T is the sample size. For each model, the null hypothesis is that the series has unit root, I(1). The ordinary least squares (OLS) method is used to obtain estimates and standard errors for the parameters of the both models of ADF and PP tests.

The null hypothesis of KPSS test is: series is stationary against series are non-stationary. The KPSS test uses Lagrange multiplier test of the null hypothesis that the innovations in the random walk have zero variance. The null hypothesis of KPSS test is that the series is stationary against the alternative that the series has a stochastic trend. Full details of the test are available in Kwiatkowski, Phillips, Schmidt and Shin (1992).

If food prices contains a unit root, then the persistence of food prices is unquestionably large and its variance is unbounded and infinite memory. The existence of a permanent component is commonly examined by testing for unit roots in autoregressive lag operator polynomials. The presence of a unit root in a series provides evidence for the existence of persistence. To investigate the random walk nature (issue of unit roots) of empirical food price behavior, the ADF test, the PP test, and the KPSS test are implemented on logarithm of the food price series in the study.

#### ii) The Rescaled Range Statistic (R/S)

The rescaled range statistic (R/S) is most widely used. Hurst (1951), English hydrologist proposed a statistic called the "rescaled range" or the range over standard deviation or "*R/S*" statistics to detect long range dependence of a series. This statistic has been refined by Mandelbrot (1971, 1972, 1975), and others (Mandelbrot & Taqqu, 1979); Mandelbrot & Wallis 1968, 1969a-1969c) in several important ways. This statistic was used as a long memory statistical test in the early period.

The classical *R/S* is the range of the partial sums of deviations of a time series from its mean, rescaled by its standard deviation. For a sample of an observation $\{X_1, X_2, \ldots X_n\}$, the *R/S* statistic is defined by $1 \le k \le n$

$$[5.16] \qquad (R/S)_n = \frac{1}{s_n}\left[ Max\sum_{j=1}^{k}(x_j - \bar{x}_n) - Min\sum_{j=1}^{k}(x_j - \bar{x}_n) \right],$$

let $\overline{X}_n$ denote sample mean. $R(n)$ is the range of the first n values, and $S(n)$ is the maximum likelihood estimator of the standard deviation, defined as in Equation [5.17]

$$[5.17] \qquad S_n = \left[ \frac{1}{n}\sum (X_j - \overline{X}_n)^2 \right]^{1/2}$$

The first term in the bracket in Equation [5.16] is the maximum (over *k*) of the partial sums of the first *k* deviations of $X_j$ from the full sample mean. This maximum is always nonnegative. The second bracketed term is the corresponding minimum (over *k*) of this same sequence of partial sums, hence it is always non- positive. The difference of these two quantities is called "range", is always nonnegative. This statistic is known as the rescaled range; range over standard deviation or R/S statistic.

The Hurst exponent (*R/S*) is used as a measure of the persistent behavior of a time series from the Rescaled Range analysis. The Hurst exponent is referred to as the "index of long-range dependence". The Hurst exponent, *H*, is defined in terms of the asymptotic behaviour of the rescaled range as a function of the time span of a time series as follows:

$$[5.18] \qquad E[R(n)/S(n)] = C\,n^H \quad \text{as } n \to \infty$$



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where $R(n)$ is the range of the first $n$ values, and $S(n)$ is their standard deviation, $E(.)$ is the expected value, $n$ is the time span of the observation (number of data points in a time series) and $C$ is a constant. The Hurst exponent is estimated by fitting the power law to the data. The rate of decay is determined by the so called Hurst exponent ($H$) (Beran, 1994). $H$ parameter is estimated by the $R/S$ method.

If $0.5<H<1$, the series possess long memory. If $0.0 < H < 0.5$, then the series is called ant-persistent. This behavior is sometimes called mean or trend reversions. A value of $H$=0.5 can indicate a completely uncorrelated series, but in fact, it is the value applicable to series for which the autocorrelations at small time lags can be positive or negative but where the absolute values of the autocorrelations decay exponentially quickly to zero. This is called random walk. It implies a non-deterministic process, one in which the past history does not influence the future course of the series. The Hurst exponent has already been employed in many fields of Mathematics such as chaos theory, engineering, and fractal analysis (Mandelbrot, 1969). H statistics were estimated in Excel-the computer program written in C++, Excel macro by Martin Swell (2010). However, this technique is not robust to the short range persistence and heteroscedasticity. This test is very sensitive to series length influencing standard deviation and the mean (Granero *et al*., 2008). Lo (1991) stated that R/S test is sensitive to the short memory. Lo has suggested a modified statistic (Lo's R/S statistic) to solve the above problem (Skare & Stjepanovic, 2013).

### iii) Geweke and Porter-Hudak Method

Semi-parametric approaches evade the misspecification issue developed from parsimonious parametric models. Geweke and Porter-Hudak (1983) proposed a semi-parametric procedure to estimate long memory parameter '*d*'. The estimate of long memory parameter, $\hat{d}$, is obtained by estimating log periodogram regression by OLS method. The log periodogram regression is given in Equation [5.19]

[5.19] $$\log(I(\omega_j)) = \alpha + d\log\left(\left\{2\sin\frac{\omega_j}{2}\right\}^{-2}\right) + \varepsilon_t, \qquad j=1,2,\ldots\ldots, n.$$

where $I(\omega_j)$ is the periodogram at the harmonic frequency $\omega_j = \frac{2\pi_j}{T}$, $\varepsilon_t$ is a random error term. $n = T^{\mu}$ for $0 < \mu < 1$ is the number of low frequency ordinates used in the regression. The periodogram $I(\omega_j)$ is computed as product of 2/T and the square of the exact finite Fourier transform of the series at the respective harmonic ordinate. Geweke and Porter-Hudak (1983) display the least square estimate of *d* provides a consistent estimate of *d* and hypothesis testing the value of *d* can be based on the standard *t* statistic. The OLS estimator of *d* is given by equation [5.20] as

[5.20] $$\hat{d} = \frac{\sum_{s=1}^{m} y_s \log I_s(\lambda_s)}{2\sum_{s=1}^{m} y_s^2}$$

Phillips (1999a) pointed out that this semiparametric method did not address the case of *d*=1 (unit root) , $\hat{d}$ (estimate) of GPH was inconsistent when *d* >1. These problems were solved by Phillips' modified log periodogram regression estimator. The null hypothesis of GPH test and LWE test is a short memory, $H_0 : d = 0$, in the series. Against the alternative hypothesis of long memory, $H_0 : d > 0$. If the null hypothesis is rejected, it implies that the series has a long memory.

### iv) Long Memory Parameter '*d*' of ARFIMA and FIGARCH Models

Using the theoretical knowledge given in Chapter 4, it is tested whether food price series has long memory?. The testing procedure using ARFIMA and FIGARCH models is a parametric test procedure. Granger and Joyeux (1980) and Hosking (1981) introduced the ARFIMA model that is widely used in practice. This model is given by Equation 4.16. ARFIMA model is used to estimate long memory parameter (*d*) of food price, food price inflation series. In the case of the volatility of food price inflation series, FIGARCH model is used to estimating long memory parameter (*d*).

## 5.5.3 Co-integration Test

This section briefly describes cointegration analysis empirically in the study. In order to understand the underlying long run relationship between GFPI and domestic prices, cointegration test is employed to achieve the second, third and fourth objectives. The simple correlation analysis does not account for dynamics and lead-lag relationships between global food price and domestic prices. Thus, this study employs the above mentioned methods to estimate global food price transmission to domestic prices. Even though individual variables may not be stationary, linear combinations of them can be stationary if they are co-integrated (Granger & Newbold, 1974). Thus, the theory of co-integration gives a way to reconcile findings of non-stationarity with the possibility of testing relationship among the levels of economic variables.

### 5.5.3.1 Co-integration Test: The Johansen's Procedure

A brief description of the Johansen test is given below in order to understand the theoretical background. Vector autoregressive based model (VAR) is used to test whether shocks in GFPI are passed on to the producer food price index (WFPI) and the consumer food price index (CFPI) and overall consumer price index (CPI), consumer nonfood price index (CNFPI), wholesale price (WPI) in Sri Lanka. The VAR model allows us to measure the pass-through while controlling for other determinants of inflation. Non stationary characteristics give rise to the possibility of co-integrated long run relationships. Thus, this study employs multivariate co-integration analysis, proposed by Johansen (1988, 1991) and Johansen and Juselius (1990) to investigate the dynamic co-movement between domestic prices and global food prices and the adjustment process toward long term equilibrium. Johansen's procedure specifies the full vector autoregression (VAR) model which characterizes the joint distributions of the data without imposing priori structural relationships. This approach offers a more unified framework for the estimation and testing of the co-integration relationships in the context of VAR error correction models. This method allows determination of all 'r' co-integration relationships and ensures that coefficient estimates have the smallest bias in median and sample dispersion. Estimators are asymptotically efficient. This method can provide estimates of co-integrating vector (long run coefficient), the adjustment parameter, the short run coefficient matrices, and the variance and covariance matrix of residuals. As this method allows for detailed analysis of the dynamic properties of the model, the Johansen method is employed in this study. It is flexible enough to capture a rich dynamic structure and interactions of the system. This procedure overcomes the problem of non-stationarity and allows the investigation into both levels and first differences of variables. This method employs full information maximum likelihood (FIML) to estimate co-integrating vectors and to test for the order of co-integrating vectors. It also allows for testing for co-integration in a whole system of equations in

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one step and without requiring a specific variable to be normalized. Co-integrated vector autoregressive (VAR) framework has the form given in Equation [5.21]

[5.21] $Y_t = \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + ......... + \phi_p Y_{t-p} + \psi X_t + \varepsilon_t$

$Y_t$ is a vector consisting variables global food price, domestic *CPI, CFPI, CNFPI, WPI, WFPI, ER*, all variables except dummy are in natural logarithmic form. $\varepsilon_t$ is a vector of disturbance terms. *X* is a deterministic term (dummies, constants, exogenous variables, trends). Using first difference operator, $\Delta$ defined by $\Delta Y_t = Y_t - Y_{t-1}$, VAR(p) can be re-parameterized in vector error correction form (Johansen & Juselius, 1990). The co-integrating relations are not explicitly apparent in levels VAR. But co-integrating relations are explicitly apparent in the VECM. Granger representation theorem states that if two variables are cointegrated, the relationship between the two can be expressed as ECM. Johansen analysis is expressed in VECM. ECM combines the long run, co-integration relationship between the levels variables and the short run relationship between the first differences of the variables. It also has the advantage that all the variables in the estimated equation are stationary, hence, there is no problem of spurious correlation. Granger Representation Theorem states that, if underlying variables in a regression are co-integrated, then there exists a valid error-correction representation of the data. Under the error correction mechanism, the short run behavior of variables is corrected so that it becomes consistent with the long run equilibrium. Long run equilibrium corresponds to a steady state growth path.

#### 5.5.3.2 Vector Error Correction Mechanism

Having identified the long run relationships, the next step is to consider the short run evolution of the response variable. To understand the short run dynamics of the variable, an error correction model is formulated. A relationship between I(1) variables is referred to as a long run relationship if the residuals of co-integration regression are I(0), and a relationship between I(0) variables is referred to as a short run relationship. This model allows for the existence of an underlying link between variables (long run relationship) as well as for short run adjustments (i.e. changes) between variables, including adjustments to achieve the long run relationship. This model separates the effects into a long run and short run components. The vector error correction models (VECM) allows us to examine how much the response variable change in response to a change in the explanatory variable, as well as the speed of the change. Thus, VECM is used to estimate the degree of price transmission. The VECM captures the interactions between the world and domestic prices. If the variables are non-stationary and co-integrated, the adequate method to examine the causal relations is the VECM (Granger, 1988). Engle and Granger (1987) point out that ECM corrects a proportion of the disequilibrium from one period to the next period. VAR model, under the presence of co-integrating relationship, is re-parameterized to obtain VECM. The standard linear vector error correction representation of the VAR model for the n variables that are integrated order one, I(1) has the form as given in Equation [5.22].

$$[5.22] \quad \Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \Psi X_i + \varepsilon_t$$

The model is estimated by regressing $\Delta Y_t$ against the lagged differences of $\Delta Y_t$, exogenous variables and $Y_{t-1}$. The eigenvalues of $\Pi$ are calculated in order to find co-integrating vectors. The rank of $\Pi$ is denoted by *r* is the number of co-integration vector and decided based on the statistical significance of its eigenvalues under the null hypothesis. Two statistics; trace statistic and Max eigenvalue statistic are used to test the null hypothesis of no cointegration. Critical values for both statistics are provided by Johansen and Juselius (1990). A very useful feature of the Johansen procedure for co-integration is that it allows us to test for restricted forms of the co-integrating vectors. Restrictions are imposed by substituting them into the relevant $\alpha$ or $\beta$ matrices as appropriate.

When the rank of $\Pi$ is zero ($r$=0), there are no cointegrating relationships. The VAR polynomial $\Phi(z)$ contains n unit roots, n stochastic trends. In which case, all of the variables are non-stationary. There are no stationary long run relations among the elements of $Y_t$. In this case, the variables do not have common stochastic trend and hence do not move together over time. Therefore, it is not possible to obtain stationary cointegration relations between the levels of the variables. When $\Pi$ has full rank, $r=n$, all of the variables in levels are stationary and standard inference applies. $\Phi(z)$ has its roots outside the unit circle. There are no any stochastic trends. All variables are I(0) , the issue of cointegration is not relevant. When $\Pi$ is less than full rank but not equal to zero. i.e. $0 < r < n$, intermediate rank. There are r linear combinations of the non-stationary variables that are stationary, i.e. there are $r$ cointegrating relationships. The polynomial $\Phi(z)$ has n-r unit roots, common stochastic trends. This indicates that $\Pi Y_{t-1}$ is I(0). In this case, $\Pi$ can be written as $\Pi = \alpha\beta'$. The system $\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \Psi X_t + \varepsilon_t$ can be estimated by full system Maximum Likelihood that $\varepsilon_t \sim N(0,\Sigma)$ and iid. Let the parameter $\Gamma_i$ be collected in a matrix

$\Gamma = [\Gamma_1,.....\Gamma_{n-1}]$ and the variables $\Delta Y_{t-i}$ in $Z_t = [\Delta Y'_{t-1},.........\Delta Y'_{t-n+1}]$ such that $\Delta Y_t = \Pi Y_{t-1} + \Gamma Z_t + \varepsilon_t$.

The likelihood function is then

$$[5.23] \quad L(\alpha,\beta,\Sigma,\Gamma) = (2\pi)^{-(Tn/2)} |\Sigma|^{-T/2} \, exp\left( -\frac{1}{2}\sum_t (\Delta Y_t - \Gamma Z_t - \psi X_t - \Pi Y_{t-1}) \right)$$

with $\alpha\beta' = \Pi$.

In Johansen's procedure, Gaussian maximum likelihood is used to estimate all parameters of the ECM. This procedure is an asymptotically nuisance parameter free. The coefficients of the matrices $\alpha$ and $\beta$ are estimated through a procedure known as reduced rank regression. The estimated parameters on the ECM can be partitioned to provide information on the long run relationship and short run dynamics. $\beta$ is the cointegrating parameter that characterizes the long run equilibrium relationship between variables. The long run relationship can be identified through testing hypothesis on $\beta$. Parameters contained in $\Gamma$ matrices measures short run effects. The short run dynamics can be identified through testing hypothesis in $\Gamma$. The test for cointegration between these variables is calculated by looking at the rank of the $\Pi$ matrix via its eigenvalues. The matrix $\Pi$ contains the information on the co-integrating relationships between the non-stationary variables in $Y_t$. The rank of a matrix is equal to the number of its non-zero characteristics roots (eigenvalues $(\lambda_i)$). The rank of a matrix $\Pi$ is the number of co-integrating relationships between the variables in $Y_t$. Let the rank of $\Pi$ being $r$. The number $r$ can be more than one and can go up to $n-1$. The matrix $\Pi$ is called long run response matrix that measures the cumulative long run effects. The $\Pi$ can be portioned as $\Pi = \alpha\beta'$. Now the error correction model is as given in Equation [5.24].

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \Psi X_t + \varepsilon_t \qquad [5.24]$$

where the co-integrated relationships are explicitly parameterized by the vector $\beta$ coefficients which provide estimate of the long run response. $\beta$ is the matrix of the long run coefficients, called the co-integrating matrix. The r columns of this matrix are called co-integrating vectors. The elements of $\alpha$ the matrix are known as the adjustment coefficients (error correction coefficients) to the long run equilibrium. It measures the speed of adjustments. A larger value $\alpha_i$ indicates a faster convergence toward long run equilibrium in cases of short run deviations from long run equilibrium. The speed of the adjustment to the equilibrium sub-space is important to the policy makers and investors. The coefficients $\Gamma_i$ estimate the short run dynamic effect of shocks to the variables on $\Delta Y_t$.

#### 5.5.3.3 Determining the Number of Cointegration Relations

The number of cointegration relations is measured by the rank of $\Pi$. According to Johansen (1988) and Johansen and Jusellus (1990), there are two different likelihood ratio (LR) statistics to test for cointegrating vectors, namely (i) the trace test statistic, (ii) the $\lambda_{\max}$ test statistic. Test statistics are based on the characteristic roots (eigenvalues, $\hat{\lambda}_i$) obtained from the estimated $\Pi$ matrix.

i) the trace test statistic $(\lambda_{\text{tarce}})$ is defined in Equation [5.25].

[5.25] $$\lambda_{trace}(r) = -T\sum_{i=r+1}^{n}\ln(1-\hat{\lambda}_i)$$

ii) Maximal Eigenvalue Statistics, ( $\lambda_{\max}$ ) is defined in Equation [5.26].

[5.26] $$\lambda_{\max}(r, r+1) = -T\ln(1-\hat{\lambda}_{r+1})$$

#### 5.5.3.4 Optimum Lag

It is very crucial to choose an optimum lag order of the model specification before performing the test for the existence of cointegration. Thus, the first step in the analysis is to determine the optimal lag. In the study, the optimal number of lags is determined based on conventional models selection criteria such as Akaike's Information Criterion (AIC), Hannan-Quinn Information Criterion (HQIC) and Schwarz Information Criterion (SIC). The smallest values of these criteria are used to select optimal lag length. Boswijk and Franses (1992) emphasized the sensitivity of the cointegration test to the choice of the lag length.

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#### 5.5.3.5 Speed of Adjustment

The speed of adjustment towards the long run equilibrium relationship is given by the matrix of loading, $\alpha$. The coefficients ($\alpha$) are error correction coefficients. They show how much the response variables respond to the cointegrating error. If the value of the error correction coefficient is negative, its absolute value is less than one, and the coefficient is statistically significant, they ensure the system is not explosive. The error correction coefficients can be used in exogeneity inference.

### 5.5.4 Granger's Causality Test

Granger causality test is employed to identify the direction of causal relationship between the variables. Causality theory describes dynamic interactions between variables. Granger causality tests (GCT) are valid for stationary series as standard statistical tests are valid under stationary assumptions. Therefore, log difference series are used for causality analysis in the study. Considering two series, $X_t$ and $Y_t$, integrated order one, the GC test is in the form as:

$$[5.27] \quad \Delta X_t = \alpha_1 + \sum_{i=1}^{n1} \alpha_{11,i} \Delta Y_{t-i} + \sum_{j=1}^{m1} \alpha_{12,j} \Delta X_{t-j} + u_{X,t}$$

$$[5.28] \quad \Delta Y_t = \alpha_2 + \sum_{i=1}^{n1} \alpha_{21,i} \Delta X_{t-i} + \sum_{j=1}^{m1} \alpha_{22,j} \Delta Y_{t-j} + u_{Y,t}$$

where $u_{x,t}$ and $u_{y,t}$ is stationary random processes intended to capture other pertinent information not contained in lagged values of $X_t$ and $Y_t$. The lag lengths, $n$, and $m$ are decided by AIC in the study. The series $Y_t$ fails to Granger-cause $X_t$ if $\alpha_{11}(j) = 0$ ($j$ = 1, 2, 3,.. $m_1$); and the series $X_t$ fails to Granger-cause $Y_t$ if $\alpha_{21}(i) = 0$ ($i$ = 1, 2, 3, ..$n_1$).

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Three types of causality tests: i) pairwise Granger causality ($F$-test) from the single equation, ii) Wald tests for Block causality under VAR framework (Granger causality/Block Exogeneity) and iii) Wald tests for Block causality under VEC framework (Granger causality/Block Exogeneity) are performed to validate the cointegration results. Following cointegration analysis, causality tests (for a short run and long run) are carried out to identify the direction of causal relationship between the variables. The first one is the standard Granger-causality test (Granger 1969), the other one is based on VAR and the third one is based on ECM developed by Granger (1986, 1988) and Engle and Granger (1987). Block causality test is useful for detecting whether to incorporate a variable into a VAR or VECM. The likelihood ratio test is used to test block causality test. The likelihood ratio statistic has the asymptotic Chi-square distribution with degrees of freedom equal to the number of restrictions in the system. Block causality test provides more information than standard Granger causality test. It provides whether explanatory variable (GFPI) is exogenous. It accounts for current and past values of the explanatory variable. It tests all coefficients (current and lag) equal to zero. Even lag variables ($GFPI_{t-1}$ coefficients are not rejected, and current value coefficient of $GFPI_t$ is rejected, then CPI is not exogenous to GFPI. Therefore block causality test is useful to detect and incorporate a variable in the model.

Engle and Granger (1987), Granger (1988) and Miller and Russek (1990) showed that there are two potential sources of causation of $Y_t$ by $X_t$ in the error correction model. Consider the error correction model similar to the following

[5.29] $\Delta Y_t = \alpha_0 + \gamma ECT_{t-1} + \sum \alpha_i \Delta Y_{t-i} + \sum \beta_j \Delta X_{t-j} + \varepsilon_{Y,t}$

In this model (ECM), there are two possible sources of causation of $y_t$ by $x_{t-1}$ either through the error correction term $ECT_{t-1}$, or (lagged) $\Delta X_{t-j}$ if they present in the equation. i.e. through $\beta_j$, through $\gamma$ ($ECT_{t-1}$). In contrast to the standard Granger causality test, the ECM model allows for the detection of a Granger causal relation from X to Y. The coefficient of $ECT_{t-1}$ measures the long run causal relationship while $\beta_j$ measures the short run causal relationship. Further, Granger (1988) notes that cointegration between two or more variables is sufficient to indicate there exist Granger-causal relationship in at least one direction.

To analyse food price dynamics further, Granger-causality analysis is performed between food price inflation and its volatility. Long term uncertainty of food price inflation is more important as risk involves in decision making. Friedman's (1977) and Ball's (1992) hypotheses say that higher inflation invokes more inflation uncertainty. In contrast, Cukierman and Meltzer's (1986) hypothesis is that higher inflation uncertainty leads to more inflation. Both these hypotheses are examined using Granger causality tests.

### 5.5.5 Impulse Response Analysis

Impulse response function analysis is employed to examine food price dynamics further and validate the global food price transmission effect to domestic prices. This section describes IRF, its application and its derivation from VAR frame work. IRF show the size of the impact of the shock and the rate at which the shock dissipates. IRF analysis will cover GFPI shocks on how it affects domestic prices, and domestic CFPI, WFPI shocks on how they affect general inflation.

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Impulse response function (IRF) is also used to provide dynamic simulations of the effects of shocks of known size. IRF show the effects of shocks on the adjustment path of the variables. The impulse response functions map out the dynamic response path of a variable (food price inflation) due to a one period standard deviation shock to other variable (food price inflation) in the VAR system. In the study, it shows the impact on food price inflation at time $t+1$ of a shock in one of the innovations at time $t$. If the value of IRF is positive and less than one, it indicates that the response dies down monotonically, approaching zero. Hence, IRF analysis through VAR helps us in understanding the permanent nature of food price inflation dynamics. IRF trace out the dynamic effects of domestic prices originating from a shock from global food prices in this study. IRF take into account the knock-on and feed-back effects that exist between the variables. Plots of the IRF over time provide a graphical illustration of the period by period simulation, describing both adjustment path and long run effect on the domestic prices in response to the shock. Thus, IRF is employed to get a more complete picture of the dynamic effects of GFP, CFPI, WFPI changes.

### 5.5.6 Volatility Transmission Test

Literature shows that there have been different techniques that have been employed in the analysis of volatility transmission. Various forms of GARCH models are used in the literature. However, this study uses FIGARCH model to generate volatility of food price inflation as it accommodates long memory phenomena.

#### 5.5.6.1 Generalized Autoregressive Conditional Heteroscedasticity Model

The general autoregressive conditional heteroscedasticity model is specified in the set of equations given in [5.30]

$$\begin{aligned} &\pi_t = \mu + e_t \\ [5.30] \qquad &e_t \mid \Omega_{t-1} \sim d(0, h_t) \\ &h_t = \omega + \alpha e_{t-1}^2 + \beta h_{t-1} \end{aligned}$$

In this example, price changes are equal to a constant $\mu$ plus a serially uncorrelated error $e_t$. The error is sampled from some arbitrary distribution D with mean zero and variance $h_t$ conditional on a set of information $\Omega_{t-1}$, and the conditional variance $h_t$ evolves based on last period's conditional variance and the realized value of last period's squared innovation $e_{t-1}^2$. $h_t = \omega + \alpha\, e_{t-1}^2 + \beta\, h_{t-1}$, allows for a wide range of temporal patterns in the conditional variance of price innovations. The GARCH model does not consider long memory process. Thus, this study uses FIGARCH model to derive volatility of food price inflation.

#### 5.5.6.2 The Fractional Integrated Conditional Heteroscedasticity Model

The fractionally integrated GARCH model proposed by Baillie, Bollerslev, and Mikkelsen (1996) is denoted by FIGARCH*(p,d,q).* FIGARCH model aollows accounting for the long memory of volatility within a dynamic framework. The FIGARCH(1,*d*,1) model assumes the growth variable (inflation) follows Equations [5.31] –[5.32]

[5.31] $y_t = \sigma_t \varepsilon_t$

where $\sigma_t > 0$, $\varepsilon_t \sim i.i.d.(0,1)$ and

[5.32] $\sigma_t^2 = \omega + \beta\sigma_{t-1}^2 + [1 - \beta L - (1-\delta L)(1-L)^d]y_t^2$

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FIGARCH process displays short memory for $d$=0. For FIGARCH model, the persistence of a shock at long lags is proportional to $j^{-d-1}$. Persistence is inversely related to the $d$ for $0 < d < 1$. This FIGARCH model captures long memory in volatility. By generating volatility of global food price inflation using FIGARCH model, the global food price volatility transmission is analyzed by employing cointegration technique and VECM for each domestic price series models.

### 5.5.7 Diagnostic Checking

The diagnostic tests, comprising coefficients stability tests and residual diagnostic tests are used to check the validation of the results of the study. For stability test, CUSUM test is used. For residual diagnostic analysis: serial correlation test; the autocorrelation Lagrange Multiplier (LM) test, and for heteroscedasticity test: ARCH test are employed. Appropriate lag lengths are selected by using the Akaike and Schwarz information criteria.

The design of analysis and analytical tools employed to achieve the objectives of the study are summarized in Table 5.1.

**Table 5.1**
***Summary of Design Analysis***

| Specific Objectives | | Methods |
|---|---|---|
| i). to examine the nature of food price behavior in Sri Lanka | → | -Graphs<br>-Unit root tests<br>-Rescale-Ranged Statistics(R/S)<br>- Gewke and Porter-Hudak (GPH) log-periodogram Regression<br>-ARFIMA Model<br>-FIGARCH Model |
| ii) to estimate transmission effect of global food prices on domestic prices | → | - Co-integration technique,<br>-Granger causality analysis<br>-Impulse Response Function<br>-Diagnostic checking |
| iii) to examine pass-through effect of global food price volatility on domestic prices; and | → | -Co-integration technique,<br>-Granger causality analysis<br>-Impulse Response Function<br>-FIGARCH<br>-Diagnostic checking |
| iv) to identify the spillover effects of domestic food price | → | - Co-integration technique,<br>- Granger causality |

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| | |
|---|---|
| increases on headline inflation in Sri Lanka. | analysis<br>- Impulse Response Function<br>-Diagnostic checking |

## 5.6 Conclusion

This chapter provided detailed information on the variables justification, data, and method of analysis employed in the study. The first objective is achieved by employing parametric, semi parametric and nonparametric methods. Second, third and fourth objectives are analyzed using cointegration ECM and Granger causality test. Impulse response function analysis is further used to understand food price dynamics in deep.

# CHAPTER SIX

# RESULTS AND DISCUSSION

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## 6.1 Introduction

This chapter provides a discussion of empirical results of the study. Specifically, Section 6.2 presents descriptive statistics while section 6.3 provides results for correlation analysis. Section 6.4 provides the results of testing for the order of integration of the series. Section 6.5 designates the long memory tests and answers the first objective of the study. Section 6.6 presents the results from the analysis of global food price transmission to domestic prices in Sri Lanka using cointegration and ECM to answer for the second objective of the study. Section 6.7 presents the results of global food price inflation volatility transmission to domestic prices to answer the third objective of the study while Section 6.8 describes the results of domestic food price transmission to overall consumer price in domestic markets to answer the fourth objective of the study. Section 6.9 displays the results of Ganger causality analysis while Section 6.10 explains the causal relationship between food price inflation and volatility of food price inflation. Section 6.11 describes the results of impulse response analysis. Section 6.12 concludes Chapter 6.

## 6.2 Descriptive Statistics

Descriptive statistics of price series in level form are presented to observe the structure of the data set at glance (see Table 6.1). The average food price during the sample period is higher than the non-food price (CNFPI) and consumer price (CPI) for all items. The variability of the variables is measured by the coefficient of variation and standard deviation (SD) of the variables. Based on this measure, the variability of consumer food price (CFPI) is higher than that of CPI for all items and CNFPI during the study period. Food prices are much more volatile than nonfood prices. The domestic food price variability is very close to the global food price variability. The instantaneous growth rates are defined as log difference of level series. For example, CPI growth rate is defined as $\pi = ln(CPI_t) - ln(CPI_{t-1})$.

Table 6.1
*Summary Statistics of Price Series, 2003M1-2014M12*

| | **CFPI** | **CNFPI** | **CPI** | **GFPI** | **WFPI** | **WPI** | **ER** | **OILP** |
|---|---|---|---|---|---|---|---|---|
| Mean | 203.38 | 181.45 | 190.29 | 167.16 | 200.98 | 207.94 | 112.25 | 141.38 |
| Median | 219.40 | 188.02 | 201.97 | 171.36 | 216.83 | 221.02 | 110.43 | 140.42 |
| Maximum | 317.86 | 252.71 | 278.09 | 237.92 | 328.07 | 313.37 | 132.87 | 249.66 |
| Minimum | 100.50 | 106.10 | 104.20 | 94.48 | 91.15 | 98.59 | 94.51 | 47.75 |
| SD | 70.37 | 47.08 | 56.62 | 44.77 | 72.65 | 70.14 | 11.29 | 52.65 |
| C.V | 34.60 | 25.95 | 29.75 | 26.78 | 36.15 | 33.73 | 10.06 | 37.24 |
| Skewness | -0.08 | -0.05 | -0.07 | -0.13 | -0.03 | -0.09 | 0.48 | -0.12 |
| Ex.Kurtosi | -1.45 | -1.26 | -1.37 | -1.48 | -1.38 | -1.39 | -0.91 | -1.14 |
| Jarque-Bera | 12.77 | 9.53 | 11.33 | 13.60 | 11.51 | 11.76 | 10.48 | 8.17 |
| probability | (0.001) | (0.008) | (0.003) | (0.001) | (0.003) | (0.002) | (0.005) | (0.016) |

Note: *p*-values are in parenthesis

The summary statistics of the growth rate of variables used in the study are presented in Table 6.2. It shows that the average food price inflation exceeds the average headline inflation. The average monthly growth rates of food prices are in the range of 0.5 and 0.8. The coefficient of variation (CV) in Table 6.2 shows that food price inflation seems to be more volatile than nonfood price inflation with the value of 2.3 and 1.8 respectively. Surprisingly, the producer food price inflation seems to be higher than consumer's food price inflation in average and variability. Global food price inflation is also more volatile (5.8) than domestic food price inflation (2.3).

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Table 6.2

*Descriptive Statistics of Growth rates of Variables*

| | CFPIG | CNFPIG | CPIG | GFPIG | WFPIG | WPIG | OILPIG | ERG |
|---|---|---|---|---|---|---|---|---|
| Mean | 0.7 | 0.6 | 0.7 | 0.5 | 0.8 | 0.8 | 0.5 | 0.2 |
| Median | 0.5 | 0.4 | 0.6 | 0.4 | 0.5 | 0.7 | 0.00 | 0.00 |
| Maximum | 5.4 | 6.4 | 4.1 | 7.5 | 9.8 | 7.5 | 17.4 | 6.8 |
| Minimum | -2.6 | -3.1 | -1.6 | -13.1 | -8.2 | -5.7 | -31.6 | -5.1 |
| SD | 1.6 | 1.1 | 0.9 | 2.9 | 2.9 | 2.4 | 8.2 | 1.1 |
| C.V($\sigma / \bar{X}$ ) | 2.3 | 1.8 | 1.3 | 5.8 | 3.6 | 3.0 | 16.4 | 5.5 |
| Skewness | 0.334 | 2.113 | 0.485 | -0.747 | 0.161 | 0.018 | -1.228 | 1.013 |
| Excess.Kurtosis | -0.017 | 10.755 | 0.839 | 3.367 | 0.250 | 0.259 | 2.556 | 10.600 |
| Q1 | -0.004 | 0.001 | 0.001 | -0.010 | -0.012 | -0.009 | -0.035 | -0.002 |
| Q3 | 0.021 | 0.008 | 0.013 | 0.020 | 0.026 | 0.022 | 0.063 | 0.005 |
| Jarque-Bera | 2.845 | 795.605 | 9.788 | 80.856 | 0.988 | 0.410 | 75.134 | 693.899 |
| | (0.241) | (0.000) | (0.007) | (0.000) | (0.610) | (0.815) | (0.000) | (0.000) |
| Q(50) Stat | 228 | 52.775 | 98.850 | 181.040 | 111.660 | 92.836 | 66.040 | 107.610 |
| | (0.000) | ( 0.367) | (0.000) | (0.000) | (0.000) | (0.000) | (0.064) | (0.000) |
| Observations | 143 | 143 | 143 | 143 | 143 | 143 | 143 | 143 |

Note: $p$ -values are in parenthesis, growth rates of food prices are called food price inflation

Further, all of the growth series are positively skewed except GFPI and OILP. Excess kurtosis of all the growth (inflation) series except CFPI are having positive values. This result indicates that those inflation series seem to be peaked (leptokurtic) relative to the normal distribution. Global food price inflation is negatively skewed and highest positive excess kurtosis indicates that GFPI inflation series tend to have peaked and have fat tail distribution than a normal distribution. In addition, significant values of the Jarque–Bera test statistics also confirm the non-normal behavior of the growth series. However, CFPI and WFPI inflation series seem to be close to normal distribution. The Box-Pierce test statistics of the inflation series Q(50) indicate that all inflation series are having serial correlation except CNFPI growth series.

The total sample period is divided into two in order to describe the differences between Period I and Period II. Period I is known as pre food crisis period while

Period II is known as post food crisis period. Table 6.3 exhibits the descriptive statistics for the two periods.

Table 6.3
*Summary Statistics of CFPI Inflation and GFPI Inflation for Period I and II*

| | **Period I 2003M1-2006M12** | | **Period II 2007M1-2014M12** | |
|---|---|---|---|---|
| | **CFPG** | **GFPG** | **CFPG** | **GFPG** |
| Mean | 0.74 | 0.73 | 0.78 | 0.34 |
| Median | 0.52 | 0.93 | 0.53 | 0.26 |
| SD | 1.51 | 1.52 | 1.66 | 3.38 |
| Skewness | -0.13 | -0.01 | 0.50 | -0.62 |
| Excess.Kurtosis | -0.77 | -0.97 | -0.05 | 2.0 |
| CV | 2.00 | 2.08 | 2.13 | 11.3 |
| N | 47 | 47 | 95 | 95 |

Average domestic food inflation per month in Period II has increased slightly from Period I. However, average growth of GFPI has decreased from Period I to Period II. The volatility of CFPI inflation has slightly increased in Period II compared to Period I. Volatility of GFPI inflation has increased significantly in Period II (CV=11.3) compared to Period I (CV=2.1). In addition, the rate of increase in the GFPI inflation volatility is higher than that of the CFPI inflation variability. Positive kurtosis indicates leptokurtosis (peakedness). The tails of the distribution of the GFPI inflation series are fatter in Period II than that of the GFPI inflation for period I. However, relatively the degree of fatness is higher in the case of the GFPI inflation than in the other price inflation series.

## 6.3 Correlation Analysis

Correlation analysis describes the strength of the linear relationship between two variables. This section covers the correlation analysis for variables concerned in the study. The results of correlation analysis for price series for both periods I and II are reported in Table 6.4

Table 6.4

*Correlation Coefficients between Price Indices: 2003M1-20014M12*

Period II:2007M1-2014M12

Period I : 2003M1-2006M12

| | CPI | CFPI | CNFPI | GFPI | WFPI | WPI | OILPI | ER |
|---|---|---|---|---|---|---|---|---|
| CPI | **1.000** | 0.992 | 0.991 | 0.598 | 0.953 | 0.969 | 0.539 | 0.867 |
| | ----- | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| CFPI | 0.993 | **1.000** | 0.965 | 0.629 | 0.969 | 0.974 | 0.538 | 0.826 |
| | (0.000) | ----- | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| CNFPI | 0.995 | 0.977 | **1.000** | 0.552 | 0.919 | 0.947 | 0.527 | 0.891 |
| | (0.000) | (0.000) | ----- | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| GFPI | 0.947 | 0.936 | 0.948 | **1.000** | 0.676 | 0.718 | 0.891 | 0.129 |
| | (0.000) | (0.000) | (0.000) | ----- | (0.000) | (0.000) | (0.000) | (0.230) |
| WFPI | 0.893 | 0.921 | 0.860 | 0.859 | **1.000** | 0.988 | 0.564 | 0.747 |
| | (0.000) | (0.000) | (0.000) | (0.000) | ------ | (0.000) | (0.000) | (0.000) |
| WPI | 0.981 | 0.985 | 0.967 | 0.934 | 0.949 | **1.000** | 0.638 | 0.783 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | ------- | (0.000) | (0.000) |
| OILPI | 0.940 | 0.919 | 0.948 | 0.887 | 0.781 | 0.898 | **1.000** | 0.222 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | ------ | (0.038) |
| ER | 0.926 | 0.938 | 0.907 | 0.922 | 0.934 | 0.942 | 0.781 | **1.00** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | ----- |

*p*-values are in parenthesis.

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It seems that all price series are significantly positively correlated each other in both periods. For period I, (Before food crisis), correlation results are given in below diagonal, for period II, after food crisis, correlation results are given above diagonal in the above table. GFPI is not correlated significantly with Sri Lankan exchange rate. The reason is that Sri Lankan economy is small in the world market.

## 6.4 Unit Root Tests

Testing the stationarity and order of integration of a time series is an important pre-requisite for time series analysis. Many economic time series are non-stationary in the sense that their means and variances change over time. A nonstationary series would have a different mean (or variance) at different points in time. If a time series is stationary, then its mean, variance and auto-covariance remain the same over time. They are time invariant and having the property of mean reversion. A stationary series is often called 'integrated of order 0, I(0)' and non-stationary is often called 'integrated of the first order, I(1)'. If a time series must be differenced *d* times before it becomes integrated of order zero, then it is said to be integrated of order *d*, denoted by I(*d*). As the order of integration of the series can influence the behaviour and properties of an economic time series, there is a need to test the order of integration of a time series. In this study, standard unit root tests; the ADF test, the PP test and KPSS tests are carried out, as prerequisite tests, to check for the (integer) order of integration of the variables and volatility proxy series used in the study in this section.

### 6.4.1 Unit Root Tests of Variables

In this section, the ADF test, PP test, and KPSS tests are carried out to test the null hypothesis of a unit root for the variables used in the study. The results of ADF, PP, and KPSS test are reported in Table 6.5.

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Table 6.5
*Unit Root Test Results for Variables*

| | Level Intercept with Trend | | | First Difference[1] Intercept | | | Order of Integration |
|---|---|---|---|---|---|---|---|
| | Test Statistics | | | Test Statistics | | | |
| **Variables** | **ADF** | **PP** | **KPSS** | **ADF** | **PP** | **KPSS** | |
| LCFPI | -1.53 | -0.78 | 0.28 | -7.54* | -7.37* | 0.18 | I(1) |
| LCNFPI | -2.35 | -2.19 | 0.34 | -10.82* | -10.91* | 0.08 | I(1) |
| LCPI | -0.37 | -1.48 | 0.29 | -8.24* | -8.13* | 0.12 | I(1) |
| LGFPI | -2.47 | -1.79 | 0.18 | -6.30* | -6.33* | 0.15 | I(1) |
| LWFPI | -2.21 | -0.58 | 0.23 | -9.23* | -9.37* | 0.06 | I(1) |
| LWPI | -2.48 | -0.96 | 0.28 | -6.73* | -10.83* | 0.09 | I(1) |
| LER | -2.92 | -0.85 | 1.27 | -4.90* | -8.19* | 0.03 | I(1) |
| LOILP | -1.91 | -2.10 | 0.19 | -5.39* | -7.78* | 0.17 | I(1) |

Note: * indicates significance at 5% level, [1] indicates that trend is not significant at first difference, unit root test regression model is selected with intercept only

According to these tests, all series are nonstationary at their level. A significant test statistic would reject the null hypothesis. The results show that the null hypothesis of a unit root for each variable is not rejected at the 5 percent level. The *p*–value for the corresponding test statistic for each case is greater than 0.05. These results suggest that variables are not stationary series. On the other hand, the results from first difference indicate that all test statistics are statistically significant as the corresponding *p*-values for each test statistic is less than 0.05. Therefore, all the series in the study are I(1).

### 6.4.2 Unit Root Test for Volatility Proxy Series

Volatility phenomena of a variable are proxied by absolute growth rate, squared growth rate or log squared growth rate and conditional variance derived from the FIGARCH model. The stationarity property of volatility series of the variables is examined in this section. Test results for the first three proxies are presented in Table 6.6.

According to ADF test results, the Table 6.6 shows that all volatility proxy series are stationary series. However, the result of KPSS test for the volatility proxy for WPI variable differs from ADF test results. According to KPSS test, the volatility proxy for WPI is not stationary as test statistic is rejected for the null hypothesis of stationarity at 5 percent level and the other volatility proxy variables are stationary at 5 percent levels.

Table 6.6

*Unit Root Tests of Volatility Proxy Series.*

| | ADF test | | | KPSS Test | | |
|---|---|---|---|---|---|---|
| | Absolute return $\lvert r_t \rvert$ | Square return $r_t^2$ | Log square return $\mathrm{Ln}(r_t^2)$ | Absolute return $\lvert r_t \rvert$ | Squared return $r_t^2$ | Log squared return $\ln(r_t^2)$ |
| CFPI | -7.810* | -8.238* | -8.518* | 0.242 | 0.186 | 0.305 |
| CNFPI | -11.739* | -12.006* | -10.006* | 0.372 | 0.049 | 0.138 |
| CPI | -8.916* | -10.188* | -8.838* | 0.339 | 0.239 | 0.110 |
| GFPI | -6.954* | -7.014* | -8.977* | 0.269 | 0.248 | 0.288 |
| WFPI | -10.980* | -11.679* | -10.735* | 0.111 | 0.389 | 0.047 |
| WPI | -10.664* | -6.493* | -9.896* | 0.184[1] | 0.192[1] | 0.254[1] |
| OilPI | -4.671* | -5.305* | -10.061* | 0.222 | 0.122 | 0.289 |
| ER | -8.628* | -9.837* | -9.799* | 0.056 | 0.067 | 0.142 |

Note:

[1] intercept+ trend; From KPSS test, volatility series of WPI are nonstationary. In the case of WPI volatility series, ADF and KPSS tests results are not the same. ADF and PP tests indicate that WPI volatility series is stationary but KPSS indicates that it is nonstationary. This contradiction results motivate to further statistical investigation. However, this study is not attempting to study this issue.

* indicates statistically significant at 5 % level. The critical value for ADF, KPSS tests at 5 %, the level is -2.8818, 0.4630 in intercept model, -3.4417, and 0.1460 for an intercept with trend respectively. The critical value for ADF, KPSS tests at 10 %, the level is -2.5776, 0.3470 in intercept model, -3.1454, and 0.1190 for an intercept with trend model respectively.

The ADF and PP test results for the conditional variance of global food price inflation are reported in Table 6.7.

Table 6.7

*Unit Root Tests of Conditional Variance of Global Food Price Inflation Series.*

| Variable | Level (intercept with Trend) | | First difference (with intercept) | | Order of Integration |
|---|---|---|---|---|---|
| | ADF | PP | ADF | PP | |
| LCVGFPG | -1.65 | -1.86 | -16.61* | -29.52* | I(1) |

Note: LCVGFPG refers log of conditional variance of global food price growth (inflation)

The test statistic is not significant as the p-values are more than 0.05 and suggests that conditional variance of GFP inflation (CVGFPG) is a nonstationary series and integrated of order one, I(1).

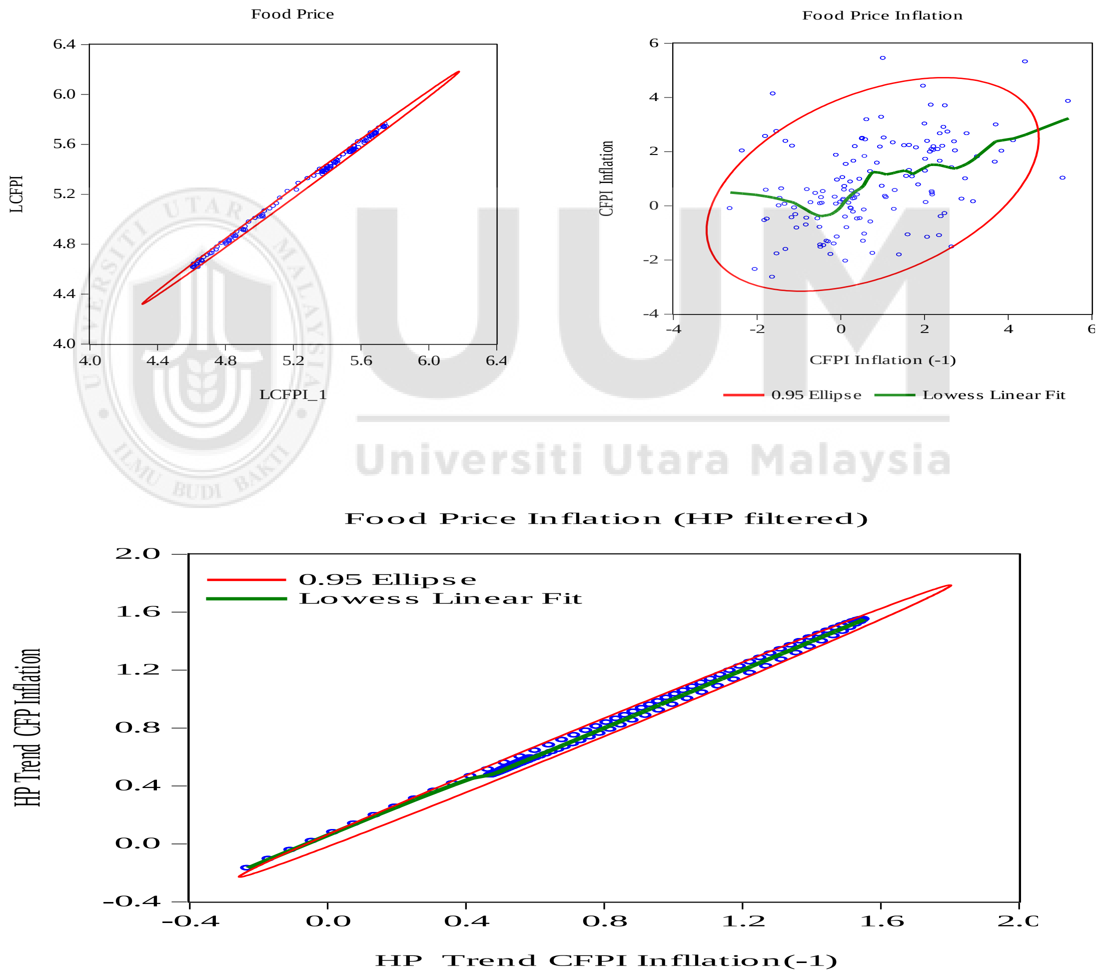
## 6.5 Long Memory Analysis

This section attempts to answer the first objective of the study; to test whether the shocks of food price inflation is transitory or permanent in Sri Lanka. It consists of long memory analysis of food price inflation series and food price inflation volatility series. This investigation covers the first two moments' dynamics of food price inflation distribution using classical and updated recent advanced statistical tools. First is the mean process (first moment) and the second is the variance (volatility) process (second moment) of food price inflation. The unit root tests (ADF, PP, and KPSS) employed in this study showed that food price inflation (log differenced) series are stationary. Since the unit root test results have not given fractionally differenced parameter values and long memory information, therefore, the next section investigates food price series to gain long memory information.

### 6.5.1 Food Price Inflation

Firstly, the visual detection of long memory characteristics of food price inflation series has been conducted using confidence ellipse, correlogram, and periodogram. Then, this is followed by the estimates of the fractional integrating parameter (*d*) (long memory parameter) for food price and food price inflation by using nonparametric, semi parametric and parametric approaches.

The lagged scatter plot with confidence ellipse, Nearest Neighbor fit (Lowess linear fit) shows that food price series highly depend on its lag value. Figure 6.1 exhibits three scatter plots with 95 percent confidence ellipse; (i) scatter plots of LCFPI of month *t* against LCFPI of month *t-1* (ii) scatter plots of INFCFPI of month *t* against INFCFPI of month *t-1* and (iii) food price inflation derived from HP filtered trend of food price month *t* against the food inflation of month *t-1*. The scatter plots (i) and (iii) in Figure 6.1 are dense around the centre line which suggests that food inflation has the properties associated with random walk. The second and third scatter plots with confidence ellipse indicate that food price inflation is also autocorrelated positively. Thus, food price series is highly positively autocorrelated. These scatter plots with confidence ellipse show the dependence nature of the food price dynamics in level as well as in the rate of changes.

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*Note* food price inflation is difference of log CFPI, HP filtered food price inflation is derived from HP filtered log food price series

Figure 6.1
*Autocorrelation Nature of Food Price, Food Price Inflation of Sri Lanka, 2003M1-2014M12*

Figure 6.2 describes the sample autocorrelation behavior. The sample autocorrelation coefficients of log food prices, LCFPI, LWFPI and LGFPI started at a very high value (0.983) and declines slowly toward zero as the lag length increases. Autocorrelations for the first 36 lags range between approximately 0.973 and 0.270, provides strong evidence of the presence of serial correlation. These autocorrelation behavior implies that each of the CFPI, WFPI, and GFPI series has a long memory and is largely persistent with lagged coefficients that are clearly statistically significant. The impact of a shock $\varepsilon_t$ on CFPI does not diminish over time. Therefore, the shocks on food prices are persistent.

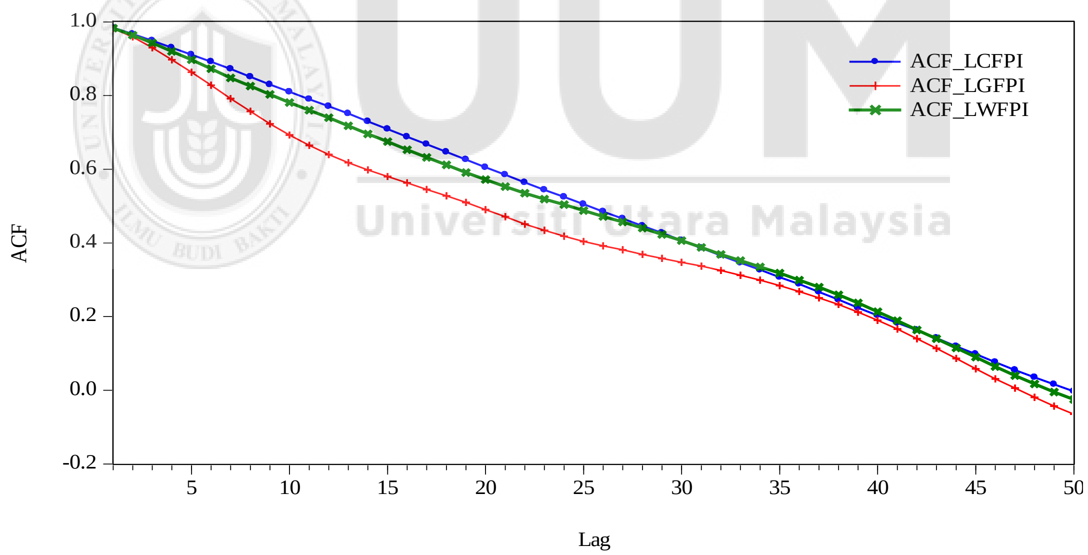

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Figure 6.2
*Autocorrelation Function for Food Price Series*

Figure 6.3 presents the autocorrelation function of food price inflation series. The ACF of food price inflation for CFPI, WFPI, GFPI series exhibit sluggish decline and large oscillations. This very slow decay of ACF ACF of food price inflation implies that food price inflation possesses long memory.

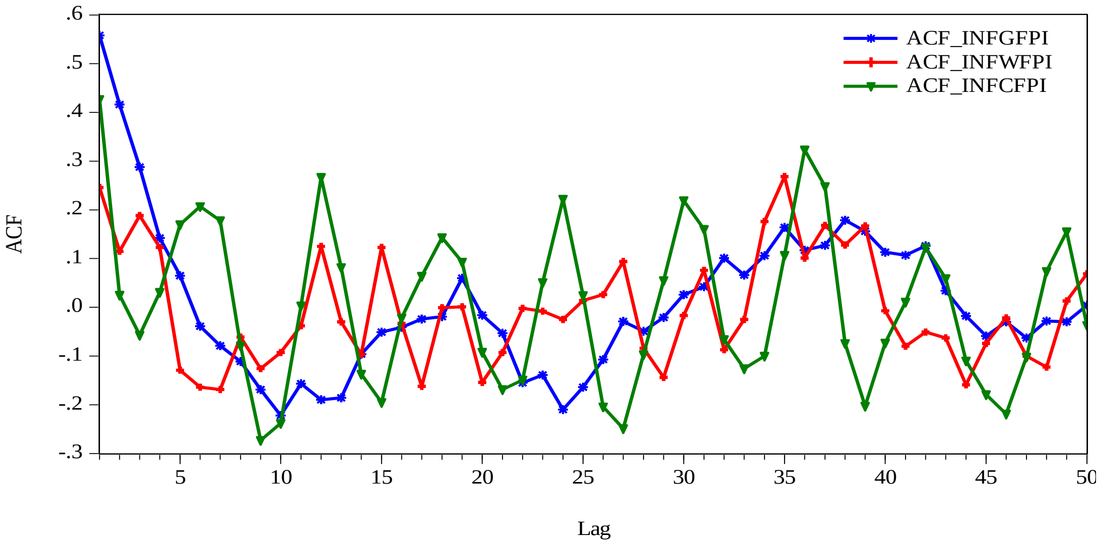


Figure 6.3
*ACF for Food Price Inflation Series,*

As these series exhibit sluggish decline and oscillations and in order to highlight hidden feature of them, inflation trend is separated from cycles using HP filter method. After removing cycles from food price inflation, ACF of HP filtered trend for all food price inflation series is given in Figure 6.4.

ACF of HP filtered trend for food price inflation starts high and positive for 24 months. The ACFs decay very slowly. This declining trend is explicitly visible. This proves that food inflation series has very slow decay ACF. This hidden feature is uncovered by the HP filtering technique. ACF has been used by various authors, for example, Baillie (1996) for wheat price index, Granger and Ding (1996) for the stock price to identify long memory of those series.

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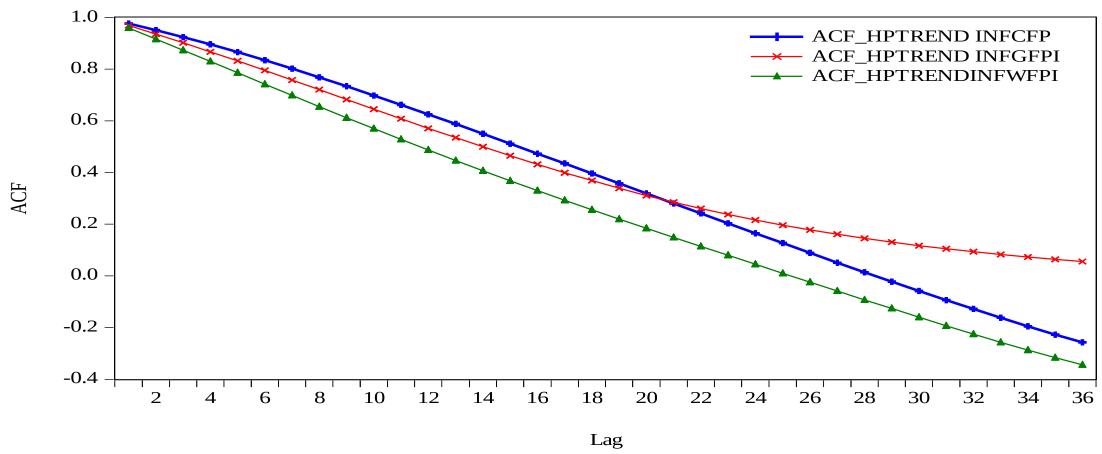


Figure 6.4

*Autocorrelation Function for HP Filtered Food Price Inflation Trend Series*

These sample ACFs show that the impact of a shock $\varepsilon_t$ on food inflation does not diminish immediately. The past shocks continue to play a significant role in determining the future food price path. Therefore, the shocks on food prices are persistent. It is useful to note the relationship between the fractional difference parameter *d* and rate of convergence stated by Baillie (1996). It can be shown that if data are fractionally integrated, I(*d*), sample autocorrelations are consistent estimators with the following convergence rates as shown in Table 6.8 (Baillie, 1996).

Table 6.8
*Type of Convergence of Autocorrelation Function*

| ***d*** | **Rate of Convergence of ACF** |
|---|---|
| $-0.5 < d < 0.25$ | $T^{0.5}$ |
| $d = 0.25$ | $(T/\ln(T))^{0.5}$ |
| $0.25 < d < 0.50$ | $T^{0.5-d}$ |

In this respect, identification of long memory by use of the sample ACF is well-founded.

Further, the autocorrelation coefficient significant tests, Ljung-Box Q test and Box Pierce test, are also used to test for autocorrelation. These tests examine the overall randomness based on a number of lags (the joint significance of the autocorrelation coefficients). The results obtained from the correlogram analysis showed that each food price inflation series has a long memory as each has positive and significantly different from zero autocorrelations even for large lags.

In addition, spectral methods in frequency domain analysis (nonparametric) are also useful to uncover key characteristics of economic time series for model building. The plot of the intensities against the frequencies is periodogram. The periodogram for the three food price series (a) consumer food price (CFPI), (b) global food price (GFPI) and (c) wholesale food price (WFPI), are displayed in Figure 6.5.

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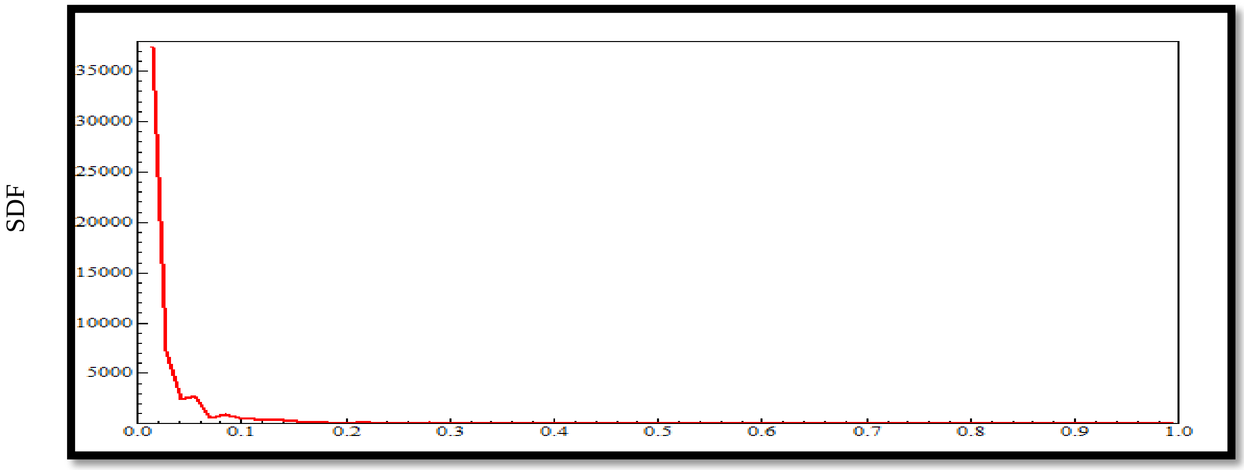
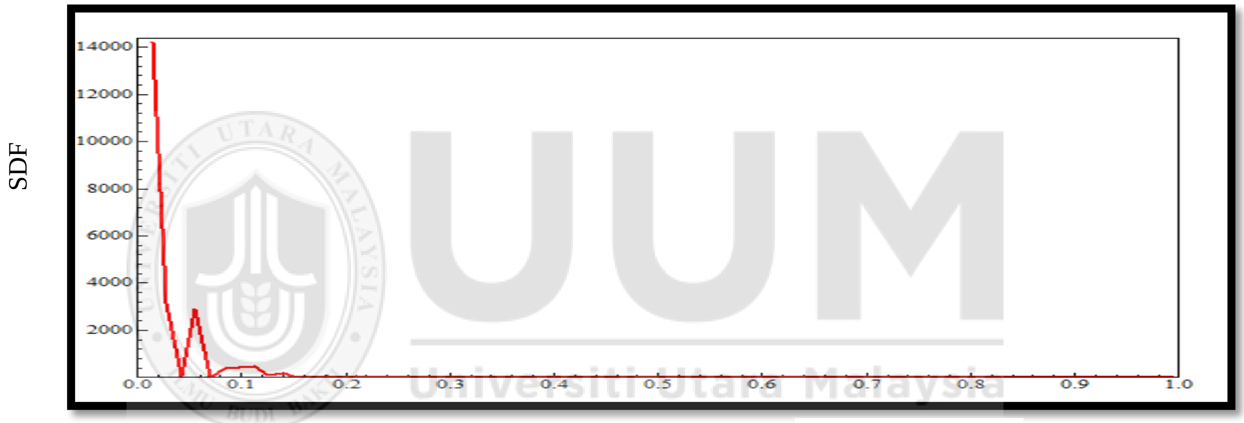
The estimated spectral density function (SDF) of each food pice series indicates that spectral densities are concentrated at low frequencies and decrease to zero as frequency increases. When frequency tends to zero, SDF tends to infinity. These characteristics indicate that the food price series possess long memory.




Frequency

a) Consumer Food Price

$(\omega)$

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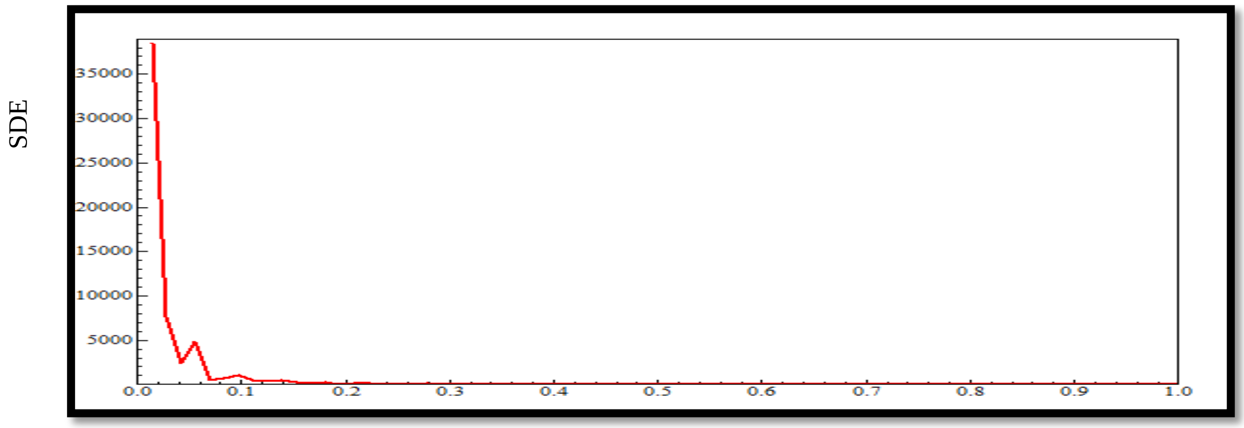
Frequency $(\omega)$

b) Global Food Price




Frequency

c) Wholesale Food Price

$(\omega)$

Figure 6.5
*Periodogram for Food Price Series*

In the case of food price inflation series, the periodogram for each food price inflation series of CFPI, GFPI anf WFPI is displayed in Figure 6.6.

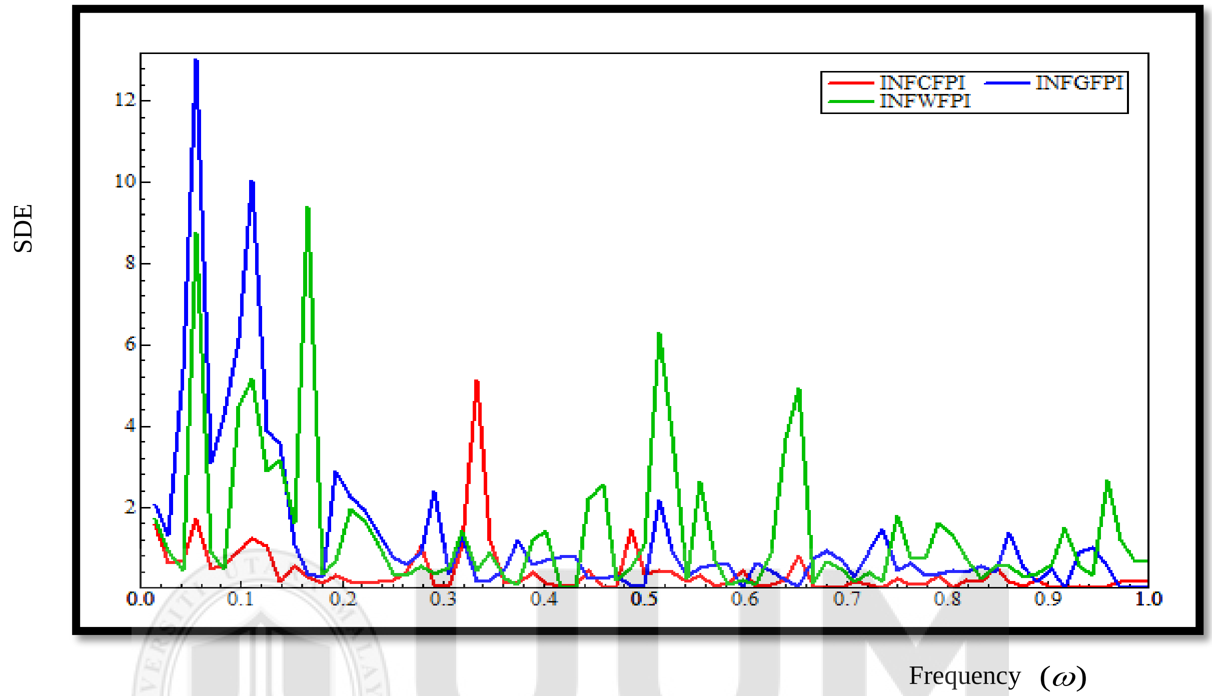



Figure 6.6
*Periodogram for Food Price Inflation*

They show that SDF of each food price inflation series is a decreasing function of frequency when frequency tends to zero, SDF increases without limit. This type of characteristics of SDF indicates that food price inflation series have a long memory.

In the case of HP filtered food price inflation series, the SDF of each food price inflation (HP filted) is exhibited in Figure 6.7.

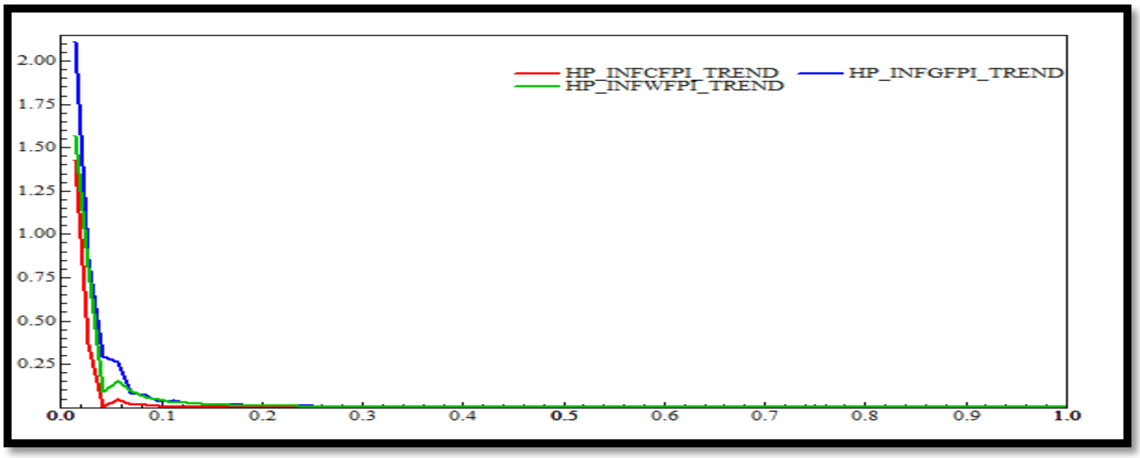



Figure 6.7
*Periodogram for HP Filtered Food Price Inflation*

Note: SDE=spectral density

It shows that SDFs are unbounded at zero or near zero frequency. The characteristics of finite spectrum at all frequencies, infinite spectrum at zero frequency, and decreasing function of frequency are indicating long memory of food price inflation series.

The presence of noncyclic long run statistical dependence in food price inflation is presented by HP filtered trend. Figure 6.7 reveals clearly that food inflation has long memory features of periodogram, This evidence points to the possibility that food price series and food price inflation series exhibit long memory. The spectrum of food price inflation tends to infinity as frequency approach zero. There is evidence in the literature that ACF and SDF are used to measure long memory. For examples; Skare and Stjepanovic (2013) found the long memory of real output for Croatia using ACF and periodogram. Bollerslev and Wright (2000) found the long memory of volatility of Japan exchange rate using periodogram.

Figure 6.8 illustrates the relationship between log (time), versus log(R/S), for each food price inflation case. It shows approximately a positive straight line relationship between log(R/S) and log(time). The Hurst exponent (*R/S*) *H* is the slope of the best fitted trend line that shows the relationship between log(*R/S*) and log(time). The exponent *H* takes values on [0, 1]. Values close to zero indicate an anti-persistent series. Figure 6.8 (a to c) exhibits visually that Hurst exponent values are greater than 0.5 and less than 1. If $0.5 < \hat{H} < 1$, it indicates that there is strong evidence for long memory (persistent) in the series and are positively related. The rescaled range statistic plots are exhibited in three panels of Figure 6.8 (a, b and c).

In the case of CFPI inflation, Figure 6.8a exhibits the relationship between logarithm of time and logarithm of (*R/S*) for CFPI inflation. The estimated Hurst exponent (*R/S*) *H* estimate for CFPI inflation seems to be within the range of $0.5 < \hat{H} < 1$. This evidence indicates that food price inflation possess long memory. Figure 6.8b exhibits the *H* estimate for GFPI inflation. The estimate of *H* also falls with the range of $0.5 < \hat{H} < 1$ which confirms that GFPI inflation has a long memory. In the case of WFPI inflation, Figure 6.8c exhibits the *H* estimate for WFPI inflation. This estimate also lies within the range of $0.5 < \hat{H} < 1$ which suggests that WFPI inflation has a long memory.

The domestic CFPI inflation has highest value of *H* estimate than the other two inflation series, indicating that CFPI inflation has highest long memory than the other two; GFPI, WFPI inflation series. The slope-estimates are above 0.5 in all three food

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price inflation series indicating long memory. Peters (1994) and Van Quang (2005) have also used *R/S* plot to show the long memory in their analysis

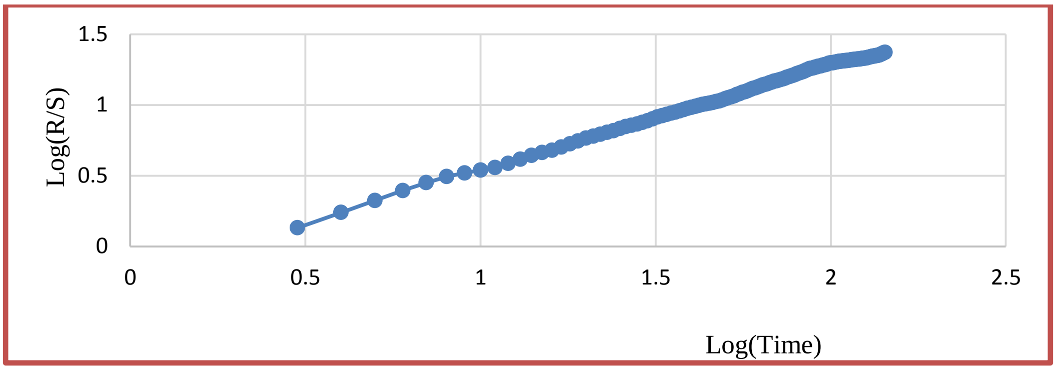


**Figure 6.8a Consumer Food Price Inflation**

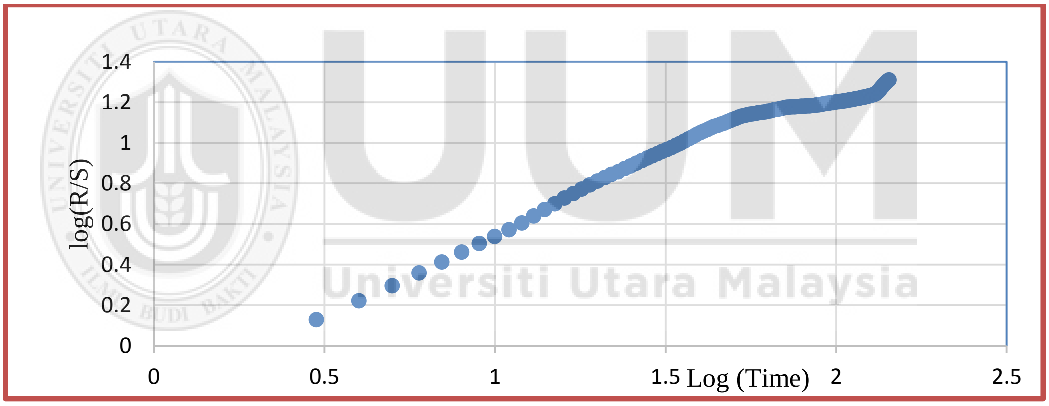


**Figure 6.8b Global Food Price Inflation**

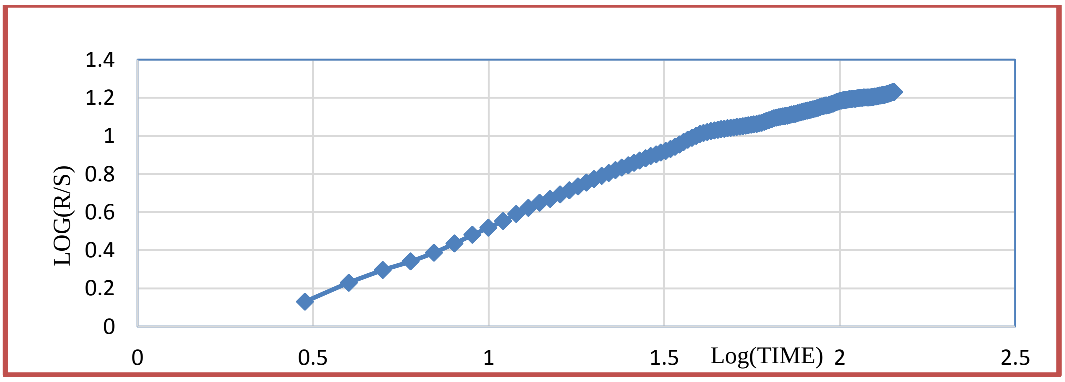


**Figure 6.8c Wholesale Food Price Inflation**

Figure 6.8

*The Rescaled Range Statistic Plot for Food Price Inflation*

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In order to validate these conclusions, the inferential analysis is further performed using nonparametric, semiparametric and parametric approaches. First, the application of a nonparametric approach is presented. Table 6.9 reports the estimated values of Hurst exponent estimator (*H*) for all food price inflation series.

Table 6.9
*Hurst Estimate of Food Prices and Food Price Inflation*

| Variable | Hurst estimate ( $\hat{H}$ )[1] | | Hurst estimate ( $\hat{H}$ )[2] | |
|---|---|---|---|---|
| | **Price** | **Inflation** | **Price** | **Inflation** |
| CFPI | 1.029 (0.012) | 0.707 (0.024) | 1.009 (0.005) | 0.973 (0.019) |
| CNFPI | 1.013 (0.008) | 0.685 (0.066) | 1.003 (0.003) | 0.933 (0.025) |
| CPI | 1.016 (0.005) | 0.813 (0.036) | 1.007 (0.001) | 0.983 (0.016) |
| WFPI | 1.016 (0.016) | 0.631 (0.055) | 1.006 (0.005) | 0.942 (0.018) |
| WPI | 1.024 (0.014) | 0.685 (0.035) | 1.006 (0.000) | 0.971 (0.014) |
| GFPI | 1.011 (0.008) | 0.705 (0.054) | 1.007 (0.005) | 0.953 (0.015) |

Note: [1] denotes with cycle component, [2]: without cycle component (using Hodrick-Prescott filter),
$0 < H < 0.5$: Anti-persistent,
$H = 0.5$: Random walk,
$0.5 < H < 1$:Persistence,
$p$ –values are in parenthesis.
$H_0 : H = 0.5$ vs $H_1 : H > 0.5$

The *H* estimates for all food price series are close to 1. This indicates that all series are clearly having a long memory. However, the *H* estimates for all food price inflation series are greater than 0.5 and less than one. These estimates indicate strong evidence ( $0.5 < H < 1$) of long memory behavior in all food price inflation series. It implies that all price series and all food price inflation series are persistent.

Second, the results of semi-parametric tests using two statistics; (i) Geweke and Porter-Hudak estimator and (ii) Local Whittle estimator (LWE) are reported in Table 6.10.

Table 6.10

*Geweke and Porter-Hudak Estimates and Local Whittle Estimates, 2003M1-2014M12*

| **Variables** | **Price Series** | | **Growth Series** | |
|---|---|---|---|---|
| | **LWE ($\hat{d}$)** | **GPHE ($\hat{d}$)** | **LWE ($\hat{d}$)** | **GPHE ($\hat{d}$)** |
| CFPI | 0.905 (0.000) | 1.013 (0.000) | 0.349 (0.000) | 0.468 (0.000) |
| CNFPI | 0.929 (0.000) | 1.043 (0.000) | 0.088 (0.136)# | 0.165 (0.068) |
| CPI | 0.916 (0.000) | 1.028 (0.000) | 0.292 (0.000) | 0.439 (0.001) |
| WFPI | 0.911 (0.000) | 1.023 (0.000) | 0.199 (0.001) | 0.206 (0.024) |
| WPI | 0.918 (0.000) | 1.024 (0.000) | 0.129 (0.029) | 0.184 (0.068)# |
| GFPI | 1.063(0.000) | 1.074 (0.000) | 0.469 (0.000) | 0.376 (0.008) |

Note: $LWE \sim Z(0,1)$ ,
$GPHE \sim t(0,v)$ ,
*p*-values are in parenthesis,
# indicates not significant at 5% Level

The null hypothesis of LWE and GPH tests is a short memory, $H_0 : d = 0$ against the alternative hypothesis of long memory, $H_1 : d > 0$. The results show that the null hypothesis of short memory for CFPI, GFPI and WFPI inflation series are rejected at 5 percent level as *p* values of these tests are less than 0.05. However, the null hypothesis of short memory is rejected in the case of each price series as *p* values are less than 0.05.

GPH estimates for food price and price inflation series are all significant except CNFPI and WPI inflation series. Thus, the food price series and food price inflation series are fractionally integrated and have a long memory. The estimated values of "*d*" of GPH range from 0.21 to 0.47. Local Whittle test results also indicate that most of the food price and food price inflation series are long memory series.

Third, the results for a parametric approach for food prices, food price inflation series and HP filtered food price inflation series are reported in Table 6.11, Table 6.12 and Table 6.13 respectively.

Long memory parameter $d$ of ARFIMA model is estimated using maximum likelihood method in order to describe the long run behavior of food price series in Sri Lanka. First, ARFIMA model is fitted for food price series. The results of the selected ARFIMA model, for all price series, are given Table 6.11.

Table 6.11
*Results from ARFIMA (p,d,q) Models for Price Series.*

| **Variables** | **Constant** | **AR** | **MA** | ***d*** | **LL** | **Wald-Chi$^2$** |
|---|---|---|---|---|---|---|
| CFPI | - | 0.998 | 0.452 | 0.149 | -365.534 | 65389 |
| | | (0.000) | (0.000) | (0.020) | | (0.000) |
| CNFPI | - | 0.996 | - | 0.200 | -314.234 | 79928 |
| | | (0.000) | | (0.000) | | (0.000) |
| CPI | - | 0.994 | - | 0.349 | -281.614 | 44036 |
| | | (0.000) | | (0.000) | | (0.000) |
| GFPI | - | 0.924 | - | 0.474 | -416.660 | 1688 |
| | | (0.000) | | (0.000) | | (0.000) |
| WFPI | 219.242 | 0.981 | - | 0.277 | -459.846 | 6282 |
| | (0.025) | (0.000) | | (0.001) | | (0.000) |
| WPI | 213.798 | 0.989 | - | 0.239 | -431.057 | 12958 |
| | (0.030) | (0.000) | | (0.001) | | (0.000) |

Note: This table shows the results of selected ARFIMA ($p$, $d$, 0) models. AR indicates the autoregressive parameter, LL indicates the log likelihood, $d$ indicates the long memory parameter (fractional difference), $p$-values are in parentheses

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The orders of ARFIMA are selected based on the Schwarz Information Criterion (SIC). In all cases, estimates of long memory parameter $d$ are highly statistically significant at the 5 percent level and lie in the interval (0, 0.5), implying that the series are stationary but exhibit long memory. Global food price has a relatively higher value of long memory parameter.

Long memory indicates that shocks to these prices may persist over a long period of time. These evidences imply predictability of future food prices based on historical prices. The significant $d$ parameter estimates for each food price series ranges from 0.149 to 0.474. It is well known that a series with $0.5 < d < 1$ is mean-reverting even though it is non-stationary. These estimates of *d* indicate that food price series are persistent and possess long memory behavior in Sri Lanka.

Furthermore, long memory parameter of food price inflation series is estimated using ARFIMA regression with no constant for all food price inflation series by the maximum likelihood estimation technique. Hassler and Wolters (1995) and Ooms and Hassler (1997) showed that the ARFIMA(0,*d*,0) model fits consumer price inflation series of many OECD countries rather well. The estimates of long memory parameter of the conditional mean for food price inflation series are reported in Table 6.12

Table 6.12

*ARFIMA(0,d,0)–Long Memory Parameter Estimates ($\hat{d}$) for Food Inflation Series*

| **Inflation** | $\hat{d}$ | **LL** | **Wald-Chi$^2$** |
|---|---|---|---|
| INFCFPI | 0.348 (0.000) | -261.045 | 25.62 (0.000) |
| INFCNFPI | 0.219 (0.000) | -213.873 | 19.88 (0.000) |
| INFCP | 0.348 (0.000) | -176.617 | 40.41 (0.000) |
| INFGFPI | 0.440 (0.000) | -330.725 | 62.86 (0.000) |
| INFWFP | 0.228 (0.002) | -356.300 | 11.70 (0.001) |
| INFWPI | 0.186 (0.001) | -327.052 | 10.47 (0.001) |

Note: *p*-values are in parenthesis, $H_0$: $d$=0,

According to Table 6.12, estimated long memory parameter estimates are: *d*=0.348 (*p*=0.00) for headline inflation, *d*=0.348 (*p*=0.00) for food inflation, and *d*=0.219 (*p*=0.000) for nonfood price inflation. These results indicate that food inflation series possess long memory, and stationary. The results show that long memory parameters are statistically significant at the 5 percent level. Hence, all domestic food price inflation and global food price inflation series have a long memory that implies a high degree of dependence in the series.

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The estimated parameters of an ARFIMA model were used to estimate spectral density for each food price inflation series. The integral of spectral density over ( $-\pi,\ \pi$) is the variance of the food price inflation time series. Figure 6.9 shows the estimated spectral densities implied by the ARFIMA parameter estimates for food inflation series. The estimated spectral density indicates that the low frequency random components are more important than the high frequency components and implies that these food price inflation series have a long memory. The curve is highest at frequency 0 and it tapers off toward zero or a positive asymptote.

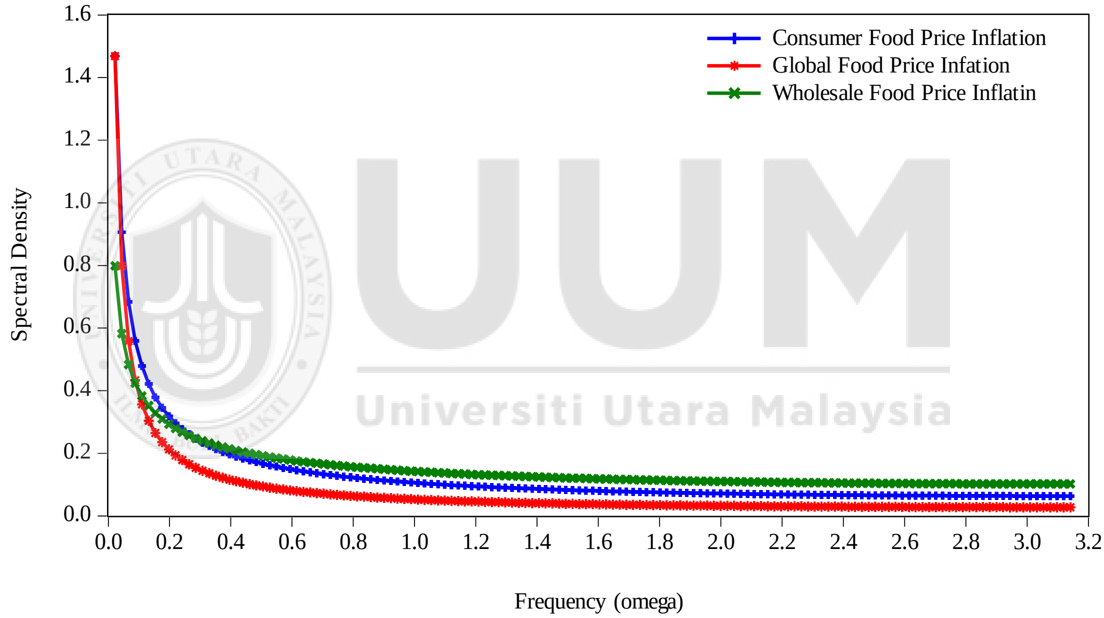


Figure 6.9
*Spectral Density for Food Price Inflation from Estimated ARFIMA Model*

Further, an experiment is tested in ARFIMA framework for the HP filtered inflation series after removing the cyclic part by the HP method. Long memory parameter is estimated for the filtered series now. The results are reported in Table 6.13.

Table 6.13
*ARFIMA–Long Memory Parameter Estimates of HP filtered trend of Inflation Series*

| Variables | $\tilde{d}$ | LL | Wald-Chi$^2$ |
|---|---|---|---|
| INFCFPI | 0.499 (0.000)* | -568.502 | 1051233.27 (0.000)* |
| INFCNFPI | 0.499 (0.000)* | -513.567 | 2315089.67 (0.000)* |
| INFCPI | 0.499 (0.000)* | -538.737 | 1551741.27 (0.000)* |
| INFGFPI | 0.499 (0.000)* | -491.748 | 1551741.27 (0.000)* |
| INFWFPI | 0.496 (0.000)* | -572.860 | 945646.11 (0.000)* |
| INFWPI | 0.499 (0.000)* | -568.039 | 1111236.75 (0.000)* |

*Note:* $\tilde{d}$ = Estimated from the filtered the series by the HP method, * indicates significance at 5% level. p-values are in parenthesis

These results also confirm that all food price inflation underlying trend (HP filtered) series possess long memory. The null hypothesis of short memory series (not long range dependent) is rejected at 5 percent level for each series. The long memory parameter estimates lie in the interval (0, 0.5). The results from visual inspection and inferential tests of nonparametric, semiparametric and parametric methods show that food price inflation is neither an I(1) nor an I(0) process. They are stationary, mean reverting and long memory process. In general, price series may have long memory not only in the first moment of the series but also in the second moments of the series. Therefore, the volatility (second moment) of the food price series is investigated in the following section.

### 6.5.2 Volatility of Food Price Inflation

This section examines the long memory property in volatility (the second moment) of food price inflation using visual inspection, non-parametric, semi-parametric and parametric estimation methods. Understanding food price volatility remains one of the most persistent challenges. In order to test for long memory in the volatility of food price inflation series, the absolute inflation ( $|\pi_t|$), squared inflation ($\pi_t^2$), logarithm of squared inflation $\ln(\pi_t^2)$ and conditional variance estimated by

FIGARCH models are used as proxies for the volatility of food price inflation. The volatility series (proxies) for food price inflation series are exhibited in Figure 6.10

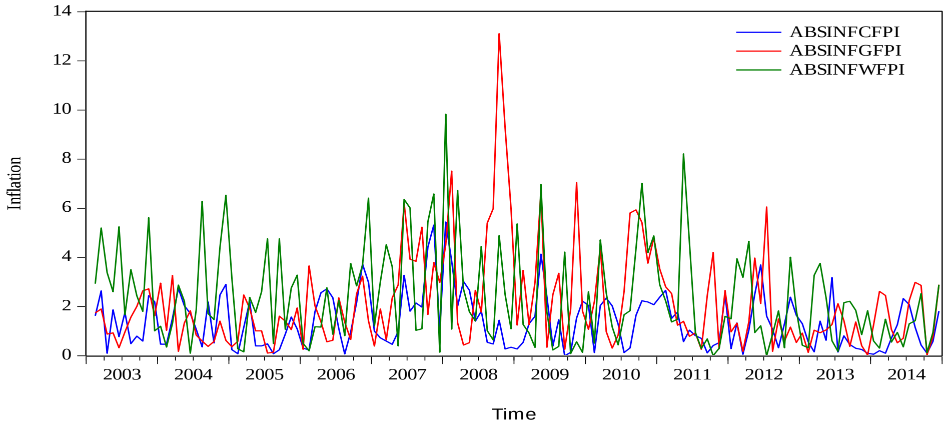


**Figure 6.10 a. Absolute Food Price Inflation**

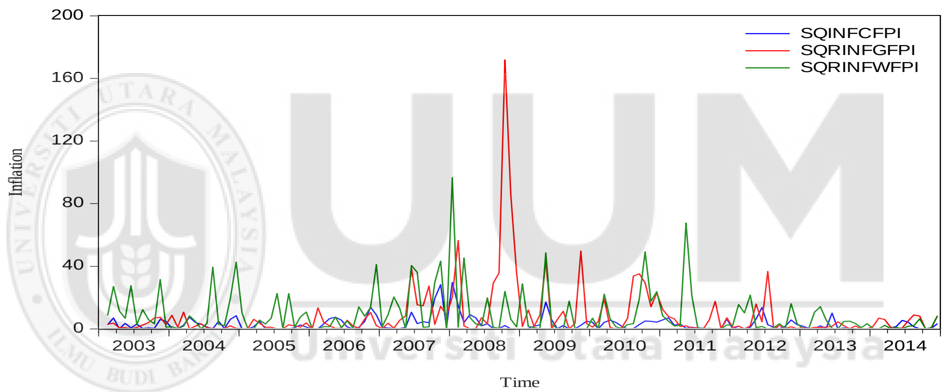


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**Figure 6.10b. Squared Food Price Inflation**

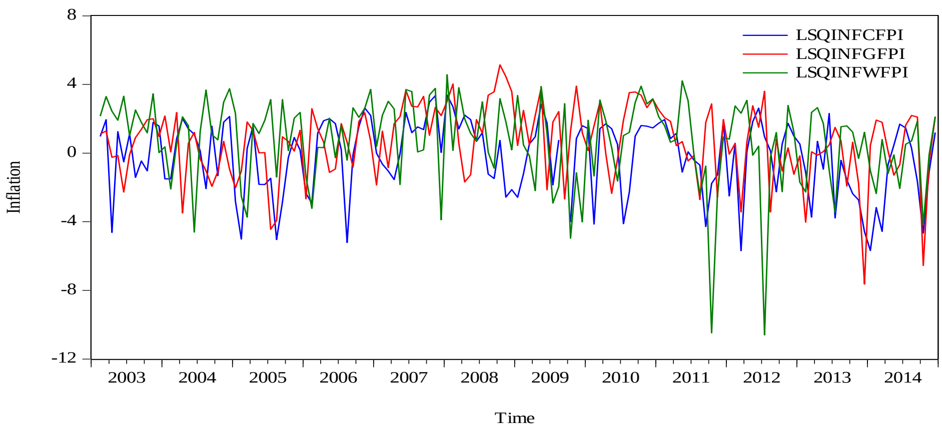


**Figure 6.10c. Log squared Food Price Inflation**

Figure 6.10
*Proxies for Food Price Inflation Volatility, 2003M1-2014M12*

It can be seen that these line graphs display the volatile behavior of food price inflation. Volatility tends to change very slowly over time. The volatility nature can be assessed by visual inspection of (a) absolute food price inflations, (b) squared food price inflations, (c) log squared food price inflations. These three cases are displayed in Panel A, Panel B, and Panel C in Figure 6.10. They suggest that the volatility series are not behaving like white noise. There are periods of both small and large changes.

For the absolute, squared and log squared inflation series, the ACF remain positive and statistically significant for a substantial number of lags. The sample ACFs of absolute, squared and log squared food price inflation can be used to assess the evidence for long memory visually. These three cases are displayed by Panel A, Panel B, Panel C in Figure 6.11.

While Panel A displays the ACF of absolute food price inflation, Panel B and C display the ACF of squared food price inflation and the ACF of log squared food price inflation respectively. The ACF of absolute price changes (inflation) decays slowly as a function of time lag according to the power law.

Further, it can be seen that ACF is very small except for the first two lags. Mandelbrot (1963), Fama (1965) and Taylor (1986) had also noticed that the absolute values of stock returns had very slow decaying autocorrelations. Ding, Granger and Engle (1993) showed that the effects of a shock take a considerable time to die out in absolute stock return series compared to return series.

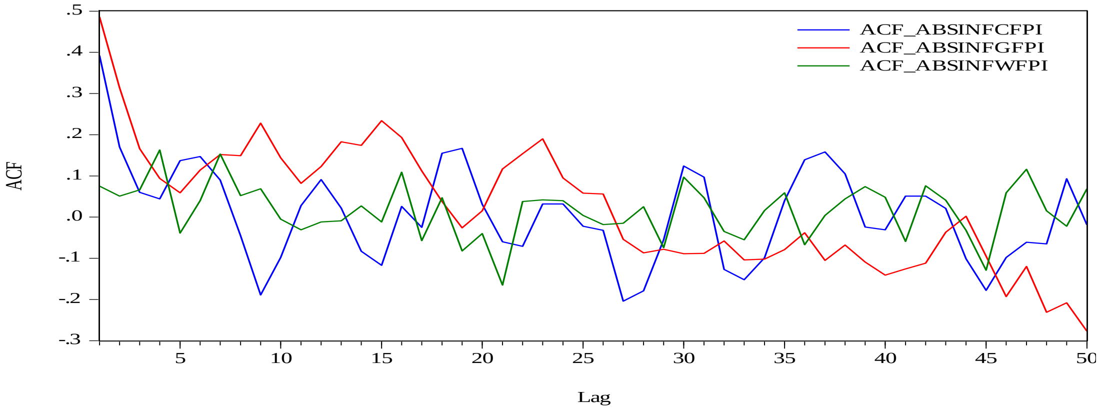


Figure 6.11a ACF of Absolute Food Price Inflation

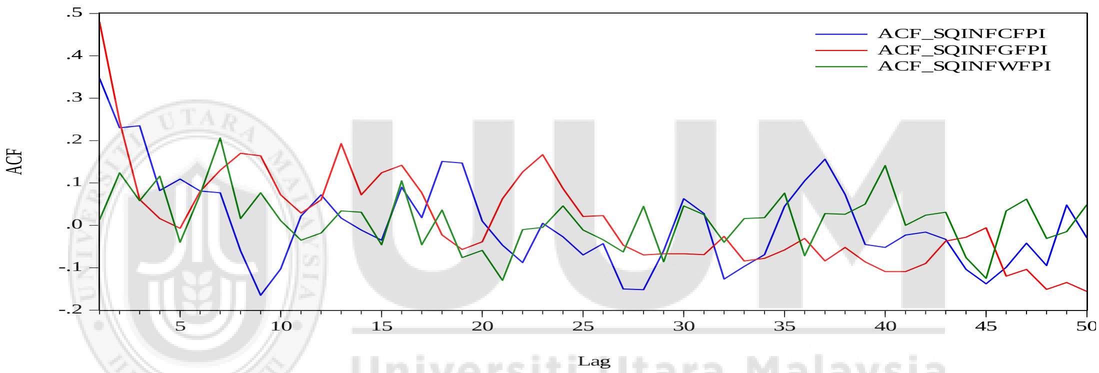


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Figure 6.11b ACF of Squared Food Price Inflation

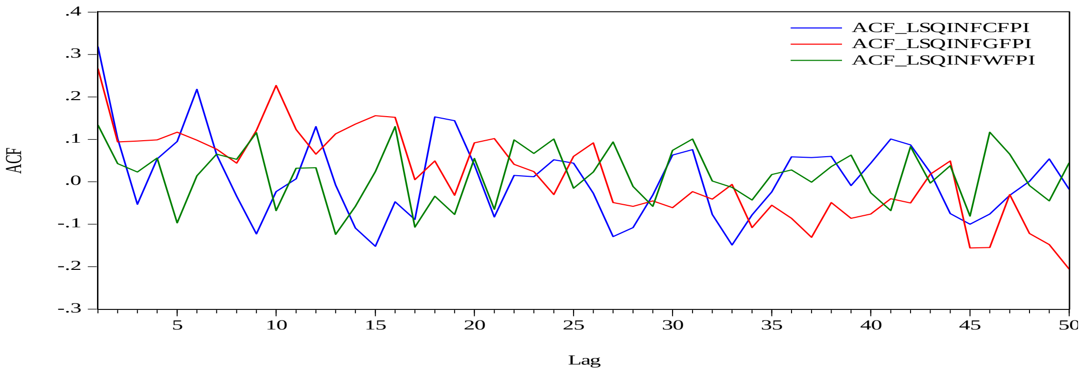


Figure 6.11c ACF of Log Squared Food Price Inflation

Figure 6.11
*Autocorrelation Function of Volatility of food Price Inflation*

The estimated correlogram of food price inflation volatility series in Figure 6.11 displays significant autocorrelations at high lags and with slow hyperbolic decay characteristic of long memory processes. This is a quantitative sign of the well-known phenomenon of volatility clustering. This behaviour suggests that there is some kind of long-range dependence in the food inflation volatility series.

In this respect, identification of long memory by using the sample ACF is well bounded. The ACF of each series in all panels in Figure 6.11 decays at a hyperbolic rate. The slow decay ACF of volatility series is a sign of long range dependence in volatility.

Further, long memory of volatility series is examined by using spectral density function. Absolute, squared and log squared food price inflation are used to inspect the long memory phenomena using periodogram. The spectral density function for each volatility series for all three proxies is displayed in Figure 6.12.

The estimated spectral density function of food price inflation volatility series in Figure 6.12 also indicates that volatility series of food price inflation have a long memory. In a spectral density graph, when frequency tends to zero, spectral density increases without limit which is one indicator of long memory. Almost all proxies have the same pattern of periodogram.

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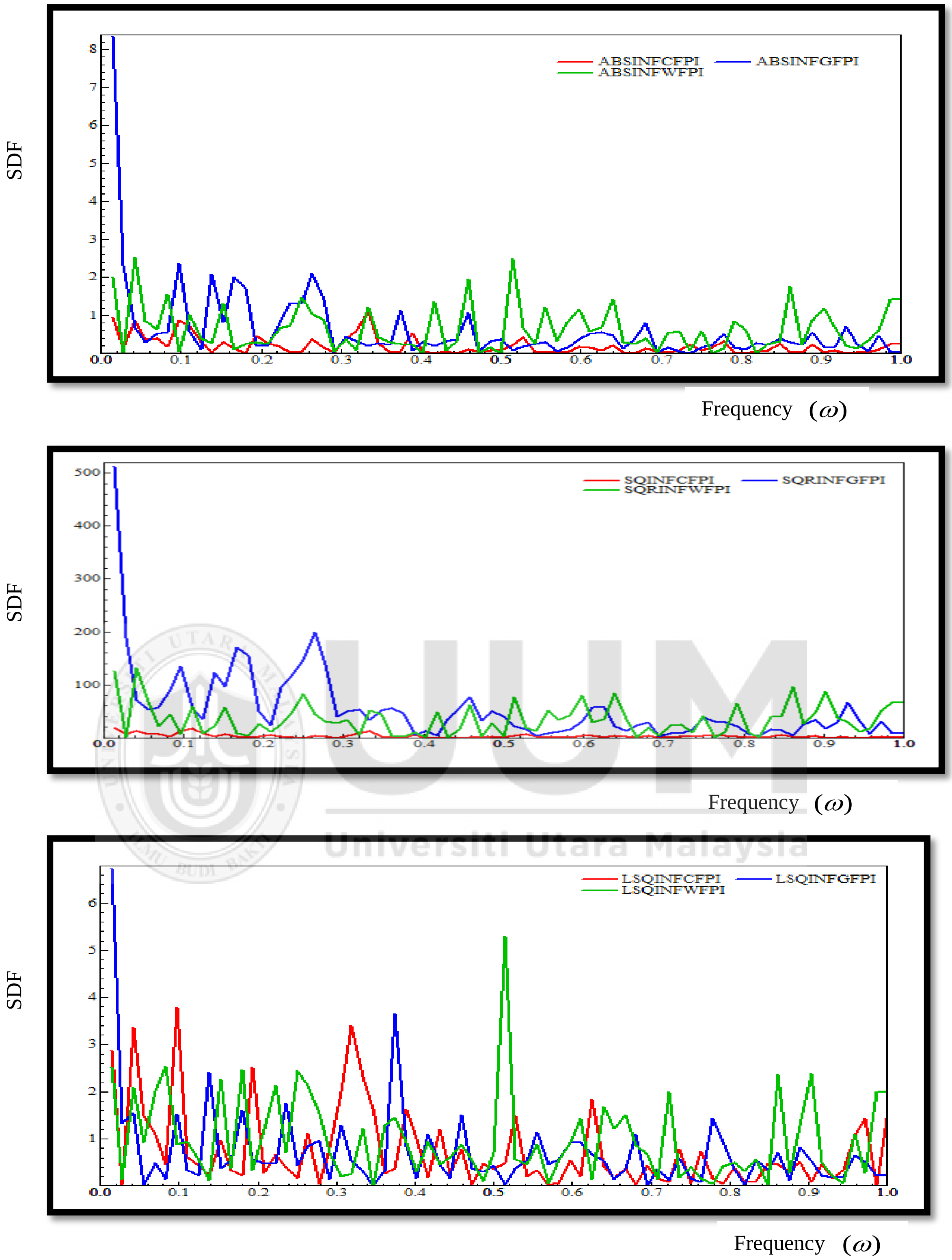


Figure 6.12
*Spectral Density Function for Food Price Inflation Proxies of CFPI,WFPI, GFPI*

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Further, the results derived from visual inspection are validated by evaluating inferential analysis in the next section. The inferential analysis was performed using nonparametric, semiparametric and parametric methods.

First, the long memory fractional differencing parameter for volatility series of food price inflation is estimated using the Rescaled Range Statistic (R/S) Hurst Exponent Estimator. The Hurst estimates for all three proxies of each food price inflation volatility series are presented in Table 6.14.

Table 6.14
*Hurst Estimates-Long Memory in Volatility, 2003M1-2014M12*

| **Variable** | **Hurst Exponent Estimate** | | |
|---|---|---|---|
| | **Absolute Inflation** ($\lvert\pi_t\rvert$) | **Squared Inflation** ($\pi_t^2$) | **Log Squared Inflation** ($\ln(\pi_t^2)$) |
| CFPI | 0.725 (0.003) | 0.722 (0.023) | 0.702 (0.138) |
| CNFPI | 0.618 (0.081) | 0.435 (0.041) | 0.687 (0.099) |
| CPI | 0.778 (0.028) | 0.747 (0.040) | 0.791 (0.022) |
| WFPI | 0.674 (0.015) | 0.689 (0.018) | 0.658 (0.028) |
| WPI | 0.791 (0.038) | 0.726 (0.041) | 0.808(0.089) |
| GFPI | 0.869 (0.053) | 0.783 (0.043) | 0.818 (0.039) |

Note: *p*-values are in parenthesis, $0 < H < 0.5$: Anti-persistent, $H = 0.5$: Random walk, $0.5 < H < 1$: Persistence

The estimates of Hurst exponent for all proxies of the volatility of food price inflation series are greater than 0.5 and lie in the range $0.5 < H < 1$. The significant Hurst estimate ($H$) values in the range of $0.5 < H < 1$ indicate that the volatility series possess long memory. Most of the estimates are statistically significant at the 5 percent level and some coefficients for nonfood price inflation and WPI inflation are significant at the 10 percent level. These results are consistent with Kumar's (2015) findings on the volatility of the Indian banking sector stock return series. He found that the estimates of Hurst exponents for absolute daily returns fall the range of 0.680-0.833 and for squared daily returns fall within the range of 0.668-0.708.

Second, the volatility proxy series are examined for long memory characteristics using semi parametric procedures. GPH test and LWE test are performed to examine the long memory characteristics. The null hypothesis of these tests are short memory in the volatility series, against the alternative hypothesis of long memory, $H_0 : d = 0$ vs $H_1 : d > 0$. Table 6.15 reports the estimated values of long memory parameter *d* with probability values in parenthesis for the GPH and LW tests for food and nonfood price volatility proxy series.

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Table 6.15
*Semi parametric Estimates for Long Memory of Food Price Inflation Volatility, 2003M1-2014M12*

| | **Absolute Inflation ,** $\lvert\pi_t\rvert$ | | **Squared Inflation,** $\pi_t^2$ | | **Log Squared Inflation,** $\ln(\pi_t^2)$ | |
|---|---|---|---|---|---|---|
| **Variable** | **LW Estimate (** $\hat{d}$ **)** | **GPH Estimate (** $\hat{d}$ **)** | **LW Estimate (** $\hat{d}$ **)** | **GPH Estimate (** $\hat{d}$ **)** | **LW Estimate (** $\hat{d}$ **)** | **GPH Estimate (** $\hat{d}$ **)** |
| CFPI | 0.308* | 0.368* | 0.277* | 0.357* | 0.243* | 0.282* |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.006) |
| CNFPI | 0.025 | 0.072 | -0.034 | -0.001 | 0.079 | 0.012 |
| | (0.669) | (0.425) | (0.560) | (0.986) | (0.180) | (0. 904) |
| CPI | 0.217* | 0.379* | 0.147* | 0.262* | 0.228* | 0.317* |
| | (0.000) | (0.000) | (0.012 | (0.010) | (0.000) | (0.003) |
| WFPI | 0.089* | 0.084* | 0.226* | 0.198 | 0.111 | 0.180 |
| | (0.130) | (0.443) | (0.014) | (0.164) | (0.059) | (0.053) |
| WPI | 0.174* | 0.086 | 0.262* | 0.104 | 0.211* | 0.148 |
| | (0.003) | (0.392) | (0.003) | (0.565) | (0.000) | (0.144) |
| GFPI | 0.361* | 0.391* | 0.372* | 0.425* | 0.212* | 0.167 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.059) |

Note: $LWE \sim Z(0,1)$, $GPHE \sim t(0,v)$, *p*-values are in parenthesis.

The estimates of both LW and GPH statistics for the long memory parameter *d* of each consumer food inflation series are statistically significant as the null hypothesis of $d=0$ is rejected at the 5 percent level. In the case of CNFPI, there is no significant evidence of long memory volatility. In general, nonfood prices are less volatile compared to food prices. In the case of WPI, GPH estimates are not significant for all three proxies. This implies that there is no evidence of long memory for the volatility series of WPI inflation.

Third, the long memory parameter for food price volatility series is estimated by using fractional integration GARCH (FIGARCH) model for variance equation. To study long memory characteristics in conditional volatility of food price inflation, FIGARCH (1, d, 1) model is used. Chang, McAleer and Tansuchat (2012), Hyun, Darren and Frechette (2004), Barkoulas, Labys and Onochie (1997), Bollerslev and Wooldridge ( 1992) had found that FIGARCH (1,d,1) model performs significantly better than the traditional conditional volatility models such as GARCH (1,1) and EGARCH(1,1) for modeling agricultural price inflation. The FIGARCH (1, *d,* 1) model is estimated by the quasi maximum likelihood (QML) estimation method. Results show that volatility of the food price inflation series is serially correlated. The estimated results of FIGARCH model are reported in Table 6.16.

Table 6.16
*Memory Parameter Estimates from Fitted FIGARCH (1,d,1)Model for Inflation Series*

| | **INFCFPI** | **INFWFPI** | **INFGFPI** | **INFCNFPI** | **INFCPI** |
|---|---|---|---|---|---|
| $\mu$ | 0.674* | 3.361* | 0.541* | 0.349* | 0.674* |
| | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) |
| ARCH($\alpha_1$) | 0.689* | 0.422* | 0.241* | 0.557* | 0.689* |
| | (0.002) | (0.000) | (0.000) | (0.000) | (0.002) |
| GARCH($\beta_1$) | 0.795* | 0.622* | - | 0.161 | 0.795* |
| | (0.000) | (0.000) | | (0.214) | (0.000) |
| $d$ | 0.384* | 0.213* | 0.377* | 0.212* | 0.384* |
| | (0.000) | (0.009) | (0.000) | (0.000) | (0.000) |
| ARCH-in–mean | - | -0.345 | - | - | - |
| $\varepsilon_t \mid \Omega_{t-1} \sim$ | G.E.D | G.E.D | G.E.D | student t | G.E.D |
| $\ln(L)$ | -264.410 | -353.072 | -326.043 | -174.217 | -264.410 |
| SIC | 3.872 | 5.146 | 4.699 | 2.575 | 3.872 |
| Qs(20) | 17.515 | 17.428 | 24.055 | 5.392 | 17.515 |
| | (0.488) | (0.494) | (0.194) | (0.999) | (0.488) |
| ARCH-LM(10) | 0.728 | 1.119 | 0.701 | 0.201 | 0.728 |
| | (0.697) | (0.353) | (0.722) | (0.996) | (0.697) |

Note: Qs (20) = Ljung-Box statistic for squared standardized residuals.
ARCH-LM : heteroscedasticity,
G.E.D: generalized error distribution, *p*-values are in parenthesis.
* refers statistical significance.

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The results show that the estimated long memory parameter *d* for the volatility of food price inflation is statistically significantly different from 0 or 1. The significant long memory parameter indicates that volatility series of food price inflation possesses long memory. The FIGARCH model describes the long memory in conditional volatility well. The non-significant Ljung-Box *Q* statistic for squared standardized residuals, *Q*s(20) and ARCH-LM test of heteroscedasticity at the 5 percent level of significance indicate that the FIGARCH model is robust. The non-significant values of these tests statistics imply that FIGARCH model fits well for all food price inflation series. It seems that there are no GARCH effects left.

The findings from the parametric approach are consistent with the findings of the other two approaches.

Further, periodogram visual technique (SDF) is employed to check long memory of the conditional variance for food price inflation time series. Therefore, periodograms for each conditional variance of food price inflation derived from the FIGARCH model are illustrated in Figure 6.13. This also indicates that conditional volatility series for CFPI, WFPI, and GFPI inflation series consist of characteristics of long memory.

The results from most of the tests show that food price inflation and volatility of food price inflation series have a long memory and they are fractionally integrated. Thus, results indicate that food price series are not transitory in nature and have significant permanent components. Therefore, the results show a strong evidence of long memory in food price inflation in Sri Lanka. These results contradict the results of other studies for food prices as I(1) or I(0) for food price inflation. Thus, the assumption that food prices do not contribute to the underlying inflationary pressures in the economy is improper. The evidence of long memory remains important for forecasts in large horizons and implies that policy makers and analysts should take into considerations the long memory in food price inflation and volatility of food price inflation.

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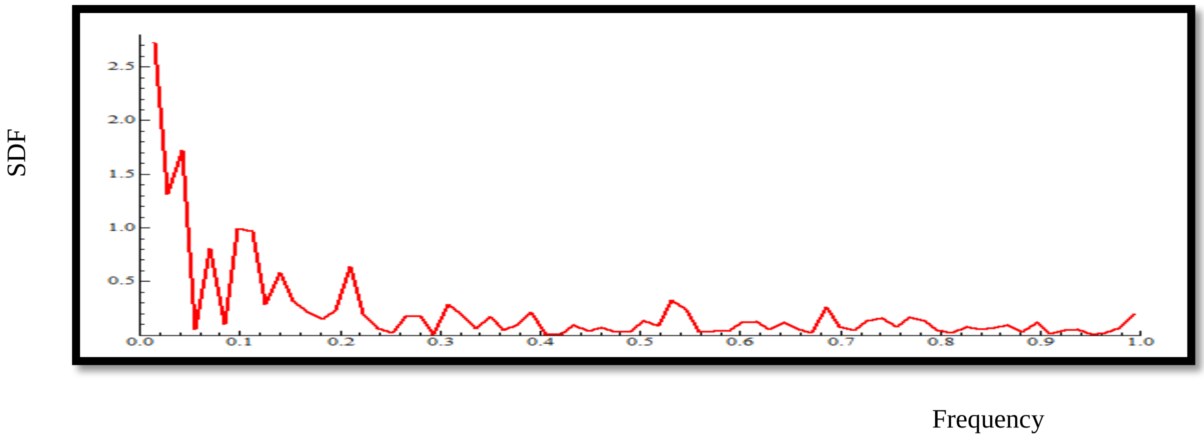
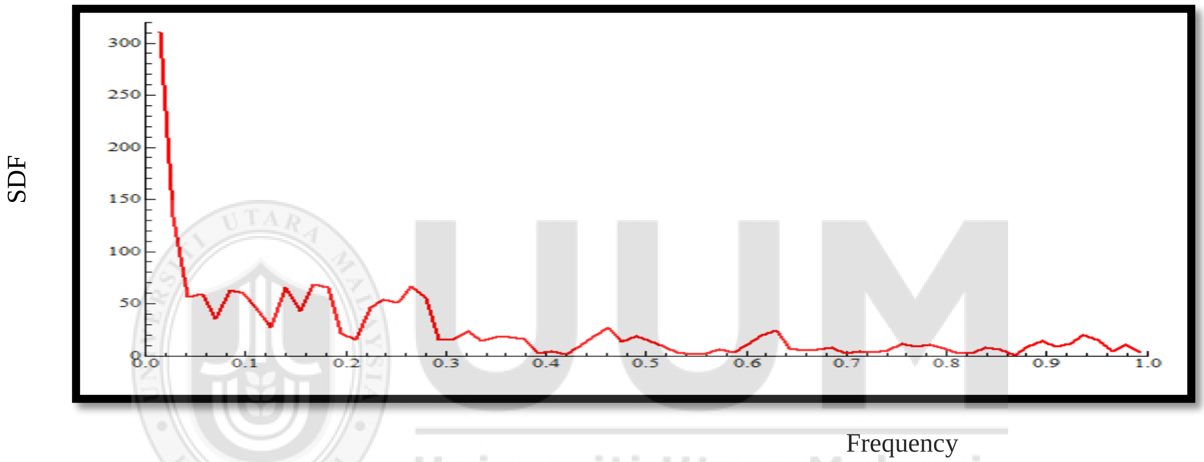



**a) Conditional Variance for CFPI inflation**




b) **Conditional Variance for GFPI inflation**

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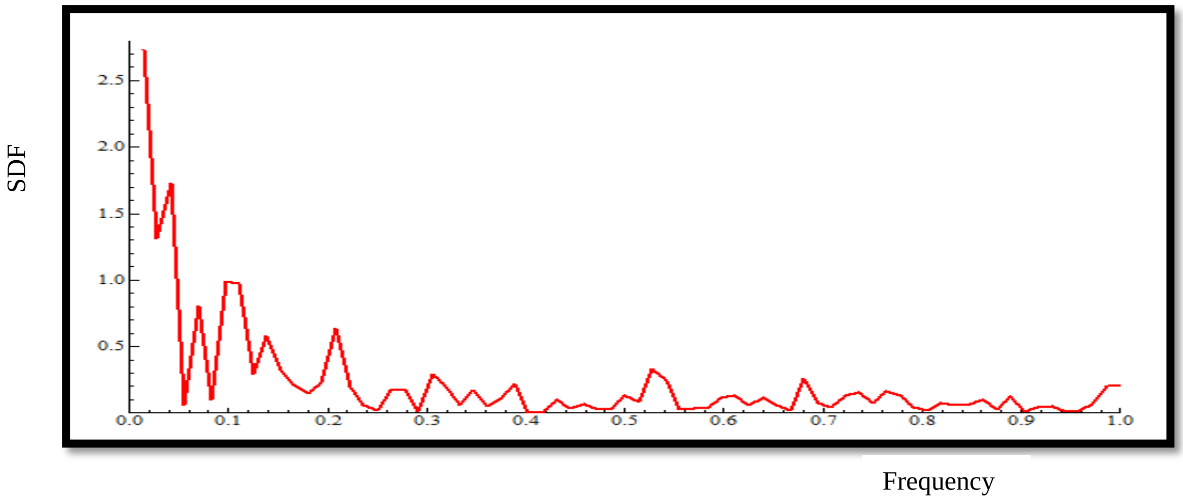


**c) Conditional Variance for WFPI inflation**

Figure 6.13
*Periodogram for Conditional Variance of Food Price Inflation*

## 6.6 Global Food Price Transmission to Domestic Prices

This section illustrates how the second objective of this study is achieved by examining the global food price transmission to domestic prices using cointegration analysis, Granger causality analysis, and impulse response analysis.

First, cointegration analysis is performed using the Johansen method to estimate long run equilibrium relationship between global food price and domestic prices in Sri Lanka. Five models are estimated separately for five domestic response prices namely, CPI, CFPI, CNFPI, WFPI, and WPI. Unit root test results in Section 6.4 showed that all variables in level are nonstationary, and are stationary in first difference. Therefore, the order of integration of each variable is I(1). In addition, Table 6.5 showed that all series are in the same order of integration, I(1).

### 6.6.1 Determining the Optimal Lag

Before performing the test for the existence of cointegration, it is vital to choose an appropriate lag order of the model specification. The Johansen method is known to be sensitive to the lag length (Banerjee *et al*., 1993). Therefore, first, the optimal lag is estimated. The appropriate lag length for the co-integration test is selected based on VAR lag order selection criteria; Akaike's information Criterion (AIC), the Schwarz information criterion (SIC) and Hannan-Quinn information criterion (HC). The results reported in Table 6.17 show that the optimal lag is 2 for each domestic price series. The same lag length for all equations indicates that it preserves the symmetry of the system, and is able to use OLS efficiently. Then, co-integration tests are carried out for all five domestic price models.

Table 6.17
*VAR Lag Order Selected Criteria*

| Model | AIC | SC | HQ |
|---|---|---|---|
| LCPI | -20.227(2) | -19.457 (2) | -19.914 (2) |
| LCFPI | -19.016 (2) | -18.245 2) | -18.703 (2) |
| LCNFPI | -19.675 (2) | -18.904 (2) | -19.362 (2) |
| LWFPI | -17.806 (2) | -17.035 (2) | -17.493 (2) |
| LWPI | -18.204 (2) | -17.433 (2) | -17.890 (2) |

Note: AIC: Akaike information criterion, SC: Schwarz information criterion, HQ: Hannan-Quinn information criterion, optimum lag values are in parenthesis.

In order to examine the transmission from GFPI to domestic prices, the Johansen cointegration test is carried out to find out the long run relationship between the domestic prices and world food prices using the full information Maximum Likelihood method. Based on economic theory and objective of the study, normalization is done. Domestic prices are deliberately chosen as the dependent variable (normalized to one) to examine the global food price transmission to the domestic prices in Sri Lanka. The Johansen test procedure for co-integration among the variables is used by looking at the rank of the long run impact matrix $\Pi$ via its eigenvalues. Using Trace statistic and Maximum Eigenvalue statistic, the sequential procedure is done to find the number of co-integrating relations. The results of the Johansen co-integration test for each domestic price model are presented in Table 6.18 that provides the evidence from both Trace and Maximum eigenvalue tests for cointegrating rank determination for each model.

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Table 6.18

*Rank Test of Cointegration for Global Food Price Transmission*

| | **Trace Statistics** | | | **Max-Eigenvalue Statistics** | | |
|---|---|---|---|---|---|---|
| | **No of CEs** | | **Test Statistic** | **No of CEs** | | **Test Statistic** |
| **Model** | **Ho** | $\mathbf{H_1}$ | $\lambda_{Trace}$ | **Ho** | $\mathbf{H_1}$ | $\lambda_{Max}$ |
| LCPI | $r=0*$ | $r\geq 1$ | 75.145 (0.000) | $r=0*$ | $r=1$ | 46.430 (0.000) |
| | $r\leq 1$ | $r\geq 2$ | 28.714 (0.211) | $r=1$ | $r=2$ | 13.432 (0.515) |
| LCFPI | $r=0*$ | $r\geq 1$ | 59.444 (0.015) | $r=0*$ | $r=1$ | 33.438 (0.011) |
| | $r\leq 1$ | $r\geq 2$ | 26.005 (0.342) | $r=1$ | $r=2$ | 12.472 (0.608) |
| LCNFPI | $r=0*$ | $r\geq 1$ | 57.576 (0.000) | $r=0*$ | $r=1$ | 34.009( 0.002) |
| | $r\leq 1$ | $r\geq 2$ | 23.566 (0.061) | $r=1$ | $r=2$ | 13.655 (0.188) |
| LWFPI[1] | $r=0*$ | $r\geq 1$ | 95.023 (0.000) | $r=0*$ | $r=1$ | 70.148 (0.000) |
| | $r\leq 1*$ | $r\geq 2$ | 24.876 (0.042) | $r=1$ | $r=2$ | 14.997 (0.126) |
| LWPI[1] | $r=0*$ | $r\geq 1$ | 106.588(0.000) | $r=0*$ | $r=1$ | 81.709 (0.000) |
| | $r\leq 1*$ | $r\geq 2$ | 24.878 (0.042) | $r=1$ | $r=2$ | 15.601(0.104) |

*Note:* *p*- values are in parenthesis, *r*=number of cointegration, * denotes Ho is rejected at 5 % level, [1] HP filtered trend of GFPI is used instead of GFPI

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The Rank test (Trace and Maximum eigenvalue tests) shows that the null hypothesis of no co-integration, $H_0 : r=0$ is rejected at the 5 percent level in favour of at least one co-integrating relationship. In addition, it is noted that the trace statistic indicates that there are two cointegration relations at the 5 percent level for WFPI and WPI models whereas the maximum eigenvalue statistic indicates that there is one cointegration vector among the concerned variables for all five models. The maximum eigenvalue test is more powerful than the Trace test (Johansen and Juselius, 1990). Therefore, a number of cointegration vectors are selected based on Maximum eigenvalue statistic. It is also noted that LWFPI and LWPI are not cointegrated with LGFPI in level form. However, LWFPI and LWPI are found to be cointegrated with HP filtered trend of GFPI in Model 4 and Model 5 respectively.

The co-integrating vector and speed of adjustment parameters are estimated for characterizing the extent of global food price transmissions and the disequilibrium behavior of domestic prices respectively. The results revealed GFPI and all domestic prices are having long run equilibrium relationship. This implies that GFPI and domestic prices never diverge too far from each other and they move together.

### 6.6.2 Long Run Global Food Price Inflation Transmission Elasticities

The long run parameter estimates of cointegration analysis are reported in Table 6.19 for each Model of CPI, CFPI, CNFPI, WFPI and WPI.

Table 6.19
*Global Food Price Transmission Elasticities in Long Run, 2003M1-2014M12*

| **Variables** | **Coefficient estimates** | **Std .Error** | ***t* –value** |
|---|---|---|---|
| **Model 1: LCPI** | | | |
| LGFPI | 0.410* | 0.143 | 2.867 |
| LER | 1.040* | 0.232 | 4.483 |
| LOIL | 0.246* | 0.094 | 2.617 |
| Constant | 2.852* | 0.880 | 3.241 |
| **Model 2: LCFPI** | | | |
| LGFPI | 0.789* | 0.232 | 3.400 |
| LER | 1.214* | 0.353 | 3.439 |
| LOIL | 0.140 | 0.147 | 0.959 |
| Constant | 5.044* | 1.322 | 3.815 |
| **Model 3: LCNFPI** | | | |
| LGFPI[1] | 0.093 | 0.183 | 0.508 |
| LER | 0.615* | 0.107 | 5.747 |
| LOILP | 0.397* | 0.109 | 3.642 |
| **Model 4: LWFPI** | | | |
| LGFPI[1] | 1.037* | 0.125 | 8.296 |
| LER | 0.097 | 0.092 | 1.054 |
| LOILP | 0.055 | 0.067 | 0.821 |
| **Model 5: LWPI** | | | |
| LGFPI[1] | 0.878* | 0.068 | 12.912 |
| LER | 0.101* | 0.050 | 2.02 |
| LOILP | 0.099* | 0.036 | 2.75 |

Note: * indicates significant at 5% level, others are not significant. Critical values for 5% level is 1.645,
[1] indicates HP filtered trend, Dummy is used as exogenous variable, D=1 for food crisis period, D=0 otherwise

Table 6.19 shows that the coefficient for GFPI in each CFPI, WFPI, CPI and WPI model is statistically significantly different from zero at the 5 percent level. This implies that GFPI is influencing domestic price positively and significantly. Therefore, one can conclude that GFPI co-moves with (cointegrated) all domestic food prices (CFPI, WFPI), overall consumer price (CPI), producer price (WPI) except CNFPI indicating that a long run relationship exists between GFP and CFPI, WFPI, CPI, and WPI. The estimated significant coefficient of GFPI implies that GFPI transmits positively and significantly to domestic food and overall prices.

The estimated transmission elasticity indicates that when GFPI increases by one percent, average CPI will increase by 0.41 percent, domestic average consumer food price (CFPI) increases by 0.79 percent, average wholesale food price increases by 1.04 percent and average wholesale price increases by 0.88 percent. All transmission elasticities are positive and significantly different from zero. When the absolute value of transmission elasticities are less than one, it is called incomplete transmission. The results show that global food price transmission elasticities to all domestic prices except for wholesale food price are less than one in Sri Lanka. But, GFPI does not affect nonfood prices significantly even at 10 percent significant level. Global food price transmission elasticity is higher in magnitude for food prices (CFPI, WFPI) compared to CPI, WPI in Sri Lanka.

One interesting point is that global food price transmission significantly increases the domestic food prices on average in Sri Lanka and hence contributes to the overall price inflation. The transmission results of this study are in line with the estimates of GIEWS (global information and early warning system) based statistics. They show that average long run world food price transmission coefficient value is around 0.70 to 80 (Greb *et al*., 2012). It is roughly three quarters of global food price changes are transmitted to domestic prices.

The results in Table 6.19 show that the exchange rate coefficients in most cases are statistically significant and positive. When exchange rate [LKR/US$] increases by one percent, average domestic CPI, CFPI, CNFPI, WPI will increase by 1.04, 1.21, 0.61, 0.10 percent respectively. Further, Table 6.19 shows that the coefficient of crude oil price is also significant in CPI, CNFPI, and WPI models. These results indicate that when oil price increases by one percent, average CPI will increase by 0.25 percent, average CNFP will increase by 0.40 percent. However, the coefficients of oil price are positive but not significant in the case of average CFPI and average WFPI equations.

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As there exist co-integration among the variables, there exists an error correction mechanism, therefore, vector error correction model (VECM) is employed to study short run and long run dynamics. VECM provides useful insights such as short run and long run causality information, exclusively for policy makers.

### 6.6.3 Short Run Relationships

The short run dynamics of global food price transmission to domestic prices are described in this section. In the short run, there may be disequilibrium. The ECM allows us to examine how much response variable will change to a change in GFPI as well as the speed of the change (by ECTt-1). The estimated results for the short run relationships of global food price transmission to domestic prices are reported in Table 6.20.

Table 6.20
*Global Food Price Transmission Results from VECM, 2003M1-2014M12*

| **Variables** | **Model 1 DLCPI** | **Model 2 DLCFPI** | **Model 3 DLCNFPI** | **Model 4 [1]DLWFPI** | **Model 5 [1]DLWPI** |
|---|---|---|---|---|---|
| D(DV(-1)) | 0.092 | 0.353* | -0.141* | 0.214* | 0.097 |
| | [1.094] | [4.181] | [-1.648] | [2.464] | [1.103] |
| D(DV(-2)) | -0.209 | -0.249* | -0.083 | 0.125 | 0.173* |
| | [-2.515] | [-3.017] | [-0.966] | [1.394] | [2.010] |
| D(LGFPI(-1)) | 0.066* | 0.111* | 0.002 | 7.149 | 6.554 |
| | [2.3628] | [2.113] | [0.039] | [0.708] | [0.814] |
| D(LGFPI(-2)) | 0.058* | 0.093 | 0.016 | -8.688 | -7.636 |
| | [1.914] | [1.636] | [0.397] | [-0.846] | [-0.924] |
| D(LUSD(-1)) | 0.089 | 0.078 | 0.149* | 0.364 | 0.400* |
| | [1.506] | [0.715] | [1.884] | [1.470] | [2.111] |
| D(LUSD(-2)) | 0.002 | -0.040 | -0.041 | -0.360 | -0.350* |
| | [0.031] | [-0.374] | [-0.528] | [-1.496] | [-1.835] |
| D(LOILP(-1)) | 0.0003 | -0.019 | 0.019 | 0.007 | 0.014 |
| | [0.033] | [-1.092] | [1.442] | [0.199] | [0.515] |
| LOILP(-2) | -0.007 | -0.030* | 0.012 | 0.021 | 0.041 |
| | [-0.691] | [-1.744] | [0.938] | [0.609] | [1.502] |
| Dummy | 0.004* | ------ | 0.0006 | 0.013 | 0.009 |
| | [2.097] | | [0.289] | [1.551] | 1.453] |
| ECTt-1 | -0.042* | -0.046* | -0.047* | -0.054* | -0.065* |
| | [-6.389] | [-5.23] | [-5.635] | [-2.277] | [-2.094] |

Note; [1] HP trend of GFPI is in the model, DV refers dependent variable, ECT refers error correction term, *refer significant at 5 % level. Critical values for 5% level is 1.645, "t" statistic values in [ ]

In the case of Model 1 (DLCPI), the significant coefficient of GFPI indicates that GFPI increases CPI significantly in the short run. Nevertheless, exchange rate and oil price do not affect CPI significantly in the short run. In the case of Model 2, (DLCFPI), GFPI increases CFPI significantly. Further, exchange rate and oil price do not affect domestic CFPI significantly.

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In addition, the coefficient restriction tests (Wald test) also indicates that GFPI affects domestic CPI and CFPI significantly. In the case of Model 3 (DLCNFPI), Model 4 (DLWFPI) and Model 5 (DLWPI), GFPI does not affect CNFPI, WFPI, and WPI significantly in the short run. The exchange rate has a significant positive impact on CNFPI and WPI. The oil price does not affect these domestic prices significantly. Lagged values of the response variable (domestic prices) account for any persistence in the behavior of the domestic price inflation and also could account for lagged adjustment or expectations of domestic price inflation.

The findings of VECM confirm the heterogeneity of price transmission that implies transmission effects vary for different prices in Sri Lanka. It is also noted that global food price transmission is high for food prices compared to nonfood prices in the short run. The main finding of this section is that GFPI has significant positive effect on CFPI and CPI in the short run suggesting that an increase in GFPI is contributing to general inflation even in short run. Thus, these results suggest that policy makers need to account for global price dynamics in policy formulation.

The last row in Table 6.20 displays the estimated coefficient of error correction term (ECT) for each domestic price response variables of LCPI, LCFPI, LCNFPI, LWFPI, and LWPI. All of the coefficients are statistically significant at the 5 percent level. The larger value of $ECT_{t-1}$ is the greater the response of domestic prices to the previous period's deviation from long run equilibrium. All the coefficients are with correct signs and absolute values of them are less than one. This implies the stability of the corresponding model and each response variable (domestic prices) moves towards the long run equilibrium path. Further, the coefficient value of ECT for each

Model is reported as follows: 4.2 percent for LCPI, 4.6 percent for LCFPI, 4.7 percent for LCNFP, 5.4 percent for LWFPI and 6.5 percent for LWPI of the corresponding disequilibrium error of each system is corrected each month.

The coefficient estimate of the $ECT_{t-1}$ shows that the percentage of the deviation of the actual response variable from its long run level (disequilibrium) is corrected each month. These results of the adjustment speed seem to be lower than the GIEWS's estimates of adjustment speed and the average values of the past literature estimates of adjustment speed.

It is also noted that different speed of adjustment indicates that different price series behave differently for global food price changes. The value of the speed of the adjustment is less than seven percent which is very slow. The slow speed implies that the effects of GFPI changes take a longer time to dissipate. Conforti (2004) has also provided evidence of price transmission of basic food commodities and found incomplete price transmission and that the adjustment speed was slow in his study. Thus, the degree of GFPI transmission to domestic prices is higher in the long run compared to short term.

In practice, it seems that the government intervention in Sri Lanka in the form of subsidies, and price controls, for necessary food items due to political reasons distort the market forces. Therefore, consumers in the domestic market do not face the market price of those goods. Thus, consumer prices in domestic market are not fully adjusted to global food price changes.

Cointegration analysis display the long relationship between variables while ECM describes the short term relationship between variables. The coefficient estimates from cointegration analysis are higher than that of ECM results. In short term, effects are transitory. In long term, effects are accumulated. The significant adjustment speed can cause these difference.

### 6.6.4 Diagnostic Checking

This section presents results of the diagnostic tests. The residual diagnostic tests involve serial correlation test using LM test and heteroscedasticity test using ARCH test. Meanwhile, the parameter stability is tested using CUSUM test. These tests results are shown in Table 6.21.

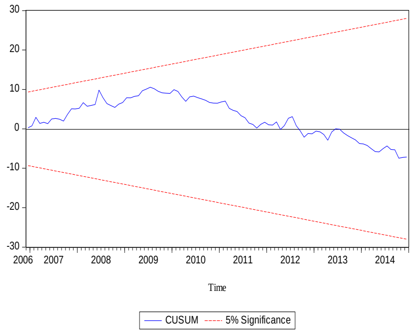
Table 6.21
*Serial Correlation , Heteroscedasticity Tests*

| | **Breusch-Godfrey Serial Correlation: LM Test** | | **Heteroscedasticity Test: ARCH Test** | |
|---|---|---|---|---|
| **Variables** | *F* statistic | Obs*R-squared | *F* statistic | Obs*R-squared |
| LCPI | 1.139 (0.323) | 2.448(0.294) | 2.491 (0.117) | 2.482 (0.115) |
| LCFPI | 0.797 (0.452) | 1.723 (0.422) | 0.359 (0.549) | 0.364 (0.546) |
| LCNFPI | 2.058(0.131) | 4.361 (0.113) | 0.008 (0.928) | 0.008 (0.927) |
| LWFPI | 2.205 (0.114) | 4.661 (0.097) | 0.012 (0.913) | 0.012 (0.912) |
| LWPI[1] | 3.543 (0.030) | 7.342 (0.025) | 1.035 (0.311) | 1.042 (0.307) |

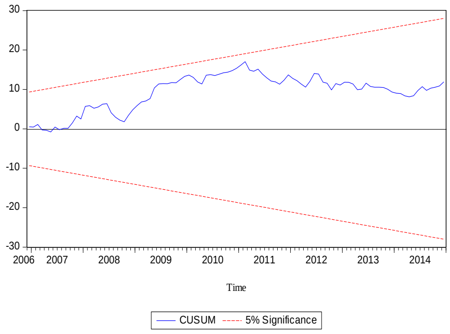
Note [1] indicates there is serial correlation, *p*-values are in parenthesis

These results indicate that the findings from VECM are robust and not affected by serial correlation and heteroscedasticty problems except WPI. One contradiction is seen in WPI model in which residual has serial correlation. In addition, CUSUM test is used to test the parameter stability. CUSUM test is based on the cumulative sum of the recursive residuals. If the cumulative sum goes outside the area between the two critical lines (5 percent significance lines), the test indicates parameter instability.

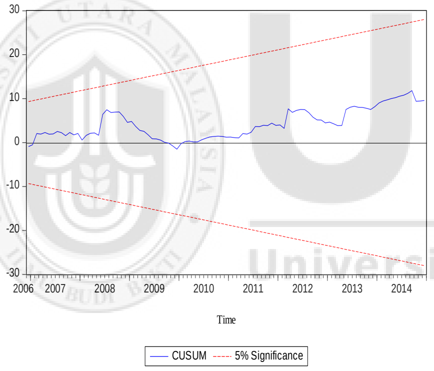
The results of the CUSUM test for all five models are reported in Figure 6.14. According to the results, all models are stable as the cumulative sum of standardized recursive residuals (CUSUM) statistics lie within the two critical lines. Thus, these results provide evidence of stable GFP transmission to domestic prices in Sri Lanka.



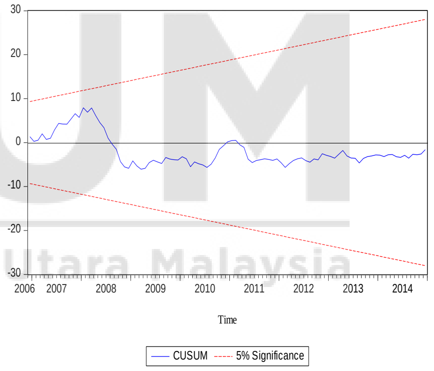

CUSUM- CPI Model



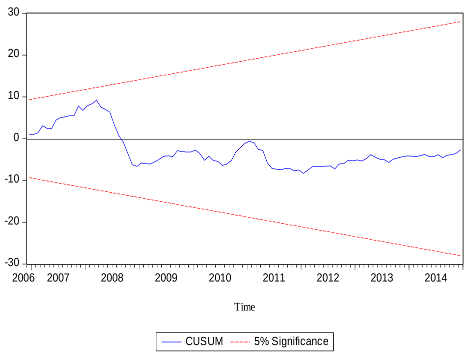

CUSUM- CFPI Model




CUSUM -CNFPI Model




CUSUM-WFPI Model




CUSUM - WPI Model

Figure 6.14
*CUSUM test for Parameter Stability-Global food Price Transmission Model*

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## 6.7 Global Food Price Volatility Transmission to Domestic Prices

This section examines the global food price inflation volatility transmission to domestic prices corresponding to the third objective of the study. The empirical models formulated in Chapter Five: Equation 5.9 to Equation 5.13 are estimated here. ADF and PP unit root tests show that log value of the conditional variance of global food price inflation (LCVGFPI) has a unit root and the order of integration of the series is I(1) which is the same as other variables in the proposed models. The results from cointegration tests of Max-eigenvalue test are reported in Table 6.22

Table 6.22
*Rank Test of Cointegration for Volatility Transmission*

| Model | **Trace Statistics** | | | **Max-Eigenvalue Statistic** | | |
|---|---|---|---|---|---|---|
| | No of CEs | | Test Statistic | No of CEs | | Test Statistic |
| | Ho | $H_1$ | $\lambda_{Trace}$ | Ho | $H_1$ | $\lambda_{Max}$ |
| LCPI | $r = 0*$ | $r \geq 1$ | 70.727 (0.000) | $r = 0*$ | $r = 1$ | 41.214 (0.000) |
| | $r \leq 1*$ | $r \geq 2$ | 29.512 (0.010) | $r = 1*$ | $r = 2$ | 19.003 (0.032) |
| LCFPI | $r = 0*$ | $r \geq 1$ | 66.512 (0.002) | $r = 0*$ | $r = 1$ | 37.356 (0.003) |
| | $r \leq 1$ | $r \geq 2$ | 29.156 (0.193) | $r = 1$ | $r = 2$ | 14.071 (0.455) |
| LCNFPI | $r = 0*$ | $r \geq 1$ | 65.416 (0.000) | $r = 0*$ | $r = 1$ | 36.793 (0.000) |
| | $r \leq 1*$ | $r \geq 2$ | 28.623 (0.013) | $r = 1$ | $r = 2$ | 17.788 (0.050) |
| LWFPI | $r = 0*$ | $r \geq 1$ | 69.839 (0.015) | $r = 0*$ | $r = 1$ | 32.883 (0.040) |
| | $r \leq 1$ | $r \geq 2$ | 36.956 (0.174) | $r = 1$ | $r = 2$ | 17.128(0.447) |
| LWPI | $r = 0*$ | $r \geq 1$ | 73.331(0.006) | $r = 0*$ | $r = 1$ | 37.856 (0.009) |
| | $r \leq 1$ | $r \geq 2$ | 35.475(0.226) | $r = 1$ | $r = 2$ | 16.294(0.518) |

*Note: p*-values are in parenthesis, *r* = number of cointegration,
* denotes Ho is rejected at 5 % level., CE:cointegration equation,

Table 6.22 exhibits that there are two cointegration vectors for some models. However, in order to analyse the objective of global food price inflation volatility

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transmission to domestic prices, one cointegration equation is selected for the analysis. Finally, these results indicate that at least one cointegration exists in each model.

### 6.7.1 Long Run Volatility Transmission Elasticities:

The long run transmission elasticities of domestic prices with respect to global food price inflation volatility are reported in Table 6.23.

Table 6.23
*Global Food Price Inflation Volatility Transmission Elasticities in the Long run*

| **Variables** | **Coefficient estimates** | **Std.Error** | ***t* -value** |
|---|---|---|---|
| | **Model 1: LCPI** | | |
| LCVGFPI | 0.078* | 0.027 | 2.888 |
| LER | 0.547* | 0.055 | 9.945 |
| LOIL | 0.550* | 0.054 | 10.185 |
| constant | -- | --- | --- |
| | **Model 2: LCFPI** | | |
| LCVGFPI | 0.191* | 0.022 | 8.681 |
| LER | 1.955* | 0.264 | 7.402 |
| LOIL | 0.374* | 0.058 | 6.448 |
| constant | 6.017* | 1.033 | 5.824 |
| | **Model 3: LCNFPI** | | |
| LCVGFPI | 0.025 | 0.024 | 1.025 |
| LER | 0.664* | 0.046 | 14.529 |
| LOILP | 0.437* | 0.045 | 9.711 |
| | **Model 4: LWFPI** | | |
| LCVGFPI | 0.130* | 0.019 | 6.842 |
| LER | 0.080 | 0.418 | 0.191 |
| LOILP | 0.071 | 0.077 | 0.922 |
| Trend | 0.008* | 0.001 | 8.000 |
| | **Model 5: LWPI** | | |
| LCVGFPI | 0.096* | 0.012 | 8.190 |
| LER | 0.134 | 0.260 | 0.515 |
| LOILP | 0.188* | 0.048 | 4.000 |
| Trend | 0.006* | 0.001 | 6.808 |

The results indicate that volatility of global food price inflation is highly significant in influencing domestic prices except CNFPI in the long run. The coefficient estimates of LCVGFPI indicate that when global food price inflation volatility increases by one percent, average CPI increases by 0.078 percent, average CFPI increases by 0.191 percent, average WFPI increases by 0.130 percent, and average WPI increases by 0.096 percent. These elasticity values show that domestic consumer food price is affected more by global food price inflation volatility compared to the other domestic prices. Exchange rate and oil prices also determine consumer food prices.

### 6.7.2 Short Run Relationships

Short run dynamics of global food price volatility transmission to domestic prices are analysed in this section. Table 6.24 displays the short run estimates of the global food price volatility transmission model.

According to Table 6.24, volatility of global food price inflation does not play an important role in the short run even it has a significant impact. However, the magnitude of the transmission is very negligible. Exchange rate depreciation has a positive and significant impact on only WPI and WFPI. However, GFPI volatility does not affect domestic prices significantly in the short run.

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Table 6.24
*Short Run Transmission Effects of Global Food Price Inflation Volatility*

| Variable | **Model 1 DLCPI** | **Model 2 DLCFPI** | **Model 3 DLCNFPI** | **Model 4 DLWFPI** | **Model 5 DLWPI** |
|---|---|---|---|---|---|
| D(DV(-1)) | 0.255* | 0.454* | -0.110 | 0.208* | 0.116 |
| | [2.994] | [5.603] | [-1.288] | [2.460] | [1.349] |
| D(DV(-2)) | -0.159 | -0.241* | -0.049 | 0.134 | 0.165* |
| | [-1.827] | [-2.913] | [-0.561] | [1.528] | [1.914] |
| D(LCVGFPI(-1)) | -0.003* | -0.007* | -0.002 | -0.001 | -0.008 |
| | [-2.832] | [-2.904] | [-1.425] | [-0.307] | [-2.047] |
| D(LCVGFPI(-2)) | -0.0001 | 0.000 | -0.002* | 0.003 | 0.002 |
| | [-0.184] | [0.201] | [-1.877] | [0.711] | [0.489] |
| LUSD(-1) | 0.069 | 0.054 | 0.138* | 0.344 | 0.396* |
| | [1.111] | [0.493] | [1.742] | [1.435] | [2.143] |
| LUSD(-2) | -0.009 | -0.117 | -0.051 | -0.431* | -0.371* |
| | [-0.144] | [-1.051] | [-0.644] | [-1.856] | [-1.988] |
| LOILP(-1) | 0.0176* | 0.024 | 0.019 | 0.032 | 0.024 |
| | [1.908] | [1.524] | [1.695] | [0.978] | [0.906] |
| LOILP(-2) | 0.007 | 0.012 | 0.014 | 0.042 | 0.055 |
| | [0.782] | [0.802] | [1.165] | [1.270] | [2.050] |
| ECTt-1 | -0.026* | -0.045* | 0.045* | -0.104* | -0.101* |
| | [-5.002] | [-3.773] | [-5.245] | [-3.144] | [-2.522] |

Note: * indicates significant at 5% level, ECT refers error correction term,
Critical values for 5% level is 1.645, *"t"* statistic values in [ ],

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The last row of Table 6.24 display all estimated coefficients of the $ECT_{t-1.}$ All coefficients have a negative sign and are statistically significant at 5 percent level. The negative sign indicates that each response variable moves towards the long run equilibrium time path. The absolute value of the coefficient of $ECT_{t-1}$ is less than one. This indicates that the system is not explosive and also indicates the stability of the corresponding model. The estimate of adjustment coefficient for DLCPI, DLCFPI DLCNFPI models shows that the disequilibrium error (the discrepancy between long term and short term response variable) is corrected in the speed of less than 5 percent in every month. However, the speed of the adjustment for DLWFPI, and DLWPI is around 10 percent. It is interesting to note that adjustment speed of error correction differs for different prices. It is important to note that CPI and CFPI response variables have lowest adjustment speeds of three and five percent respectively.

### 6.7.3 Diagnostic Checking

This section presents the results of residual diagnostic tests and coefficient stability test in Table 6.25. The residual diagnostic tests involve serial correlation test using LM test and heteroscedasticity test using ARCH test. These residual diagnostic tests results indicate that the findings from VECM are robust and not affected by serial correlation and heteroscedasticty problems in all models except WP model. Because, the null hypothesis of no serial correlation, no heteroscedasticity are not rejected by *F* test and Chi-square test for each model is greater than 0.05. One contradiction is seen in WPI model in which residual has a serial correlation.

Table 6.25
*Diagnostic Tests of Volatility Transmission Model*

| **Models** | **Breusch-Godfrey Serial Correlation LM Test** | | **Heteroscedasticity Test: ARCH Test** | |
|---|---|---|---|---|
| | ***F* statistic** | **Obs*R$^2$-** | ***F* statistic** | **Obs*R$^2$** |
| LCPI | 0.616 (0.541) | 1.335 (0.513) | 2.256 (0.135) | 2.252 (0.133) |
| LCFPI | 0.310 (0.734) | 0.675 (0.713) | 0.174 (0.677) | 0.176 (0.674) |
| LCNFPI | 2.093(0.150) | 2.234 (0.135) | 0.009 (0.924) | 0.009 (0.923) |
| LWFPI | 1.351 (0.262) | 2.916 (0.232) | 0.206 (0.650) | 0.209 (0.647) |
| LWPI | 6.311 (0.013)$^{\#}$ | 6.576 (0.010)$^{\#}$ | 1.150 (0.285) | 1.157 (0.282) |

Note $^{\#}$ indicates there is serial correlation, but VEC residual serial Correlation LM test shows that no serial correlation, *p*-values are in parenthesis. Obs*R$^2$ ~Chi-Square distribution,

Meanwhile, CUSUM test is carried out to test the parameter stability. The parameter stability test results are shown in Figure 6.15 that indicates that the cumulative sum of standardized recursive residuals (CUSUM) statistics lie within the area between the two critical lines. This indicates that all five volatility transmission models are stable.

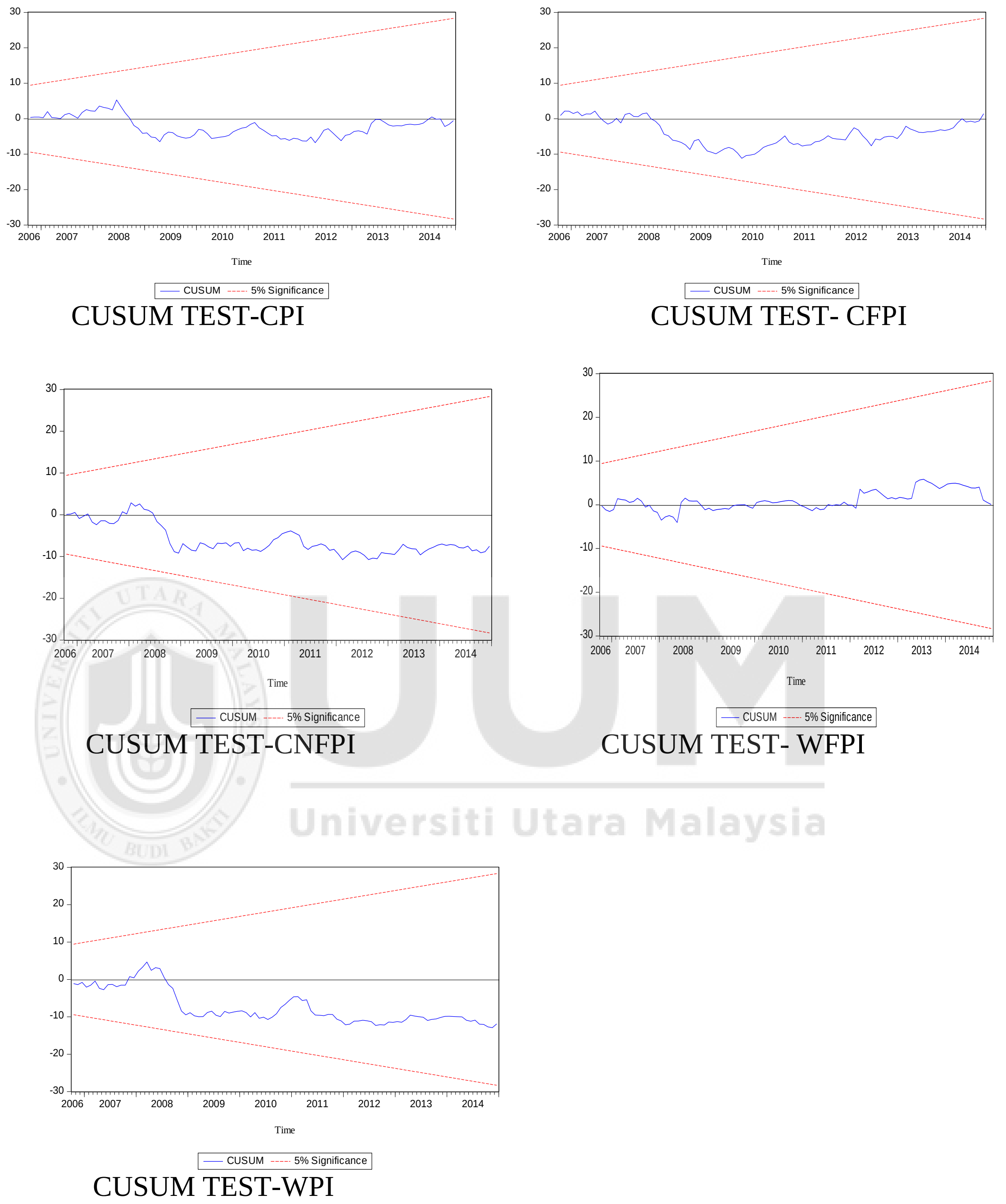


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Figure 6.15
*CUSUM Test for Parameter Stability –Global Food Price Volatility Transmission Model*

In sum, global food price inflation volatility affects significantly all domestic prices except nonfood price in Sri Lanka. In addition, results of this analysis are robust as indicated by all the diagnostic tests. Volatility transmission effects take a long time to dissipate which is indicated by the speed of the adjustment of each response variable.

## 6.8 Transmission of Food Prices to Overall Consumer Price in Domestic Markets

This section analyses the food price transmission to overall consumer prices in the domestic market to achieve the fourth objective of the study. The optimal lag of 2 is selected based on the selection criteria of SIC and HQ. Then, the number of cointegration relationship is identified based on Maximum eigenvalue tests. The results obtained from the cointegration test for domestic food price transmission are reported in Table 6.26. It shows that there is at least one cointegration vector for each model.

Table 6.26
*Rank Test for Cointegration Analysis for Domestic Food Price Transmission*

| **Model** | **Trace Statistics** | | | **Max-Eigenvalue Statistic** | | |
|---|---|---|---|---|---|---|
| | **No of CEs** | | **Test Statistic** | **No of CEs** | | **Test Statistic** |
| | **Ho** | **$H_1$** | $\lambda_{Trace}$ | **Ho** | **$H_1$** | $\lambda_{Max}$ |
| LCPI[1] | $r = 0*$ | $r \geq 1$ | 91.672 (0.000) | $r = 0*$ | $r = 1$ | 53.730(0.000) |
| | $r \leq 1*$ | $r \geq 2$ | 37.941 (0.025) | $r = 1$ | $r = 2$ | 21.586(0.063) |
| LCPI[2] | $r = 0*$ | $r \geq 1$ | 95.976 (0.000) | $r = 0*$ | $r = 1$ | 53.121(0.000) |
| | $r \leq 1*$ | $r \geq 2$ | 42.855(0.006) | $r = 1*$ | $r = 2$ | 22.848(0.042) |

Note: [1] LCPI=f(LCFPI, LUSD, LOILP, Dummy), [2]: LCPI=f(LWFPI, LUSD, LOILP, Dummy)
*p*- values are in parenthesis. * significant at 5 percent level.

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### 6.8.1 Long Run Relationship

The results of cointegration analysis for Equation 5.14 and Equation 5.15 are given in Table 6.27.

Table 6.27
*Long Run Price Transmission from Domestic Food Price to Overall Consumer Price*

| Variable | Model 1 | Variable | Model 2 |
|---|---|---|---|
| | **LCPI** | | **LCPI** |
| LCFPI | 0.587* | LWFPI | 0.468* |
| | (0.031) | | (0.052) |
| | [18.935] | | [9.000] |
| LER | 0.400* | LER | 0.429* |
| | (0.081) | | (0.151) |
| | [4.938] | | [2.860] |
| LOILP | 0.137* | LOILP | 0.212* |
| | (0.020) | | (0.037) |
| | [6.850] | | (5.729) |
| C | 0.403 | C | 0.240 |
| | (0.288) | | 0.548 |
| | [1.399] | | [0.439] |

Note: t statistics in [ ], standard error is in parenthesis, * significant at 5 % level

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It shows that both food prices (CFPI and WFPI) significantly influences CPI. The food price transmission elasticity of CPI with respect to CFPI is 0.59. This implies that one percent increase in CFPI will increase CPI by 0.59 percent. In contrast, for an one percent increase in WFPI, CPI will increase by 0.47 percent. This specifies that CFPI influences CPI more compared to WFPI in the long run.

### 6.8.2 Short Run Relationships

The estimated results of VECM reported in Table 6.28 show that CFPI and WFPI impact CPI significantly and positively in the short run. Therefore, both CFPI and WFPI influence CPI not only in the long run but also in the short run. It is also found that the influence of CFPI on CPI is higher than that of WFPI in the long run and in the short run. In addition, there is a positive impact of exchange rate and oil price on CPI.

Table 6.28

*Short run Transmission from Domestic Food Prices to CPI*

| **Variable** | **Model 1** | **Variable** | **Model 2** |
|---|---|---|---|
| | **DLCPI** | | **DLCPI** |
| D(LCPI(-1)) | -0.109 | D(LCPI(-1) | 0.110 |
| | [-0.889] | | [1.291] |
| D(LCPI(-2)) | -0.209 | D(LCPI(-2)) | -0.234 |
| | [-1.686] | | [-2.755] |
| D(LCFPI(-1)) | 0.231* | D(LWFPI(-1)) | 0.037* |
| | [3.524] | | [1.603] |
| D(LCFPI(-2)) | -0.017 | D(LWFPI(-2)) | 0.047 |
| | [-0.253] | | [1.966] |
| D(LER(-1)) | 0.098 | D(LER(-1)) | 0.149* |
| | [1.615] | | [2.368] |
| D(LER(-2)) | -0.006 | D(LER(-2)) | -0.007 |
| | [-0.105] | | [-0.121] |
| D(LOILP(-1)) | 0.016* | D(LOILP(-1)) | 0.001 |
| | [1.846] | | [1.247] |
| D(LOILP(-2)) | 0.005 | D(LOILP(-2)) | -0.001 |
| | [0.616] | | [-0.066] |
| Dummy | 0.004* | Dummy | 0.003 |
| | [2.562] | | [1.851] |
| $ECT_{t-1}$ | -0.141* | $ECT_{t-1}$ | -0.079* |
| | [-5.965] | | [-6.365] |

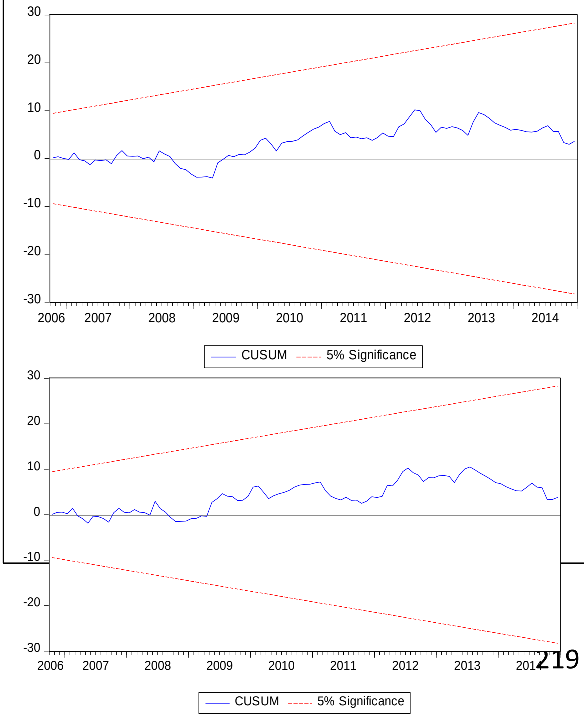
Note: t statistic in [ ], * indicates significant at 5% level

The last row of the Table 6.28 displays the estimates of the speed of adjustment of CPI due to the shocks of CFPI in model 1 and the shocks of WFPI in model 2. The coefficients of error correction term in both model carry negative sign and are statistically significant. The speed is higher in the case of shocks from CFPI compared to WFPI. In the case of CFPI shocks, 14 percent of the disequilibrium is corrected each month while 8 percent of disequilibrium is corrected each month for the case of WFPI. WFPI transmission effects take long time to dissipate than that of CFPI transmission effects to CPI because the speed of adjustment in the case of WFPI shocks is very slow compared to the shocks of CFPI in domestic markets.

### 6.8.3 Diagnostic Checking

The results from serial correlation test and heteroscedasticity test show that the estimated model CPI[1] is robust. Serial correlation LM test $F$ statistic =0.787 ($p$=0.376) and ARCH test, $F$ statistic =0.400 ($p$=0.528) both indicate that there are no problems of serial correlation and heteroscedasticity. In the case of Model CPI2, the residual and stability tests indicated that the estimated model is robust. Serial correlation LM test statistic, F statistic is 1.748 ($p$=0.178) indicating that there is no serial correlation as the null hypothesis is not rejected. The ARCH test shows that there is no heteroscedasticity in residual. $F$ statistics is 0.103 ($p$=0.748).

The CUSUM test results given in Figure 6.16 indicate that the parameters in both models are stable as the cumulative sum of standardized recursive residuals (CUSUM) statistics lie within the two critical lines.



## 6.9 Granger-Causality Analysis

This section intends to support and validate the results found in Section 6.6, Section 6.7, and Section 6.8 of the transmission effects of various forms. The results of pairwise Granger causality test, block causality test under VAR framework, and block causality test under VECM framework are reported in Table 6.29, Table 6.30 and Table 6.31 respectively.

### 6.9.1 Pairwise Granger Causality Test

The results of pairwise Granger causality tests are reported in Table 6.29.

Table 6.29
*Pairwise Granger Causality Test Results-Inflation Series, 2003M1-2014M12*

| Null Hypothesis | | | ***F*-Statistic** | **Prob.** |
|---|---|---|---|---|
| D(LGFPI) | does not Granger cause | D(LCPI) | 9.471* | 0.00 |
| D(LGFPI) | does not Granger cause | D(LCFPI) | 5.765* | 0.01 |
| D(LGFPI) | does not Granger cause | D(LCNFPI) | 4.311* | 0.02 |
| D(LGFPI) | does not Granger cause | D(LWFPI) | 4.151 * | 0.02 |
| D(LGFPI) | does not Granger cause | D(LWPI) | 9.607* | 0.00 |
| D(LCFPI) | does not Granger cause | D(LCPI) | 3.776* | 0.03 |
| D(LWPI) | does not Granger cause | D(LCFPI) | 7.255* | 0.00 |
| D(LWPI) | does not Granger cause | D(LCPI) | 7.829* | 0.00 |
| D(LWPI) | does not Granger cause | D(LCNFPI) | 4.501* | 0.01 |
| D(LWFPI) | does not Granger cause | D(LCFPI) | 5.315* | 0.01 |
| D(LWFPI) | does not Granger cause | D(LCPI) | 4.501* | 0.01 |
| D(LCNFPI) | does not Granger cause | D(LCPI) | 4.164* | 0.02 |
| D(LCVGFPI) | does not Granger cause | D(LCPI) | 1.657 | 0.19 |
| D(LCVGFPI) | does not Granger cause | D(LCFPI) | 3.059 | 0.05 |
| D(LCVGFPI) | does not Granger cause | D(LWFPI) | 3.017 | 0.05 |
| D(LCVGFPI) | does not Granger cause | D(LWPI) | 2.081 | 0.13 |

Note: "*" significant at 5 percent level, CVGFPI refers conditional variance of global food price inflation

The *p*-values given in Table 6.29 indicate that each null hypothesis of no–causality, is rejected at the five percent level. These results show that global food price Granger-causes domestic prices (CPI, CFPI, CNFPI, WPI, and WFPI) significantly. But, global food price inflation volatility does not Granger cause domestic prices significantly. Based on these results, one can conclude that GFP would help to predict these domestic mean price series. These results imply that domestic market depends on world market situation. These results indicate that global food price inflation Granger-cause all domestic food price inflation and nonfood price inflation and general price inflation significantly in the short run.

Table 6.29 reports the evidence of causality running from global food price inflation to domestic price inflation. As Sri Lanka is a price taker, the direction of causality from global food price inflation to domestic price inflation is consistent with international economic trade theory.

The results indicate that GFPI inflation has a causal relationship with five domestic price inflations while WFPI has Granger causal relationship with CPI and CFPI domestic prices while WPI has Causal relationship with CPI, CFPI CNFPI domestic prices.

The above linkages are represented in a schematic form in Figure 6.17 in order to understand the direction of short run causality relation and display vividly. The direction of the causal relationship is marked by the arrow mark. It shows that global food price inflation Granger causes CFPI, WFPI, CNFPI, WPI, and CPI.

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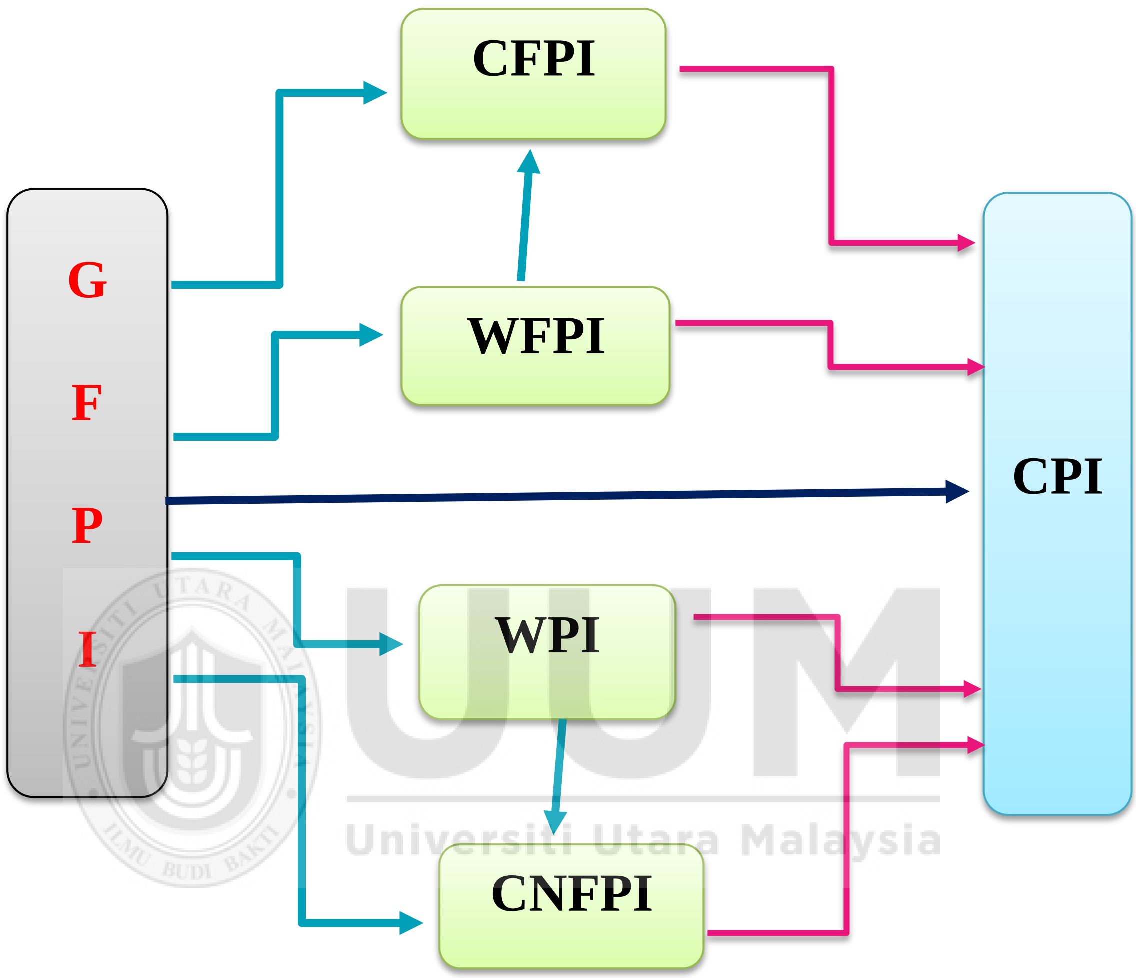


Note: GFPI, CPI, CFPI , WFPI, CNFPI and WPI in this figure refer inflation of those prices.

Figure 6.17
*Inflation Causality Linkages*

Further, Block causality (Wald) test is carried out under VAR and VECM framework in order to check the consistency of the causality results.

### 6.9.2 Block Causality Test

First, the block causality under VAR framework is investigated for the causal relationship between domestic price inflations and global food price inflation, global food price inflation volatility. The results from Block causality under VAR framework are reported in Table 6.30.

Table 6.30
*Wald Test Statistic* $\chi^2$ *Values for Block Causality under VAR Framework*

| **Excluded variables** | **Response Variables** | | | | |
|---|---|---|---|---|---|
| | **Model 1** $\Delta LCPI$ | **Model 2** $\Delta LCFPI$ | **Model 3** $\Delta LCNFPI$ | **Model 4** $\Delta LWFPI$ | **Model 5** $\Delta LWPI$ |
| $\Delta LGFPI$ | 9.903* | 11.653* | 2.375 | 16.159* | 20.187* |
| | (0.007) | (0.002) | (0.305) | (0.000) | (0.000) |
| $\Delta$ (LCVGFPI) | 3.314 | 6.118* | 3.749 | 6.034* | 4.161 |
| | (0.197) | (0.046) | (0.153) | 0.048) | (0.125) |

Note: *p*-values in parenthesis,
* significant at 5 % level

The estimates of Chi-square test statistic and corresponding *p*-values are reported in Table 6.30. It shows that global food price inflation Granger cause CPI, CFPI, WFPI, and WPI significantly. This test helps to answer whether to include the variable in the system. In addition, the table shows that global food price inflation volatility growth Granger cause only domestic food price inflation (CFPI and WFPI) whereas bivariate Granger causality analysis indicated that they are not significant.

Further, the results from Block Causality under VECM Framework reported in Table 6.31 show that GFPI inflation Granger-cause CPI, CFPI. But, GFPI does not Granger cause CNFPI, WFPI, and WPI in the short run. It is true that wholesalers have stock in general therefore, they do not change immediately wholesale price according to global prices. But retailer sellers change their price in the short run so that consumer food prices, hence overall consumer prices change according to world market prices. World food prices do not generally affect domestic nonfood prices in the short run. It is possible for second round effects in the long run. In addition, volatility of global food price inflation also Granger-cause CPI and CFPI. However, it is interesting to note that the uncertainty generated by GFPI Granger cause WPI significantly. In general, wholesale decision makers are concerned about the market uncertainty and that may be the reason that the volatility of global food price inflation Granger cause wholesale price inflation.

Table 6.31

*Wald Test Statistic* $\chi^2$ *Values for Block Causality under VECM Framework*

| Excluded Variables | Response Variables | | | | |
|---|---|---|---|---|---|
| | **Model 1** $\Delta LCPI$ | **Model 2** $\Delta LCFPI$ | **Model 3** $\Delta LCNFPI$ | **Model 4** $\Delta LWFPI$ | **Model 5** $\Delta LWPI$ |
| $\Delta LGFPI$ | 14.116* (0.000) | 9.122* (0.010) | 0.205 (0.903) | 2.459 (0.292) | 1.714 (0.424) |
| D(LCVGFPI) | 8.832* (0.012) | 12.426* (0.002) | 4.221 (0.121) | 1.052 (0.591) | 7.526* (0.023) |

Note: *p*- values of Wald test statistics, ( $\chi^2$ ) are in parenthesis, * Significant at 5 percent level,

Section 6.9.1 and section 6.9.2 covered only short run aspects. They have not shown causality results in the long run situation. Thus, the next section provides long run Granger-causality results.

### 6.9.3 Long Run Causality

It is also useful look at long run causality results that are presented in Table 6.32. The coefficients of ECT in GFPI transmission cointegration equation and GFPI volatility transmission equation are significantly different from zero. Thus, GFPI inflation and

GFPI inflation volatility Granger cause all the food and nonfood prices significantly in the long run in Sri Lanka.

Table 6.32
*Long Run Causality Measure, 2003M1-2014M12*

| | Response Variable (DV) | | | | |
|---|---|---|---|---|---|
| **Variable** | **Model 1 DLCPI** | **Model 2 DLCFPI** | **Model 3 DLCNFPI** | **Model4 DLWFPI** | **Model 5 DLWPI** |
| $ECT_{t-1}^{a}$ | -0.042* [-6.389] | -0.046* [-4.201] | -0.046* [-5.635] | -0.054* [-2.276] | -0.065* [-2.094] |
| $ECT_{t-1}^{b}$ | -0.026* [-5.002] | -0.045* [-3.773] | -0.045* [-5.245] | -0.104* [-3.144] | -0.101* [-2.522] |

Note: DV refers dependent variable, * Significant at 5 percent level, "*t*" statistic values in [ ],
[a] GFPI mean inflation long run causality ,
[b] GFPI inflation volatility long run causality

In sum, Causality test results are given in Table 6.30- 6.32 show that global food price Granger causes domestic prices except nonfood prices in Sri Lanka in the short run. ECM analysis shows that global food price inflation Granger causes domestic prices in the long run (Table 6.32). Long run causality information is indicated by the negative sign and significance of the coefficient of ECT. Therefore, GFP inflation helps to predict the domestic price inflation series. These results imply that domestic market depends on the world market situation. It is also noted that there is no two way causal relationship between GFPI and domestic prices that are consistent with small country trade theory. From the causality results, one can conclude that GFPI inflation and volatility of GFPI inflation Granger cause domestic food prices in the short run as well as in the long run.

## 6.10 Causality Relationship between Food Price Inflation and Volatility of Food Price Inflation

This section is presented here to supplement some evidence of some features of food price dynamics though it is not specified in the objectives in the study. The dynamic relationship between inflation level and uncertainty (variance) of food price inflation is analysed using Granger causality analysis in this section.

Empirical results of bivariate Granger causality analysis and block causality under VEC framework are reported in Table 6.33 and 6.34 respectively. First, the results from bivariate Granger causality analysis are reported in Table 6.33. It shows the evidence of causality relationship between food price inflation and food price inflation uncertainty series. According to these results, all inflation series Granger causes its own volatility of inflation series in the short run. The *p*-values of the *F* test statistics for the null hypothesis that inflation does not Granger cause uncertainty are given in the last column. It indicates that all null hypotheses are rejected at five percent level. This evidences support the Friedman-Ball hypothesis.

Table 6.33
*Bivariate Granger Causality Test between Inflation and Inflation Volatility*

| Null Hypothesis | | | *F* Statistic | *p*-value |
|---|---|---|---|---|
| INFCFPI | does not Granger cause | CVCFPI | 8.18* | 0.000 |
| INFCPI | does not Granger cause | CVCPI | 11.58* | 0.000 |
| INFGFPI | does not Granger cause | CVGFPI | 3.23* | 0.042 |
| INFWFPI | does not Granger cause | CVWFPI | 2.65* | 0.074 |
| INFWPI | does not Granger cause | CVWPI | 5.36* | 0.022 |

Note: CV… refers for condition variance of the inflation variable, * indicates significance at 5 % level

However, Cukierman–Meltzer (1986) hypothesis, inflation uncertainty affects inflation, is not supported by the bivariate Granger causality analysis. But, block causality test under VEC framework supports Cukierman-Meltzer hypothesis. Table

6.34 reports these evidence. According to the Table 6.34, all *p* values of for the test statistics are less than 0.05. Thus, the null hypothesis related to CFPI and CPI are rejected at five percent level. Therefore, one can conclude that conditional variance of CFPI, CPI inflation series Granger cause its own inflation series significantly and positively.

Table 6.34
*Wald Statistic* $\chi^2$ Values for *Block Causality under VEC Framework*

| Null Hypothesis | | | Chi$^2$ Statistic | *p*-values |
|---|---|---|---|---|
| D(CVCFPI) | does not Granger cause | INFCFPI | 6.758* | 0.034 |
| D(CVCPI) | does not Granger cause | INFCPI | 7.251* | 0.027 |
| D(CVWFPI) | does not Granger cause | INFWFPI | 5.331 | 0.069 |
| D(CVWPI) | does not Granger cause | INFWPI | 5.880 | 0.052 |

Note: CV… refers for condition variance of the inflation variable,
* indicates significance at 5 % level

The analysis is further extended based on the transmission theory. Inflation dynamics of one food price can affect the price inflation volatility of other prices or volatility of one price inflation may affect the price inflation dynamics of others. Table 6.35 reports the evidence of price inflation of one food Granger-cause inflation volatility of other prices. For example, inflation of CFPI and GFPI Granger cause wholesale food price inflation volatility. Wholesale food price inflation also Granger-causes volatility of consumer food price inflation. Nonfood price inflation also Granger-causes overall inflation volatility.

In contrast, volatility of inflation of one price Granger-cause another price inflation is not common. Only one example is found. Only volatility of food price inflation Granger cause consumer nonfood price inflation.

Table 6.35

*Examples for Inflation Causal Relationship with Volatility of other Price Inflation*

| **Null Hypothesis** | | | ***F*- Statistic** | ***p*-values** |
|---|---|---|---|---|
| INFCFPI | does not Granger cause | CVWFPI | 4.314* | 0.015 |
| INFGFPI | does not Granger cause | CVWFPI | 3.305* | 0.039 |
| INFWFPI | does not Granger cause | CVCFPI | 5.526* | 0.005 |
| INFWPI | does not Granger cause | CVCFPI | 5.974* | 0.003 |
| INFCNFPI | does not Granger cause | CVCPI | 14.102* | 3E-05 |

Note: CV refers for condition variance of the inflation variable,
* significance at 5 % level

There is another type of relationship between the volatility of one food price inflation Granger-cause volatility of another food price inflation. Examples are reported in Table 6.36.

Table 6.36

*Causal Relationship between Different Food Price Inflations Volatility Series*

| **Null Hypothesis** | | | ***F* Statistic** | ***p*-values** |
|---|---|---|---|---|
| CVGFPI | does not Granger cause | CVWPI | 5.229* | 0.006 |
| CVWFPI | does not Granger cause | CVWPI | 7.068* | 0.001 |
| CVWPI | does not Granger cause | CVWFPI | 4.671* | 0.011 |
| CVCFPI | does not Granger cause | CVCPI | 4.068* | 0.019 |
| CVCFPI | does not Granger cause | CVWPI | 5.727* | 0.004 |
| CVCFPI | does not Granger cause | CVWFPI | 6.644* | 0.002 |

Note: CV refers for condition variance of the inflation variable, * indicates significance at 5 % level

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In sum, the results are supportive of both the Friedman-Ball and the Cukierman-Meltzer

(1986) hypotheses. In addition, there are some evidence for price inflation volatility of one food price affects the volatility of related other food price inflation and food price inflation level. Therefore, the Central Bank of Sri Lanka should try to stabilize the inflation rate in the face of inflationary shocks. The results of the study are consistent with the results of Gilbert and Morgan (2010) who say that price levels and price volatilities are likely to be positively associated.

## 6.11 Impulse Response Function Analysis

This section presents the impulse response function (IRF) analysis. A positive one standard deviation shock to the global food prices is simulated and the IRFs are exhibited in Figure 6.18-Figure 6.22. The x axis on each graph shows the time horizon in months over which the IRF are performed. The solid line represents the point estimates of the IRF with 5 percent standard error bands (broken line) on either side of the IRF to judge the statistical significance of the IRF. A positive shock to global food prices has an immediate positive impact on domestic food prices with the impacts disappearing in a delayed transmission effects to domestic prices. The impulse responses of INFCPI in Figure 6.18 indicate the direct inflationary effects due to INFGFPI increases for some time then dies out to zero. A positive shock to GFPI has an immediate significant positive impact on domestic CFPI and CFPI increase up to three months then declines very slowly up to 10 months. The magnitude of the response is positive for longer periods. A shock in GFPI increases CNFPI till up to three months then start to decay to zero for more than 10 months very slowly (Figure 6.19). A positive shock to GFPI can also induce CPI, WFPI, and WPI in the domestic market. Due to shock to GFPI increase CPI, WFPI, and WPI up to two months and then declines slowly for 9-10 months as shown in Figures 6.20, Figure 6.21, and Figure 6.22 respectively. The responses of these prices remain positive for longer periods. This longer period effects may be due to second round effects. Every response of domestic prices increases for some times and then dies out to zero. In sum, global food price induces all domestic prices, CPI, CFPI CNFPI WFPI and WPI in Sri Lanka.

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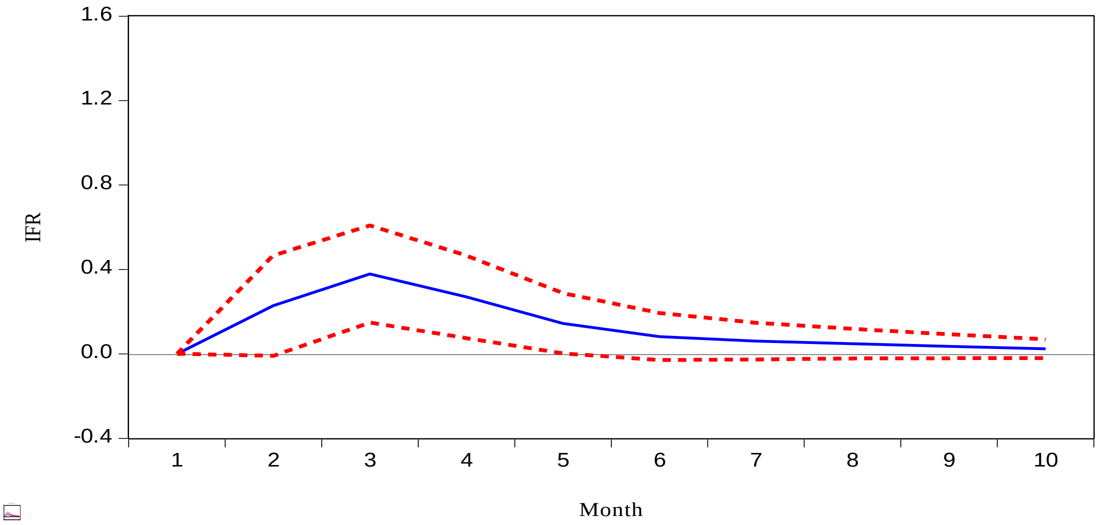


Figure 6.18
*Impulse Response of INFCFPI to INFGFPI*

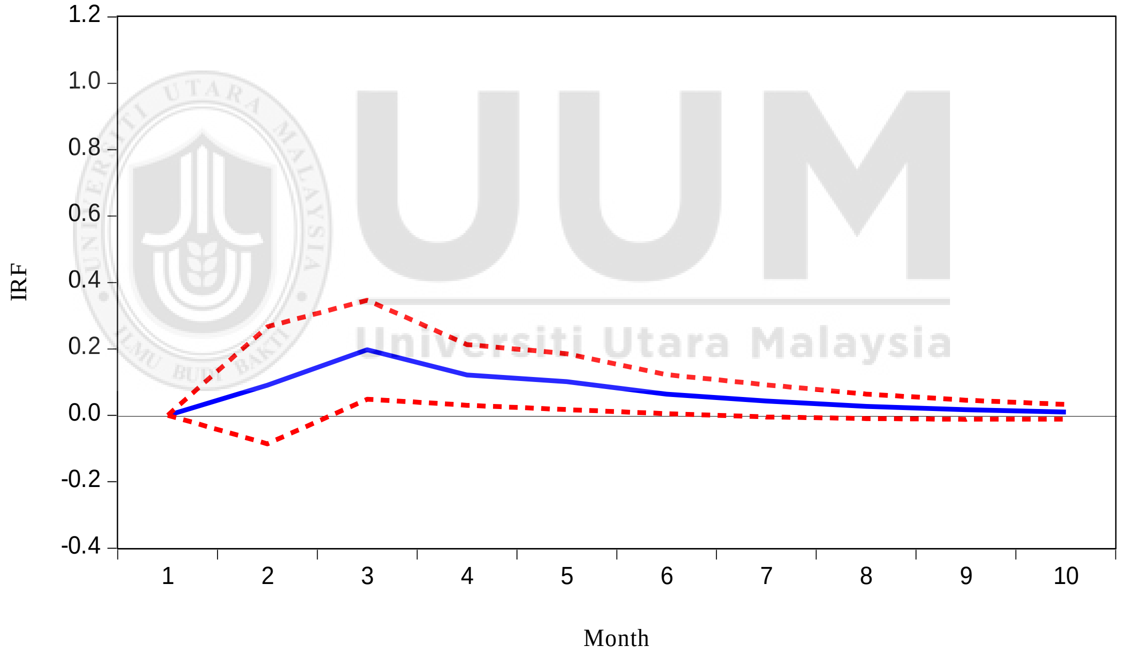


Figure 6.19
*Impulse Response of INFCNFPI to INFGFPI*

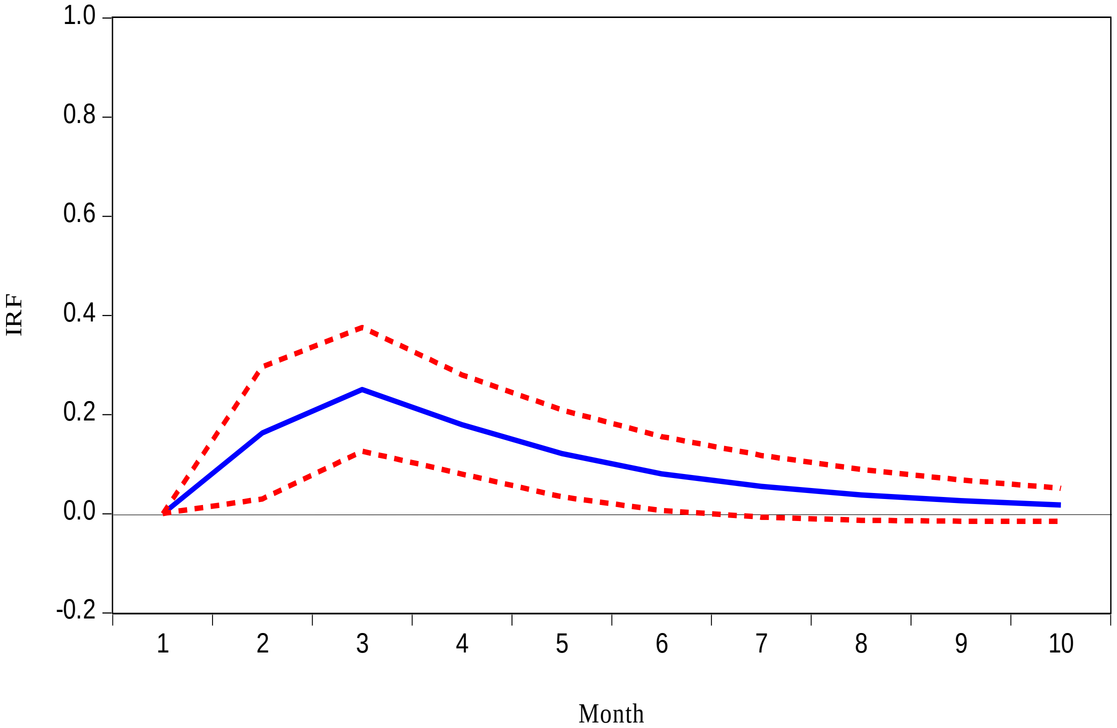


Figure 6.20
*Impulse Response of INFCPI to INFGFPI*

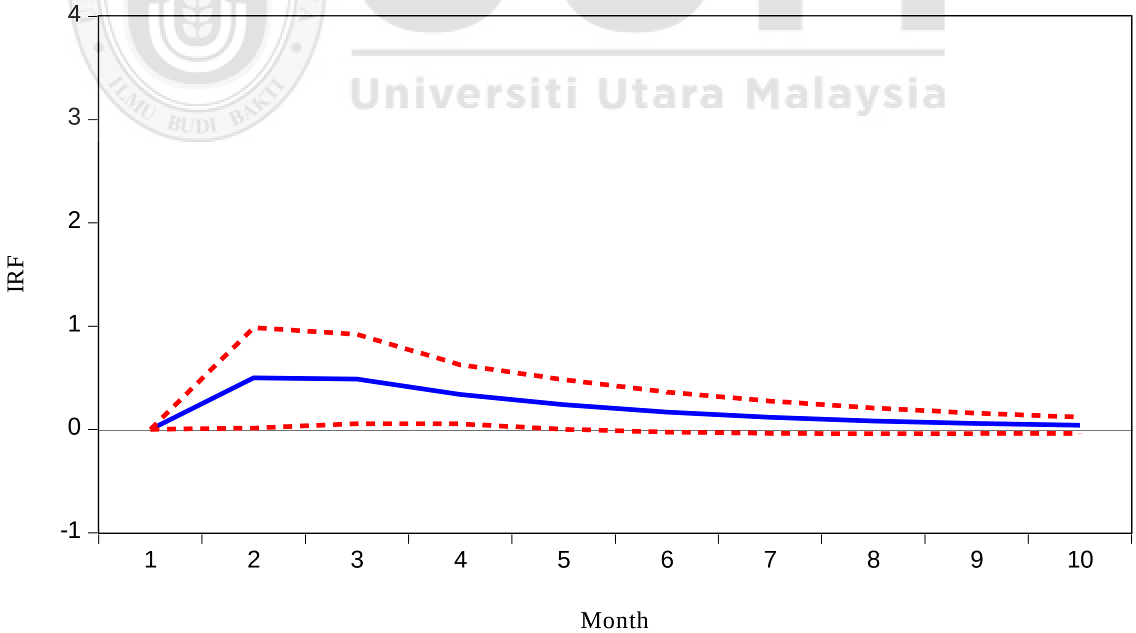


Figure 6.21
*Impulse Response of INFWFPI to INFGFPI*

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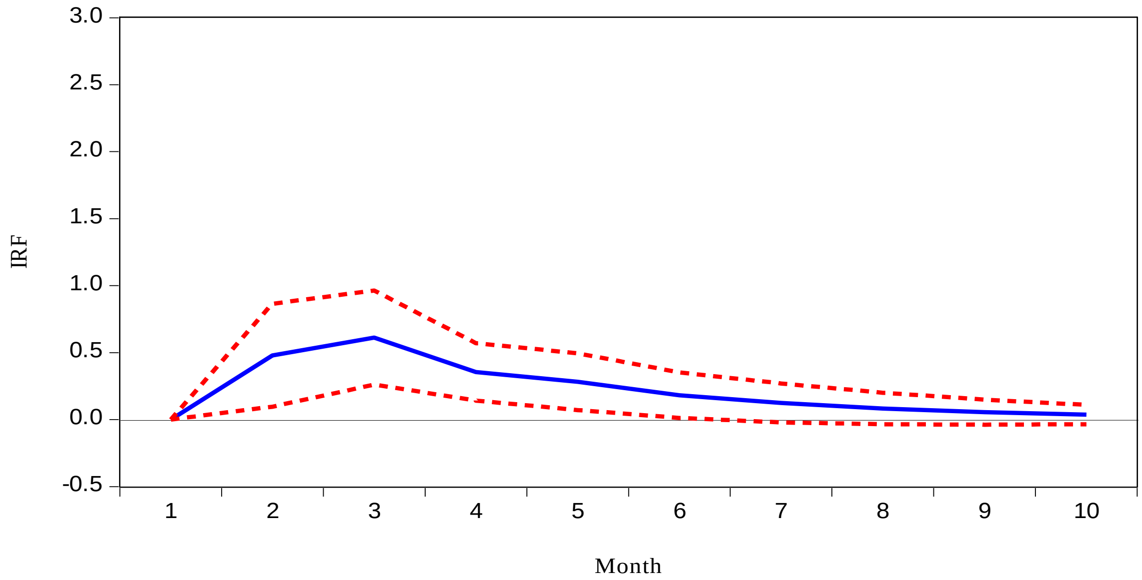


Figure 6.22
*Impulse Response of INWPI to INFGFPI*

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### 6.12 Conclusion

In conclusion, long memory analysis shows that all food price, food price inflation and food price inflation volatility series are not transitory in nature possess long memory. Cointegration analysis results show the evidence of statistically and economically significant international food price transmission effects to domestic price inflation dynamics in Sri Lanka. The co-integration test results confirm that global food price cointegrated almost all domestic prices. Global food price does not influence nonfood price inflation statistically and significantly in the short run. The increases in global food prices generate increases in headline inflation and domestic food inflation. Granger causality test results indicate that there are causal relationship i) between food price inflation series ii) between inflation and its volatility series, iii) among volatility of food price inflation series and its volatility inflation series. Further, there are evidence that one food price inflation can affect other price inflation and volatility of them. The volatility of one food price inflation also affects other food price inflation series. Impulse response results show that shocks to GFPI have positive effects on domestic prices even in the long term, overall, impulse responses are in line with economic theory. In sum, the results from all tests show a positive and statistically significant effect on domestic inflation from global food price shocks.

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# CHAPTER SEVEN

# CONCLUSION AND POLICY RECOMMENDATION

## 7.1 Introduction

This chapter presents the summary of the key findings of the study according to the research objectives. In addition, it gives policy recommendations, limitations of the study, and suggestion for future research.

## 7.2 Summary of Findings and Conclusions

This study has tried to answer four research questions: i) is food price inflation transitory or permanent?, ii) do increases in global food prices transmit to domestic prices in Sri Lanka?, iii) Does volatility of global food prices pass-through to domestic prices in Sri Lanka? and iv) does domestic food prices affect headline inflation in Sri Lanka?, using a battery of non-parametric, semi-parametric and parametric techniques. The period of this study covered was 2003M1-2014M12. This study deals with four issues; long memory, global food price transmission to domestic markets, global food price volatility transmission to domestic markets, and domestic food price spillover to general inflation.

Summary statistics show that food price inflation has been higher, and more volatile than nonfood price inflation in Sri Lanka. The results from standard unit root tests showed that means and variances of all the log price series vary over time. It implies the series are nonstationary. The means and variances of first difference of log food price series are constant over time. This implies that the series are stationary at first difference.

Findings corresponding to the first objective showed that food prices and food price inflation volatility possess long memory. All of the econometric tests (nonparametric, semi-parametric and parametric estimation techniques) carried out to test long memory in the study (the R/S, GPH, LWE and FIGARCH model) showed that food price inflation series at both moments( food price inflation and food price inflation volatility) are long range dependent (long memory) processes. In sum, findings suggest that food price series, food price inflation and food price inflation volatility are not transitory in nature and have a significant long memory which implies strong evidence of persistence in food inflation in Sri Lanka.

The findings of global food price transmission to domestic prices which are corresponding to the second research objective of the study showed that there exists a significant global food price transmission to domestic prices in the long run as well as in the short run. In particular, the impact of global food price transmission on consumer food prices and producer food prices is higher than that of nonfood prices, because global food price transmission elasticity is higher in magnitude for food prices compared to nonfood price. Granger causality test results also showed that global food price Granger causes consumer prices and producer prices in Sri Lanka in the short run. These results imply that domestic market reacts immediately to world market situation even in the short run. There is a one way causality running from global food price to domestic prices. In addition, significant error correction term of each model indicates that global food prices Granger-cause domestic food prices in the long run. These findings show that there are spillovers from global food price inflation and volatilities to domestic food prices hence to overall prices. In addition, the findings of the study suggest that food prices have been consistently important in driving overall inflation in Sri Lanka. Simple statistical contemporaneous correlation analysis also confirms the strong positive correlation between global food price and domestic food prices.

The findings of cointegration analysis for the examination of third objective of the study: how global food price volatility affects domestic prices show that global food price inflation volatility influenced (increased) significantly on domestic prices of CPI, CFPI, WFPI and WPI in the long run. Specifically, the findings revealed that global food price volatility has a higher impact on domestic consumer food prices and wholesale food prices in the long run. The transmission effects vary for different domestic prices in Sri Lanka. In addition, block Granger causality results support the conclusion of the cointegration results.

Global food price in terms of level and volatility transmission has a higher impact on domestic food prices than nonfood prices in Sri Lanka in the short run as well as in the long run. A positive shock to global food price has significant positive effects on domestic prices and last for longer periods.

The food price spillover evidence from the examination of fourth research objective of the study showed that both food prices (CFPI and WFPI) influence overall CPI positively. It is also significant at five percent level not only in the short run but also in the long run. The adjustment speed of CPI is higher in the case of shocks from CFPI compared to WFPI. Granger causality results have also shown that CFPI and WFPI Granger cause CPI.

Further, some of the other results identified in the study showed each of the inflation series Granger causes its own volatility of inflation series. This evidence supports Friedman-Ball hypothesis. Block Granger causality under vector error correction (VEC) framework showed that Cukierman-Meltzer hypothesis; conditional variance of CFPI, CPI, WFPI and WPI inflation series Granger cause its own inflation series significantly and positively. This study discovered the link between the food price inflation and its volatility and showed that there exist a bi-directional causal relationship between inflation and volatility of inflation. Our results are supportive of both the Friedman-Ball and the Cukierman-meltzer (1986) hypotheses. Further, inflation affects not only its own price volatility, but also it can affect the price inflation volatility of others. In contrast, volatility of price inflation of one affects not only its own inflation but also affect the price inflation dynamics of others.

Further, impulse response analysis also shows that a positive shock to GFPI can also raise CPI, CFPI, WFPI, and WPI in the domestic market. A positive shock to GFPI has significant positive effects on domestic prices and last for longer periods.

In sum, this study contributes to the existing literature in various ways. It provides a comprehensive analysis dealing with the area of statistical memory properties of food price dynamics, memory properties of food price volatility dynamics, world food price food price volatility transmission to Sri Lankan domestic markets. A closer look at the specific problems and characteristics of Sri Lankan economy and in depth analysis would help address the country's problems more effectively.

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## 7.3 Policy Recommendations

This section provides policy recommendations based on the findings that emerged from the analysis. Understanding the dynamics of food price, its volatility and inflation help in planning policy design and policy responses. The high and volatile food dynamics pose significant challenges for developing countries including Sri Lanka where households spend a larger share of their income on food. Thus, the findings of this study can have a number of important policy implications for food production, trade, and monetary policy makers. In addition, a few implications of our findings for the monitoring, modeling, and forecasting of food prices in Sri Lanka are worth mentioning.

A forensic examination of statistical properties of the food price series in Sri Lanka using parametric, semi-parametric and non-parametric approaches in the study showed that food price movements are neither independent and identically distributed nor normally distributed. Means and variances of the food price inflation appear to change over time. All the tests used to examine the order of integration of food prices, food price inflation and food price inflation volatility series in Sri Lanka showed that food price, inflation and inflation volatility series have long memory and they are fractionally integrated. Hence, results suggest that food price series are not transitory in nature and have significant permanent components. These characteristics have several momentous implications for the econometric analysis of food price dynamics. The statistical procedure should take into account heteroscedasticity. The researchers should select the correct specification of the model. They also need to be aware of the inter-temporal dependence characteristics of their data in order to avoid errors in estimation, inference, and interpretation of food price analysis. New methods

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are needed to account for the special distributional characteristics of long memory variables. These properties do also play a vital role in international economics and international finance-risk management. Economic theories advocate that monetary policy should deal with core inflation as food and energy price inflation is generally assumed to be elicited by supply side effects assuming they are transitory. In the case of developing economies like Sri Lanka, this may not be true. Long memory estimates are also related to the measurement of inflation. Correlogram analysis shows that effect of a shock even after 50 months has not died out. This is a clear indication of fractional integration. Therefore, the inclusion of food prices in inflation measure could provide a clear representation of underlying inflation trends. The results of long memory tests suggest that neglecting food prices may reduce the core inflation, a biased measure of long run inflation reflecting an incorrect picture. Forecasts of future inflation are also underestimated. The slow dissipation of a shock on food price could lead to higher food inflation and overall inflation expectations. Discounting food price can lead to an underestimate of the global food price transmission effects on domestic overall inflation. In sum, ignoring food price inflation in monetary policy preparation can lead to policy mistakes. Policy makers need to account and include food prices in the computation of any official measure of inflation.

Results from the investigation of the second objective imply that understanding the dynamics of global food price shocks on domestic prices is also an important issue for macroeconomic policy. In a globalized world, global food price transmission, pass through effects on domestic markets is indispensable. We find evidence of statistically and economically significant global food price transmission effects to domestic price in the long run in Sri Lanka. The findings of this study show that domestic prices have co-moved with the international food prices. The co-integration test results confirm that world food price cointegrated almost all domestic food and nonfood prices. Global food price increases do not affect nonfood price inflation in the short run significantly. The increases in global food prices generate increases in headline inflation and domestic food inflation significantly so that global food price become an important contributor to food price and general inflation in Sri Lanka. Food price inflation has also generated significant second round effects on non-food price inflation due to the high share of food in household's expenditure, credit constrained consumers, long memory of food prices. Therefore, it can lead to influence on wage setting in medium or longer term. Further, food price inflation plays a crucial role in notifying inflation expectations and accelerating wages.

Results derived from achieving the third objective of this study showed that, in a globalized world, the volatility of the global food price derived from FIGARCH model increases domestic prices in the long run and hence become an important factor in determining domestic inflation in Sri Lanka. The GFPI volatility affects wholesale food prices positively at a higher rate than consumer food prices. Sustained food price volatility can generate considerable uncertainty and affect vulnerable people. The uncertainty can increase risks in productive activities and weaken food security in a country particularly a developing country like Sri Lanka. Persistent volatility of food prices can also have adverse macroeconomic consequences. Friedman (1976) explains in depth how price volatility undermines economic decision making, resource allocation and the efficiency of the price system. High and more volatile food price inflation can also lead to malnutrition and increase political insecurity. The volatility of inflation rate is also an important determinant of the degree of risks associated with the investment opportunities. Granger causality results imply Sri Lanka is a price taker and dependent on the world market, a rise in the level of food price inflation raises its uncertainty about future food price inflation so that it would have significant costs and deadweight loss.

As Sri Lanka is an open and dependent economy, Sri Lanka is highly vulnerable to shocks in the global food prices. Further, the imported food component in the food consumption basket is also large. Food import accounts for around 40 percent of total expenditure for consumer goods imported. The key food items of imports are sugar, wheat, milk and milk products, dhal, big onions, potato and dried fish. It is almost 9-12 percent of total imports expenditure. Under comparative advantage theory, Sri Lanka's domestic resource cost for selected food items like wheat, milk and sugar is higher than that of trading partners. Therefore, it is challenging to ban those imports. Policy attention needs to shift toward efforts to increase food production, investing in agricultural research, promoting diversification in staples consumption in the long term plan.

As 80 percent of the households in Sri Lanka spend more than 40 percent of their income on food, Sri Lankan government needs to develop a safety net program for the poor and a longer term poverty reduction strategy. Thus, more has to be done in terms of short and long term policies to ensure price stabilization.

### 7.4 Limitations of the Study

It is also worth to note some limitations of the study for future work. Nonlinearity and asymmetric aspects of food price dynamics are not considered in the study. The

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VECM in Equation 5.22 is linear in two senses. First, all of the parameters in the model are assumed to be constant over the study period. Second, the dependent variable responds linearly to changes in the independent variables. Therefore, future empirical work in this area should attempt for a more comprehensive analysis to investigate the aspects of international food price nonlinearities and asymmetric price transmission.

Aggregate food price indices are used in the study for analysis. It would be more informative and useful to use individual food commodities prices. This would help policy planers.

Long memory estimation is carried out for Sri Lanka in the study. It would be an interesting topic to consider estimation of long memory for food prices for Asia. In this case, panel data technique could be used to get more information.

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## Appendix 1: End Notes

[1] Campbell and Mankiw (1987) assumed that stationary process, $\Delta y_t$ can be represented by an ARMA(p,q) process , $\phi(L)(\Delta y_t - a_0) = \theta(L)u_t$, $u_t \sim WN(0, \sigma_u^2)$, where $\phi(L)$, $\theta$(L) are the lag polynomials of AR and MA coefficients respectively. Then, $A(1) = \left[\frac{\theta(1)}{\phi(1)}\right]^2$. Campbell and Mankiw (1987) estimated $\phi(1)$, $\theta(1)$ by substituting Gaussian MLEs of the coefficients into these polynomials.

[2] Sum of MA coefficients. The impact of shock in period t on the level of Y series in period $t+k$ is $A_k$. is $A(1)=A_0+A_1+\ldots+A_k$. the ultimate impact of the shock on the level Y series equal the infinite sum of these of moving average coefficients, denoted by $A(1)$.

[3] The ratio of variance is defined as $VR = \frac{1}{k}\frac{\mathrm{var}((Y_{t+k+1} - Y_t)}{\mathrm{var}(Y_{t+1} - Y_t)} = 1 + 2\sum_{j=1}^{k}\left(1 - \frac{j}{k+1}\right)\rho_j$, where $\rho_j$ is the jth autocorrelation of $\Delta y_t$. This measure can be written in another form as $VR \equiv \frac{\sigma_{lrv}^2}{\sigma_{\Delta y}^2}$, where $\sigma_{lrv}^2$, $\sigma_{\Delta y}^2$ are the long run and the unconditional variances of $\Delta y_t$. and $\sigma_{lrv}^2 \equiv A(1)\sigma_u^2$,

$$\sigma_{\Delta y}^2 \equiv (1 + \sum_{j=1}^{\infty} a_j^2)\sigma_u^2$$

[4] $\pi_t = \alpha_0 + \sum_{j=1}^{p}\alpha_j \pi_{t-j} + \varepsilon_t$

[5] The CIRF = $\frac{1}{1-\rho}$, where $\rho$ is the sum of autoregressive coefficients, SARC= $\rho = \sum_{j=1}^{p}\alpha_j$

[6] ARFIMA($p,d,q$) model : $\phi(L)(1-L)^d(y_t - \mu_z) = \theta(L)\varepsilon_t$

[7] The specification of SV is

$$\pi_t = \sigma_t \varepsilon_t$$
$$\ln \sigma_t = h_t = \alpha + \beta h_{t-1} + \eta_t,$$

$$\varepsilon_t \sim IID(0,1),$$

$$\eta_t \sim IID(0, \sigma_\eta^2)$$