

UNIVERSITY OF ZULULAND

DEPARTMENT OF ECONOMICS

FACULTY OF COMMERCE, ADMINISTRATION, AND LAW(FCAL)



**Import and Export Demand Functions and the Orcutt Hypothesis:
Evidence from South Africa**

Author: Samkelo K. Myeni

Student number: 201151881

Cell: 0798364684

Email: msamkelo963@gmail.com

Supervisor

Prof. I. Kaseeram

Co-supervisor

Prof. E. Contogiannis

DECLARATION

I, the undersigned, hereby declare that this work, is the product of my own effort. I have, to the best of my knowledge and belief, acknowledged all the resources of information utilised in this study, as per the normal academic treaties. I further certify that this thesis is original, and has not been submitted before, at this or any other institution, for the attainment of any degree.

Samkelo Kholwa Myeni

15 January 2018

ACKNOWLEDGEMENTS

I would like to thank God and my family for giving me support and strength for the completion of this thesis.

My sincere and utmost gratitude goes to Professor I. Kaseeram and Professor E. Contogiannis for their tremendous support and guidance during the course of writing this thesis.

I would also like to thank all those who supported me through prayers. Without their encouragement and prayers, I would not have been able to complete this work.

ABSTRACT

The South African economy is subject to balance-of-payments constraints that retard the growth process before it is able to deliver higher per capita incomes to all South Africans. Whilst most studies that have embarked on addressing this phenomenon have used price and income elasticities as primary determinants of foreign trade, the present study uses the Orcutt hypothesis to investigate whether South Africa's trade flows respond to exchange rate changes faster than they respond to relative price changes. Particularly, we employ the vector error correction (VECM) technique to estimate both the import and export demand functions and generate the generalised impulse response functions based on cointegration and error correction procedures of Johansen and Juselius (1990) to test the Orcutt hypothesis. Our results of the cointegrated models indicate that South Africa's trade flows are predominantly influenced by income-both domestic and foreign-, relative prices, exchange rates. The results of the generalised impulse response analysis confirm the existence of Orcutt hypothesis in the South African import demand model and reject it in the case of export demand. According to the results, it takes about two quarters for South African imports to adjust to changes in relative prices and one quarter to adjust to changes in the nominal exchange rate. Meanwhile, export demand, on the other hand, takes about two to respond to changes in relative price and four quarters to respond to changes in the exchange rate. Therefore, on the basis of these results, we recommend that in order to reduce balance -of- payment constraints, South Africa should focus more on strengthening domestic industries and expanding the domestic markets. This should be done by paying a close attention to how exchange rate devaluation policies influence demand for foreign produced goods and by applying more intense commercial policy measures on imports, such as imports taxes and quotas as expenditure switching tools to boost domestic exporting industries.

Keywords: exchange rate, Orcutt hypothesis, relative prices, trade flows and VAR-VECM

LIST OF ABBREVIATIONS AND ACRONYMS

1. ADF	Augmented Dicky-Fuller test
2. AIC	Akaike's Information Criteria
3. ARDL	Autoregressive Distributed Lag
4. COMESA	Common Market for Eastern and Southern Africa
5. CCR	Canonical cointegrating regressions
6. CIBS	China, India, Brazil and South Africa
7. DOLS	Dynamic Ordinary Least Squares
8. FMOLS	Fully Modified Ordinary Least Squares
9. IMF	International Monetary Fund
10. FPE	Final Prediction Error
11. GDP	Gross Domestic Product
12. GIRF	Generalised impulse response function
13. HQIC	Hannan and Quinn Information Criteria
14. IMF	International Monetary Fund
15. IRF	Impulse Response Function
16. KPSS	Kwiatkowski- Phillips –Schmidt-Shinn
17. LR	Likelihood Ratio
18. OLS	Ordinary Least Squares
19. PP	Phillips-Perron test
20. USA	United States of America
21. VAR	Vector Autoregressive
22. VDC	Variance Decomposition
23. VECM	Vector Error Correction Model

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CHAPTER 1: OVERVIEW OF THE STUDY

1.1 INTRODUCTION

Ever since the abolishment of the Bretton Woods fixed exchange rate system in the early 1970s, the adjustment of imports and exports to changes in relative prices and exchange rate began to receive a lot of attention in literature of international trade studies. Policy makers and research scholars wanted to understand the effectiveness of currency devaluation on the trade balance of both developed and developing countries. Before the breakdown of this system, research effort was mainly focused on analysing the effect of relative prices on trade flows, commonly known as “price elasticity”. The earliest contribution to the literature, on the estimation of elasticities in trade, can be traced back to studies by Orcutt (1950) and Kreinin (1967), who modelled trade flows (imports and exports) as a function of domestic prices relative to foreign prices. The major interest of these studies was to assess how flows of trade (imports and exports) adjust to exogenous shocks in relative prices. For decades thereafter, the estimation of price elasticity became the most important tool for trade policy formulation and evaluation, becoming a popular research topic in both developed and developing countries.

However, Houthakker and Magee (1969), Golden and Khan (1975), Wilson and Takacs (1977), and Bahmani-Oskooee (1984) criticised this type of specification where trade flows is a function of relative prices alone, arguing that income is a more important determinant of a country’s trade flow and even more important than relative prices. Wilson and Takacs (1977) and Vika (2010) pointed out that in a two-country model, changes in a country’s trade balance is largely dependent on income elasticity than on changes in relative prices. They argued that even if incomes grow at the same rates and prices are fixed, differences in income elasticities will always cause changes in each country's trade balance. In theory, income elasticities of exports actually describe how much of productivity growth in foreign output is translated into growth in exports. The income elasticity of import demand, on the other hand, shows how much of the productivity growth in domestic output is translated into growth in importing industries. Therefore, this insight implies that a country with higher import-income elasticity (assuming an initial balanced trade) is more likely to experience higher growth in its imports than exports, thereby worsening the negative gap between imports and exports and creating a downward pressure on the domestic currency (Vika, 2010). The inclusion of income variables then became well known and empirically important in literature of international studies, which therefore made the specification of trade flow to be a function of a relative prices of each trade flow and income measured by either economic productivity or industrial production index of a country. The inclusion of the income variable is also supported by the gravity model, which suggests that the direction and volumes of a country’s trade flows are not necessarily only determined by prices of traded goods but are also dependent on the economic productivity of trading countries and the distance between them. This model of trade opines that countries with higher growth potential or strong economic performance are more likely to trade with each other than with countries with lower economic performance. However, that trade relationship is also dependent on the distance which separates those two economies. The shorter the distance and the stronger the economic performance, the higher is the trade volume. Conversely, the lower the economic performance and the larger the distance, the lower is the trade volume. The proponents of trade elasticities argue that estimation of price and income elasticities have an important role in the analysis of a country’s trade policy or providing appropriate policy choices to stabilise the external trade balance of a country and improve its competitiveness in the foreign market.

Trying to take a closer look at the impact of exchange rate on trade flows, Warner and Kreinin (1983) criticised previous studies for using composites of relative prices as a proxy for the prices of traded goods. They argued that the separation of price variable and exchange rate is much more appropriate than a composite of relative prices in order to examine their individual influence on trade flows. In fact, it was Orcutt (1950) who first noticed that trade flows sometimes tend to respond faster to changes in exchange rate than they do to changes in relative prices and that the policy implication of such behaviour is not the same. He argued that the estimates of price elasticities are slightly biased and tend to reject the effectiveness of currency devaluation in influencing the behaviour of a country’s trade flows. Wilson and Tackacs (1977) supported Orcutt’s argument by asserting that the reason why price elasticities are downward biased is because, in most cases, its estimates for trade flow demand for longer term price variations are usually much higher than for price variation which appear to be temporary in nature. In most cases, Orcutt’s idea is often interpreted to mean that the response of trade flow (imports or exports) will be much quicker to respond to a change in exchange rate than to changes of the same magnitude in relative prices of the same magnitude. In the literature, this differential response of trade flows to changes in these two aforementioned variables is attributed to five economic time lags; namely, recognition lag, decision lag, delivery lag, replacement lag, and production lag. As a result of that, Junz and Rhomberg (1977) argued that, since the response to exchange rate adjustment is much faster than to the response due to shocks in relative prices it basically suggests that an immediate policy

response is needed whenever there are tremendous shocks to the exchange rate than to relative prices. Again, since these two variables appear to be the most important determinants of trade flows when it comes to formulating policy recommendations, it also suggests that their empirical estimation should always be renewed to cope with changes in the structure of the economy as reflected in time series data for better policy recommendation and appropriate responses by the authorities. Hence, in contemporary literature, empirical estimations of price, income and exchange rate elasticity are perceived as fundamental tools to choose between exchange rate devaluation and commercial policy.

These two policies play a very important role in dealing with imbalances in a country's trade balance or trade flow. In traditional literature, the effectiveness of exchange rate devaluation policy and commercial policy is entirely dependent on the estimates of price elasticity of that particular trade flow. If the price elasticity is found to be lower, it suggests that commercial policy is no longer effective to deal with shocks in a country's trade flow. The opposite is true when the estimate of price elasticity is found to have a larger magnitude. In cases where price elasticity is found to be lower, an exchange rate devaluation policy is recommended. However, as already discussed above, Orcutt criticised this approach and suggested that price elasticities are biased and not statistically reliable. Following his suggestions, the choice of choosing between these two policies relies on the responsiveness of each trade flow to changes in exchange rate and relative prices, not on magnitude (elasticity). Exchange rate devaluation policy is recommended for countries where these responses are found to be more sensitive to changes in exchange rate, meaning that imports or exports respond faster to adjustments to exchange rate than to changes in relative prices. The commercial policy option is adopted when trade flows responses are found to respond more quickly to relative prices, compared to changes in exchange rate.

There are two internationally accepted procedures for assessing the Orcutt (1950) hypothesis. The first method is the imposition of the lag structures on relative prices and nominal exchange rate. Once the lags have been imposed, the decision of whether to accept or reject the Orcutt hypothesis will depend on the length of structures imposed on each of variable. In this method, the Orcutt hypothesis will be accepted if the lags in exchange rate variable are shorter than the lags in relative price variable. In this case, the country should adopt the use of the exchange rate devaluation policies in order to manage a shock in its trade flow. The second method of assessing the Orcutt hypothesis is the impulse response analysis approach. In this method, the Orcutt hypothesis is assessed by analysing the impulse responses of each trade flow to changes in exchange rate and relative prices. In this method, the Orcutt hypothesis is sustained if the shocks in exchange rate elicits a quicker response to trade flows compared to shocks in relative prices. In other words, the focus is on the length of time it takes each trade flow to respond to shocks to relative prices or exchange rates. For the hypothesis to hold it requires that, the impact of a shock to the exchange rate should be felt immediately or earlier than the impact of a shock to relative prices.

The list of studies which have been conducted on this subject in the South African context is very limited. In contrast to the voluminous amount of empirical studies from other countries, especially developed countries, there are only two studies which have been conducted to test for the Orcutt hypothesis in South Africa (see, Bahmani-Oskooee, 1984; and Bahmani-Oskooee and Kara, 2008). Although these studies have made the first contribution to international trade studies in South African literature, their empirical contribution is too outdated and no longer relevant for policy evaluation, considering the historical evolution of South Africa's trade policy since 1994 and after the financial crises of 2008. In addition to that, notwithstanding the lack of literature in most developing countries, empirical literature worldwide still show that the topic still receives a lot of research interest in developed countries. Very recent empirical studies conducted in other countries include those by Bahmani-Oskooee and Ebadi (2015), Bahmani-Oskooee and Hosny (2015), Bahmani-Oskooee (2016), Bahmani-Oskooee and Durmaz (2017). In addition, prior to these studies Omisakin *et al.* (2010) also conducted a similar study for ECOWAS countries. Among all these empirical studies, no study was done for South Africa.

Therefore, with all these in context, the main aims of this study are to do two things: firstly, to estimate both imports and exports demand elasticities for South Africa and secondly, to investigate the existence of the Orcutt (1950) hypothesis in the South African trade flows, using fairly recent quarterly time series data. This study is also motivated by two things: firstly, according to the researcher's knowledge, this study is the first one to utilise the Johansen (1988; 1990) cointegration analysis to generate the generalised impulse response functions from the VECM, as suggested by Bahmani-Oskooee and Ebadi (2016) to investigate the Orcutt hypothesis in the context of South Africa. Secondly, it will also be the first one to utilise the multi-variate models (VAR-VECM) for the estimation of trade elasticities in the South African literature of international trade studies. The reason why we utilise the generalised impulse response functions (GIRFs) instead of orthogonalised impulse response functions (OIRFs) it is because the GIRFs does not require any systematic ordering of variables in the system, while the Orthogonalised impulse response functions (OIRFs) do. Secondly, most empirical studies based in the context of South Africa have been highly focused on the estimation import demand function and they are all based on single static equations (for example see Ziramba, 2008; Thaver and Ekanayake, 2010;

Narayan and Narayan, 2010; and Zhou and Dube, 2011). Therefore, this study allows us to compare the results of multivariate equations with those produced by single equations, as found in most empirical studies.

1.2 PROBLEM STATEMENT

The major challenge facing the policy makers of South Africa today is how to reduce current account deficit in the balance of payments of this country without causing instabilities in other macro-economic objectives, such as economic growth, unemployment and inflation. Over the past few years the South African current account deficit has reached its highest levels ever, sitting at about 7.2% and 5.8% of GDP in 2008 and 2013, respectively. Historical figures show that trade has been the largest contributor towards these deficits. In 2013 the trade deficit was 2.2% of GDP (73.6 billion in rands). This is the second largest trade deficit ever recorded in South Africa since 1970. This is illustrative of how influential trade flows are in determining the position of South Africa's account position.

Most studies have shown that empirical estimations of trade elasticities and responsiveness of trade flows to unexpected shocks in relative prices and exchange rates provide useful insight for determining the appropriate trade policy needed for the economy in order to deal to with unexpected shocks in a country's trade flows. Empirically, imbalances in a country's current account can be corrected by two policy choices: an outward oriented policy or an inward oriented policy. Thus, the main aim of the present study is to use the multi-equation dynamic models for imports and exports to determine the effectiveness of exchange rate devaluation strategy as an outward oriented policy and commercial policy as an inward oriented strategy to influence the behaviour of South African trade flows. It is worth mentioning that the use of dynamic models is also supported by many great economists for their strong forecasting ability, hence this makes this study far more superior than other previous studies conducted in the context of South Africa.

1.3 RESEARCH IMPORTANCE

Firstly, this study contributes to the body of literature by estimating both imports and exports demand elasticities rather than focusing on one trade flow. As highlighted in the previous subsections, trade elasticities have a very important implication in the formulation and implementation of foreign trade policy. They inform policy makers about the possible implication as a result of a change in trade policy governing the flow of traded goods in the economy. Depending on the objectives of the policy makers, elasticities of trade help policy them to choose between commercial or expenditure switching policies and exchange devaluation policy to influence the behaviour of a country's trade flows in a way that will help them to achieve the desired objective.

Secondly, this study seeks to contribute to the body of South African literature on international trade studies, the first investigation of the existence of Orcutt (1950) hypothesis in the South African trade flows, using the generalized impulse response function analysis. The third contribution is that this present study will be the first one to utilise the vector autoregressive (VAR) and Vector error correction models (VECM) to estimate elasticities of trade in South Africa.

1.4 THE AIM OF THE STUDY

The main aim of this research is:

- to estimate the aggregate import and export demand elasticities for South Africa with respect to relative prices, incomes and nominal effective exchange rate using the advanced VAR/VECM systems approach.

1.5 RESEARCH OBJECTIVES

The primary objectives of this research can be summarized as follows:

- to re-estimate the long-run and short-run aggregate import and export demand functions for South Africa using more recent time series data and econometric technique.
- to test for the Orcutt hypothesis in South African trade flows.
- to determine the speed of adjustment of South African trade flows to changes in nominal effective exchange rate and the relative prices.

1.6 RESEARCH HYPOTHESES

The following hypotheses will be tested in order to attain the objectives of this study:

- **Hypothesis 1:** The long-run and short-run aggregate import demand function for South Africa is significantly explained by changes in relative prices, domestic income and nominal effective exchange rate.
- **Hypothesis 2:** South African trade flows respond quicker to a change in nominal effective exchange rate than they do to changes in relative prices (as hypothesized by Orcutt, 1950).
- **Hypothesis 3:** South African trade flows adjust quickly in the short run to restore equilibrium to the long-run relationship.

1.7 ORGANISATION OF THE STUDY

The rest of the thesis is organised as follows. It has five chapters excluding Chapter 1, which gives the background of the study, Chapter 2 of this research gives a detailed discussion of some international trade theories and trade models and the conceptual framework of the Orcutt (1950) hypothesis. Chapter 3 will provide a detailed analysis of empirical literature based on trade elasticities and the Orcutt hypothesis. Chapter 4 is the methodological section of the entire thesis. In this chapter we review and discuss all the econometric empirical estimation techniques utilised in the study. Subsequently, Chapter 5 will present all empirical findings of the study, as well as the presentations thereof. Lastly, Chapter 6 will present the concluding remarks of the study based on the findings laid out and discussed in chapter 5. It will also outline some policy recommendations based on the basis of these findings.

CHAPTER 2: THEORETICAL LITERATURE

2.1 INTRODUCTION

The assessment of the Orcutt hypothesis ideally involves the empirical estimation of imports and exports demand functions. From theoretical perspective, the differential response of trade flows responses to exchange rate and price adjustments is dependent on how quickly and often consumers and producers update their information and change their buying and buying decisions in response to changes in these variables. Orcutt (1950) argued that these responses are usually much quicker and larger for exchange rate adjustments than for changes in relative prices. The investigation of this proposition has become a major topic of debate and research interest. Policy makers wants to know how quickly are the economic agents will adjust their importing and exporting decisions in response to changes in exchange devaluation policy and to commercial policy.

In the literature, the theoretical framework of the Orcutt hypothesis is usually linked to theories of trade elasticities and exchange rate movements. Therefore, this chapter provides a review of trade theories related to trade elasticities and the conceptual literature dedicated to the assessment of the Orcutt hypothesis. In addition to that, this chapter also gives a review of the theoretical relationship between exchange rate movements and trade flows to explore the channels through which exchange rate movements influence the directions and volumes of trade flows (imports and exports) as a key variable in the assessment of Orcutt proposition.

The rest of the chapter is therefore organised as follows: section 2.2. gives a discussion of trade theories related to trade elasticities. Section 2.3. presents a discussion of two trade models. Section 2.4. discusses conceptual literature related to the assessment of the Orcutt hypothesis. Lastly, section 2.4. focuses on the discussion of the theoretical relationship between exchange rate and trade flows as an important variable in the assessment of Orcutt hypothesis which is not well explained by trade theories related to trade elasticities.

2.2 TRADE THEORIES

There are three major theories of trade elasticities suggested in most international studies: the neoclassical trade theory of comparative advantage, the Keynesian Trade multiplier, and the new trade theory (imperfect competition). The main aim of discussing these theories is to show how each one explains the influence of relative price and income on trade flows as the most important variables in both the estimation of trade elasticities and the assessment of Orcutt's hypothesis.

2.2.1 The Neoclassical Trade Theory of Comparative Advantage

The second contribution to the theory of comparative advantage after David Ricardo (1817) was made by Heckscher (1919) and Ohlin (1933), which led to the birth of the H-O theory, also known as the "factor proportion theory." In this theory Heckscher (1919) and Ohlin (1933) extend the Ricardian theory of comparative advantage by arguing that international trade is not only explained by differences in labour productivity but also by differences in factor supplies (endowments) which exist between different countries. This theory is particularly concerned with how the volumes and directions of international trade are influenced by differences in factor supplies between countries, while leaving the effect of a change in income unexplained. The general model of this theory assumes that the output of each economy is given by its production possibility frontier and employment is fixed between countries. According to this theory, international trade between countries could be beneficial if each country is allowed to specialise only in the production of a commodity that involves the extensive application of a country's cheapest and most plentiful resources, while importing those commodities whose production requires the application of the country's most expensive and limited resources.

Unlike in the Ricardian trade theory, where international trade can only be beneficial if each country is able to shift its means of production to industries in which its labour is more productive and efficient, the H-O theory assumes that there is incomplete specialisation between countries, meaning that, even after trade, both countries would still continue producing both commodities but sacrificing most of it resources in the production of the cheaper commodity. In this manner, both countries would be able to enjoy greater quantities of both commodities after trade. The second impression we get from the Ricardian theory is that the distribution of incomes in each trading country is not affected by trade. However, in reality, trade has a significant impact on the distribution of incomes within each trading nation. There are two possible ways in which trade may affect the distribution of income in each trading economy. Firstly, production means (resources) cannot be freely moved from one industry to another without affecting the distribution of incomes. Each time factors of production are moved from less productive industries to more productive ones, incomes from factors of production from less productive industries fall, and rise in more productive industries. The second reason is that, different industries

often demand different resources. In this way, a shift in the mix of goods and services that a nation produces will consequently retard the demand for some resources in the economy and increase the demand for others, thus creating an uneven distribution of incomes within different sectors of the economy.

Therefore, the primary interest of the H-O theory is to examine the impact of international trade on income distribution among factors of production in two trading economies (Helpman, 2011). In this theory, technology, preferences and tastes are assumed to be the same across all countries. This precisely implies that every country has equal access to the same choice of input per unit of production, and both countries are facing the same demand curve (Helpman, 2011). The overall analysis of the theory is based on the following assumptions (as discussed by Salvatore, 2014):

1. *There are two countries (Country A and Country B), two commodities (wheat and clothes) and two inputs (labour L and capital K).*
2. *Production of these goods and services use the same technology in both countries.*
3. *Wheat is labour intensive while clothes is capital intensive in both countries.*
4. *In both countries, wheat and clothes are produced under constant returns*
5. *There is incomplete specialisation in production in both countries*
6. *Both countries face the same demand curve*
7. *Both countries have perfect competition in both goods markets and factor markets*
8. *Factors of production are freely mobile locally and immobile internationally.*
9. *There are no barricades to the international trade of goods and services from one country to another.*
10. *All factors of production (capital and labour) are fully utilised in both countries*
11. *Trade between country A and country B is fully balanced.*

The production function for each good produced in each country can take the following form of expression:

$$Q_w = Q_w(K_w, L_w),$$

$$Q_c = Q_c(K_c, L_c),$$

where, Q_w and Q_c denote the quantities of wheat and of clothes produced respectively; K_w and L_w are the amounts of capital and labour utilised in the production of wheat, and lastly K_c and L_c represent the quantities of capital and labour employed in the production of clothes. Assumption 4 stated above suggests that the unit cost of producing either wheat or clothes in both countries is equal to factor prices, not on the geographic location of the production (Helpman, 2011). According to this theory, if both countries have the same factor prices, they should also have the same unit cost, in which case no country would have a cost advantage over the other in their production processes. As outlined by Helpman (2011) there are two specific conditions that have to be met for trade to occur under these circumstances: first, there should be differences in relative scarcity of factors of production (*factor intensity*) between country A and country B. Secondly, there should be differences in comparative costs (*factor prices*) between the two countries. If these two conditions do not hold, then both countries will have the same production costs in all industries, thereby eliminating the need for trade and specialisation. Similarly, if the countries have the same proportion of production inputs, then both countries will experience the same relative production costs in all industries, thus also eliminating the need for trade and specialisation.

The H-O theory predicts that, because trade enables countries to share resources, in the long run international differences in relative factor prices (w/r) between countries will be reduced and possibly converge with relative commodity prices (P_w/P_c) in each trading economy (assuming zero trade obstructions). This is generally referred to as the “factor-price-equalization (FPE) theorem”. The analysis of this theorem suggests that, in the world of two trading economies, a country which sacrifices the least capital in its production process will specialise in the production of the capital intensive commodity (*clothes*) and the country with lower labour costs will specialise in the production of the labour-intensive commodity (*wheat*). In essence, this theorem suggests that patterns of specialisation and international trade between countries are primarily determined by factor prices and factor intensity, both influenced by the availability of productive resources in each economy. Thus, factor endowments remain the most important factor in this theory.

Factor intensity (abundance) is generally defined in terms of physical units and in terms of relative prices of capital and labour. The first definition only considers the total amount of labour and of capital available in each country. The second definition only considers the factor prices in each country. According to the first definition, Country A would be a labour- abundant country if the total amount of labour to capital (TL/TK) available in its economy is greater than that in Country B. However, according to the second definition Country A is labour-abundant if the ratio of the price of labour to the rental price of capital (w/r) available in its economy is less than that in Country B. Thus, if these two countries were to trade and specialise, each country would have to produce a commodity whose

production requires the extensive utilisation of a country's abundant resource. For instance, if Country A has a high ratio of capital to labour than Country B, Country A is capital-abundant and country B is labour-abundant. This means that, since wheat production is labour intensive, country B's production possibility frontier as a labour abundant country will shift out more in the production of wheat. The opposite is true in the case of Country A. This is generally known as the *Heckscher-Ohlin theorem*. The basic logic behind this theorem is that, a capital-rich country will always produce and export the capital-intensive commodity, and import the commodity whose production requires the extensive use of a country's labour services. In short, this theorem asserts that in a world of trade, each country will produce and export the commodity whose production process requires the extensive application of a country's cheap and plentiful resource, and import the commodity whose production requires the intense application of a country's scarce(limited) and expensive resource (Salvatore, 2014).

The tendency of factor price convergence, as pointed out by Heckscher and Ohlin in this theory, has been frequently diagnosed by many scholars in literature. Among these scholars are Samuelson (1948), whose most popular work was the first to investigate and prove the validity of the "factor-price equalization theorem". As a matter of fact, because of his contribution, the H-O theory was renamed the "Heckscher-Ohlin-Samuelson theorem (H-O-S theorem)". This theorem also predicts that international trade across countries will cause incomes of homogeneous factors of production to be identical in all trading countries, assuming that all the basic assumptions of the H-O theory holds. In essence, this implies that international trade will cause wages of homogeneous labour with the same level of expertise, training and productivity to be the same across countries (Salvatore, 2014). This theorem further asserts that the expansion of trade does not only converge factor prices (wages and rent) but it also causes relative commodity prices to equalise between two trading countries. When both relative factor prices and commodity prices are equal in both countries, both economies begin to experience constant returns to scale.

However, according to Helpman (2011), this theorem can only hold when differences in factor supplies between trade partners are not too large. In reality, true factor prices are not identical in every country. For instance, wages paid to bank tellers in the United States (US) are not the same as wages received by bank tellers in South Africa despite the fact that they are in the same industry, with the same technology and expertise. This is absolute evidence that this model (H-O) cannot eloquently define all aspects of the reality (Helpman, 2011). The remaining question however, is whether it really accurately reflects the real structure of global trade or not. The first empirical study to attempt to test the robustness of the H-O theory was conducted by Leontief (1953). He investigated the relationship between factor intensities in traded goods (imports and exports) and the factor abundance in relation to imports and exports, by analysing America's 1947 labour- abundant and capital- abundant trade flows. Intuitively, it was *a priori* expected that since the U.S was far more capital intensive during the post World War II period, it should have exported more capital- intensive products and imported more labour- intensive products. However, Leontief's input-output tables revealed that, during the same period, U.S exports were largely dominated by labour-intensive products, which then led to a lot of scepticism about the relevance of the H-O theory in defining the flow and directions of trade. This controversy was then later referred to as the Leontief paradox. For years, this blew the H-O model out of literature, until the arrival of Leamer's work (1980), which criticised Leontief (1953) for using gross values of trade flows (imports and exports) instead of net values. In his findings, he revealed that the Leontief paradox disappears and the H-O model prediction holds when net values of trade flows are utilised instead of gross values. He therefore, concluded that Leontief's paradox was a result of a misunderstanding of the basic features of the theory, which resulted in the analysis of wrong datasets. Nonetheless, Leamer's findings did not bring an end to the debate around the paradox in the literature, as it was later criticised for false interpretation of coefficients (Rautala, 2015). In fact, Venek (1968) believed that the H-O model could be best analysed in the world of multi-country -goods -and factors of production. He also assumed that there are no obstructions to trade and that the prices of factors of production are the same across all countries. This basically implies that the composition of inputs (technology, capital or labour) used in the production process is the same across all countries due to factor price equalisation. By implication these inputs are also perceived to differ across sectors but the similar across countries at an industrial level (Helpman, 2011). Intuitively, this means that all countries are assumed to have the same production function (input-outputs table). Consequently, all these sets of assumptions led to a slight modification of the traditional H-O model; it was therefore referred to as the H-O-V model.

Bowen *et al.* (1986) tested this model (H-O-V) in 27 countries and 12 factors of production in 1967. They used the U.S input-output tables to calculate the factor intensity of net exports. Unfortunately, their results did not find any evidence of the causality effect running from factor abundance to exports, as predicted by the H-O-V model, as well as the traditional H-O model in a 2x2x2 model framework. Trefler (1995) also followed Bowen *et al.* (1986), analysing 1983 trade datasets from 33 countries and in nine production inputs. They also found that trade in factor abundance is much higher than trade caused by differences in factor intensity. This phenomenon is commonly defined as "missing trade" (Helpman, 2011). Therefore, they concluded that Vanek's model does not provide a good explanation of trade flows (Helpman, 2011).

Coming back to the traditional H-O model, Leamer (1995) revisited his earlier papers. He strictly focused much of his analysis explaining the trade patterns of four advanced economies (U.S, Germany, Japan, and Sweden). He found that there is a sectoral link between factor abundance and exports in these four economies. Contrary to the H-O predictions, he also discovered that there is no strong link between net exports of manufactured goods and factor abundance in these countries. In his view, the H-O model fails for two reasons: firstly, it links factor abundance with distribution of incomes through Stolper-Samuelson and FPE theorems (Rautala, 2015). Secondly, the H-O model fails to take into consideration different levels of human capital applied in production (Rautala, 2015). In the first reason he argued that if these two theorems are true, the wages of low skilled labourers are expected to vary because of the postulation of the FPE theorem, which suggests that wages for low skilled labourers will fall in high income countries and rise in low income countries. But due to trade liberalisation this is highly unlikely to occur. He argues that if trade liberalisation improves the productivity levels of all trading nations, it is also logical to expect higher average wages in all trading nations.

Here are also some other reasons why the H-O model may be implausible in reality. Salvatore (2014) argues that, in reality countries do not have the same technology, transport costs are not equal across countries, and most countries have trade barriers, which therefore cancel out the validity of factor-price equalisation across trading countries. In addition, he also argued that the assumption of constant returns to scale across countries is not plausible because most countries are dominated by imperfect competition market structures with either increasing or decreasing returns to scale. However, he also mentioned that, this does not completely refute the validity of the factor-price equalisation theorem in reducing the international differences in factor prices. He stated, however, that these prices cannot be completely equal. He further argued that, even though international trade does not completely equalise factor prices between countries, it still remains relevant in the literature, because it provides important information about the general equilibrium of trade model and identifies important forces affecting international factor prices (Salvatore,2014).

Another most important aspect which, by implication, is covered by the H-O theory, is the effect of international trade on the distribution of real income in each trading economy. The H-O theory that we have discussed thus far only tells us about how international trade equalise factor prices as explained by the “factor-price equalization theorem” but it does not tell us how it affects international dissimilarities in per capita incomes. Salvatore (2014) argues that, even if real wages were equal among all countries, due to uneven distribution of factors of production, their per capita incomes would still be widely unequal. According to this theory, international trade will cause the prices of a country’s plentiful and cheap resource to rise and reduce the price of the country’s most expensive and scarce resource, thereby, creating income disparities between owners of capital and labour. This implies that, since Country A is rich in capital (k), Country A’s wage rate will rise, while its rental price for capital is falling. Conversely, the opposite is true in the case of Country B. This is true in the case of South Africa; most labourers working for mining companies are paid less, compared to the engineers and other professions working in secondary and tertiary industries. At an international level, trade causes the real income of capital owners to fall in capital abundant countries while decreasing the real income of labour in labour abundant countries. This is called the “Stolper-Samuelson theorem”. Unlike the H-O theorem, this theorem assumes a unique relationship between factor-commodity price ratios. It postulates that, with tariffs imposed on domestic factor prices, a rise in the relative price of a product will cause an increase in the incomes of the factors of production that have been intensely used in the production process and a fall in the incomes of factors of production that are not intensely used in the production process. What makes this theory distinctly from the Ricardian theory of comparative advantage is that it explains the effect of foreign trade on both price and income distribution through the factor-price equalisation and Stolper-Samuelson theorems.

However, as noted by Salvatore (2014), this theory still lacks the ability to explain the effect of external economies on international trade due to its unrealistic assumption of constant returns to scale. In an attempt to test the strength of this theory, many scholars, such as Krugman (1987), Helpman (1981), Grossman and Dixit (1980) investigated the effect of economies of scale on trade, which then led to the birth of the “new trade theory” also known the “imperfect completion theory of trade”.

2.2.2 The New Trade Theory.

Rautala (2015) noticed two types of stylised facts based on trade data and statistics, which are not well explained in either the Ricardian theory of comparative advantage or the Heckscher-Ohlin theory of international trade (the neoclassical trade theory). Firstly, he noticed that most trade in the developed world is between countries that are similar in nature, share similar production methods and similar natural resources. Meanwhile, the H-O theory, on the other hand, predicts that countries will trade mostly with those countries with unique resources, except technology. In essence, the prediction of this theory, in contrast to the reality that Rautala observed, is that developed countries will mostly trade with developing countries, due to the resource differences existing between the two. The second fact he noticed is that, most developed countries tend to trade homogeneous goods and services within industries not across sectors (Rautala, 2015). The H-O and the Ricardian theory of comparative advantage, conversely, actually predict that countries will always specialise in the production of a good which utilises the most abundant and cheapest resource, or as per the Ricardian theory,

in which it has a comparative advantage. The second fact, creates what is called “intra-industry trade”. In fact, Helpman (1987;1990) and Krugman & Helpman (1985) noticed these incongruities in the literature and argued that they can be explained by monopolistic competition market structures. They defined intra-industry trade as the “*two-way exchange of goods and services in which no country seems to have a comparative cost advantage*”. So, the primary interest of the so-called “new trade theory”, also known as the imperfect competition trade theory, is to explain the concept of intra-industry trade by analysing the effect of production scale economies on international trade, differentiated products, and monopolistic competition on foreign trade. In this discussion we will start by explaining the impact of product differentiation, followed by economies of scale, and lastly, monopolistic competition.

Product differentiation has recently been recognised as one of the primary causes of international trade. Differentiated products make up a larger fraction of world trade flow today compared to homogeneous products. It has also been observed that such trade takes place between two similar industries (intra-trade industry) in two different countries rather than two different industries (inter-trade industry). In addition to this, Helpman (2011) utilised the Grubel-Lloyd index to measure the proportion of trade flows within industries, as opposed to sectors, commonly known as “intersectoral trade” for 17 developed countries. He found that in most countries, intra-industry trade constitutes a larger proportion of trade flows when compared to trade across sectors. He also found that the proportions of intra-industry trade do not only vary across countries, but also in industries. According to his own view these variations are caused by product differentiation within industries. For instance, if Chinese clothes are not a perfect substitute for Brazilian clothes, then both countries can export clothes to one country. The same reasoning applies at an industry level. Industries will trade the same products if both products are not perfect substitutes for each other. Historically, the trade of differentiated products was accepted into the theory of international trade in the 1980s, when economists began to discover models that can be used to model market structures with economies of scale and differentiated products.

Economies of scale occur when a proportion of output produced grow faster than the proportion of an increase in inputs (Salvatore, 2014). Krugman *et al.* (2012) argued that economies of scale can lead to more gains from trade and add to those from comparative advantage because it allows countries to specialise in different sectors, and thus generate more gains from increasing returns. Many years ago, before this concept was integrated into trade theory, Graham (1923) and Ohlin (1933) once argued that “*economies of scale can be an independent source of specialisation and can therefore affect the structure of global trade across countries.*” The basic logic behind this idea is that, a country that is able to achieve large-scale production with the lowest unit cost at an industry level, tends to export more of that commodity and import the one whose production entails a higher unit cost. Therefore, under this positive circumstance, with specialisation and trade, both countries would be able to enjoy larger economies of scale and lower costs of production per unit. This condition will further allow both countries to reduce prices paid by both domestic and foreign consumers. So basically, in that way, economies of scale can also be considered as independent sources of gains from trade attained through lower prices (Helpman, 2011).

However, Graham (1923) was particularly concerned with the possibility that foreign trade might hurt a country when production in some of its industries is subject to increasing returns to scale, and that such a country might be better off if it protects its import-competing industries through tariffs (Helpman,2011). In supporting his argument, he assumed an economy of two industries, Industry A and B. Suppose that Industry A is operating under increasing returns to scale and B is generating constant returns to scale. In this situation, when foreign trade opens up, the country’s economic resources will shift from Industry A to Industry B (constant returns to increasing return industry). When that happens, Graham argues that the value of productivity will rise in Industry A (constant return industry) but will fall and remain flat in Industry B (increasing return industry), thus leading to a fall in a country’s GDP at constant prices and welfare. He therefore, argued that, if the industry with economies of scale competes with imports, tariff protection is the only tool that can be used to prevent the reallocation of economic resources from industries with increasing returns to those with constant returns, thereby avoiding the possibility of welfare and GDP contraction.

On the other hand, Knight (1924) criticised Graham’s view, arguing that it is impossible to apply standard competitive models to situations with increasing returns to scale (Helpman, 2011). However, Ethier (1982a) supported Graham’s view, arguing that tariff protection can be relevant and beneficial for a country in conditions where foreign trade leads to the reallocation of resources from a country’s increasing-returns, import-competing industries and leads to welfare losses. According to Helpman (2011), the debate between these two scholars laid a very important foundation in the literature, which led to a rise of noteworthy considerations of issues concerning the operation of market structures with increasing returns to scale production which has been commonly known as the imperfect competition theory of international trade.

The advocates of this new trade theory argue that the dominance of imperfect competition is self-evident in sectors where government or large companies perform most international transactions. Examples of these sectors are agricultural and manufacturing industries. They describe imperfect competition as a result of the existence of economies of scale in production. This occurs when a bigger firm

takes a cost advantage over a small firm and becomes more efficient, and productive, and also charges lower prices than other firms (particularly small firms) in the industry. This type of economies of scale is called “internal economies of scale” because the cost advantage is dependent on the plant size of an individual firm, while external economies of scale are dependent on the size of an industry. The larger an industry, the lower the average production cost. This therefore, enables the industry to charge lower prices for every output it produces. These two (internal and external economies of scale) are important sources of international trade because of the different implications they have for market structures (Krugman *et al.*, 2012).

Krugman (1987) developed a simple, formal model to integrate these three elements (economies of scale, differentiated products, and monopolistic competition) and show how they can be applied to issues that cannot be implemented in more conventional trade models. He assumed a world of two imperfect economies of scale in production and costless differentiated products produced by two different firms. In his analysis he revealed that economies of scale incentivise both domestic and foreign producers to produce a variety of goods and services at a lower cost through increased international sectoral specialisation, specialized suppliers and knowledge spill-overs. Moreover, Wangwe (2003) also argued that the analysis of economies of scale should also be applied at international level rather than national level, especially, if economies of scale arises from the production of tradable intermediate goods. Hence, following Wangwe’s idea, one can also contend that external economies of scale resulting from increased specialisation, labour market pooling, and knowledge spill-overs depend on the size of the world market (international industry level) rather than the national industry level.

The existence of economies of scale has two important implications on both trade and microeconomic theory. Firstly, it implies that the uniqueness of free trade equilibrium and gains from trade assumed by the H-O model cannot be guaranteed. Secondly, if economies of scale continue to occur, they will violate the equilibrium condition of a perfectly competitive market structure, since a reduction in marginal cost pricing, as required by the market condition would imply losses (Wangwe, 2003). To avoid these losses, economies of scale would only be beneficial if their analysis is based on other market structures that allow prices to go above the marginal cost. Years back, economies of scale did not receive much empirical attention in the theoretical framework of international trade, due to the problem of modelling increasing returns based on market structure. Helpman and Krugman (1985) argued that the main reason why economies of scale have, for many years, remained unaccepted in the theory of trade it is because they are inconsistent with the standard competitive models of market, especially in the case of “unexhausted scale economies”. In an attempt to deal with this problem, the literature advocates the use of the following three approaches, the Marshallian, Chamberlain and the Cournot. These approaches are primarily used to define the impact of imperfect competitive market structures on foreign trade.

The Cournot approach is based on the view that economies of scale or increasing returns arise from the oligopolistic market structure and treats imperfect competition as the main actor (Wangwe, 2003). The advocates of this approach believe that increasing returns are possible only if domestic markets are fully protected to help domestic producers to increase their productivity levels. Such protection will also help to create an increased competitiveness among domestic industries, resulting from lower average production costs. Trade between countries will actually lead to an increased market penetration and competition on both domestic and foreign markets. The existence of oligopolistic market structures on both economies will make the demand for domestic produced commodities by foreign countries exceed its domestic sales. Thus, each nation will be able to increase both its international competitiveness and domestic productivity at a lower average cost.

The Marshallian approach is different from the Cournot approach in that, it allows perfect competition to exist and assumes that economies of scale are completely external to the firm. The conceptual foundation of this approach to the analysis of international trade under increasing returns is linked to Frank Graham's popular protection argument for tariffs. In this approach, economies of scale are often introduced in the general equilibrium models in ways which allow a general competitive equilibrium to hold (Wangwe, 2003).

The Chamberlainian Approach assumes that increasing returns are possible in a market structure where there is a greater choice of product variation and product differentiation. The simultaneous demand for these exported and imported differentiated goods and services often leads to intra-industry trade. Hence, according to this theory, and to the H-O model, in a world of two trading economies where tastes and preferences are the same, both countries will end up trading the same the types of commodities. Gains from trade will then occur in the form of greater consumer choice, as both foreign and domestic consumers are able to choose among a variety of goods and services produced by both countries. Hence, output prices in both countries also go down due to lower production costs resulting from increased external economies of scale. The most elegant exposition of these three approaches to market structures that gives rise to increasing returns as a major determinant of international trade, can be discovered in studies by Dixit and Norman (1980), Helpman (1981), Krugman (1987), Grossman (1992) and Wangwe (2003). The general presumption in any of these three

market structures is that the opening of foreign trade will create a larger market, reduce unit costs, lead to more output and trade (Bathalomew, 2010).

2.2.3 Keynesian Trade Multiplier (Export Multiplier) Theory

This theory extends the Keynesian multiplier theory from a closed economy model to one featuring a two-country trading world. The overall analysis of the theory is focused on the income generation process through the foreign trade multiplier in each trading economy. From this theory, we can divide trade into two categories; “income-” induced trade and autonomous trade. Induced trade refers to changes in imports and exports that are caused by changes in income, measured by income elasticity for foreign produced goods(imports) and domestic produced goods(exports). Autonomous trade, on the other hand, refers to trade flow (exports and imports) adjustments that are caused by changes in other factors, such as consumer’ preference and taste, producers’ production conditions, changes in tariffs, transport costs, subsidies and other trade restrictions and promotion mechanisms. However, one should note that this theory is in fact based on the assumption that export demand is wholly exogenous, meaning that it is not dependant on domestic income. While, imports are viewed as a function of domestic income and other factors (autonomous). According to this theory, repercussions in export demand are caused by changes in income from abroad, while repercussions in imports are due to changes in domestic income. Hence,

$$\text{Imports} = f(y)$$

while,

$$\text{Exports} = f(y^f)$$

where, y and y^f represent domestic income and foreign income, respectively. There are two ratios utilised by the Keynesian trade multiplier to define the import demand function of a trading economy, marginal propensity to export/import (MPS/MPI). Exports demand on the other hand, is assumed to be determined by external factors such as tastes and preferences of the foreign residents and (empirically) by the national income of the foreign country. This suggests that an increase in exports will lead to an increase in the exporting country’s national income and in the wages of exporting industries, while an increase in imports will lead to a fall in the national income of the importing country. It predicts that the propensity to consume domestically produced products is negatively related to the marginal propensity to import (to buy foreign produced products) and to save. If people decide to save a larger portion of their incomes, consumption of goods and services fall. Similarly, if they decide to use a larger portion of their incomes on the purchase of foreign produced products, consumption of domestically produced products falls, while a flow of income from the domestic economy to the rest of the world(leakage) escalates.

Empirically, the analysis of trade flows (imports and exports) should not only confine itself to autonomous and income-induced trade but should also include the price effect. However, in this theory, because of the assumptions of rigid labour costs (wage rates), perfectly elastic supply curves and the availability of unused productive resources, price effect is perceived to be an autonomous factor. This theory further stipulates that, the export demand in a small, open economy will be affected by changes in foreign income, but there is no income transmission effect from a small open economy to the rest of the world. This implies that, if a country is large (e.g. US), it may transfer its own income repercussions to foreign countries, and, in turn be affected by their income instabilities. A decrease in the income of an importing country leads to a fall in import demand, thus creating repercussions in the export demand of the exporting country and condensing the magnitude of its foreign trade multiplier.

At equilibrium level of national income of a trading economy, the aggregate imports and savings are equal to the sum of exports and investment in the economy and imports and exports are equal in the trade account. At this point, savings and domestic investment are also equal. Any deviations from a country’s level of savings or investment will cause problems in a country’s trade profile through the income multiplier effect. However, this theory did not receive much attention in the literature of international trade because of its unrealistic assumptions. Firstly, the analysis of this theory is based on a fixed exchange rate system, which is a very rare case, since most trading countries have now adopted flexible exchange rates systems. Secondly, this theory also assumes that there are no trade obstructions such as import tariffs and import quotas between trading countries. In reality, most countries have high tariff rates and import quotas on certain commodities to protect domestic industries.

2.3 TRADE MODELS

The analysis of all three neoclassical theories predicts that directions and volumes of trade flows across different countries will differ in terms of their factor endowments, economies of scale and their level of incomes, influenced by the values of MPI (marginal

propensity to import) and MPS (marginal propensity to save). In a nutshell, this basically suggests that countries with higher productivity levels, large differences in factor endowments and large-scale production, are more likely to have higher trade flows. Intuitively, it also implies that higher trade flows are more likely to take place across industrial countries and less between industrial and less-developed economies. However, this analysis is still not enough, to provide a full understanding of the full scope of foreign trade one would need to explore other special determinants of foreign trade, which are not clearly captured in the theoretical framework of international trade theories.

In an attempt to bring robustness and to gauge the analysis gap not taken into account by the above trade theories, Tinbergen (1962) suggested an empirical approach towards the specification of trade flows using the so-called “Gravity Equation”. The word “gravity” was extracted from the physics term “gravitation”. In physics the law of gravitation states that there is a pull between two particles of matter which is directly proportional to the product of their masses and inversely related to the square of the distance between them. In the field of international trade Tinbergen (1962) suggested that trade flows between two countries are also directly related to the product of their market sizes, as measured by the productivity levels of each country, and inversely related to the distance that keeps them apart. The distance between countries is accounted for because it affects the shipping costs and the amount of tariff charged for each traded commodity.

2.3.1 The Gravity Model

As already explained above, this model asserts that the trade attraction between two countries is partially offset by the distance between them d_{ij} , which acts as a resistance factor (Jordaan, 2015), proportional to the product of the country's GDP_i and destination countries' GDP_j , and inversely proportional to the distance (d_{ij}) between the two countries (Allen and Atkin, 2016),

$$X_{ij} = \alpha \frac{gdp_i * gdp_j}{D_{ij}}$$

Thus, the theoretical expectation of the general specification of the model is that countries with strong GDP growth rates and closer to each other will experience higher bilateral trade volumes. Conversely, the smaller the GDP and the further the countries are from one another, the less trade would occur (Jordaan, 2015).

The Generalised gravity model can be expressed as follows:

$$X_{ij} = K_{ij} \gamma_i \delta_j$$

where K_{ij} represents the resistance between i and j , γ_i denotes the productivity level of the origin country and δ_j represents the productivity size of the destination country (Allen and Atkin 2016). However, to make it more relevant and to influence the model to make an economic sense, simple economic notations that represent real economic variables were later included in the model. According to Kareem (2014) the early version of this model as used by Tinbergen (1962) and Poyhonen (1963) can be expressed as follows:

$$X_{ij} = \beta_0 (gdp_i)^{\beta_1} (gdp_j)^{\beta_2} (D_{ij})^{\beta_3} \mu_{ij}$$

where X_{ij} represents the export volumes, gdp_i, gdp_j is the gross domestic product of the importing country and the economic activity of the exporting country, respectively, D_{ij} is the distance between nation i and nation j and lastly, μ_{ij} denotes the random error term of the model.

It is worth noting that the traditional Tinbergen'-method does not support the factor proportion approach to international trade. However, Helpman (2011) argues that it does, but only when we augment it to include product differentiation. He reasoned that in cases of product differentiation in all industries, trade flows comply with the foundations of the gravity equation. In the presence of product differentiation, for every commodity traded, each country offers a unique brand into the international market. Thus, as a result, demand for all commodities produced in the world economy exists in all countries. Hence, assuming a world with no tariffs or any form of trade impediments but with common homothetic preferences and tastes in all countries, every country's demand for every brand is proportional to its size (Helpman, 2011). This implies that if the size of a country is 3% of the world economy, it will demand 3% of every brand produced and traded by its trading partners. Similarly, if the size of a country is 6% of the world economy, it means that it will import 6% of each country's GDP. Thus, trade flows between these two countries consist of 3% of the latter country's productivity level plus 6% of the former country's productivity level. But since the first country's productivity level is 3% of the world's productivity while the other one is 6% of world's productivity level, the trade volume between them is proportional to the product of their productivity levels.

Nonetheless, most empirical studies have proven this model not be true in reality. The first major challenge of the model revolves around the validity of the log-linear expression of the gravity model in the presence of heteroscedasticity and zero trade obstructions (Kareem, 2014). The second major weakness of this model is that it does not explain the effect of a change in tariffs in the flow of trade between two countries. Hence, Head and Mayer (2013) and Kareem (2014) suggested that this model can only just be used as a toolkit and a cookbook in the empirical estimation of a country's trade elasticities.

There are two major challenges associated with imports and exports demand functions. The first one is that both imports and exports are not perfect substitutes for domestically produced commodities. Secondly, the specification of import and export demand functions suffers from the problem of endogeneity and price taking behaviour, especially in developing countries. To address this problem empirical studies suggested two important trade models; the imperfect and perfect substitution models.

2.3.2 The Imperfect and Perfect Substitution Model

The difference between these two models is that the imperfect substitution model assumes that both exported commodities and imported commodities are not perfect substitutes of foreign- produced and domestically produced goods, respectively. Meanwhile, on the other hand the perfect substitution model is based on the idea that foreign- produced commodities are perfect substitutes of domestic goods and those domestically produced goods are also a perfect substitute of foreign goods. This type of model is commonly used in cases of highly disaggregated time series data. However, it has been heavily criticised by many scholars due to its unrealistic assumption that a country can only be an importer or an exporter of the traded commodity but not both. As a result of that, its application in most empirical studies has remained relatively low when compared to the imperfect substitution trade model. The imperfect substitution model is usually applied in aggregated time series studies.

This model postulates that the demand function for any imported good is derived from a consumer utility maximisation problem subject to a budget constraint. The export demand function, on the other hand, is derived from the supply side, where the producers are assumed to maximise profits subject to a cost constraint. The economic theory around this model asserts that imports depend positively on domestic income and negatively on the relative price of imported goods and that the export supply function is positively related to a country's productivity level and export prices, and depends negatively on the domestic cost of production. Therefore, it may also be right to contend that, since we assume that traded goods are imperfect substitutes for each other, the demand for a particular commodity is a function of a price vector and income. Thus, the empirical specification of import and export demand functions under imperfect substitution models can be expressed as follows:

$$D_i^m = g(P_i^m, P_i^e, Y_i),$$

$$D_i^x = g(P_j^m, P_j^e, Y_j),$$

where D_i^m and D_i^x represent import and export demand functions, respectively.

P_i^m and P_j^m denote the price of imports for the importing country and the rest of the world, respectively. Meanwhile, P_j^e and Y_j represent the domestic price for the importing country for commodities that are produced domestically and real income from the rest of the world, respectively. In line with the concept of the demand and supply relationship, at equilibrium the law of one price between two countries must hold if: $P_i^m e^{ij} = P_j^m$, where e^{ij} represent the exchange rate that exists between two countries. Furthermore, by incorporating the concept of imperfect substitution model in conjunction with the rational expectation permanent income model as suggested by Rashid and Razzaq (2010), who assume that a consumer consumption function is based on two goods, that is, a home good and a foreign good. It may be concluded that import demand depends on the level of domestic permanent income and on relative prices of an imported good. Meanwhile, exports demand is ought to depend positively on the foreign permanent income and negatively on the relative price of domestic exports. The addition of the rational expectation income model will allow both the imports and exports to possess the permanent component as required by the properties of time series data and language of econometrics. Therefore, in the light of the combination of these two models it may be concluded that the export demand function depends positively on foreign income and on export prices, and negatively on the domestic costs. Thus: $X^d = f(YW, P, Dc)$.

2.4 THE CONCEPTUAL FRAMEWORK OF THE ORCUTT HYPOTHESIS

The Orcutt (1950) hypothesis has great importance to policy makers concerned with the length of time it takes for alternative policies such as export subsidies, import tariffs and exchange rate devaluation to influence trade flows. The Orcutt hypothesis allows us to observe the speed and magnitude at which trade flows respond to changes in relative prices and to nominal effective exchange rate. The first variable (relative prices) measures the time it could take for import tariffs and export subsidies (commercial policy) to affect

the behaviour of trade flows. The second variable (exchange rate) measures the magnitude and the time it could take exchange rate devaluation policy to affect trade flows.

An overdue(delayed) response of trade flows to changes in relative prices and exchange rate can be attributed to various economic factors that affect domestic and foreign consumption patterns, such as recognition, decision, delivery, replacement and production lags (Ebadi, 2015). **The recognition lag** refers to the time it takes buyers and sellers to recognise changes in exchange rate and relative prices, and adjust their consumption patterns accordingly. This delay is expected to be longer in the case of international trade compared to the domestic economy, due to difficulties associated with the information spill-over effect, caused by different languages spoken in the two trading countries and the distance that keeps them apart. However, Ebadi (2015) argues that global network communication (internet) has significantly reduced the effect of this lag, and economic agents are now able to respond faster to changes in exchange rate and relative prices than they were years ago. The internet as a global networking system has simplified the communication problem among economic agents such as consumers and producers around the world and the level of information asymmetry has been reduced. This has helped policymakers to easily comprehend the overall economic conditions of their trading partners, thereby enabling concerned economic agents to make appropriate predictions about future changes in their consumption patterns and help them to adjust to those changes more quickly than they were a few years ago.

The second lag, **decision lag**, is the time it takes economic agents to substitute local products with those produced in a foreign country. It also refers to the time it takes both local and foreign producers to apply different inputs in their production processes in order to remain competitive in the global market (Bahmani-Oskooee and Ebadi, 2016). The third lag, **“delivery lag,”** is caused by the distance that exists between two trading nations, which directly or indirectly influences the length of time it takes producers to respond to new demand in the market. This type of a gap can have a significant impact on a producer’s power in a country where a change in relative price has occurred. Producers are normally sluggish to respond to a change in the global market until they receive their new orders. This also affects the time it takes a country’s trade flows to respond to changes in relative prices and exchange rate.

The fourth lag is the **replacement lag**, which occurs just after the third lag has occurred; the subsequent lag that is discussed in most literature studies is the time that it usually takes producers to replace old materials with new inventories to adjust to changes in the global market (Bahmani-Oskooee and Ebadi, 2016). The main cause of these sluggish adjustments is that most producers’ place their material orders and hold binding contracts with the material producers. These contracts are normally regulated by international trade regulations and they cannot be cancelled easily. The fifth lag is **production lag**; which refers to the period of time it takes producers to change their production process as a means of responding to new exchange rate policies or changes. All these lags together influence the responsiveness of trade flows to changes in relative prices or exchange rates in the short run and long run. Therefore, for sound policy analysis, it is always important to take into consideration the effect of these lags in applying trade policies.

2.5 EXCHANGE RATE MOVEMENTS AND TRADE FLOWS

The main aim of this sub-section is to show the theoretical relationship between exchange rate movements and imports and exports as a second variable of interest in the assessment of the Orcutt hypothesis. The major weakness of the theories of trade in the foregoing discussion is that they do not explain the impact of exchange rate movements to the volumes of a country’s imports and exports. Lewis (2015) argues that trade flow’s’ response to changes in relative prices, entirely depends on both how often and by how much destination prices move after a change in exchange rate. This technically implies that part of the changes in trade volumes are due to changes in exchange rate, which exist between two trading countries.

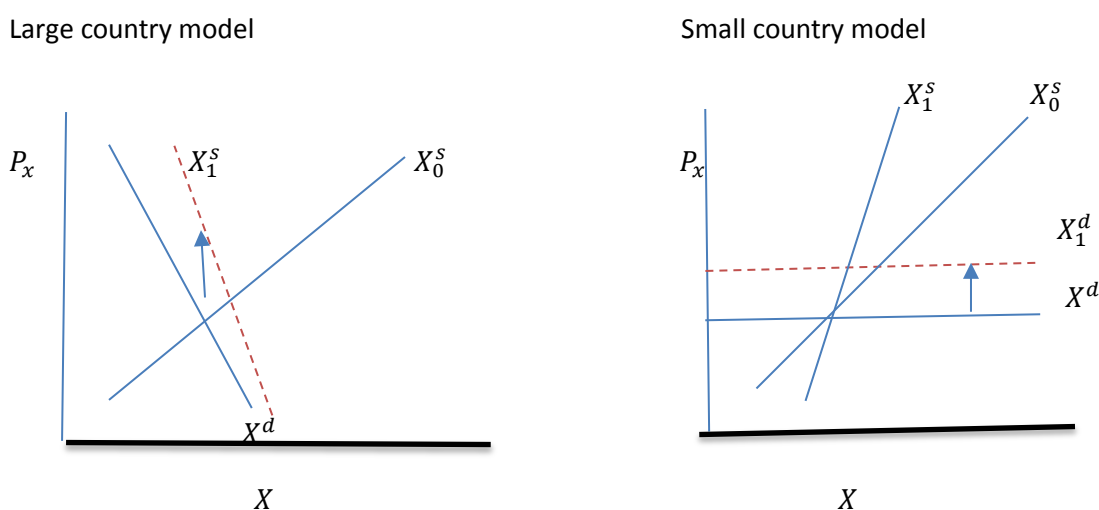
The impact power of exchange rate movements over imports and exports volume depends on price setting strategy and on the degree of exchange rate to prices (Bacchetta and Wincoop, 2000). Exchange rate movements do two things in an open market economy; firstly, they affect the country’s trade competitiveness and price levels both on traded and non- traded goods. Secondly, exchange rate movements affect prices of financial assets, such as commodities. Lewis (2015) argued that exchange rate movements have no power to influence the patterns of trade flows if domestic prices are fixed. The only condition in which exchange rate variations may influence the patterns of a country’s trade flows is when exporting firms decide not to fully pass through the exchange rate shock into local prices based on the effective demand curve they face in the market. According to Bacchetta and Wincoop (2000)’s general model of exchange rate and trade flow, the effect of exchange rate movements on trade flow is sensitive to price setting. They argue that if foreign exporters set their prices in the domestic currency of the importing country for all imported goods, then domestic importing consumers will not be directly affected by changes in the exchange rate. However, if there are differences between domestic prices and foreign prices, minor changes in exchange rate movements will cause significant changes in trade flow movements. This implies that if the exporting country(foreign) decides to sell their products at a lower price level relative to the price level in the

importing country (home), the level of trade will increase. The second channel, outlined by Bacchetta and Wincoop (2000), through which exchange rate movements can affect trade flow movements, is when exporters decide to price their products in their own currency and do not discriminate between foreign and domestic markets. In that case, imports and exports will fluctuate with changes in nominal exchange rate (number of units of domestic currency per units of foreign currency) and cause changes in the prices of traded goods. Bacchetta and Wincoop's model framework is based on four conclusions regarding the impact of exchange rate variations to trade flows:

- ✓ Trade flow sensitivity to variations in exchange rate depends on the price setting strategy adopted by two trading countries
- ✓ Trade flow responses to exchange rate movements are more likely to be significant when differentiated pricing strategy is adopted.
- ✓ The presence of assets markets such as future contracts retard the sensitivity of trade flows to variations in exchange rate, but it does not completely eliminate it.
- ✓ International integration in financial markets makes all countries to adopt producer currency pricing strategy.

In contrast to Bacchetta and Wincoop (2000)'s general equilibrium model, Edward and Garlick (2008) on the other hand developed a simple a simple import and export demand models based on demand and supply equilibrium to illustrate the theoretical relationship between exchange rate variations and imports and exports. According to this model, export supply (X^s) is upward sloping, indicating that as export prices (P_x) in domestic currency rises relative to production costs or prices (P_d), the profitability of exports productions rises and increases domestic exporting firms' willingness to supply goods. Meanwhile, the demand for exports (X^d) by foreign consumers is negatively related to export prices ($P_{x/e}$) expressed in foreign currency, which suggests that as the price of exports rises, foreign consumers tend to demand less of domestic production. The intersection of demand and supply determines the equilibrium exports volumes (X) and prices (P_x). The response of exports to exchange rate adjustments depends on the elasticities of both exports supply (X^s) and demand (X^d) because changes in exchange rate affects both the price paid by the importing country and received by the exporting country. However, the effects of exchange rate variations usually have a much bigger impact on larger countries than on small countries mainly because small countries are general regarded as price taking economies. So, their response to changes in exchange rate are general, much less significant when compared to large economies. Figure 2.1 below present Edward and Garlick's model of export demand model for a small country and a large country based on the demand and supply framework.

Figure 2.1 Exchange rate and export demand



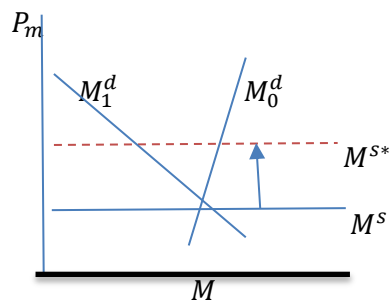
Source: Edward and Garlick (2008)

As shown on the right hand side of figure 2.1 above, small countries are facing a horizontal demand curve in the international market. This means that, in a small country, domestic export prices (P_x) are always set equal to world exports prices (P^*) (valued in units of local currency, $P_x = eP^*$). An appreciation in the exchange rate (fall in e) will cause the demand curve to shift downward (X_1^d), thus reducing the local currency export price by full appreciation. Consequently, this will cause export volumes, expressed in units of local currency, to fall as profitability in exports falls, with a larger decrease in elastic export supply. The left- hand side of the model shows that, in a large country, firms can influence the world export price of their products through product differentiation. In these countries, exporting firms are able to pass on some of the exchange rate adjustments to foreign importing countries. In a case of a currency depreciation, the exchange rate pass-through effect makes the exporting prices of large exporting countries (expressed in local currency) rise by less than the depreciation (Edward and Garlick, 2008). Thus, there are two reasons why exports rise with currency depreciation: firstly, a rise in exchange rate (depreciation) increases exports prices expressed in domestic currency; secondly, currency depreciation allows exporting industries to reduce their export prices expressed in foreign currency, which in turn, creates an increase

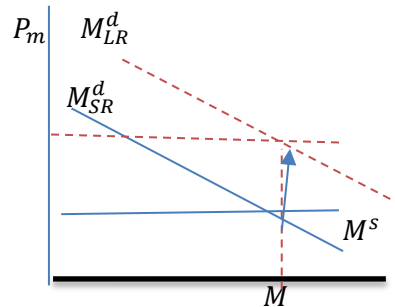
in the demand for domestic produced goods by importing countries. Therefore, this concludes that exports' response to exchange rate variations will be larger if export demand and supply is more elastic. In contrast, it can also be argued that export response to exchange rate adjustment is more likely to be small if the export demand and supply is inelastic.

Figure 2.2 Exchange rate and import demand

Small country import model



Large country import model with inflation



Source: Edward and Garlick (2008)

Apart from real exchange rate adjustments, the responsiveness of trade flows to changes in exchange rate can also be influenced by the inflationary impact between two trading economies. Higher inflation causes domestic costs of production to rise and erode the profitability of export supply. This, consequently, makes exporting firms find it hard to reduce their export prices expressed in foreign currency, thus causing exports demand to decrease in response to higher prices. Therefore, for economies (like South Africa) with a high tendency towards price instabilities, it is crucial that the assessment of trade flows' response to exchange rate variations is performed in nominal terms, as suggested by Orcutt (1950), Tegene (1991), Bahmani-Oskooee and Ebadi (2015).

In the language of simple macroeconomics, a depreciation in nominal exchange rate causes the prices of imported intermediate production inputs, domestically produced competing inputs and unit costs of production for any domestic firm to increase. This will, in turn, lead to higher consumer prices and wages in the domestic economy, thus increasing the cost of production and reducing the volumes of exports. According to Edward and Garlick (2008) an asymmetric response of exports to either nominal appreciation or depreciation may only arise if local prices and wages are downward sticky but upwardly flexible. They also argued that the effect of exchange rate adjustments on different sectors is not symmetric due to differences in factor abundance. Bacchetta and Wincoop (2000) argue that exchange rate movements only affect the movements of trade flows when prices in domestic markets and foreign markets are fully symmetric (i.e. $P^d = P^f$). In that case movements in trade flows respond only to changes in exchange rate, not to changes in relative prices.

The theoretical relationship between trade flows and exchange rate variations is also explained by the concepts of the elasticity approach. This approach is based on two theoretical frameworks; the Marshall-Lerner condition and the J-curve phenomenon. The central point of focus of these two theoretical frameworks is on how trade flows (imports and exports) respond to adjustments in the exchange rate. The impact of exchange rate depreciation on imports and exports depends on how prices of traded goods respond to currency devaluation.

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According to the Marshall-Lerner condition a nominal depreciation in exchange rate has a positive impact on a country's balance of trade only if the sum of price elasticities (in absolute values) of imports and exports is greater than one unit. Unlike in the case of a large country, the response of imports and exports to nominal exchange rate depreciation is said to effect ambiguous improvements in the trade balance for small countries with inelastic supply. This proposition is called the "Bickerdike-Robinson-Metzler (BRM) condition". The analysis of the BRM model regarding the relationship between exchange rate movements and trade flows is rooted in the assumption of constant domestic prices.

However, Edward and Garlick (2008) criticise this model, arguing that the entire analysis of the BRM framework completely rejects the effectiveness of domestic inflation arising from currency depreciation to influence the initial change in imports and exports volumes. They also argued that the BRM condition may also fail when possibility of trade flow (imports and exports) lagged responses to exchange rate variations is considered. The possibility of such delayed trade responses may be ascribed to the fact that

most international transactions are done on contracts that can be renegotiated only with difficulty, thus slowing down traders' ability to respond to changes in exchange rate.

2.6 THEORETICAL FRAMEWORK FOR IMPORT AND EXPORT MODEL SPECIFICATION

The general specification of trade functions followed by these studies assert that trade flows (exports and imports) are a function of incomes, relative prices and exchange rate. In theory, the specification of trade flows can also be derived on the foundations of the neoclassical microeconomic consumer theory and the producer theory. The combination of these two theories is based on the core principles of competitive markets theory, which holds the idea of a market equilibrium to reconcile demand and supply. The most elegant discussion of these two approaches in deriving trade functions based on microeconomics producer and consumer theory in literature is found in studies by Diewert (1986) and Kamau (2014). According to microeconomic theory a consumer utility maximisation function in the context of international trade is based on two goods: a domestic good (H) and an imported good (M).

$$\text{Max } u(M, H) \dots \dots \dots 3.1$$

Subject to constraint,

$$P_m + P_h = Y \dots \dots \dots 3.2,$$

where, u is utility, and M and H denote the consumption of the imported good and domestic good, respectively. In the second equation (3.2) P_m and P_h respectively denote the price of the imported commodity and the price of the domestic good that a consumer would have to pay in order to maximise his or her utility, respectively. Y represents the income of a consumer. If we were to extend this into a case of international trade, in more specific terms P_m would represent foreign prices and P_h would represent domestic prices. Y denotes the level of domestic income.

Therefore, to simplify this further we use the langragian composition concept to bring equation 3.1 and 3.2 together.

$$U(M, H) = M, F - \lambda(P_m M + P_H H - Y) \dots \dots \dots 3.3$$

First Order Conditions for utility maximisation

$$\frac{\partial U}{\partial M} = H - \lambda P_m = 0 \dots \dots \dots 3.4$$

$$\frac{\partial U}{\partial H} = M - \lambda P_H = 0 \dots \dots \dots 3.5$$

$$\frac{\partial U}{\partial \lambda} = P_m M + P_H H - Y = 0 \dots \dots \dots 3.6$$

From the above first derivatives we can now derive the first order condition of South African import demand function,

$$M = \frac{Y}{2P_m} \dots \dots \dots 3.7$$

However, this condition does not hold in reality because imports does not only depend on the level of domestic income and prices of imported goods but it is also affected by other external factors such as exchange rate and foreign exchange reserves. Nevertheless, the assessment of the Orcutt hypothesis specifically requires that imports and exports should be modelled as a function of their relative prices, domestic income (imports), foreign income (exports), and exchange rate. Thus,

$$\text{import demand} = f(\text{domestic income, relative import prices, exchange rate})$$

$$\text{export demand} = f(\text{foreign income, relative export prices, exchange rate})$$

As already stated in the previous chapters, the central focus of the Orcutt hypothesis assessments in these variables is on relative prices and exchange rate. In theory, there is a positive relationship between a country's income and import demand and there is also a positive relationship between foreign income and export demand.

2.7 CONCLUSION OF THE CHAPTER

From a theoretical perspective it appears that international trade and comparative advantage is primarily driven by differences in technology (Ricardo, 1963), factor endowments (Heckscher; 1919, and Ohlin; 1933) and market structures (the new trade theory). According to the Heckscher-Ohlin, theory trade is driven by differences in the availability of productive resources across countries, which in turn influences prices of factors of production and distribution of incomes in both trading economies. The Keynesian trade multiplier is focused on analysing two hypothetical trading economies with constant prices, no international capital movement, and

variable employment in each nation. In essence, this theory concentrates on analysing the relationship between income and trade flows demand (imports and exports) in the short run at aggregate level (Hong, 1999). According to this theory, trade flows demand functions can be defined by two ratios; marginal propensity to save and import (MPS/MPI). An increase in the values of MPS and MPI leads to a fall in the consumption of domestically produced goods. The marginal propensity to import, specifically, measures the amount of imports induced by income changes in the domestic economy.

Moreover, the gravity model suggests that trade attraction between two countries is partially offset by one country's GDP_i and the destination country's GDP_j , and is inversely proportional to the distance (d_{ij}) between the two countries (Allen and Atkin, 2016). Imperfect substitution models describe traded goods as imperfect substitutes of each other. The conceptual framework of the Orcutt hypothesis, to be discussed later, reveals the importance of estimating and comparing exchange rate and relative price elasticities as an alternative tool of scrutinising the behaviour of trade flows.

CHAPTER 3: EMPIRICAL LITERATURE REVIEW

3.1 INTRODUCTION

The empirical literature of this study is divided into two parts. The first part provides a review of empirical studies based on import and export demand functions in South Africa and outside south Africa. The second part will give a review of empirical literature based on Orcutt Hypothesis.

3.2 LITERATURE REVIEW ON IMPORT AND EXPORT DEMAND FUNCTION

The literature review presented herein provides a number of local and international studies which have attempted to estimate trade functions. However, literature on export demand function is still very scarce for South Africa, compared to other countries, especially developed countries. Among these studies we have country-specific studies, cross-sectional studies, and panel data based studies. Some studies are based on disaggregated models (product specific) while others are focused on aggregate models. Nonetheless, the specification of each model (both import and export) across all these studies is the same. They all regress (model) imports (exports) against income and relative prices. In some studies, additional variables such as investment, inflation and foreign reserves have also been investigated. Therefore, for the sake of consistency, all these studies will be reviewed in this study to compare their income and price elasticity estimates as our main variables of interest for the specification of import and exports demand functions for South Africa. The first sub-section will only concentrate on the most recent studies conducted in the context of South Africa since year 2008, after the financial crisis. The second subsection will then give a review of all empirical studies conducted in other countries.

3.2.1 South African Literature Based on Price and Income Elasticity

Ziramba (2008) utilised an unrestricted error correction model (UECM) based on the Bounds testing approach of Pesaran *et al.* (2001) to analyse the aggregated import demand function for South African using annual time series data from 1970-2005. The results indicated that there is a long run cointegrating relationship between South Africa imports, relative prices of imports and domestic income. In the long-run both price and income were found to be perfectly elastic with elasticity values of -1,43 and 2,04, respectively.

Narayan and Narayan (2010) utilised the Bounds tests for cointegration approach to re-estimate both import and export demand functions for Mauritius and South Africa using annual time series data. The results suggest that there exists a long-run relationship between import/exports, domestic income/foreign income, and relative prices in both countries. In the long run both income elasticity and relative price elasticity of imports have significant effects on imports demand functions for both countries, with income being the most important determinant. The results also show that the income variable is statistically significant for Mauritius and insignificant for South Africa in the export demand models, while coefficients of relative prices of exports were found to be statistically insignificant in both countries.

Thaver and Ekanayake (2010) also utilised the Bounds testing cointegration technique and error correction mechanism, developed by Pesaran *et al.* (2001), to investigate the impact of apartheid and international sanctions on the import demand function for South Africa using annual time series data from 1950 to 2008. They used two separate dummy variables to capture the effect of these two economic events, 1950-1994 for apartheid and 1981-1994 for international sanctions. They utilised the autoregressive distributed lag model (ARDL) to estimate the short-run and long-run elasticities of demand during these years. Elasticities of other important variables (such as relative import prices, domestic income and foreign exchange reserves) were also observed. In their results, they reported that apartheid had a significant short-run negative impact on the South African aggregate import demand and an insignificant one in the long-run. International sanctions, on the other hand had a positive impact in the short run and a negative one in the long run. In addition, it was also found that there is a long run positive association between South African imports and domestic economic activity and foreign reserves, relative prices of imports exert a negative impact on imports. They therefore recommended that in order to reduce balance of payment instability, South Africa needs to strengthen her trade relations with other developing countries and apply policies that would reduce import demand, while diversifying her export base.

Zhou and Dube (2011) also employed the Bounds testing approach to test for the validity of cointegration in five different import demand functions for CIBS countries (China, India, Brazil and South Africa). These models include; the traditional import demand model used by Hong (1999) and Tang (2003); the Senhadji (1998) model, which modifies the traditional import demand model-by replacing the RGDP with real GDP minus exports; the disaggregated import demand model, which decomposes the real domestic activity variable into three broad categories; and lastly, the dynamic structural import demand model proposed by Xu (2002), which

derives the import demand function using the intertemporal optimisation approach. The results indicated that in all these five models the long-run income elasticity is much higher compared to earlier studies and to short-run elasticities. Contrary to other previous studies, they found that price elasticity coefficients for all four CIBS countries is not statistically significant and negative. However, they justified their findings by arguing that this is because CIBS countries are generally classified as growing economies whose imports consist mainly of capital goods and production inputs needed for development purposes for each economy, hence they are demanded even if their relative prices are increasing.

Baiyegunhi and Sikhosana (2012) conducted a study using an annual time series from 1971 to 2007 to estimate the South African import demand function for wheat. The results of the double logarithmic linear function indicate that per capita income proxied by real gross domestic product, wheat prices, price of sugar as a complement product of wheat and domestic production of wheat are all statistically significant in explaining any form of changes in import demand function for wheat in South Africa. Moreover, income elasticities were found to have a positive inelastic (0.163) effect on South African import demand for wheat. As anticipated, import relative prices was also found to have a negative inelastic (0.1207) effect on South African import demand for wheat from the rest of the world.

Thaver (2012) utilised the error correction model (ECM) and cointegration analysis technique developed by Pesaran *et al.* (2001) to examine the long-run disaggregated import demand function for South Africa from Tanzania using annual time series data (1980:2010). The results indicated that there is a stable long-run association between imported goods and services, the ratio of domestic prices to Tanzanian import prices, real foreign reserves, exchange rate volatility, consumption expenditure, investment, and South African exports of goods and services to Tanzania. Two dummy variables were also utilised in this study. The first dummy covers the period of 1980 to 1994 and the second one covers the period of 1996 to 2010. The purpose of including these dummy variables was to investigate the impact of apartheid and post-apartheid policy commitments to increase South African trade volumes with other African countries, respectively. The results demonstrated that apartheid had a negative impact on South African import demand for Tanzanian commodities with a significant negative coefficient of (-14.24). On the other hand, the coefficient of the second dummy variable suggests that policy commitments by the Post-apartheid government to increase South African trade volumes with other African countries had an inelastic positive impact on South African imports from Tanzania.

Ekanayeka *et al* (2012) studied the effects of the real exchange rate volatility on South Africa's imports and exports with the European Union during the period of 1980 to 2009 using quarterly time series data. The results of the Bounds testing approach to cointegration and the error-correction model revealed that South Africa's imports are positively related to domestic productivity levels and foreign exchange reserves but depend negatively on relative import prices and exchange rate volatility. In addition, exports are positively related to foreign income but depend negatively on relative export prices and exchange rate volatility. Furthermore, the study established a mixed effect of the exchange volatility in the short-run and in the long-run.

Moreover, Triplett and Thaver (2015) also employed the Bounds testing approach to estimate the import demand function for South Africa with China using time series data from 1993 to 2012. The results showed that there is evidence of a long-run relationship between demand for imports, relative prices of imports and domestic income. In the results, they found that in the long run, income plays a major role in the determination of import demand of goods and services from China. Contrary to other previous studies but consistent with the findings of Zhou and Dube (2011), their results show that real relative prices of imports are positively related to import demand. Unlike Zhou and Dube (2011), whose justification was entirely based on the dependence rate of CIBS countries on foreign-produced capital goods and production inputs, Triplett and Thaver (2015) argue that such findings confirm results of other studies based on low-income countries. Therefore, on the basis of these results they predicted that South Africa's deficit in her trade account with China will continue expanding in spite of the real devaluation in the value of the rand.

Table 3.1 Summary of South African empirical literature on trade elasticities

Author and year	Trade flows	Econometric estimation technique	Empirical findings
V.Gumede (2000)	Sectorial Import demand	ECM based on bound testing approach	Long-run income elasticity is greater than long-run price elasticity
Ziramba (2008)	Import demand	UECM based on Bound testing	Long-run income elasticity is greater than long-run price elasticity
Thaver and Ekanayake (2010)	Import demand	Bound testing approach	Long-run income elasticity is greater than long-run price elasticity
Narayan and Narayan (2010)	Import and export demand	Bounds testing approach	Long-run income elasticity is greater than long-run price elasticity NB: income elasticity for exports was found to be insignificant
Zhou and Dube (2011)	Import demand model	Bounds testing procedure	Long-run income elasticity is greater than long-run price elasticity
Triplett and Thaver (2015)	Import demand	Bounds testing procedure	Long-run income elasticity is greater than long-run price elasticity

Source: Author's own table

In empirical studies discussed above, it is notable that none of them have included exchange rates in their models. The main focus of these studies was on the estimation of price and income elasticities only. Thus, this current study aims to gauge this gap by adding exchange rate as an additional determinant of trade flows. Moreover, this present study is also different from these previous ones because it aims to estimate both trade functions using a multi-variable model, rather than relying on the estimates of single static equations. The empirical literature based on the Orcutt hypothesis is discussed in the subsequent section after the empirical literature review of non-South African studies.

3.2.2 Non-South African Literature Based on Price and Income Elasticity

Maziya *et al.* (2016) used the LSDV fixed-effects model to examine the determinants of export demand for Swazi sugar and the effect of the EU reform on exports for Swazi sugar on selected markets (SACU, EU, USA and COMESA). The study utilised a panel data approach by using time series data from 1997 to 2012 on an annual basis. In this study export prices, importer's GDP and the EU reform were found to be significant in explaining the export demand for Swazi sugar with coefficients of -121.069 and -2.682, respectively. The coefficient of EU suggested that it had an overall positive impact on export demand for Swazi sugar. Export prices, foreign income, producer prices and real exchange rate were found to be inelastic with coefficients of 0.35289, 0.00168, and 0.04256 and 0.28572, respectively, for all the markets (SACU, EU, USA and COMESA). All explanatory variables in the individual markets were found to be highly elastic. The study, therefore, recommended that Swaziland needs to exploit the EU change and contribute more to sugar production as it is adversely influenced by the EU reform.

Nwogwugwu *et al.* (2015), on the other hand, utilised the ARDL Bounds testing approach developed by Pesaran *et al.* (2001) to estimate Nigeria's price and income elasticities of import demand using time series data from 1970 to 2013. Their results show that there is a long-run cointegrating relationship between Nigerian import demand, relative price of imports and domestic income as proxied by real GDP. The estimates of price and income elasticities were found to be 0.03 and 0.55, respectively. Among other critical issues, this study also further investigated the credibility of the imperfect substitution framework in the Nigerian economy. The result reflected that the long-run coefficient of domestic prices, which was also regarded as the cross-price elasticity of imports with respect to home-made goods was found to be 0.0062 and statistically insignificant. Hence, evidence of imperfect substitution between foreign-made goods and domestically produced goods was found to hold in the Nigerian foreign trade sector. The results from the short-run dynamics of the model obtained from the parsimony error correction model, reflected that about 67 percent of the disequilibrium between the long term and short term of Nigeria's import demand function is corrected each year. Based on the results it was therefore concluded that higher taxes and interest rates, as a tool of expenditure switching policies, has a very limited impact on Nigeria's balance of trade with other countries, while currency devaluation as an import substitution tool appears to have no influence on Nigeria's balance of trade position.

Yahia (2015) used a double-log transformation estimation procedure to estimate and evaluate the aggregate import demand model for Libya. His main results show that the behaviour of Libya's import demand is highly affected by the changes in GDP, relative import prices, and partial adjustment of her imports. The specification of the main model included three important dummy variables, each of which captures the impact of oil price fluctuations on Libya's national income in three sub-periods (1975-1985, 1986-1998, and 1999-2008). These periods represent an increase in oil prices, years of lower oil prices and the period of higher oil prices, respectively. His results show that fluctuations in oil prices have completely upset the import-income relationship in Libya during the periods of decline in oil prices. Finally, it was also found that both short-term and long-term elasticity of Libyan imports demand with respect to its income are highly elastic, with estimated elasticity values of 1.2 and 3.12, respectively.

Rashid and Razzaq (2010) on the other side, utilised an ARDL and DOLS econometric estimation techniques to estimate structural import demand for Pakistan, with special interest in binding foreign exchange constraint. They used annual time series data running from 1975 to 2008. The results of this study in both models (ARDL and DOLS) show that price and income elasticity coefficients are statistically significant at 5%. However, the income elasticity coefficient for an ARDL model has been found to be slightly higher than that of the DOLS estimate. The results of these two models reported that income elasticity is 1.065 (ARDL) and 0.98 (DOLS), both statistically significant at 5% level. The ARDL estimate of relative price coefficient was found to be slightly lower than the one produced by the DOLS estimate in absolute magnitude. These two econometric techniques reported that the relative price coefficient is -0.918 and -0.948, respectively. The ARDL and DOLS coefficients estimates of scarcity premium variable (as a proxy for binding foreign exchange constraint) was found to meet theoretical expectation, but more statistically significant only in the case of ARDL model, thus supporting the presence of binding foreign exchange constraints on Pakistan's import demand.

Amiri *et al.* (2013) conducted a panel study to investigate the impact of domestic demand, exports, real effective exchange rate, oil prices and current account balance on demand for imported goods and services for oil exporting countries. These countries include Saudi Arabia, Iran, Qatar, Nigeria, United Arab Emirates (UAE) and Kuwait. The results of the panel cointegration analysis produced by this study show that import demand in these countries is positively related to domestic demand, exports, real effective exchange rate and on oil prices, but negatively related to current account balance. All coefficients were estimated using the ordinary least squares (OLS) fixed-effect model and they are all statistically significant except for oil prices.

Sultan (2014) utilised the Bounds testing approach to cointegration developed by *Pesaran et al.* (2001) to estimate Saudi Arabia's export demand function in the period of 1980 - 2010. His results showed that there is a long-run, cointegrating relationship between Saudi Arabia's export demand, world income, and real effective exchange rate. The elasticity estimates of Saudi Arabia's exports demand with respect to foreign income, and real effective exchange rate was found to be greater than one (elastic) in both the long-run and the short-run. However, when compared, elasticity was found to be substantially higher in the short-run than in the long-run in both variables.

Altintas and Turker (2014) evaluated Turkish exports and imports demand functions by examining the effects of national income, foreign direct investment, real exchange rates, and relative prices of Turkish imports and exports, using annual time series data from 1987 to 2011. The study utilised a unit root, cointegration analysis and Granger causality analysis through the vector autoregressive model to estimate both aggregate import and export demand functions for the Turkish economy. The results suggested that there is a one-way short term Granger causality relationship between Turkish export demand, foreign income, real exchange rate and export price. In the import model, the results reported that there is a one-way long-run Granger causality relationship among Turkish import demand, real GDP, foreign direct investment, and real exchange rate. The study also shows that there is a one-way Granger causality relationship running from foreign direct investment, real exchange rate and import prices to Turkey's import demand.

Nassr (2013) investigated the effect of gross domestic product, consumer price index exchange rate on Palestine's import demand function, using quarterly time series data from 1997 to 2010. The results revealed that there is a positive relationship between Palestine's import demand, consumer price index and gross domestic product. There was no relationship found running from Palestine's exchange rate to import demand. According to the researcher, this is due to the fact that Palestine's economy is highly dependent on foreign trade.

Ibrahim (2015) estimated the demand function for Saudi Arabian merchandise imports, using the ordinary least squares (OLS) and the error correction model, during the period 1975-2011. The results indicated that, both in the short run and long run, Saudi Arabian merchandise import demand is significant and positively related to changes in real gross domestic product, gross fixed capital formation, private consumption expenditure, gross consumption expenditure and relative prices. On the other hand, in both the short-run and the long-run, international reserves had a positive but insignificant impact on Saudi Arabia's merchandise import demand.

Yazici (2012) employed the Bounds testing approach and the error correction model to estimate the agricultural import and export demand functions for the Turkish economy using annual time series data for 1970-2003. For the import demand, the results indicated that, relative price is a significant determinant in both the short-run and the long-run, while nominal effective exchange rate matters only in the long-run, but domestic income is not at all a significant determinant for Turkish agricultural import demand. For the export demand, all determinants were found to affect the export demand significantly in the short-run, but not in the long-run.

Maqbool (2014) utilised the ordinary least squares (OLS) model to assess the effect of exchange rate, real per-capita income and foreign exchange reserves on Pakistan's import demand for the time period 1973-2012. The results indicated that exchange rate and real per capita income are the main determinants of Pakistan's imports demand. Exchange rate had a significant negative impact on Pakistan's import, while real per capita income had a significant positive effect. In addition, this study did not find evidence to support the importance of foreign exchange reserves in Pakistan's import demand function.

Elite (2013) on other hand, estimated the Marshall-Lerner condition of Namibia, using annual time series data from 1991 to 2011. In this study, both import and export demand models were regressed on two variables-domestic income/foreign income and real effective exchange rate. The results of the cointegrated auto-regressive model indicated that world income has a positive effect on exports, while real exchange rate appreciation discourages exports. Imports were found to respond positively to both domestic incomes and exchange rate appreciation. Both exports and imports respond significantly to a change in exchange rate.

Yeboah *et al.*, (2015) examined the export demand function for U.S meat products to some Asian countries, using annual time series data from 1980 to 2013. They regressed exports on the per capita GDP of the importing Asian countries (proxied by OCED real GNP), exchange rate of the currency of the importing Asian countries to the U.S Dollar and WTO membership. The Asian countries included in the study include; Japan, Malaysia, Vietnam, Brunei, and Singapore. The results suggested all variables are important determinants of the quantity of pork and chicken exported to Asian countries. However, GDP per capita and exchange rate have an insignificant influence on the determination of turkey exported to these countries. Meanwhile, demand for exported beef has been found to be positively related to price and World Trade Organisation (WTO) member of countries. Therefore, based on these results, the researchers concluded that price, GDP per capita and WTO membership of countries are all important determinants of the U.S export demand function for Asian countries.

Culha and Kalafatcilar (2014) estimated the export demand function for Turkey using the vector autoregressive (VAR) model for the period 2003 to 2013. Specifically, the study was particularly interested in three Turkish exports destinations: the Euro Area, Middle East, and Africa. The results of the VAR model confirmed the existence of regional disparities in the determinants of export demand across different destinations. Among other things, it was particularly found that Turkish export demand elasticities are substantially higher in high-income countries, mainly in the Euro Area, and relatively lower in low income countries. Contrary to the other regions, the results report that elasticity estimates of the real effective exchange rate of Turkish exports in Middle East and Africa are both statistically significant and high in absolute values. This suggests that Turkish exports to MEA are highly driven by exchange rate movements.

In contrast, Bozok *et al.* (2015) utilised bilateral trade data from Turkey from 2000Q1 to 2004Q4 to estimate the long run income and price elasticities of Turkey with 67 countries from a selected group of geographic regions (EU27, other European countries, Asia, MENA, developed and developing countries). For empirical estimation, DOLS, Mean Group and Common Correlated Effects Mean Group estimation techniques were utilised. The end results of these authors were relatively the same as those estimated by Culha and Kalafatcilar (2014). They found that, estimates of income elasticity of Turkish imports are statistically significant in all groups of countries, and income elasticity estimates of exports to all European countries and advanced economies are highly elastic, price elasticity estimates, on the other hand, are only statistically significant to the EU27 countries, MENA and developing countries, and insignificant to the industrialised countries.

Moreover, Thaver and Bova (2014) utilised the Bounds testing approach to cointegration to estimate Ecuador's export demand function with the U.S spanning from 1965 to 2011, with special emphasis on the impact of dollarisation's on Ecuador's exports. The study used two models. In the first, exports were regressed on real exchange rate volatility, U.S real GDP, relative prices, and dollarisation. In the second model, real exports were regressed on U.S real GDP, real exchange rate volatility, and dollarisation. In both models, the study confirmed the existence of a unique cointegrating relationship between exports and its regressors. The result also indicated that GDP is positive and elastic, while volatility is positive and inelastic. Relative prices in model 1 and real exchange rate in model 2 were found to be statistically insignificant, while dollarisation is significant, but negative and inelastic to determine Ecuador's exports to the U.S.

3.3 EMPIRICAL LITERATURE ON THE ORCUTT HYPOTHESIS

Despite, the intensive empirical improvement in data analysis and immense developments of more robust econometric estimation techniques brought forward by econometricians and statisticians, there is still no consensus among economists regarding the time-path of the response of trade flows to changes in exchange rate and relative prices. The first empirical evidence on this topic includes studies by Junz and Rhombery (1973), Wilson and Takacs (1979), Bahmani-Oskooee (1984;1986) and Tegene (1989;1991). Each of these studies were primarily interested in examining the response of trade flows to exchange rate changes and to changes in relative prices. Even though these studies are given special attention in literature due to their immense contribution into the body of knowledge of international trade, especially during periods of floating exchange rate regimes. They have been criticised by Bahmani-Oskooee (2003) for failure to take into account issues of integration and cointegration in the time series, which therefore makes their results statistically unreliable. Nonetheless, for consistency purposes our empirical review will also discuss some of these studies to trace the empirical development made by researchers regarding this topic and, most importantly, to observe the impact of non-stationary data on their results as opposed to post-2003 studies based on stationary data. The review of all empirical studies will include both South African based and international studies. However, the researcher could not find any recent literature concentrated in the context of South Africa. In fact, based on the researcher's knowledge this study is the third one to investigate Orcutt's conjecture in South Africa after Bahmani-Oskooee (1984) and Bahmani-Oskooee and Kara (2008) and the first one to apply the generalised impulse response analysis in the context of South Africa.

Bahmani-Oskooee (1984) used quarterly data from floating exchange rate regime which covers the period of 1973 to 1980, to test for the Orcutt's (1950) hypothesis in a sample of seven developing countries (South Africa, Greece, India, Thailand, Brazil, Israel, and Korea). Just like previous studies he began by estimating both import and export models, before imposing appropriate lags on exchange rates and relative prices. To mitigate the problem of multicollinearity among lagged regressors, different lag lengths on exchange rate and relative prices were imposed using the Almon estimation procedure. The results obtained before imposing appropriate lags were as follows: for the import demand model, the results indicate that relative price coefficients are significant and negative for South Africa, Korea, and Thailand, while, nominal effective exchange rate coefficients, on the other hand, are significantly positive only in the case of Brazil's and Greece's import demand models. The estimated coefficients for income are significant and positive for all countries except for India and Israel.

For the export demand model, the results suggest that relative prices of exports are statistically significant and negatively related to export demand in the case of Brazil, India, and Israel. Foreign income, on the other hand, demonstrates that the export demand function of South Africa and India (respectively) are positively related to changes in economic activities of their trading partners and significantly negative in the case of Israel. The exchange rate is significant and negatively related to export demand only in the case of Greece, South Africa and Israel.

In this study, Orcutt's hypothesis was confirmed in nine of out 14 equations and rejected in five. In the import demand model, the Orcutt hypothesis was rejected in the case of South Africa, Greece and Thailand, where lags in imports' relative prices were found to be equal to the lag length in nominal effective exchange rate. The Orcutt conjecture was also rejected in the case of Brazil and Thai exports, where lags in relative export prices were found to be larger than lags in nominal effective exchange rate. Based on the results, the study decided to accept the Orcutt hypothesis.

Following Bahmani-Oskooee (1984)'s procedure, Tegene (1989) tested the Orcutt hypothesis in a sample of seven less developed countries. For the import demand model, as expected, his results suggest that imports are significant and negatively related to its relative prices. However, the study reported contrary results regarding the effect of nominal effective exchange rate in the case of Malawi and Mauritius. According to the results, imports are significant and negatively related to import demand in these two countries. The results also showed that income is significant and positively related to imports in most countries, except for Malawi. In the export demand models, his results suggest that relative export prices are significant and negatively related to export demand in all countries. Meanwhile, nominal effective exchange rate carries an expected significant negative sign only in the case of Malawi, Tunisia, Cote d'Ivoire, and Mauritius. In the case of Kenya and Zambia, nominal effective exchange rate was found carrying an unexpected significant positive sign. Moreover, the income elasticity was only significant in the case of Tunisia, Kenya and Ethiopia. When testing for the Orcutt hypothesis he found that lags of nominal effective exchange rate are slightly greater than lags in relative prices on both import and export demand models of all less-developed countries (except for Tunisia's import demand model), thus supporting Orcutt's idea that trade flows could respond faster to changes in exchange rate than they do to changes in relative prices.

However, when using the vector autoregressive (VAR) model to estimate the Ethiopian trade functions (imports and exports demand functions), Tegene (1991) found the opposite results. In this study, Tegene (1991) investigated the existence of Granger-causality

between trade flows and their regressors (relative price, income and nominal effective exchange rate). The results of this study reported that there is an insignificant, one-way Granger causality between trade flows (import and export) and relative prices and nominal effective exchange rate. In addition, the results also showed that both Ethiopian imports and exports demand have similar reactions to shocks in relative prices and nominal effective exchange rate. In particular, the study found that period-by-period responses of trade flows (imports and exports) were more responsive to shocks in nominal effective exchange rate than relative prices, thus supporting the Orcutt conjecture in the Ethiopian economy.

After taking into account issues of stationarity and cointegration in the time series data, Bahmani-Oskooee and Kara (2003) utilised the ARDL to Bound testing approach developed by Pesaran and Shin (1997) to investigate the Orcutt hypothesis in eight industrialised countries for the period of 1973 to 1998. These countries are United States, Australia, France, Germany, Japan, Denmark, Canada and Italy. Their results showed that price elasticities of both import and export demand are highly elastic in all eight countries, while, income elasticity of import demand appears to be higher than income elasticity for export demand in all countries. Moreover, exchange rate elasticity was found to be equal to price elasticity in all models, thus completely rejecting the credibility of Orcutt conjecture in high-income countries.

Bahmani-Oskooee and Kara (2008) used the ARDL approach to test for Orcutt's hypothesis in a sample of 12 developing countries (Colombia, Greece, Hong Kong, Hungary, Israel, Korea, Pakistan, Philippines, Poland, Singapore, South Africa, and Turkey). The Orcutt's hypothesis was accepted only in the import demand function for Colombia, Hungary, Pakistan, and Poland. It was rejected in the case of Philippines, Korea, Turkey, Singapore and Israel. Meanwhile, in the case of three remaining countries, (South Africa, Greece and Hong Kong) the time lags in the exchange rate variable were found to be equal to time lags in relative prices of imports. The study reflects the same findings also in the case of export demand models. Thus, overall, Bahmani-Oskooee and Kara's (2008) study rejects the validity of the Orcutt (1950) hypothesis in four and accepts it in seven out of 12 countries. It is worth noting that these results support those reported by Bahmani-Oskooee (1984) in the case of South Africa in a sample of seven developing countries.

Bahmani-Oskooee and Ebadi (2015) tested the Orcutt hypothesis in eight industrial countries (Canada, Japan, Spain, UK, USA, Germany, Italy and Australia), using quarterly data from 1973I–2013IV. They used the generalised impulse response analysis to one standard deviation to innovations in relative prices and one standard deviation to innovations in exchange rate. The analysis of this approach basically looks at how long each shock lasts in the system. Based on the analysis of this approach, for the Orcutt hypothesis to hold, the impact of exchange rate innovations should be shorter than the impact of shocks in relative prices. The approach of this study was based on cointegration and the ECM approach of Johansen and Juselius (1990) in which the order of lags is the identical in all variables. The results reported that, out eight countries, the Orcutt hypothesis was only accepted in the import demand model of Germany and Japan and in the export demand model for the United States.

Bahmani-Oskooee and Ebadi (2016) tested the Orcutt (1950) hypothesis, using an error correction model. The study used a time series data for eight countries, which includes five industrialised nations and three developing states for sample periods of 1973 to 2013, which covers two sub-periods: post-1990 and pre-1990. These eight countries are the United States, UK, Spain, Japan, Italy, Hong Kong, Pakistan, and Singapore. These sub-periods were selected on the basis of the assumption that the speed with which trade flows adjust to changes in exchange rate and relative prices was much faster during post-1990 as compared to pre-1990, due to technological advancement, which commenced in the early 1990s. This hypothesis was supported in ten out of 16 trade models estimated by this study for eight advanced economies. However, when tested for the entire period, the study could not find any support for the Orcutt hypothesis in all cases.

Bahmani-Oskooee and Ebadi (2015) on the other hand, utilised the impulse response analysis approach to test for the Orcutt hypothesis in six developing countries (namely, Hong Kong, Turkey, Thailand, Singapore, Korea, and Pakistan). The study reported similar results, as in the case of industrial countries. Similar results are also found in a study conducted by Omsakin *et al.* (2010) for selected ECOWAS countries. This study used the Bounds testing approach and the ARDL model to specify the error correction model for import and export demand functions for ECOWAS countries. The results suggested that ECOWAS imports respond quicker to exchange rate changes than to changes in relative prices, while exports respond quickly to changes in relative prices than they do to changes in exchange rate.

Bahmani-Oskooee and Hosny (2015) investigated Orcutt's hypothesis for 59 industries between Egypt and the European Union, using the ARDL approach. For import demand, the short-run coefficients indicated that only 20 out of 59 industries support Orcutt's hypothesis since the lag length of nominal exchange rate was shorter than the lag length on relative prices. However, most of the industries captured in this study were small industries, except for vegetable and fruit, manufactures of metals, office machines,

professional and scientific apparatus. The results also show the rejection of the Orcutt hypothesis in nine industries, four of which were large industries (iron and steel, specialised machinery for particular industries, General industries machinery, telecommunication and sound-recording and producing apparatus). Meanwhile, the lag lengths of exchange rate and relative prices for the other 30 remaining industries was found to be the same. Among these industries, very few were big industries. The long-run coefficients illustrated that Egypt's income coefficients are significant for 32 industries, in which 21 are negative. The relative prices were found to have a significant and negative sign in 47 of 59 industries. The nominal exchange rate was found to carry an expected negative sign and to be statistically significant in 11 industries.

For export demand the short-run coefficients Orcutt's conjecture is supported in 21 industries, among which four are large industries (cork and wood, machinery specialised for particular industries, general industrial machinery, road vehicles). However, in seven industries results indicate the opposite and illustrated the same lag length in 31 industries. Additionally, the long-run coefficients of European income were found to be significant in 32 industries, among which 21 were positive and 11 were negative. Moreover, the exports price was found to have an expected statistically significant negative sign in 38 industries. In the import demand case, exchange rate coefficients reflected a positive and significant sign in 24 industries.

Bahmani-Oskooee and Durmaz (2017) used monthly time series data for commodity trade and prices of 54 industries that engage in trade between the United States and Turkey to investigate evidence of the Orcutt hypothesis from January 1996 to December 2014. A maximum of 10 lags were chosen following Akaike's information criterion. For import demand, almost 30% of Turkish importing industries supported the Orcutt hypothesis, while it was rejected in 13 industries. Meanwhile, in 25 industries the results reflected the same number of lags for both exchange rate and relative prices. Nonetheless, in the long run nominal exchange rate and relative prices was found to carry an expected negative coefficient in 23 and 18 Turkish importing industries, respectively. For the United States export model to Turkey, the results indicated that in the short run the Orcutt hypothesis was found to hold in 20 and rejected in four U.S exporting industries. The study also reported that income variable was only positive and significant in 11 U.S exporting industries. Meanwhile nominal exchange rate was found to carry its expected negative coefficients in 13 cases.

3.4 CONCLUSION OF THE CHAPTER

From the review of empirical literature based on the topic of the Orcutt hypothesis discussed above, it appears that there are two strands of methodological approaches to investigating the existence of the Orcutt hypothesis. The first strand of literature is based on lag structure imposition procedure. This approach suggests that the validity of the Orcutt hypothesis should be judged on the basis of time lags. In this approach, the Orcutt hypothesis is accepted if the time lags in the exchange rate variable are shorter than time lags in the relative price variable. The second strand consists of those studies that utilise the impulse response analysis to judge the validity of the hypothesis. In this approach the rejection and acceptance of the Orcutt hypothesis solely depends on how long it takes shocks on exchange rate or relative prices to die out in the system.

Prior to that, the review of empirical studies based on the measurement of trade elasticities reveal two important empirical literature gaps. Firstly, comparing both local and international studies, it appears that previous ones have been much interested into Bound testing approach. In South Africa, almost all empirical studies have been based on either Bound testing or ARDL approach. Even in the international literature, very few studies have attempted to utilise dynamic models such as VAR-VECM, FMOLS, CCR, and DOLS models for the estimation of trade elasticities. These types of econometric estimation techniques have been highly recommended by many great economists for forecasting ability. Therefore, the major contribution of this study comes from the methodological section. We utilise the VAR-VECM econometric estimation technique to estimate both import and export demand functions. In addition to that, we utilise the generalised impulse response functions based on Johansen vector error correction mechanism for the analysis of the Orcutt hypothesis.

CHAPTER 4: METHODOLOGY

4.1 INTRODUCTION

This chapter presents a detailed discussion of all methodological aspects that will be covered in Chapter 5. The overall chapter is organised as follows: the first section presents a theoretical discussion of the methodological framework adopted in this study and the selection of each variable under investigation. This theoretical analysis and common sense economic reasoning will help to identify the model specifications of both the import and export demand functions. There are various forms of stationarity and the behavior of economic relationships in time series data. The overall discussion will be focused on weak stationarity, wide-sense stationarity, and covariance stationarity also commonly known as second-order stationarity.

The second section gives a detailed description of each variable under investigation and their corresponding units of measurement as per their respective sources. The third section gives a thorough discussion of stationarity issues and various forms of pre-testing strategies for unit roots as a mitigation procedure against the problem of spurious regression, such as the augmented dickey-fuller (ADF) tests, and the Phillips-Peron tests. The visual inspection methods, such as the graphical illustrations of Correlograms are also discussed as alternative approaches to unit root testing. The fourth section gives the discussion of all econometric estimation techniques used in this study. The last part of the chapter presents a discussion of various diagnostic inspection techniques, such as descriptive analysis of residuals, examination of residuals through formal tests and model stability analysis strategies.

4.2 TIME SERIES MODELLING

As highlighted by Enders (2010), most time series data have the following fundamental characteristics:

- ✓ a clear trend, meaning that current values tend to be highly dependent on the past values of the series. This often poses a great challenge in the statistical analysis.
- ✓ a small shock in the time series data tends to persist for a very long time.
- ✓ time variant.
- ✓ some series tend to have the same movement overtime.
- ✓ some contains significant outliers.

On the other hand, many empirical studies have long proven that time series data containing any of these characteristics create a lot of statistical challenges in the estimated regression model, such as serial correlation, multicollinearity (resulting from co-movements of the series) and spurious regression. Therefore, in order to ensure that we produce quality results, unbiased and trustworthy, we will start by examining all statistical properties embedded in the time series data utilised in this study.

4.2.1 Graphical Preliminary Examination of Data

Graphs are an important tool used in economics utilised to observe the movements of the series overtime. Through graphical plots, one can also be in a position to make predictions about the stationarity of the series and presence of any structural breaks without applying any statistical tests. If two variables are plotted together in one graph, one can also observe the underlying correlations the two economic variables pose before generating the covariance matrix. In addition, graphical plots also help the researcher to observe if the series under investigation is truly reflecting the current economic outlook as it is or not. For instance, during the periods of recession it is expected that the series of GDP will show a downward trend and an upward trend during periods of prosperity. Therefore, before computing any statistical tests in this study, we shall start by generating graphical plots of each variable under observation to observe how they have been behaving overtime.

4.2.2 Stationarity and Non-stationarity in the Data

The common understanding among many econometricians and statisticians regarding time series data is that all time series data contain either stochastic trends or deterministic components (or both). Meanwhile, by definition, time series can be defined as “a set of random observations or numbers recorded in successive order in a regular interval,” and theoretically, all-time series data follow a stochastic process (Gujarati, 2009; Maddala and Lahiri, 2009). These series are either stationary or non-stationary. Stationary series, by implication have a constant mean, variance and auto covariance. Non-stationarity, on the other hand, simply means that the expected values, covariance and auto covariance of the series are time variant. As discussed in the first section above, non-stationary data are not desirable in econometric analysis because they generate spurious results. As a matter of fact, for years, stationarity tests have remained quite essential in all empirical studies based on time series data. A good regression model requires the use of time

invariant series, whose joint probability distribution is constant over time and contains no trend “strict stationarity”. For weak stationarity, let’s assume a basic data generating process of y depending on its past values y_{t-s} and on the values of its normal distributed random shock μ_t with constant mean and variance, thus:

$$y = py_{t-s} + \mu_t \quad (4.1)$$

Note that from this equation (4.1), weak stationarity exists when:

$$E(y) = \mu \quad (4.2.)$$

$$Var(y_t) = E(y_t - \mu)^2 = \delta^2 \quad (4.3)$$

$$\lambda\kappa = E[(y_t - \mu)(y_{t+s} - \mu)] \quad (4.4)$$

where all expected values $E(y)$, variance $Var(y_t)$, and autocovariance $\lambda\kappa$ values of y are fixed and finite. Strict stationarity will only hold when:

$$E(y) = \mu \quad (4.5.)$$

$$Var(y_t) = E(y_t - \mu)^2 = \delta^2 \quad (4.6)$$

$$corr(y_t, y_{t-s}) = \frac{\delta_{t,t-s}}{\delta^2} = p_{t,t-s} \quad (4.7)$$

where the joint distribution of the series is only a function of its own lags and not dependant on time variations. The term joint distribution refers to the statistical measurement of the probability of two variables, for instance, y_t and y_{t-1} taking the same distribution or pattern in the future. If these series follow this order, it makes it easier to predict the future behaviour (pattern) of the series. Under strict stationarity conditions, the joint distribution of k observations of $y(t_1), y(t_2), y(t_3), \dots, y(t_k)$ is identical as the distribution of $y(t_1 + n), y(t_2 + n), y(t_3 + n), \dots, y(t_k + n)$ for all k observations.

The series is non- stationary if it fails to meet either of the conditions. As noted by Enders (2010), it is common to encounter nonstationary series in a time series study. Unlike stationary series, nonstationary series have time reverting mean, variance and auto covariance. There are two types of non-stationary series: random walk with and without a drift, and series with deterministic trend processes. A pure random walk process can be defined by this model;

$$y_t = y_{t-1} + \varepsilon_t \quad (4.8)$$

A random walk in the nonstationary series contains a trend and its process can be defined by the following equation;

$$y_t = y_{t-1} + c + \varepsilon_t \quad (4.9)$$

In this case, if $c > 0$ the series will show an upward drift, and a downward drift if $c < 0$. This type of series can also show both a deterministic trend and stochastic process at the same time. Assume that c in equation 4.9 is equal to zero, therefore;

$$y_t = y_0 + ct + \sum_{t=1}^k \varepsilon_t \quad (4.10)$$

where $y_0 + ct$ represent a deterministic component in the series, and $\sum_{t=1}^k \varepsilon_t$ a stochastic trend in the series. The series has a deterministic trend/component if it has a time varying mean and constant variance (Enders, 2010). If one decides to estimate a regression model using a series which contains both the deterministic and stochastic trend, the following outcomes are expected:

- ✓ very high R-squared
- ✓ very low Durbin Watson statistic value
- ✓ very high t statistics for the coefficients.

In econometric language, all these outcomes are an indication of a spurious regression, meaning that the estimated coefficients cannot be trusted. The only possible way of dealing with such a situation is by first differencing the series. Thus,

$$\Delta y_t = c_0 + \beta_1 x_t + \mu_t \quad (4.11)$$

Therefore, it is on the basis of all these reasons that, before computing any statistical analysis, we shall start by testing for the stationarity of the series under investigation. In addition, a stationarity test helps us to identify the order of integration and cointegration of variables in a model. Once the condition regarding the stationarity of variables is established it leaves the researcher in a suitable position to decide on suitable methodology appropriate to the stationarity of the series. Additionally, in vector

autoregressive (VAR) models, unit root testing is essential because it serves as a primary tool of identifying if either trend removal or differencing is appropriate to make a series stationary, since such models are estimated with stationary variables.

4.3 STATIONARITY TEST.

There are three ways of conducting stationarity tests on time series data: graphical plots, correlograms (autocorrelation plot) and unit root analysis. The first two are the informal tests based on graphical analysis. Correlograms, in particular, tests the unit root memory in the past values of the time series data. However, despite the mention of all these three variables, this study will only rely up-on unit root analysis.

4.3.1 Unit Root Testing

Unit root testing is an econometrics term which refers to the empirical way of investigating the stationarity of time series data. As proposed by Dickey and Fuller (1979, 1981) unit root testing involves checking for statistical significance on the differenced parameter of y_{t-1} illustrated by equation (4.8). The process of checking unit roots involves running a simple random walk model as outlined by equation (4.1). In this process, the main interest is to check whether parameter p has a unit root or not. Philips and Perron (1998) advocated an alternative approach to test for unit roots, which corrects the problem of serial correlation and heteroscedasticity in the error terms by slightly modifying the expression of the ADF test. The difference between the two tests is that the ADF is based on parametric, while the P-P tests are based on non-parametric modifications of the DF equations.

4.3.2 The Augmented Dickey-Fuller (ADF) Test

The Augmented Dickey-Fuller (ADF) test is an extension of Dickey-Fuller (DF) test developed by Dickey and Fuller (1981). As stated above, it tests for the presence of unit roots in a differenced parameter. The problem with the DF test was its inability to deal with the autocorrelation among the error terms. Therefore, ADF test was specifically developed to whiten the errors of a series by introducing the lag operator on the dependant variable. In its computation, the ADF tests the following hypotheses:

$$H_0 = y_t \text{ has a unit root}(p = 1)$$

$$H_\alpha = y_t \text{ has no unit root}(p < 1)$$

To test for these hypotheses, ADF computes the following three basic models: intercept, intercept and trend and none (or no trend and no intercept) model, respectively.

$$\Delta Y_t = \delta Y_{t-1} + \sum_{i=1}^p \beta_i Y_{t-i} + \mu_i \quad (4.12)$$

$$\Delta Y_t = c + \delta Y_{t-1} + \sum_{i=1}^p \beta_i Y_{t-i} + \mu_i \quad (4.13)$$

$$\Delta Y_t = c + \delta Y_{t-1} + \beta_2 t + \sum_{i=1}^p \beta_i Y_{t-i} + \mu_i \quad (4.14)$$

where μ_i represents the white noise errors and $Y_{t-1} = (Y_{t-1} - 2)$. The number of appropriate differenced terms to be included in each equation is usually decided by either the AIC (Akaike information criteria) or by the SC (Swartz Bayesian criteria). In all these three equations, unit root hypothesis testing is performed by comparing the tabulated tau (τ) statistic value with the corresponding MacKinnon critical values (1996), also known as (τ) statistic values. The tau statistic values are calculated by dividing the p parameter by their corresponding standard errors. In short, if regressed y_t on $y_t - 1$, then;

$$\tau = \frac{\hat{p}-1}{se(\hat{p})} \quad (4.15)$$

However, if a differenced operator of y_t is introduced (Δy_t on $y_t - 1$), then

$$\tau = \frac{\hat{p}}{se(\hat{p})} \quad (4.16)$$

The decision rule for all cases follows that: y_t has no unit root if the tau statistic value in its absolute is greater than the critical tau statistic value (Mackinnon critical value (1996), we reject the null hypothesis (H_0) in favour of the alternative (H_α) and conclude that $y_t \sim I(0)$, or follows a stationery process. However, if the calculated tau statistic value is greater than critical tau statistic value, we do not reject the null hypothesis. In that case we would conclude that the series of y_t has a unit root.

The p value of the ADF across almost all empirical studies is decided by either the Akaike information criterion (AIC) or the Schwartz criterion (SC). One of the fundamental weaknesses of the ADF test is that it is too sensitive to the lag structure: if the AR order p

value for the ADF test is under-specified, the test will be mis-sized. Conversely, if the AR order p is over-specified the test will lose its power. Hence, for confirmatory purposes, this study will also use the Philips-Perron test as an alternative test for unit root testing. The advantage of using this test is that it does not need any specification of AR order p ; it is based on non-parametric models.

4.3.3 The Phillips-Perron (PP) Test

The PP test is the modification of the ADF test procedure based on nonparametric models. It was developed by Phillips and Perron (1988). Unlike the ADF test, the PP test corrects the problem of serial correlation in the errors without adding the differenced operator in the dependant variable. The PP test takes a form of a less prohibitive nature of error process. Instead of correcting higher order serial correlation in the errors as the ADF tests does, the PP test corrects the estimates of the t-statistic of the coefficient of the dependant variable from the AR (1) regression model to account for the problem of serial correlation in the residuals (errors).

In addition, the P-P test also involves the use of “bandwidth” parameter selection for the computation of the Newly-West covariance estimator that produces finite samples analogous to those connected to the lag length selection issues in applying the ADF test. This makes the P-P test a powerful one for two reasons: first, it is able to deal with issues of lag length and to correct for the problem of serial correlated residuals and heteroscedasticity in the autoregressive (AR) model. Secondly, it takes into account the same estimation procedure as the ADF tests which put it into a position to serve as a confirmatory test for the ADF results. The PP test can also be performed in three models: constant, constant and trend, and none. The null hypothesis is the same as the one for ADF test (the series has a unit root). Moreover, the PP test also follows the same asymptotic distribution t – statistic as the ADF for unit root testing (Gujarati, 2009).

4.3.4 Remedial Actions

In a case where no unit root is identified in the series, the series is integrated of order zero I (0) and is a good position to be used for statistical analysis purposes. However, if the unit root is identified, the researcher would have to transform the series in other to make them stationary. The appropriate transformation of each series will be determined by the nature of the series in question (Enders, 2010). For instance, if the series has a deterministic trend, the researcher would have to detrend the series time to make them stationary. Stationarised series of this nature follows a trend stationary process, hence they are called “trend stationary series”. If the series requires that it has to be differenced in order to become stationary, it is called “differenced stationary process/series”. The series can be differenced once, twice or, in very rare case, can also be differenced three times. However, the current version of Eviews only provides us with two options of differencing: the 1st and the 2nd. The series is said to be integrated of order one (I (1)) if it requires that first differencing should be made in order to get rid of unit root in the series. Similarly, the series is integrated of order two (I (2)) if necessary that it has to be differenced twice in order to induce stationarity.

Therefore, in this study we intend to adhere to the rule of stationarity by utilising both ADF and PP tests to investigate features of stochastic processes (unit root) in all variables. If the unit root is identified, appropriate remedial actions shall also be applied to make the series stationary. Moreover, if the results of the ADF and PP tests give contradictory results, the KPPS (Kwiatkowski-Phillips-Schmidt-Shin) test shall be applied to obtain conclusive results.

4.4. COINTEGRATION

As highlighted in the preceding subsection, the use of trended series or I (1) series may lead to spurious regression, which contains very high R squared, statistic values and very low Durbin Watson statistic values. However, if all series in the regression model share the same stochastic trend, they are said to be cointegrated and they can produce reliable results. Cointegration occurs when a linear combination of I (1) are integrated of order zero (I (0)). In essence, cointegration looks at the integration order of a linear combination of all I (1) variables. Since all I (1) series are nonstationary, if the error terms produced by a regression model of nonstationary series are tested for stationarity and found to be stationary, the series are said to be cointegrated to each other. The underlying assumption about cointegrated variables is that they will always be attracted by their long run relationship (Ssekume, 2011). For illustration purposes, let’s consider a series of I(1) variables, y and z :

A linear combination of these series will be as follows;

$$y_t = \alpha_0 + \alpha_1 z_t + \mu_t \quad (4.16)$$

where, μ_t represents the residuals or error terms of a regression model of these two I(1) variables. Now, we rewrite this equation and regress the residuals as follows

$$\hat{\mu}_t = y_t - \hat{\alpha}_0 - \hat{\alpha}_1 z_t \quad (4.17)$$

Then if $\hat{\mu}_t$ is tested for unit root and found to be $I(0)$, it implies that y and z are cointegrated. The coefficients $\hat{\alpha}_0$ and $\hat{\alpha}_1$ are also called cointegrating vectors. On the other hand, Enders (2010) and Asteriou and Hall (2016) argue that if two variables are cointegrated of different orders, the cointegration cannot exist among those variables. If they are linearised together, the behaviour of the $I(1)$ variable will dominate the behaviour of the $I(0)$ variable, thereby disturbing the entire process of cointegration between them.

This implies cointegration is quite essential in time series modelling because it tells you more about the underlying relationship of the variables under investigation. Apart from that, cointegration is also critical important in making the decision about the appropriate econometric estimation technique. In conditions where all variables are integrated of order zero (not cointegrated) a simple VAR model is utilised. An ARDL is used if the order of integration of variables is mixed. However, if the series are all $I(1)$ and cointegrated a VAR error correction mechanism is applied (VECM).

4.4.1 Testing for the existence of cointegration

There are three methods whereby cointegrating properties in time series from $I(1)$ variables can be traced. (1) Engle-Granger (EG) method, (2) Philips-Ouliaris (PO) test, and (3) the Johansen's cointegration procedure. The first two methods are based on single equations, while the later one is based on multivariate equations. Therefore, for the purpose of this study, we will use all three cointegration tests. The first two tests shall be tested within the estimated Fully-Modified Ordinary least squares (FMOLS), the canonical co-integrating regressions (CCR), and the Dynamic Ordinary least squares (DOLS).

4.4.1 (a.) Engle-Granger Test

The EG test is a single-equation technique also known as the “two-step estimation procedure” which, by definition, predicts that time series variables, say y_t and x_t , are cointegrated of order d, b where $d \geq b \geq 0$, expressed as $x_t, y_t \sim CI(d, b)$ if both variables are $I(d)$, and their linear combination $\beta_1 x_t + \beta_2 y_t$ is $I(d, b)$, where, β_1, β_2 denote cointegrating vectors. In the Engle-granger estimation procedure, cointegrating properties of the series under investigation is tested by applying the unit root test on the residuals produced by the OLS regression model. The null and alternative hypothesis of the EG test can be expressed as follows

$H_0: \delta=0$ (series are not cointegrated)

$H_1: \delta < 0$ (series are cointegrated)

The decision of either accepting or rejecting the null hypothesis is taken by comparing the t –statistic on the regression coefficient δ , to the corresponding critical values depending on the number of independent variables included in the computed regression model. If the residuals are found to be unit root free $I(0)$, it implies that the series under investigation have a long-run relationship (cointegrated). Hence, they can be modelled together without any fear of obtaining spurious results.

However, many empirical studies have criticised this approach (see, Gujarati, 2011, and Asteriou and Hall, 2016), arguing that the EG test may give misleading results if there are structural breaks in the series and if the sample size of the series under observation is too large. Therefore, these pose a greater threat to the reliability of the estimates produced by this estimation procedure. According to Asteriou and Hall (2016) the EG can also results to in autocorrelation and biased long-run estimates in conditions of very large sample sizes. These challenges are addressed by running alternative tests such as the Philips-Ouliaris estimated within the framework of three cointegrating equations.

4.4.1(b). Philips-Ouliaris Cointegration Test

Unlike the EG test, the Philips-Ouliaris (PO) test uses two residual based tests to investigate cointegrating properties in the series. The first test is called “variance ratio test”. The second one is based on multivariate trace statistics. The PO test is more powerful because it is invariant to the ordering of variables in terms of endogeneity but the results remain the same. Similar to the EG test, this test also tests for “no cointegration” null hypothesis. However, empirically there are no studies which have applied the Philips-Ouliaris test in the investigation of cointegration alone but (as stated above) it is always generated within the framework of three cointegrating equations.

There are three cointegrating single static equations: fully modified ordinary least squares (FMOLS), dynamic ordinary least squares (DOLS), and conical cointegration regression (CCR). All three econometric estimation methods are based on the assumption of one cointegrating vectors in the system. The fully-modified ordinary least squares (FMOLS) modifies the ordinary least squares (OLS) to take into account the effect of serial correlation and endogeneity in the cointegrated regressors as a result of the long-run relationship

among regressors. It provides more efficient estimates when variables are cointegrated in their first differences I (1). The dynamic ordinary least squares (DOLS) can be described as an asymptotically efficient estimator that eliminates the feedback in the cointegrating equations. The conical cointegrating regression (CCR) estimator deals with the derivation of variables that remove the second-order bias ordinary least squares estimator in the cointegrating equations. Properties of estimating these models are available in Eviews 9.5.

4.4.1(c). Fully-modified Ordinary Least Squares (FMOLS)

This is a long-run cointegration single-static equation developed by Philips and Hensen (1990). This method assumes that there is only one cointegrating vector in the system, and that there is no cointegration among the explanatory variables. Assuming that these assumptions hold, the FMOLS model can be explained as follows:

$$X_t = \delta_0 + \delta_1' Z_t + \mu_t, \quad t = 1, 2, 3, \dots, n \quad (4.18),$$

where X_t is an I(1) endogenous variable and Z_t denotes a $(k \times 1)$ vector of unco-integrated I(1) regressors. The first difference stationary process of Z_t can be expressed as follows;

$$\Delta Z_t = \varphi + \lambda_t, \quad t = 2, 3, \dots, n \quad (4.19),$$

where φ represents a $k \times 1$ vector of parameters and λ_t denotes a $k \times 1$ vector of I(0) explanatory variable. The unbiased estimation procedure of this model is given by the following equation:

$$\hat{\varphi}_{FMOLS} = \begin{bmatrix} \hat{\theta} \\ \hat{\lambda}_1 \end{bmatrix} = [\sum_{t=1}^T D_t D_t']^{-1} \left[\sum_{t=1}^T D_t X_t^+ - T \begin{bmatrix} \hat{\delta}_{12} \\ 0 \end{bmatrix} \right] \quad (4.20),$$

where $D_t = (Y_t, X_t)'$, $X_t^+ = X_t - \hat{\varphi}_{12} \hat{\Omega}_{22}^{-1} \hat{\omega}_2$ indicates the transformed data, while $\hat{\delta}_{12} - \hat{\varphi}_{12} \hat{\Omega}_{22}^{-1} \hat{\eta}_{22}$ is the estimated long run bias correction term and covariance matrices $\hat{\Omega}$, $\hat{\Lambda}$ and their respective elements calculated using residuals $\omega_t' = (\omega_{1t}' \omega_{2t}')'$. Options for computing these long-run matrix covariance for a FMOLS is given by the scalar estimator,

$$\Omega_{12} = \Omega_{11} - \Omega_{22}^{-1} \Omega_{21} \quad (4.21)$$

4.4.1(d). Dynamic Ordinary Least Squares (DOLS)

Dynamic ordinary least square is the second cointegration equation provided by Eviews properties. It was initially developed by Saikkonen (1992) and Stock and Watson (1993). The estimation procedure of this method involves the augmentation of cointegrating regressions with p lags and k leads of Δy_t so that residuals of the new cointegrating regression is orthogonal to the entire history of the stochastic regressor innovation:

$$(X - p)_t = Y_t' \beta D_{1t}' \delta_1 + \sum_{j=-q}^k \Delta Y_{t+j}' \gamma + v_{1t} \quad (4.22)$$

The underlying assumption in this procedure is that augmenting the p lags and k leads of ΔX_t (differenced regressors) will absorb or reduce all the long-run correlation between v_{1t} and v_{2t} , so that the least squares estimates of $\hat{\varphi}_{DOLS} = (\beta', \lambda')'$ will have the same asymptotic distribution as the one produced by FMOLS and CCR estimators.

4.4.1(e). The Conical Cointegration Regression (CCR)

The CCR method is a non-parametric estimation procedure for testing cointegration vectors in models with I (1) variables. This method is kind of similar to the FMOLS, the only difference is that CCR focuses on data transformation, while FMOLS concentrates on both data and transformation of estimates. The CCR method can also be applied even in a multivariate model without any modifications (Park, 1992). The estimates of this method in a single equation are asymptotic as efficient as the estimates of the Johansen (1998) maximum likelihood method. The estimation procedure of these estimates is computed using the following equation:

$$\hat{\varphi}_{CCR} = \begin{bmatrix} \hat{\lambda} \\ \hat{\beta}_1 \end{bmatrix} = (\sum_{t=1}^T X_t^* X_t^{*'})^{-1} \sum_{t=1}^T X_t^* (Y - p)_t^*, \quad (4.23),$$

where, $X_t^* = (G_t^{*'} D_t^{*'})'$

Data transformation is represented by,

$$(Y - p)_t^* = (Y - p)_t - \left(\sum^{-1} \Lambda_2 \beta + \begin{bmatrix} 0 \\ \hat{\varphi}_{22}^{-1} \hat{\psi}_{21} \end{bmatrix} \right)' \hat{\mu}_t, \quad (4.24)$$

In this presentation the conical cointegration regression takes the following form,

$$Y_{1t}^* = \delta' Y_{2t}^* + u_{1t}^*$$

$$\text{where } \mu_{1t}^* = \mu_{1t} - \varphi_{12} \varphi_{22}^{-1} \mu_{2t}$$

The main purpose of doing all these transformations in variables is to eliminate the problem of asymptotically endogeneity caused by long run relationship (correlation) between Y_{1t} and Y_{2t} and to make the CCR estimate asymptotic equivalent to the Johansen (1998) ML estimates.

4.4.1(f). Problems Associated with Single Equations

Single equations have a number of shortfalls when it comes to identification of cointegration in conditions where n cointegrating relationships exist in the data. As indicated earlier on, they are only effective in cases where there is only one clear cointegrating vector in the series. The Engle-Granger (1987), on the other hand does not take into account the short-run dynamics when estimating the long-run cointegrating vectors in the series. Consequently, the short run dynamics tend to shift towards the error terms, thereby causing the problem of serial correlation in the estimated residuals. In addition, single equations are also unable to take into account any possible simultaneous relationships between variables. To address these, the literature suggests the use of multivariate estimation techniques because of its ability to deal with n co-integrating vectors in the system and in addressing the problem of simultaneous relationships among the variables.

4.4.2 Johansen Cointegration Test

This test was developed by Johansen and Johansen (1988,1994) as an alternative approach of testing for cointegration in a multivariate regression model. It was formulated on the foundations of Sims' (1980) understanding that most macroeconomic variables are interdependent, and thus need to be treated equally through the use of a VAR system. The Johansen cointegration test was therefore developed to test for cointegration rank within the VAR system, using the likelihood ratio test (Asteriou and Hall, 2016). Similar to the EG test, the Johansen test also start by checking the order of integration of each variable through unit root testing (Enders, 2010). After the order of integration have been checked, the next step is to determine the optimal VAR order (p) or lag length through the use of lag length information criterion. In order to identify the correct cointegrating relationships in the system, the Johansen test requires that the appropriate model regarding the deterministic component in the VAR system should be identified. After all these steps has been followed, then the correct co-integrating rank can be identified through the use of likelihood ratio tests.

To illustrate how the J-J test works, let's assume a hypothetical data generating process of a vector x_t of k explanatory variables. We shall specify a simple unrestricted VAR model involving up to n lags of x_t

$$x_t = \forall_1 x_{t-1} + \dots + \forall_n x_{t-n} + \mu_t, \quad (4.25),$$

where x_t is $(k \times 1)$, \forall_i represent $(k \times k)$ matrix on parameters. The ECM presentation of this equation can be presented as follows

$$\Delta x_t = \Gamma_1 \Delta x_{t-1} + \dots + \Gamma_{n-1} \Delta x_{t-n+1} + \Pi x_{t-n} + \mu_t \quad (4.26),$$

where $\Gamma_i = -(I - \forall_1 - \dots - \forall_i)$, $i = 1, \dots, n-1$ and $\Pi = -(I - \forall_1 - \dots - \forall_n)$. Also note that, if we assume that x_t represents a vector of non-stationary series $I(1)$, then all components involving Δx_t ought to be stationary, $I(0)$, and Πx_{t-n} should also be stationary for μ_t to follow a white noise process. Similar to the EG test, stationarity of μ_t would imply that a linear combination of all the $I(1)$ variables included in the model are $I(0)$, thus the variables under investigation have a long-run cointegrating relationship in levels.

The Johansen cointegration tests also correct for the short-run dynamics from shifting their effects towards the error terms by regressing Δx_t and x_t in two separate equations. In order to do that the Johansen test transforms the previous equation as follows:

$$\Delta x_t + \alpha \beta' x_{t-n} = \Gamma_1 \Delta x_{t-1} + \dots + \Gamma_{n-1} \Delta x_{t-n+1} + \mu_t, \quad (4.27)$$

where $\alpha \beta' = \Pi$, β and α represents long-run coefficient matrix and the speed of adjustment to equilibrium, respectively. From this equation we can obtain vector η_{0t} and η_{nt} as follows:

$$\Delta x_t = P_1 \Delta x_{t-1} + \dots + P_{n-1} \Delta x_{t-n+1} + \eta_{0t} \quad (4.28)$$

$$x_{t-n} = T_1 \Delta x_{t-1} + \dots + P_{n-1} \Delta x_{t-n+1} + \eta_{nt}$$

The residual form equation can be as follows

$$\omega_{ij} = T^{-1} \sum_{t=1}^T \eta_{it} \eta'_{jt} \quad i, j = 0, n \quad (4.29)$$

The ML estimates of β from the highest eigenvalues resulting from solving the equation as follows:

$$|\lambda \omega_{nn} - S_{n0} S_{00}^{-1}| = 0 \quad (4.30)$$

This equation gives an n number of eigenvalues $\hat{\lambda}_1, \hat{\lambda}_2, \hat{\lambda}_3, \dots, \hat{\lambda}_n$ with respective eigenvectors $\hat{V}_1, \hat{V}_2, \hat{V}_3, \dots, \hat{V}_n$. The overall cointegration testing process is undertaken on the basis of the following null hypothesis:

$$H_0: r = 0, H_0: r = 1, H_0: r = 2, \text{ or } H_0: r = m$$

which is then tested by computing the following maximum likelihood ratios (LR):

The Trace test

$$LR_{tr}(m) = -(T - p) \sum_{i=m+1}^k \ln(1 - \hat{\lambda}_i) \quad (4.31)$$

The trace test examines the null hypothesis of r cointegrating relationships against the m alternative hypothesis.

The Maximum Eigenvalue

$$LR_{max}(m) = -(T - p) \sum_{i=m+1}^k \ln(1 - \hat{\lambda}_i + 1) \quad (4.32)$$

The Max-Eigenvalue tests for r cointegrating relationships against the $r + 1$ alternative hypothesis. It is always important to note that the trace test usually picks the larger values when the summation of the remaining eigenvalues is large. That is if $\lambda \approx 1$, then $-\ln(1 - \hat{\lambda}_1)$ will be greater. The trace test is generally regarded as a superior test than the maximum eigenvalue because of its ability to account for the degrees of freedom and to cope with excessive kurtosis and skewness. Therefore, in any case, if the results of these two tests contradict each other, we will rely on the estimates of trace statistics.

4.4.2(a). Problems Associated with Johansen Cointegration

The first major critique directed to this test for cointegration is that it assumes that co-integrating relationships among the series remain constant throughout the period under investigation. According to Enders (2010), in real-life situations, it is highly possible that cointegration relationships between two economic variables can change. He argued that such changes can be caused by so many things, such as technological progress, changes in people's preferences and tastes, policy regimes, economic crises, etc. Asteriou and Hall (2016), on the other hand, also argued that Johansen cointegration parameter estimates are somehow are unreliable because of the existence of contemporaneous effects of equations within its system. Nonetheless, for the objective of this study we still prefer to rely on this method despite all these critiques. In the next subsection we discuss the methodological framework of a VAR system, followed by the Johansen vector autoregressive approach to VECM.

4.5 VECTOR AUTOREGRESSIVE (VAR) AND VECTOR ERROR CORRECTION (VECM) MODELS

Vector autoregressive models are specially designed to capture the dynamics of multiple time series and the short-run and long-run dynamics of macroeconomic variables necessary for policymaking decisions. These models presuppose that each variable is a linear function of its own past values, plus current and past values of other variables included in the model. Sims (1980) who is the founder of the vector autoregressive models, heavily criticised large-scale macroeconomic models, arguing that they tend to impose strong restrictions in their parameters. According to Sims (1980), most macroeconomic variables are interrelated therefore they deserve to be treated equally without exploiting their simultaneity relationships. In his arguments, he suggested that macroeconomic variables should be applied in a model where each variable will be given an equal opportunity to become an endogenous variable, which then led to the development of VAR models. VAR models consist of multiple equations, each one having an equal number of regressors. The nature of these models only allows for the exploration of short run relationship among the variables. As a result, all the coefficients produced by the VAR system are interpreted as short-run elasticities.

These models were then later extended by Johansen and Julius (1990, 1992) by incorporating the concept of cointegration and developed an error correction mechanism called the "Vector Error Correction Model". As opposed to standard VAR, Vector error correction models (VECM) are often used to analyse the long-run relationships in a multivariate model using $I(1)$ variables. The advantages of using a combination of these models is that they are able to handle both $I(0)$ and $I(1)$ variables (Mascagni and Timmis, 2014). However, the problem of using such a non-structural modeling technique is that it is not theoretical supported due to the dynamic nature of its specification which allows all variables to be both exogenous and endogenous in all equations. In these models,

all variables in the system are assumed to be endogenous, no *a priori* assumptions and distinctions are attached to the causality direction of the variables used in the model.

There are three forms of autoregressive models; reduced form, recursive and structural VAR. The common goal among all these three autoregressive models is to recover coefficient parameters of y_t , x_t and ε_t , assuming that y_t and x_t are the only variables included in a VAR system. A reduced VAR form treats each endogenous variable in the system as a linear function of its lags and those of other variables that are included in the model. Each equation obtained from a VAR system is then estimated by the ordinary least squares (OLS) econometric estimation technique. The underlying assumption of this form of VAR is that error terms are regarded as the result of unexpected shocks in the variables after taking past values into account and that if the variables are correlated with each other, then the error terms will also be correlated. This form of VAR is normally used for forecasting and economic policy analysis purposes. A recursive VAR is used to determine the structure of the model by carefully including in some of the equations the contemporaneous values of other variables as regressors that are not found in other equations. This process allows the error term in each regression to be uncorrelated with the error terms in other equations produced by the VAR system. Meanwhile, in a structural VAR, economic theory is used to construct the contemporaneous relationships between the variables in each equation. This form of a VAR is often used to investigate the response to shocks, fluctuations in business cycle and structural policy analysis. Both recursive and structural VAR forms are restrictive in nature, and as a result, ML estimates of a recursive or structural VAR are usually not consistent with OLS estimates. Meanwhile, in the case of an unrestricted VAR, ML estimates are always equal to the OLS estimates. This problem is associated with a number of restrictions involved in a structured VAR and if the restrictions are true, the ML estimates become consistent with the OLS estimates. Therefore, due to the restriction problems involved when dealing with a structured VAR, this study will adopt the use of an unstructured VAR, where the system is allowed to produce its own estimates freely without involving any sorts of restrictions. The general specification of an unrestricted VAR model opines that all variables should be treated equally to avoid unnecessary *a priori* differentiation between exogenous and endogenous variables and each equation has the same set of regressors. Any assumptions regarding endogeneity and the impact of unexpected shocks among the variables can be tested within the VAR framework. With this framework, each variable is treated as a linear function of its past values and those of other variables included in the model.

4.5.1 VAR (p) Specification

Let's take for example, a simple VAR model of two variables, X_t and Y_t assuming that X_t and Y_t are stationary variables and their values are affected by their past values and values of other regressors included in the model. The appropriate lags are decided by a number of tests. These tests include AIC, SC, HQ, LR and FPE. Therefore, the overall VAR model can be best described by the following bivariate models:

$$\begin{aligned} y_t &= \alpha_{10} - \phi_{12}x_t + \gamma_{11}y_{t-1} + \gamma_{12}x_{t-1} + \mu_{yt} \\ x_t &= \alpha_{20} - \phi_{21}y_t + \gamma_{21}y_{t-1} + \gamma_{22}x_{t-1} + \mu_{xt} \end{aligned} \quad (4.33)$$

The key underlying assumption of these two models is that both x_t and y_t are stationary and that μ_{yt} and μ_{xt} are uncorrelated white noise innovations, with standard deviations σ_y and σ_x and zero covariance. However, these equations are not in a reduced form and they cannot be estimated, since both x_t and y_t have a contemporaneous impact on each other given by $-\phi_{21}$ and $-\phi_{12}$, respectively. If these equations can be estimated in this nature without being reduced, the consequence is that the error terms of both equations can be partially correlated and they cannot be estimated by the OLS. Therefore, to solve this problem we rewrite equations (4.33) in a matrix by sending all endogenous variables in the left-hand side of the matrix form:

$$\begin{bmatrix} 1 & \phi_{12} \\ \phi_{21} & 1 \end{bmatrix} \begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} \alpha_{10} \\ \alpha_{20} \end{bmatrix} + \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ x_{t-1} \end{bmatrix} + \begin{bmatrix} \mu_{yt} \\ \mu_{xt} \end{bmatrix} \quad (4.34)$$

We can also express this equation as follows:

$$Bz_t = \Gamma_0 + \Gamma_1 Z_t + \mu_t \quad (4.35)$$

Where:

$$B = \begin{bmatrix} 1 & \phi_{12} \\ \phi_{21} & 1 \end{bmatrix}$$

$$Z_t = \begin{bmatrix} y_t \\ x_t \end{bmatrix}$$

$$\Gamma_0 = \begin{bmatrix} \alpha_{10} \\ \alpha_{20} \end{bmatrix}$$

$$\Gamma_1 = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}$$

$$\mu_t = \begin{bmatrix} \mu_{yt} \\ \mu_{xt} \end{bmatrix}$$

To simplify this problem further, let us we multiply both sides of equation (4.35) by \mathbf{B}^{-1} to obtain a reduced form of a VAR.

$$z_t = a_0 + a_1 Z_{t-1} + e_t \quad (4.36)$$

Where:

$$a_0 = \mathbf{B}^{-1} \Gamma_0,$$

$$a_1 = \mathbf{B}^{-1} \Gamma_1$$

$$e_t = \mathbf{B}^{-1} \mu_t$$

This equation (4.37) represents a reduced form of a VAR and it can be estimated efficiently using ordinary least squares (OLS) for each equation produced by the system. In this form of a VAR, the estimator of OLS is said to be identical to the GLS estimator. In addition, for a normal distributed where $\mu_t \sim N(0, \Sigma \mu)$ the OLS estimator is also the same to the ML estimator, but conditional on the initial pre-sample values.

4.5.2 VAR Stability Condition

One of the most important aspects of the VAR model is that it must be stable. If the system is not stable it produces infinite shocks and unreliable coefficients. This could be an indication that series used in the estimation are not stationary or are cointegrated. For demonstration purposes, let's assume a vector autoregressive process of order ρ of the following form

$$Z_t = \forall_1 Z_{t-1} + \dots + \forall_p Z_{t-p} + \delta y_t + \varepsilon_t \quad (4.38),$$

where Z_t is a k vector of endogenous variables, y_t is a d vector of exogenous variables, \forall_1, \forall_p and δ represent matrices of parameters to be estimated and ε_t is a vector of innovations that may be contemporaneously correlated but uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables. Hence, these series are assumed to have a K -dimensional zero white noise error term $\mu_t = \mu_{1t} \dots \dots \mu_{kt}$, with a covariance matrix $E(\mu_t \mu_t') = \Sigma \mu$, which implies that $\mu_t \sim N(0, \Sigma \mu)$. Using the lag process denoted by L which assumes that for the autoregressive process $AR(p)$ to be stable we need to find the matrix and the roots polynomial, which states that the absolute value of the roots of the polynomial should be bigger than one ($|z| > 1$) for the series to be stationary. Therefore, following the lag operator process, let $\forall(L)$ be as $\forall(L) = IK - \forall_1 L \dots - \forall_p L^p$ then the $AR(p)$ of the above equation can be equivalently expressed as;

$$\forall(L)Z_t = \mu_t \quad (4.39)$$

Then the VAR(p) (4.38)/ (4.39) would be stable if

$$\det \forall(x) = \det(IK - \forall_1 L \dots - \forall_p L^p) \neq 0 \text{ for } x \in \mathbb{C}, (|x| \leq 1),$$

This basically implies that Z_t will be stable if all roots of the determinantal polynomial are within boundary of the complex circle (Hashimzade and Thornton, 2013) and then we regard Z_t as a variable that follows a stationary process, $I(0)$. But if $\det \forall(x) = 0$ for $x = 1$ and all other determinantal polynomial roots are not within the complex circle, then it would give an indication that some or all variables in the VAR (ρ) process have a unit root or are cointegrated. If the VAR system is cointegrated, the VAR estimates would not be able yield robust and trustworthy results due to cointegrating relations that exist among the series. These cointegrating relations can only be capable of producing trustworthy results if the VAR system in its level form is transformed to its first difference. This form of a VAR is called a Vector Error Correction Mechanism or Model (VECM). For simplicity's purposes, consider the following levels Vector autoregressive model of order (p) for the $(n \times 1)$ vector X_t .

$$X_t = \beta D_t + \Pi_1 X_{t-1} + \dots + \Pi_p X_{t-p} + \varepsilon_t \quad (4.40)$$

$$t = 1 \dots T$$

D_t =Deterministic component

This VAR (p) would be stable if,

$$\det(I_n - \Pi_1 z \dots - \Pi_p z^p) = 0 \quad (4.41)$$

This means that all roots are inside the complex unit root circle. If the VAR system is found to be unstable, the ideal solution will be to specify this VAR (p) in its first difference which is normally referred to as a VECM.

$$\Delta X_t = \beta D_t + \Pi X_{t-1} + \Gamma_1 \Delta X_{t-1} + \dots + \Gamma_{p-1} \Delta X_{t-p+1} + \varepsilon_t \quad (4.42)$$

In this equation, ΔX_t and lags are cointegrated of order zero.

4.6 VECTOR ERROR CORRECTION MODEL

A VECM is a vector autoregressive (VAR) tool specially developed for use with nonstationary series that are known to be cointegrated (Louli and Agnieszka, 2011). It provides long term relationships and short term dynamics among variables included in a model by measuring the speed at which the system corrects disequilibrium conditions. According to Louli and Agnieszka (2011) the vector error correction model matches to a VAR of order $p - 1$, where p is the number of lags determined from the cointegration analysis, for the first differenced series. The ultimate procedure of this model is that there should be an error correction term in each equation, one for each cointegrating vector which measures the speed at which the system adjusts to changes in equilibrium conditions.

4.6.1 VECM Specification

Assume a given VAR(p) of non-stationary cointegrated variables $I(1)$

$$y_t = \alpha_1 y_{t-1} + \dots + \alpha_p y_{t-p} + \varepsilon_t \quad (4.43)$$

The vector matrix form of a VECM from this form of a VAR(p) can be represented by the following expression

$$\Delta y_t = \phi + \Pi y_{t-1} + \sum_{i=1}^{p-1} \theta_i \Delta y_{t-i} + \varepsilon_t \quad (4.44)$$

Where Δy_t is an $m \times 1$ vector matrix of the first difference of the variables in y_t , ϕ is an $m \times 1$ vector of intercept coefficient, Π and θ_i are $m \times m$ coefficients of matrices, ε_t is an $m \times 1$ error vector with contemporaneous correlation, with no autocorrelation, like in the case of a VAR. The underlying assumption here is that y_t is $I(1)$, Δy_t and ε_t are $I(0)$. In addition, if the vector error correction system is internally consistent, then Πy_{t-1} should also be $I(0)$ even if y_{t-1} is $I(1)$. Thus, the VECM is generally regarded as a superior error correction mechanism for VAR system because of its ability to produce cointegration linear combinations of y_{t-1} that are $I(0)$ by pre-multiplying y_{t-1} with Π . These cointegrating linear combinations show that there is a long-run relationship in the components of y_t . It is also important to mention that, Π predicts the cointegrating relationships among the variables, while θ_i illustrate the short run dynamics.

4.7 VAR-VECM ESTIMATION PROCESS

The estimation process of VAR/VECM involves a lot of steps, starting from identification of order of integration to the estimation of the VAR system and VECM followed by their diagnostic inspection tests. Below is the discussion of other important steps that needs to be undertaken in the process of estimating VAR/VEM. Note: some of these elements have already been highlighted in the previous sections.

4.7.1 VAR Order Lag Selection Criteria

One of the important aspects of specifying a VAR and VECM is the determination of the relevant order lag (p) of the VAR model. The importance of determining the correct lag length is demonstrated by Braun and Mittnik (1993) as cited by Mazenda (2014) who emphasised that estimates of a VAR whose lag length differs from the true lag length are inconsistent, as are the impulse response functions and variance decompositions derived from the estimates of VAR. Lutkepohl (1993) argues that over-fitting of lag length increases the mean-square-forecast errors of the VAR, while under-fitting generates auto-correlated errors.

Vector autoregressive models are estimated using the same lag length across all equations. However, according to Ozcicek and McMillin (1999), there is no enforcement from the economic theory perspective which insists that lag length should be the same across all equations. This procedure has been frequently used in the literature because of the belief that symmetric lag length across all

equations produces better VAR estimates and efficient ordinary least squares (OLS) estimates. The most powerful lag selection criteria that are frequently used in most VARs models include Akaike's Information criterion (AIC), Schwarz Bayesian Criterion (SBC) also known as the BIC and Hannan-Quinn (HQ).

The Akaike information criteria (AIC) seek to select the most parsimonious model by correcting the likelihood for the number of parameters in the autoregressive model. The AIC was designed to produce the most appropriate unbiased estimator of the Kull-Leibler index of the fitted model in relation to the true model. According to Mainassara (2012) the conventional model of the AIC criterion can be written as follows: $AIC = -2\log L_n(\hat{\beta}_n) + 2k$, where, n is the sample size and β represents the estimated parameters. The advantages of using this information criterion is that it validates both nested and non-nested models, able to compare models with different error distribution and to avoid multiple testing issues. It functions better in models with minimum AIC value. Under ordinary least squares (OLS) this AIC assumes that all residuals are normally distributed; that is, they have a constant mean and variance.

$$AIC = n\log\left(\frac{RSS}{n}\right) + 2k. \quad (4.45)$$

However, this criterion had the problem of selecting an over-parameterised model which then led to the development of the Bayesian information criteria, as consistent order selection criteria, which overcomes the problem of selecting the over-parameterised models. The Bayesian information criteria (BIC) are also known as the Swartz Bayesian criteria (SBC) developed by Swartz (1978). According to Swartz (1978) the p th order of an autoregressive model with the minimum SBC or BIC is always preferred to avoid the problem of overfitting the model as we increase its parameters. The Bayesian information criteria or Swartz Bayesian criteria is similar to Akaike's information criteria in the sense that they both attempt to avoid the problem of overfitting the auto regression model by introducing the penalty term for the number of parameters in the model. However, this penalty term is usually greater in the BIC or SBC than in the AIC.

where, n number of observations, $\hat{\delta}^2$ is the estimated error variance of the fitted AR(p) model, while p and q is the order of autoregressive and moving average components, respectively. Hannan and Rissanen (1982) modified the earlier version of this criterion by replacing the term $\ln(\ln n)$ by $\ln n$ to speed up the convergence of HQ. This revised version of HQ, however, was found to contain a similar problem with the AIC by overestimating the AR(p) model orders.

$$BIC = (n - p - q)\ln\frac{n\hat{\delta}^2}{n-p-q} + n(1 + \ln 2n) + (p + q)\ln\left[\frac{\sum_{t=1}^n X_t^2 - n\hat{\delta}^2}{p+q}\right] \quad (4.46)$$

Another well-known information criterion that has received a lot of attention in the literature is the Hannan-Quinn criterion, developed by Hannan and Quinn (1979) and Hannan (1980) from the law of the repeated logarithm to provide a strong penalty function which decreases as sample size increases. The Hannan-Quinn (HQ) was specially developed to select the order selection criteria in a multivariate autoregressive moving average ARIMA or Autoregressive AR models where the p th order of the model is unknown. The power of the HQC lies between the AIC and the SBC and under certain regularity circumstances it can be exposed that the HQC tends to provide the same estimates as the SBC, especially in large samples cases. According to this criterion the unknown p th order of the AR or ARIMA model can be given as:

$$HQ = \ln\hat{\delta}^2 + 2(p + q)\frac{\ln(\ln n)}{n} \quad (4.47)$$

4.7.2 Deterministic Component of Cointegrating Relations by Model

In order for cointegrating vector autoregression (VAR) to be correctly specified or estimated the correct identification of a number of cointegrating relations by model is necessary. These cointegrating relationships in VAR equations be explained by five model cases. The correct VAR estimation is decided among these five model cases, **Case 1:** suggest a constant VAR model with no trend and intercept. **Case 2:** suggest a constant VAR model with intercept but no trend. **Case 3:** suggest a linear VAR model with intercept but with no trend. **Case 4:** contains a VAR model with linear with both trend and intercept. Lastly, **Case 5:** suggest a quadratic VAR model with both intercept and trend. According to the empirical literature, Case 2,3 and 4 are normally labelled as structural intercept VAR with no trends, unstructured intercept VAR with no trends and unstructured intercept VAR with structured trends, respectively. A common practice in most empirical studies is to ignore case 5 because it specifies models that, in reality, are not consistent with the behaviour of macroeconomic time series data. Case 1 is too simplistic while Case 5 is not generally observed in time series data. These cases can only be applied if there are strong economic reasons. The decision rule regarding the appropriate model for this study is undertaken following the Pantula Principle advocated by Johansen (1992). According to this principle the appropriate way of choosing a suitable model should be that all cases are estimated and the smallest r value based on Trace and Max-Eig statistic is adopted.

4.7.3 Impulse Response Analysis

Because a VAR system consists of past and present values of each variable in each equation, it remains critical for the researcher to take into account the historical patterns of correlations among these different variables. The impulse response functions therefore enable us to trace these historical patterns and the responsiveness of each exogenous variable in a VAR system to innovations or shocks from each of the variables in the model. There are two forms of impulse response functions: orthogonalised impulse response, based on Cholesky decomposition and generalised impulse response function. In both cases, innovations or shocks in a VAR system enter through the residual vector $e_t = (e_{1t}, \dots, e_{zt})$. We shall consider a simple two variables (y_t and z_t) VAR model:

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} \quad (4.48)$$

Or

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} y \\ z \end{bmatrix} + \sum_{i=0}^{\infty} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^i \begin{bmatrix} e_{1t-i} \\ e_{2t-i} \end{bmatrix}$$

where, e_{1t} and e_{2t} are white noise residual vectors following a Gaussian white noise process. These vector errors can be expressed as follows:

$$\begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} = \frac{1}{1-b_{12}+b_{21}} \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{zt} \end{bmatrix} \quad (4.49)$$

If we substitute these to equation 1 above, we get:

$$\begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix} = \begin{bmatrix} \bar{y}_t \\ \bar{z}_t \end{bmatrix} + \frac{1}{1-b_{12}+b_{21}} \sum_{i=0}^{\infty} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^i \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \begin{bmatrix} \varepsilon_{1t-i} \\ \varepsilon_{2t-i} \end{bmatrix} \quad (4.50)$$

From this equation we can now derive the most compact orthogonalised impulse response equation:

$$\begin{aligned} \Phi_i &= \frac{A_i}{1-b_{12}+b_{21}} \begin{bmatrix} 1 & -b_{12} \\ -b_{21} & 1 \end{bmatrix} \\ \begin{bmatrix} y_t \\ z_t \end{bmatrix} &= \begin{bmatrix} \bar{y}_t \\ \bar{z}_t \end{bmatrix} + \frac{1}{1-b_{12}+b_{21}} \sum_{i=0}^{\infty} \begin{bmatrix} \Phi_{11}(i) & \Phi_{12}(i) \\ \Phi_{21}(i) & \Phi_{22}(i) \end{bmatrix}^i \begin{bmatrix} \varepsilon_{1t-i} \\ \varepsilon_{2t-i} \end{bmatrix} \end{aligned} \quad (4.51)$$

where Φ represents the coefficients to be estimated by the system. These coefficients Φ_i can also be used to generate the effects of shocks (ε_{yt} and ε_{zt}) on the entire time path.

$$\alpha_t = \mu + \sum_{i=0}^{\infty} \Phi_i \varepsilon_{t-1}. \quad (4.52)$$

But because both VAR and VECM are symmetrically systems of equations, we can therefore also reverse the system and forecast the future behaviour of a certain variable in a VAR system in response to a shock in a system.

$$\begin{bmatrix} y_{t+i} \\ z_{t+i} \end{bmatrix} = \begin{bmatrix} \bar{y}_t \\ \bar{z}_t \end{bmatrix} + \frac{1}{1-b_{12}+b_{21}} \sum_{i=0}^{\infty} \begin{bmatrix} \Phi_{11}(i) & \Phi_{12}(i) \\ \Phi_{21}(i) & \Phi_{22}(i) \end{bmatrix}^i \begin{bmatrix} \varepsilon_{1t+i} \\ \varepsilon_{2t+i} \end{bmatrix} \quad (4.53)$$

However, this form of impulse response has been heavily criticised in many recent studies. Many have argued that, this approach is sensitive to ordering of variables in a system and it omitted some important variables which in turn affects the residuals of the system and potentially leads to major distortions in the impulse responses and Granger-causality relationships. As a result, Koop *et al.* (1996) proposed a promising way of investigating impulses in a VAR system that is not affected by any order of variables and does not require the orthogonalisation of innovations or shocks in the VAR system. This approach is known as ‘‘Generalised impulse response function/analysis’’. It also works well in the construction of order-invariant forecast error variance decompositions. The general setup of the generalised impulse response can be explained as follows: let’s consider a VAR system with p dimensional series y_t given by

$$y_t = \theta A_t + \sum_{i=1}^h \beta_i y_{t-i} + \varepsilon_t; t = 1, \dots, T; \quad (4.54)$$

where A_t represents a vector with a deterministic component, and h is the number of forecast steps or periods ahead or backward. In this model the series y_t may have a stationary covariance and integrated of order one, while ε_t is assumed to be i.i.d with zero mean and positive definite covariance matrix Θ . From equation (4.54) the h steps forecast error for y process can be given by

$$y_{t+h} - E[y_{t+h} | \lambda_t] = \sum_{j=0}^{h-1} k_j \varepsilon_{t+h-j}, \quad (4.55)$$

Where λ_t is a set of information which includes both the current and historical values of y_t process as well as the entire time path of A_t . The $p \times p$ matrices k_j are given by $k_0 = k_p$ and

$$k_j = \sum_{i=1}^{\min h,j} \beta_i k_{j-i}, j \geq 1,$$

such that all k_j matrices can be determined recursively from the β_i matrices. According to Koop *et al.* (1996), the generalised form of impulse response can be given by the following equation:

$$GI_y(k, \delta, \beta_{t-1}) = E(y_{t+h} | \varepsilon_t = \delta, \beta_{t-1}) - E(y_{t+h} | \varepsilon_t = \beta_{t-1})$$

where δ is the unknown vector. In a VAR system this implies that

$$GL_y(k, \delta, \beta_{t-1}) = \beta_h \delta,$$

Where δ denotes the time profile of determining any impulse response function in the VAR system. In this system we also consider shocking one element of residual vectors ε_t in such that $\varepsilon_{jt} = \delta_j$. Hence, one can also define the generalized impulse response as:

$$GI_y(k, \delta, \beta_{t-1}) = E(y_{t+h} | \varepsilon_{jt} = \delta, \beta_{t-1}) - E(y_{t+h} | \varepsilon_t = \beta_{t-1}), \quad (4.56)$$

Given that all the residual vectors follow a Gaussian process and that $\delta_j = \sqrt{\sigma_{jt}}$ (standard deviation of residual vectors ε_t), it follows that:

$$E[\varepsilon_t | \varepsilon_{jt} = \sqrt{\sigma_{jt}}] = \Theta e_j \sigma_{jj}^{-1/2}$$

where e_j denotes the j :th column of k_p . This will in turn make the generalised impulse response in a VAR system to be defined as follows:

$$GI_y(k, \sqrt{\sigma_{jj}}, \beta_{t-1}) = k_p \Theta e_j \sigma_{jj}^{-1/2} \quad (4.57)$$

This equation defines the response in y_{t+h} resulting from one standard deviation shock or innovation to residual vectors ε_{jt} , where the correlation between j th and i th residual vectors have been taken into account. Moreover, the generalised impulse response can also be expressed in a matrix form. Suppose we define the $p \times p$ diagonal matrix Σ as follows:

$$\Sigma = \text{diagonal} \begin{bmatrix} (e_1' \Theta e_1)^{-1/2} \\ (e_2' \Theta e_2)^{-1/2} \\ \vdots \\ (e_p' \Theta e_p)^{-1/2} \end{bmatrix} \quad (4.58)$$

The generalised impulse response function will therefore be as follows;

$$GL_y(k, \sqrt{\sigma_{11}}, \dots, \sqrt{\sigma_{pp}}, \beta_{t-1}) = k_p \Theta \Sigma = k_p B = A_p \quad (4.59)$$

where $GI_y(k, \sqrt{\sigma_{jj}}, \beta_{t-1})$ is given by the j th column, Θ is diagonal, which then implies that $B = \Theta^{1/2} = \Sigma^{-1}$.

4.7.4 Variance Decomposition Analysis

Just like the impulse response function, the variance decomposition or forecast error variance is one of the most important econometric tools used by many economists to aid the interpretation of multivariate time series models. While the impulse response function traces the effects of shocks or innovations to one endogenous variable on the other variables in the VAR system, variance decomposition measures the amount of information each variable contributes to other variables in the system. It is developed under the assumption that the forecast error variance of each variable in the system could be influenced by its own shocks and those of other variables included in the system. Similar to the impulse response function, variance decomposition or forecast error variance decomposition also has two versions: the traditional version and the generalised variance or forecast error variance decomposition analysis. The later version is preferred in this study because it is not affected by the restriction identification problem. The general setup of the generalised variance decomposition can be explained as follows: We shall assume a K –dimensional VAR(p) model in a SMA representation matrix order,

$$\begin{bmatrix} y_{1t+h} \\ y_{2t+h} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \theta_{11}^{(0)} & \theta_{12}^{(0)} \\ \theta_{21}^{(0)} & \theta_{22}^{(0)} \end{bmatrix} \begin{bmatrix} \varepsilon_{1t+s} \\ \varepsilon_{2t+s} \end{bmatrix} + \dots + \begin{bmatrix} \theta_{11}^{(h)} & \theta_{12}^{(h)} \\ \theta_{21}^{(h)} & \theta_{22}^{(h)} \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \quad (4.60)$$

Based on this equation, the forecasting ability of variable y_1 and y_2 at time t and $t + h$ based on information available at time t is influenced by variations in structural shocks ε_1 and ε_2 between time t and $t + h$. According to the Wold representation theorem the y at time $t + h$ can be given by the following expression;

$$y_{t+h} = \mu + u_{t+h} + \Psi_1 u_{t+h-1} + \dots + \Psi_{h-1} u_{t+1} + \Psi_h u_t + \Psi_{h+1} u_{t-1} + \dots \quad (4.61)$$

From this equation, the best linear forecast of y at time $t + h$ based on the information at time t is given by

$$\hat{y}_{t+h|t} = \mu + \Psi_h \mu_t + \Psi_{h+1} \mu_{t-1} + \dots$$

The forecast error is;

$$y_{t+h} - \hat{y}_{t+h|t} = \mu_{t+h} + \Psi_1 \mu_{t+h-1} + \dots + \Psi_{h-1} \mu_{t+1}$$

If we use $\varepsilon_t = \mathbf{B}^{-1} \mathbf{u}_t$, we may re-write the forecast error equation in terms of the structural shocks

$$y_{t+h} - \hat{y}_{t+h|t} = \mathbf{B}^{-1} \varepsilon_{t+h} + \Psi_1 \mathbf{B}^{-1} \varepsilon_{t+h-1} + \dots + \Psi_{h-1} \mathbf{B}^{-1} \varepsilon_{t+1} = \Theta_0 \varepsilon_{t+h} + \Theta_1 \varepsilon_{t+h-1} + \dots + \Theta_{h-1} \varepsilon_{t+1}$$

The matrix form of this forecast error equation can be given by

$$\begin{bmatrix} y_{1t+h} - \hat{y}_{1t+h|t} \\ y_{2t+h} - \hat{y}_{2t+h|t} \end{bmatrix} = \begin{bmatrix} \theta_{11}^{(0)} & \theta_{12}^{(0)} \\ \theta_{21}^{(0)} & \theta_{22}^{(0)} \end{bmatrix} \begin{bmatrix} \varepsilon_{1t+h} \\ \varepsilon_{2t+h} \end{bmatrix} + \dots + \begin{bmatrix} \theta_{11}^{(h-1)} & \theta_{12}^{(h-1)} \\ \theta_{21}^{(h-1)} & \theta_{22}^{(h-1)} \end{bmatrix} \begin{bmatrix} \varepsilon_{1t+1} \\ \varepsilon_{2t+1} \end{bmatrix} \quad (4.62)$$

Since ε_t is assumed to be independent and identically distributed (i.i.d) where D is diagonal, the variance of the forecast error from this matrix can therefore be decomposed as

$$\begin{aligned} \text{var}(y_{1t+h} - \hat{y}_{1t+h|t}) &= \sigma_1^2(h) = \\ &= \sigma_1^2 \left((\theta_{11}^{(0)})^2 + \dots + (\theta_{11}^{(h-1)})^2 \right) + \sigma_2^2 \left((\theta_{12}^{(0)})^2 + \dots + (\theta_{12}^{(h-1)})^2 \right) \end{aligned}$$

The proportions of $\sigma_1^2(h)$ and $\sigma_2^2(h)$ due to shocks in ε_1 and ε_2 can therefore be given by the following, respectively,

$$\rho_{1,1}(h) = \frac{\sigma_1^2 \left((\theta_{11}^{(0)})^2 + \dots + (\theta_{11}^{(h-1)})^2 \right)}{\sigma_1^2(h)}$$

$$\rho_{1,2}(h) = \frac{\sigma_2^2 \left((\theta_{12}^{(0)})^2 + \dots + (\theta_{12}^{(h-1)})^2 \right)}{\sigma_1^2(h)}$$

The same approach will also apply for the computation of forecast error variance for y_{t+h} .

4.7.4 Granger Causality Test

Granger Causality is necessary to test for causal links between two economic variables in the VAR/VECM system. Granger (1969) defined Granger causality as a statistical test of causal links based on the prediction of vector autoregression models. The causality link between two economic variables can either be bidirectional, unidirectional or none. The bi-directional causality means that there is a two-way causal link between two economic variables (x and y). Unidirectional, on the other hand suggests, a one-way causal effect between two economic variables that is, the relationship is from x to y or from y to x but there is no symmetry feedback coming from either side. Lastly, the non-causality, implies that there is no causal link existing between the economic variables under investigation.

This test was developed by Granger (1969), specifically to determine the causality relationship of two economic variables in a cointegrated model. In economic theory, a variable Granger causes another variable if its current and past values determine the current values of the variable concerned. According to Granger (1969), if variables are I(1), granger causality should be conducted in the error correction model. In the case of a VAR system, the Granger causality test is conducted in the VECM system. A simple granger presentation of two variables x and y can be presented by the following equations:

$$y_t = \sum_{i=1}^k \alpha_i y_{t-i} + \sum_{i=1}^k \gamma_i x_{t-i} + \mu_i$$

$$x_t = \sum_{i=1}^k \alpha_i y_{t-i} + \sum_{i=1}^k \gamma_i x_{t-i} + \mu_i$$

However, if variables are cointegrated, the following causality analysis is conducted in the ECM or VECM in a case of a multivariate equations.

$$\Delta y_{t-1} = \sum_{j=1}^k \alpha_j y_{t-1} + \sum_{j=1}^k \gamma_j x_{t-1} + \delta \varepsilon_{1t-1} + \mu_i$$

$$\Delta y_{t-1} = \sum_{j=1}^k \alpha_j y_{t-1} + \sum_{j=1}^k \gamma_j x_{t-1} + \delta \varepsilon_{1t-1} + \mu_i$$

where ε_1 and ε_2 represent the lagged values of the white noise error terms from the cointegrating equations. The following null hypotheses are tested

$$H_0: \alpha_j = 0 \quad j = 1 \dots \dots k$$

$$H_0: \gamma_j = 0 \quad j = 1 \dots \dots k$$

where the first hypothesis states that y_{t-1} does not Granger cause changes in x_{t-1} and the opposite is true with respect to x_{t-1} in the second hypothesis.

4.8 DIAGNOSTIC INSPECTION

After a vector auto-regression has been estimated, it is also wise to do a battery of diagnostic tests to check for common issues such as, serial correlation, heteroscedasticity and normality. The presence of these issues is not good for any regression model because they violate the classical assumption of the ordinary least squares (OLS) and invalidate the parameters estimated. One of the most important classical assumptions of the OLS is that a good regression model should have no serial correlation, no heteroscedasticity and its residuals should be normally distributed. Hence, in this section we shall be discussing these issues and their relevant tests quite extensively.

4.8.1 Serial Correlation

One of the classical assumptions of the regression model postulates that the error terms μ_i are uncorrelated, that is the error term at time t is not correlated with the error term at time $(t - 1)$ or any other error term in the past (Gujarati, 2009). Hence, their covariance is also expected to be equal to zero,

$$cov(u_i, u_j / x_i x_j) = E(u_i, u_j) = 0 \quad i \neq j,$$

If error terms become correlated they make the estimation of OLS model inefficient and results in heteroscedasticity problems because it cuts down the existence of the minimum variance assumption among all linear unbiased estimators, $E(u_i u_j) \neq 0 \quad i \neq j$. The presence of autocorrelation would increase the chances of underestimating the true σ^2 because of residual variance $\hat{\sigma}^2 = \frac{\sum \hat{u}_t^2}{(n-2)}$ and as a result we are more likely to overestimate R^2 (Gujarati, 2009; 423). Moreover, the usual t and F tests of significance are no longer valid; hence we might end up wrongfully accepting the null hypothesis because of wider confidence intervals.

There are two important tests that are commonly used to check for residual autocorrelation in the VAR system: the Breusch-Godfrey LM test and the portmanteau tests. The portmanteau hypothesises that all residual auto-covariances are equal to zero,

$$H_0: E(\mu_t \mu'_{t-i}) = 0 \quad (i = 1, 2, 3, \dots)$$

Against the alternative of none zero residuals auto-covariance,

$$H_0: E(\mu_t \mu'_{t-i}) \neq 0 \quad (i = 1, 2, 3, \dots)$$

The residuals auto-covariance of the portmanteau is given by

$$\hat{C}_j = T^{-1} \sum_{t=j+1}^T \hat{\mu}_t \hat{\mu}'_{t-j},$$

where $\hat{\mu}'_t$ are the mean adjusted estimated residuals. The statistic value for the portmanteau test is given by,

$$Q_h = T \sum_{j=1}^h tr(\hat{C}_j' \hat{C}_0^{-1} \hat{C}_j \hat{C}_0^{-1}),$$

Or

$$Q_h^* = T^2 \sum_{j=1}^h \frac{1}{T-j} \text{tr}(\hat{c}_j' \hat{c}_0^{-1} \hat{c}_j \hat{c}_0^{-1}),$$

These two versions of the portmanteau test for serial correlation have the same asymptotic properties and for an unstructured VAR(p) process their null distribution can be estimated by a $\chi^2(k^2(h-p))$ distribution if T and $h \sim \infty$ such that $h/T \rightarrow 0$ (Lutkepohl, 2011). For small sample sizes, the choice of h values is very crucial for this test. At small values of h the χ^2 estimation to the null distribution may be very poor but if h is chosen at higher values, this may also reduce the power of the test. According to Lutkepohl (2011) the portmanteau test should be applied to check for higher order serial correlation and the Breusch-Godfrey LM test should be used for low-order autocorrelation. The Breusch-Godfrey LM test can be generally viewed as a test for zero coefficient matrices in the vector autoregression model for residuals. The test statistic for this test is computed in a form of an auxiliary regression model,

$$\mu_t = \alpha_1 \mu_{t-1} + \dots + \alpha_h \mu_{t-h} + \varepsilon_t$$

where ε_t is the white noise error term.

Unlike the portmanteau test, this test is also more appropriate for levels of the VAR process with unknown cointegration ranks, because for both I(0) and I(1) systems the BG test has the same asymptotic $\chi^2(hk^2)$ –distribution properties for all null hypothesis. The null and alternative hypothesis of this test can be expressed as follows:

$$H_0: \alpha_1 = \dots = \alpha_h = 0$$

against

$$H_1: \alpha_i \neq 0 \text{ for at least one } i \in \{1, \dots, h\}$$

Under the condition of no serial correlation μ_t will be equal to ε_t (white noise error term).

4.8.2 Non-normality Test for a VAR Process

Multivariate normality tests are the generalisation of the univariate normality tests. The importance of running a normality test in a VAR system is to ensure that the series of random vectors in the system are Gaussian distributed and are in compliance with classical assumption of normal distribution, which states that the error terms of a good regression must have a zero mean and a constant variance overtime. If residuals are not normally distributed, the F-statistic and t-statistic are rendered invalid. Therefore, in order to take care of this problem, statisticians and econometricians have suggested the use of the Jarque-Bera test, developed by Jarque and Bera (1990). This test assesses normality by making use of skewness and kurtosis as measures of distribution of errors. The overall test statistic of the univariate JB test can be given by the following equation:

$$JB = \frac{n-k+1}{6} \left(s^2 + \frac{1}{4}(c-3)^2 \right)$$

where n is sample size, k is the number of regressors, s is skewness and c is the sample kurtosis. For a stationary and stable VAR process to be normally distributed, it requires that the white noise error terms of VAR process μ_t must be Gaussian, meaning that they should have a symmetric, positive, and contain a semidefinite covariance (Austeriou and Hall, 2016). Mardia (1970) proposed that skewness and kurtosis should be slightly modified in order capture the exact distribution of vectors in a multivariate case by adding an error correction term into the skewness test statistic. Mardia's presentation of skewness and kurtosis for normality can be expressed as follows, respectively:

$$\hat{\phi}_{1,p} = \frac{1}{n^2} \sum_{i=1}^n \sum_{j=1}^n m_{ij}^3$$

$$\hat{\phi}_{2,p} = \frac{1}{n} \sum_{i=1}^n m_{ii}^2$$

According to Mardia (1970), for normality to hold, the test statistic for skewness should be approximately χ^2 distribution with $p(p+1)(p+2)/6$ degrees of freedom. Meanwhile, on the other hand, the kurtosis statistic test is said to be approximately Gaussian, distributed with a mean $p(p+2)$ and variance $8p(p+2)/n$.

4.8.3 Heteroscedasticity

The presence of heteroscedasticity in a regression model leads to underestimation of variances, and standard errors, thereby leading to overestimated and misleading t and F -statistics. The Breusch-Pagan (1979) is one of the most celebrated and widely used tests for checking the presence of heteroscedasticity in a regression model, followed by the White (1980) tests. Because of the robustness and the popularity of the Breusch-Pagan tests, in this study only the Breusch-Pagan tests in Eviews 9.5 will be applied for the detection of the heteroscedasticity problem.

4.8.4 Stability Tests

Stability analysis of parameters has become a very important task in most modern empirical analysis. Such analysis helps the researcher to identify the presence of any structural breaks in the data generating process. Unexpected shifts in time series data can lead to major forecasting errors. Hence these shifts need to be recognised and fixed. There are three structural shifts expected in the underlying series, especially in the import demand model. The first structural shift would be checked between the period of 1969 to 1970 (the end of international sanctions). The second shift is expected in 1994 (the beginning of the democratic governance in South Africa) and during the period of 2008/2009 financial crises. The CUSUM, CUSUMQ, recursive and Chow tests shall be used to investigate this problem in our underlying generating series, which may influence the parameter's stability in our VAR system. The difference between these tests and the Chow test is that the Chow test can only be used if the break dates are known.

The CUSUM and CUSUMQ tests are given by the following formulas, respectively:

$$C_T = \sum_{t=m+1}^T \frac{\hat{u}_t^{(r)}}{\hat{\sigma}_u}$$

$$CQ_t = \sum_j^t = k + 1 \hat{u}_j^2 / \sum_j^n = k + 1 \hat{u}_j^2$$

This test is more powerful if the break in the regression model is an intercept. However, the CUSUMQ test gives more robust results if the break of the regression model is in the slope coefficient or variance of the residuals. Unlike the Chow (1960) test the CUSUM and CUSUMQ tests do not require the knowledge of the exact point of the hypothesised structural break (Abujiya *et al.*, 2010).

4.9 MODEL SPECIFICATION

As highlighted in Chapter 2, the methodological specification of the import and export demand function for this study follows the specification utilised by Bahmani-Oskooee (1986, 2003), Tegene (1989;1991), Bahmani-Oskooee and Kara (2008), Bahmani-Oskooee and Ebadi (2016) and Ebadi (2015). In these studies, imports and exports are regressed as follows, respectively:

$$M_t = F(Y, MRP, NEER)$$

$$X_t = F(YW, XRP, NEER)$$

where, M_t and X_t represent import and export demand, respectively. Similarly, Y , MRP , and $NEER$ in equation 4.8 represent domestic income, relative import prices and nominal effective exchange rate, respectively, while, YW , XRP , and $NEER$ in equation 4.9 represent foreign income (proxied by industrial production index of advanced economies), relative exports prices, and nominal effective exchange rate, respectively.

Moreover, the inclusion of the nominal effective exchange rate in this study was done with the purpose of investigating the validity of the Orcutt hypothesis in South African trade flows. As already stated on the previous chapters, we specifically want to check Orcutt's conjecture, which states that trade flows could respond faster to changes in exchange rate than they do to changes in relative prices. Thus, the unrestricted VAR (4) of short run import and export demand functions can be expressed by the following systems of equations, respectively.

Model 1 (Import demand function)

$$M_t = \beta_{01} + \sum_{p=0}^n \beta_{11p} \Delta M_{t-p} + \sum_{p=0}^n \beta_{21p} \Delta MRP_{t-p} + \sum_{p=0}^n \beta_{31p} \Delta Y_{t-p} + \sum_{p=0}^n \beta_{41p} \Delta neer_{t-p} + \mu_t$$

$$Y_t = \beta_{02} + \sum_{p=0}^n \beta_{12p} \Delta M_{t-p} + \sum_{p=0}^n \beta_{22p} \Delta MRP_{t-p} + \sum_{p=0}^n \beta_{32p} \Delta Y_{t-p} + \sum_{p=0}^n \beta_{42p} \Delta neer_{t-p} + v_t$$

$$MRP_t = \beta_{03} + \sum_{p=0}^n \beta_{13p} \Delta M_{t-p} + \sum_{p=0}^n \beta_{23p} \Delta MRP_{t-p} + \sum_{p=0}^n \beta_{33p} \Delta Y_{t-p} + \sum_{p=0}^n \beta_{43p} \Delta neer_{t-p} + \varepsilon_t$$

$$Neer_t = \beta_{04} + \sum_{p=0}^n \beta_{14p} \Delta M_{t-p} + \sum_{p=0}^n \beta_{24p} \Delta MRP_{t-p} + \sum_{p=0}^n \beta_{34p} \Delta Y_{t-p} + \sum_{p=0}^n \beta_{44p} \Delta neer_{t-p} + \omega_t$$

Model 2 (Export demand function)

$$X_t = \beta_{01} + \sum_{p=0}^n \beta_{11p} \Delta X_{t-p} + \sum_{p=0}^n \beta_{21p} \Delta XRP_{t-p} + \sum_{p=0}^n \beta_{31p} \Delta YW_{t-p} + \sum_{p=0}^n \beta_{41p} \Delta neer_{t-p} + \omega_t$$

$$XRP_t = \beta_{02} + \sum_{p=0}^n \beta_{12p} \Delta X_{t-p} + \sum_{p=0}^n \beta_{22p} \Delta XRP_{t-p} + \sum_{p=0}^n \beta_{32p} \Delta YW_{t-p} + \sum_{p=0}^n \beta_{42p} \Delta neer_{t-p} + \varepsilon_t$$

$$YW_t = \beta_{03} + \sum_{p=0}^n \beta_{13p} \Delta X_{t-p} + \sum_{p=0}^n \beta_{23p} \Delta XRP_{t-p} + \sum_{p=0}^n \beta_{33p} \Delta YW_{t-p} + \sum_{p=0}^n \beta_{43p} \Delta neer_{t-p} + \mu_t$$

$$Neer_t = \beta_{04} + \sum_{p=0}^n \beta_{14p} \Delta X_{t-p} + \sum_{p=0}^n \beta_{24p} \Delta XRP_{t-p} + \sum_{p=0}^n \beta_{34p} \Delta YW_{t-p} + \sum_{p=0}^n \beta_{44p} \Delta neer_{t-p} + v_t$$

In each system, $\beta_1, \beta_2, \beta_3$ and β_4 are the short term coefficients of each variable, respectively. β_0 , is the constant of each equation. $\omega_t, \varepsilon_t, \mu_t, \varepsilon_t$, and v_t are the white noise error correction terms. Moreover, in case where variables are found to be cointegrated, then the following Vector Error Correction Model will be estimated. VECM models reconcile the short-run dynamics with long-run information through error correction terms. A VECM is nothing but the expression of a VAR system in its first differenced form.

Model 1 (import demand model)

$$\Delta M_t = \beta_{01} + \phi_{1p} ect_{t-p} + \sum_{p=0}^n \beta_{11p} \Delta M_{t-p} + \sum_{p=0}^n \beta_{21p} \Delta MRP_{t-p} + \sum_{p=0}^n \beta_{31p} \Delta Y_{t-p} + \sum_{p=0}^n \beta_{41p} \Delta E_{t-p} + \sum_{p=0}^n \gamma_{1\rho} Z_{t-\rho} + \mu_t$$

$$\Delta MRP_t = \beta_{02} + \phi_{2p} ect_{t-p} + \sum_{p=0}^n \beta_{12p} \Delta M_{t-p} + \sum_{p=0}^n \beta_{22p} \Delta MRP_{t-p} + \sum_{p=0}^n \beta_{32p} \Delta Y_{t-p} + \sum_{p=0}^n \beta_{42p} \Delta E_{t-p} + \sum_{p=0}^n \gamma_{2\rho} Z_{t-\rho} + v_t$$

$$\Delta Y_t = \beta_{03} + \phi_{3p} ect_{t-p} + \sum_{p=0}^n \beta_{13p} \Delta M_{t-p} + \sum_{p=0}^n \beta_{23p} \Delta MRP_{t-p} + \sum_{p=0}^n \beta_{33p} \Delta Y_{t-p} + \sum_{p=0}^n \beta_{43p} \Delta E_{t-p} + \sum_{p=0}^n \gamma_{3\rho} Z_{t-\rho} + \varepsilon_t$$

$$\Delta E_t = \beta_{04} + \phi_{4p} ect_{t-p} + \sum_{p=0}^n \beta_{14p} \Delta M_{t-p} + \sum_{p=0}^n \beta_{24p} \Delta MRP_{t-p} + \sum_{p=0}^n \beta_{34p} \Delta Y_{t-p} + \sum_{p=0}^n \beta_{44p} \Delta E_{t-p} + \sum_{p=0}^n \gamma_{4\rho} Z_{t-\rho} + \omega_t$$

Model 2 (export demand model)

$$\Delta X_t = \beta_{01} + \phi_{1p} ect_{t-p} + \sum_{p=0}^n \beta_{11p} \Delta X_{t-p} + \sum_{p=0}^n \beta_{21p} \Delta XRP_{t-p} + \sum_{p=0}^n \beta_{31p} \Delta YW_{t-p} + \sum_{p=0}^n \beta_{41p} \Delta E_{t-p} + \sum_{p=0}^n \gamma_{4\rho} Z_{t-\rho} + \mu_t$$

$$\Delta YW_t = \beta_{02} + \phi_{2p} ect_{t-p} + \sum_{p=0}^n \beta_{12p} \Delta X_{t-p} + \sum_{p=0}^n \beta_{22p} \Delta XRP_{t-p} + \sum_{p=0}^n \beta_{32p} \Delta YW_{t-p} + \sum_{p=0}^n \beta_{42p} \Delta E_{t-p} + \sum_{p=0}^n \gamma_{\rho} Z_{t-\rho} + v_t$$

$$\Delta XRP_t = \beta_{03} + \phi_{3p} ect_{t-p} + \sum_{p=0}^n \beta_{13p} \Delta X_{t-p} + \sum_{p=0}^n \beta_{23p} \Delta XRP_{t-p} + \sum_{p=0}^n \beta_{33p} \Delta YW_{t-p} + \sum_{p=0}^n \beta_{43p} \Delta E_{t-p} + \sum_{p=0}^n \gamma_{3\rho} Z_{t-\rho} + \varepsilon_t$$

$$\Delta E_t = \beta_{04} + \phi_{4p} ect_{t-p} + \sum_{p=0}^n \beta_{14p} \Delta X_{t-p} + \sum_{p=0}^n \beta_{24p} \Delta XRP_{t-p} + \sum_{p=0}^n \beta_{34p} \Delta YW_{t-p} + \sum_{p=0}^n \beta_{44p} \Delta E_{t-p} + \sum_{p=0}^n \gamma_{4\rho} Z_{t-\rho} + \omega_t$$

Where γ on both VECM equations represents the error coefficient, which estimates the speed of adjustment. It must carry a significant negative sign to show that the model reverts back to a state of equilibrium should there be any deviation between short-run and long-run dynamics in the system. The notation sign Δ on the other hand, is the first difference operator and is a vector of long-run parameters.

4.10 JUSTIFICATION OF VARIABLES

Import and export of goods and services are the two important components of trade balance used to measure the flow of goods and services in the economy. They reflect the total amount of goods and services exported and imported by the country in a specific period of time. In order to attain balance of payment stability it is required that the value of these two should be equal. If the value of exports happens to be greater than imports, we call it a trade surplus. If import exceeds exports, it is called trade deficit. Most economic theories, such as the mercantilist view of trade, postulate that an increase in export will eventually lead to an increase in economic growth, so it remains vitally important on both theoretical and empirical perspectives to study the behaviour of these two variables overtime. The only way to predict or influence the future behaviour of these two economic variables is through estimation of import and export demand elasticities. These elasticities serve as a prediction tool to discover how trade flows react to changes in the consumer's income, international prices, exchange rate and foreign exchange reserves. Policymakers need these elasticities to make informed policy decision that would help the country to achieve the desired objective.

Income variable (domestic and foreign income) is one of the most crucial and unavoidable determinants of a country's trade flows. Economic theory teaches us that an increase in domestic income leads to an increase in demand for foreign-produced goods and services, while an increase in incomes of the foreign countries (if it is our trading partner) leads to an increase in the demand for domestic-produced goods and services. However, this theoretical background does not always hold in all cases. The empirical literature teaches us that the magnitude of change in trade flows due to a change in income solely depends on the elasticity of demand, which exists within that country. Higher domestic income elasticity basically implies that a small increase in income will result in a huge change in the quantity of goods and services imported. This usually holds in countries where larger proportions of production inputs are being imported from other countries. Moreover, the imperfect substitution model of trade on the other hand, also predicts that there is a positive direct relationship between a country's export and foreign income. According to this model, an increase in the economic activities of foreign countries increases the demand for our domestically produced goods, *ceteris paribus*. Thus, in this study we expect all income coefficients to carry a positive sign. Foreign income is proxied by composite industrial production indices of advanced economies (following, Bahmani-Oskooee 1984;1986; and 2003) and other studies such as Tegene (1989;1991) and Ebadi (2015). No calculations have been performed in these variables. These variables are available in the IMF (IFS statistics data) website.

Exchange rate is also one of the most important determinants of trade volumes in any given trading economy. Trade of goods and services between economies involve monetary payments in foreign currencies such as US dollars, yen, pound and other major currencies in the world. Hence, for every imported good or service, South African citizens would have to make payments to the exporting country in terms of these currencies. The amount of each rand that a South African importing / exporting consumer would pay or receive in a particular day is quoted by the prevailing market exchange rate that exists between South Africa and its trading partners. The Mundel-Flemming model postulates that exchange rate appreciation causes exports to fall, and an increase in imports of the country whose currency has gained value, while currency depreciation (exchange rate depreciation) causes exports to rise and imports to decrease. Thus, estimation of exchange rate elasticity is very essential for trade policy-decision making. According to Orcutt (1950; Bahmani-Oskooee, 1986; Tegene, 1991; and Ebadi,2015), information on exchange rate elasticity help policy makers to decide whether exchange rate devaluation policy is relevant for the economy or not. There are no prior expectations in literature regarding the coefficient sign of the exchange rate elasticity. It can either be positive or negative. A positive coefficient of exchange rate will mean a currency appreciation (fall in exchange rate), which will cause export demand to decrease and imports demand to increase. In contrast, a negative coefficient will mean a currency depreciation, which will cause export demand to increase and demand for imports to decrease.

Relative prices (of imports and exports) is the most important determinant of trade flows found in the literature. Initially, estimation of trade elasticities was estimated with respect to prices alone before income was added as a second determinant (Vika, 2010). According to microeconomic theory, price is a major determinant of any demand and supply model. In the context of international trade, relative prices reflect the relative competitiveness of exports and imports of the country (Moniruzzaman, 2011). From the general law of demand, it is expected that when the relative price goes up quantity of imported goods demanded goes down and vice versa, *ceteris paribus*. The law of supply on the other hand states that when relative price goes up it causes the quantity of goods supplied (exported) to go up and vice versa, assuming other things have remained the same. Thus, in this study we expect the coefficient of relative prices to be negative for imports and positive for exports equations. Relative price elasticity also has a very important implication on policy making decisions because they help policy makers to decide whether expenditure switching policies are relevant or not. There is only one way of computing relative prices, that is; for relative price of imports:

$$mrp = \frac{PM}{PD}$$

where, PM and PD represent world import prices and domestic prices, respectively. As indicated in the table above, domestic prices are proxied by consumer price index (CPI), while world import prices are proxied by import unit value index of advanced economies.

For relative prices of exports

$$xrp = \frac{PX}{PXW}$$

where, PX and PXW are domestic prices of exports and world exports price, respectively. Again, as highlighted in the previous section, export prices are proxied by South African producer price index (PPI), while world export prices are proxied by the export unit value index for advanced economies.

4.11 DATA SOURCES AND DESCRIPTION OF VARIABLES

The sample of this research for the import demand function has 226 observations, starting from 1960:1 to 2016:3. However, due to data constraint our export demand function has only 103 observations spanning from 1990:1 to 2016:3. All time series data for this study is extracted from various secondary sources as presented in table 4.1. below:

Table 4.1. Data sources and description of units of measurement

Variable	Source	Description	Unit of measurement
Import (M)	SARB(KBP 6014)	Imports of goods and services at 2010 constant prices	R millions
Exports(X)	SARB(KBP 6013)	Exports of goods and services at 2010 constant prices	R millions
Domestic income(Y)	SARB(KBP 6006)	Gross domestic product at 2010 constant prices	R millions
World income(YW)	IMF(IFS)	Industrial production index for advanced economies	Index
Domestic prices(PD)	IMF(IFS)	Consumer price index	Index
Export prices(px)	IMF(IFS)	Producer price index	Index
World import prices(PM)	IMF(IFS)	Import unit value index for advanced economies	Index
World export prices(PXW)	IMF(IFS)	Export unit value index for advanced economies	Index
Exchange rate	IMF(IFS)	Units of foreign currency per unit of domestic currency	Index

Source: Author's table.

4.12 CONCLUSION OF THE CHAPTER

This chapter has given a comprehensive discussion of all the econometric techniques and tests that we intend to utilise in the empirical section of this study for the estimation of imports and exports demand models and empirical investigation of the Orcutt hypothesis in South African trade flows. In the first section we gave a detailed discussion of issues involving time series data modelling as well as appropriate remedies that need to be applied in resolving those issues. After the first section we then gave a detailed discussion regarding the concept of cointegration and also highlighted various issues related to various types of cointegration tests. Most importantly, in this chapter we also provided a comprehensive discussion of the Vector autoregressive models and their estimation processes. As part of cointegration analysis we also provided a comprehensive discussion of three cointegrating single equations; FMOLS, CCR and DOLS. Furthermore, a theoretical presentation of model specification has also been highlighted and illustrations of how each model has been derived are shown. Lastly, data sources, justification of selection of variables and econometrical reasoning of impulse response analysis and variance decomposition analysis have also been discussed in this chapter. The following chapter then provides all the empirical estimations of everything that have been discussed above.

CHAPTER 5: EMPIRICAL ANALYSIS OF RESULTS

5.1 INTRODUCTION

As previous chapters have already established, the primary objective of this study is to estimate trade functions and investigate the Orcutt (1950) hypothesis in the South African context. Therefore, the objective of this chapter is twofold. Firstly, it outlines the empirical estimation approaches used to quantify the relationship between trade flows and its regressors and to test for the Orcutt (1950) hypothesis. Secondly, it provides the presentation and interpretation of all empirical findings.

Among other things contained in this chapter, the first part, **Section 5.2** presents data issues and preliminary analysis of the series in order to understand and observe how the series utilised in the study has been behaving overtime. This includes a presentation of basic graphical plots of each variable. Graphical plots are the informal way of checking stationarity in time series data. Periods of economic tragedies (such as recession, sanctions, policy changes, etc.) can also be observed during this process by tracing the trends of the series. **Section 5.3** is concerned with stationarity issues or determination of the order of integration of each variable. This process is executed through the use of the Augmented Dickey Fuller (ADF) and the Phillips-Perron (PP) tests. **Section 5.4 and 5.5** presents all the estimations of VAR and VECM processes and presentation and coefficients interpretation of estimated results, respectively. **Section 5.6** includes the presentation and interpretations of generalised impulse response functions generated from the VECM system. The diagnostic tests of each VECM system is presented in **Section 5.7**. Moreover, **Section 5.8** then presents the results of the FMOLS, DOLS, and CCR models as confirmatory estimation models to VECM as a multi-variable model. The summary of the overall results and the conclusion of the chapter is presented in **Section 5.9**, and **5.10**, respectively.

5.2 PRELIMINARY ANALYSIS OF DATA

As presented in Chapter 4, the time series data for import volumes, export volumes and domestic income (gross domestic product) are sourced in millions of Rands. Meanwhile, the other remaining variables are sourced as indices. All series under investigation will be transformed into natural logarithmic using Eviews 9.5 version, except those sourced in percentage form. The benefit of logarithmic transformation is that it allows the researcher to interpret all estimated coefficients as partial elasticities.

After transforming all variables into logarithmic form, the second step we took before conducting any empirical analysis is we examined the basic features of the data series being investigated in order to understand and observe any internal structure of the series (such as outliers, autocorrelation and seasonal changes) that should be accounted for in judging the validity of the estimated results.

5.2.1 Graphical Inspection of the Data

The graphical inspection of data utilised in this study is conducted by plotting the observations of each variable against time, both in levels and first differenced form. Consequently, Figure 5.1(a) and 5.1(b) below display the results of graphical plots of each variable in levels included in model 1 (import demand) and 2 (export demand), respectively. Accordingly, Figure 5.1(c) and (d) display graphical plots of each variable in first difference for model 1 and model 2, respectively. The results show that all variables are likely to be non-stationary in levels and become stationary after first differencing.

The results shown in figure 5.1(a) and (b), demonstrates that domestic income ($\ln Y$), foreign income ($\ln YW$), exports ($\ln X$), imports ($\ln M$), and relative price of exports ($\ln XRP$) are showing an upward trend, while, the relative price of imports ($\ln MRP$) and nominal effective exchange rate ($\ln NEER$) exhibit a downward trend. On the other hand, the results of figure 5.1(c) and (d) show that when plotted in their first difference form all variables tend to revert around their mean. Thus, on the basis of this visual inspection we may suspect that the series under observation is integrated of order one $I(1)$. In order to make conclusive judgement and to confirm the researcher's suspicion, statistically reliable unit root tests are computed in section 5.3 of this chapter.

Figure 5.1(a) Graphical plots in levels

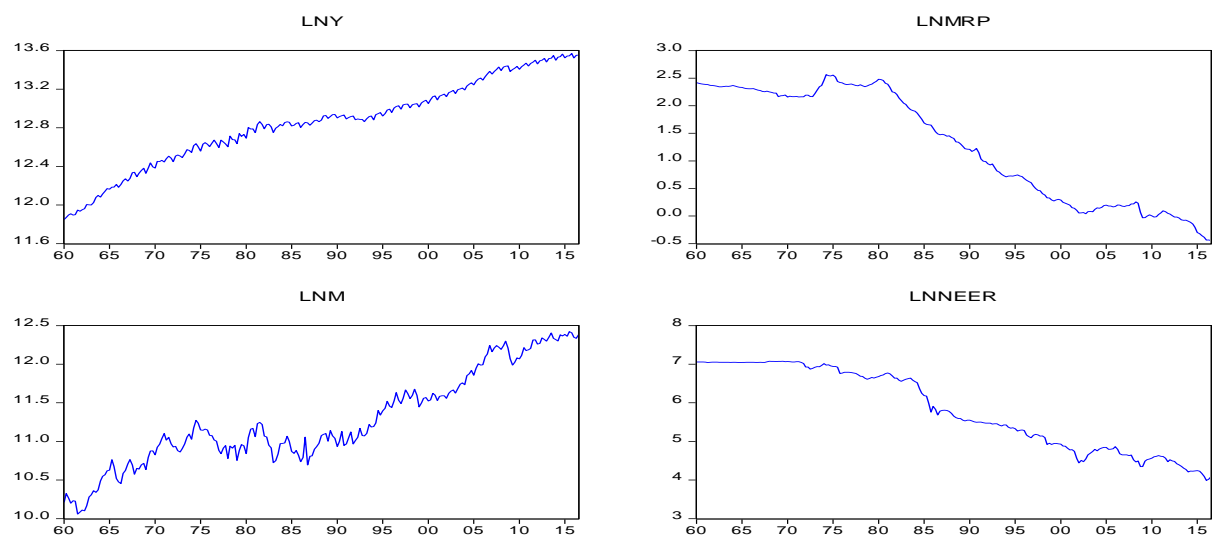
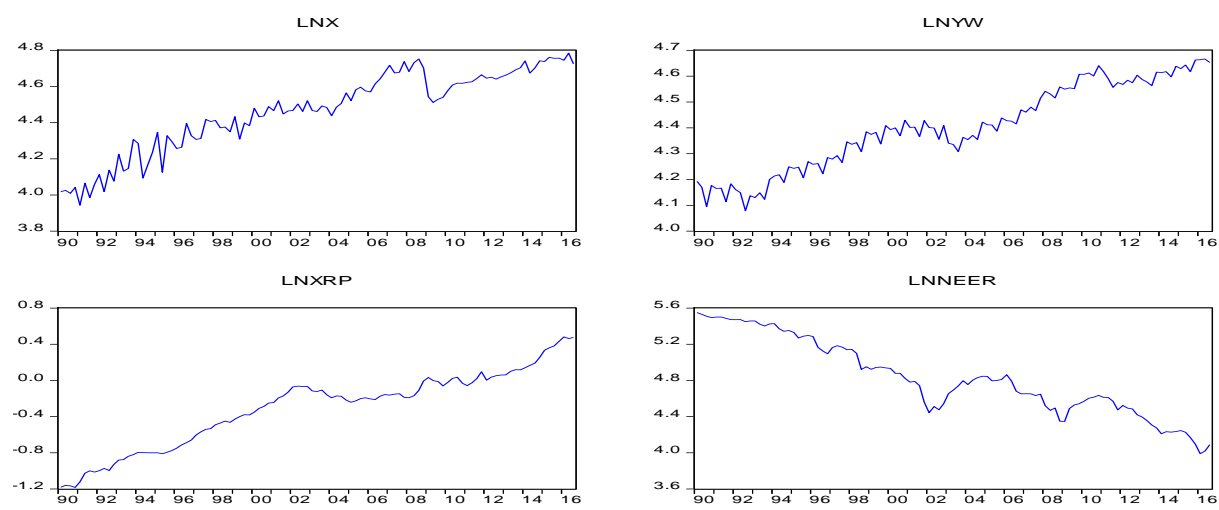


Figure 5.1(b) Graphical plots in levels



Source: Generated by the researcher, using Eviews 9.5

Figure 5.1(c) Graphical plots in 1st difference

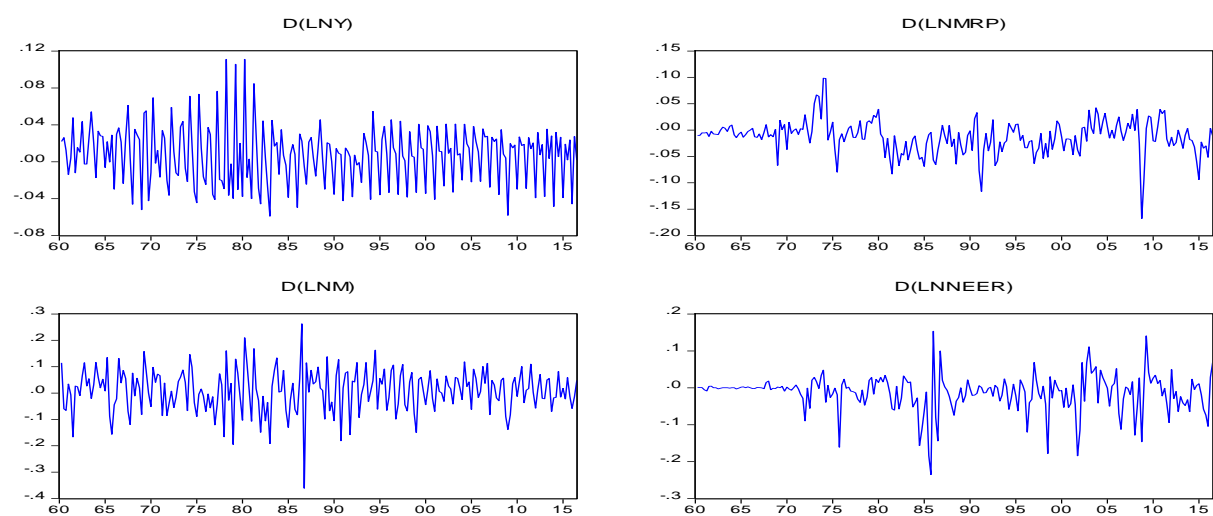
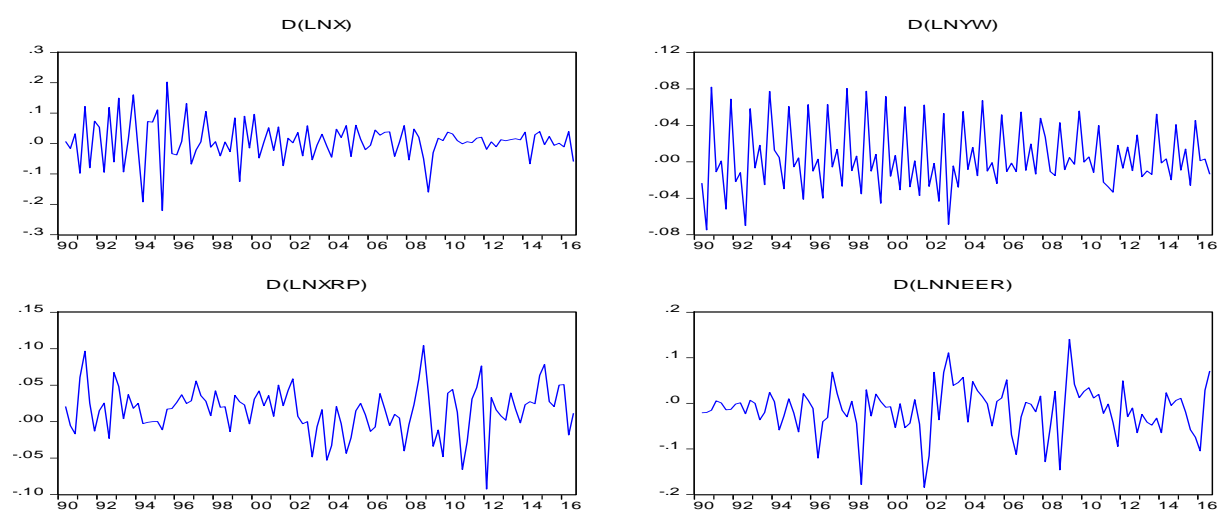


Figure 5.1(d) Graphical plots in 1st difference



Source: Generated by the researcher, using Eviews 9.5

5.2.2. Descriptive Statistics of Each Variable in Logarithmic Form

Descriptive statistics is a very important part of data visual inspection which gives a clear view of the distribution of each variable to be utilised in the study. Accordingly, table 5.1 (a) and (b) below present the descriptive statistics of model 1(import demand) and model 2(export demand) variables employed in this study, respectively.

Table 5.1(a) Descriptive statistics for model 1 variables

	LN Y	LNMRP	LN M	LNNEER
Mean	12.84731	1.273375	11.27068	5.817697
Median	12.87857	1.407592	11.09267	5.653600
Maximum	13.56929	2.563541	12.42111	7.078126
Minimum	11.84938	-0.444762	10.05899	3.989340
Std. Dev.	0.443685	0.999959	0.610664	1.039832
Skewness	-0.311089	-0.155164	0.322668	-0.097634
Kurtosis	2.414436	1.365718	2.223759	1.426281
Jarque-Bera Probability	6.904488 0.031674	26.17292 0.000002	9.638122 0.008074	23.78507 0.000007
Sum	2916.339	289.0561	2558.445	1320.617
Sum Sq. Dev.	44.48961	225.9817	84.27770	244.3625
Observations	227	227	227	227

Source. Author's own table, computed using Eviews 9.5

As per the results of the descriptive statistics of model 1 variables displayed in table 5.1(a) above, it appears that all variables of model 1 follow a normal distribution pattern since their mean values and medians are relatively equal and their respective skewness values are also close to 0. It can also be seen that domestic income (lnY), relative price of imports ($lnMRP$), and nominal effective exchange rate ($lnNEER$) contain relatively larger left-tails (negatively skewed), while imports (lnM) is skewed to the right. The respective values of maximum and minimum descriptive statistics of each variable suggest that domestic income, relative price of imports, and imports have been fairly stable over the period covered in this study, except nominal effective exchange rate. However, it should also be noted that all variables are follow the platykurtic distribution, since their respective kurtosis values are slightly lower the standard norm of 3, except relative import prices and exchange rate. These lead us to a suspicion of non-normality distribution among the series. The trusted method of testing for normality in the time series is the Jarque-Bera test, known as the J-B test. According to this test, a normal distributed series should have a skewness and kurtosis value of 0 and 3, respectively. Hence, based on the J-B statistic values and its respective p-values of each variable it appears that all variables under observation are actually not normally distributed.

Table 5.1(b) Descriptive statistics for model 2 variables

	LN _{YW}	LN _{XR}	LN _X	LN _{NEER}
Mean	4.402660	-0.309220	4.462381	4.845435
Median	4.400749	-0.192488	4.488636	4.790570
Maximum	4.666375	0.481687	4.784153	5.703249
Minimum	4.078917	-1.183295	3.943522	3.975686
Std. Dev.	0.164897	0.422300	0.222472	0.457854
Skewness	-0.112720	-0.384288	-0.603564	0.243793
Kurtosis	1.881569	2.316535	2.382185	2.064897
Jarque-Bera Probability	5.803463 0.054928	4.716174 0.094601	8.198223 0.016587	4.958369 0.083812
Sum	471.0846	-33.08652	477.4747	518.4616
Sum Sq. Dev.	2.882232	18.90371	5.246345	22.22081
Observations	107	107	107	107

Source: Author's own table, computed using Eviews 9.5

The descriptive statistics of the model 2 variables displayed in the above also appear to share the same characteristics as the one shown in table 5.1(a) for model 1 variables. The Jarque-Bera statistics values and their respective p-values for each variable suggest that model 2 variables are also not normally distributed. According to the results, world income (*ln_{YW}*), relative price of exports (*ln_{XR}*), and exports (*ln_X*) are skewed to the left-hand side of the distribution table, while nominal effective exchange rate (*ln_{NEER}*) is positively skewed to the right. However, it should be noted that the mean and median values of each variable are not too different from each other and their standard deviation values are not too high. In addition, the Kurtosis values are also not too low and the p-values of the JB test are not too significant, except world income, which contains a kurtosis value of 1.88. Note: the reason why nominal effective exchange rate is negatively skewed in model 1 and positively skewed in model 2 is because of different sample sizes utilised in each model.

5.3 STATIONARITY TESTS/UNIT ROOT TESTING

From the graphical inspection conducted in section 5.2. above it has been established that the series being investigated are more likely to be non-stationary and can be stationarised by first differencing them. The main aim of this section is to verify the results reflected by the graphical plots and establish the order of integration of each variable under investigation using the Augmented Dickey-Fuller and the Philips Perron test. As indicated in the previous chapter (Chapter 4), these two tests examine the null hypothesis which states that the series has a unit root. The decision rule of either accepting or rejecting this hypothesis is taken on the basis of comparing the calculated statistic values (also known as the *tau statistic*) of each test with the corresponding MacKinnon (1996) critical values. If the calculated statistic, or the *tau statistic* value, is found to be greater than the corresponding MacKinnon (1996) critical value, then the null hypothesis is rejected in favour of the alternative hypothesis. This will therefore draw a conclusion that the series has no unit root. Alternatively, if the calculated statistic value is found to be less than the critical value, the null hypothesis is accepted and concludes that the series has a unit root. Accordingly, table 5.2(a) and (b) below present the unit roots results of each variable under investigation.

Table 5.2(a) Unit root tests for model 1 variables

ADF TEST				P-P TEST				
	t-value	Lag	t-value	Lag	t-value	N.W.B	t-value	N.W.B
C	Levels		1 st Difference		Levels		1 st Difference	
<i>ln_M</i>	-0.9648	6	-7.3561***	5	-0.6958	9	-17.3946***	9
<i>ln_Y</i>	-2.2359	8	-4.1427***	7	-2.7296	15	-22.8123***	14
<i>ln_{MRP}</i>	0.6434	1	-8.9533***	0	0.6685	8	-9.7973***	7
<i>ln_{NEER}</i>	0.1011	3	-6.5787***	2	0.3924	6	-12.6510***	6
T & C								
<i>ln_M</i>	-2.1607	8	-7.3303***	5	-2.6550	10	-17.3542***	9
<i>ln_Y</i>	-3.0676	8	-4.4855***	7	-3.2174	14	-24.3423***	14
<i>ln_{MRP}</i>	-1.8023	1	-9.0537***	0	-1.7659	8	-9.8542***	7
<i>ln_{NEER}</i>	-2.7567	3	-6.6074***	2	-2.516	6	-12.6694***	12
None								
<i>ln_M</i>	2.5733	6	-5.1230***	7	-2.2853	9	-16.8398***	9

lnY	3.1014	8	-2.2983***	7	6.2134	15	-18.4446***	13
lnMRP	-1.8504	3	-5.0724***	2	-2.1591	9	-8.6310***	8
lnNEER	-2.5466	3	-5.9595***	2	-	7	-12.2784***	7
					3.1943**			

Note: ***, ** represent 1% and 5% level of significance, respectively. The number of lags in the ADF test are decided by AIC. N.W.B represent Newly-West Bandwidth selection for the P-P test is decided by Barlett Kernel.

Source: Author's own table

Table 5.2(a) above shows that the results of both tests (ADF and P-P) agree that the null hypothesis of the presence of unit root cannot be rejected when *LN*, *LNMRP*, *LNNEER*, and *LN* are in levels. This means that the series under investigation are stochastic in nature and have no constant mean or variance. However, after first differencing, both tests concur that the null hypothesis should be rejected in all variables. Therefore, this concludes that all model variables are I(1) in levels and they only become unit root free (stationary) after first difference. Hence, they are first difference stationary or integrated of order one I(0), confirming the results established by the graphical plots presented in figure 5.1 (a) and (c) above.

Table 5.2(b) Unit root tests for mode 2 variables(exports)

ADF TEST				P-P TEST				
	t-value	Lag	t-value	Lag	t-value	N.W.B	t-value	N.W.B
C	Levels		1 st Difference		Levels		1 st Difference	
lnX	-1.7172	4	-9.5628***	2	-1.6981	7	-19.2459***	4
lnYW	-1.0771	8	-2.8001*	7	-0.3910	11	-18.9284***	9
lnXRP	-0.9076	1	-8.0049***	0	-0.9232	2	-7.9586***	2
lnNEER	-0.6135	0	-8.2536***	0	-0.6135	0	-8.2037***	2
T & C								
lnX	-2.6903	4	-9.6439***	2	-5.1999	8	-19.4238***	4
lnYW	-3.5924	8	-2.7894	7	-5.8291	10	-18.8146***	9
lnXRP	-2.0160	1	-7.9781***	0	-1.8371	3	-7.9298***	2
lnNEER	-2.739973	1	-8.2096***	0	-2.5223	3	-8.1583***	2
None								
lnX	2.6640	3	-5.4427***	3	2.0919	7	-18.1992***	6
lnYW	2.0745	8	-1.8298***	7	2.5255	11	-16.3961***	9
lnXRP	-2.6332	1	-6.8568***	0	-2.8742	5	-6.8785***	4
lnNEER	-	0	-7.8680***	0	-2.7489***	0	-7.8243***	2
	2.7489***							

Note: ***, ** represent 1% and 5% level of significance, respectively. The number of lags in the ADF test are decided by AIC. N.W.B represent Newly-West Bandwidth selection for the P-P test is decided by Barlett Kernel.

Source: Author's own calculations

Table 5.2(b) above shows unit roots results for model 2 variables, tested both in levels and first difference form. According to the results of both tests (ADF and P-P) it appears that all model 2 variables are also non-stationary in levels and only become stationary after differencing. This also suggests that model 2 variables are I(1) in levels and in order to make them stationary, or I(0), they need to be tested in their first difference form. However, one may notice that some variables are demonstrating some stationarity conditions where no intercept and trend were included. We decided to ignore these results, since from the graphical inspection observations, the variables possess both trends and intercepts. Therefore, the final conclusion that we can make about these results is that all variables have the same order of integration. Now, since the order of integration has been identified for all the variables, the next task is to investigate if there are any cointegrating relationships among the variables appearing in models one and two. To do that this study employed the Johansen cointegration technique for multivariate models. However, since we are using the VAR/VECM technique, the next procedure is to generate the Johansen cointegration test from the VAR output. Thus, the first task before testing for cointegration is to estimate the unrestricted VAR models for both mode 1 (import demand) and 2 (export demand), respectively.

5.4 VAR MODEL SELECTION PROCESS

This section of this chapter is rooted in two tasks: the selection of an appropriate VAR lag length and VAR stability test. If the VAR system is found to be unstable, the following section will then focus on deciding on the appropriate model needed for the Johansen cointegrating VAR model.

5.4.1. VAR Lag-order (p) Selection

As discussed in the previous chapter, lag selection is one of the important aspects of specifying a correct VAR and the subsequent VECM model. The importance of determining the correct lag length is demonstrated by Braun and Mitnik (1993) as cited by Mazenda (2014), who emphasised that estimates of a VAR whose lag length differs from the true lag length, are inconsistent as are the impulse response functions and variance decompositions derived from the estimates of VAR. Moreover, Lutkepohl (1993) on the other hand also argues that over-fitting of lag length increases the mean-square-forecast errors of the VAR system, while under-fitting generates auto-correlated errors. Thus, before running a VAR system it is always imperative that the lag length for the VAR system is correctly identified. For this study, the optimal lags to be utilised in the estimation process are generated from the unrestricted VAR output produced by Eviews.

Accordingly, the results of model 1 reported in table 5.3(a) and displayed in the appendix section (Appendix B) indicate that the suitable optimal lag length for model 1 is five lags. These results were decided on the basis of both Aikaike, and Swartz information criteria and they are also supported by the estimates of FPE and HQ tests. For model 2 the results reported in table 5.3(b) demonstrate that the Swartz information criteria leads to the selection of an appropriate lag length of one lag, while AIC, FPE and HQ criteria suggest an appropriate minimum lag length of six lags. In this case, considering the size of our sample, the researcher decided to adopt the estimates of six lags as an appropriate lag length for export demand model as recommended by FPE and AIC, as well as the HQ. This concludes that the fifth order ($p = 5$) and sixth order ($p = 6$) VAR for import and export demand model should be estimated in this study, respectively. After estimating the unrestricted VAR model, the next step is to perform the stability test of the VAR system since our variables are integrated of order one.

Table 5.3(a) Lag selection criteria for model 1 (import demand)

Lag selection criterion.						
lag	LogL	LR	FPE	AIC	SIC	HQ
0	-11.99568	NA	1.36e-05	0.146079	0.207980	0.17079
1	1490.160	2935.719	1.73e-11	-13.42612	-13.11661	-13.30112
2	1533.684	83.47091	1.35e-11	-13.67748	-13.12037	-13.45248
3	1575.678	79.00299	1.06e-11	-13.91487	-13.11016	-13.58987
4	1679.455	191.4414	4.78e-12	-14.71648	-13.66417	14.29148
5	1733.707	98.09982	3.37e-12*	-15.06581*	-13.76590*	-14.54082*
6	1746.097	21.95230	3.49e-12	-15.03285	-13.48533	-14.40785

* indicates lag order selected by the criterion
 LR: sequential modified LR test statistic (each test at 5% level)
 FPE: Final prediction error
 AIC: Akaike information criterion
 SC: Schwarz information criterion
 HQ: Hannan-Quinn information criterion

Source: author's own calculations

Table 5.3(b) Lag selection criteria for model 2 (export demand)

Lag selection criterion.						
lag	LogL	LR	FPE	AIC	SC	HQ
1	709.6089	N/A	9.65e-12	-14.01230	-13.59289*	-13.84261
2	737.0566	50.45924	7.67e-12	-14.24357	-13.40474	-13.90418
3	753.3537	28.64346	7.65e-12	-14.24957	-12.99133	-13.74048
4	78.2975	45.17845	6.17e-12	14.47066	12.79300	-13.79187
5	830.3880	79.94368	3.14e-12	-15.15937	-13.06230	-14.31089*

6	853.6550	35.25186*	2.75e-12*	-15.30616*	-12.78968	-14.28799
7	862.2736	13.79636	3.21e-12	-15.17724	-12.24135	-13.98938

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

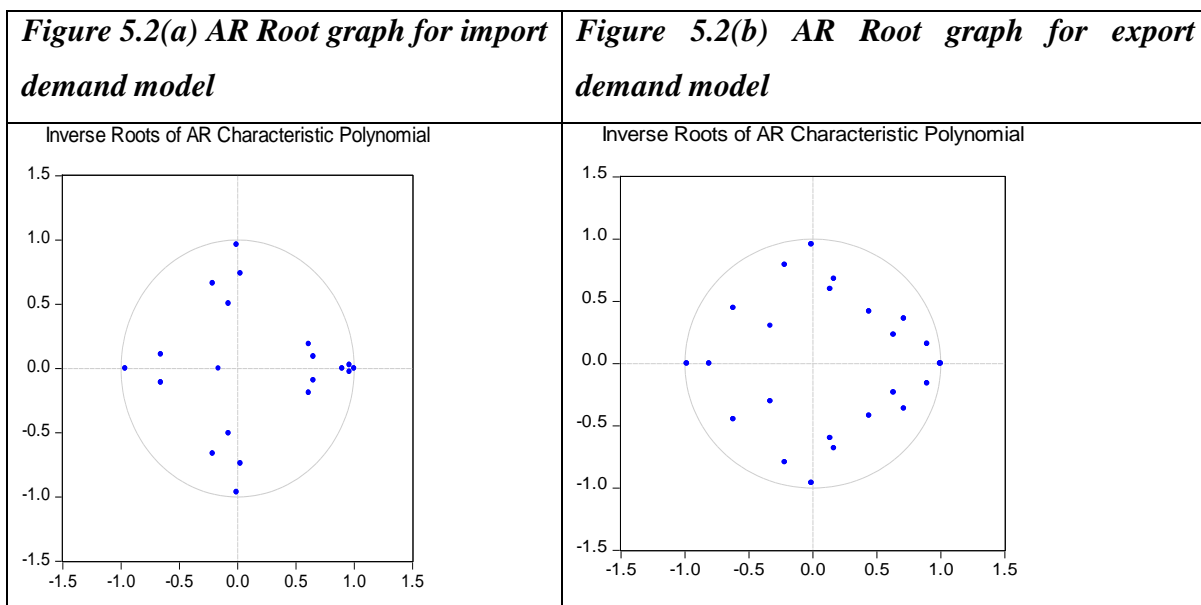
Source: Author's own calculations

5.4.2 Unrestricted VAR stability tests and cointegration

The AR root and the polynomial characteristic root table are utilised to examine the stability of VAR processes estimated in this study. According to Lutkepohl (2004b), if all the roots have less than one modulus, it means that all variables included in the VAR system are actually $I(0)$ and they require no first differencing. The Johansen cointegration approach on the other hand also postulates that once cointegrating relationships have been identified in the system, it automatically cancels out the relevance of the VAR system and necessitates the use of VECM.

From the estimated results based on the polynomial characteristic root circle presented in figure 5.2 (a) and (b) respectively as labeled below, it can be seen that both models contain root points that are too attached to the circle but not really outside the boundary of the root circle. Moreover, the AR root tables, on the other hand, also contain a root modulus very close to 1. The VAR system for model 1 (import demand) has the highest modulus of 0.998086 which is almost equal to 1. Model 2 (export demand), on the other side, also shows similar results with the highest modulus of 0.999254, which is also very close to 1. According to the rule, the VAR system ought to be stable if all the points are within the root circle. In the polynomial root table, the VAR stability is satisfied if the root modulus is strictly less than 1. Therefore, the results indicate that the VAR system for both models might be unstable which provide the motivation to estimate the Johansen VECM for both models. The analysis of both impulse response and variance decomposition functions will also be generated from the estimated VECM system. However, the original estimated output of the VAR system from which the VECM systems are derived is displayed in the appendix section (see, appendix C, table A1 (a) and (b)).

AR ROOT GRAPHS



Source: Author's own table, computed using Eviews 9.5

AR ROOT TABLES

Table 5.4(a) AR Root table for import demand model (Model 1)	Table 5.4(b) AR Root table for exports demand model (Model 2)																																																																																												
Roots of Characteristic Polynomial Endogenous variables: LNY LNMLNMRP LNNEER Exogenous variables: C Lag specification: 1 5 Date: 11/11/17 Time: 16:11	Roots of Characteristic Polynomial Endogenous variables: LNYW LNXRP LNX LNNEER Exogenous variables: Lag specification: 1 6 Date: 11/11/17 Time: 16:18																																																																																												
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Source: Author's own calculations

5.5. VECM ESTIMATION PROCESS

The results of the AR root table and the polynomial characteristic in the above sub-section indicate that the series under investigation are actually integrated of order $I(1)$ and can thus be best analysed within the VECM framework. Next, we sought to test for cointegration among the series using the Johansen cointegration test before we went on to derive the VECM systems for both models. If cointegration within the estimated equations is identified, it will provide solid proof that the variables are indeed sharing a long-run relationship and they need to be estimated within the VECM system. However, before doing that, the first port of call is the identification of the deterministic component that needs to be ascertained in the Johansen cointegration test from the unrestricted VAR output.

5.5.1 Model Identification for Cointegrating Relations

In order for the cointegrated VAR model to be correctly specified or estimated, the correct identification of a number of cointegrating relations by the model is necessary. Cointegrating relationships in cointegrated VAR equations can be explained in five model cases (as discussed in the previous chapter). **Case 1:** constant with no trend and intercept model, **Case 2:** constant with intercept but no trend model, **Case 3:** Linear with intercept but no trend model, **Case 4:** linear with trend and intercept model and **Case 5:** quadratic-with intercept and trend model. Case 2, 3 and 4 are normally labelled as structural intercept VAR with no trends, unstructured intercept VAR with no trends and unstructured intercept VAR with structured trends, respectively. In practice, models presented by case 1 and 5 are rarely used because they are too far away from true exhibition behavior of most macroeconomic time series. They can only be applied if there are strong economic reasons. Thus, only models presented by case 2, 3 and 4 will be considered in this study. The decision rule regarding the appropriate model for this study will be decided following the Pantula principle advocated by Johansen (1992). According to Johansen (1992), the appropriate way of choosing a suitable model should be that all cases are estimated and the smallest r value based on Trace and Max-Eigen statistic is adopted. Hence, as per the results presented in table 5.5(a) (model 1) and table 5.5(b) (model 2) below show that the lowest r value decided by both Trace and Max-Eigen statistics under case 3 on both models (respectively) as suggested by the Pantula principle. Also note that case 3 suggests that the series under investigation contain a linear deterministic trend component, therefore the VECM system should be based on intercept and contain no trend on both models.

Table 5.5(a) Summary of cointegrating test assumptions for model 1(import demand)

Data Trend:	None	None	Linear	Linear	Quadratic
Test type	No intercept	With intercept	With intercept	Intercept	Intercept
	No trend	No trend	No trend	Trend	Trend

Trace	2	2	1	1	4
Max-Eig	2	2	1	1	0

****critical values based on Mackinnon-Haug-Michelis (1999)***

Source: Author's own calculations

Table 5.5(b) Summary of cointegrating test assumptions for model 2(export demand)

Data Trend:	None	None	Linear	Linear	Quadratic
Test type	No intercept No trend	With intercept No trend	With intercept No trend	Intercept Trend	Intercept Trend
Trace	2	2	1	1	1
Max-Eig	0	1	1	1	1

***critical values based on Mackinnon-Haug-Michelis (1999)**

Source: Author's own calculations

5.5.2 Identification of Cointegrating Vectors

The long-run relationship tested in this study involves the long-run co-integrating properties logarithmic data of imports, domestic income, relative prices, and logarithmic of nominal effective exchange rate. Therefore, as discussed in the previous chapter the Johansen cointegration test is based on two likelihood ratios: trace and maximum-Eigenvalue statistic. Each of these two tests have different approaches of testing for cointegration but they usually provide similar results. The trace statistic tests the null hypothesis that $r \leq k$ (assuming that r and k represent the number of cointegrating vectors and variables, respectively) against the alternative. The maximum-Eigenvalue, on the other hand, examines the null hypothesis of the number of co-integrating variables is r against the $r + 1$ alternative hypothesis (Asteriou and Hall, 2016). For both tests, the decision rule states that if the calculated statistic value exceed the corresponding critical value, then the null hypothesis is rejected and the opposite is true if the calculated statistic is less than the corresponding critical value. Moreover, both tests are sequential testing techniques. That is to say, if the number of co-integrating relationships is at almost zero, the null hypothesis is rejected in favor of the alternative.

As per the results presented in table 5.6(a) and 5.6(b) below, both trace and max-Eigenvalue reject the null hypothesis of $r = 0$ since their t-statistic values of 67.88667 and 42.33717 (respectively) exceed their corresponding 5% critical values of 47.85613 and 27.58434, respectively. However, both tests could not reject the null hypothesis of, at most, one co-integrating equation, since their t-statistic values are less than their corresponding critical values. This concludes that there is only one co-integrating relationships among the variables on both model 1 and 2, respectively. Hence, this also further justifies that VECM is indeed an appropriate estimation technique for this study.

Table 5.6(a) Johansen unrestricted cointegration rank for model 1(import demand)

Unrestricted cointegration rank (Trace test)				
No. of Hypothesised cointegrated Eq(s)	Eigenvalue	Trace Statistic	5% Critical value	Prob**
None*	0.173626	67.88667	47.85613	0.0002
At most 1	0.058262	25.54951	29.79707	0.1427
At most 2	0.048646	12.22328	15.49471	0.1465
At most 3	0.005177	1.152286	3.841466	0.2831
Trace test indicates 1 cointegrating equation at 5% level				

Unrestricted cointegration rank (Max-Eigenvalue)				
No. of Hypothesised cointegrated Eq(s)	Eigenvalue	Max-Eigenvalue Statistic	5% Critical value	Prob**
None*	0.173626	42.33717	27.58434	0.0003
At most 1	0.058262	13.32622	21.13162	0.4227
At most 2	0.048646	11.07100	14.26460	0.1507
At most 3	0.005177	1.152286	3.841466	0.2831
Max-Eigenvalue indicates 1 cointegrating equation at 5% level				

Note:* denotes rejection of the null hypothesis at 5% level, ** are the P-values by Mackinnon-Haug-Michelis (1999)

Source: Author's own table, computed using Eviews 9.5

Table 5.6(b) Johansen unrestricted cointegration rank for model 2 (export demand)

Unrestricted cointegration rank (Trace test)				
No. of Hypothesised cointegrated Eq(s)	Eigenvalue	Trace Statistic	5% Critical value	Prob**
None*	0.250859	55.56211	47.85613	0.0080
At most 1	0.148866	26.39051	29.79707	0.1175
At most 2	0.077329	10.11070	15.49471	0.2723
At most 3	0.019432	1.981962	3.841466	0.1592
Trace test indicates 1 cointegrating equation at 5% level				

Unrestricted cointegration rank (max-Eigenvalue)				
No. of Hypothesised cointegrated Eq(s)	Eigenvalue	Max-Eigenvalue Statistic	5% Critical value	Prob**
None*	0.250839	29.17160	27.58434	0.0310
At most 1	0.148866	16.27981	21.13162	0.2089
At most 2	0.077329	8.128742	14.26460	0.3658
At most 3	0.019432	1.981962	3.841466	0.1592
Max-Eigenvalue indicates 1 cointegrating equation at 5% level				

Note:* denotes rejection of the null hypothesis at 5% level, ** are the P-values by Mackinnon-Haug-Michelis (1999)

Source: Author's own table, computed using Eviews 9.5

5.5.3 Vector Error Correction (VECM) Estimated Results and Interpretation

As a result of cointegration, the VECM results of one co-integrating relationships for both models are estimated and presented in table B11(a) and B11(b) in Appendix B. In the estimation process, imports and exports in their respective models were normalised to 1 to allow for meaningful economic interpretation of the results. The appropriate number of lags for model 1 is four lags (p-1), with five lags for model 2 as decided by AIC, SC, FPE and HQ as shown in section 5.4 above (see table 5.3(a) and 5.3(b), respectively). As indicated by table 5.6(a) and 5.6(b) above, assumption 3, using trend and no intercept, was utilised on both models.

The important element of the Johansen multivariate procedure is that it requires that all variables should be endogenous and interdependent on each other (Feddersen, 2013). However, it is also possible, on the basis of economic theory, to treat certain variables as weakly exogenous in the estimation process of long-run relationship among the variables (Feddersen, 2013). This helps, not explore the existence of long-run relationship that is conditional on weakly exogenous variables in the system, but it also to relate the empirical estimation to the realistic nature of the variable in relation to the dependent variable, as suggested by economic theory. Ignoring the economic theory assertion often results to the loss of power, invalidates the results and makes any further tests generated from the system spurious. Therefore, the ordering of variables utilised in this study is determined on the basis of economic theory. For model 1, domestic income (lnY) proxied by gross domestic product was entered as a highly exogenous variable in the system because of its relative lack of sensitivity to changes in relative prices, imports and exchange rates, as suggested by the economic theory. The second variable entered in the system was relative prices of import because of its sensitivity to domestic income. Thus, it is assumed to be affected by the contemporary value of income and to lags of imports and exchange rate. The nominal effective exchange rate is considered as a highly endogenous variable, i.e. it is affected by the contemporary values of all the variables in the system; hence it

was entered last in both models. The other variables utilised in the specification of the export demand model took the following order: foreign income (WY), relative price of exports (XRP), and lastly, exports (X).

hence, *model 1 = lnY, lnmrp, lnm, lnneer*

model 2 = lnyw, lnxrp, lnx, lnneer

After cointegration has been ascertained on each system, the next task is the normalisation of the third variable (dependent variable) in each system (which is *lnm* and *lnx*, respectively). As indicated earlier on, normalisation is important because it allows for the interpretation of coefficients in an economically meaningful way. Below is the presentation and economic interpretation of long-run coefficients for both models.

a). Long run estimates of import and export demand models

Equation 5.7.1 below illustrates the long-run effects of the natural log of domestic income, relative price of imports, as well as the natural log of nominal effective exchange rate on South African imports. The values underneath represent standard errors (in round brackets) and the t-statistics of each long-run coefficient (in square brackets), respectively.

Model 1 (import demand)

$$\ln M_t = -14.02348 + 1.732 \ln Y_t - 0.655 \ln MRP_t + 0.665 \ln NEER_t \quad (5.7.1)$$

s.e (0.17395) (0.17833) (0.20604)

t – statistic [9.95697] [-3.67191] [3.22520]

The above results were extracted from the Eviews generated results presented in Appendix B, Table B11. Note that the coefficients presented in equation 5.7.1 are opposite to those presented in Table B11, because they appear in an ECM format with a lag in the table. The results show that the individual coefficient signs of all variables are in correspondence with all theoretical and prior expectations of this study stated in the previous chapter and they are all statistically significant. The results show that the long run income elasticity of South African imports demand is 1.73 (significant at the 1% significance level), meaning that a 1% increase in domestic income will cause demand for imported goods and services in South Africa to increase by 1.73% per quarter, holding other factors constant. This may signify the role of imports in satisfying production shortages in the domestic market, especially for consumer goods and intermediate inputs. Similar results are quite evident in the literature. For example, Narayan and Narayan (2010) found that the income elasticity of South Africa’s import demand is 1.67. Gumede (2000) on the other hand, estimated the income elasticity of import demand to be 2.04% which was slightly higher than the estimates of the most recent studies. Nonetheless, it is now part of the common knowledge in the South African empirical literature that South Africa’s import demand with respect to domestic income is relatively elastic, which might indicate that in a booming economy more intermediate and capital goods are demanded for domestic production and the reverse occurs in a weak economy, especially since South Africa’s production processes are heavily reliant on imported inputs. Furthermore, and to a lesser extent it is plausible that consumers can easily switch to import substitutes (when incomes fall) which in turn reflects a relatively high degree of industrialisation. In terms of the international monetary fund (IMF) grouping of countries, South Africa, China, Brazil, India and others are classified as newly industrialised economies. This could be a reasonable explanation for this high income elasticity.

The estimated price elasticity for imports demand for this present study is -0.66 and it is significant at 1% level of significance. This coefficient suggests that, a 1% increase in relative import prices causes import demand to fall by 0.66% per quarter, *ceteris paribus*. This relatively low price elasticity (-0.66) suggests that the application of commercial policy as a primary tool for domestic demand management would be ineffective to stabilise the current external balance of payments position of this country. Perhaps, outward oriented policies should be adopted to gauge the gap between imports and exports by discouraging imports. According to the results, consumers or economic agencies appear to be much more sensitive to income changes than to price changes which also suggest that income policy could also play a great role in restraining unnecessary import demand. However, since an alternative policy is exchange rate devaluation, it is necessary to assess its effectiveness in influencing the behavior of imports in this country.

According to the results presented in equation 5.7.1 above, the import demand elasticity with respect to exchange rate (units of foreign currency per unit of domestic currency) is 0.66% and is significant at the 1% significance level. This coefficient suggests that a 1% appreciation in the South African currency causes import demand to improve by 0.66% per quarter, *ceteris paribus*. The inelastic response of import demand to exchange rate movement is indicative of the reality that South Africa’s imports are comprised largely of

essential intermediate inputs necessary for the production processes. Hence import demand is not highly responsive to exchange rate movements.

Model 2 (export demand)

$$\ln X_t = 4.7431 + 0.35250 \ln YW_t - 0.0255 \ln XRP_t - 0.3801 \ln NEER_t \quad (5.7.2)$$

$$s.e \quad \quad \quad (-0.19541) \quad \quad (-0.17085) \quad \quad (-0.17462)$$

$$t\text{-statistic} \quad [1.80395] \quad \quad [-0.14906] \quad \quad [-2.17650]$$

The individual coefficients of the equilibrium relationship for exports shown by Equation 5.7.2 above suggest that world income ($\ln YW$) has a significant (at 10% significance level) positive inelastic relationship with export demand. According to the results, the estimated income elasticity of demand for South African exports is 0.35%. This indicates that, a 1% improvement in world income should cause growth in exports to increase by 0.35% per quarter, holding all other variables constant. These results are considerably consistent with the findings established by Narayan and Narayan (2010) using the ML estimator. They found that foreign income elasticity for South Africa's demand for exports is 0.25%, which is slightly less than our estimates in terms of magnitude. Inelastic demand is indicative that South Africa's exports are largely commodity based, while manufacturing sector forms a small percentage of our total exports to the rest of the world. Foreign firms' demand for raw material inputs are typically inelastic. In regard to relative price of exports ($\ln XRP$), despite the coefficient having the correct negative sign, there is no statistically significant relationship with export demand at conventional significance levels. Contrary to these findings Vika (2010) found statistically significant results for relative price of exports in the case of Albania. Concerning the nominal effective exchange rate ($\ln NEER$) there is a significant long-run relationship at the 5% significance level. This coefficient suggests that a 1% rise (appreciation in Rand) in the nominal effective exchange rate causes a 0.38% fall in export demand.

Since the vector error correction model produces both short-and long-run coefficients, the next task is to interpret the short-run dynamics of the model and the speed of adjustment of each model. The following section is focused on the presentation and interpretation of all short run coefficients for both models (1 and 2). Accordingly, impulse response functions, are also presented and interpreted in the subsequent sections after Short-run dynamics.

b). Short run dynamics of import and export demand functions

According to the Granger representation theorem (1987), once cointegration has been identified, the most appropriate way of specifying a relationship between variables is to estimate an error correction model (Feddersen, 2013). Hence, the results of the Johansen cointegration test estimated in the previous section (see, table 5.6a and 5.6b) indicate that both model 1 and 2 have only one cointegrating vector in their systems, respectively. Therefore, this justifies that an error correction model should be estimated in this study. Accordingly, two error correction terms were estimated in this study. The first one is for import demand and the other is for export demand model.

In a time-series model, the error correction term is targeted to measure the speed of adjustment or the amount of time taken by the cointegrated equation to restore the long-run equilibrium of the dependent variable if a shock occurs in the system. For this to happen, the coefficient of the error term has to be negative and significant at all times. Equations 5.7.3 and 5.7.4 below present the short-term dynamics of South African import and export demand models (respectively) and their respective error correction terms (*ECT*).

$$\begin{aligned} \Delta \ln M_t = & -0.127319^{***} ECT + 0.775^{***} \Delta \ln Y_{t-1} + 0.444 \Delta \ln Y_{t-2} + 0.733^{***} \Delta \ln Y_{t-3} + 1.173^{***} \Delta \ln Y_{t-4} + 0.094 \Delta \ln MRP_{t-1} \\ & + 0.325^* \Delta \ln MRP_{t-2} + 0.312^* \Delta \ln MRP_{t-3} - 0.040 \Delta \ln MRP_{t-4} - 0.219^{***} \Delta \ln M_{t-1} - 0.129^* \Delta \ln M_{t-2} \\ & - 0.187^{***} \Delta \ln M_{t-3} + 0.154^* \Delta \ln M_{t-4} + 0.080 \Delta \ln NEER_{t-1} + 0.333^{***} \Delta \ln NEER_{t-2} - 0.118 \Delta \ln NEER_{t-3} \\ & + 0.170 \Delta \ln NEER_{t-4} \end{aligned} \quad (5.7.3)$$

In Equation 5.7.3, *, ** and *** represent, 10%, 5% and 1% level of significance, respectively. These symbols will be used throughout this paper. The above equation indicates that the error correction coefficient for the import demand model is -0.127319 and it is negative and significant at 1% level of significance. This signifies that when imports overstep their equilibrium relationship with the co-integrating vector (long-run relationship) in the previous period, then in this period about 13% of the deviation is restored and it will take about 8 quarters for the disequilibrium to be fully restored. Apart from the error correction term, a number of other first differenced lagged variables also play a role in the short-run adjustment of import demand. These are the same variables that appear in the long-run relationship in levels. Summing the lagged coefficients of a particular variable will indicate the overall short term effect of that variable on the adjustment of import demand. For example, summing the statistically significant coefficients on $\ln Y$ suggests that 2.28% of the current change in import demand comes from lagged income changes, 0.637% of the adjustment is caused by lagged

price changes and only 0.333% arises from lagged changes in the exchange rate movement. Note that these are anticipated or known lagged changes in the variables, hence the largest effect on import demand is from income, followed by relative price changes and least of all is exchange rate movements.

$$\begin{aligned}
 \Delta LNX_t = & -2.216*ECT + 0.557\Delta LNYW_{t-1} - 0.336\Delta LNYW_{t-2} + 0.412*\Delta LNYW_{t-3} + 0.412\Delta LNYW_{t-4} - 0.527\Delta LNYW_{t-5} \\
 & - 0.120\Delta LNMRP_{t-1} - 0.263\Delta LNMRP_{t-2} - 0.274\Delta LNMRP_{t-3} + 0.228\Delta LNMRP_{t-4} - 0.254\Delta LNMRP_{t-5} \\
 & - 0.411***\Delta LNX_{t-1} - 0.082\Delta LNX_{t-2} + 0.038\Delta LNX_{t-3} + 0.187\Delta LNX_{t-4} + 0.085\Delta LNX_{t-5} - 0.007\Delta LNNEER_{t-1} \\
 & - 0.080\Delta LNNEER_{t-2} + 0.090\Delta LNNEER_{t-3} + 0.260**\Delta LNNEER_{t-4} \\
 & - 0.122\Delta LNNEER_{t-5} \qquad \qquad \qquad (5.7.4)
 \end{aligned}$$

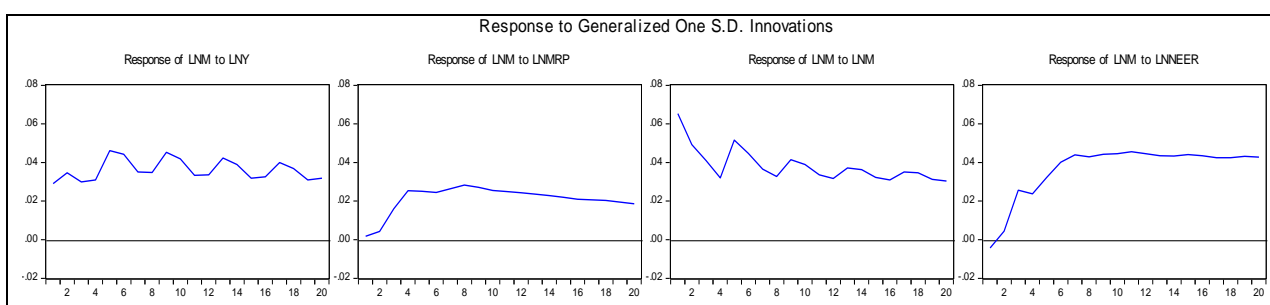
In Equation 5.7.4, *, ** and *** represent the level of significance at 10%, 5% and 1%, respectively. The above results show that the error correction coefficient for the export demand model is -0.216202 and it is negative and statistically significant at 1% level of significance. This suggests that about 22% of the deviations in exports is restored when export demand overstep its equilibrium relationship with the cointegrating vector (long-run relationship) in the previous period, then in this period. However, the coefficient of the first difference lagged values of relative prices suggests that, in the short run, export demand is not significantly influenced by changes in relative prices. Furthermore, the summed values of statistically significant coefficients suggest that the first difference lagged values of exports affect the current values of export demand by -0.411% at 1% level of significance. The summation of the other remaining statistically significant coefficients of the other variables show that 0.412% and 0.260% of the current change in export demand comes from lagged world income changes and from changes in the exchange rate adjustments, respectively. In summary, the overall results suggest that, in the short run, changes in export demand are mainly caused by changes in world income (*LNYW*), followed by changes in exchange rate (*LNNEER*) movements.

5.6 IMPULSE RESPONSE ANALYSIS

The impulse response analysis is an important element of VAR-VECM because it reveals the interconnection and patterns of systematic feedback between variables within the VAR/VECM system, resulting from unexpected shocks. However, instead of relying on the Cholesky decomposition impulse response function, as other studies have, we utilised the generalised impulse response because of its ability to take into account all historical patterns of correlated shocks in the system (Mazenda, 2014). Mazenda (2014) argued that, in circumstances where the series are $I(1)$ or non-stationary, impulse response functions will have to be generated from the VECM to ensure that the estimates of forecasts error variance are consistent and asymptotically optimal. Another benefit of utilising this approach instead of Cholesky decomposition, is that it does not require any orthogonalisation of shocks and ordering of variables in the system, thereby avoiding any possibility of obtaining spurious results. Accordingly, Figure 5.3(a) below presents the generalised version of impulse responses for South African import demand to shocks in domestic income, relative import prices and nominal effective exchange rate, respectively generated from the VECM system of model 1.

From these results, we expect a positive shock on domestic income, and nominal effective exchange rate (units of foreign currency per unit of domestic currency) to have a positive impact on imports demand, while shocks on relative prices of imports are expected to have a negative impact on import demand. -For model 2 (export demand) it is expected that a positive shock in world income will affect exports volumes positively, while shocks on nominal exchange rate and relative prices of exports are expected to exert a positive impact on exports. The length of the impulse response function computed in this study only captures the period of five years, i.e., 20 quarters.

Figure 5.3(a) Generalised impulse response functions for model 1



Source: computed by the researcher, using Eviews 9.5.

The results of Figure 5.3(a) presented above show how import demand (*LNM*) responds to one standard deviation unanticipated positive shocks from domestic income (*LNY*), nominal effective exchange rate (*LNNEER*) and to a unit standard deviation negative shocks from its relative prices (*LNMRP*). As expected, the results suggest that a positive shock in domestic income (*LNY*) leads to a

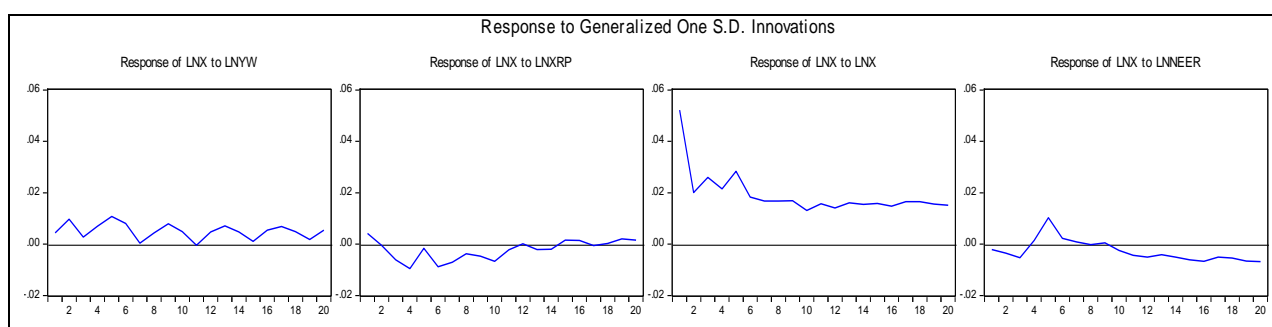
positive shock in import demand ($LNIM$), which fluctuates within a narrow band but persists well beyond 20 quarters. A negative one standard deviation shock in relative prices of imports ($LNMRP$) will cause a positive shock in import demand ($LNIM$), which starts to take effect at the beginning of the second quarter and gradually adjusts to a lower level from quarter 4 onwards. Notice the effect of the shock, which peaks at 0.02% after quarter 4, and thereafter declines gently, and is persistent beyond the 20 quarters. Lastly, a one standard deviation positive shock on nominal effective exchange rate ($LNNEER$) leads to a positive shock in imports, which starts to take effect immediately after the shock has happened and peaks at 0.04% in quarter 7 and thereafter persists well beyond 20 quarters.

In summary, these results suggest that, in the long-run, imports' response to relative price changes and nominal effective exchange rates is similar but is much higher for income. The short-run adjustment of import demand suggests that lagged income changes continue to have a maximum impact followed by relative prices, which dominate the effect of exchange rates. However, in the case of unanticipated shocks, both exchange rate and income have the dominant impact, but the income effect fluctuates around a narrow band, while price movement impact is half that of exchange rates. Therefore, with regard to the Orcutt hypothesis (in spite of the similar responses), this study accepts the Orcutt proposition because imports' response is much stronger for changes in exchange rates than for variations in relative prices and they persist well beyond 20 quarters.

Moreover, figure 5.3(b) below shows the impulse response functions of the variables related to the export demand. According to the results, exports demand ($LNEX$) responds positively to unit standard deviation shocks in world income ($lnYW$). However, this effect is quite subdued, where it fluctuates between 0.01 and 0, which gradually diminishing beyond 20 quarters, and eventually returns back to zero in quarter 8 and rises again up to quarter 9 and starts to diminish thereafter. In addition, figure 5.3(b) also shows that a positive shock on nominal effective exchange rate has a subdued negative effect on exports where initially there is a marginal decline followed by exports peaking at 0.01% in quarter 5 and thereafter the economy returns to equilibrium.

In the first quarter, exports respond negatively to a shock from ($LNNEER$) movements and persist up to quarter 3, where it starts to react positively and becomes negative again after quarter 5. A similar relationship is also established with respect to relative prices of exports. As per the results, export demand falls marginally below equilibrium and fluctuates in this region for about 10 quarters before returning to equilibrium. The conclusion one may draw is that exports are relatively inelastic to world income exchange rate movements and are completely inelastic to relative export prices in the long run. In the short run a disequilibrium arising out of exports overstepping the long-run co-integrating relationship is eliminated within five quarters, i.e., the effects do not persist. Furthermore, in the short-run, export demand is not responsive to anticipated relative price changes and responses to foreign income and exchange rate movement occurs after four lags with income effect dominating the exchange rate effect by about twice as much. In regard to unanticipated shocks the effects are marginal and short lived in most cases. Based on these results, the Orcutt hypothesis is not found to be present in the South African export demand model. As per the results, in the long-run, both exchange rate and price effects are similar, while income effects predominate. Short-run results suggest that, although both variables cause an immediate response to exports, the exchange rate effect has a steeper slope and is twice that of the relative prices. Moreover, relative prices persist beyond 20 quarters, but that effect starts to decline gently, while exchange effects persists at peak levels beyond 20 quarters. Thus, rejecting the Orcutt's conjecture which suggest that trade flow responses are much larger or stronger for changes in exchange rate than to relative prices. Our results, suggest that export demand has similar responses to changes in exchange rate and relative prices, and that exports response to exchange rate movements occurs after 4 lags.

Figure 5.3(b) Generalised impulse response functions for model 2



Source: computed by the researcher, using Eviews 9.5

5.7 DIAGNOSTIC TEST FOR VECM SYSTEMS

The purpose of conducting diagnostic tests in this study is to make sure that the estimated models are dynamically stable and trustworthy. To execute this purpose, the following tests are conducted: Breusch-Godfrey test, Jarque-Bera test, Breusch-Pagan test, and CUSUM tests, to probe for serial correlation, normality, heteroscedasticity, and stability of the model, respectively. The results in

each test, except the CUSUM test, are interpreted using the following procedure. In each test, the null hypothesis is accepted if the P-value is greater than 0.05. Conversely, if the probability turns out to be less than 0.05, the alternative hypothesis is accepted. Table 5.7(a). presents summary results for serial correlation, normality and heteroscedasticity. The full version of these results is displayed in the appendix section (Appendix B). Note that all diagnostic test results are generated from the OLS presentation of the estimated VECM system of each trade flow.

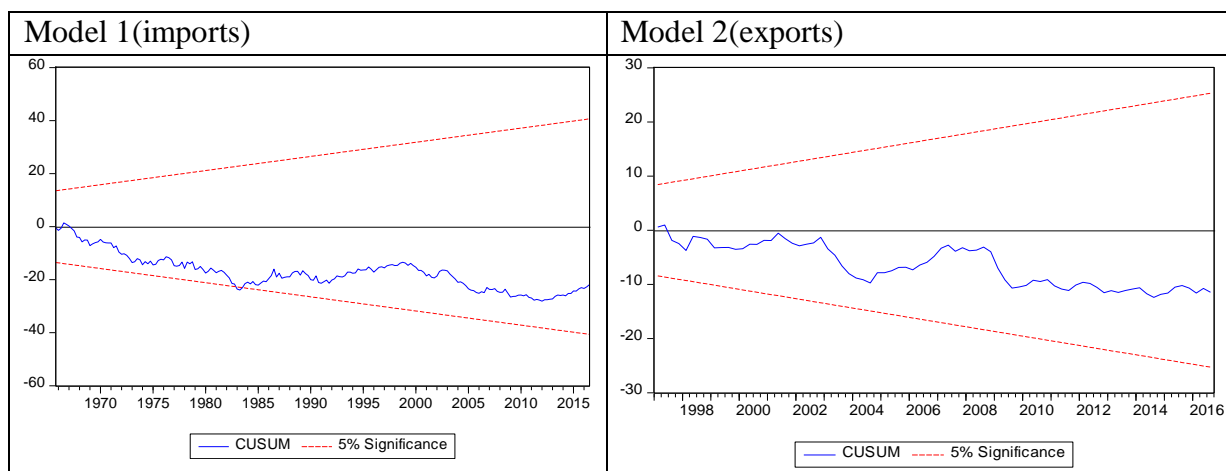
Table 5.7(a) Diagnostic test for model 1(imports) and model 2(exports) VECM equations.

Diagnostic tests	Null hypothesis	Model 1 (imports)	Model 2 (exports)
Breusch-Godfrey LM test	No serial correlation	0.0196	0.9143
Jarque-Bera test	Errors are normal distributed	0.651935	0.846319
Breusch-Pagan test	No heteroscedasticity	0.1313	0.4562

Source: author's own table

The results shown in the table above indicate that both models pass the normality test and heteroscedasticity test, since the p-values from the Jarque-Bera and Breusch-Pagan test are greater than 5%. This implies that model 1 (imports) and model 2 (exports) errors are normally distributed and homoscedastic. Model 2 (exports) also passes the serial correlation test, meaning that the error terms of model 2 for the export demand model are not serially correlated. The null hypothesis for serial correlation was accepted for model 1 (imports). This concludes that model 1(import demand) has a problem of serial correlation. Moreover, the stability test also show that model 1 slightly departs from the critical lines in the 1980s. This problem may be caused by the presence of structural breaks, which is more likely to exist in a very large sample size like the one utilised in model 1. Nonetheless, for the rest of the periods it appears to be stable. We are quite satisfied with these models since they have both passed the normality test and stability tests (see figure 5.4(b) below) and their coefficients seem confirm the results of previous studies. However, since model 1 seems to have some problems we found it critically important to run single equations for both models as confirmatory models. Hence the next section presents the summary results of single equations and the interpretation of their coefficients. The subsequent section compares the results of single equations and the VECM results.

Figure 5.4(b) Cusum tests for model 1(imports) and model 2(exports)



Source: Author's own table

5.8 SINGLE EQUATIONS

It is a general practice among many empirical studies to use single cointegrated equations to verify the findings of the Johansen cointegration test. Just like the Johansen cointegration test, these models are able to identify the existence of cointegration in the model via Engle-Granger and Philips-Ouliaris tests. To fulfil our verification purpose, we adopted the use of FMOLS, DOLS and CCR models to verify the findings of VECM reported above. Table 5.8(a) and (b) below present a summary of co-integrating equations for import demand and export demand functions, respectively.

Table 5.8(a) Summary results of single cointegrating models for import demand

Model	Variables	Coefficients	P-Values
FMOLS	$\ln Y$	1.378651	0.0000
	$\ln m_{rp}$	-0.586507	0.0003
	$\ln neer$	0.561079	0.0006
DOLS	$\ln Y$	1.398105	0.0000
	$\ln m_{rp}$	-0.578975	0.0007
	$\ln neer$	0.564170	0.0035
CCR	$\ln Y$	1.374597	0.0000
	$\ln m_{rp}$	-0.584615	0.0002
	$\ln neer$	0.557619	0.0019

Source: compiled by the researcher using results produced by Eviews 9.5

The results of all three cointegration equations (FMOLS, DOLS and CCR) presented in table 5.8(a) above demonstrate that all the estimated coefficients in each regression model for import demand are statistically significant from zero and have expected signs. It is further observed that both domestic income and nominal effective exchange rate have a significant positive impact on South African import demand at 1% level of significance. As expected, relative prices of imports, on the other hand, are found to have a significant negative impact on the demand for imported goods and services, significant at 1% level. According to the results, the import elasticity estimates produced by FMOLS with respect to domestic income, relative import prices and nominal effective exchange rate are 1.38%, -0.59% and 0.56%, respectively. For DOLS regression model the elasticity estimate of imports is 1.40% with respect to income, -0.58% with respect to relative prices of import, and 0.56% with respect to nominal effective exchange rate. Lastly, the elasticity estimates of CCR suggest that income elasticity of import demand is 1.37%, price elasticity is -0.58%, and 0.56% for nominal effective exchange rate. From these results it can be observed that all the estimated coefficients of domestic income produced by these three regression models (FMOLS, DOLS, and CCR) are relatively similar to the VECM estimates reported in equation 5.9.1 above. This confirms that indeed, South Africa's import demand is positively related to domestic income, and nominal exchange rate, and negatively related to variations in relative prices. According to the estimate South Africa's imports are highly elastic to income changes and inelastic to changes in both relative prices of imports and on nominal effective exchange rates.

Table 5.8(b) Summary results for single cointegrating models for export demand

Model	Variable	Coefficient	P-Values
FMOLS	$\ln Y_w$	0.402018**	0.0493
	$\ln x_{rp}$	0.341289**	0.0141
	$\ln neer$	-0.000123	0.9993
DOLS	$\ln Y_w$	0.374048	0.1095
	$\ln x_{rp}$	0.333244*	0.0529
	$\ln neer$	-0.025063	0.8856

CCR	<i>lnYw</i>	0.398782*	0.0556
	<i>lnxrp</i>	0.342127**	0.0116
	<i>lnneer</i>	-0.000418	0.9976

Source: compiled by the researcher using results produced by Eviews 9.5

For exports, the results of the FMOLS, DOLS and CCR, summarised in the table above, demonstrate that foreign income is the main determinant of the South African export demand function among these variables but it is also inelastic as suggested by the estimates of the VECM. It can also be noted from the results that coefficients of foreign income and nominal effective exchange rate appear to have expected signs and support the findings established by the VECM estimates discussed in the previous sub-section. However, all three models, show nominal effective exchange coefficients are insignificant to explain long- run variations in export demand. Therefore, on the basis of these findings, we may conclude that changes in nominal effective exchange rate have the power to influence the behavior of exports in South Africa in the long run.

According to the results of the first model (FMOLS), a 1% increase in foreign income cause demand for South African exports to increase by 0.40% per quarter, holding other factors constant. For nominal effective exchange rate, a 1% appreciation in the South African Rand will cause our exports to fall by less than 1% per quarter, *ceteris paribus*. The coefficient of foreign income and relative export prices are 0.40% and 0.34%, respectively, implying that a 1% increase in either world income or relative prices of exports, will cause exports volumes to increase by less than 1% in each quarter, respectively.

Moreover, the individual coefficients produced by the DOLS model suggest that the income elasticity of South African exports is 0.37%, which is somehow slightly less than the estimates of the FMOLS. This implies that a 1% increase in economic productivity of industrialized economies will cause South Africa's exports to increase by less than 1% per quarter, *ceteris paribus*. Export price elasticity is estimated to be 0.33%, implying that a 1% increase in prices of exports cause exports to improve by 0.33% per quarter, holding other variables fixed. Lastly, the exchange rate export elasticity is -0.03%, indicating that a 1% appreciation in rand will cause exports to retard by less than 1% per quarter, assuming other things have remained unchanged.

The individual estimates of CCR model show that income elasticity of exports is 0.40% which is the same as the one established by the FMOLS. The economic implication of this estimate is the same as the one reported under FMOLS. The price and exchange rate elasticity are 0.34 and -0.004, respectively. The interpretation and economically reasoning behind is also the same with the ones discussed above.

5.8.1 Cointegration Tests Based on Single Equations

The second objective of utilizing FMOLS, DOLS and CCR models was to verify co-integrating properties in the series. As discussed in Chapter 4, these three tests employ the Engle-Granger (1987) and the Phillips-Ouliaris to investigate co-integrating properties in the series. Accordingly, from the results displayed in Appendix B, both Engle-Granger and Phillips-Ouliaris indicate that there is some existence of co-integrating properties within the series employed in this study, concurring with the results obtained by the Johansen cointegration test for multivariate equations.

5.8.2 Diagnostic Tests for Single Equations

Normality tests have been computed as diagnostic tests for single equations. With this test we want to verify if the errors in each regression model are following the Gaussian process or not. The null hypothesis of this test states that errors are normally distributed. Accordingly, the results shown in the Appendix B accept this hypothesis and reject the alternative, which therefore concludes that residuals of each regression model are normally distributed.

5.9 SUMMARY OF THE OVERALL RESULTS

The main purpose of this study was to estimate the import and export demand function and test for the Orcutt (1950) hypothesis for South Africa. As shown and discussed above, VAR/VECM estimation was used to quantify the effect of price, income and nominal effective exchange rate on South African trade flows. The fully modified ordinary least squares (FMOLS), Dynamic ordinary least squares (DOLS), and the canonical cointegrating regressions (CCR) to verify the estimates of the VECM. Lastly, the Orcutt (1950) hypothesis was tested using the generalised impulse response functions generated from the Johansen Vector error correction model. Table 5.9(a) and (b) below present the summary of the VECM elasticity estimates of imports and exports with respect to relative price, domestic/foreign income, and nominal effective exchange rate, together with the estimates of the single static equations, respectively. The coefficients of the short-run elasticity are based on one period lag of each variable. Our main purpose in displaying a summary of the overall results is to compare the estimates produced by the VECM, with those obtained by the single equations. What could be

observed from these two sets of models is that all coefficients carry expected signs, however the elasticity estimates of single equations are slightly less than those produced by the VECM. The overall findings of this study confirm that imports are positively related to domestic income and to nominal effective exchange rate and negatively related to improvements in relative prices, with income being perfectly elastic. In the second model, the overall results indicate that demand for exports is positively related to world income, and respond negatively to adjustments in nominal effective exchange rate and to relative prices of exports. Thus, since both sets of models (VECM and single equations) seem to share the same idea, we can conclude that our results are empirically plausible.

Table 5.9(a) Summary results for model 1 (imports demand)

VARIABLE	Multivariate Model		Single equations		
	VECM		FMOLS	DOLS	CCR
	Long run	Short run			
LnY	1.73	0.78	1.38	1.40	1.37
LnMRP	-0.66	0.09	-0.59	-0.58	-0.58
LnNEER	0.66	0.08	0.56	0.56	0.56

Source: own calculations

Table 5.9(b) Summary results for model 2 (exports demand)

VARIABLE	Multivariate Model		Single equations		
	VECM		FMOLS	DOLS	CCR
	Long run	Short run			
LnYw	0.35	0.56	0.40	0.37	0.40
LnXRP	-0.03	-0.12	0.34	0.33	0.34
LnNEER	-0.38	-0.01	-0.0001	-0.03	-0.0004

Source: own calculations

5.10 CONCLUSION OF THE CHAPTER

In this study we estimated the trade elasticity of South Africa and investigated the Orcutt hypothesis by applying the vector error correction model and impulse response functions as portrayed in Chapter 4. First of all, the introductory phase of the chapter dealt with data issues and the computation of preliminary tests and unit root tests, as well as cointegration tests. After the cointegration test was detected, we then proceeded to specify and estimate the VECM models for both import and export demand functions. Within the process of all empirical estimation, a summary of results was also displayed and interpreted accordingly. Subsequently, we also generated the generalised impulse response functions from the VECM models to test for the Orcutt hypothesis. To verify the results produced by the VECM, we computed all three sets of long-run single equations (FMOLS, DOLS and CCR). Diagnostic tests were also generated and interpreted for each model. In the last part we concluded with a summary of all estimated elasticities from both sets of models (VECM and single equations). The following chapter will do the overall conclusion of the whole thesis and make some policy recommendations based on the results generated from this study.

CHAPTER 6: CONCLUDING REMARKS

6.1 INTRODUCTION

This chapter provides a brief summary of the overall outline of this dissertation, a summary of the main results, and policy recommendations. After conclusions have been drawn and relevant policy recommendations have been made, the next section will discuss the limitations of the study and make recommendations on areas of further research.

6.1.1 Summary of the Study

The main purpose of this study was to estimate import and export demand elasticities and to investigate whether the Orcutt (1950) hypothesis is observable in the South African trade flows. In the process of doing that, Chapter 2 of this study provided the theoretical foundation and conceptual framework related to estimation of trade elasticities and the Orcutt hypothesis. Theories of trade elasticities discussed included the neoclassical theory of comparative advantage, new trade theory and, the Keynesian trade multiplier, and two models of international trade (imperfect substitution and gravity model). The discussion of theories and models provided the basis for understanding the role of income and relative prices in influencing the volumes and directions of trade. Trade models, on the other hand, also shed light on how import and export demand should be modelled. The conceptual framework related to the Orcutt hypothesis shared an understanding of factors that could possibly affect the immediate response of trade flows to changes in the exchange rate and relative prices. In addition to that, the content of Chapter 2 of this study also provided the review of theoretical frameworks related to the relationship between exchange rate movements and trade flows.

The empirical literature discussed in Chapter 3 has shown that, in most studies, empirical findings are consistent with the theoretical relationship between trade flows, income and relative prices. However, empirical literature on the Orcutt hypothesis is still scarce, especially for developing countries, and the results in the existing literature are still mixed. The reviewed literature has presented to us two empirical approaches for assessing the Orcutt hypothesis; the impulse response approach and the lag imposition approach. Previous studies based on the South African context used the second approach. Therefore, this current study opted to assess the proposition using the first approach. The methodological section of this study, presented in Chapter 4 contains the discussion of all empirical approaches, a presentation of model specification, and justification of selected variables utilised in Chapter 5. The conceptual framework for the Augmented Dickey-Fuller test, and the Phillips-Perron were discussed as unit root tests utilised by the study. The Johansen cointegration test theoretical framework was also reviewed. In addition to that, this chapter contained a discussion of the VAR/VECM framework as the main model of this study. For the assessment of the Orcutt hypothesis, this chapter also provided a thorough discussion of both versions of impulse response functions: the generalised and the orthogonalised impulse response functions. The FMOLS, DOLS, and the CCR was also discussed as confirmatory single equations models. The last section of this concluded with the discussion of diagnostic tests.

Chapter 5 provided the results of all estimated regressions and tests conducted in order to achieve the desired objective of this study. As discussed in Chapter 4, the first requirement of utilising the Johansen VAR/VECM modelling technique is that all variables should be cointegrated and be integrated of the same order. The first section of this study presented the results and interpretation of stationarity tests. After the determination of the correct order of integration, series were also tested for cointegration using the multivariate technique as suggested by Johansen and Juselius (1990). The Pantula principle was used to select the most appropriate Johansen VECM from five possible cases.

6.6.2 Summary of the Overall Results and Policy Recommendations

The empirical findings of this research suggested that domestic income has a greater influence on South African imports than relative prices and exchange rate. There are three key reasons that could be ascribed to this behaviour. First, South Africa's production processes are heavily reliant on essential imported intermediate inputs, which cannot be substituted by domestic sources. Hence when national output (income) rises, import demand moves in the same direction. Secondly, as a newly industrialising economy, South Africa's imports consist mainly of capital goods and heavy machinery needed for the industrialisation process of the economy. Thirdly, as national income falls, where firms can source local intermediate goods they do so and, added to this the growing upwardly mobile middle class (with blacks swelling the ranks since 1994) switch to local substitutes. By implication, this suggests that the effective utilisation of income policy (i.e. the taxation of imports when the economy is booming) could play a major role in restraining unnecessary imports and promote consumption of local products. However, such a policy must guard against being in conflict with the current tariff regimes negotiated with World Trade Organisation. Furthermore, the results of the Orcutt hypothesis discussed in the previous chapter also show that (in the case of unanticipated shocks) currency devaluation policy could play a decisive role in stabilising the behaviour of South African imports demand. However, such policies will conflict with the current policy stance of a

floating exchange rate regime, accompanied by targeting inflation to lie within a narrow band of 3 to 6 percent through the use of the repo rate. The analysis of the Orcutt hypothesis has shown that imports' responses to exchange rate variations and to domestic income are much stronger than to changes in relative prices. As a result of prices having a weak effect on import demand, an imposition of import tariffs and quotas will be ineffective. However, income policies and exchange rate depreciation policies might gain more traction but they will contradict the existing policy stance as noted above.

Orcutt's conjecture suggests that "trade flows (imports and exports) respond more quickly to exchange rate changes than they do to relative prices". Our empirical findings from generalised impulse responses show that both effects cause immediate changes in imports demand, but with the exchange rate effect being more pronounced (steeper slope) and persisting well over 20 quarters, while the price effect is half of the exchange rate effect and shows a gentle decline but persists beyond 20 quarters.

Empirical findings of model 2 (export demand) suggested that export demand is relatively inelastic with respect to world income and exchange rate in the long run, and completely inelastic with respect to relative exports prices. In the short run, the disequilibrium arising out of exports overstepping the long-run relationships is eliminated within five quarters, i.e., the effects do not persist. Furthermore, it has also been found that in the short run export demand is not responsive to unanticipated shocks in relative prices, while the response to world income and exchange rate movements occurs after four lags with income dominating the exchange rate effect by twice as much. To verify the results produced by the multi-equation setting we opted to estimate single equations as confirmatory models and similar results were established regarding the relationship between export demand and relative prices, and exchange rate. However, contrary to the multi-equation model in the single equation models, the exchange rate was found to be insignificant while relative prices of exports were significant at a 10% level of significance, thus implying that export demand is not responsive to exchange rate movements. Nonetheless, the analysis of generalised impulse response functions for the Orcutt hypothesis suggested that export demand's responses to changes in relative prices and exchange rate are similar while income effects dominate, thus, rejecting the idea that exports could respond quicker to exchange rate adjustments than to changes in relative export prices. Therefore, by implication, this suggests that in order to manage an unanticipated shock in export demand, policy authorities would have to put more focus on instruments of commercial policy (such as export subsidies) as a tool for promoting outward oriented policies.

Returning to the income elasticity, the magnitude of export income elasticity obtained in this study suggests that there is still more work to be done in terms of promoting South African exports in the foreign markets of industrialised countries. Nonetheless, these results are not unique; similar results have been reported in the literature (see Stucka, 2004, in the case of Croatia; and Ogutu, 2014, in the case of Kenya). Narayan and Narayan (2010) also found similar results for South Africa in a comparative study between South Africa and Mauritius. It is arguable that the main reason for this inelastic response of exports to changes in relative prices is because of a misdiagnosis of the problem. For many years, many developing countries have been intensely focusing on improving their export promotion strategies rather than on diversification of their exports base. Most developing countries' (especially African countries) export base consist mainly of primary and agricultural products whose demand is relatively price inelastic. South Africa is no exception, since most of her exports consist of agricultural products and minerals. This is also the reason why the price elasticity has been found to be inelastic in this study. Thus, in order to benefit from a growth in economic activities of industrialised countries, the central focus point of South African trade policy should be on diversification of the export base, rather than on export promotion strategies. By doing so, the country would be able to increase its international competitiveness and increase its export volumes.

6.6.3 Limitations of the Study and Recommendations for Further Research

The first limitation of this study is that it is based on aggregate datasets, which makes our results more likely to suffer from aggregate biasness. Nonetheless, all our coefficients appear to meet all the theoretical expectations and they are also relatively similar to those established by previous studies found in the literature. However, for further research we recommend the following: firstly, the use of disaggregate data and the use of alternative proxy variables for world income, since South Africa's top trading partners now involve both industrialised and industrialising economies. Secondly, the Orcutt hypothesis can also be investigated on demand for a specific product or at sectoral level, rather than on aggregate trade data.

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APPENDICES

APPENDIX A

VAR SYSTEM FOR IMPORT DEMAND MODEL 1

VAR SYSTEM FOR IMPORT DEMAND MODEL 1

TABLE B10(a)

Vector Autoregression Estimates

Date: 08/05/17 Time: 12:03

Sample (adjusted): 1961Q2 2016Q3

Included observations: 222 after adjustments

Standard errors in () & t-statistics in []

	LN Y	LNMRP	LN M	LNNEER
LN Y(-1)	0.563858 (0.06819) [8.26887]	0.063407 (0.11671) [0.54328]	0.734473 (0.28075) [2.61613]	0.148548 (0.20663) [0.71891]
LN Y(-2)	0.048063 (0.04691) [1.02461]	0.102862 (0.08029) [1.28120]	-0.388735 (0.19313) [-2.01286]	0.103053 (0.14214) [0.72500]
LN Y(-3)	0.056432 (0.04783) [1.17986]	-0.009406 (0.08186) [-0.11490]	0.253739 (0.19692) [1.28854]	-0.004586 (0.14493) [-0.03164]
LN Y(-4)	0.841963 (0.04750) [17.7243]	-0.031478 (0.08130) [-0.38717]	0.434192 (0.19558) [2.22006]	0.012649 (0.14395) [0.08788]
LN Y(-5)	-0.511112 (0.06752) [-7.56931]	-0.134109 (0.11557) [-1.16040]	-0.932352 (0.27801) [-3.35372]	-0.251518 (0.20461) [-1.22924]
LNMRP(-1)	0.067362 (0.04121) [1.63449]	1.416768 (0.07054) [20.0852]	0.041186 (0.16968) [0.24273]	0.106671 (0.12488) [0.85417]
LNMRP(-2)	-0.031710 (0.07157) [-0.44305]	-0.599222 (0.12250) [-4.89172]	0.237314 (0.29467) [0.80537]	-0.160922 (0.21687) [-0.74201]
LNMRP(-3)	-0.027328 (0.07537) [-0.36260]	0.302824 (0.12899) [2.34760]	-0.008718 (0.31029) [-0.02810]	0.107167 (0.22837) [0.46926]
LNMRP(-4)	0.012727 (0.07228) [0.17607]	-0.055239 (0.12371) [-0.44651]	-0.340138 (0.29759) [-1.14299]	-0.024090 (0.21903) [-0.10999]
LNMRP(-5)	-0.035908 (0.04247) [-0.84557]	-0.086252 (0.07268) [-1.18668]	0.022463 (0.17484) [0.12848]	-0.021296 (0.12868) [-0.16549]
LN M(-1)	0.036447 (0.01848) [1.97271]	-0.006562 (0.03162) [-0.20750]	0.671190 (0.07607) [8.82369]	-0.090835 (0.05599) [-1.62247]
LN M(-2)	-0.011474 (0.02074) [-0.55326]	-0.027785 (0.03550) [-0.78274]	0.096788 (0.08539) [1.13351]	0.066918 (0.06285) [1.06480]
LN M(-3)	-0.020356 (0.02050) [-0.99286]	-0.010714 (0.03509) [-0.30531]	-0.044186 (0.08441) [-0.52347]	0.033324 (0.06213) [0.53639]
LN M(-4)	0.013244 (0.02015) [0.65732]	-0.011119 (0.03449) [-0.32243]	0.336811 (0.08295) [4.06023]	-0.099678 (0.06105) [-1.63263]
LN M(-5)	-0.021314 (0.01631) [-1.30664]	0.058555 (0.02792) [2.09735]	-0.176728 (0.06716) [-2.63153]	0.083449 (0.04943) [1.68829]
LNNEER(-1)	0.018481 (0.02369) [0.78021]	0.092247 (0.04054) [2.27535]	0.097115 (0.09752) [0.99582]	1.188030 (0.07178) [16.5517]
LNNEER(-2)	0.017395 (0.03575) [0.48663]	-0.041864 (0.06118) [-0.68427]	0.270750 (0.14717) [1.83975]	-0.309280 (0.10832) [-2.85537]
LNNEER(-3)	-0.024659 (0.03579) [-0.68901]	0.015574 (0.06125) [0.25425]	-0.458976 (0.14735) [-3.11493]	0.405412 (0.10845) [3.73832]
LNNEER(-4)	0.012159 (0.03706)	-0.088388 (0.06342)	0.308043 (0.15256)	-0.404281 (0.11229)

	[0.32812]	[-1.39363]	[2.01913]	[-3.60044]
LNNEER(-5)	-0.009244 (0.02550) [-0.36254]	0.040454 (0.04364) [0.92703]	-0.203288 (0.10497) [-1.93659]	0.111377 (0.07726) [1.44159]
R-squared	0.998707	0.999314	0.988954	0.998004
Adj. R-squared	0.998585	0.999249	0.987915	0.997816
Sum sq. resids	0.051416	0.150619	0.871537	0.472112
S.E. equation	0.015954	0.027306	0.065685	0.048344
F-statistic	8208.725	15482.20	951.8767	5315.609
Log likelihood	614.1191	494.8158	299.9550	368.0028
Akaike AIC	-5.352424	-4.277620	-2.522117	-3.135160
Schwarz SC	-5.045877	-3.971073	-2.215570	-2.828613
Mean dependent	12.86899	1.247996	11.29375	5.789802
S.D. dependent	0.424105	0.996577	0.597517	1.034517
Determinant resid covariance (dof adj.)		1.53E-12		
Determinant resid covariance		1.05E-12		
Log likelihood		1801.580		
Akaike information criterion		-15.50973		
Schwarz criterion		-14.28354		

VAR SYSTEM FOR MODEL 2

TABLE 10(b)

Vector Autoregression Estimates

Date: 08/05/17 Time: 12:07

Sample (adjusted): 1991Q3 2016Q3

Included observations: 101 after adjustments

Standard errors in () & t-statistics in []

	LNYPW	LNXP RP	LN X	LNNEER
LNYPW(-1)	1.146184 (0.09918) [11.5567]	0.022894 (0.23592) [0.09704]	0.660405 (0.38667) [1.70792]	-0.027142 (0.40749) [-0.06661]
LNYPW(-2)	-0.344744 (0.10376) [-3.32240]	-0.092355 (0.24683) [-0.37417]	-0.925780 (0.40455) [-2.28845]	0.003875 (0.42632) [0.00909]
LNYPW(-3)	-0.055452 (0.05821) [-0.95268]	0.167320 (0.13846) [1.20844]	0.615231 (0.22693) [2.71107]	-0.224189 (0.23915) [-0.93744]
LNYPW(-4)	0.831411 (0.05763) [14.4265]	-0.024347 (0.13709) [-0.17760]	0.155706 (0.22469) [0.69299]	0.222695 (0.23678) [0.94050]
LNYPW(-5)	-1.059861 (0.09810) [-10.8034]	-0.088069 (0.23337) [-0.37738]	-0.942420 (0.38248) [-2.46395]	0.071216 (0.40307) [0.17668]
LNYPW(-6)	0.389463 (0.08669) [4.49269]	0.087168 (0.20621) [0.42272]	0.590383 (0.33797) [1.74683]	-0.018405 (0.35617) [-0.05167]
LNXP RP(-1)	-0.046175 (0.05209) [-0.88646]	1.039791 (0.12391) [8.39174]	-0.027239 (0.20308) [-0.13413]	0.222962 (0.21401) [1.04182]
LNXP RP(-2)	0.177329 (0.07758) [2.28565]	-0.280059 (0.18455) [-1.51750]	-0.181783 (0.30248) [-0.60098]	-0.524472 (0.31876) [-1.64535]
LNXP RP(-3)	-0.075954 (0.08190) [-0.92740]	0.105779 (0.19482) [0.54296]	0.026896 (0.31931) [0.08423]	0.514215 (0.33649) [1.52815]
LNXP RP(-4)	-0.068789 (0.08277) [-0.83114]	0.125149 (0.19688) [0.63567]	0.498307 (0.32268) [1.54428]	-0.352730 (0.34005) [-1.03729]
LNXP RP(-5)	0.041651 (0.08131) [0.51226]	-0.045431 (0.19341) [-0.23489]	-0.474487 (0.31700) [-1.49680]	0.018116 (0.33406) [0.05423]
LNXP RP(-6)	-0.041762 (0.05142) [-0.81211]	-0.104733 (0.12233) [-0.85618]	0.291066 (0.20049) [1.45178]	0.148425 (0.21128) [0.70250]
LN X(-1)	0.045629 (0.02855) [1.59801]	0.076661 (0.06792) [1.12866]	0.327797 (0.11132) [2.94454]	-0.137037 (0.11732) [-1.16809]
LN X(-2)	-0.046853 (0.02876) [-1.62910]	0.073107 (0.06841) [1.06863]	0.292736 (0.11213) [2.61077]	-0.098172 (0.11816) [-0.83082]
LN X(-3)	0.009589 (0.03005) [0.31910]	-0.008139 (0.07149) [-0.11386]	0.100871 (0.11716) [0.86095]	-0.010499 (0.12347) [-0.08503]
LN X(-4)	0.031650 (0.02892) [1.09437]	-0.054375 (0.06879) [-0.79040]	0.157564 (0.11275) [1.39743]	0.071828 (0.11882) [0.60450]
LN X(-5)	0.020429 (0.02856) [0.71520]	-0.064688 (0.06795) [-0.95205]	-0.073343 (0.11136) [-0.65860]	-0.100589 (0.11736) [-0.85712]
LN X(-6)	0.033075 (0.02755) [1.20068]	0.015744 (0.06553) [0.24028]	-0.042282 (0.10740) [-0.39370]	0.228804 (0.11318) [2.02163]
LNNEER(-1)	0.021290 (0.02993) [0.71144]	-0.094609 (0.07119) [-1.32903]	-0.018017 (0.11667) [-0.15442]	1.282263 (0.12295) [10.4289]
LNNEER(-2)	-0.016521 (0.04645) [-0.35567]	-0.023027 (0.11049) [-0.20840]	-0.084351 (0.18110) [-0.46578]	-0.497534 (0.19085) [-2.60697]
LNNEER(-3)	0.024939 (0.04785)	-0.009585 (0.11381)	0.187399 (0.18654)	0.340719 (0.19658)

	[0.52125]	[-0.08422]	[1.00462]	[1.73325]
LNNEER(-4)	0.003912 (0.04825) [0.08108]	0.109943 (0.11478) [0.95786]	0.190241 (0.18812) [1.01127]	-0.256501 (0.19825) [-1.29384]
LNNEER(-5)	0.009948 (0.04723) [0.21062]	-0.040487 (0.11236) [-0.36035]	-0.376845 (0.18415) [-2.04641]	0.091280 (0.19406) [0.47037]
LNNEER(-6)	-0.045266 (0.03306) [-1.36905]	-0.051948 (0.07865) [-0.66050]	0.193248 (0.12891) [1.49915]	0.057670 (0.13584) [0.42453]
R-squared	0.994612	0.994733	0.948444	0.985615
Adj. R-squared	0.993002	0.993160	0.933044	0.981318
Sum sq. resids	0.013493	0.076349	0.205091	0.227767
S.E. equation	0.013237	0.031489	0.051609	0.054388
F-statistic	617.9662	632.3095	61.58760	229.3745
Log likelihood	307.1835	219.6590	169.7579	164.4621
Akaike AIC	-5.607594	-3.874437	-2.886295	-2.781428
Schwarz SC	-4.986179	-3.253022	-2.264880	-2.160013
Mean dependent	4.417038	-0.259856	4.488828	4.782881
S.D. dependent	0.158243	0.380743	0.199450	0.397908
Determinant resid covariance (dof adj.)		1.11E-12		
Determinant resid covariance		3.76E-13		
Log likelihood		871.5532		
Akaike information criterion		-15.35749		
Schwarz criterion		-12.87183		

IMPORT DEMAND (MODEL 1)

TABLE B11(a)

Vector Error Correction Estimates

Date: 08/05/17 Time: 11:29

Sample (adjusted): 1961Q2 2016Q3

Included observations: 222 after adjustments

Standard errors in () & t-statistics in []

Cointegration Restrictions:

B(1,3)=1

Convergence achieved after 1 iterations.

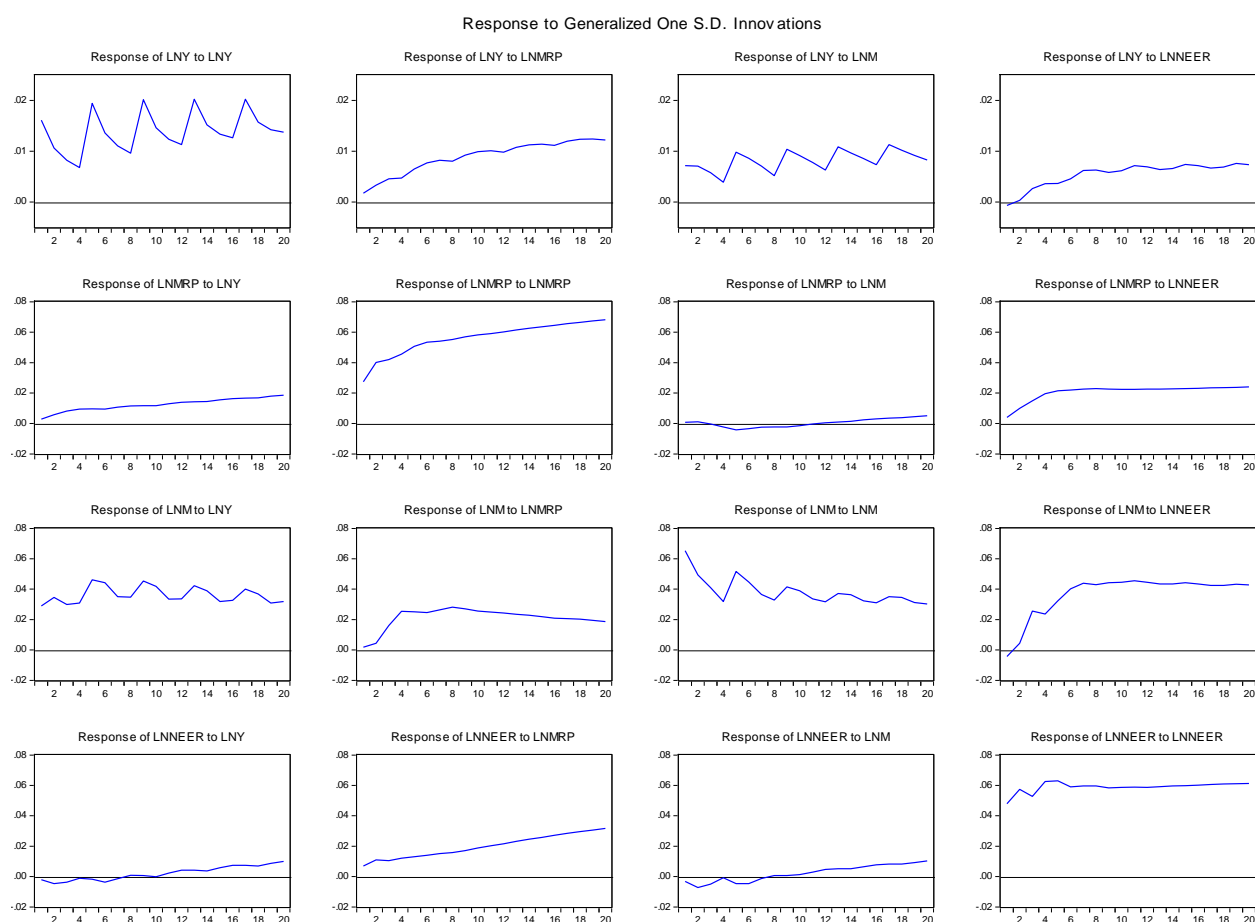
Restrictions identify all cointegrating vectors

Restrictions are not binding (LR test not available)

Cointegrating Eq:	CointEq1			
LN(-1)	-1.732053 (0.17395) [-9.95697]			
LNMRP(-1)	0.654821 (0.17833) [3.67191]			
LN(-1)	1.000000			
LNNEER(-1)	-0.664515 (0.20604) [-3.22520]			
C	14.02348			
Error Correction:	D(LNY)	D(LNMRP)	D(LNM)	D(LNNEER)
CointEq1	0.010038 (0.00646) [1.55268]	-0.003865 (0.01102) [-0.35056]	-0.127319 (0.02624) [-4.85165]	0.028601 (0.01924) [1.48639]
D(LNY(-1))	-0.419986 (0.06633) [-6.33140]	0.128370 (0.11312) [1.13478]	0.774902 (0.26927) [2.87781]	-0.012096 (0.19744) [-0.06127]
D(LNY(-2))	-0.375537 (0.07217) [-5.20319]	0.241687 (0.12308) [1.96361]	0.444244 (0.29298) [1.51632]	0.056382 (0.21482) [0.26246]
D(LNY(-3))	-0.319594 (0.07267) [-4.39793]	0.233947 (0.12393) [1.88779]	0.733380 (0.29498) [2.48617]	0.049794 (0.21629) [0.23022]
D(LNY(-4))	0.517856 (0.06928) [7.47494]	0.198920 (0.11815) [1.68369]	1.172723 (0.28122) [4.17009]	0.067488 (0.20620) [0.32728]
D(LNMRP(-1))	0.073658 (0.04138) [1.77987]	0.436401 (0.07057) [6.18361]	0.094372 (0.16799) [0.56178]	0.085578 (0.12318) [0.69476]
D(LNMRP(-2))	0.034317 (0.04515)	-0.174339 (0.07699)	0.325350 (0.18326)	-0.074252 (0.13437)

	[0.76016]	[-2.26448]	[1.77538]	[-0.55259]
D(LNMRP(-3))	0.010711 (0.04543) [0.23575]	0.135255 (0.07748) [1.74561]	0.312272 (0.18443) [1.69315]	0.028789 (0.13523) [0.21288]
D(LNMRP(-4))	0.008860 (0.04250) [0.20845]	0.077730 (0.07248) [1.07239]	-0.040311 (0.17253) [-0.23364]	-0.027231 (0.12651) [-0.21525]
D(LNM(-1))	0.036258 (0.01740) [2.08429]	-0.007551 (0.02967) [-0.25455]	-0.219210 (0.07061) [-3.10432]	-0.077471 (0.05178) [-1.49622]
D(LNM(-2))	0.025482 (0.01815) [1.40434]	-0.039060 (0.03094) [-1.26227]	-0.129171 (0.07366) [-1.75371]	-0.000214 (0.05401) [-0.00396]
D(LNM(-3))	0.006224 (0.01757) [0.35419]	-0.049509 (0.02997) [-1.65218]	-0.186606 (0.07133) [-2.61616]	0.033856 (0.05230) [0.64733]
D(LNM(-4))	0.021737 (0.01639) [1.32649]	-0.057361 (0.02795) [-2.05262]	0.153505 (0.06652) [2.30772]	-0.071647 (0.04877) [-1.46897]
D(LNNEER(-1))	0.018936 (0.02389) [0.79254]	0.085650 (0.04075) [2.10203]	0.080107 (0.09699) [0.82594]	0.202156 (0.07112) [2.84261]
D(LNNEER(-2))	0.037391 (0.02385) [1.56804]	0.045160 (0.04067) [1.11053]	0.332784 (0.09680) [3.43795]	-0.110042 (0.07098) [-1.55041]
D(LNNEER(-3))	0.005829 (0.02471) [0.23583]	0.058876 (0.04215) [1.39690]	-0.117850 (0.10032) [-1.17470]	0.285017 (0.07356) [3.87454]
D(LNNEER(-4))	0.021565 (0.02548) [0.84619]	-0.028919 (0.04346) [-0.66539]	0.170482 (0.10345) [1.64796]	-0.111945 (0.07585) [-1.47579]
C	0.013697 (0.00232) [5.91303]	-0.009100 (0.00395) [-2.30363]	0.004794 (0.00940) [0.50978]	-0.009666 (0.00689) [-1.40196]
R-squared	0.763727	0.317354	0.405203	0.149943
Adj. R-squared	0.744038	0.260467	0.355637	0.079105
Sum sq. resids	0.052873	0.153768	0.871235	0.468415
S.E. equation	0.016099	0.027455	0.065351	0.047918
F-statistic	38.78881	5.578651	8.174961	2.116706
Log likelihood	611.0165	492.5190	299.9934	368.8754
Akaike AIC	-5.342491	-4.274946	-2.540481	-3.161040
Schwarz SC	-5.066598	-3.999053	-2.264588	-2.885147
Mean dependent	0.007462	-0.012754	0.009683	-0.013349
S.D. dependent	0.031821	0.031926	0.081412	0.049934
Determinant resid covariance (dof adj.)		1.48E-12		
Determinant resid covariance		1.06E-12		
Log likelihood		1801.066		
Akaike information criterion		-15.54114		
Schwarz criterion		-14.37626		

IMPULSE RESPONSE FUNCTIONS FOR MODEL 1(IMPORT)



MODEL 1 DIAGNOSTIC TESTS

LM TEST

TABLE B12(a)

VEC Residual Serial Correlation LM Tests
 Null Hypothesis: no serial correlation at lag order h
 Date: 08/05/17 Time: 11:49
 Sample: 1960Q1 2016Q3
 Included observations: 222

Lags	LM-Stat	Prob
1	25.90073	0.0554
2	24.18991	0.0854
3	21.58785	0.1570
4	33.63470	0.0061
5	26.56751	0.0465
6	13.15410	0.6615
7	21.92860	0.1455
8	16.68005	0.4066
9	18.09968	0.3181
10	13.90036	0.6061
11	15.30385	0.5025
12	15.53744	0.4857

Probs from chi-square with 16 df.

NORMALITY TEST

TABLE B13(a)

VEC Residual Normality Tests
 Orthogonalization: Cholesky (Lutkepohl)
 Null Hypothesis: residuals are multivariate normal
 Date: 08/05/17 Time: 11:59
 Sample: 1960Q1 2016Q3
 Included observations: 222

Component	Skewness	Chi-sq	df	Prob.
1	0.049260	0.089782	1	0.7645
2	-0.601401	13.38229	1	0.0003
3	-0.309069	3.534375	1	0.0601
4	-0.638882	15.10228	1	0.0001
Joint		32.10873	4	0.0000

Component	Kurtosis	Chi-sq	df	Prob.
1	3.357169	1.180020	1	0.2774
2	6.112536	89.61287	1	0.0000
3	3.328039	0.995391	1	0.3184
4	6.113896	89.69120	1	0.0000
Joint		181.4795	4	0.0000

Component	Jarque-Bera	df	Prob.
1	1.269803	2	0.5300
2	102.9952	2	0.0000
3	4.529765	2	0.1038
4	104.7935	2	0.0000
Joint	213.5882	8	0.0000

EXPORT DEMAND MODEL (MODEL 2)

TABLE B11(b)

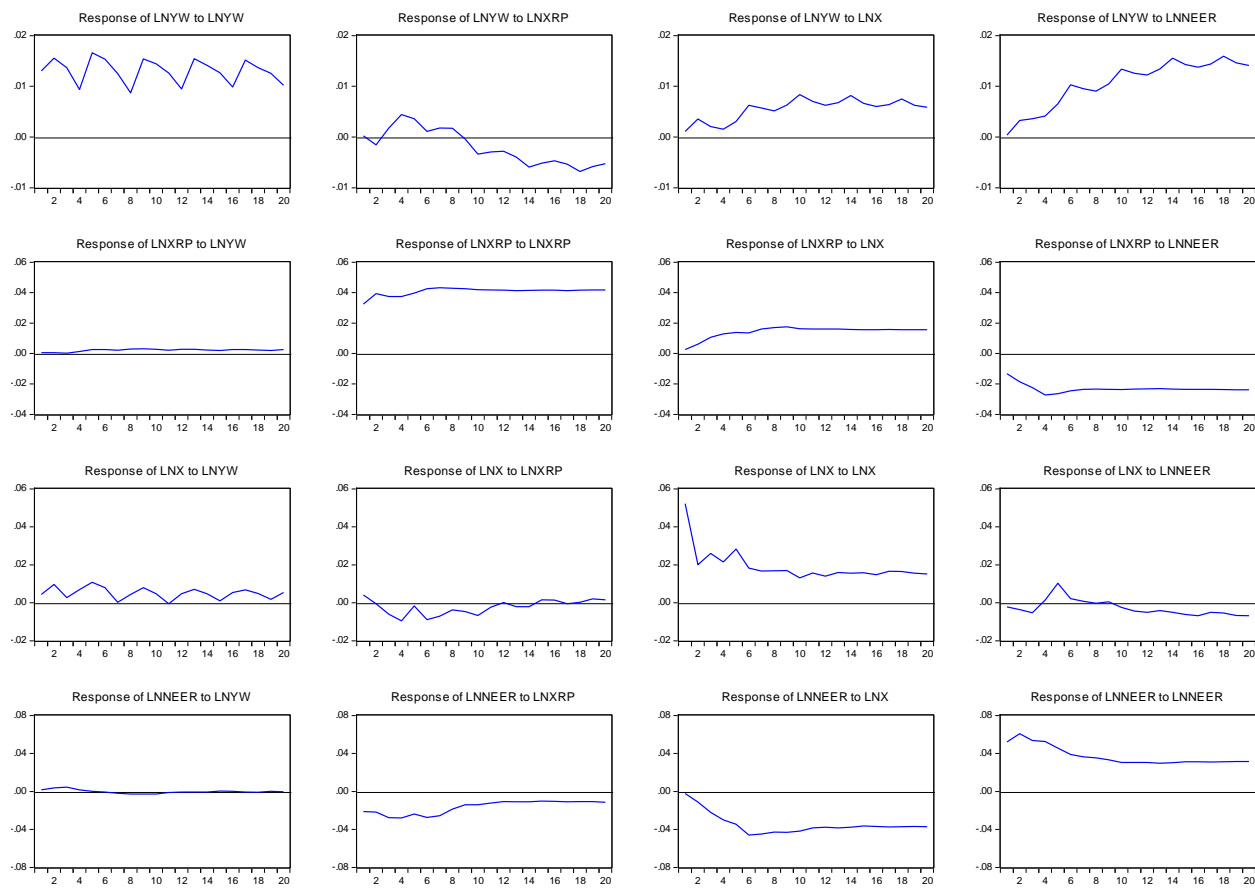
Vector Error Correction Estimates
Date: 08/05/17 Time: 11:44
Sample (adjusted): 1991Q3 2016Q3
Included observations: 101 after adjustments
Standard errors in () & t-statistics in []

Cointegration Restrictions:				
B(1,3)=1				
Convergence achieved after 1 iterations.				
Restrictions identify all cointegrating vectors				
Restrictions are not binding (LR test not available)				
Cointegrating Eq:	CointEq1			
LNYP(-1)	-0.352506 (0.19541) [-1.80395]			
LNXP(-1)	0.025467 (0.17085) [0.14906]			
LN(-1)	1.000000			
LNNEER(-1)	0.380067 (0.17462) [2.17650]			
C	-4.743101			
Error Correction:	D(LNYP)	D(LNXP)	D(LN)	D(LNNEER)
CointEq1	0.109108 (0.02890) [3.77484]	0.001382 (0.07207) [0.01918]	-0.216202 (0.11581) [-1.86683]	-0.267993 (0.11543) [-2.32168]
D(LNYP(-1))	0.212285 (0.09239) [2.29759]	-0.021400 (0.23037) [-0.09290]	0.556799 (0.37021) [1.50402]	0.090530 (0.36899) [0.24535]
D(LNYP(-2))	-0.178453 (0.06238) [-2.86058]	-0.060833 (0.15554) [-0.39111]	-0.335777 (0.24996) [-1.34334]	0.129487 (0.24913) [0.51975]
D(LNYP(-3))	-0.217651 (0.05823) [-3.73790]	0.103242 (0.14518) [0.71113]	0.275607 (0.23331) [1.18130]	-0.159954 (0.23254) [-0.68786]
D(LNYP(-4))	0.629256 (0.05776) [10.8941]	0.041962 (0.14402) [0.29137]	0.411630 (0.23144) [1.77859]	0.081488 (0.23067) [0.35326]
D(LNYP(-5))	-0.447949 (0.08386) [-5.34182]	-0.033808 (0.20908) [-0.16170]	-0.527494 (0.33600) [-1.56993]	0.047766 (0.33489) [0.14263]
D(LNXP(-1))	-0.032767 (0.04815) [-0.68052]	0.163548 (0.12005) [1.36231]	-0.120099 (0.19293) [-0.62251]	0.136008 (0.19229) [0.70730]
D(LNXP(-2))	0.140330 (0.04899) [2.86434]	-0.149749 (0.12215) [-1.22592]	-0.263289 (0.19630) [-1.34124]	-0.361499 (0.19565) [-1.84763]
D(LNXP(-3))	0.073604 (0.05279) [1.39431]	-0.009973 (0.13162) [-0.07577]	-0.273659 (0.21151) [-1.29381]	0.084789 (0.21082) [0.40219]
D(LNXP(-4))	0.002538 (0.05149) [0.04928]	0.123982 (0.12839) [0.96568]	0.228038 (0.20632) [1.10524]	-0.240073 (0.20564) [-1.16742]

D(LNXRP(-5))	0.050988 (0.05016) [1.01641]	0.050056 (0.12508) [0.40021]	-0.253649 (0.20100) [-1.26194]	-0.226178 (0.20034) [-1.12899]
D(LNX(-1))	-0.061682 (0.03517) [-1.75408]	0.058787 (0.08768) [0.67049]	-0.411265 (0.14090) [-2.91885]	0.090565 (0.14044) [0.64489]
D(LNX(-2))	-0.108207 (0.03651) [-2.96351]	0.104610 (0.09104) [1.14908]	-0.081980 (0.14630) [-0.56035]	-0.028673 (0.14582) [-0.19664]
D(LNX(-3))	-0.097659 (0.03553) [-2.74838]	0.069138 (0.08860) [0.78037]	0.037787 (0.14238) [0.26541]	-0.051307 (0.14191) [-0.36155]
D(LNX(-4))	-0.064234 (0.03399) [-1.88952]	0.009087 (0.08476) [0.10721]	0.186730 (0.13621) [1.37089]	0.007642 (0.13576) [0.05629]
D(LNX(-5))	-0.041722 (0.02766) [-1.50855]	-0.039490 (0.06896) [-0.57266]	0.084705 (0.11082) [0.76437]	-0.132435 (0.11045) [-1.19903]
D(LNNEER(-1))	0.006681 (0.02891) [0.23110]	-0.059689 (0.07208) [-0.82815]	-0.007485 (0.11583) [-0.06462]	0.296403 (0.11545) [2.56746]
D(LNNEER(-2))	-0.016117 (0.02975) [-0.54178]	-0.075848 (0.07417) [-1.02263]	-0.079578 (0.11919) [-0.66765]	-0.180114 (0.11880) [-1.51613]
D(LNNEER(-3))	0.017728 (0.03027) [0.58574]	-0.085066 (0.07546) [-1.12727]	0.090037 (0.12127) [0.74245]	0.107201 (0.12087) [0.88691]
D(LNNEER(-4))	0.020910 (0.03004) [0.69602]	0.045400 (0.07491) [0.60609]	0.259916 (0.12038) [2.15921]	-0.142445 (0.11998) [-1.18725]
D(LNNEER(-5))	0.032030 (0.03049) [1.05037]	-0.007185 (0.07603) [-0.09451]	-0.122440 (0.12218) [-1.00210]	-0.065727 (0.12178) [-0.53971]
C	0.004846 (0.00212) [2.28811]	0.007858 (0.00528) [1.48815]	0.018912 (0.00849) [2.22855]	-0.003993 (0.00846) [-0.47215]
R-squared	0.887322	0.157340	0.494572	0.258862
Adj. R-squared	0.857370	-0.066659	0.360218	0.061851
Sum sq. resids	0.013414	0.083389	0.215355	0.213938
S.E. equation	0.013031	0.032489	0.052211	0.052039
F-statistic	29.62449	0.702414	3.681102	1.313946
Log likelihood	307.4792	215.2048	167.2918	167.6253
Akaike AIC	-5.653053	-3.825837	-2.877066	-2.883669
Schwarz SC	-5.083423	-3.256207	-2.307436	-2.314039
Mean dependent	0.004819	0.014858	0.006526	-0.013976
S.D. dependent	0.034503	0.031458	0.065275	0.053727
Determinant resid covariance (dof adj.)		1.09E-12		
Determinant resid covariance		4.07E-13		
Log likelihood		867.5499		
Akaike information criterion		-15.35742		
Schwarz criterion		-12.97533		

IMPULSE RESPONSE FUNCTIONS FOR MODEL 2(EXPORT)

Response to Generalized One S.D. Innovations



DIAGNOSTIC TEST FOR MODEL 2

LM TEST

TABLE B12(b)

VEC Residual Serial Correlation LM Tests
 Null Hypothesis: no serial correlation at lag order h
 Date: 08/05/17 Time: 11:50
 Sample: 1990Q1 2016Q3
 Included observations: 101

Lags	LM-Stat	Prob
1	13.38709	0.6443
2	13.14182	0.6624
3	14.54521	0.5582
4	20.24442	0.2094
5	6.658730	0.9793
6	8.660564	0.9267
7	12.04468	0.7409
8	9.532895	0.8899
9	11.30575	0.7902
10	16.68474	0.4063
11	9.602731	0.8865
12	14.66224	0.5495

Probs from chi-square with 16 df.

NORMALITY TEST

TABLE B13(b)
 VEC Residual Normality Tests
 Orthogonalization: Cholesky (Lutkepohl)
 Null Hypothesis: residuals are multivariate normal
 Date: 08/05/17 Time: 11:57
 Sample: 1990Q1 2016Q3
 Included observations: 101

Component	Skewness	Chi-sq	df	Prob.
1	-0.256873	1.110723	1	0.2919
2	-0.265054	1.182599	1	0.2768
3	-0.042149	0.029905	1	0.8627
4	-0.317414	1.695991	1	0.1928
Joint		4.019218	4	0.4034

Component	Kurtosis	Chi-sq	df	Prob.
1	3.376910	0.597840	1	0.4394
2	4.303952	7.155393	1	0.0075
3	3.117363	0.057966	1	0.8097
4	3.373217	0.586181	1	0.4439
Joint		8.397379	4	0.0781

Component	Jarque-Bera	df	Prob.
1	1.708563	2	0.4256
2	8.337991	2	0.0155
3	0.087871	2	0.9570
4	2.282173	2	0.3195
Joint	12.41660	8	0.1336

APPENDIX B

SINGLE EQUATIONS

IMPORT DEMAND

FMOLS

Dependent Variable: LNM
Method: Fully Modified Least Squares (FMOLS)
Date: 08/05/17 Time: 12:30
Sample (adjusted): 1960Q2 2016Q3
Included observations: 226 after adjustments
Cointegrating equation deterministics: C
Long-run covariance estimate (Bartlett kernel, Newey-West fixed bandwidth
= 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNYP	1.396067	0.147986	9.433779	0.0000
LNMRP	-0.592467	0.149331	-3.967463	0.0001
LNNEER	0.574263	0.172212	3.334621	0.0010
C	-9.248947	2.534841	-3.648728	0.0003

R-squared	0.908300	Mean dependent var	11.27537
Adjusted R-squared	0.907061	S.D. dependent var	0.607905
S.E. of regression	0.185325	Sum squared resid	7.624668
Durbin-Watson stat	0.199556	Long-run variance	0.126096

Cointegration analysis of FMOLS

Engle granger test

Cointegration Test - Engle-Granger
Date: 08/05/17 Time: 12:35
Equation: UNTITLED
Specification: LNM LNYP LNMRP LNNEER C
Cointegrating equation deterministics: C
Null hypothesis: Series are not cointegrated
Automatic lag specification (lag=0 based on Schwarz Info Criterion,
maxlag=14)

	Value	Prob.*
Engle-Granger tau-statistic	-3.501011	0.1978
Engle-Granger z-statistic	-22.67772	0.1969

*MacKinnon (1996) p-values.

Phillips-Ouliaris

Cointegration Test - Phillips-Ouliaris

Date: 08/05/17 Time: 12:36

Equation: UNTITLED

Specification: LNM LNY LNM RP LNNEER C

Cointegrating equation deterministic: C

Null hypothesis: Series are not cointegrated

Long-run variance estimate (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

No d.f. adjustment for variances

	Value	Prob.*
Phillips-Ouliaris tau-statistic	-3.271138	0.2888
Phillips-Ouliaris z-statistic	-19.42696	0.3098

*MacKinnon (1996) p-values.

DOLS

Dependent Variable: LNM

Method: Dynamic Least Squares (DOLS)

Date: 08/05/17 Time: 12:37

Sample (adjusted): 1960Q3 2016Q2

Included observations: 224 after adjustments

Cointegrating equation deterministic: C

Fixed leads and lags specification (lead=1, lag=1)

Long-run variance estimate (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNY	1.412734	0.154428	9.148164	0.0000
LNM RP	-0.581921	0.159259	-3.653925	0.0003
LNNEER	0.573429	0.184431	3.109185	0.0021
C	-9.472255	2.665214	-3.554032	0.0005

R-squared	0.921438	Mean dependent var	11.27467
Adjusted R-squared	0.916970	S.D. dependent var	0.602753
S.E. of regression	0.173682	Sum squared resid	6.364927
Durbin-Watson stat	0.263467	Long-run variance	0.124246

Cointegration test for DOLS model

Engle-granger

Cointegration Test - Engle-Granger
 Date: 08/05/17 Time: 12:40
 Equation: UNTITLED
 Specification: LNM LNY LNMRP LNNEER C
 Cointegrating equation deterministic: C
 Null hypothesis: Series are not cointegrated
 Automatic lag specification (lag=0 based on Schwarz Info Criterion,
 maxlag=14)

	Value	Prob.*
Engle-Granger tau-statistic	-3.501011	0.1978
Engle-Granger z-statistic	-22.67772	0.1969

*MacKinnon (1996) p-values.

Phillips-Ouliaris

Cointegration Test - Phillips-Ouliaris
 Date: 08/05/17 Time: 12:41
 Equation: UNTITLED
 Specification: LNM LNY LNMRP LNNEER C
 Cointegrating equation deterministic: C
 Null hypothesis: Series are not cointegrated
 Long-run variance estimate (Bartlett kernel, Newey-West fixed bandwidth =
 5.0000)
 No d.f. adjustment for variances

	Value	Prob.*
Phillips-Ouliaris tau-statistic	-3.271138	0.2888
Phillips-Ouliaris z-statistic	-19.42696	0.3098

*MacKinnon (1996) p-values.

CCR

Dependent Variable: LNM
 Method: Canonical Cointegrating Regression (CCR)
 Date: 08/05/17 Time: 12:42
 Sample (adjusted): 1960Q2 2016Q3
 Included observations: 226 after adjustments
 Cointegrating equation deterministic: C
 Long-run covariance estimate (Bartlett kernel, Newey-West fixed bandwidth
 = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNY	1.392049	0.145171	9.589033	0.0000
LNMRP	-0.590596	0.148173	-3.985859	0.0001
LNNEER	0.570815	0.170734	3.343297	0.0010
C	-9.179357	2.492527	-3.682752	0.0003
R-squared	0.908308	Mean dependent var		11.27537
Adjusted R-squared	0.907069	S.D. dependent var		0.607905
S.E. of regression	0.185317	Sum squared resid		7.624020
Durbin-Watson stat	0.199154	Long-run variance		0.126096

Cointegration test for CCR

Engle granger

Cointegration Test - Engle-Granger
 Date: 08/05/17 Time: 12:44
 Equation: UNTITLED
 Specification: LNM LNY LNMRP LNNEER C
 Cointegrating equation deterministic: C
 Null hypothesis: Series are not cointegrated
 Automatic lag specification (lag=0 based on Schwarz Info Criterion,
 maxlag=14)

	Value	Prob.*
Engle-Granger tau-statistic	-3.501011	0.1978
Engle-Granger z-statistic	-22.67772	0.1969

*MacKinnon (1996) p-values.

Phillips-Ouliaris

Cointegration Test - Phillips-Ouliaris
 Date: 08/05/17 Time: 12:44
 Equation: UNTITLED
 Specification: LNM LNY LNMRP LNNEER C
 Cointegrating equation deterministic: C
 Null hypothesis: Series are not cointegrated
 Long-run variance estimate (Bartlett kernel, Newey-West fixed bandwidth =
 5.0000)
 No d.f. adjustment for variances

	Value	Prob.*
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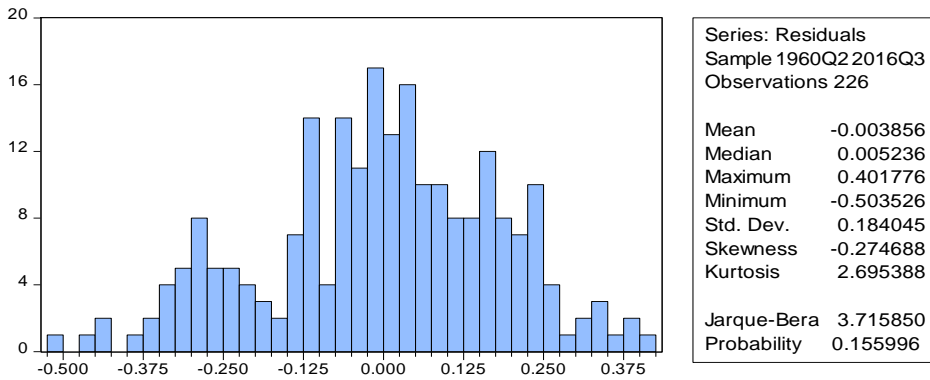
Phillips-Ouliaris tau-statistic	-3.271138	0.2888
Phillips-Ouliaris z-statistic	-19.42696	0.3098

*MacKinnon (1996) p-values.

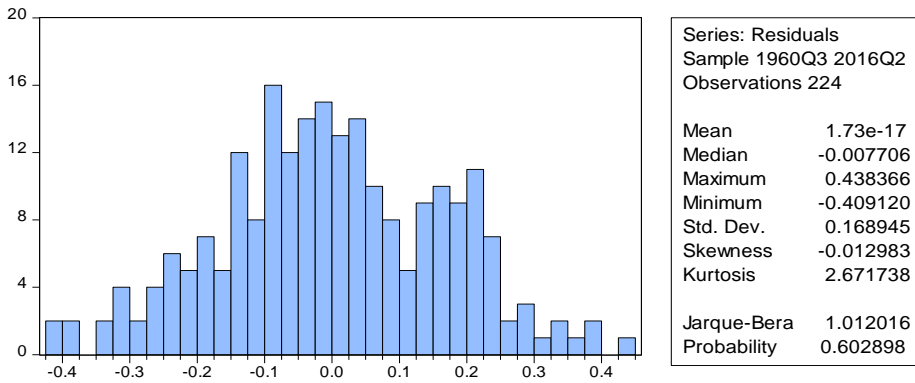
DIAGNOSTIC TESTS FOR SINGLE EQUATIONS FOR IMPORT DEMAND

NORMALITY TEST

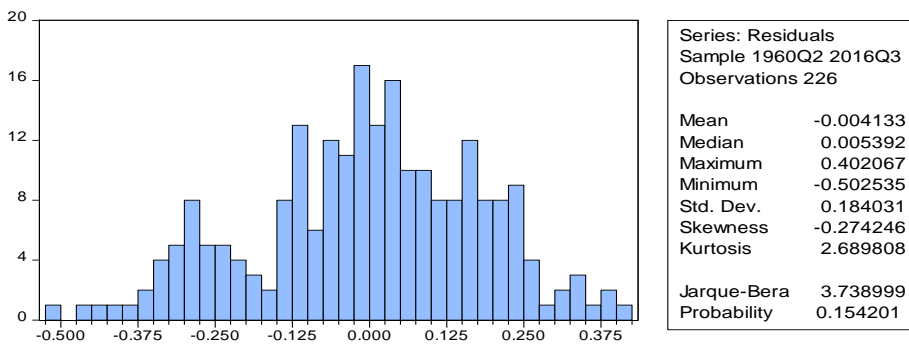
FMOLS



DOLS



CCR



SINGLE EQUATIONS FOR EXPOT DEMAND MODEL

FMOLS

Dependent Variable: LNX
 Method: Fully Modified Least Squares (FMOLS)
 Date: 08/05/17 Time: 14:10
 Sample (adjusted): 1990Q2 2016Q3
 Included observations: 106 after adjustments
 Cointegrating equation deterministic: C
 Long-run covariance estimate (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNYP	0.402018	0.201093	1.999161	0.0483
LNXP	0.341289	0.136650	2.497540	0.0141
LNNEER	-0.000123	0.136839	-0.000902	0.9993
C	2.798362	1.236436	2.263249	0.0257

R-squared	0.886770	Mean dependent var	4.466571
Adjusted R-squared	0.883440	S.D. dependent var	0.219245
S.E. of regression	0.074852	Sum squared resid	0.571489
Durbin-Watson stat	0.838414	Long-run variance	0.013031

Cointegration test of FMOLS

Engle granger

Cointegration Test - Engle-Granger
 Date: 08/05/17 Time: 14:11
 Equation: UNTITLED
 Specification: LNX LNYP LNXP LNNEER C
 Cointegrating equation deterministic: C
 Null hypothesis: Series are not cointegrated
 Automatic lag specification (lag=4 based on Schwarz Info Criterion, maxlag=12)

	Value	Prob.*
Engle-Granger tau-statistic	-2.881587	0.4864

Engle-Granger z-statistic -23.71685 0.1438

*MacKinnon (1996) p-values.

Phillips-Ouliaris

Cointegration Test - Phillips-Ouliaris
 Date: 08/05/17 Time: 14:13
 Equation: UNTITLED
 Specification: LNX LNYW LNXRP LNNEER C
 Cointegrating equation deterministics: C
 Null hypothesis: Series are not cointegrated
 Long-run variance estimate (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)
 No d.f. adjustment for variances

	Value	Prob.*
Phillips-Ouliaris tau-statistic	-5.414436	0.0016
Phillips-Ouliaris z-statistic	-48.08699	0.0007

*MacKinnon (1996) p-values.

DOLS

Dependent Variable: LNX
 Method: Dynamic Least Squares (DOLS)
 Date: 08/05/17 Time: 14:13
 Sample (adjusted): 1990Q3 2016Q2
 Included observations: 104 after adjustments
 Cointegrating equation deterministics: C
 Fixed leads and lags specification (lead=1, lag=1)
 Long-run variance estimate (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNYW	0.374048	0.231412	1.616372	0.1095
LNXRP	0.333244	0.169878	1.961665	0.0529
LNNEER	-0.025063	0.173679	-0.144307	0.8856
C	3.034817	1.488900	2.038295	0.0444

R-squared	0.907990	Mean dependent var	4.468331
Adjusted R-squared	0.895857	S.D. dependent var	0.215549
S.E. of regression	0.069560	Sum squared resid	0.440317
Durbin-Watson stat	1.005344	Long-run variance	0.012939

Cointegration test for DOLS

Engle-granger

Cointegration Test - Engle-Granger
 Date: 08/05/17 Time: 14:14
 Equation: UNTITLED
 Specification: LNX LNYW LNXRP LNNEER C
 Cointegrating equation deterministics: C
 Null hypothesis: Series are not cointegrated
 Automatic lag specification (lag=4 based on Schwarz Info Criterion, maxlag=12)

	Value	Prob.*
Engle-Granger tau-statistic	-2.881587	0.4864
Engle-Granger z-statistic	-23.71685	0.1438

*MacKinnon (1996) p-values.

Phillips-Ouliaris

Cointegration Test - Phillips-Ouliaris
 Date: 08/05/17 Time: 14:15
 Equation: UNTITLED
 Specification: LNX LNYW LNXRP LNNEER C
 Cointegrating equation deterministics: C
 Null hypothesis: Series are not cointegrated
 Long-run variance estimate (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)
 No d.f. adjustment for variances

	Value	Prob.*
Phillips-Ouliaris tau-statistic	-5.414436	0.0016
Phillips-Ouliaris z-statistic	-48.08699	0.0007

*MacKinnon (1996) p-values.

CCR

Dependent Variable: LNX
 Method: Canonical Cointegrating Regression (CCR)
 Date: 08/05/17 Time: 14:15
 Sample (adjusted): 1990Q2 2016Q3
 Included observations: 106 after adjustments
 Cointegrating equation deterministics: C
 Long-run covariance estimate (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNYW	0.398782	0.205956	1.936249	0.0556
LNXRP	0.342127	0.133044	2.571538	0.0116
LNNEER	-0.000418	0.135690	-0.003077	0.9976
C	2.814327	1.266863	2.221492	0.0285

R-squared	0.886746	Mean dependent var	4.466571
Adjusted R-squared	0.883415	S.D. dependent var	0.219245
S.E. of regression	0.074860	Sum squared resid	0.571614
Durbin-Watson stat	0.837723	Long-run variance	0.013031

Cointegration test for CCR

Engle granger

Cointegration Test - Engle-Granger
 Date: 08/05/17 Time: 14:16
 Equation: UNTITLED
 Specification: LNX LNYW LNXRP LNNEER C
 Cointegrating equation deterministics: C
 Null hypothesis: Series are not cointegrated
 Automatic lag specification (lag=4 based on Schwarz Info Criterion, maxlag=12)

	Value	Prob.*
Engle-Granger tau-statistic	-2.881587	0.4864
Engle-Granger z-statistic	-23.71685	0.1438

*MacKinnon (1996) p-values.

Phillips-Ouliaris

Cointegration Test - Phillips-Ouliaris
 Date: 08/05/17 Time: 14:17
 Equation: UNTITLED
 Specification: LNX LNYW LNXRP LNNEER C
 Cointegrating equation deterministics: C
 Null hypothesis: Series are not cointegrated
 Long-run variance estimate (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)
 No d.f. adjustment for variances

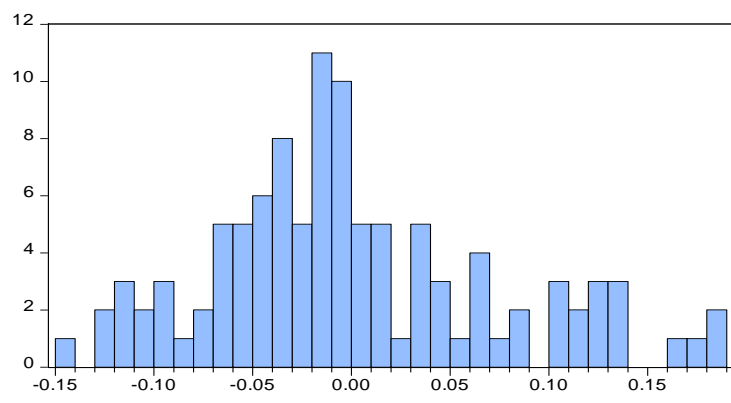
	Value	Prob.*
Phillips-Ouliaris tau-statistic	-5.414436	0.0016
Phillips-Ouliaris z-statistic	-48.08699	0.0007

*MacKinnon (1996) p-values.

Diagnostic tests for Model 2(Export demand model)

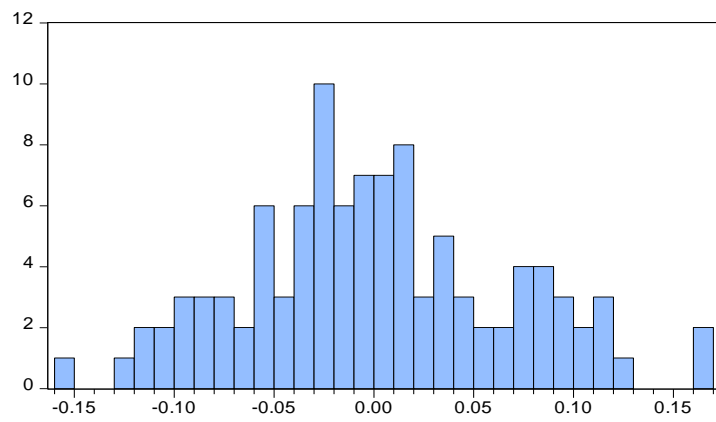
Normality tests

FMOLS



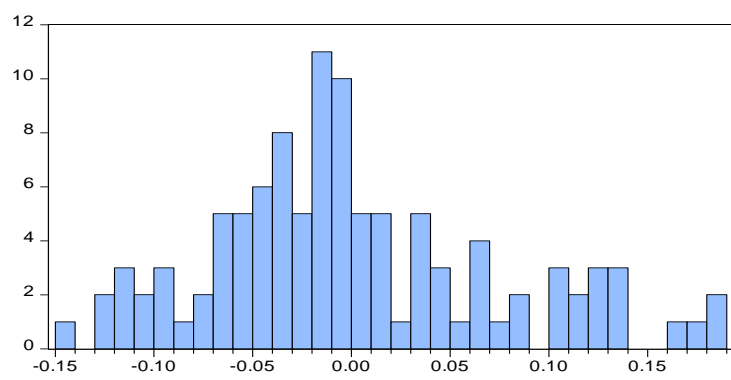
Series: Residuals	
Sample 1990Q2 2016Q3	
Observations 106	
Mean	0.000782
Median	-0.010869
Maximum	0.188769
Minimum	-0.145541
Std. Dev.	0.073771
Skewness	0.577769
Kurtosis	2.958400
Jarque-Bera	5.905085
Probability	0.052207

DOLS



Series: Residuals	
Sample 1990Q3 2016Q2	
Observations 104	
Mean	-2.56e-16
Median	-0.006326
Maximum	0.162716
Minimum	-0.158410
Std. Dev.	0.065383
Skewness	0.188500
Kurtosis	2.720390
Jarque-Bera	0.954677
Probability	0.620432

CCR



Series: Residuals	
Sample 1990Q2 2016Q3	
Observations 106	
Mean	0.000739
Median	-0.010810
Maximum	0.188937
Minimum	-0.145469
Std. Dev.	0.073779
Skewness	0.578688
Kurtosis	2.960103
Jarque-Bera	5.923250
Probability	0.051735