FORECASTING SOUTH AFRICAN FOOD INFLATION

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DECLARATION

I, Günther Griessel, hereby declare that this dissertation submitted for the degree of Magister Scientiae Agriculturae in the Faculty of Natural and Agricultural Sciences, Department of Agricultural Economics at the University of the Free State, is my own independent work, and has not previously been submitted by me to any other university. I furthermore cede copyright of the thesis in favour of the University of the Free State.

_______________________ _______________________

Günther Griessel Date

Bloemfontein

DEDICATION

This dissertation is dedicated to my parents,
Francois and Shirley Griessel,
without whom I would never be where I am today.

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To have been able to complete this thesis would not have been possible without the help of a select few people. These people were instrumental in helping me achieve my goal of completing this thesis in their own unique ways. They contributed either financially, through emotional and spiritual support, or through freely offering their expertise, to get me where I am today.

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LIST OF ACRONYMS AND ABBREVIATIONS

ADF	AUGMENTED DICKEY-FULLER
AIC	AKAIKE INFORMATION CRITERION
AR	AUTOREGRESSIVE
ARIMA	AUTOREGRESSIVE INTEGRATED MOVING AVERAGE
CPI	CONSUMER PRICE INDEX
FEVD	FORECAST ERROR VARIANCE DECOMPOSTION
FOMC	FEDERAL OPEN MARKET COMMITTEE
GDP	GROSS DOMESTIC PRODUCT
HQ	HANNAN-QUIN CRITERIA
IMF	INTERNATIONAL MONETARY FUND
MA	MOVING AVERAGE
MSE	MEAN SQUARE ERROR
NAMC	NATIONAL AGRICULTURAL MARKETING COUNCIL
PPI	PRODUCER PRICE INDEX
QE	QUANTITATIVE EASING
REPO	REPURCHASE RATE
RMSE	ROOT MEAN SQUARED ERROR
SA	SOUTH AFRICA
SARB	SOUTH AFRICAN RESERVE BANK
SC	SCHWARZ CRITERIA
US	UNITED STATES
VAR	VECTOR AUTOREGRESSION
VEC	VECTOR ERROR REGRESSION

ABSTRACT

Since the sharp increase in food prices, both domestically and internationally, in 2008/2009 the need to forecast food inflation has become more and more prominent, especially in developing countries. This is because a higher percentage of household income is spent on food in these countries. Food inflation therefore, plays an important role in overall inflation in South Africa and ultimately affects monetary policy decisions.

The primary objective of this study was to fit a multivariate model for the food component of the South African Consumer Price Index (CPI), so as to forecast food inflation in South Africa. Various models were identified but the Vector Autoregressive model was deemed suitable as per literature.

A food inflation forecasting model was developed with CPI without the food component, nominal effective exchange rate, money supply, domestic food supply balance sheet, oil prices, producer price index, SARB repurchase rate and international food prices included as independent variables, as prescribed by literature reviewed. These data were entered at monthly intervals.

Forecasting of data involves understanding the short run linkages between variables. This was captured by means of impulse response functions and forecast error variance decomposition. In the short run it was found that shocks in nominal effective exchange rate, gross domestic product and CPI without the food component explained the majority of variance in food inflation. To determine long run cointegrating relationships between the variables, Johansen cointegration testing was carried out. With the presence of cointegrating variables, a Vector Error Correction Model was constructed for forecasting purposes.

Sample forecasts were then made and compared with actual data in order to determine current accuracy of the model in terms of deviation from currently available data at the time of writing. The model was then simply solved for two years ahead to produce a two year-ahead forecast of South African food inflation. The resulting forecasts yielded an expected food inflation index to reach 117.75 index points in a years' time (May 2014 to May 2015) and 125.58 index points in two years' time (May 2014 to May 2016).

The need for construction of a more representative CPI for South Africa was identified, but is beyond the scope of this study.

Keywords: **Vector Autoregressive Model, Vector Error correction model, Inflation, Food Inflation, Forecasting, Monetary Policy**

CHAPTER 1
INTRODUCTION

1.1 Background and motivation

Between mid-2007 and mid-2008 the food price index of the World Bank increased by almost 86% (Wright, 2009). The causes for the sudden rise in international food prices ranged from higher energy costs and increased food demand, to use of grain to produce biofuels. This international spike in food prices had various effects on respective countries' domestic inflation but was of greater significance to the developing world due to the higher expenditure on food as a percentage of household income (Gomez, Gonzalez, Melo and Torres, 2006).

In Sub-Saharan Africa the greatest impact of rising food prices was evident in poverty levels. Wodon and Zaman (2010) found that an increase in food prices by just 50 per cent resulted in a 4.4 per cent increase in the poverty headcount in Sub-Saharan Africa. With almost a quarter of the South African population living beneath the national poverty line (with an income of less than R306 per month), the effect of high food prices were devastating.

Various case studies demonstrated the vulnerability of low income households in terms of food security. Mosoetsa (2011) found that of the households sampled in KwaZulu-Natal and Mpumalanga, more than 50 per cent were either struggling to provide for basic needs or just able to provide food. In another study cited by Dube (2013), almost 40 per cent of households surveyed were reported to be food insecure. Onyango (2010) observed that the majority of respondents questioned in Orange Farm, Gauteng, were unable to provide for basic food needs with some not even being able to spend any money on food at all. Most of the respondents who could no longer afford basic food items were eventually attracted to illegal activities as an alternative source of income.

The social implications of high food prices were found to be wide, feeding into criminal activities in an already crime-rife country. Social support nets were broken down as household members readily engaged in conflict over how household income should be spent. Government social grants were often found to be the only deciding factor between eating and complete starvation (Meintjies, 2013). The decreased purchasing power of these lower income households forced them to not only buy less food but also less nutritional food, which eventually leads to malnutrition. As of 2010/2011 80 per cent of the 25 328 households, surveyed in the income and expenditure survey by Statistics South Africa (2011), were unable to purchase a nutritionally adequate diet.

Despite the vulnerability of these communities to rising food prices, food expenditure is not adequately represented in the Consumer Price Index (CPI). The current weighting of food and non-alcoholic beverages in the consumer basket is a mere 14.8 per cent (Stats SA, 2012). The National Agricultural Marketing Council (NAMC), on the other hand, found that the current (as at February 2014) food basket makes up 44.4 per cent of all income expenditure of the poorest 30 per cent of the South African population (NAMC, 2014). Food inflation currently stands at 4.3 per cent with headline inflation at 5.8 per cent, year-on-year from January 2013 to January 2014 (Stats SA, 2014).

It is clear that there is a disagreement between numbers when comparing published and observed inflation data. The indirect contribution to CPI, of food inflation, is also seldom seen.

Rangasamy (2010) observed that due to the second-round effects of rising food prices the actual impact of food inflation in South Africa was much higher and persistent than previously thought. The contribution of food inflation to CPI was found to be 1.4 times its published weight, from 2000 to 2008. From these findings Rangasamy (2010) suggested an increased focus on food inflation when monetary policy-making is implemented.

So, not only does food inflation severely hamper purchasing power of already poor households, its role in headline inflation is of greater importance than suggested by statistical publications.

1.2 Problem statement and objectives

It is clear that the impact of rising food inflation has extremely detrimental effects on the poor. A relook at the weighting of food items in the consumer basket would help to improve the price stability function of monetary policy. Apart from this option, an improved understanding of food inflation and its impact is also needed to guide monetary policy.

The inflation situation in South Africa has been improving in recent years, but remains highly volatile. Part of this improving inflation outlook can be attributed to the relatively recent advent of inflation targeting which South Africa formally adopted in 2000. In their study, Mishkin and Schmidt-Hebbel (2007) observed that countries that adopted inflation targeting regimes were able to contain runaway inflation and buffer domestic prices from international shocks.

Inflation targeting involves the adjustment of various monetary policies with changes in the repurchase rate, the most commonly used tool to stabilise inflation in South Africa. These policies tend to lower excessive consumer expenditure and restrict credit availability so as to ultimately lower prices of goods and services in the country (Sveriges Riksbank, 2011).

Such changes in policy affect consumer expenditure drastically but only after a period of time. Kerschoff, Laubscher and Schoombee (1999) and De Waal and Van Eyden (2014) found that the impact of changes in the South African Reserve Bank (SARB) policies were only observed between 12 to 24 months after implementation, on the economy and inflation. The SARB therefore, has adopted a more forward-looking approach to inflation targeting, which highlights the need for forecasting inflation (Osie Van der Merwe, SARB, personal interview, 7 April 2014). The volatility and limited understanding of food inflation makes it an ideal candidate for study.

Such a forward-looking approach is shared by Gomez, *et al.,* (2006) who also recommended that developing countries should develop reliable food inflation forecasting models so as to gather greater understanding of the monetary policy transmission mechanism. One of the ways through which monetary policy is transmitted to the economy is by inflation expectations.

These expectations play a large role in current inflationary environment through wage adjustments and increased persistence of a food inflation shock (Gomez *et al*., 2006). By understanding how food inflation might change in the future, formulation of monetary policy can be done more efficiently, thereby advancing the objective of price stabilization.

The need to forecast food inflation can thus be derived from three basic points:

1) The ever-present vulnerability of a large number of poor households to rising food prices in South Africa;
2) The overlooked importance of food inflation as a major contributor to CPI;
3) The forward-looking approach of monetary policy setting in an environment where the results of decisions made now, are only observed in the future.

The main objective of this study is to fit a multivariate model for the food component of the CPI as accurately as possible so as to forecast food inflation in South Africa.

In order to achieve the primary objective, the following secondary objectives must be addressed:

- To identify major factors affecting food inflation in South Africa.
- Make policy recommendations specifically aimed at monetary policy makers.

1.3 Significance of the Study

Food inflation is a vital component of the South African CPI. It is clear that this component is underweighted in the headline index and does not properly reflect the reality of the South African inflation situation (Rangasamy, 2010). Ignoring the importance of this component will affect the poor of South Africa as they are the most vulnerable to changes in food inflation. With an inflation targeting regime in place, dedicated to price stability, South African monetary policy makers are in a position to make decisions which can drastically increase or control food inflation.

Understanding how food inflation might behave in the future will also allow these policy makers to anchor monetary policy decisions to accurate models that incorporate underweighted and overlooked factors such as food inflation. This will enable timely and efficient decisions to be made.

The ignorance of the effect of monetary policy decisions on the poor can lead to further income inequality as food inflation erodes wealth in low income individuals faster than high income individuals.

1.4 Dissertation Outline

This study is divided into 5 chapters. The introductory chapter will be followed by Chapter Two in which an overview of current literature is presented. Chapter Three covers the methodology employed and the source of data collected. In Chapter Four, the results derived from estimating the fitted model are interpreted, followed by conclusions of the study in Chapter Five.

CHAPTER 2
LITERATURE REVIEW

2.1 Introduction

Inflation is the continuous rise in the general price level of goods and services in any economy over a period of time (Blanchard, 2000). Deflation, on the other hand, entails a continuous decrease in the general price level of goods and services over a period of time. Therefore, inflation leads to a subsequent decrease in purchasing power of the consumer participating in the economy. Inflation is expressed in a number of ways, the most common of which are: the Producer Price Inflation (PPI), the gross domestic product deflator (GDP deflator) and Consumer Price Index (CPI).

The GDP deflator measures price levels of all final goods and services produced within a country as well as exported goods and services (Litra, 2009). The PPI tracks the change in prices received by domestic producers for their locally produced goods. This index includes three components: domestic output, exported commodities and imported commodities (Statistics South Africa (Stats SA), *s.a.*). PPI affects CPI through a pass-through effect whereby changes in the prices of final goods and services are eventually passed on to the consumer at a certain rate or lag.

Litra (2009) found, in a comparison between the GDP deflator and CPI that the CPI gives a more exact perspective of what consumers are paying for goods and services. This is mainly due to the "basket" of goods concept, tracked by CPI, which is tailored to consumer spending habits. The GDP deflator does not include prices of imported goods and services; thus, using it as an inflation measure in an open economy such as South Africa would give false indications of what consumers are actually paying or rather the rate of price increases.

The CPI tracks the changes in consumer inflation by means of a set "basket" of goods and services, consisting of various items such as food and beverages, clothing, transport, to name a few. The price of this basket is compared to the price of the basket a month ago or a year ago, with the difference representing the monthly or yearly CPI. CPI is also referred to as headline inflation or inflation. These terms will be used interchangeably to refer to the full basket of consumer goods from here onwards (Stats SA, 2009).

The effects of inflation on the economy are of such a magnitude that it is commonly seen as an important component of monetary policy of central banks. By forecasting inflation, monetary policy formulation can be guided to better achieve price stability (Rangasamy, 2010). Inflation behaves and is managed differently in different economies. The main objective of this chapter, therefore, is to discuss the relevant literature that will assist in understanding where inflation dynamics fit within the South African context. Literature on general inflation, food inflation and forecasting techniques are reviewed. Furthermore, some background on how inflation is calculated and compiled will be given. The next section will take a look at how inflation is perceived and experienced globally.

2.2 Global Inflation

2.2.1 Monetarist and Structuralist Perspectives

Globally, the inflation phenomenon is commonly discussed under two schools of thought namely, monetarist and structuralist, as noted by Abdullah and Kalim (2011). The monetarist viewpoint holds that prices (inflation) will increase proportionately to an increase in money supply as proposed by Friedman (Friedman, 1970). The monetarist viewpoint was famously summarised by Friedman's (1963) quote: "Inflation is always and everywhere a monetary phenomenon".

Structuralists, on the other hand, argue that supply-side factors such as wages, import prices and food prices are responsible for upward pressure on inflation (Abdullah and Kalim, 2011). The type of factors to include in a food inflation predicting model will depend heavily on which one of these inflationary arguments are followed. Thus, it must be decided beforehand.

The monetarist view was supported by Khan and Schimmelpfenning (2006) in Pakistan, where monetary factors were found to be the main drivers of strong upward inflationary trends. Supply side factors were found to play a lesser role, but it can be argued that including only the wheat price in the model was insufficient, as it fails to capture other overarching factors which could affect inflation.

Johnson (2008) cites much stronger global demand for food crops and lower agricultural supply (which have not increased with demand) as main drivers of global inflation, following the structuralist viewpoint. Loening *et al.,* (2009) found that international prices and agricultural supply were driving factors behind inflationary pressure with money supply playing a significant role in short-run non-food price inflation dynamics. Meaning a sort of "hybrid" monetarist, structuralist effect was observed.

The Asian Development Bank (2011) found that adverse weather is affecting food supplies (with carryover stocks depleting fast) and increasing oil prices of up to 30 percent had increased global food prices by at least 30 percent. This prompted monetary policy responses in various Asian countries highlighting the importance of money supply as an important determinant of food inflation, albeit as a countermeasure.

Another important concept applied by structuralists is that of inertial inflation. Inertial inflation is also known as inflationary expectations and can be explained by means of the Cost-Push Theory. Forward-looking inflation or inflationary expectations are based on past values of inflation; so if a country has relatively high past inflation, expectations on inflation will also be high (Habib, 2014). Inertia can also refer to the sluggish movement (or lagging behind) of inflation when an inflationary shock occurs (Juillard, Kamenik, Kumhof and Laxton, 2007). The point is that these expectations are not just intangible predictions, but are used by businesses and monetary policy makers to make important decisions, such as wage increases or interest rate hikes. Sometimes these expectations are brought forward, causing price adjustments of goods and services to occur before they are actually set to change. Thus, being able to accurately predict this lagged inflationary rate accurately is just as important as reading the current inflation rate in a country.

The important question for this study is whether or not inflation in South Africa is a monetary or structural phenomenon. Adusei (2013) addressed this question at length and found that inflation in South Africa is not exclusively a monetarist or structuralist phenomenon, but is affected by both monetary (money supply) and structural (global goods prices, inflation in the United States of America) factors. This study will therefore, follow the combination monetarist/structuralist perspective of assessing inflation. Evidently a "one size fits all" approach to inflation is not the correct way to assess it. The next logical question is to consider whether inflationary dynamics are the same across global economies, or are there some clear disparities among developed and developing economies?

2.2.2 Developed and Developing Economy Inflation

Inflation dynamics vary between developed and developing countries. It is imperative to identify the level of development and the most important factors involved when forecasting inflation.
Globally, year-on-year inflation stands at 2.6 per cent for 2013, as opposed to 2.9 per cent in 2012, despite recent Quantitative Easing and very low interest rates adopted by debt-ridden western countries' central banks. Increased money supply in these economies was set to improve demand for goods and services, thus accelerating inflation, but was muted by high unemployment and depressed energy prices. Countries in transition and developing countries are set to experience increased inflation of 7.3 per cent and 5.6 per cent in 2013, respectively (United Nations (UN), 2013). These increases are mainly attributed to rising minimum wages and fast credit growth. There is a clear discrepancy between inflation rates in developed and developing economies. The World Economic Outlook database of the International Monetary Fund (IMF) (IMF, 2013) demonstrates this contrast in the numbers as shown in Table 2.1.

Table 2.1 Average consumer inflation per country group (percentage change year on year)

Country Group Name	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Developed economies	1.85	2.03	2.34	2.36	2.19	3.40	0.12	1.55	2.71	1.97	1.37
Major advanced economies (G7)	1.76	2.00	2.36	2.36	2.18	3.21	-0.11	1.39	2.59	1.89	1.29
Other advanced economies	1.66	1.91	2.02	2.05	2.03	4.30	1.31	2.21	3.08	2.02	1.52
Emerging market and developing economies	6.64	5.91	5.90	5.71	6.51	9.23	5.25	5.87	7.15	6.06	6.18
Sub-Saharan Africa	10.61	7.45	8.70	7.13	6.38	12.85	9.36	7.41	9.34	9.03	6.90

Source: IMF (2013)

From Table 2.1 it is clear that developed nations experienced much lower and much more stable inflation than developing nations during this period. The inflation of developed economies ranges from a low of 0.12 per cent to a high of 3.4 per cent, as opposed to those of developing economies with a low of 5.25 per cent and a high of 9.23per cent. Inflation in Sub-Saharan Africa is of particular interest as inflation figures are consistently higher than those of average developing economies. There is a general decrease in inflation since the 1980's with developing countries actually performing well (from average inflation of 31 per cent in the 1980's, to today's 6 per cent) with the exception of outliers (Rogoff, 2003). What, then, are the main factors influencing these global inflation rates and why are there differences between them?

Levin and Piger (2004) support the viewpoint that the advent of inflation targeting (initially adopted by advanced economies) paralleled the steady, global deflation of the 1990's. Rogoff (2003) also found that stronger, proactive central bank involvement in price stability has contributed greatly to a continual disinflation pattern, especially in developed economies. He also stated that no sole factor was responsible for such a decline in inflation but rather a combination of factors ranging from deregulation to globalization.

The way in which developed economies evolved post World War Two, also gives some insight into differences between developing and developed nation inflation. Conventional wisdom held that exchange rates since the disintegration of the Bretton Woods agreement were fairly flexible, thus, providing effective control measures against foreign shocks to inflation. This posits that most countries abandoned fixed exchange rates for floating exchange rates, relying on foreign reserves to determine foreign currency value. Reinhart and Rogoff (2002) challenged this assumption and found that countries who adopted an effective floating exchange rate were, when strictly classified, actually following a form of currency pegging. Now, with the US Dollar becoming the reserve currency after the gold standard abolition in 1971, developing countries had little to no monetary tools with which to protect themselves against exchange rate shocks, which were in turn dictated by developed world powers. This meant that the mechanism used to insulate developing economies from foreign shocks was, in fact, not functioning as originally intended. This ultimately meant that inflation in developing economies were subject to a larger range of factors, that were supposed to be muted by floating exchange rate control (Ciccarelli & Mojon, 2005).

The effect of this process can still be seen today in developing economies. The quantity theory has been used to help explain the role of money supply and demand in inflation fluctuation. Moriyama (2008) followed this theory and found a strong link between headline inflation and nominal exchange rates in Sudan, a developing country, suggesting greater vulnerability to international money supply and price movements translating into more volatile inflation figures (reiterating vulnerability noted by Reinhart & Rogoff, 2002). Loening *et al.,* (2009) found similar results in Ethiopia where inflation was closely linked to agricultural supply shocks, exchange rates, money supply and international goods prices. This inflationary fluctuation, again, shows how vulnerable developing nations are to external shocks.

Growth in developed countries, on the other hand, has been fuelled by energy intensive industrial action, supporting energy prices in these economies. The IMF (2008) demonstrated that inflation in advanced economies was more influenced by increasing energy costs. This is graphically illustrated in Figure 2.1.

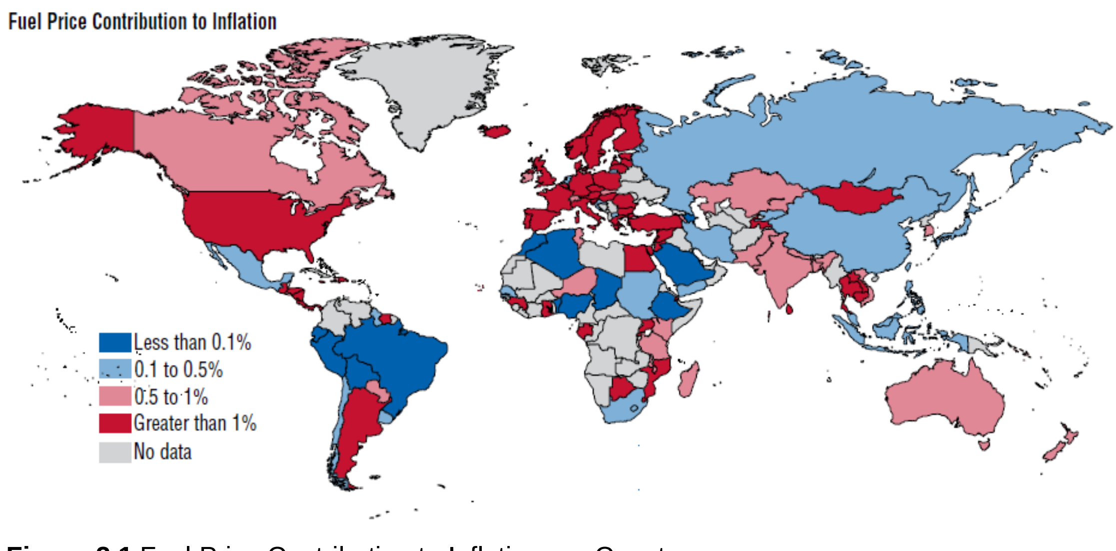

Figure 2.1 Fuel Price Contribution to Inflation per Country
Source: IMF (2008)

From Figure 2.1 it is clear that energy prices contribute more to inflationary pressures in developed economies than developing economies. Energy prices contribute only 0.1 per cent to 0.5 per cent to overall inflation in South Africa, as shown in Figure 2.1. This is contested by Rangasamy (2010) though, who advocates that food inflation contributes at least 9 per cent to 12 per cent to inflation.

The IMF (2008) contends the exact pass-through effect of energy prices onto inflation per country, as various taxes and subsidies are in place and differ per country which could distort the picture slightly. This representation also changes significantly if data is denominated in dollars or domestic currency.

Furthermore, another important role player contributing to inflation in developing countries was food. This can be seen in Figure 2.2.

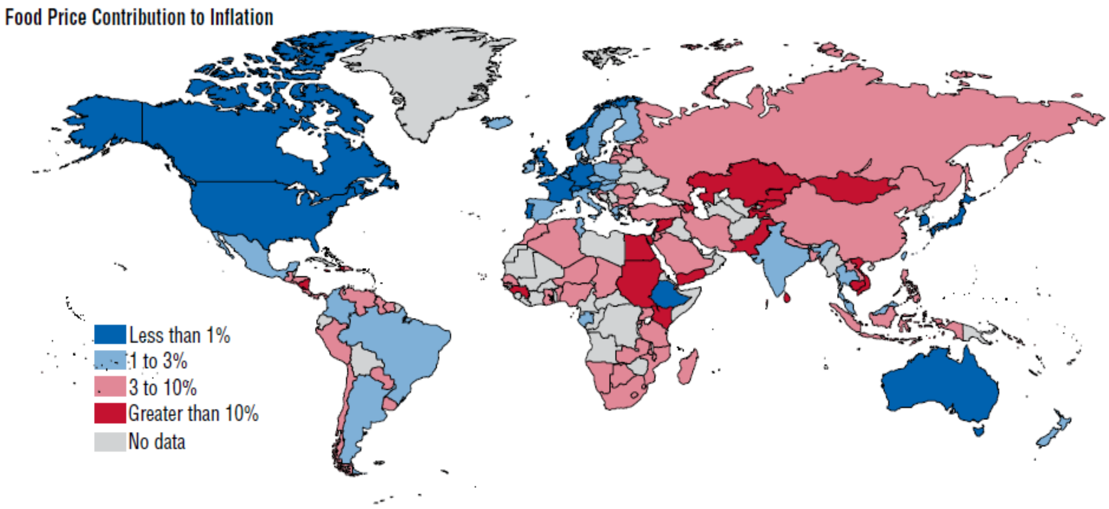

Figure 2.2 Food Price Contribution to Inflation per Country
Source: IMF (2008)

The contrast between Figure 2.1 and Figure 2.2 is clear. Where inflation in most developed countries is greatly affected by energy/fuel prices, inflation in developing countries is more vulnerable to food inflation. From figure 2.2 we see that South Africa falls in this developing country group with food inflation contributing 3 per cent to 10 per cent to total headline inflation.

The result of these divergent adaptions to exchange rate volatility and different contributing factors has resulted in different monetary policy approaches in managing inflation between developed and developing economies. Developing countries commonly track a so-called core inflation index which excludes food due to its volatility. But Rangasamy (2010) strongly advocates the use of headline inflation (as opposed to core inflation), with particular emphasis on food inflation, in policy decision-making in developing countries like South Africa. Rangasamy (2010) clearly states:

"Core measures of inflation that exclude food price movements may not accurately reflect the underlying inflationary pressures in the economy and could compromise the attainment of the goal of price stability."

Abbott and Borot de Battisti (2011) found that global food inflation was likely to continue increasing rapidly and would remain highly volatile into the near future. This was mainly attributed to commodity price spikes and overly aggressive policy responses to incorrect inflation-inertia assumptions. The effects of this increasing global food inflation will be of greater significance in developing economies like South Africa

A much larger share of a developing nation's household budget is devoted to buying food than in developed countries. Food inflation is therefore, more heavily weighted in headline inflation in developing nations (e.g. the total share of food inflation in headline inflation was 30 per cent for countries like Colombia, as opposed to 13 per cent in advanced countries like New Zealand) (Gomez *et al.,* 2006). On top of this larger contribution to overall inflation, technology available to ensure a steady supply of food is not as advanced in developing countries, further exerting upward pressure on food prices. Food inflation currently stands at 4.3 per cent (Stats SA, 2014) with an overall contribution of 14.8 per cent (Stats SA, 2012) which is four times higher than New Zealand's 1.6 per cent annual food inflation, which is a developed country.

What is even more illuminating is that a food basket currently costs 30 per cent of the poorest South Africans' at least 41.9 per cent of their income (July 2013) which is an increase from 39.7 per cent in July 2012, according to the comprehensive National Agricultural Marketing Council (NAMC) Food Price Monitor (2013). It is therefore, important to be able to model and predict food inflation accurately, being both an essential, heavily weighted and volatile component of the South African headline inflation (and ultimately monetary policy decisions).

Inflation is an important component of a country's overall economic health and by understanding the ways in which it affects an economy, can lend guidance to model construction.

2.3. Effects of Inflation

Understanding the far-reaching effects of inflation provides valuable knowledge which will assist in modelling its dynamic nature. Before analyzing food inflation, one first has to understand the effects of inflation as a whole, of which food inflation is a sub-component. When the general price levels of goods and services in a country change, there are certain knock-on effects that follow. Much of the effects caused by inflation are actually induced by the initial reaction monetary policy to inflation. Some of the main effects of inflation are documented in this section.

2.3.1. Purchasing Power

The most obvious effect of inflation is its ability to erode the purchasing power of consumers within a nation. This means that each unit of currency in the economy will be able to purchase fewer goods and services over time (Walgenbach, Norman, Dittrich and Hanson, 1973).

2.3.2. Central Bank Policy

Rising inflation affects central bank policy, especially in an inflation targeting country such as South Africa. The capacity of central bank policies to influence a country's economy is extensive, to say the least. Now, considering that most of the South African Reserve Bank policy revolves around keeping inflation in a narrow target band, it becomes clear that the far-reaching effects of inflation are almost as extensive as central bank policies itself, if not, synonymous (Bennet, 2014). Central banks react to rising inflation through the use of various monetary policy adjustments. The most well-known method used to ensure price stability in a country, is the alteration of interest rates. These rates refer to the interest paid by commercial banks to borrow money from central banks, also known as the repurchase or repo rate. If the repo rate increases then the interest rates at which commercial banks lend money to consumers will also increase and *vice versa* (Investopedia, 2014; South African Reserve Bank, 2014).

Generally, if inflation is undesirably high, repo rates are increased to decrease the money supply in the economy which will lower consumer spending. This is mostly true for the upper income brackets for people who qualify for loans and must therefore contribute more of their income to debt financing. Amongst lower income groups in South Africa, qualifying for loans at commercial banks is almost impossible, forcing them to resort to micro-lending for financing. Currently the costs for micro-loans are limited to an interest of no more than 5 per cent a month as stipulated by MicroFinance South Africa. These rates are indeed tied to the repo rate by multiplying the repo rate by 2.2 and adding an extra 5 per cent to 20 per cent depending on the length of the loan (Van Rensburg, 2014). So in effect, repo rate hikes in South Africa are actually magnified by means of exorbitant micro-lending costs. This lower consumer expenditure will translate to a slowdown in rate at which prices for goods and services are increasing because of lower demand for these products. In this way the amount of credit in circulation in an economy is controlled (Sveriges Riksbank, 2011). Figure 2.3 provides a visual representation of how the monetary policy mechanism works.

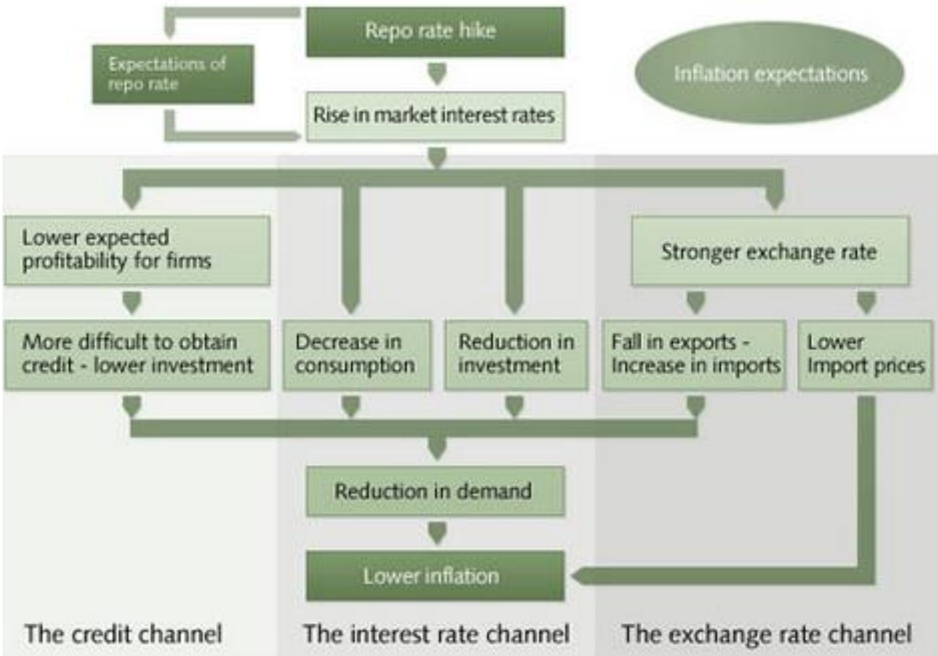

Figure 2.3 Monetary Policy Transmission Mechanism
Source: Sveriges Riksbank (2011)

Figure 2.3 refers to three different channels through which a repo rate increase plays out in an economy. The credit channel refers to activity in an economy concerning investment tempo. Higher rates will lead to less borrowing and less investing by consumers and companies. The interest rate channel denotes the effect on domestic demand of goods and services which will decrease with an increased repo rate. The exchange rate channel describes the effect of a repo rate increase on the value of the domestic currency used. An increased repo rate will strengthen the currency's value by attracting capital inflows which will lead to more imports and fewer exports. This is at least the theory behind the monetary policy transmission mechanism, but it is not universally accepted that this relationship is always relevant in this direction.

2.3.3. Assets

Most investors try to beat inflation by ensuring they have returns on investments at rates higher than inflation. This means that, when inflation does start to erode earning ability they will start moving their money to assets which offer higher than inflation returns or that maintain their store of value well (e.g. gold). This will cause an increased demand for and prices of assets in an economy, such as equities and property. This rise in asset prices is beneficial to the consumer who wishes to purchase these assets and beneficial to the investor who wants to sell his/her assets later on (Cochrane, 2011).

With recent Quantitative Easing (QE) which started late November 2008, carried out in three separate rounds by the United States Federal Reserve, the Federal Reserve buys bonds from the

United States government in order to stimulate the economy with an injection of money. This was done because interest rates could not be decreased any lower as they were already at a so called “Federal Target Funds Rate of between 0 per cent and 0.25 per cent”. Thus, other measures were needed to stimulate economic growth. Many investors anticipated this increased money supply to translate into much higher inflation, as explained previously. This caused many investors to look to equity markets and gold to hedge against inflation eroding returns (Fratzcher, Duca and Straub, 2013). As a result, equity and asset prices reached record levels never before witnessed globally.

2.3.4. Hyperinflation

Hyperinflation occurs when inflation runs into double digit figures. Hyperinflation results in consumers being able to buy substantially less and less goods and services with the country’s denominated currency. The currency can be so ineffective in meeting consumer needs, that barter is used and the currency is abandoned completely. Barter entails the direct exchange of goods and services for other goods and services without using a standardised currency (i.e. money) (O’Sullivan & Sheffrin, 2003). This in turn causes tumultuous market inefficiencies and ultimately, economic failure. Other currencies may also be adopted to be used in the country, with the most recent example being Zimbabwe, where hyperinflation brought the economy to its knees, eventually causing the local currency to be abandoned and replaced by the South African Rand and US Dollar (British Broadcasting Corporation, 2009).

2.3.5. Cost Push Theory

The cost push theory in its simplified form, suggests that when inflation increases, employees will demand increased wages to be able to afford goods and services. These employees usually convince their employers by means of labour unions to increase their wages. The employers submit, and duly increase wages for employees but also prices of their products, to cover increased labour costs. This means real earning power of the employees has, in effect, been reduced as goods and services are more expensive than before wage adjustments. Inflation will continue to rise as both wages and prices for goods and services are caught up in an eternal balancing act and possibly a “price-wage spiral” (Encyclopaedia Britannica, 2014).

2.3.6. Social Unrest

Higher inflation causes lowered subjective well-being of households as proven by Alem & Köhlin (2013). Discontent among consumers quickly spreads as more people are unable to afford basic goods and services. This, in turn, increases the propensity of consumers to embark on strikes and other forms of social unrest. The most recent example of such inflation-fuelled unrest was that of the Arab Spring revolts, initiated in Tunisia and spreading throughout the Middle Eastern and

North African countries such as Egypt, Yemen and Syria (Dewey, Kaden, Marks, Matsushima and Zhu, 2012).

2.3.7. Mundell Tobin Effect

The Mundell-Tobin effect explains the impact inflation has on real interest rates in an economy. Simply stated, when inflation increases, higher price levels will prompt consumers to demand less cash (money) and demand more assets (such as government bonds). This will in turn, induce increased capital formation, increasing a country's capacity to produce goods and services, which ultimately results in a decrease in real interest rates (Mundell, 1963 and Tobin, 1965).

These are only a few of the many effects a change in inflation has on an economy, but already the significance of these effects is clear. Because of its defining role in an economy, inflation is thoroughly tracked over time and managed by governments the world over to ensure price stability. The next section will give an overview on how inflation is tracked and how governments attempt to keep inflation under control.

2.4. Determining Inflation

To determine year-on-year, or monthly inflation, central banks or national statistical agencies construct a basket of goods and services with which they aim to represent household spending as accurately as possible. The bank then follows the price changes per basket item and assigns a certain weight of importance to the item group. Weighting of each item is done by expressing the actual expenditure as a percentage total expenditure on all items, giving an average expenditure per item. In South Africa this is probably not an accurate way by which to assign weights to different items due to the huge income disparity in the country. A better method might be to assign weights according to either per capita expenditure (as opposed to household) or according to median expenditure. This is referred to as headline inflation, CPI or plainly as inflation. The prices of thousands of goods and services are tracked and are divided into eight major groups. These groups include: food and beverages, housing, clothing, transportation, medical care, education and communication and other goods and services (Federal Reserve Bank of Cleveland, 2013). In South Africa, Stats SA (2) (2013) follow this method when constructing a headline inflation index.

Reweighting of the abovementioned sub-indices in the consumer basket is recommended to take place every five years by the International Labour Office and the United Nations so as to capture changing consumer habits effectively. These recommendations are followed by Stats SA with the most recent reweighting taking place in December 2012 (Stats SA, 2012).

The consumer basket is also measured for different areas of the country. The areas measured are grouped into primary and secondary urban areas along with rural areas next to the urban areas. Although inflation in the rural areas are measured, only the figures obtained for all urban areas are actually used in inflation targeting in South Africa (Bennet, 2014). Table 2.2 shows the composition and respective weights of the components of the South African consumer basket, currently in effect.

Table 2.2 Composition of South African CPI for all urban areas and respective weights of sub-categories (reweighted December 2012)

Product/Service	**Weight (%)**
Food and non-alcoholic beverages	15.41
Alcoholic beverages and tobacco	5.43
Clothing and footwear	4.07
Housing and utilities	24.52
Household contents, equipment and maintenance	4.79
Health	1.46
Transport	16.43
Communication	2.63
Recreation and culture	4.09
Education	2.59
Restaurants and hotels	3.5
Miscellaneous goods and services)	14.72

Source: Stats SA (2) (2013)

From Table 2.2, it can be seen that food and non-alcoholic beverages, housing and utilities and transport are heavily weighted in the consumer basket at 15.41 per cent, 24.52 per cent and 16.43 per cent respectively. Food and non-alcoholic beverages will from now on be referred to as food inflation.

What sets the food inflation component apart from transport and housing is its highly volatile nature. Food prices in South Africa have been found to increase at a faster rate than headline inflation and were also found to be much more exposed to a large range of factors from drought to depreciating currency (Aaron & Muellbauer, 2012). Food inflation can be broken down into its sub-components as shown in Table 2.3.

Table 2.3 Food inflation components and percentage change from December 2012 to December 2013

Category	Percentage Increase
Total Food and non-alcoholic beverage Inflation	8.45
Bread and cereals	4.4
Meat	-1.8
Fish	6.6
Milk, eggs and cheese	6.3
Oils and fats	1.3
Fruit	-6.5
Vegetables	5.4
Sugar, sweets and deserts	4.6
Other food	5.8
Non-alcoholic beverages	3.6

Source: Stats SA (3) (2013) and own calculations

The greatest percentage increase in the various categories was observed with fish and milk, eggs and cheese, at 6.6 percent and 6.3 percent respectively. Table 2.3 also shows that the greatest percentage decrease was observed in meat and fruit products at -1.8 percent and -6.5 percent respectively. Overall food inflation stood at 8.45 percent for the year 2013.

2.4.1. Calculation of Inflation

Inflation is calculated by tracking the predefined basket of goods and services and converting them into an index, which allows for month-on-month or year-on-year comparisons for an indication of percentage change in the cost of the basket. The basic inflation calculation formula is known as the Laspeyres formula. It measures inflation change in period *t* and is calculated as follows:

$$CPI_t = \frac{\sum W_i \frac{P_t}{p_0}}{\sum W_i} \times 100$$

Where W_i is the weight of importance given to commodity *i* and P_t is price of commodity *i* in the current period *t*, whereas p_0 is the initial price of commodity *i* (Neda, 2011).

Stats SA (1) (2013) uses the Young index to calculate inflation in South Africa. The Young index makes use of an elementary index called the Jevons index to derive inflation. The Jevons index is merely an un-weighted geometric average with which pure basket item prices are converted into index form. The Young index incorporates the Jevons index so as to assign weight and time frame elements in calculating the CPI. The Young index is calculated as follows:

$$I^{0:t} = \sum w_i^b I_i^{0:t}, \sum w_i^b = 1$$

Where $I^{0:t}$ is the CPI from period 0 to *t*, w^b_i is the weight assigned to each of the elementary (Jevons) indices with $I^{0:t}$ denoting this elementary index. Period 0 is usually referred to as the reference or base period, and is the period from which the elementary index was initially tracked or rebased to. The current base period for South Africa has been rebased from 2008 to 2012, so the official inflation index is 100 for December 2012 (Stats SA (1), 2013). The overall inflation index is subsequently used in monetary policy decision-making. One of the most applicable policy responses to discuss regarding South Africa is that of inflation targeting.

2.4.2. Inflation Targeting

Due to the consequential effect of eroding purchasing power of a nation's citizens, indirect influencing of the rate at which prices increase has been adopted by a number of leading economies. Restricting inflation to a narrow band (today known as inflation targeting) can be done by means of various monetary tools which originated with the establishment of the central banking system in the industrialized nations. Some monetary tools include: adjusting interest rate levels levied on borrowed money (usually the commercial lending rate known as the repo rate), controlling the volume of credit available and providing commercial banks with credit at very low interest rates to help them meet their short-term liquidity obligations (Central Bank of Belize, *s.a.*). Of these monetary tools, adjustment of lending rates to commercial banks (interest rates) is most widely used in inflation targeting regimes. It is important to be able to include this monetary reaction in any model where inflation forecasting is carried out as demonstrated by Iklaga (2009).

One of the first real supporters of this method of inflation control was Keynes (1924), who suggested that a policy of maintaining a flexible exchange rate would counteract negative international inflationary pressures.

The first country to officially adopt inflation targeting was New Zealand, by means of the Reserve Bank of New Zealand Act, on February 1, 1990. This Act, in effect, made the Reserve Bank of New Zealand responsible for stabilising prices within the country by setting an initial annual inflation rate target of 3-5 per cent. Due to the small size and openness of the New Zealand economy, sudden exchange rate fluctuations affected inflation rates much faster than changing national interest rates. This resulted in the Reserve Bank relying more heavily on the secondary mechanism of inflationary targeting, *i.e.* manipulating exchange rates (Mishkin, 2000).

Several countries resorted to an inflation targeting policy framework shortly after its advent in 1990. South Africa formally adopted inflation targeting in the year 2000, after incumbent monetary policy regimes, such as exchange rate pegging and money growth targeting, were found to be insufficient by the government (Jonsson, 2001).

One of the most recent proponents of inflationary targeting is the United States Federal Open Market Committee (FOMC) led by Ben S. Bernanke. The committee stated, in a press release, that it aimed to keep inflation at 2 per cent (Board of Governors of the Federal Reserve System, 2012). This is in stark contrast with management under Alan Greenspan (Chairman of the Federal Reserve 1987-2006), who supported the viewpoint that controlling inflation was possible without announcing a target band in which it should operate. Some argue that, a publicly declared inflation target does provide more certainty and theoretically, less volatility for consumers and investors (Coy, 2005). Mishkin and Schmidt-Hebbel (2007) decisively argued that inflation targeting effectively reduced inflationary response to shocks internationally, such as oil prices and exchange rate movements.

The problem with certain inflation targeting regimes is that different inflation definitions are used to base targeting on. Some countries use core inflation as a target band, whereas others track CPI (total consumer inflation). Core inflation targeting is mainly used by developed nations, where highly volatile inflation items such as food and energy are removed to provide a more stable measurement to work with.

Durevall, Loening and Birru (2009), maintained that ignoring such volatile, short run components in inflation forecasting in developing countries can lead to “misguided policy decisions”. Gomez, Gonzalez, Melo and Torres (2006) suggested that volatile components must be included in inflation tracking, targeting and forecasting of developing countries because of the large role these factors play in monetary policy and, ultimately, inflation expectations. It is, therefore, of great importance for a developing country’s central bank to develop accurate models for forecasting and tracking volatile components, such as food inflation.

The Reserve Bank of South Africa uses the All Urban CPI as its inflation targeting figure. This includes all major urban areas, and all components in the consumer basket. The official target band for South African CPI currently lies between 3-6 per cent (Bennet, 2014). The inclusivity of the inflation measure used by the Reserve Bank of South Africa is not the debate, but rather the weighting of items in the consumer basket of goods.

Tarrant (2013) interviewed Lamberti form ETM Analytics about their own CPI basket that they had tracked throughout the year. The results showed a stark contrast between official annual inflation figures published (6 per cent) and those recorded by ETM Analytics (14 per cent). It can be argued that the decreasing weightage of the food component in the consumer basket has played a role in producing misleading data. The food inflation component weight in the CPI (all country) was 26.6 per cent in 2000 and declined to 18.28 per cent in 2008 and further to 15.41 per cent in 2013 (Stats SA, 2008; Stats SA (2), 2013). In South Africa (a developing country) 31.3 per cent of the population lives under the poverty line, food weightage in household expenditure should, realistically, be around 30-40 per cent, as advocated by Gomez *et al.,* (2006) for the Colombian case. Yet the published South African CPI does not reflect this. The next question is then: is inflationary targeting in South Africa being carried out using data that is comprehensively representative of its real consumer spending habits? But this is beyond the purpose of the research, albeit a valid point.

Modeling food inflation in a developing country is therefore more complex than it seems, but various models are available for just this purpose. The next section reviews the applicability of these models to the South African case and takes a look at some important factors to be considered when constructing such a model.

2.5. *Modelling of a Food Inflation Forecasting Model*

In the light of inertial effects, weightage in headline CPI, high volatility and the important role played in monetary policy decision-making, derived from reviewed literature it is clear that formulating an accurate food inflation forecasting model is imperative. Further review of literature offers various models with which to build such a model and will now be discussed.

The most appropriate modeling technique and most significant factors that affect food inflation must first be identified to enable accurate model fitting for use in forecasting. Some studies done abroad can be applied to the South African example due to similar economic make-up of the selected study countries.

2.5.1. Models used in predicting inflation and food inflation

Gomez *et al.,* (2006) investigated different models employed by the Colombian Central bank with which to forecast food inflation. The need for the models arose when it was discovered that the recently indicted inflation targeting regime failed to meet its inflationary targets due to unforeseen price shocks of volatile components of inflation such as oil and food. The different models employed included:

- Autoregressive integrated moving average with exogenous variables (ARIMAX)-forecasts by using patterns observed in previous food inflation values with applicable independent variables (in this case rainfall) (Borghers & Wessa, 2014).
- Group 6 Model – uses an error correction model to see how fast an independent variable (food inflation) returns to equilibrium after a change in one or more independent variables occurs (Best, 2008). This model disaggregates the food basket into six different main groups.
- Group10 Model – this model is the same as the Group 6 model but disaggregates the food basket further into 10 main categories.

- Neural Network Model – a complex self-training algorithm that can makes forecasts based on previous values (Vonko, 2009).
- Naïve model – this model uses previous periods' values to forecast future values, but does not try to identify or include the causal factors of the changing data (Business Dictionary, 2014).

Gomez *et al.,* (2006) compared these models and tested their accuracy, and found that disaggregation of the food baskets into unprocessed, processed and food away from home and by using combination forecasting improved the model forecasting accuracy. Combination forecasting involves the aggregation of different forecasting models into a single forecast model; the complexity and scope of which this study is not equipped for.

Bokhari & Feridun (2006) evaluated ARIMA and Vector Autoregression models (VAR) in predicting inflation in Pakistan. The VAR model looks for relationships between several time series and can be used to predict the conjoint evolution of the time series over time. Bokhari & Feridun (2006) found that by minimising the number of factors present in the ARIMA model and lowering the number of lags selected (i.e. how far ahead models were to predict) relative mean square error (MSE) was reduced (a measure of deviation by predicted values to actual values), thus improving forecasting accuracy.

VAR, autoregressive (AR) and factor models were compared using respective root mean squared error (RMSE, similar to MSE mentioned above) by Krusec (2007) in the Slovenian economy. The models were used to forecast inflation and selected sub-components. It was found that the factor models outperformed AR models but a conclusion could not be reached on whether or not factor models outperformed VAR models as results were marginal. It was found that factor models work best when using a small dataset with few variables.

Lack (2006) did an overview of the VAR models used to forecast inflation by the Swiss National Bank. It was found that combining forecasts from models with different variables would allow for a so-called diversification effect in which using a single model is avoided. Furthermore, using raw data at levels was found to be more accurate than when the data was differenced.

Riaz (2012) investigated the accuracy testing techniques used in selecting the best forecasting model. Instead of relying solely on common accuracy testing techniques such RMSE and MSE, Riaz (2012) followed a technique called rationality testing. This type of testing includes criteria such as information efficiency and unbiasedness alongside RMSE and MSE. It was found that the VAR model used to forecast food price inflation in Pakistan was found to be "strongly rational" under the rationality testing criteria, deeming it more than sufficient.

Another method seldom used in forecasting inflation is the Phillips Curve. In its original form the Phillips Curve shows how unemployment and inflation are negatively correlated, thus forecasting on the basis of the assumption that high aggregate demand leads to employment, raising average incomes and thereafter prices of goods and services (Dureval *et al.,* 2009). Some researchers (Kapur, 2013; Andrle, Berg, Morales, Portillo and Vleck, 2013) have however, used this technique to forecast (whether or not this was done accurately is subjective) and successfully identify inflationary drivers. Rumler and Valderrama (2010) concluded that using such a structural model of forecasting (the Phillips Curve) proved successful only for a longer forecast, but were outperformed by VAR models over shorter periods (up to 3 months ahead). Dureval *et al.,* (2009) also concluded that limited labour market directive and high degree of informality of most markets in Sub-Saharan Africa, would nullify the assumed relationship between demand and wages and ultimately inflation, meaning the Phillips Curve would not be suitable for the purposes of this study. Kapur (2013) and Andrle *et al.,* (2013) were able to identify imported food prices, monetary policy (via its effect on nominal exchange rate) and international non-fuel commodity prices as strong influences on food and non-food inflation in respective study areas.

Batool and Shabbir (2011) addressed many forecasting issues that, once corrected, provide greater insight and forecasting ability when using VAR models. One observation was that accounting for seasonality when modelling food inflation produced more sensible results as opposed to strict academic outcomes. Another was that instead of just testing for normal unit roots, seasonal unit roots were tested for and accordingly differenced greatly influencing the outcome of the model.

Neda (2011) forecasted inflation, food inflation and non-inflation rates for Ethiopia by fitting a VAR model and predicting future values by means of a vector error correction (VEC) model. The forecasting models were then evaluated using RMSE and MSE techniques, but when compared to other studies of the same nature, accuracy of the model developed was found to be fairly inaccurate. It must be said that Neda (2011) could not include certain vital factors such as money supply, GDP and wages as they were not available. Inclusion of these factors would have (as seen in reviewed literature) improved forecasting accuracy. Once a model is selected, significant factors which could contribute to model relevance for the South African case, must be selected.

2.5.2. Important factors to consider when forecasting food inflation

When considering the work of Batool and Shabbir (2011) it is important to note that according to the NAMC (2013), one of the main drivers of food inflation was vegetable and milk production which followed a seasonal drop during the winter months. The approach of analysing (but not forecasting) food inflation in a disaggregated fashion by the NAMC (2013) also provides a base to work from to apply what Gomez *et al.,* (2006) advocated regarding improved for casting accuracy through disaggregation of factors.

Golinelli and Orsi (2001) also employed VAR models to identify important factors affecting inflation. Although the study was aimed at making the relationships between prices, wages and exchange rates more clear during the assimilation period of the Czech Republic, Hungary and Poland into the European Union, it still sheds some light on inflation drivers. It would appear that the exchange rates and output gap (that is the difference between actual and potential Gross Domestic Product) were the main determining factors of inflation.

Tafere (2008) investigated the sources of inflation in Ethiopia and found that inflation was both sector (food and non-food) and time period dependant. The VAR model employed showed that long run food inflation was greatly affected by real income, money supply, inflation expectation and global food prices. Short run determinants were cited as wages, exchange rates, and international prices. (It is interesting to note that inflation expectations were quantified as having a tangible effect on food inflation). Alemu and Ogundeji (2010) also found that the pass-through effect of increasing producer prices also affected inflation in South Africa.

Dureval *et al.,* (2009) identified the particular significance of cereal markets and prices as determinants of food inflation due to household spending habits (the majority of which is centred on buying food). Money supply was found to have a significant impact on food inflation in the short run suggesting monetary policy is, when applied effectively, a complementary, albeit blunt, tool in controlling food inflation. But on the other side of the world, short run inflation in Croatia was found to be more responsive to supply side (price mark-ups) and exchange rates than to money supply or monetary sector shocks (Vizek and Broz, 2007). These studies are contradictory, but Dureval *et al.,* (2009) provides a deeper insight into the inflationary process by including sub-sectorial price movements in the model as opposed to Vizek and Broz's (2007) narrow monetary (money supply and excess money) and broad country wide (GDP output gap and price mark-up) factors.

Rangasamy (2010) uses the flow diagram presented in Figure 2.4 to explain some of the main factors influencing food inflation and ultimately headline inflation.

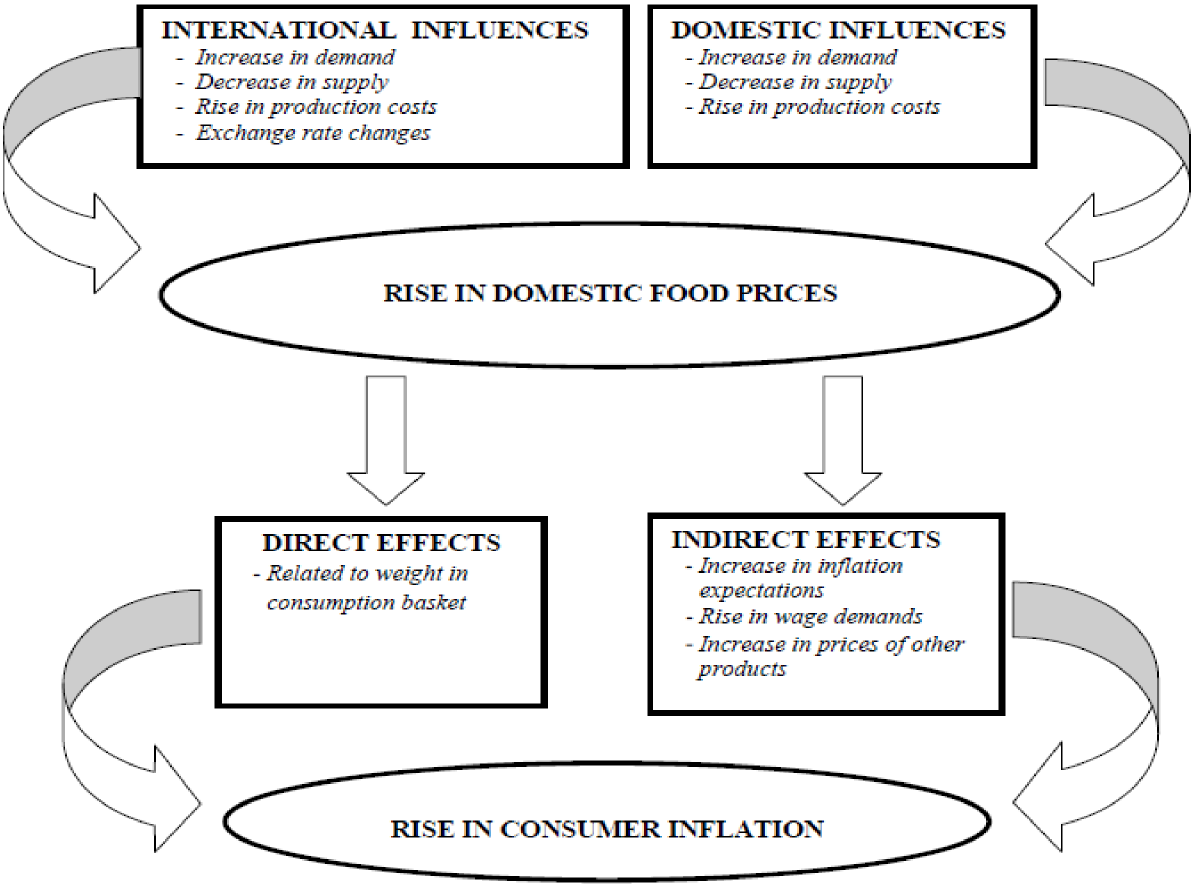

Figure 2.4 Impact of food price increases on consumer South African inflation

Source: Rangasamy (2010)

Figure 2.4 reiterates previous literature almost exactly but for the South African case, in terms of causes of food and headline inflation. Rangasamy (2010) elaborates further by stating that although international factors (oil price, exchange rate and pricing practices of international producers) indeed do have an effect on food inflation in South Africa, domestic factors (production costs, supply shocks, e.g. drought) are of greater causal significance.

2.6. *Conclusion*

From available literature it is clear that food inflation warrants further investigation due to its dynamic and volatile nature. Global food inflation can be explained by two different schools of thought, but South African food inflation can be classified under both schools of thought. This brings us to the fact that there are clear discrepancies in the inflation dynamics of developed and developing countries, mostly due to expenditure habits, and production capability. In South Africa food inflation has a greater effect on the CPI than what is currently assumed; this is due, in part, to the social makeup of the Republic.

The effects of inflation (driven by food inflation) are both far-reaching and innumerable. In South Africa, with the huge income gap between rich and poor, food inflation has different wealth-eroding effects on these different income classes. These income classes are divided into five different expenditure quintiles as follows: quintile one – up to R21 399; quintile two – R21 400 up to R35 750; quintile three – R35 751 up to R61 624; quintile four – R61 625 up to R142 083 and quintile five – R142 084 and more (Stats SA 2014 (4)). Stats SA attempts to capture these varying effects of inflation on different income groups by means of constructing an inflation index, but as the index is carefully scrutinized it is clear the index falls short of accurate representation. This has many implications for monetary policy, which is based on this inaccurate index. Monetary policy reaction to inflation is geared by means of inflation targeting.

When modeling all of the dynamics of food inflation, various models are at our disposal. From literature the best model for the purposes of this research was the Vector Autoregressive model (VAR) as advocated by Krusec (2007), Riaz (2012), Kapur (2013), Andrle, Berg, Morales, Portillo and Vlcek (2013), Dureval (2009) and Neda (2011). Now, before the actual modelling could be done, literature had to be the guide in showing us which factors would explain food inflation the most accurately and ultimately gives us the most accurate forecast.

The important factors identified from literature for the South African context include: CPI without the food component (Neda, 2011, Tafere, 2008), nominal effective exchange rate (Golinelli and Orsi, 2001, Tafere, 2008) money supply (Vizek and Broz, 2007), domestic food supply balance sheet (Dureval *et al.*, 2009), oil prices (Rangasamy, 2010), producer price index (Alemu and Ogundeji, 2010), SARB repurchase rate (Rangasamy, 2010, Mishkin and Schmidt-Hebbel, 2007) and international food prices (Gomez, Gonzalez, Melo and Torres, 2006, Loening *et al.*, 2009). This brings us to Chapter 3 where the data and methodologies used will be discussed.

CHAPTER 3
DATA AND METHODOLOGY

3.1. Introduction

The main objective of this chapter is to highlight the approaches and models that can be used to forecast food inflation in South Africa. The decision on the data sets to be used in the modeling of food inflation was derived from literature available. These factors include CPI without the food component, nominal effective exchange rate, money supply, domestic food supply balance sheet, oil prices, producer price index, SARB repurchase rate and international food prices. These data were collected from Statistics South Africa's time series database and are in monthly intervals over the period January 2003 to May 2014. All data was capture in Excel, and processed with Eviews 7 statistical package.

3.2. Methodology

Time series analysis can be done using either univariate or multivariate models. Univariate analysis can be carried out by Autoregressive integrated moving average modelling (ARIMA). This fitted model makes use of past values of a single time series data set and introduces an error term to capture information about fluctuations over time in the data (Neda, 2011). Multivariate time series analysis is used to better understand more than one time series, by explaining both individual changes of each time series over time and interactions between time series in the dataset. This thesis is concerned with multivariate time series analysis. Firstly, the statistical properties of the data need to be examined followed by a review of modeling activities.

3.2.1. Statistical properties of the data

3.2.1.1. Testing Stationarity

Time series must be stationary before certain models can be fitted to the series, other models are available for non-stationary data, but for the purpose of this study, the data must be stationary. Economic data is usually non-stationary, exhibiting various trends over time, which can cause spurious regression in a fitted model (Vosvrda, 2014). A time series found to be non-stationary can be transformed into stationary data, in which the auto-covariances and mean of the series remains the same over time.

The conditions for a stochastic process, Y_t, which is stationary, are therefore expressed, as (Hu, 2006):

Condition 1: $E(Y_t) = \mu, \text{ constant for all } t$ [3.9]

Condition 2: $Cov(Y_t\, Y_{(t-j)}) = \beta_j = E[(Y_t - \mu)(Y_{(t-j)} - \mu)^{T}] = \beta_{(-j)}^{T}$ for all t and j = 0,1,2,… [3.10]

Equation [3.9] specifies that all Y_t exhibits the same finite mean vector µ. Condition [3.10] specifies that auto-covariances of the process must depend on the time period, t-j, of the two vectors Y_t and Y_{t-j}, not just t or j (i.e. first and second moments do not change with time) (Hu, 2006).

When considering an autoregressive process correlated at one lag (AR(1)) :

$$Y_t = pY_{t-1} + X_t' \gamma + \varepsilon_t \qquad [3.11]$$

Where X_t represent optional exogenous regressors, p and γ are parameters that need to be estimated and ε_t represents the white noise or error term. Now if parameter p is found to be |p|>1, the variance of Y_t increases with time, Y_t is therefore a non-stationary series. Y_t is considered to be a stationary series if |p|<1. Stationarity testing, therefore, is simply testing whether the absolute value of p is strictly less than one (Hamilton, 1994).

To test for stationarity, two widely used methods exist namely Augmented Dickey Fuller (ADF) and Phillip Perron (PP) (Neda, 2011). The Augmented Dickey Fuller test was found to be superior to the Phillip Perron test by Davidson and McKinnon (2004) when processing finite samples of data. Thus the ADF test is better suited to this study's data set.

3.2.1.2. Augmented Dickey Fuller Test

The Dickey Fuller test is carried out by subtracting y_{t-1} from equation [3.11] as follows (Dickey and Fuller, 1979):

$$Y_t = \alpha Y_{t-1} + X_t' \gamma + \varepsilon_t \qquad [3.12]$$

In [3.12] α =p-1 and Y_t=Y_t - Y_{t-1}. With the null and alternative hypotheses:

H_o: $\alpha=0$

H_a: $\alpha<0$ [3.13]

Which can be evaluated by means of the conventional t-ratio for α:

$$t_\alpha = \frac{\hat{\alpha}}{se(\hat{\alpha})} \qquad [3.14]$$

With $\hat{\alpha}$ representing an estimate of α, and $se(\hat{\alpha})$ denoting the coefficient standard error.

Thus, Dickey and Fuller (1979) found that under the null hypothesis of a unit root that the test statistic deviates from the standard student's t-distribution. Asymptotic results are derived, from which critical values for different sample sizes are simulated. These sets of simulations were later expanded by MacKinnon (1994). This standard unit root test can only be used for an autoregressive order one process. If the series is correlated at higher order lags (i.e. >1), then the assumptions about white noise, ε_t, are violated (i.e. normal, independent and identical distribution with zero mean) (Kleijnen, 2006). The Augmented Dickey Fuller test overcomes this problem, by first constructing a parametric correction for higher order correlation (by means of assuming the series follows an autoregressive process of order p or AR(p), and then by including lagged difference terms of the dependent variable to the right-hand side of the regression:

$$\Delta Y_t = \alpha Y_{t-1} + X_t'\gamma + \theta_1 \Delta Y_{t-1} + \theta_2 \Delta Y_{t-2} + \cdots + \theta_p \Delta Y_{t-p} + U_t \qquad [3.15]$$

This specification [3.15] is considered an augmented version of the standard [3.12] and is subsequently used to test hypothesis [3.13] using the t-ratio specified in [3.14]. It must be noted that the number of lagged difference to add in [3.15] depends on the significance of θ by means of t statistic testing), or, alternatively making sure there is no serial correlation between error terms U_t, which can lead to either over or underestimation of ordinary least squares estimates of standard errors (Gujarati, 2003). If a time series is found to be non-stationary, it can be converted to stationary data by means of differencing. The final step in data property analysis is to determine whether or not long-run relationships exist between variables.

3.2.1.3. Cointegration Analysis

The possibility of a long-run equilibrium relationship existing between variables of the VAR, can affect the model output. This can cause any deviating variable to be gradually equilibrated with this long-run relationship, or cointegrating vector, (Hendry and Juselius, 2001). A VAR model with a cointegrating vector that has a significant '*attractor*' effect on the variables must, therefore, be augmented with an Error Correction term. This term corrects for deviation from long-run equilibrium by means of partial short-run adjustments in the model.

A cointegrated set of variables must therefore, be detected before running the model, so as to discern whether or not an Error Correction term is needed.

3.2.1.4. Johansen Cointegration Testing

Cointegration testing can be done by means of the Johansen's cointegration test. According to Johansen's methodology (Johansen, 1988, 1991) the VAR model of order p is expressed as follows:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + Bx_t + \varepsilon_t \qquad [3.20]$$

Y_t represents a *k*-vector of non-stationary I(1) variables (similar to [3.1]). I(d) refers to a non-stationary time series which has been differenced *d* times to make it stationary, and is therefore integrated of order *d*. x_t represents a d vector of deterministic variables with ε_t being the difference between the measurement vector and the predicted measurement vector, also known as the innovations vector (Neda, 2011). This VAR can be simplified as:

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \vartheta_i \Delta Y_{t-i} + Bx_t + \varepsilon_t \qquad [3.21]$$

where:

$$\Pi = \sum_{i=1}^{p} A_i - I, \vartheta_i = -\sum_{j=i+1}^{p} A_j \qquad [3.22]$$

According to Granger's representation theorem (Engle and Granger, 1987) there exist k x r matrices α and β with rank r so that $\Pi=\alpha\beta$ and $\beta' y_t$ is **I**(0), if the coefficient matrix Π has reduced rank $r<k$. From this theorem r is the number of cointegrating relations where each column of β represents the long run relationship detected (or the cointegrating vector). The adjustment parameters in the Vector Error Correction Model (VECM) are represented by α. Estimating Π from an unrestricted VAR and testing whether or not restrictions implied by the reduced rank of Π can be rejected, are the steps taken in Johansen's test (Belke and Polleit, 2009).
To estimate the number of cointegrating vectors, two tests are used: the Trace statistics and Maximum Eigenvalue.

Trace statistics testing evaluates the null hypothesis which states that no more than r cointegrating relations exist. This is evaluated against the alternative hypothesis of n cointegrating relations. n denotes the number of variables present for r = 0, 1, 2…n-1. (Johansen, 1988). The maximum Eigenvalue test, alternatively, tests the null hypothesis of r cointegrating vectors against the alternative hypothesis of r + 1 cointegrating vectors for r = 0,1,2…n-1.
The trace statistic and Eigenvalue test statistic can be written as (Hjalmarsson and Österholm, 2010):

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} [\log[1 -] \lambda_i] \qquad [3.22]$$

$$\lambda_{\max(r,r+1)} = -T log(1 - \lambda_{r+1}) \qquad [3.23]$$

With T representing the sample size and λ_i is the i^{th} largest correlation. Once all data properties have been identified and corrected for, work on the actual modeling of the data can be done.

3.3. Modelling the data

The next section will review the modelling processes that need to be performed to analyse the data.

3.3.1. Vector Autoregressive Models (VAR)

The VAR model is particularly suited for financial and economic data because it can describe the dynamic nature of these types of data. The VAR model has also proven to be more accurate than univariate and simultaneous equation models when it comes to forecasting (Zivot and Wang, 2006).

3.3.2. Stationary Vector Autoregressive Model

The stationary VAR model is expressed as follows:
Let Yt = (y_{1t}, y_{2t},…, y_{nt}) represent an (nx1) vector of time series variables. The p-lag vector autoregressive model (VAR(p)) is then written as:

$$Y_t = \mathbf{c} + \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \cdots + \Pi_p Y_{t-p} + \varepsilon_t, \text{ t=1,…,T} \qquad [3.1]$$

where c represents an *n* x 1 vector of constants and Π_j an *n* x *n* matrix of autoregressive coefficients for *j*= 1, 2,…, *p* (Hamilton, 1994). The *n* x 1 vector of constants, $\mathcal{E}_t$, denotes the white noise component:

$$E(\varepsilon_t) = \mathbf{0} \text{ and } E(\varepsilon_t \varepsilon_s') = \begin{cases} \Sigma\ t = s \\ 0\ t \neq s \end{cases} \qquad [3.2]$$

where Σ is an (nxn) symmetric positive definitive matrix.

Let c_i represent the i^{th} element of the vector c and let $\Pi_{ij}^{(1)}$ represent the row (*i*) and column (*j*) elements of the matrix Π_1. Hence, the first row of the vector system in [3.1] can be written as (Neda, 2011):

$$Y_t = c_1 + \Pi_{11}^{(1)} Y_{1,t-1} + \Pi_{12}^{(1)} Y_{2,t-1} + \cdots + \Pi_{1n}^{(1)} Y_{n,t-1} + \Pi_{11}^{(2)} Y_{1,t-2} + \Pi_{12}^{(2)} Y_{2,t-2} + \cdots + \Pi_{1n}^{(2)} Y_{n,t-2} + \cdots$$
$$+ \Pi_{11}^{(p)} Y_{1,t-p} + \Pi_{12}^{(p)} Y_{2,t-p} + \cdots + \Pi_{1n}^{(p)} Y_{n,t-p} + \varepsilon_{1t}$$

[3.3]

So from [3.3] it is evident that a VAR model is a system whereby each variable is simply regressed on a constant and *p* lags of its own and on *p* lags of the other variables included in the model.

The lag operator notation of [3.1] is therefore transcribed as (Lütkepohl, 2011):

$$\Pi(L) Y_t = c + \varepsilon_t \qquad [3.4]$$

With: $\Pi(L) = I_n - \Pi_1 L - \cdots - \Pi_p L^p$

Further, when:

$$\det\left(I_n - \Pi_1 z - \cdots - \Pi_p Z^p\right) = \mathbf{0} \qquad [3.5]$$

lie outside of the complex unit circle, the VAR (p) is considered stable. This is also true if the eigenvalues of the companion matrix expressed as (Hakkio and Morris, 1984):

$$F = \begin{pmatrix} \Pi_1 & \Pi_2 & \cdots & \Pi_n \\ I_n & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \ddots & \mathbf{0} & \vdots \\ \mathbf{0} & \mathbf{0} & I_n & \mathbf{0} \end{pmatrix} \qquad [3.6]$$

have a modulus of less than one. This stable VAR(p) is then stationary with covariance, means and auto-covariances remaining constant over time.

The unconditional mean can be expressed as:

$$\mu = ((I)_n - \Pi_1 - \cdots - \Pi_p)^{-1} c$$

if Y_t in [3.1] is covariance stationary. The VAR (p) can then be written in its mean-adjusted form:

$$Y_t - \mu = \Pi_1 \left(Y_{t-1} - \mu\right) + \Pi_2 \left(Y_{t-2} - \mu\right) + \cdots + \Pi_p \left(Y_{t-p} - \mu\right) + \varepsilon_t \qquad [3.7]$$

This VAR (p) model lacks some deterministic terms (e.g. seasonal dummy variables) and exogenous variables which can improve data representation. The VAR (p) is therefore specified as:

$$Y_t = \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \cdots + \Pi_p Y_{t-p} + \alpha D_t + G X_t + \varepsilon_t \qquad [3.8]$$

This general form VAR (p) model [3.8] improves on the basic VAR (p) [3.1] by including deterministic elements by means of an (*l* x 1) matrix represented by D_t. Exogenous variables are also include by means of an (*m* x 1) matrix of these variables, represented by X_t. Lastly, parameter matrices α and G, describing the relative contribution of each model to the VAR (p), are also added (Neda, 2011).

3.3.3. Lag Length Selection of the VAR

Lag length selection of the VAR model is one of two important steps in model specification. The second step is imposing restrictions on the VAR model itself. These steps are followed so as to avoid model specification error or bias (Gujarati, 2003).
Lag selection can be done by means of model selection criteria. This is done by simply fitting a VAR model with orders m = 0,…,p_{max} and selecting the value of m which violates model selection criteria the least. Model selection criteria models have the general form (Lütkepohl, 2005):

$$C(m) = log(|\hat{\Sigma}_m|) + c_T \cdot \sigma(m,k) \qquad [3.16]$$

$\hat{\Sigma}_m = T^{-1}\Sigma_{t=1}^{T}\hat{\varepsilon}_t\hat{\varepsilon}_t$ represents the residual covariance matrix estimator for a model of order m. $\sigma(m,k)$ is a function, also of order m, by which large VAR orders are penalized and c_T represents a sequence by which the specific criterion is selected, which depends on the sample size.
Three widely used information criteria for selection the lag order are the Akaike (AIC), Schwarz (SC) and Hannan-Quin (HC) information criteria. These criteria can be written as (Akaike, 1998; Hannan and Quin, 1979; Schwarz, 1978):

$$AIC(m) = log(|\hat{\Sigma}_m|) + \frac{2}{T} mk^2 \qquad [3.17]$$

$$SC(m) = log(|\hat{\Sigma}_m|) + \frac{logT}{T} mk^2 \qquad [3.18]$$

$$HQ(m) = log(|\hat{\Sigma}_m|) + \frac{2loglogT}{T} mk^2 \qquad [3.19]$$

Where $\varphi(m,k) = mk^2$ represents the number of VAR parameters in a model of order *m* with *k* variables.

When choosing the VAR order, the respective criteria is minimized as much as possible over orders m = 0,…,p_{max}. The suggested order of the VAR model differs among the information criteria, with AIC suggesting the largest order, SC the smallest and HQ suggesting an order in between (Lütkepohl, 2005). It is possible that all three criteria can agree in their choice of lag order, with HQ and SC being the most consistent with each other. This lag order selection does depend partly on the magnitude of p_{max} chosen. Choosing too large or too small p_{max} can result in spuriousness or an appropriate model not presented in the set of models. Such an issue is can be detected when carrying out model checking (residual autocorrelation and normality testing) (Lütkepohl, 2009).

3.3.4. Vector Error Correction Models (VEC)

If it is known that a non-stationary series within a VAR are cointegrated, then the model must be augmented with a Vector Error Correction Term (VEC). The VEC allows for short run adjustments dynamics but restricts long-run cointegrating relationships of endogenous variables. The VAR is therefore considered a restricted VAR, due to restrictions placed on the model by the error correction term. This is done so as to avoid misspecification and omission of important constraints in the model. This restricted VAR can be re-written in the VECM form as (Hauser, 2013):

$$\boldsymbol{\Delta} Y_t = \Pi Y_{t-\mathbf{1}} + \sum_{i=\mathbf{1}}^{p-\mathbf{1}} \vartheta_i \,\boldsymbol{\Delta} Y_{t-i} + B x_t + \varepsilon_t \qquad [3.24]$$

where:

$\Pi = -I_n + \sum_{i=\mathbf{1}}^{p} A_i,\ \vartheta_i = -\sum_{j=i+\mathbf{1}}^{p} A_j,$ with I_n representing an identity matrix

Matrix Π can be broken down to its constituents $\Pi=\alpha\beta$ with α representing an *n*x*r* matrix of speed of adjustment and β representing an *n*x*r* matrix of parameters determining the cointegation relationship of long run coefficients. The columns of β represent the actual long-run equilibrium relationship between the variables with the matrix α showing how fast the variables adjust towards it. If α values are close to zero, it implies slow convergence (slow equilibrium correction).

3.3.5. Model Checking

3.3.5.1. Autocorrelation

When different variables in a series exhibit correlation between each other in different time periods, it is known as autocorrelation. Autocorrelation is not the same as autoregression, as error terms are linearly related in different periods under the assumption of autocorrelation. Autocorrelation can reveal trends and information about future values of a series, making it useful in forecasting. It can also cause problems as true covariance between time series might be harder to identify (Meko, 2013).

Testing for autocorrelation in a multivariate time series can be done using the Lagrange Multiplier test (LM). This test is superior to the Rao F-Test as demonstrated in a Monte Carlo experiment by Hatemi-J (2004). The LM test is also suited for AR(1) and higher order processes.

The LM test assumes a VAR model with an error term of u_t of:

$$u_t = D_{\mathbf{1}} u_{t-\mathbf{1}} + \dots + D_{\mathbf{h}} u_{t-\mathbf{h}} + v_t \qquad [3.25]$$

Where v_t represents the error term. So to test for autocorrelation in u_t $H_o{:}D_1=\ldots=D_h=0$ is tested against $H_1{:}D_j\neq 0$ for at least one j<h. This test is done by estimating the regular VAR model with $u_t=v_t$ under the null hypothesis H_o. To specify the test statistic the auxiliary regression model is first specified from which a least squares estimator can be derived.

The auxiliary regression can be specified as (Lindsey, 2008):

$$\hat{U} = BZ + D\hat{U} + E \qquad [3.26]$$

Where:

$\hat{U} = [\mu\hat{\square}_1 \ldots \mu\hat{\square}_T]$

$Z_t = [1^T y_t^T \ldots y_{t-p+1}^T]^T$

$Z = [Z_0 \ldots Z_{T-1}]$

$D = [D_1 \ldots D_h]$

Let F_i be:

$$\hat{U}F_i\hat{U}^T = \sum_{t=i+1}^{T} \hat{u}_t \hat{u}_{t-i}^T \qquad [3.28]$$

Then:

$F = [F_1 \ldots F_h]$

$$\hat{U} = (I \emptyset \hat{U})F^T \qquad [3.29]$$

Giving the least squares estimate of D

$$\hat{D} = \hat{U}\hat{U}^T[\hat{U}\hat{U}^T - \hat{U}\hat{Z}^T(ZZ^T)^{-1}Z\hat{U}^T]^{-1} \qquad [3.30]$$

The standard χ^2 test statistic for testing for no autocorrelation is then:

Under the null hypothesis:

$$H_0\ \lambda_{LM}(h) = vec(\hat{D})^T \left([\hat{U}\hat{U}^T - \hat{U}\hat{Z}^T(ZZ^T)^{-1}Z\hat{U}^T] \emptyset \sum_u \square \right) vec(\hat{D}) \qquad [3.31]$$

$$\lambda LM\square(h) \xrightarrow{d} \chi^2(hk^2) \qquad [3.32]$$

3.3.5.2. Jarque-Bera Normality Testing

The Jarque-Bera test is used to ascertain whether or not sample data is normal distribution (aggregated around a common mean) and was developed by Jarque and Bera (1987). This is done by determining whether the skewness and kurtosis of the sample data match that of a normal distribution (bell-shaped curve). More specifically, the skewness and kurtosis of the u_t of the multivariate series is evaluated (Foltz, 2012).

A normally distributed series has skewness of zero and kurtosis of three (with the Jarque-Bera test statistic then being zero); therefore, the null and alternative hypotheses apply when testing against the normality of the sample data (Gujarati, 2003):

$$\begin{aligned} H_0 &= E(u_t^s)^3 = 0(skewness) \\ &= E(u_t^s)^4 = 3(kurtosis) \\ H_1 &= E(u_t^s)^3 \neq 0(skewness) \\ &= E(u_t^s)^4 \neq 3(kurtosis) \end{aligned} \qquad [3.33]$$

The Jarque-Bera test can be written as (Gujarati, 2003):

$$JB = \frac{n}{6\left(S^2 + \frac{1}{4(K-3)^2}\right)} \qquad [3.34]$$

With *n* representing the sample size, S shows the skewness coefficient of the sample, and K is the kurtosis coefficient of the sample. Skewness is measured in the third moment of the variable about the mean and gives an indication of symmetry of the distribution. Kurtosis is measured in the fourth moment and shows how much the distribution is peaked. Skewness and kurtosis are calculated by (University of Alabama, 2014):

$$Skewness = \frac{\hat{\mu}_3}{\hat{\sigma}^3} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^{\frac{3}{2}}} \qquad [3.35]$$

$$Kurtosis = \frac{\hat{\mu}_4}{\hat{\sigma}^4} = \frac{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)^2} \qquad [3.36]$$

In both formulae, $\hat{\mu}_3$ and $\hat{\mu}_4$ represent the third and fourth moments, $\bar{x}$ represents the sample mean with $\hat{\sigma}^3$ and $\hat{\sigma}^4$ representing the estimates of variance in the third and fourth moments, respectively.

3.3.6. Forecasting

Multivariate time series analysis is generally carried out not only to discover underlying relationships between variables, but also to forecast future values. VAR models have been found to be relatively stable when forecasting economic data (Bruneauy, De Bandtz, Flageollety and Michauxx, 2004). Zivot and Whang (2006) set out a specific methodology for forecasting, which this section of the study will be based on.

Firstly, let us assume that Y_t consists of parameters Π, in a VAR(*p*) process. The parameters are assumed to be known and exhibit no deterministic terms or exogenous variables. For this process the best linear predictor, when considering measures of accuracy, for a one-step ahead forecast from time T (the time period up to which data will be available):

$$Y_{(T+1|T)} = c + \Pi_1 Y_T + \cdots + \Pi_p Y_{T-p+1} \qquad [3.37]$$

Now to forecast for longer periods ahead the chain rule of forecasting may be used and can be written as:

$$Y_{(T+h|T)} = c + \Pi_1 Y_{(T+h-1|T)} + \cdots + \Pi_p Y_{(T+h-p|T)} \qquad [3.38]$$

in this case $Y_{T+j|T} = Y_{T+j}$ for $j \le 0$. This forecasting method is also known as the h-step ahead forecast. The errors for the h-step ahead forecast are written as:

$$Y_{T+h} - Y_{(T+h|T)} = \sum_{s=0}^{h-1} A_s \varepsilon_{T+h-s} \qquad [3.39]$$

Matrices A_s are derived from:

$$A_s = \sum_{j=1}^{p-1} A_{s-j} \Pi_j \qquad [3.40]$$

From [3.40] parameters $\Pi_j = 0$ for all j>p. These forecast errors have expectation zero with (i.e. no covariance between forecast errors and independent variables) (Lambert, 2013) meaning they are unbiased. The mean squared error (MSE) (the average of the squares of the difference between estimated and estimator) for $Y_{t+h|T}$ is written as:

$$\begin{aligned} \Sigma(h) &= MSE\left(Y_{T+h} - Y_{(T+h|T)}\right) \\ &= \sum_{s=0}^{h-1} A_s \Sigma A_s' \end{aligned} \qquad [3.41]$$

When the parameters of a VAR(p) process are estimated by means if multivariate least squares to forecast for Y_{T+h} then the best linear predictor becomes:

$$\hat{Y}_{(T+h|T)} = \hat{\Pi}_1 \hat{Y}_{(T+h-1|T)} + \cdots + \hat{\Pi}_p \hat{Y}_{(T+h-p|T)}$$

[3.42]

From [3.42] $\hat{\Pi}_j$ now represented the estimated parameters matrices; therefore the h-step forecast is changed to:

$$Y_{T+h} - \hat{Y}_{(T+h|T)} = \sum_{s=0}^{h-1} A_s \varepsilon_{T+h-s} + \left(Y_{T+h} - \hat{Y}_{(T+h|T)}\right)$$

[3.43]

Now the term (Y_{T+h} - $\hat{Y}_{(T+h|T)}$) defines the component of forecast error which is caused by parameter estimation. The MSE matrix of this h-step forecast is then given as:

$$\hat{\Sigma}(h) = \sum_{s=0}^{h-1} \hat{A}_s \hat{\Sigma} A_s' \qquad [3.44]$$

So by using [3.43] with unbiased forecast errors [3.44] dependant variable Y_t (i.e. Food inflation) can be forecast for h steps ahead.

3.3.7. Structural Vector Autoregressive Analysis (SVAR)

The VAR model has many parameters, which can interact with each other or may cause changes in one another over time. These complex interactions can make interpretations deduction a hard task. To overcome this issue, a structural analysis must be carried out (Iida, 2008). The three main tools used in structural analysis include: Granger causality testing; impulse response functions and forecast error variance decompositions.

3.3.7.1. Granger Causality

The logic behind the Granger causality testing follows that if a (group of) variables x_1 is found to lend itself to predicting another (group of) variables x_2, then x_1 is assumed to Granger cause x_2. If x_1 is found to Granger cause x_2 and x_2 is also found to Granger cause x_1 this signifies the presence of a feedback system or relationship between the variables (Neda, 2011).

To test for Granger causality two pairs of regressions are estimated:

$$X_{1t} = \sum_{i=1}^{n} \alpha_i X_{2t-i} + \sum_{j=1}^{n} \beta_j X_{1t-j} + \mu_{1t} \qquad [3.45]$$

$$X_{2t} = \sum_{i=1}^{n} \gamma_i X_{2t-i} + \sum_{j=1}^{n} \delta_j X_{1t-j} + \mu_{2t} \qquad [3.46]$$

Where x_{1t} and x_{2t} are two different variables and u_{1t} and u_{2t} represent white noise terms assumed to have no correlation between them (Günay and Keçeci, 2011). From these two regressions it is

tested whether or not lags of x_1 are significant in x_2, and vice versa. If lags of x_1 are significant in x_2 then x_1 Granger causes x_2 and, again, *vice versa*.
For a process Y_t (Goldstein, 2013):

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \cdots \beta_p Y_{t-p} + \gamma_0 X_{t-1} + \gamma_p X_{t-p} + \varepsilon \qquad [3.47]$$

The null and alternative hypotheses for Granger causality are stated as:

$$H_0: \gamma_0 = \gamma_1 = \gamma_2 = \cdots = \gamma_p = 0$$
$$H_a: \gamma_0 \neq \gamma_1 \neq \gamma_2 \neq \cdots \neq \gamma_p \neq 0$$

[3.48]

If the null hypothesis is rejected then Granger causality is assumed from an x to y direction.

3.3.7.2. Impulse Response Functions

An impulse response shows what output results when an impulse (or shock) is experienced by, or applied to the system, or process Y_t
Firstly a process Y_t with k-dimensional vector series is written as (Hu, 2006):

$$Y_t = A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + U_t$$
$$= \emptyset(B) U_t = \sum_{i=0}^{\infty} \emptyset_i U_{t-i}$$
$$I = \left(I - A_1 B - A_2 B - \cdots - A_p B^p\right) \emptyset(B) \qquad [3.49]$$

Where cov(U_t)= $\Sigma, \emptyset_i$ represents the moving average (MA) coefficients tracking the impulse response with $\emptyset_{jk,i}$, for example, showing the response of variable *j* to an impulse which occurred in the i^{th} period in variable *k*. Now Σ is often times a non-diagonal matrix (i.e. entries outside the principal diagonal of the matrix are not all zero), which means that if all other variables are fixed, it is impossible to shock only one variable, which calls for a Cholesky decomposition transformation (Hu, 2006). Firstly, let P represent a lower triangular matrix where Σ=PP' so that [3.49] is rewritten as:

$$Y_t = \sum_{i=0}^{\infty} \theta w_{t-i} \qquad [3.50]$$

With $\theta_i = \emptyset_i P, w_t = P^{-1} U_t$ and $(w_t w_t') = I$. Secondly, let D represent a diagonal matrix with same diagonals P and W = PD^{-1} and ʌ=DD'. Y_t can now be written as:

$$Y_t = B_0 Y_t + B_1 Y_{t-1} + \cdots + B_p Y_{t-p} + V_t \quad [3.51]$$

With $B_0 = I_k - W^{-1}, W = PD^{-1}, B_i = W^{-1}A_i$. B_0 is therefore a lower triangular matrix with 0 diagonals. This means that recursive causal structure is imposed in the direction of top variables to bottom variables but not in reverse (bottom variables to top variables) (Press, Teukolsky, Vetterling and Flannery, 1992).

Now that the recursive ordering has been established the Wold representation of Y_t (Y_t written as the sum of one deterministic time series and one stochastic time series) with orthogonal (or uncorrelated) errors n_t is written as:

$$Y_t = \mu + \theta_{0 n_t} + \theta_{1 n_{t-1}} + \theta_{2 n_{t-2}} + \ldots \quad [3.52]$$

With $\theta_0 = B^{-1}$ representing the lower triangular matrix. The responses to these orthogonal shocks are then:

$$\frac{\alpha y_{i,t+s}}{\alpha n_{j,t}} = \frac{\alpha y_{it}}{\alpha n_{j,t-s}} = \sigma_{ij}^{s}, j = 1 \ldots n; s > 0$$

[3.53]

Where σ_{ij}^{s} is the $(i,j)^{th}$ element of θ_s . This [3.53] is then known as the orthogonal impulse response function. If there are *n* number of variables, then n^2 impulse response functions can exist.

3.3.7.3. Forecast Error Variance Decomposition

Once the VAR model has been fitted, it is important to determine how much of the forecasting error variance can be explained by any exogenous shocks to the system and its variables. This can be done with the forecast error variance decomposition (FEVD). Firstly an h-step ahead forecast error vector with orthogonal shocks n_t and known VAR coefficients is written as (Zivot and Wang, 2006):

$$Y_{T+h} - Y_{(T+h|T)} = \sum_{s=0}^{h-1} \theta_s \, n_{T+h-s} \quad [3.54]$$

When determining a forecast for a particular variable $y_{i,T+h}$ the forecast error is expressed as:

$$y_{i,T+h} - y_{(i,T+h|T)} = \sum_{s=0}^{h-1} \emptyset_{i1}^{s} \, n_{1,T+h-s} + \cdots + \sum_{s=0}^{h-1} \emptyset_{in}^{s} \, n_{n,T+h-s} \quad [3.55]$$

Now because the structural errors are orthogonal the variance of this h-step ahead forecast is given as:

$$var\left(y_{i,T+h} - y_{(i,T+h|T)}\right) = \sigma_{n1}^2 \sum_{s=0}^{h-1} \left(\emptyset_{i1}^s\right)^2 + \cdots + \sigma_{nn}^2 \sum_{s=0}^{h-1} \left(\emptyset_{in}^s\right)^2 \qquad [3.56]$$

With $\sigma_{nj}^2 = var(n_{jt})$. The part of $var\left(y_{i,T+h} - y_{(i,T+h|T)}\right)$ then caused by shock n_j is determined by FEVD:

$$FEVD_{i,j}(h) = \frac{\sigma_{nj}^2 \sum_{s=0}^{h-1} \left(\emptyset_{ij}^s\right)^2}{\sigma_{n1}^2 \sum_{s=0}^{h-1} \left(\emptyset_{i1}^s\right) + \cdots \sigma_{nn}^2 \sum_{s=0}^{h-1} \left(\emptyset_{in}^s\right)^2}$$

[3.57]

With [3.57] it can be determined how much of the forecasting variance can be explained by the exogenous shock applied to the system.

3.4. Conclusion

The various methodologies covered in Chapter Three were used in modelling and processing the raw data obtained. These methodologies were applied and followed by means of Eviews 7 statistical processing program. The results of the different methodologies will now be presented in Chapter Four, providing an insight into the quantitative characteristics of the various factors and how they build up to ultimately forecasting food inflation in South Africa.

CHAPTER 4
RESULTS

4.1. Introduction

This chapter gives a detailed description of the output obtained from fitting a VAR model to the data collected, in order to model, and then forecast, food inflation. This chapter starts off by firstly, describing the statistical properties of the data set used, after which the results of the VAR model specification are reviewed. The next section follows the model specification of the VEC model, followed by several model checking diagnostic tests.

The diagnostic test results include: residual autocorrelation and normality testing. These tests are followed by model or structural analyses namely Granger causality testing, impulse response functions and vector error correction decomposition. The chapter is concluded by the resulting forecasted food inflation output obtained from the VEC model estimated.

4.2. Descriptive Statistics

The data sets used include: the FAO's domestic food balance sheet for cereal crops for South Africa (referred to as CEREAL); the South African CPI without the food component included (CPIEXFOOD); the South African food inflation figure (FOOD); South African Gross Domestic Product (GDP); the FAO's International Food Price Index (INTFOOD); the M3 broad money supply for South Africa as specified by the South African Reserve Bank; the international Brent crude oil prices (OIL); the South African Nominal Effective Exchange Rate as specified by the SARB; the South African Producer Price Index and finally the SARB repurchase rate.
All series were first put through basic statistical analysis to determine the mean, maximum, minimum and standard deviation of the raw data. The results were tabulated in Table 4.1.

Table 4.1. Descriptive statistics of series 2003M01 to 2014M05

Series	Mean	Maximum	Minimum	Std. Dev.	Observations
Domestic Cereal Balance Sheet (CEREAL)	9019807	9410411	8619000	252728.7	137
CPI-exfood (CPIEXFOOD)	82.42	109.3	65.9	13.46	137
Food (FOOD)	75.33	109.8	53.2	17.63	137
GDP (GDP)	4375	513279	343995	46623.48	137
International Food Price Index (INTFOOD)	167.03	240.09	93.89	45.78	137
M3 Broad Money Supply (M3)	1677884	2640479	722172	587741.1	137
Brent Crude Oil Price (OIL)	76.87	138.4	23.6	30.16	137
Nominal Effective Exchange Rate (NEER)	99.53	129.79	66.06	16.74	137
PPI (PPI)	80.11	114	56.57	17.71	137
Repurchase Rate (REPO)	7.74	13.5	5	2.42	137

The interesting phenomenon to note from Table 4.1 is the comparison between the standard deviation of CPIEXFOOD, FOOD and INTFOOD. Both food (domestic and international) have higher standard deviations of 17.63 (FOOD) and 45.78 (INTFOOD) as opposed to the low 13.46 (CPIEXFOOD). CPIEXFOOD is less volatile because the food component has been excluded. This tells us that the domestic and international food prices are quite volatile, due to the unpredictability of food production linked to changing climate patterns. All data were then converted into log form to minimize any problems with heteroskedacity and to improve interpretability of the data (hence the ‘l’ before every series henceforth). Before data can be used the statistical properties of the data must be determined.

4.3. Statistical properties of the data

4.3.1. Unit Root Testing

Time series data must be tested for stationarity before it can be used in any VAR/VEC model (Gujarati, 2003). The ADF test is commonly used to test for stationarity. This test is done by testing the null hypothesis (H_0) against the alternative hypothesis (H_a). If data is found to be non-stationary it can be transformed into stationary data by means of differencing. If the data is of order I(2) then it needs to be differenced twice. In this case the hypotheses are stated as follows:

H_0: The series is non-stationary

H_a: The series is stationary

The result for the ADF test is presented in Table 4.2.

Table 4.2 Test statistic for unit roots in variables

Series	Level			First difference		
	Test statistic	**95% Critical Value***	**Decision**	**Test statistic**	**95% Critical Value***	**Decision**
ICEREAL	-2.17	-3.44	Don't reject	-11.70	-3.44	Reject
ICPIEXFOOD	-2.03	-2.88	Don't reject	-6.79	-2.88	Reject
IFOOD	-2.16	-3.44	Don't reject	-5.32	-3.44	Reject
IGDP	-2.79	-3.45	Don't reject	-4.03	-3.45	Reject
IINTFOOD	-2.29	-3.44	Don't reject	-6.20	-3.44	Reject
IM3	-0.37	-3.44	Don't reject	-11.29	-3.44	Reject
INEER	-2.64	-3.44	Don't reject	-9.04	-3.44	Reject
IOIL	-2.93	-3.44	Don't reject	-9.26	-3.44	Reject
IPPI	-0.61	-2.88	Don't reject	-5.86	-3.45	Reject
IREPO	-2.24	-3.44	Don't reject	-4.73	-3.44	Reject

*MacKinnon (1996) one-sided p-values

Data was first tested for stationarity at level (no differencing) and then (if necessary) at first difference. From Table 4.2 all series' test statistics were insignificant at 95 per cent confidence level, meaning that the null hypothesis must be not be rejected. Therefore, statistics of all series were found to be non-stationary at level. After first differencing was done, the null and alternative hypotheses were tested against each other again. In this case, it was found that test statistics of all series were significant at 95 per cent confidence level, meaning the null hypothesis must be rejected and the alternative hypothesis accepted.

Therefore, all series were found to be stationary at first difference at 95 per cent confidence level. This implies that all the variables are integrated of order I(1).
The next step is to determine the number of lags to select which will later be used in the moedlling processes.

4.3.2. Lag Length Specification

Four main lag selection criteria were used to determine the correct number of lags to be included in the model. These criteria are known as: final prediction error (FPE), Akaike (AIC), Schwarz (SC) and Hannan-Quin (HQ) information criteria. The results of these lag selection criteria are summarized in Table 4.3.

Table 4.3 VAR lag order selection criteria results

Lag	FPE	AIC	SC	HQ
0	8.07E-27	-31.70327	-31.48157	-31.61319
1	3.47E-38	-57.87911	**-55.44051***	-56.88826
2	1.12E-38	-59.03541	-54.3799	**-57.14378***
3	1.20E-38	-59.03085	-52.15844	-56.23845
4	1.15E-38	-59.21103	-50.1217	-55.51785
5	9.37E-39	-59.6399	-48.33367	-55.04595
6	7.11E-39	-60.27904	-46.75589	-54.78431
7	6.89E-39	-60.86347	-45.12341	-54.46796
8	**5.98e-39***	**-61.83508***	-43.87812	-54.5388

Asterisk indicates lag order selection by the criterion

From Table 4.3, SC and HQ criteria selected one and two lags respectively, but FPE and AIC both agree on eight lags. Therefore, the optimal number of lags to choose that minimizes FPE, AIC, SC and HQ is eight lags. One or two lags cannot be selected as the lag selection criteria SC and HQ individually and not jointly, agree on this number of lags. The majority rule therefore applies, with both FPE and AIC selecting eight lags. Since the number of lags to include is now known, testing whether long-run relationships exist between the variables, can now be performed.

4.3.3. Cointegration Analysis

Cointegration testing confirms whether or not long run equilibrium relationships exist between the variables of a VAR. Now, because all of the variables were found to be integrated of order I(1), ordinary least squares are not suited for estimation as this will result in spurious regression estimates. All variables were therefore analysed using the Johansen test for cointegration so as to check whether or not one or multiple cointegrating relationships exist between the variables.

The Johansen cointegration test is a maximum likelihood test using a maximum Eigen value and trace of the stochastic matrix in the regression. Testing involves comparing the null and alternative hypotheses against one another. For the Eigen value test the hypotheses are as follows:

H_0: r = 0 (confirmation of cointegrating vector)
H_a: r = 1 (confirmation of no cointergating vector)

The Trace test has compared the following hypotheses against each other:

H_0: r = 0 (confirmation of cointegrating vector)
H_a: r = 1 (confirmation of no cointergating vector)

Finally a combined testing of:

H_0: r = 1 (confirmation of cointegrating vector)
H_a: r > 1 (confirmation of no cointergating vector)
was also done.

Table 4.4 shows the results of the Johansen cointegration testing.

Table 4.4 Results of cointegration test

Number of Cointegrating vectors	Trace Test			Maximum Eigenvalue Test		
	Test Statistic	95% Critical value	Probability	Test Statistic	95% Critical value	Probability
None *	731.50	239.24	0.00	228.01	64.50	0.00
At most 1 *	503.49	197.37	0.00	124.01	58.43	0.00
At most 2 *	379.48	159.53	0.00	114.72	52.36	0.00
At most 3 *	264.77	125.62	0.00	89.02	46.23	0.00
At most 4 *	175.74	95.75	0.00	63.20	40.08	0.00
At most 5 *	112.55	69.82	0.00	38.80	33.88	0.01
At most 6 *	73.74	47.86	0.00	32.63	27.58	0.01
At most 7 *	41.11	29.80	0.00	27.12	21.13	0.01
At most 8	14.00	15.49	0.08	9.95	14.26	0.22
At most 9 *	4.05	3.84	0.04	4.05	3.84	0.04

Single asterisk indicates statistical significance at 95 per cent confidence level

From Table 4.4, it was found that there is cointegration amongst the variables included in the VAR tested at a 95 per cent confidence level. A total of nine cointegrating equations were identified from the Johansen cointegration test. A VAR with cointegrating variables can cause the problem of misspecification and omission of important constraints in the model. It is for this reason that an error term must be introduced, hence the construction of a Vector Error Correction model or VEC.

4.4. Modelling the data

The VAR model is specifically suited for the type of data used in this study, as it can accurately capture the interactions and long-run relationships not only between the independent and dependant variables but also between different independent variables (Zivot and Wang, 2006). Firstly, the lag length must be specified in order to make sure model specification bias or error does not occur (Gujarati, 2003).

4.5. *VEC Model Estimation*

The presence of cointergating variables in the VAR model as covered in 4.3.3, suggest long run relationships between these variables. This long-run relationship can be expressed as a function of food inflation (FOOD) as follows:

$$FOOD = -1.2217711CEREAL - 0.749807CPIEXFOOD + 0.545587GDP + 0.241733INTFOOD - 0.442861M3 - 0.691841NEER + 0.251090OIL - 1.355772PPI - 0.390503REPO$$

The above equation suggests that one unit increase in food inflation decreases the domestic food balance sheet for cereal crops for South Africa by 1.22 units, CPI-exfood by 0.75 units, M3 broad money supply by 0.44 units nominal effective exchange rate by 0.69 units, PPI by 1.36 units and repurchase rate by 0.39 units. It also suggests that one unit increase in food inflation increases GDP by 0.55 units and Brent Crude oil prices by 0.25 units. This is, to say the least, wildly counterintuitive and cannot be taken to imply actual causality. It simply tells us that long-run relationships do exist, not in which direction or of what magnitude. Such an interpretation is better left to Granger causality analysis.

To correct for this long-run trending towards equilibrium a vector error correction term is introduced so as to allow for short-run adjustment dynamics with restrictions on long run cointegrating variables.
To ensure that this VEC model gives us an accurate representation of food inflation, various tests for misspecification must be performed, which will now be discussed.

4.6. Model Diagnostics

4.6.1. Autocorrelation

Autocorrelation testing of the VEC model is important in revealing trends and information about the future value of a series, making it useful for forecasting. It also tells us whether or not a series is correlated with past values of itself. The presence of autocorrelation can also cause problems in identifying significant correlation between different time series, obscuring true relationship information between variables. The Portmanteau Q-Statistic test is commonly used to test for autocorrelation. The results of this test for the constructed VEC model are presented in Table 4.5.

Table 4.5 Results of autocorrelation test

Lags	Q-Stat	Probability	Adjusted Q-Stat	Prob.
1	69.66758	0.2927	70.21614	0.2772
2	131.1664	0.406	132.6911	0.3702
3	195.6626	0.413	198.7353	0.3543
4	262.8658	0.3706	268.1063	0.289
5	333.8602	0.2856	341.9867	0.1905
6	408.9963	0.1822	420.8179	0.0947
7	461.5112	0.3195	476.3709	0.1709
8	498.9124	0.6523	516.2655	0.4389
9	559.2212	0.6842	581.1355	0.4323
10	616.091	0.7448	642.8247	0.4612

From Table 4.5, it is clear that both the Q-statistic and Adjusted Q-statistic are not significant at 95 per cent confidence level over all 12 lags. This means that no autocorrelation is present in the model. The next section presents the test for normal distribution.

4.6.2. Normality Testing

Testing whether or not residuals of the data follow a normal distribution tells us how good the data has been modelled, or goodness of fit. The Jarque-Bera test is used to test this assumption. This test has the following null and alternative hypotheses:

$$H_0 = E(u_t^s)^3 = 0(skewness)$$
$$= E(u_t^s)^4 = 3(kurtosis)$$
$$H_1 = E(u_t^s)^3 \neq 0(skewness)$$
$$= E(u_t^s)^4 \neq 3(kurtosis)$$

Therefore, the null hypothesis can be rejected at 95 per cent confidence level if skewness and kurtosis are close to 0 and 3 respectively.

The results of the Jarque-Bera normality test for residuals are laid out in Figure 4.1.

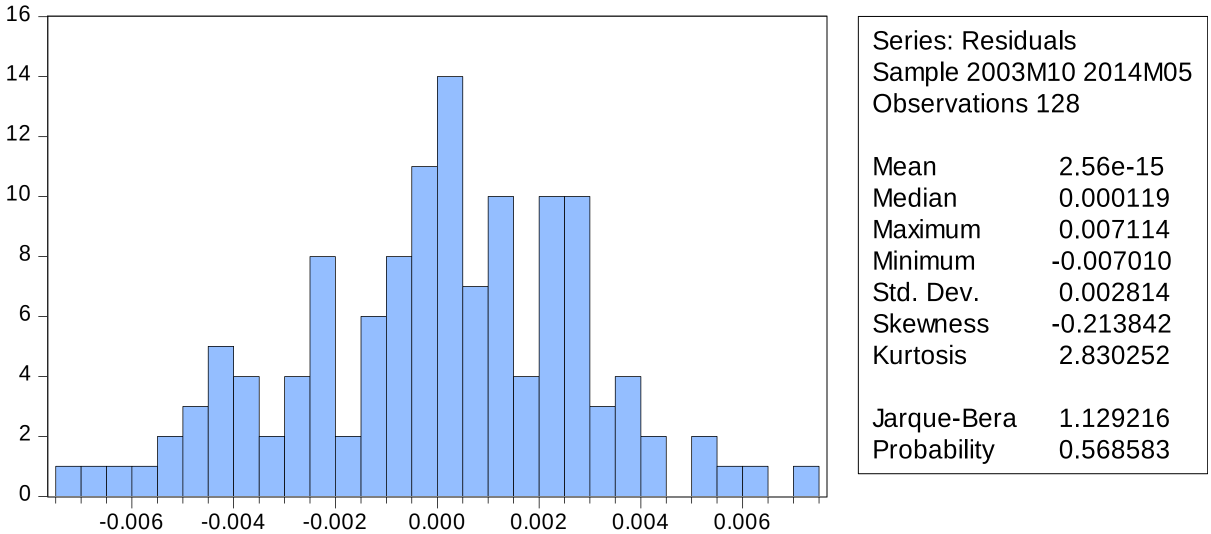

Figure 4.1 Normal distribution of residuals test results

From figure 4.1, skewness and kurtosis are close to 0 and 3 respectively, and the Jarque-Bera test statistic can be rejected at 95 per cent confidence level. This means that the null hypothesis can be accepted and the alternative hypothesis can be rejected, signaling that the residuals are indeed normally distributed. After these tests, it can be concluded that the series used in this study are, individually, sound to work with and should not cause any misspecification errors when modelling. The next section attempts to quantify and discuss these effects, by means of structural analyses.

4.7. *Structural Analysis*

To quantify the magnitude and direction of influence of variables on one another, we have three structural analysis tools at our disposal, namely: Granger Causality testing, Impulse Response Functions and Forecast Error Variance Decompositions. The next section will discuss the results obtained from these tests and simulation.

4.7.1. Granger Causality Testing

Granger causality testing, tests to see if one variable can accurately predict the behaviour of another variable. This is done in a pair-wise fashion with each of the other variables included in the VEC. If a variable is found to have some predictive power of another variable then it is said to Granger cause that variables variation, implying causality.

For a process Y_t:

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \cdots \beta_p Y_{t-p} + \gamma_0 X_{t-1} + \gamma_p X_{t-p} + \varepsilon$$

The null and alternative hypotheses for Granger causality can be stated as:

$$H_0: \gamma_0 = \gamma_1 = \gamma_2 = \cdots = \gamma_p = 0$$
$$H_a: \gamma_0 \neq \gamma_1 \neq \gamma_2 \neq \cdots \neq \gamma_p \neq 0$$

If the null hypothesis is rejected, then *x* is said to Granger cause *y*.

Table 4.6 shows the results of pair-wise Granger causality testing for variables included in the VEC model. Only variables found to be significant are included in Table 4.6, the full test results are to be found in the Appendix.

Table 4.6 Pair-wise Granger causality test result

Null Hypothesis	F-Statistic	Probability
LFOOD does not Granger Cause LCEREAL	4.93	0.01*
LCEREAL does not Granger Cause LFOOD	3.35	0.04*
LCEREAL does not Granger Cause LGDP	3.22	0.04*
LM3 does not Granger Cause LCEREAL	5.35	0.01*
LCEREAL does not Granger Cause LOIL	3.97	0.02*
LFOOD does not Granger Cause LCPIEXFOOD	10.90	0.00*
LGDP does not Granger Cause LCPIEXFOOD	11.56	0.00*
LCPIEXFOOD does not Granger Cause LGDP	9.81	0.00*
LINTFOOD does not Granger Cause LCPIEXFOOD	5.73	0.00*
LM3 does not Granger Cause LCPIEXFOOD	6.71	0.00*
LCPIEXFOOD does not Granger Cause LM3	3.43	0.04*
LOIL does not Granger Cause LCPIEXFOOD	8.64	0.00*
LPPI does not Granger Cause LCPIEXFOOD	8.35	0.00*
LGDP does not Granger Cause LFOOD	10.63	0.00*
LFOOD does not Granger Cause LGDP	5.05	0.01*
LM3 does not Granger Cause LFOOD	6.97	0.00*
LFOOD does not Granger Cause LM3	4.63	0.01*
LFOOD does not Granger Cause LNEER	3.79	0.03*
LOIL does not Granger Cause LFOOD	7.07	0.00*
LPPI does not Granger Cause LFOOD	20.55	0.00*
LFOOD does not Granger Cause LPPI	4.57	0.01*
LFOOD does not Granger Cause LREPO	4.06	0.02*
LINTFOOD does not Granger Cause LGDP	3.70	0.03*
LM3 does not Granger Cause LGDP	21.06	0.00*
LGDP does not Granger Cause LM3	3.13	0.05*
LGDP does not Granger Cause LNEER	6.04	0.00*
LOIL does not Granger Cause LGDP	6.71	0.00*
LPPI does not Granger Cause LGDP	5.93	0.00*
LINTFOOD does not Granger Cause LNEER	6.03	0.00*
LINTFOOD does not Granger Cause LOIL	8.61	0.00*
LPPI does not Granger Cause LINTFOOD	4.03	0.02*
LINTFOOD does not Granger Cause LPPI	3.62	0.03*
LNEER does not Granger Cause LM3	7.24	0.00*
LM3 does not Granger Cause LNEER	3.94	0.02*
LOIL does not Granger Cause LM3	3.34	0.04*
LM3 does not Granger Cause LOIL	3.37	0.04*
LM3 does not Granger Cause LPPI	3.24	0.04*
LOIL does not Granger Cause LNEER	7.10	0.00*
LPPI does not Granger Cause LNEER	6.98	0.00*
LOIL does not Granger Cause LPPI	4.00	0.02*
LOIL does not Granger Cause LREPO	3.35	0.04*

Single asterisk indicates statistical significance at 95 per cent confidence level

Table 4.6 shows which variables Granger cause each other over time at 95 per cent confidence level. It must be noted though, that it does not mean one variable causes another; it plainly indicates that it is a good variable with which to predict the other variable.

From Table 4.6, CEREAL Granger causes FOOD indicating that the domestic cereal balance sheet of South Africa is a good predictor of the food inflation. This is logical, as food prices influence demand by consumers for food products. As demand for food changes (with a large majority of the population consuming cereal-based staples) so too will the domestic balance sheet of cereals to keep up with or dispose of shortages or surpluses of cereals in the country. The opposite, where FOOD Granger causes CEREAL, is also true, indicating a feedback mechanism at work between food inflation and the domestic cereal balance sheet.

FOOD is also found to Granger causes CPIEXFOOD. This might be ascribed to how increasing food inflation can induce an increase in the prices of other non-food products. This is known as the Mark-up Inflation theory where food inflation has a pull effect on the prices of other non-food products (Ackley, 1978). This means food price increases may signal a future increase of other non-food product prices, acting as a good predictor.

Table 4.6 reveals that GDP Granger causes FOOD, meaning that tracking GDP is a good way of predicting food inflation. Broadly speaking, as a country's GDP increases, its citizens in turn become wealthier and incomes increase. As incomes increase, though, a lower percentage of their income is spent on food (ENGELS LAW). But food preferences shift drastically to higher priced food (say from grains to beef) which in turn fuel food inflation. But such an assumption begs debate, especially with the levels of income disparity observed in South Africa and the mythical "trickle-down effect" of wealth. A feedback system is once again present between these two variables as FOOD is also found to Granger cause GDP.

Interestingly, the VEC model manages to capture the reactionary feedback system of monetary policy (via the repurchase rate) to food inflation changes. This represents itself in the form of M3 Granger causing FOOD and FOOD Granger causing M3. This means that a feedback system (most likely in the form of monetary policy reaction) exists between these two variables. This complements the literature on inflation targeting, practiced by the SARB, where monetary supply (M3) is adjusted to indirectly influence inflation. Similarly, it is noted that FOOD Granger causes REPO, again reiterating the reactionary nature of the repurchase rate in taming inflation.

OIL is also found to Granger cause FOOD. This is an obvious assumption due to the large component that international oil prices form of the cost of producing and marketing food products. This relationship might be more obvious past the farm gate, in the form of rising transport costs of retailers, as opposed to the increased cost of physical production as producers are chiefly price takers.

The fact that PPI is found to Granger cause FOOD tells us clearly that producer prices of food products are passed on to the consumer (Alemu and Ogundeji (2010) discuss this thoroughly in their article titled "Price transmission in the South African food market".) This means that with a change in the PPI we can expect a similar change in food inflation over time, making PPI a good predictor of food inflation. The opposite is also true, signaling the presence of a feedback mechanism.

From the Granger causality test results, it is clear that various interactions exist between food inflation and the variables of the VEC. These interactions are only briefly touched upon in this section. These interactions definitely warrant further questioning, but for now we can confirm that the VEC model constructed captures these interactions, which will aid in improved forecasting accuracy. To determine how external shocks affect the VAR system as a whole, the variables of the model must be shocked individually. The reaction of the dependent variable to the shocks in the independent variables will tell us about the responsiveness of the dependent variable to shocks. To do this, an impulse response function is simulated.

4.7.2. Impulse Response Functions

An impulse response function simply takes note of the responsiveness of the dependent variables in the VAR when shocks are applied to each of the other variables. The short-run effects are identified by means of Cholesky decomposition. The results of the impulse response function for all variables are presented in the Appendix. The main interest of this study is to examine FOOD as our dependent variable. The impulse response function for FOOD is therefore presented in Figure 4.2.

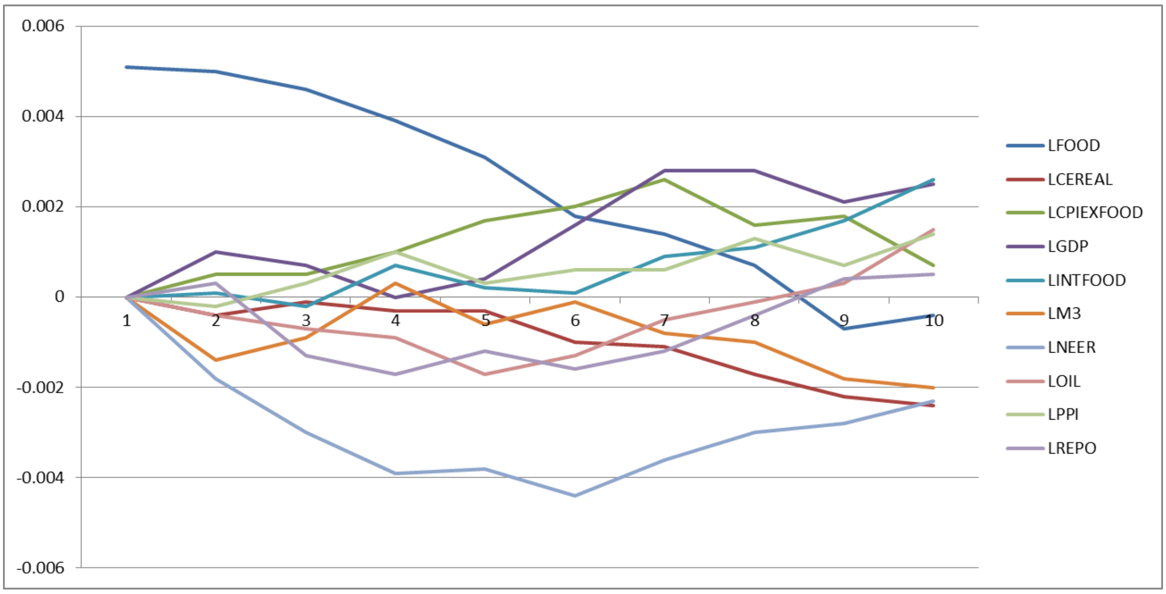

Figure 4.2 Impulse response function of LFOOD

Figure 4.2 explains the magnitude and direction of change in food inflation as a response to a shock (or one standard deviation innovation) in one of the independent variables. Figure 4.2 shows that CEREAL has a negative effect on FOOD over a 10-month period. FOOD responds reasonably to CPIEXFOOD in the positive direction up from periods 5 to 7, but then returned to where it was from period 10 onwards. FOOD responds to GDP weakly at first, but more so from period 7, after which it seems to plane out after period 9 in a positive direction. INTFOOD causes a significant positive response in FOOD, with an increasing trend from period 0 straight through to period 10. From period one onwards, M3 causes a negative response in FOOD which only increases with magnitude as the periods progress which seems counter intuitive. The same can be observed in the response of FOOD to NEER, except that the magnitude of the negative effect peaks at period 6, after which it declines.

OIL causes almost an “S” or up and down and up again response in FOOD in the negative direction. PPI causes a negative direction response in food, after which the effect thereof becomes increasingly positive. This might allure to the fact that increased producer prices initially are slow to filter through to food prices. Food responds to REPO negatively at first, up to period 8, after which it responds increasingly in the positive direction. This might be an indication of how a change in monetary policy only affects food inflation after a set period of time. To better understand how much of FOOD can be explained by the independent variables, a variance decomposition is performed.

4.7.3. Variance Decomposition

The impulse response function told us more about the direction (positive or negative) of the effect of a shock in an independent variable on the dependent variable. The variance decomposition can tell us how much of the variance in the dependent variable can be attributed to shocks in the independent variables. Again, the main interest of this study is the dependent variable FOOD, so the variance decompositions of the other variables are attached in the Appendix. The results of the variance decomposition for FOOD are represented in Table 4.7.

Table 4.7 Variance Decomposition of FOOD

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	88.23	0.33	0.38	1.64	0.02	3.44	5.43	0.31	0.11	0.13
3	78.74	0.22	0.48	1.56	0.06	3.02	13.29	0.66	0.18	1.79
4	68.18	0.23	1.09	1.11	0.46	2.21	21.26	1.09	0.96	3.41
5	60.66	0.24	2.65	0.97	0.39	2.01	25.99	2.62	0.84	3.63
6	51.75	0.72	4.29	2.04	0.32	1.67	31.10	2.97	0.90	4.25
7	44.88	1.17	6.48	5.15	0.60	1.71	32.25	2.64	0.92	4.20
8	40.38	2.18	6.77	7.61	1.01	1.96	32.39	2.37	1.51	3.82
9	36.62	3.71	7.22	8.40	1.88	2.94	32.04	2.17	1.54	3.49
10	32.83	5.20	6.60	9.42	3.76	3.94	30.40	2.68	1.96	3.21

From Table 4.7, as expected, 100 per cent of FOOD can be explained by itself in period 0. It is clear that NEER explains most of the variance in FOOD, as its contribution to a variation in FOOD stabilises at around 30 per cent. This suggests that food prices are reasonably vulnerable to shocks in the nominal effective exchange rate. Initially GDP shocks only explain 1.64 per cent of the variability in FOOD, but this increases gradually to 9.4 per cent in period 10.

CPIEXFOOD shocks follow a similar increasing trend of influence from 0.38 per cent of the variability in FOOD explained by CPIEXFOOD, but increasing to 6.6 per cent in period 10. Shocks in CEREAL have a surprisingly low contribution in explaining variability in FOOD, from an initial 0.33 per cent in period 2 to a meagre 5.2 per cent in period 10. This is surprising, considering that the majority of the population relies on cereals as a staple food. These relationships between the dependent and independent variables form the basis for forecasting. The forecasted results are discussed in the next section.

4.8. Forecast

The forecasted model of any data set is usually run over a period of time for which actual data is available. This is done to assess whether the forecast model has been built with the right assumptions, variables and relationship information to predict what is observable now before taking on what is yet to happen. Figure 4.3 represents the actual food inflation data fitted against the output of the forecast model, as well as a two-year ahead forecast from May 2014 to May 2016.

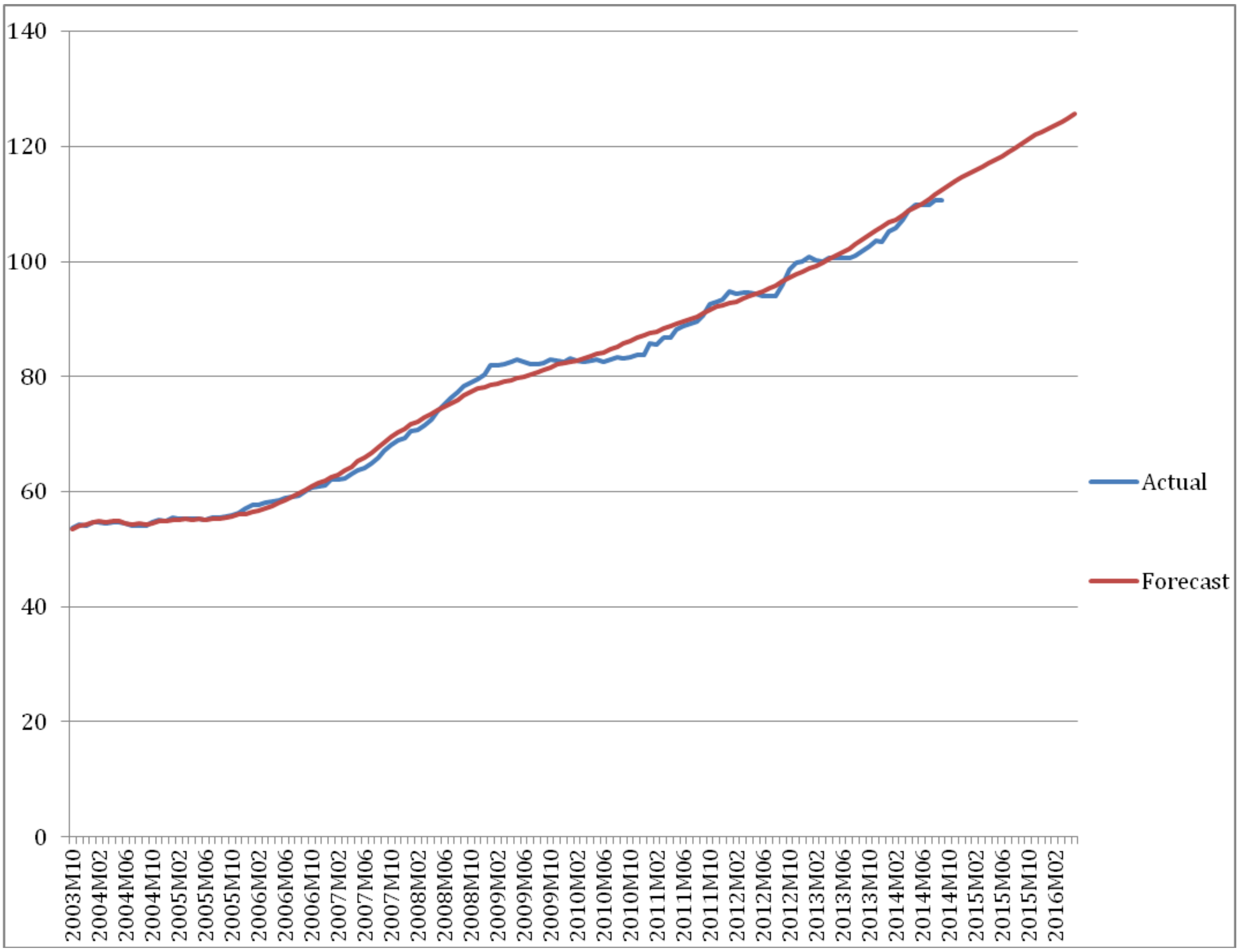

Figure 4.3 Actual and forecast South African food inflation index for the period January 2013 to May 2016

Figure 4.3 shows how closely the forecasted model output for food inflation follows the actual food inflation index values for the same period. Visually, the accuracy of the model is almost perfect from January 2003 to February 2007, after which it deviates by very little, but still noticeably, from the actual food inflation index in that period. To empirically (as opposed to visually) assess the accuracy of the forecasted model output against the actual food inflation index, a simple forecasting accuracy test was done. A root mean square error test was deemed not applicable to this model, as this test only compares the accuracy between different forecast models.

The forecast accuracy measure used was simply calculated by looking at the difference between actual and forecast values over time (i.e. a residual comparison). This was done by subtracting the forecasted values from the actual values and converting this difference into a parentage. This figure then tells us how inaccurate the model was in forecasting the actual value for that specific month. Table 4.8 gives the comparisons between absolute and nominal values in forecasting inaccuracies of both before and after mid-2007.

Table 4.8 Forecasting inaccuracy before and after mid-2007

Period	Forecast Inaccuracy (%)	
	Nominal	**Absolute**
Full sample period	-0.16	1.38
Before mid-2007	-0.10	0.77
After mid 2007	-0.23	1.73

The average inaccuracy, by this measure, for the model over the entire period for which data was available was -0.16 per cent and 1.38 per cent in nominal and absolute values respectively a shown in Table 4.9. This means that on average the model constructed, underestimated the actual food inflation value by 0.16 per cent and deviated in total from the actual food inflation value by 1.38 per cent on average. The pre and post mid-2007 comparison confirms the visual representation of lower forecasting accuracy after mid-2007. Before mid-2007 the model underestimated food inflation by only 0.10 per cent and deviated in total from the actual food inflation value by 0.77 per cent on average. From mid-2007 onwards the model underestimated food inflation by more than double the 0.10 per cent at 0.23 per cent and deviated in total from the actual food inflation value by 1.77 per cent on average.

These results shed light on how volatility in domestic food prices increased after the mid-2007 food price spike globally. This is mainly why food inflation was harder to predict post mid-2007. The volatility can mostly be ascribed to the increased speculative activity of investors in the food commodity markets of the world, which then dictate domestic food prices. This increased speculation (to both hedge against possible future food price spikes and to benefit through profit-making by selectively holding and selling cereals and grains) seemed to increase uncertainty in the global food market and consequently the domestic food price index of South Africa.
Furthermore, the predicted food index values for food inflation in South Africa from May 2014 to May 2016 are illustrated in Table 4.9.

Table 4.9 Forecasted Food inflation index values for South Africa from May 2014 to May 2016

Year/Month	Predicted food inflation index
2014M05	109.4686274
2014M06	110.0718132
2014M07	110.8213007
2014M08	111.5580407
2014M09	112.4575706
2014M10	113.2482147
2014M11	114.0568491
2014M12	114.63521
2015M01	115.2363227
2015M02	115.7529293
2015M03	116.4529117
2015M04	117.0756141
2015M05	117.7462635
2015M06	118.2834662
2015M07	118.9659122
2015M08	119.6446381
2015M09	120.4908721
2015M10	121.2359928
2015M11	122.0003605
2015M12	122.5444719
2016M01	123.1143995
2016M02	123.6132821
2016M03	124.2966441
2016M04	124.911814
2016M05	125.5783668

From Table 4.9 a steady increasing trend is visible with the food inflation index of South Africa expected to reach 117.75 index points in a years' time (May 2014 to May 2015) and 125.58 index points in two years' time (May 2014 to May 2016). This translates to a year-on-year food inflation from May 2014 to May 2015 of 7.56 per cent and a 14.72 per cent increase in food inflation over the two-year period from May 2014 to May 2016.

Table 4.9 is the final product of a combination of factors and models identified in the literature available. The next chapter will give a brief overview of the study, tying it all up into a conclusion.

4.9. Conclusion

In this chapter, all diagnostic tests and model construction discussed in Chapter 3 were applied to forecast food inflation in South Africa over a two-year ahead period. The procedures were done in two broad categories, namely statistical properties of the data and modelling the data. The statistical properties of the data were evaluated, as per the results of the unit root or ADF testing and the Johansen Cointegration testing. The presence of cointegrating equations identified under Johansen's test, meant that the VAR had to be augmented with an error correction term, meaning the subsequent use of a VEC model from there onwards. This VEC model was then assessed by checking for autocorrelation and normality testing. Furthermore, a structural analysis was done to determine Granger Causality, impulse response and variance decomposition. After these processes, the model was then used to forecast the food inflation index.

The food inflation index, according to the model constructed, is set to increase to 125.59 index points in May 2016 up from 109.47 index points in May 2014.

The next chapter will round off the thesis with a discussion of the findings and recommendations made.

CHAPTER 5
SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1. Introduction

This final chapter gives a brief overview of the study in terms of the logic and execution of analyses as well as results obtained. This section also includes recommendations regarding the outcomes of the study and other points worth noting which emerged from the study but were beyond the scope of its main objective.

5.2. Summary

In the light of recent volatility and sharp increase in food prices, both domestically and internationally, the need to forecast food inflation has become more and more prominent, especially in developing countries. This is because a higher percentage of household income is spent on food in these countries. Food inflation therefore, plays an important role in overall inflation in South Africa and ultimately affects monetary policy decisions.

The problem is that monetary policy decisions take some time (18-24 months) before impacting the economy. It is therefore important for monetary policy decision makers to be able to base their policy decisions on forward looking projections. If this is not done, monetary policy will be misaligned with the actual economic status of the low income households in South Africa, consequently furthering poverty and income disparity.

The primary objective of this study was to construct a multivariate model with which to forecast the food component of the Consumer Price Index (CPI) as accurately as possible.

5.2.1. Literature review

The literature that formed the basis of this study revealed, firstly, that a clear distinction exists between food inflation that occurs in developing countries and food inflation that occurs in developed countries. These distinctions range from the weightage of food inflation in overall inflation, to the effect on monetary policy decisions. One of the most prominent findings was the effects that the recent advent of inflation targeting adoption had on various countries. The adoption of inflation targeting in South Africa meant that the Republic could enjoy greater price stability of all goods and services than in the past.

It also meant that inflation and food inflation became a stronger role player in influencing monetary policy decisions. The most commonly used tool to keep inflation in check in South Africa then became the adjustment of the repurchase rate.

Furthermore, from literature, several factors were identified as being important contributors to food inflation, specifically in South Africa. These factors were narrowed down to those deemed most applicable to build the most accurate but simple model possible. These factors included: CPI without the food component, nominal effective exchange rate, money supply, domestic food supply balance sheet, oil prices, producer price index, SARB repurchase rate and international food prices.

Food inflation forecasting models used around the globe were also reviewed with special focus on those used in economies similar to those of South Africa. The most commonly used model that was found giving the most robust results was the Vector Autoregressive model. If there was any cointegration present between the variables, the VAR was augmented with an error correction term, meaning that a Vector Error Correction model was ultimately used in final forecasting.

5.2.2. Data and Methodology

Data was collected as per findings in the literature review from which the factors: CPI without the food component, nominal effective exchange rate, money supply, domestic food supply balance sheet, oil prices, producer price index, SARB repurchase rate and international food prices were identified. The time period for these data was from January 2003 to May 2014.

The data was then analysed before being built into the VAR, to ensure its usability. Firstly, data was checked for permanence, so that spurious regression would result from using non-stationary data. This was done using the Augmented Dickey Fuller Test. The next step was to determine the lag length selections for the VAR, by means of the AIC, SC and HC information criteria. This was done to ensure no model specification error occurred.

Once the lag lengths were determined, the variables were tested to see if any long-run relationships existed between them. The Johansen cointegration test was used to ascertain this. If long-run relationships are found to exist between independent variables, then the VAR must be augmented with a vector error correction term to correct for deviation from the long-run equilibrium. This was the case in the study and, subsequently, prompted the inclusion of this vector error correction term, meaning that the VAR would be augmented and described as a Vector Error Correction Model (VEC).

The VEC was then constructed and diagnostics tests were run on the model to ensure it represents the data generation process properly.

Two diagnostics tests were used, namely autocorrelation testing to determine true covariance between time series over time so as not to distort results and Jarque-Bera Normality testing to determine if data are aggregated around a common mean.

The final set of structural analyses included Granger Causality testing to determine which variable in the model was a good predictor of another variable; impulse response functions, which give an indication of what happens to the dependent variable when a shock is applied to an independent variable; and forecast error variance decomposition, which tells us how much of the variance in the dependant variable can be explained by different independent variables.

Finally the model now deemed suitable, was fitted to the actual data present to see how accurately it could reproduce actual data. After it was deemed accurate, the model was solved for a two-year ahead period from May 2014 to May 2016 to produce a two-year forecast of food inflation in South Africa.

5.2.3. Results

Testing for stationarity of the data by means of the ADF, revealed that all series were stationary at first difference. Thereafter, the cointegration analysis revealed the presence of at least nine cointegrating equations. This meant that the use a VAR for modelling was no longer sufficient and had to be supplemented with an error correction term resulting in the use of a VECM. The number of lags to include in the modelling phase of the data was then determined by means of the lag length selection criteria which selected eight lags. Now that the data was deemed suitable to work with, modelling of data could begin.

This VEC model was subjected to diagnostics and it was concluded that no autocorrelation was present and that the data was normally distributed. The structural analysis of the model then followed. These included Granger Causality which revealed anticipated and somewhat surprising results. As expected, CEREAL was found to Granger cause FOOD, GDP Granger causes FOOD and OIL Granger causes FOOD. Interestingly, the model seemed to be able to capture the monetary policy reactionary feedback mechanism in the form of M3 Granger causing FOOD and conversely, FOOD Granger causing M3. It was interesting to be able to quantitatively view the inflation targeting regime of South Africa.

Further structural analysis in the form impulse response functions was also done. The results of this analysis showed that FOOD responds negatively to shocks in CEREAL and M3, and positively to the rest of the variables. Interestingly, a shock to OIL caused an initial negative response in FOOD which later became positive, signalling a lag in pass-through from oil price to food inflation. This same initial negative and gradual positive effect was observed when REPO was shocked one standard deviation innovation. Also signalling that repurchase rate changes take time to affect food inflation.

The final structural analysis item to perform was the variance decomposition of FOOD. These results demonstrated that almost 30 per cent of the variance in FOOD could be explained by NEER over a 10-month period. GDP accounted for 9.4 per cent and CPIEXFOOD accounted for 6.6 per cent of the variance of FOOD over 10 months. CEREAL only explained 5.2 per cent of variance in FOOD which was surprising, considering that cereals and grains are a staple in South Africa.

Following the structural analyses, the actual forecasting of the model was done. The results of the forecast indicated that the food inflation index for South Africa would increase from 109.47 index points in May 2014 to 125.58 index points in May 2015 or a 14.72 per cent increase in food inflation over two years.

5.3. *Conclusion*

Recent volatility perceived in global food markets together with the advent of inflation targeting in South Africa have given rise to an increased need to be able to forecast food inflation in economies where household expenditure on food is high. This is the case in South Africa with the majority of households spending around 30 per cent of their incomes on food alone. This is not reflected properly in the composition of the CPI for South Africa, which states that only around 15 per cent of household income is spent on food. This means that monetary policy is made on incorrect assumptions. Apart from these assumptions, the SARB has adopted a new forward-looking policy-making plan whereby forecasts are almost as important as historical data when considering monetary policy. This is because of the lag effect between policy implementation and the effect on the economy.

Thus, for a country where a large portion of CPI is made up of food inflation, and whose monetary policy is based on this CPI, it is important to be able to determine what food inflation growth will be in the future (by at least 18 months). With the insight of the forecasts produced in the study, monetary policy that is truly forward-looking can thus be adopted.

5.4. *Recommendations*

To our knowledge no other work has been discovered in literature pertaining to forecasting food inflation in South Africa, so there is obviously a great deal more that can be done and contributed to improve this model. These recommendations include:

- Building a component into the VEC model with which the monetary policy reactionary mechanism can be modelled properly.
- Investigate how representative the food inflation component of the South African CPI really is and how these shortcomings can be addressed.
- Greater focus on forward-looking consumer price forecasts to ensure monetary policy is not just based on historical data, as this omits the volatility of price indexes which are on the rise globally.

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APPENDIX A: ADDITIONAL GRAPHS AND TABLES

Table A1 Granger Causality test results

Null Hypothesis:	Obs	F-Statistic	Probability
LCPIEXFOOD does not Granger Cause LCEREAL	135	2.18141	0.117
LCEREAL does not Granger Cause LCPIEXFOOD		1.44894	0.2386
LFOOD does not Granger Cause LCEREAL	135	4.93212	0.0086
LCEREAL does not Granger Cause LFOOD		3.35031	0.0381
LGDP does not Granger Cause LCEREAL	135	0.89817	0.4098
LCEREAL does not Granger Cause LGDP		3.22367	0.043
LINTFOOD does not Granger Cause LCEREAL	135	0.39379	0.6753
LCEREAL does not Granger Cause LINTFOOD		2.03379	0.135
LM3 does not Granger Cause LCEREAL	135	5.34558	0.0059
LCEREAL does not Granger Cause LM3		0.20922	0.8115
LNEER does not Granger Cause LCEREAL	135	0.48865	0.6146
LCEREAL does not Granger Cause LNEER		0.66095	0.5181
LOIL does not Granger Cause LCEREAL	135	0.76329	0.4682
LCEREAL does not Granger Cause LOIL		3.96993	0.0212
LPPI does not Granger Cause LCEREAL	135	1.05742	0.3503
LCEREAL does not Granger Cause LPPI		0.52343	0.5937
LREPO does not Granger Cause LCEREAL	135	2.14625	0.121
LCEREAL does not Granger Cause LREPO		0.98497	0.3762
LFOOD does not Granger Cause LCPIEXFOOD	135	10.9027	4.00E-05
LCPIEXFOOD does not Granger Cause LFOOD		1.07809	0.3433
LGDP does not Granger Cause LCPIEXFOOD	135	11.5585	2.00E-05
LCPIEXFOOD does not Granger Cause LGDP		9.81031	0.0001
LINTFOOD does not Granger Cause LCPIEXFOOD	135	5.72558	0.0041
LCPIEXFOOD does not Granger Cause LINTFOOD		0.69191	0.5025
LM3 does not Granger Cause LCPIEXFOOD	135	6.70645	0.0017
LCPIEXFOOD does not Granger Cause LM3		3.43198	0.0353
LNEER does not Granger Cause LCPIEXFOOD	135	2.22168	0.1125
LCPIEXFOOD does not Granger Cause LNEER		2.73353	0.0687
LOIL does not Granger Cause LCPIEXFOOD	135	8.63746	0.0003
LCPIEXFOOD does not Granger Cause LOIL		1.03726	0.3573
LPPI does not Granger Cause LCPIEXFOOD	135	8.34581	0.0004
LCPIEXFOOD does not Granger Cause LPPI		1.79669	0.1699
LREPO does not Granger Cause LCPIEXFOOD	135	0.38916	0.6784
LCPIEXFOOD does not Granger Cause LREPO		2.42376	0.0926
LGDP does not Granger Cause LFOOD	135	10.6256	5.00E-05
LFOOD does not Granger Cause LGDP		5.04865	0.0077
LINTFOOD does not Granger Cause LFOOD	135	8.97954	0.0002
LFOOD does not Granger Cause LINTFOOD		1.09865	0.3364
LM3 does not Granger Cause LFOOD	135	6.97151	0.0013
LFOOD does not Granger Cause LM3		4.6302	0.0114
LNEER does not Granger Cause LFOOD	135	1.6028	0.2053
LFOOD does not Granger Cause LNEER		3.78716	0.0252
LOIL does not Granger Cause LFOOD	135	7.06833	0.0012
LFOOD does not Granger Cause LOIL		2.44202	0.091
LPPI does not Granger Cause LFOOD	135	20.5511	2.00E-08
LFOOD does not Granger Cause LPPI		4.56689	0.0121
LREPO does not Granger Cause LFOOD	135	1.48316	0.2307
LFOOD does not Granger Cause LREPO		4.06035	0.0195
LINTFOOD does not Granger Cause LGDP	135	3.6973	0.0274
LGDP does not Granger Cause LINTFOOD		2.67415	0.0728
LM3 does not Granger Cause LGDP	135	21.0645	1.00E-08
LGDP does not Granger Cause LM3		3.12717	0.0472
LNEER does not Granger Cause LGDP	135	0.10129	0.9037
LGDP does not Granger Cause LNEER		6.04498	0.0031
LOIL does not Granger Cause LGDP	135	6.7096	0.0017
LGDP does not Granger Cause LOIL		2.96549	0.055
LPPI does not Granger Cause LGDP	135	5.92745	0.0034

LGDP does not Granger Cause LPPI		1.60703	0.2044
LREPO does not Granger Cause LGDP	135	0.77107	0.4646
LGDP does not Granger Cause LREPO		1.04437	0.3548
LM3 does not Granger Cause LINTFOOD	135	3.05111	0.0507
LINTFOOD does not Granger Cause LM3		0.36985	0.6916
LNEER does not Granger Cause LINTFOOD	135	0.49971	0.6079
LINTFOOD does not Granger Cause LNEER		6.0348	0.0031
LOIL does not Granger Cause LINTFOOD	135	0.64146	0.5282
LINTFOOD does not Granger Cause LOIL		8.60523	0.0003
LPPI does not Granger Cause LINTFOOD	135	4.02865	0.0201
LINTFOOD does not Granger Cause LPPI		3.61675	0.0296
LREPO does not Granger Cause LINTFOOD	135	0.58075	0.5609
LINTFOOD does not Granger Cause LREPO		0.61687	0.5412
LNEER does not Granger Cause LM3	135	7.2417	0.001
LM3 does not Granger Cause LNEER		3.9376	0.0219
LOIL does not Granger Cause LM3	135	3.34134	0.0385
LM3 does not Granger Cause LOIL		3.36947	0.0374
LPPI does not Granger Cause LM3	135	2.33559	0.1008
LM3 does not Granger Cause LPPI		3.24308	0.0422
LREPO does not Granger Cause LM3	135	2.66699	0.0733
LM3 does not Granger Cause LREPO		0.17864	0.8366
LOIL does not Granger Cause LNEER	135	7.10028	0.0012
LNEER does not Granger Cause LOIL		0.13753	0.8716
LPPI does not Granger Cause LNEER	135	6.97742	0.0013
LNEER does not Granger Cause LPPI		1.74724	0.1783
LREPO does not Granger Cause LNEER	135	2.15473	0.1201
LNEER does not Granger Cause LREPO		1.04547	0.3545
LPPI does not Granger Cause LOIL	135	2.51648	0.0847
LOIL does not Granger Cause LPPI		4.00421	0.0205
LREPO does not Granger Cause LOIL	135	2.6295	0.0759
LOIL does not Granger Cause LREPO		3.34543	0.0383
LREPO does not Granger Cause LPPI	135	0.90727	0.4062
LPPI does not Granger Cause LREPO		2.64856	0.0746

Table A2 Impulse Response of LCEREAL:

Period	**LFOOD**	**LCEREAL**	**LCPIEXFOOD**	**LGDP**	**LINTFOOD**	**LM3**	**LNEER**	**LOIL**	**LPPI**	**LREPO**
1	0.0009	0.0052	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	-0.0004	0.0039	0.0007	0.0003	0.0006	-0.0005	-0.0005	-0.0004	0.0003	0.0002
3	-0.0009	0.0027	0.0002	-0.0001	0.0008	0.0002	0.0000	0.0001	-0.0002	0.0000
4	-0.0012	0.0018	0.0002	-0.0007	0.0019	0.0003	0.0003	0.0007	0.0000	0.0004
5	-0.0019	0.0010	0.0010	-0.0010	0.0008	0.0012	-0.0001	0.0004	-0.0008	-0.0001
6	-0.0016	0.0007	0.0008	-0.0008	0.0012	0.0009	0.0003	0.0000	-0.0004	0.0001
7	-0.0021	0.0001	0.0004	-0.0012	0.0005	0.0009	0.0006	0.0004	0.0004	0.0001
8	-0.0019	0.0002	0.0001	-0.0018	-0.0007	0.0004	0.0009	0.0002	-0.0001	0.0000
9	-0.0016	-0.0001	0.0001	-0.0017	-0.0005	0.0009	0.0009	0.0009	-0.0003	0.0003
10	-0.0010	-0.0002	-0.0002	-0.0011	0.0001	0.0006	0.0015	0.0005	-0.0002	0.0003

Table A3 Impulse Response of LCPIEXFOOD:

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	0.0004	-0.0004	0.0024	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	-0.0001	0.0005	0.0017	-0.0005	0.0012	-0.0003	-0.0012	0.0009	0.0001	0.0001
3	0.0006	0.0014	0.0014	-0.0003	0.0013	-0.0001	-0.0021	0.0014	0.0001	-0.0001
4	0.0009	0.0004	0.0011	0.0007	0.0013	-0.0003	-0.0023	0.0008	-0.0002	0.0000
5	0.0006	0.0000	0.0015	0.0011	0.0019	-0.0003	-0.0027	0.0002	0.0001	-0.0001
6	0.0010	-0.0003	0.0016	0.0005	0.0022	-0.0002	-0.0027	-0.0002	0.0002	-0.0003
7	0.0015	-0.0001	0.0016	0.0005	0.0017	-0.0007	-0.0028	0.0002	-0.0003	-0.0003
8	0.0012	-0.0008	0.0014	0.0015	0.0012	-0.0004	-0.0032	-0.0001	-0.0001	-0.0006
9	0.0010	-0.0010	0.0014	0.0018	0.0012	0.0001	-0.0027	-0.0006	0.0001	-0.0012
10	0.0015	-0.0010	0.0013	0.0017	0.0008	-0.0004	-0.0021	-0.0011	0.0009	-0.0006

Table A4 Impulse Response of LGDP:

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	-0.0003	-0.0003	-0.0005	0.0032	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	-0.0006	-0.0005	-0.0011	0.0039	-0.0004	0.0005	0.0004	0.0000	0.0007	-0.0007
3	-0.0010	-0.0004	-0.0014	0.0037	0.0002	0.0007	-0.0002	0.0005	0.0011	-0.0004
4	-0.0012	-0.0002	-0.0009	0.0005	0.0002	0.0006	-0.0004	0.0013	0.0012	-0.0002
5	-0.0012	-0.0005	-0.0003	-0.0001	0.0003	0.0003	-0.0014	0.0018	0.0015	0.0002
6	-0.0011	-0.0012	0.0002	0.0000	-0.0001	0.0004	-0.0009	0.0012	0.0012	0.0001
7	-0.0003	-0.0011	0.0001	0.0007	0.0002	-0.0002	-0.0010	0.0008	0.0017	0.0000
8	0.0007	-0.0008	-0.0004	0.0012	-0.0001	-0.0012	-0.0006	0.0003	0.0006	0.0005
9	0.0013	-0.0005	-0.0009	0.0017	-0.0002	-0.0018	-0.0002	0.0003	0.0004	0.0005
10	0.0013	-0.0008	-0.0011	0.0013	-0.0006	-0.0013	0.0003	0.0001	0.0000	0.0005

Table A5 Impulse Response of LINTFOOD:

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	-0.0020	-0.0013	0.0020	0.0014	0.0169	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.0014	-0.0072	0.0036	0.0025	0.0147	0.0010	-0.0014	0.0013	0.0093	0.0016
3	-0.0010	-0.0063	0.0060	0.0049	0.0093	-0.0001	-0.0065	-0.0024	0.0069	-0.0004
4	-0.0022	-0.0042	0.0058	0.0123	0.0088	-0.0041	-0.0082	-0.0018	0.0113	0.0005
5	-0.0029	-0.0019	0.0018	0.0125	0.0045	-0.0087	-0.0041	0.0056	0.0116	0.0039
6	-0.0019	-0.0012	-0.0038	0.0146	0.0025	-0.0169	-0.0023	0.0035	0.0120	0.0078
7	-0.0026	-0.0039	-0.0035	0.0157	0.0025	-0.0168	-0.0002	0.0052	0.0115	0.0079
8	-0.0047	0.0020	-0.0095	0.0157	0.0000	-0.0150	0.0064	0.0076	0.0102	0.0084
9	-0.0040	0.0066	-0.0120	0.0119	-0.0042	-0.0122	0.0146	0.0074	0.0129	0.0077
10	-0.0046	0.0083	-0.0156	0.0078	-0.0092	-0.0119	0.0188	0.0069	0.0147	0.0110

Table A6 Impulse Response of LM3:

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	-0.0007	-0.0002	-0.0021	0.0012	0.0001	0.0068	0.0000	0.0000	0.0000	0.0000
2	-0.0009	0.0009	0.0007	0.0002	0.0014	0.0051	-0.0009	-0.0004	0.0012	-0.0020
3	0.0004	-0.0023	0.0002	0.0004	-0.0012	0.0032	-0.0015	-0.0020	0.0011	-0.0007
4	0.0006	-0.0005	-0.0003	0.0007	-0.0011	0.0024	-0.0004	-0.0020	0.0010	-0.0008
5	0.0006	-0.0011	-0.0001	0.0005	-0.0005	0.0005	0.0001	-0.0010	0.0021	-0.0008
6	0.0020	-0.0007	-0.0008	0.0026	-0.0017	0.0000	-0.0005	-0.0009	0.0020	0.0000
7	0.0010	0.0011	-0.0009	0.0010	-0.0021	-0.0003	0.0011	-0.0008	0.0029	0.0009
8	0.0007	0.0010	-0.0019	0.0028	-0.0023	-0.0009	0.0008	0.0020	0.0008	0.0007
9	-0.0007	0.0001	-0.0012	0.0031	-0.0011	-0.0003	0.0011	0.0013	0.0011	0.0012
10	-0.0020	0.0010	-0.0019	0.0038	0.0014	0.0000	-0.0025	0.0034	0.0011	0.0003

Table A7 Impulse Response of LNEER:

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	0.0040	-0.0042	-0.0047	-0.0031	-0.0084	0.0057	0.0237	0.0000	0.0000	0.0000
2	0.0086	-0.0093	-0.0079	-0.0080	-0.0136	0.0028	0.0246	-0.0011	0.0036	0.0032
3	0.0054	0.0008	-0.0045	-0.0153	-0.0074	-0.0032	0.0152	-0.0008	0.0062	0.0058
4	0.0010	0.0069	-0.0054	-0.0183	-0.0102	-0.0088	0.0120	0.0008	0.0048	0.0064
5	-0.0004	0.0077	-0.0090	-0.0150	-0.0101	-0.0115	0.0133	0.0019	0.0039	0.0079
6	-0.0039	0.0103	-0.0090	-0.0073	-0.0077	-0.0072	0.0121	0.0030	0.0006	0.0055
7	-0.0107	0.0092	-0.0023	-0.0072	-0.0034	-0.0067	0.0101	0.0015	0.0033	0.0045
8	-0.0144	0.0093	-0.0051	-0.0026	-0.0028	-0.0030	0.0122	0.0018	0.0011	0.0043
9	-0.0136	0.0113	-0.0116	-0.0031	-0.0094	0.0062	0.0207	0.0024	-0.0010	0.0025
10	-0.0124	0.0125	-0.0118	-0.0045	-0.0115	0.0066	0.0237	0.0044	-0.0022	0.0032

Table A8 Impulse Response of LOIL:

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	0.0026	0.0073	-0.0055	0.0029	0.0125	0.0148	-0.0038	0.0649	0.0000	0.0000
2	0.0289	0.0002	-0.0237	0.0209	0.0181	0.0164	-0.0082	0.0120	0.0117	-0.0001
3	0.0213	-0.0109	0.0079	0.0177	0.0126	-0.0071	-0.0307	-0.0085	0.0001	-0.0078
4	0.0228	-0.0062	0.0075	0.0223	0.0119	-0.0121	-0.0218	-0.0224	0.0135	-0.0011
5	0.0154	-0.0004	0.0153	0.0246	0.0197	-0.0059	-0.0180	-0.0129	0.0034	-0.0007
6	0.0174	-0.0117	0.0142	0.0377	0.0112	-0.0087	-0.0170	-0.0123	0.0048	-0.0054
7	0.0144	0.0014	0.0171	0.0480	0.0108	-0.0135	-0.0196	-0.0131	0.0016	-0.0055
8	0.0017	0.0027	0.0098	0.0501	0.0117	-0.0143	-0.0046	-0.0123	0.0102	0.0002
9	-0.0004	0.0291	-0.0064	0.0366	-0.0011	-0.0134	0.0169	-0.0051	0.0154	0.0073
10	0.0055	0.0463	-0.0188	0.0277	-0.0091	-0.0083	0.0237	0.0127	0.0174	0.0105

Table A9 Impulse Response of LPPI:

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	0.0007	0.0010	-0.0008	-0.0011	-0.0003	0.0008	-0.0002	0.0016	0.0064	0.0000
2	0.0009	0.0005	0.0003	-0.0012	-0.0012	-0.0007	-0.0032	0.0019	0.0039	0.0005
3	-0.0006	0.0003	-0.0004	-0.0008	-0.0001	-0.0031	-0.0040	0.0033	0.0025	0.0005
4	-0.0010	-0.0004	-0.0003	0.0011	0.0005	-0.0040	-0.0046	0.0041	0.0007	0.0007
5	-0.0024	-0.0045	0.0000	0.0022	0.0019	-0.0040	-0.0036	0.0028	0.0011	0.0010
6	-0.0008	-0.0038	0.0003	0.0015	0.0016	-0.0030	-0.0025	0.0006	0.0008	0.0013
7	0.0005	-0.0039	-0.0001	0.0043	0.0034	-0.0020	-0.0019	0.0001	0.0004	0.0014
8	0.0026	-0.0044	0.0001	0.0063	0.0016	-0.0010	-0.0004	-0.0010	0.0009	-0.0010
9	0.0020	-0.0051	-0.0006	0.0088	0.0013	0.0000	-0.0010	-0.0009	0.0015	-0.0004
10	0.0012	-0.0042	0.0005	0.0062	0.0014	-0.0002	-0.0007	-0.0024	0.0020	-0.0014

Table A10 Impulse Response of LREPO:

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	0.0034	-0.0014	0.0051	0.0034	0.0028	-0.0130	0.0057	-0.0009	0.0072	0.0163
2	0.0008	0.0017	0.0040	0.0001	0.0020	-0.0117	0.0047	0.0034	0.0079	0.0082
3	0.0012	0.0040	-0.0005	0.0058	0.0060	-0.0178	-0.0016	0.0052	0.0038	0.0118
4	0.0043	-0.0026	-0.0048	0.0088	0.0097	-0.0095	-0.0037	0.0150	0.0084	0.0086
5	0.0006	-0.0008	-0.0029	0.0089	0.0098	-0.0114	-0.0112	0.0075	0.0075	0.0066
6	-0.0001	-0.0026	-0.0046	0.0124	0.0098	-0.0045	-0.0145	0.0054	0.0083	0.0007
7	0.0036	-0.0050	-0.0038	0.0128	0.0063	-0.0037	-0.0119	0.0044	0.0061	0.0026
8	0.0069	-0.0040	-0.0034	0.0178	0.0101	-0.0050	-0.0117	0.0063	0.0075	0.0013
9	0.0079	-0.0095	-0.0003	0.0220	0.0079	-0.0094	-0.0135	0.0009	0.0093	0.0007
10	0.0092	-0.0144	-0.0019	0.0222	0.0076	-0.0076	-0.0172	-0.0006	0.0084	-0.0011

Table A11 Variance Decomposition of LCPIEXFOOD:

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	2.02	2.77	95.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00
2	1.08	2.85	65.43	2.15	10.14	0.74	10.85	6.58	0.05	0.12
3	2.08	9.10	41.71	1.49	12.21	0.43	21.84	10.99	0.06	0.10
4	3.74	7.03	33.37	2.53	13.14	0.60	29.73	9.62	0.18	0.07
5	3.44	5.00	27.93	4.36	16.37	0.60	35.09	6.96	0.16	0.08
6	4.18	3.93	25.02	3.72	19.65	0.50	37.35	5.29	0.18	0.19
7	6.12	3.16	23.24	3.32	19.17	0.91	39.33	4.29	0.22	0.24
8	6.38	3.26	20.93	5.01	16.95	0.93	42.32	3.51	0.19	0.53
9	6.33	3.66	19.55	6.98	15.68	0.80	41.99	3.26	0.18	1.56
10	7.33	3.94	18.66	8.24	14.38	0.80	40.56	3.71	0.71	1.67

Table A12 Variance Decomposition of LGDP:

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	1.02	0.93	2.36	95.68	0.00	0.00	0.00	0.00	0.00	0.00
2	1.50	1.08	4.79	87.73	0.44	0.88	0.62	0.00	1.47	1.49
3	3.12	1.07	6.85	81.14	0.33	1.63	0.49	0.54	3.62	1.22
4	5.18	1.01	7.56	72.43	0.35	2.02	0.73	3.52	6.03	1.15
5	6.67	1.18	6.62	61.77	0.43	1.88	3.83	7.99	8.58	1.04
6	7.74	2.98	6.07	56.16	0.40	1.97	4.50	9.40	9.83	0.95
7	7.22	4.39	5.55	52.02	0.43	1.85	5.39	9.40	12.88	0.87
8	7.36	4.84	5.39	50.40	0.41	3.53	5.44	8.91	12.53	1.18
9	8.35	4.60	5.79	48.33	0.42	6.69	4.92	8.09	11.44	1.38
10	9.39	4.86	6.62	46.17	0.78	8.00	4.64	7.47	10.56	1.51

Table A12 Variance Decomposition of LINTFOOD:

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	1.33	0.56	1.34	0.69	96.09	0.00	0.00	0.00	0.00	0.00
2	0.86	7.89	2.47	1.24	73.75	0.16	0.28	0.24	12.72	0.39
3	0.71	9.68	5.54	3.42	60.98	0.11	4.62	0.75	13.89	0.30
4	0.80	7.59	5.92	12.56	45.40	1.20	7.70	0.73	17.89	0.21
5	1.04	5.94	4.66	17.66	35.46	4.81	6.72	2.18	20.57	0.96
6	0.89	4.34	3.88	20.66	25.81	14.11	5.05	2.03	20.27	2.95
7	0.89	3.78	3.35	23.09	20.09	19.03	3.90	2.33	19.48	4.06
8	1.22	3.12	4.77	24.21	16.09	20.43	4.07	3.19	17.99	4.90
9	1.29	3.36	6.57	22.31	13.40	19.35	7.29	3.61	17.73	5.09
10	1.35	3.71	8.87	18.68	11.93	17.54	11.11	3.59	17.34	5.87

Table A13 Variance Decomposition of LM3:

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	0.80	0.08	8.65	2.79	0.02	87.66	0.00	0.00	0.00	0.00
2	1.30	0.97	5.74	1.72	2.05	81.04	0.99	0.20	1.54	4.45
3	1.16	5.52	4.50	1.51	2.81	72.16	2.72	3.48	2.27	3.88
4	1.31	5.08	4.07	1.74	3.48	68.81	2.53	6.30	2.73	3.95
5	1.52	5.57	3.83	1.83	3.43	64.75	2.38	6.61	5.91	4.18
6	3.99	5.17	3.70	5.78	4.91	56.51	2.21	6.31	7.76	3.65
7	4.11	5.25	3.75	5.72	6.80	50.48	2.62	5.99	11.62	3.67
8	3.87	5.12	5.06	9.02	8.50	44.64	2.58	7.21	10.51	3.49
9	3.80	4.70	5.30	12.67	8.30	40.95	2.94	7.38	10.17	3.80
10	4.66	4.26	5.78	16.14	7.65	34.12	4.80	10.43	8.95	3.21

Table A14 Variance Decomposition of LNEER:

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	2.19	2.37	3.05	1.30	9.66	4.40	77.03	0.00	0.00	0.00
2	4.89	5.68	4.60	4.02	13.92	2.16	63.40	0.06	0.71	0.56
3	4.75	4.21	4.22	12.41	12.46	2.02	56.01	0.07	2.06	1.78
4	3.63	4.61	4.07	19.57	12.57	3.86	46.77	0.07	2.26	2.59
5	2.88	5.08	5.18	20.91	12.43	6.26	41.38	0.14	2.16	3.57
6	2.87	6.72	6.28	19.60	12.23	6.64	39.63	0.32	1.91	3.79
7	4.86	7.79	5.84	18.88	11.39	6.93	38.18	0.33	1.95	3.85
8	8.06	8.60	5.76	17.30	10.50	6.46	37.34	0.36	1.80	3.82
9	9.59	9.20	6.90	14.79	10.21	6.05	38.00	0.39	1.54	3.33
10	10.04	9.73	7.58	12.73	10.28	5.66	39.11	0.57	1.35	2.94

Table A15 Variance Decomposition of LOIL:

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	0.14	1.13	0.63	0.18	3.32	4.69	0.31	89.59	0.00	0.00
2	11.26	0.71	7.92	5.95	6.45	6.55	1.09	58.23	1.83	0.00
3	13.33	1.77	6.74	7.80	6.59	5.57	10.54	45.61	1.41	0.63
4	14.77	1.71	5.79	10.22	6.38	5.60	12.21	40.21	2.59	0.51
5	14.36	1.48	6.62	13.04	8.20	5.06	12.76	35.73	2.31	0.44
6	13.82	2.04	6.73	19.27	7.61	4.69	12.40	30.84	2.07	0.54
7	12.35	1.68	6.94	26.96	6.81	4.74	12.04	26.18	1.71	0.59
8	10.70	1.49	6.40	33.81	6.46	4.94	10.50	23.27	1.91	0.51
9	9.50	4.46	5.84	35.00	5.75	5.06	10.38	20.77	2.58	0.65
10	8.22	10.60	6.11	32.35	5.17	4.55	10.67	18.27	3.16	0.91

Table A15 Variance Decomposition of LPPI:

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	1.00	2.12	1.26	2.62	0.25	1.51	0.09	5.08	86.06	0.00
2	1.59	1.61	0.82	3.19	1.91	1.44	12.45	7.61	69.03	0.34
3	1.30	1.11	0.67	2.62	1.24	8.76	20.93	13.68	49.30	0.39
4	1.40	0.83	0.50	2.42	0.99	14.83	25.80	18.51	34.20	0.50
5	3.29	8.55	0.36	3.54	2.13	16.78	23.46	16.29	24.88	0.72
6	3.09	12.31	0.35	3.85	2.75	17.62	22.59	14.32	21.89	1.22
7	2.68	14.69	0.30	8.44	5.66	15.98	20.10	12.08	18.51	1.58
8	3.81	16.83	0.25	16.42	5.28	13.47	16.67	10.23	15.51	1.53
9	3.76	18.17	0.26	27.35	4.46	10.61	13.31	8.20	12.63	1.24
10	3.54	18.95	0.28	30.46	4.25	9.35	11.81	8.18	11.78	1.40

Table A16 Variance Decomposition of LREPO:

Period	LFOOD	LCEREAL	LCPIEXFOOD	LGDP	LINTFOOD	LM3	LNEER	LOIL	LPPI	LREPO
1	1.99	0.35	4.54	1.95	1.38	29.20	5.57	0.13	8.99	45.90
2	1.34	0.53	4.71	1.25	1.31	33.96	6.02	1.36	12.65	36.86
3	0.92	1.40	2.87	3.00	3.24	41.82	3.82	2.63	8.63	31.67
4	1.48	1.26	3.01	5.61	6.50	32.70	3.25	12.10	9.10	24.99
5	1.18	1.02	2.67	7.26	8.53	30.35	7.05	11.55	9.18	21.21
6	0.97	1.04	2.80	10.54	9.86	25.47	12.01	10.34	9.57	17.40
7	1.18	1.57	2.83	13.51	9.67	22.69	14.19	9.57	9.36	15.44
8	2.01	1.66	2.62	18.18	10.31	19.51	14.86	8.86	9.04	12.94
9	2.75	2.93	2.13	23.34	9.49	17.44	15.31	7.22	8.86	10.53
10	3.47	5.39	1.79	26.17	8.58	15.07	16.76	5.90	8.25	8.62