International Journal of Academic Research
ISSN: 2348-7666; Vol.4, Issue-12(2), December, 2017
Impact Factor: 6.023; Email: drtvramana@yahoo.co.in

Import Substitution Industrialization and Currency Devaluation: Time Series Evidence from Ethiopia

Abreham Mengistu Adera,

Lecturer Department of Economics, Arsi University, Ethiopia

Abstract : *This study examined the viability of Import substitution as well as product diversification strategies for Ethiopia by estimating the import demand function using a time series data for the period 1970/71-2010/11. The quantitative results from The Johansen's co-integration approach show that imports of the country are sensitive to changes in domestic output level and foreign exchange reserves both in the long run and in the short run. The import demand function specified in this study is stable over the sample period that it can be used for a policy purpose. The short run income elasticity of import is lower implying that the country can rely on import substitution industrialization strategy while the long run income elasticity is high that it provides evidence in favor of product diversification. The foreign trade implication of the finding is that devaluation is effective if it is supported with import restriction.*

Key Words: *Import, Diversification, Devaluation, Growth, Co-integration*

I. INTRODUCTION

Primarily initiated by IMF and the World Bank, the period 1992/93 through 2010/11 is comprised of three Economic policy reform periods that the Ethiopia's trade regime went through. The first phase started in 1992 when Birr was devalued against dollar and covered the period from 1992/93 to 1994/95.This period witnessed structural economic reform in which the government reduced import tax and introduced new tax systems. The second phase covered the period 1994/95 through 1996/97 and had an objective of nurturing the competitiveness of the industrial and agricultural sectors by following a more liberal external trade and foreign exchange policies than the first phase. In this phase, the maximum import duty on luxury items was 50 percent. The third and more liberal reform phase covered the period from 1996/97 to 2010/11.The import duties on some selected luxury goods were further lowered to 30-40 percent and Export-led growth has been followed since 2004 (NBE, 2001).

As a result of the third phase actions, the country witnessed fast economic growth for eight consecutive years registering a strong economic growth for the 8th time in 2010/11. Likewise, the import of the country has also been rising since the early 1990s. Over the period 1960/61 to 1972/4, the country witnessed average real growth rates of 3.8 and 4 for GDP and total import bills, respectively. The growth rate of GDP fall to 1.9 percent and that of import rose to 8.3 percent over the period 1973/74 to 1990/91.In the period 1990/91 -1999/2000, the average growth rates of both import bills and real GDP rose to 20.1 and 4.6 respectively (NBE, 2011).

Between 2000/01 and 2008/09, the average growth rates of real GDP and real imports were 8% and 14% respectively[1]. Total import bill stood at USD 7.7 billion in 2008/09 due to the increase in the value of import items like semi-finished goods (7.6 percent), fuel (4.3 percent),

[1] The growth rates of real GDP and imports during this period are calculated using MoFED(2012) data

capital goods (16.6 percent) and consumer goods (5.5 percent), offsetting the 40 percent slowdown in raw materials import as a result of which the share of imports in total GDP rose to 26.5 percent from 24 percent a year ago. This figure reached at USD 8.3 in 2009/10 with a marginal decline of 0.8 percent due to the decline in import items like raw materials, capital goods and consumer goods. Import bills of other commodities, particularly fuel, however, increased that the share of imports in total GDP increased to 29.6 percent from 27.8 percent. This being the case, the growth rate of real GDP rose to 11.4 percent in 2010/11 the 10.4 percent growth rate in 2009/10, placing Ethiopia among the top performing African and other developing Asian countries (NBE, 2010/11).

The rising trend in imports since the early 1990s along with the growth in GDP raises five questions: Why has the import of the country kept on increasing despite the then Import Substitution Industrialization and the devaluation policies of Ethiopia? Is the relationship between import and real GDP for granted to be positive? What variables, other than real GDP and exchange rate, can explain the growth in imports? And to what extent have other studies on the import demand behavior of the country addressed this seemingly contradictory scenario? Why is the analysis of import demand behavior so important? These questions have partly motivated this study.

One of the major concerns in the formulation of trade and/or exchange rate policies is the responsiveness of trade flows to relative price changes and income variations. The effect of trade and exchange rate policies is highly dependent upon the size of estimated price and income elasticity of both export and import for they provide a crucial link between economies, and exhibit the extent to which the external balance constraint affects a country's growth performance. Accordingly, international economists have devoted a considerable amount of effort to the estimation of import demand functions, both at the aggregated and disaggregated levels (Egwaikhide, 1999). Among others, the empirical investigations of Moran (1989), Yuan and Kochhar (1994), Senhadji (1997), Egwaikhide (1999), Rehman et al (2007), Yue (2010) and Sultan (2011) have provided considerable insights into the quantitative effects of changes in the availability of foreign exchange earnings, international reserves, openness of the economy (as measured by the effective rate of protection), relative prices, exchange rate and real domestic output on the growth of total imports. Hence, it is highly recommended to devote a considerable amount of effort to the estimation of import demand function of Ethiopia and this is the second driving engine for this study. The study specifically aims at investigating what affects import and tests the usefulness of the import demand equation for policy purpose.

II. Model Specification and Methods of Data Analysis

Most of the earliest econometric investigations of import demand function specify import as function of real income or industrial output of a country and relative price of import, the ratio of unit value of imports of the country to domestic price level, (Leamer and Stern, 1970; Khan (1974); Goldstein and Khan, 1976; Carone, 1996; Senhadji, 1997). On the other hand, there are models that give more attention to import capacity which can be measured by foreign exchange receipts and foreign exchange reserve and import restrictions. Hemphill (1974), for instance, relates import demand to foreign exchange receipts and international reserve in his model on the basis of proposition that high import restrictions and the changes in foreign exchange could measure changes in real income and relative prices. His result was consistent with the theory that import is highly dependent on capacity variables. There are also evidences where the changes in demand side factors like real income growth and relative price affect imports demand while the capacity factors are ineffective. For instance, Mah (1997) found that the exchange rate policy is ineffective in determining import demand in Korea.

In between are empirical works that account for both demand side and supply side factors. For instance, Rogers (2000) incorporates real GDP, import prices, real effective exchange rate and a measure for average tariffs in his study of Fiji's imports behaviour during the period 1968-1998. His result shows that movements in domestic demand and real effective exchange rate predominantly explain the movements in imports. Similarly, Sultan (2011) includes foreign exchange reserves, in addition to the real income and relative prices of imports, in his analysis of India's import demand function with a proposition that foreign exchange reserve (FER) is the only medium of exchange in international market and acts as a constraint for India to import necessary inputs; and that the desired level of import cannot be actualized in the absence of sufficient level of FER reserves.

It can now be inferred that omitting either the demand side or the supply variables may result in bias of a model's estimates and tends to overstate the importance of the included variables. Accordingly, Moran's (1989) import demand model, which has modified Hemphill's (1974) Stock Adjustment Import-Exchange Model, forms the theoretical basis for the import demand model of this study. Following Moran's generalization of Hemphill's model, the model is specified to be:

$$\ln(M_t) = \beta_0 + \beta_1 \ln(Y_t) + \beta_2 \ln(P_t) + \beta_3 \ln(R_t) + \beta_4 \ln(\mathrm{ER}_t) + \varepsilon_t \qquad (2.1)$$

Where, M is the value of Imports

P is the general domestic Price level (proxied by CPI);

Y is an index of real economic activity (proxied by GDP);

R is the level of foreign exchange reserves;

ER is the real effective exchange rate; and

t refers to the time period.

2.1.1. VAR and VEC Models

One problem with the specification in equation (2.1) is that it tends to treat imports as the only endogenous variable to the system. But, it is equally logical to argue that imports can have impacts on other variables of the model. Thus, a VAR approach, where all variables are assumed to be endogenous to the system, should be used. In a VAR, each endogenous variable is explained by its past values; and the lagged and current values of all other endogenous variables in the model and usually, there are no exogenous variables in such a model (Gujarati, 2004).

The VAR specification of equation (2.1) takes the form :

$$M_t = \alpha_0 + \sum_{i=1}^{q} \alpha_1 M_{t-i} + \sum_{i=0}^{q} \alpha_2 Y_{t-i} + \sum_{i=0}^{q} \alpha_3 P_{t-i} + \sum_{i=0}^{q} \alpha_4 R_{t-i} + \sum_{i=0}^{q} \alpha_5 ER_{t-i} + v_{1t}$$

$$Y_t = \beta_0 + \sum_{i=1}^{q} \beta_1 Y_{t-i} + \sum_{i=0}^{q} \beta_2 M_{t-i} + \sum_{i=0}^{q} \beta_3 P_{t-i} + \sum_{i=0}^{q} \beta_4 R_{t-i} + \sum_{i=0}^{q} \beta_5 ER_{t-i} + v_{2t}$$

$$P_t = \theta_0 + \sum_{i=1}^{q} \theta_1 P_{t-i} + \sum_{i=0}^{q} \theta_2 Y_{t-i} + \sum_{i=0}^{q} \theta_3 P_{t-i} + \sum_{i=0}^{q} \theta_4 R_{t-i} + \sum_{i=0}^{q} \theta_5 ER_{t-i} + v_{3t}$$

$$R_t = \gamma_0 + \sum_{i=1}^{q} \gamma_1 R_{t-i} + \sum_{i=0}^{q} \gamma_2 Y_{t-i} + \sum_{i=0}^{q} \gamma_3 P_{t-i} + \sum_{i=0}^{q} \gamma_4 R_{t-i} + \sum_{i=0}^{q} \gamma_5 ER_{t-i} + \upsilon_{3t}$$

$$ER_t = \vartheta_0 + \sum_{i=1}^{q} \vartheta_1 ER_{t-i} + \sum_{i=0}^{q} \vartheta_2 Y_{t-i} + \sum_{i=0}^{q} \vartheta_3 P_{t-i} + \sum_{i=0}^{q} \vartheta_4 R_{t-i} + \sum_{i=0}^{q} \vartheta_5 M_{t-i} + \upsilon_{4t}$$

Where all variables are in logarithms and q is the optimal lag length to be selected with an appropriate information criterion.

If the presence of co-integration is established, then follows the estimation of the Vector Error Correction (VEC) Model that includes both the long run and the short run information. This error correction mechanism (ECT) can be inserted in the following unrestricted short run equation as:

$$\Delta M_t = \eta_0 + \sum_{i=1}^{n} \eta_{1i} \Delta M_{t-i} + \sum_{i=0}^{n} \eta_{2i} \Delta Y_{t-i} + \sum_{i=0}^{n} \eta_{3i} \Delta P_{t-i}$$

$$+ \sum_{i=0}^{n} \eta_{4i} \Delta R_{t-i} + \sum_{i=0}^{n} \eta_{5i} \Delta ER_{t-i} + \mu ECT_{t-1} + \varepsilon_t \qquad (2.3)$$

Where n is the optimal is lag length and Δ is the first difference operator

Equation (2.3) has a one period lagged error correction term, (ECT_{t-1}). The coefficient of this term (μ) is feedback effect or the adjustment effect that measures the speed of adjustment to long run equilibrium condition (i.e. the extent of the disequilibrium created in previous period that is corrected in period t).Note that there are as many error correction terms as are the number of cointegrating vectors (sultan, 2011). The first difference lagged regressors, the coefficients of which are η_{2i}, η_{3i} , η_{4i} and η_{5i} ,are impact multipliers or short run effects measuring the immediate impact of the change in the regressors (Y_t, P_t, R_t and ER_t respectively) on the dependent variable (M_t).

Since the error correction model in equation (2.3) has a tendency of being over parameterized, Hendry's general-to-specific model selection technique, in which insignificant lags are dropped, would be pursued to obtain a parsimonious (an interpretable) error-correction model.

2.1.2. Partial Adjustment Import Demand Model

Most empirical studies employ the Partial Adjustment model for estimating import demand functions. But, the choice of a model has to depend on its forecasting ability (Yuan and Kochhar, 1994). Thus, the Partial Adjustment model for import demand is derived in this sub-section and its forecasting ability is compared with that of the VECM.

The Partial Adjustment Model can be defined as a model in which economic agents cannot adjust fully to changing conditions. In this particular case, the partial adjustment import demand model is defined as a model in which the current imports are regressed on the first lag of imports, and on the level (current) forms of other explanatory variables (Yuan and Kochhar, 1994; Sultan, 2011). Following Khan and Ross (1977), the partial adjustment model for imports for this study can be specified as:

$$\Delta M_t = \delta(M_t^* - M_{t-1}) \quad (2.4)$$
$$M_t^* = \alpha_1 + \alpha_2 Y_t + \alpha_3 P_t + \alpha_4 R_t + \alpha_5 ER_t + \nu_t \quad (2.5)$$

Where,
M_t^* is the desired level of imports.
Δ is a first difference operator ($i.e. \Delta M_t = M_t - M_{t-1}$)
δ is the coefficient of adjustment with a magnitude of less than unity ($0 < \delta < 1$)Substituting (3.5) into (3.4) and rearranging yields

$$Mt = \delta\alpha_1 + \delta\alpha_2 Y_t + \delta\alpha_3 P_t + \delta\alpha_4 R_t + \delta\alpha_5 ER_t + (1 - \delta)M_{t-1} + \delta v_t \quad (2.6)$$

We can rewrite equation (3.6) to produce the following dynamic linear import demand equation

$$M_t = \omega_1 + \omega_2 Y_t + \omega_3 P_t + \omega_4 R_t + \omega_5 ER_t + \omega_6 M_{t-1} + \varphi_t \quad (2.7)$$
$$Where\ \omega_1 = \delta\alpha_1, \omega_2 = \delta\alpha_2, \omega_3 = \delta\alpha_3, \omega_4 = \delta\alpha_4, \omega_5 = \delta\alpha_5, \omega_6 = (1 - \delta)\ \&\ \varphi_t = \delta v_t$$

In a similar fashion, we can drive the log-linear form of the partial adjustment import demand model as follows:

$$\Delta \ln M_t = \phi(\ln M_t^* - \ln M_{t-1}) \quad , \text{where } 0 < \phi \leq 1 \quad (2.8)$$
$$\ln\ln M_t^* = \beta_1 + \beta_2 \ln Y_t + \beta_3 \ln P_t + \beta_4 \ln R_t + \beta_5 \ln ER_t + \varepsilon_t \quad (2.9)$$

Substituting (2.9) into (2.8) and rearranging yields

$$\ln M_t = \phi\beta_1 + \phi\beta_2 \ln Y_t + \phi\beta_3 \ln P_t + \phi\beta_4 \ln R_t + \phi\beta_5 \ln ER_t + (1 - \phi)M_{t-1} + \phi\varepsilon_t \quad (2.10)$$

Equation (3.10) can be rewritten as:

$$lnMt = \alpha_1 + \alpha_2 lnY_t + \alpha_3 lnP_t + \alpha_4 lnR_t + \alpha_5 lnER_t + \alpha_6 M_{t-1} + v_t \quad (2.11)$$

$$where\ \alpha_1 = \phi\beta_1, \alpha_2 = \phi\beta_2, \alpha_{3=}\phi\beta_3, \alpha_4 = \phi\beta_4, \alpha_5 = \phi\beta_5, \alpha_6 = (1 - \phi) \text{and } v_t = \phi\varepsilon_t$$

Equation (2.11) is the dynamic –linear demand equation. This is the partial import demand function which shows the observable relationship between Mt and its determinants.

It can now be seen that dropping lagged imports from equation (2.11) leaves us with the general import demand function specified in equation (2.1). Note that the coefficients of equations (2.11) and (2.9) will give us the short run and the long run elasticities respectively that it is possible to calculate the coefficients of equation (2.9) from the coefficients of equation (3.11) as:

$$\phi = 1 - \alpha_6; \beta_1 = {}^{\alpha_1}/_{(1 - \alpha_6)}, \beta_2 = {}^{\alpha_2}/_{(1 - \alpha_6)}, \beta_3 = {}^{\alpha_3}/_{(1 - \alpha_6)}, \beta_4 = {}^{\alpha_4}/_{(1 - \alpha_6)}, \beta_5 = {}^{\alpha_5}/_{(1 - \alpha_6)},$$

2.1.3. Hypothesized Theoretical Signs of Variables

The theory of demand postulates a negative relationship between price of one good and the quantity demanded of another good provided that the two goods are complementary; and this relationship turns out to be positive if the two goods are substitutes under the ceteris paribus assumption. Thus, as the price of imports, in relation to the price of domestic substitutes, increases, we may expect a decrease in its demand, and vice versa. The increase in income (as measured by GDP) of the country would cause an increase in aggregate demand for imports. Yet, the relationship between the demand for import and GDP depends upon the source of growth in GDP. If the increase in GDP arises from an increase in production of import substitute goods, then import will have negative relation with GDP (Yuan and Kochhar, 1994).

Foreign exchange reserve is deemed to be a 'capacity factor' for it helps a country to make its demand effective. That is, in absence of foreign reserves, a country cannot make payment for imports whatsoever be the level of income and price. Higher reserves of a country would mean more capacity to import and vice versa.

Exchange rate devaluation is theoretically believed to have a discouraging effect on imports and an encouraging impact on exports. On the basis of these propositions and assuming that the world supply of export to Ethiopia is perfectly elastic, β_1 may take either a positive or a negative sign (β_1>0 or β_1 <0) depending on the sources of growth of GDP, β_2 is expected to carry a negative or a positive sign for β_2 (β_2 <0 or β_2>0) depending on the degree of product substitutability or complementarity; and we expect a positive sign for β_3 (β_3 > 0) and a negative sign for β_4 (β_4 <0).

2.1.4. Functional Form of the Model

The log-linear form of the models is used in this study for the following reasons. First of all, such a form allows for interpreting the coefficients of the dependent variables directly as elasticity with respect to each of the explanatory variables. Second, it accommodates the problem of hetroskedasticity. Third, the log linear form takes care of the problem of multicollinearity (Rogers, 2007; Aziz, 2008; Sultan, 2011). It is important, however, to note that a functional form affects the explanatory power of the variable. Kmenta (1986),for instance, argued that the misspecification of functional form may result in misspecification of error term, that in turn results in violation of assumption of OLS and hence, the efficiency and the biasness of a parameter.

2.2. Data Type and Sources

This study utterly employs a national level secondary data. The annual and quarterly bulletins of the National Bank of Ethiopia (NBE), and the Central Statistical Authority (CSA), the current Ministry of Finance and Economic Development (MoFED), the Ethiopian Investment Agency (EIA), Ethiopian Economic Association's Database 2012, and World Economic Outlook's Database 2011 and IMF's International Financial and Direction of Trade Statistics are the sources of data for the study. Books, Journals and Magazines have also served as supplementary sources of data.

2.3. Econometric Tests

2.3.1. Time series Characteristics of the Data

Conventionally, the import function specified in system (2.2) is estimated using ordinary least squares (OLS) method under the assumption of a stationary series. A stochastic process is said to be stationary if its mean and variance are constant over time and the value of the covariance between the two time periods depends only on the distance or lag between the two time periods and not on the actual time at which the covariance is computed (Maddala, 1992; Harris, 1995; Gujarati, 2004).

Yet, the problem with most time series is non-stationarity (a random walk); and regressions based on such non-stationary time series data are often misleading for the reason that regressions based on such a series would give a spurious or a false result (Granger and Newbold, 1974;Phillips ,1986; Stock and Watson, 1988). Hence, the first step when using time series data is to conduct test of stationary using unit root test, which has become the most popular and widely used method over the past several years. Thus, Augmented Dickey-Fuller (ADF) is employed to find out the time series characteristics of the data.The null hypothesis for the ADP test claim that the underlying series has a unit root or is not stationary against the alternative hypothesis that the series is stationary.

That is, the Augmented Dickey-Fuller (ADF) test is an extension of the Dickey-Fuller test (Dickey and Fuller, 1981) and entails estimating the following autoregressive process:

$$\Delta x_t = c_1 + \omega x_{t-1} + c_2 t + \sum_{i=1}^{\rho} d_i \Delta x_{t-i} + v_t \qquad (2.12)$$

Where, x is the relevant time series (M, Y, P, R or ER in this case); Δ is a first-difference operator, c_1 is the drift (constant) term; t is a time trend and p is the optimal lag length to be selected with an information criterion.

2.3.2. Co-integration Analysis

A stochastic trend may become stationary by running a regression on the first difference of the variables. It is, however, important to note that differencing results in losing the information on the long run relationship between variables for first differences of variables are zero in the long run (Yuan and Kochhar, 1994). Co-integration analysis suggests a way out of this dilemma.

Co-integration refers to the situation where a linear combination of two or more individually non-stationary series can be a stationary series. The two widely used co-integration testing procedures are Engle-Granger's (1987) residual based two-step approach and the Johansen (1988) full-information maximum likelihood estimation technique.

Johansen (1988) approach is used in this study since it is superior to the Engle-Granger two-step approaches for following reasons. First, The Engle-Granger approach estimation of long run equilibrium relation requires regressing one variable on rest of the variables. However, in practice, we find that one regression equation shows existence of Co-integration while reversing the order of the variables alters the result altogether and shows no co-integration. This is an undesirable feature of co-integration procedure as presence or absence of co-integration should be independent of the order of the variables presented on the left hand side or the right hand side of the equation (Dash, 2005). Opposed to this, Johansen's method does not rely on any arbitrary normalization. The other drawback of Engle-Granger approach is that it relies on two-step estimator. The first step is to generate error series and second step is to estimate a regression for this series in order to see if the series is stationary or not. Hence, any error introduced in first step is carried onto the second step. More importantly, Johansen's procedure allows for testing certain restrictions put on the variables by the economic theory such as sign and size of the elasticity estimates (Sultan, 2011).

Moreover, if the first step of the Engle-Granger co-integrating vector estimation proves that the variables are co-integrated, the OLS estimate of the co-integrating vector provides a "super consistent" estimator of the true vector in the sense that the estimators converge to the true parameters at a much faster rate than in the case of standard econometric estimators (Stock and Watson, 1988). Yet, the Engle-Granger procedure to estimate a co-integration relationship in a n-variate case does not clarify whether the estimated co-integrating vector is a unique one or is simply a linear combination of the potential $(n-1)$ cointegrating vectors. It also needs priori information that the dependent variables are endogenous and the independent variables are weakly exogenous and it is a must to identify each endogenous and weakly exogenous variable in order not to lose information about the co-integrating relationships (Harris, 1995). Johansen's (1988) full-information maximum likelihood estimating technique overcomes these drawbacks of EG's two-step method.

Technically, Johansen's procedure starts by defining a general polynomial distributed k-lag model of a vector of variables (Hall, 1989).Following Yuan and Kochhar (1994), consider for simplicity unrestricted 5 dimensional k- lags vector autoregression (VAR):

$$Z_t = \varphi + \psi_1 Z_{t-1} + \psi_2 Z_{t-2} \dots \psi_k Z_{t-k} + V_t \qquad (2.15)$$

Where, Z is a vector of the model variables, i.e. $Z = [M\ Y\ \ P\ R\ ER]'$ And V_t is independently identically distributed (i.i.d) 5-dimentional vector $(V_1, \dots, V_5)$ with mean zero and vector of variance Σ.

Reformulating the above model, we can obtain the following vector error-correction model (VECM):

$$\Delta Z_t = \sum_{i=1}^{k-1} \Gamma_i \Delta Z_{t-1} + \Pi Z_{t-k} + V_t \qquad (2.15a)$$

Where $\Gamma_i = -\mathrm{I} + \psi_1 + \cdots \psi_i$ and shows the short run speed of adjustment
$\Pi = -(\mathrm{I} - \psi_1 - \cdots - \psi_k)$,
ΔZ_t is assumed to be an I (0) vector;
I is a 5 by 5 identity matrix and
Π is a 5 by 5 stochastic matrix that contains information on long run relationships.

In the long run, $\Delta Z_t = \mathbf{0}$, thus the equation $\Pi Z = 0$ contains information about the long run relationships between the model variables. Hence, the number of cointegrating vectors (r) is given by the rank of Π. If the rank of Π is zero, then the variables in Z_t are not cointegrated. But, if Π is full rank matrix, its rank being equal to its number of rows or columns, then the variables $in\ Z_t$ are stationary at level (Harris, 1995). In general, if Z is I (d) variable, then the number of cointegrating vectors (r) is at most $N-1, i.e.\, r \le N-1$. Assuming that there are r cointegrating vectors among variables, where $0 < r < 5$, Johansen shows that the matrix Π can be decomposed into two 4 by r matrices, say α and β, such that $\Pi = \alpha\beta'$, where α represents the vector of speeds of adjustment to disequilibrium or is a matrix of the weights with which the vectors enter the equations in the system and β is a matrix of the parameters of the cointegrating vectors.

Assuming that the hypothesis about cointegration between the variables in the VAR is correct, in the long run, $\Pi Z_t = \alpha\beta' Z_t = 0$ implying that $\beta' Z_t$ is stationary though Z_t is non-stationary. Hence, $\beta' Z_t$ constitutes a set of r error correction mechanisms separating out the long-run and short-run responses in our model provided that the hypothesis concerning cointegration holds.

Johansen and Juselius (1990) present two likelihood ratios for testing the hypothesis that there are at most r cointegrating relationships among variables of a multivariate model. One test is based on the maximal eigenvalue[2] of the stochastic matrix Π to test the null hypothesis that the number of cointegrating vectors is less than or equal to *r* against the alternative of *r+1* cointegrating vectors and is based on the following test statistic

[2] Let B be an **n** by **n** matrix. If we let $|B|$ to the absolute value of the determinant of B and I to be an identity matrix, then the eigenvalues of B are the solutions to the equation $|\lambda \mathrm{I} - B| = o$

$$\lambda_{-max}(r) = -T log\left(1 - \hat{\lambda}_{r+1}\right) \quad (2.15b)$$

Where $r = o, 1, 2, \ldots, n-2, n-1$; T is the number of observations and $\hat{\lambda}_s$ are the eigenvalues obtained from the estimated II matrix.

The other test is based on the trace of the stochastic matrix and tests the null hypothesis against the alternative that there are at least *r+1* cointegrating vectors and is based on the test statistic

$$\lambda_{-trace}(r) = -T \sum_{l=r+1}^{n} log(1 - \hat{\lambda}_l), r = 0, 1, 2, \ldots, n-2, n-1 \quad (2.15c)$$

3.3.3. Testing for Granger Causality

Granger (1969) introduced the concept of causality in which a variable y is said to be Granger caused by another variable, say x, if the current values of y can be predicted with better accuracy by using past values of x. He argued that there must be causality among these variables at least in one direction if there is a co-integrating vector between them. It is worthwhile mentioning that Granger's concept of causality is not about an "event-outcome" relationship, but is about predictability, which means that x has significant incremental predictive power in the evolution of y.

Granger (1986) and Engle and Granger (1987) supply a test of causality, which takes into account the information provided by the co-integrated properties of variables, and involves estimating the following VAR in this particular study:

$$\Delta M_t = \alpha_0 + \sum_{i=1}^{n} \alpha_{1i} \Delta M_{t-i} + \sum_{i=1}^{n} \alpha_{2i} \Delta Y_{t-i} + \sum_{i=1}^{n} \alpha_{3i} \Delta P_{t-i} + \sum_{i=1}^{n} \alpha_{4i} \Delta R_{t-i} + \sum_{i=1}^{n} \alpha_{5i} \Delta ER_{t-i} + \alpha_6 ECT_{1t-1} + \epsilon_{1t} \quad (2.16a)$$

$$\Delta Y_t = \beta_0 + \sum_{i=1}^{q} \beta_{1i} \Delta M_{t-i} + \sum_{i=1}^{q} \beta_{2i} \Delta Y_{t-i} + \sum_{i=1}^{q} \beta_{3i} \Delta P_{t-i} + \sum_{i=1}^{q} \beta_{4i} \Delta R_{t-i} + \sum_{i=1}^{q} \beta_{5i} \Delta ER_{t-i} + \beta_6 ECT_{2t-1} + \epsilon_{2t} \quad (2.16b)$$

$$\Delta P_t = \theta_0 + \sum_{i=1}^{w} \theta_{1i} \Delta M_{t-i} + \sum_{i=1}^{w} \theta_{2i} \Delta Y_{t-i} + \sum_{i=1}^{w} \theta_{3i} \Delta P_{t-i} + \sum_{i=1}^{w} \theta_{4i} \Delta R_{t-i} + \sum_{i=1}^{w} \theta_{5i} \Delta ER_{t-i} + \theta_6 ECT_{3t-1} + \epsilon_{3t} \quad (2.16c)$$

$$\Delta R_t = \gamma_0 + \sum_{i=1}^{g} \gamma_{1i} \Delta M_{t-i} + \sum_{i=1}^{g} \gamma_{2i} \Delta Y_{t-i} + \sum_{i=1}^{g} \gamma_{3i} \Delta P_{t-i} + \sum_{i=1}^{g} \gamma_{4i} \Delta R_{t-i} + \sum_{i=1}^{g} \gamma_{5i} \Delta ER_{t-i} + \alpha_6 ECT_{4t-1} + \epsilon_{4t} \quad (2.16d)$$

$$\Delta ER_t = \rho_0 + \sum_{i=1}^{k} \rho_{1i} \Delta M_{t-i} + \sum_{i=1}^{k} \rho_{2i} \Delta Y_{t-i} + \sum_{i=1}^{k} \rho_{3i} \Delta P_{t-i} + \sum_{i=1}^{k} \rho_{4i} \Delta R_{t-i} + \sum_{i=1}^{k} \rho_{4i} \Delta ER_{t-i} + \alpha_6 ECT_{5t-1} + \epsilon_{5t} \quad (2.16e)$$

Where all variables are in logarithms, Δ the first is difference operator; *g, k, n q,* and *w* are the optimal lags to be selected with objective information criteria and ECT is the error correction term that captures the causality of co-integrated variables.

To see whether only imports are granger caused by other variables of the model, the first equation of system (2.16) will be estimated. In that case, the first null hypothesis would be that the coefficients of lagged Y are zeros, which implies that real income does not Granger cause imports. The following steps are involved in testing this null hypothesis. First, the current value of imports would be regressed on lags of P, R and ER but not on Y and the residual series will be obtained. Second, the residual series from the first step will be regressed on the entire set of explanatory variables and the coefficient of determination R^2 will be obtained; and finally, a Lagrange multiplier test in F distribution (LMF) will be formulated. The causality from and to imports, domestic price level, exchange rate (ER) and foreign exchange reserves(R) would be tested in a similar manner.

2.3.4. Testing for Stability of the Model

The stability of import demand function is very important for the effectiveness of trade policy (Yuan and Kochhar, 1994; Rehman, 2007; Yue, 2010). In stability test, we see whether the estimated import demand function has shifted or not over the time period included in the sample of the study. One of the first tests on structural change with unknown break point was the Standard CUSUM test which was introduced by Brown, Durbin and Evans in 1975. The CUSMUS of Squares (CUSMUSQ) test is another test which is derived from CUSUM test. Both tests are based on the cumulative sum of the recursive residuals ($\varepsilon_j{'}s$).

Under the null hypothesis of parameter stability, the two tests will have distributions defined as:

$$CUSUM: W_r = \frac{1}{s}\sum_{j=k+1}^{r} \varepsilon_j \text{ , where } s^2 = \frac{1}{n-k}\sum_{j=k+1}^{n} \varepsilon^2{}_j = \frac{1}{n-k}\sum_{j=1}^{n} \hat{\varepsilon}^2{}_j \qquad (17a)$$

$$CUSUMSQ: S_r = \sum_{j=k+1}^{r} \varepsilon^2{}_j \div \sum_{j=k+1}^{n} \varepsilon^2{}_j = \sum_{j=1}^{n} \varepsilon^2{}_j \div (n-k)s^2 \qquad (17b)$$

It is important to note that these test statistics are advantageous for they can be graphed and can identify not only their significance but also at what time point a possible break occurred. Hence, we will apply CUSUM and CUSUM of Squares Tests and Recursive coefficients to check the stability of the import demand function; and would conclude that the import demand model is stable and is correctly specified provided that neither the CUSMUS nor the CUSMUS of Squares (CUSMUSQ) test statistics exceed the bounds of the 5 per cent level of significances.

3.3.5. Impulse Responses and Variance Decompositions

A VAR analysis represents system dynamics and innovation accounting as a result of which it often centers on the calculation of impulse response functions (IRFs) and error variance decompositions so as to track the evolution of economic shocks through the system (Pesaran and Shin, 1997).

An impulse response function measures the time profile of the effect of shocks at a given point in time on the (expected) future values of variables in a dynamical system. The best way to describe an impulse response is to view it as the outcome of a conceptual experiment in which the time profile of the effect of a hypothetical m by 1 vector of shocks of size $\delta = (\delta_1, \dots, \delta_m)'$,say, hitting the economy at time t, is compared with a base-line profile at time $t + n$. In short, the Impulse Response Function analysis is used in dynamic models such as a VAR to describe the impact of an exogenous shock or innovation in one variable on the other variables of the system (Pesaran, 1997).

If the innovations to the covariance matrix of the residuals (Σ_ε) in a VAR model are diagonal or are contemporaneously uncorrelated, then the interpretation of the impulse response is that the i^{th} innovation of the residuals at time t is simply a shock to the i^{th} endogenous variable in the system. In practice, however, it turns out innovations are not diagonal and thus, the analysis of the evolution of the system caused just by an innovation in one variable may not be appropriate since it has innovation has a possibility of occurring along with another innovation. The solution to this problem is to orthogonalize the covariance matrix of residuals (Σ_ε) with the result that the evolution of shocks through the system will be uni-directional (Granger and Swanson, 1996).

Points on the IRFs could be made clear by looking at the equations specified in system (3.2).A shock to one variable in that system affects the variable itself and this affect is transmitted onto all of the endogenous variables in the system since VAR has a dynamic structure. For instance, a change in υ_{1t}will immediately have an effect on M_t and it will also change future values of Y_t, P_t, R_t and ER_t since there exist the current and lagged values of M_t in all of the five equations.

If the innovations (the error terms) are uncorrelated, then each error term is innovation for the corresponding endogenous variables in each equation. That is, υ_{1t} is innovation to M_t, $\upsilon_{2t}$is innovation for Y_t, υ_{3t} is innovation for P_t, υ_{4t} is innovation for R_t and υ_{5t} is innovation for ER_t. However, the covariance matrix of these innovations (Σ_ε) is usually correlated in real data that the variables in the VAR have a common component which cannot specifically be associated with one of them. It is possible to overcome this problem by attributing all of the effect of any common component to the variable that comes first in the VAR system. This methodology is named as Cholesky decomposition. The problem with this decomposition is that the result may change depending on the order of the variables in the VAR system. Thus; this property should be taken into account in any impulse response function analysis (Kilic, 2008).

It is can be noted from this sub-section that impulse response functions trace the effects of a shock to one endogenous variable onto the other variables of the VAR model while the variance decomposition separates the variation in an endogenous variable into the component shocks to the VAR. With this background, the current study employs both the IRFs and VDCs so as to decompose and get the relative effect of a shock on the endogenous variables of the specified VAR model.

III. PRESENTATION AND DISCUSSION OF RESULTS

3.1. Unit Root Test Results

The ADF test confirms that the first differences of lnM, lnY, lnP, lnR, and lnER are stationarity at the 1% and 5% levels of significance. This happens with a constant only; and with a constant and trend specifications for ADF test. This indicates that the variables are stationary at their first differences or are integrated of order one, I (1)[3].

[3] The results of the ADF test are left out of this article to save space

The Johansen multivariate co-integration tests require that each variable must be integrated of the same order (Sinha, 1997). The fact that the variables of the model are integrated of order one, I (1), helps in the determination of co-integrating relationships for it does not suffer from mixed order of integration; and hence, Johansen's co-integration analysis can be used to carry out the estimation of the specified import model.

3.2. Estimated Co-integrating Relationships

Using the Akaike Information Criterion (AIC), the optimal lag length for the specified VAR is the first lag. The trace test, reported in Table 3.1, shows that the null hypothesis of no co-integration vector(r=0) is rejected at the 1% level of significance since the trace test statistic (103.3230) is greater than the 5 percent critical value. Hence, the trace test predicts one co-integrating vector.

Table 3.1: Johansen Maximum Likelihood ratios test result

Null hypothesis[H_0]	Alternative Hypothesis: H_1	Eigenvalue	Trace Statistic	95%Critical Value	Probability
r=0	r≥1	0.658758	103.3230	88.80380	0.0030**
r≤1	r≥2	0.476894	62.46682	63.87610	0.0653
r≤2	r≥3	0.397240	37.84392	42.91525	0.1467
r≤3	r≥4	0.242048	18.60693	25.87211	0.3046
r ≤ 4	r≥5	0.191457	8.075812	12.51798	0.2455

Once the co-integrating vector is established to be one, then the problem at hand is that the dependent variable is not known yet. It is possible to identify the endogenous variable of the model though the test of weak exogeneity that involves imposing a zero restriction on columns of the weight (α-coefficient) matrix.

The likelihood ratio (LR) general restrictions (the Chi-square statistics) test speaks that the null hypothesis of weak exogeneity is rejected only for the logs of Import value (lnM) while the rest of the variables are found to be statistically weakly endogenous (see Table 3.2). This means that lnY; lnP, lnER and lnR are exogenous to the system that it is logical to condition or express import value on them. It can now be inferred that there is a single long run dynamic equation that links the real value of imports to those variables which wouldn't endogenously be determined from the model.

Table 3.2: Estimated Eigenvalues, Eigenvectors and Weight of the stochastic Matrix

a) Standard β' Eigenvectors

lnMt	lnYt	lnPt	lnRt	lnERt
1.0000	-1.5228	-0.17359	-0.27259	0.17542
-0.8183	1.0000	0.05188	-0.27610	0.54435
1.1152	-2.6737	1.0000	-0.14934	-0.46288
0.2563	5.7708	1.1930	1.0000	-8.0281
-19.750	153.72	-32.240	-8.9013	1.0000

b) Standard α-coefficients or Matrix of Weights

lnMt	lnYt	lnPt	lnRt	lnERt
-0.46854	-0.07253	-0.066307	0.41900	-0.30596
0.00970	-0.10362	-0.11864	0.93996	0.068981
-0.05121	0.028945	-0.04616	-0.05937	0.033387
-0.02185	-0.00590	0.00884	-0.05013	0.003193
-0.00057	0.000157	0.00107	0.00473	0.000948

The existence of one co-integrating vector suggests that only the first row of β matrix and the first column of α matrix are important for further analysis. The first column of Table 3.3(b) shows the speed of adjustments towards or deviation from the long run steady state value of each variable of the model.

Table 3.3: Tests Results of Zero Restrictions on α –coefficients

Variable	α coefficient	LR test of general restrictions: Chi^2(1)	P value
LnMt	-0.4684	13.198	[0.0003]**
LnYt	0.00970	1.7711	[0.1832]
LnPt	-0.0512	0.5684	[0.4509]
lnRt	-0.0219	0.6859	[0.4076]
LnERt	-0.0057	1.199	[0.3243]

More specifically, the values -0.4684,-0.0512, -0.0219 and -0.0057 indicate the speed of adjustment of imports, domestic price level, foreign exchange reserves and exchange rate towards their long run steady state path, respectively while the positive coefficient of domestic income level indicate the extent to which this variable deviates from its long run steady state path following a certain shock. Put it another way, the log of real income (lnY) is currently above its steady state path and will start to fall while the rest of the variables are below their equilibrium value that they will start to rise so that all variables reach their steady state value in the long run.

Having found the dynamic single equation long run relationship between the variables of the model, the next step is to formulate a test of significance on the long run coefficients (β's) of the regressors. Thus, an exclusion test, where a zero restriction is imposed on the long run β coefficients, is used so as to locate the relevant or statistically significant variables of the co-integrating vector. The output of this test is obtained from PCGIVE and is reported in Table 4.6.

As can be read from the table, domestic income and foreign exchange reserve are found to be significantly different from zero; and the null hypothesis that each variable is statistically insignificant is rejected at the conventional 1 percent level of significance. Allowing an error margin of 10 percent, domestic price level is also found to have a significant share in explaining the demand for import while the long run coefficient of exchange rate is found statistically not to be different from zero.

Table 3.4: Tests for Zero restrictions on β- coefficients

Variable	β coefficient	LR test of general restrictions: Chi^2(1)	P -value
lnY_t	-1.5228	11.157	[0.0008]**
lnP_t	-0.1736	2.807	[0.0939]
lnR_t	-0.2729	12.965	[0.0003]**
$lnER_t$	0.1754	1.435	[0.2309]

** indicates the rejection of the null hypothesis that a variable is individually insignificant

Since the model is specified and estimated in its log-linear form, the coefficients of the long run equation can be interpreted directly as elasticities. Before interpreting these coefficients, however, it is advisable to first conduct model diagnostic tests. Accordingly, various model diagnostic tests are run and the result is reported in Table 3.5 along the estimated coefficients of the long run model.

The system diagnostic tests, as reported in the lower block of table 3.5[4], confirm that the specified model is adequate in explaining the conjectured relationship. The variance inflating factor (VIF) of each vaiable is less than ten implying that there is no perfect multicollinearity between the explanatory variables of the model. There is also no indication of serial autocorrelation as shown by the Breusch Godfrey LM test for serial correlation. The nulls of homoscedastic and normally distributed error terms cannot be rejected at any conventional level of significance. The ARCH test indicates the absence of autoregressive conditional hetroscedastic errors. Ramsey's (1969) RESET test does not reject the null hypothesis of no functional misspecification of the estimated import demand equation. Finally, the VAR parameter stability test is conducted with a plot of the 1st –step recursive residuals (1st-step residuals +/-2nd) (See Appendix II);and the test result shows that the null hypothesis of overall VAR parameters' consistency cannot be rejected for recursive plots of variables oscillate around a zero

[4] See Appendix III for the full VAR diagnostic test result from PCGIVE

mean line. This implies that the estimated long run model is stable that it could be used for a policy purpose.

The long run regression output shows that only the domestic income and the foreign exchange reserves have a significant positive effect on the nation's aggregate imports demand; and both variables carry their theoretically expected sign. The aggregate import demand is found to be income elastic that a one percent increase in real income of the nation leads to, on average, a 1.523 percent increase in the nation's demand for imports. This means that imports are the sources of growth in real GDP of the nation. This finding is similar to the findings of Mwega (1993) for Kenya; Yuan and Kochhar (1994) for China; Sinha (1997) for Thailand; Egwaikhide (1999) for Nigeria; Rehman (2007) for Pakistan; Sultan (2011) for India; Girma (1982), Solomon (2000) and Yohaness (2011) for Ethiopia. It, however, refutes the findings of Muluneh (1982) and Alem (1995), each of which found a significant negative relationship between GDP and imports for Ethiopia.

Foreign exchange reserve is also found to have a significant positive impact on the import demand of the county. Keeping other things constant, a one percent rise or fall in foreign exchange reserves, on average, causes a 0.273 percent rise or fall in imports. Though its economic impact is relatively small, in particular to the size of estimated income elasticity, its turns to be an important determinant of import over the sample period. This implies that foreign exchange reserve (FER) acts as a constraint to import necessary inputs; and that the desired level of import cannot be actualized in the absence of sufficient level of FER reserves. This finding supports the findings of Sewasew (2002) in which he found a positive effect of reserves on import demand in the long run though he established no relationship between imports and real income. It is also similar to the findings of Egwaikhide (1999) for Nigeria and Sultan (2011) for India.

Domestic price level and exchange rate are found to be statistically insignificant at the conventional levels of significance. As to the domestic price level, this result supports the reality on the ground for the import of the nation is comprised of mainly intermediate and capital goods. As the economy keeps on growing, more of such goods are needed to ease the growing needs of the economy and thus, the domestic price level does hardly affect our demand for imports.

The insignificant finding on foreign exchange supports the theoretical argument of Ghei and Pritchett (1999) and is similar to the findings of Mwega (1993) for Kenya and Mah (1997) for Republic of South Korea. It refutes the argument that devaluation of an exchange rate is, by increasing the domestic price of goods as theoretically inspired by WB and IMF, meant to boost exports and discourage imports via its role of shifting consumption from domestic to export for exportable and from import to domestic importables (EEA, 2007). This is so because for a small peasant economy with a little industrial base of ours, devaluation can seldom be effective in inducing substitution of imported goods by the domestically produced ones. This is one possible explanation for the statistical insignificance of the exchange rate in explaining the demand for imports. Moreover, a devaluation measure taken along with trade liberalization may not increase the supply of import substitutes unlike the case where trade is not liberalized at the time of devaluation.

Table 3.5: Estimated long-run elasticities of Import demand model

	Domestic output level	Domestic price level	Foreign Exchange Reserves	Exchange rate
Elasticity	1.5228	0.17359	0.27259	-0.17542
VIF	8.20	7.38	3.62	9.52

System Diagnostic Tests

AR 1-2 test: F (2, 30) = 0.02944 [0.9710]

ARCH 1-1 test: F(1,35) = 0.43885 [0.5120]

Normality test: Chi^2(2) = 2.2171 [0.3300]

Hetero test: F(10,21) = 1.2396 [0.3234]

Hetero-X test: F(20,11) = 0.76946 [0.7064]

3.3. Granger Causality Analysis

As can been seen from Table 3.7, the first, the second, the third and the fifth null hypothesizes that 3 period lagged coefficient of imports, income, domestic price level and exchange rate are zeros in the short run, which implies that these variables do not Granger cause imports, cannot be rejected at the conventional levels of significance. But, this does not mean that there will not be any significance relationship between them.

Investigating the relationship between imports and foreign exchange reserves, the test result in Table 3.7 suggests that the current change in imports is granger caused, at least uni-directionally, by the first 3 lagged values of the change in reserves as the null hypothesis of no granger causality is rejected at the 5% level of significance. This finding is similar to the finding of Yuan and Kochhar (1994) for China which argues that foreign exchange reserves can be seen as a trigger for the tightening or relaxation of import controls. So far the long run relationship between imports and the remaining four variables is concerned, the feedback coefficient (-1.1660) is significant at the 5% level of significant suggesting the existence of a causality from income, price, FOREX reserves and exchange rate to imports.

Table 3.7: Granger Causality Test Result

Direction of Causation	Short run Causation(with 3 lags)				Long run Causation	
	Chi(χ^2)-square test		F-test		ECT_{1t-1}	
	Statistic	Prob.	Statistic	Prob.	coefficient	Prob.
From M to M	2.4705	0.4807	0.8235	0.4970	-1.1660	0.0354
From Y to M	2.1931	0.5333	0.7310	0.5462		
From P to M	2.3213	0.5085	0.7738	0.5229		
From R to M	10.74711	0.0131	3.5823	0.0331		
From ER to M	1.8095	0.6129	0.6031	0.6209		

3.5. The Vector Error Correction Model (VECM) of Imports

Once the variables are co-integrated of order one , I(1) and the long run relationship is established, then follows the determination of the coefficients of the short run import demand equation so that both the short run and the long run could be linked together in a Vector Error Correction Model (VECM).

For modeling the short-run import dynamics, the one period lagged Error Correction Term (ECT_{t-1}) is first generated from the residuals of the co-integrating vector. Then, all the variables are differenced once and entered into the right hand side of the model as regressors to import. It is important to note that a one period lagged error term is used to show how the time path matters in correcting errors. To this end, Hendry and Juselius (2002) argue that rational economic agents, taking all available information at time t , will rationally take actions at period $t+1$ in order that they could minimize errors.

For estimating the Single-Equation-Error-Correction import demand model, which is specified in Chapter Three, the Hendry's general to specific modeling approach is employed. In this approach, an over-parameterized import model, which includes all differenced explanatory variables along their first lags, is estimated first. Then, highly insignificant explanatory variables are continuously eliminated until a parsimonious model with fewer regressors but robust in terms of significance, economic theory and diagnostic tests are obtained.

The multiple coefficients of determination (R^2) shows that about 55 percent of the variation in imports can be explained by the combined effects of all the explanatory variables included in the short-run import model (Table 3.8 below). The model is adequate in explaining the specified relationship for the F statistic rejects the null hypothesis that all the coefficients of the model variables are jointly insignificant at the one percent error margin.

Table 3.8: The short run dynamic result for the import demand equation

Variable	Coefficient	Standard Error	t-value	t-prob	Part.R^2
Constant	0.0449157	0.02889	1.55	0.130	0.0702
ΔlnY_t	1.12150	0.3594	3.12	0.004**	0.2333
ΔlnP_t	-0.379405	0.2316	-1.64	0.111	0.0774
ΔlnR_{t-1}	0.106329	0.04387	2.42	0.021*	0.1551
$\Delta lnER_t$	-0.0334450	0.2589	-0.129	0.898	0.0005
ECT_{t-1}	-0.600191	0.1715	-3.50	0.001**	0.2769

R^2=0.548884   F(5,32) = 7.787 [0.0000]**   DW=1.86

Diagnostic tests

AR 1-2 test: F(2,30) = 0.85893 [0.4338]
ARCH 1-1 test: F(1,30) = 0.061048 [0.8065]
Normality test: Chi^2(2) = 1.3201 [0.5168]
hetero test: F(10,21) = 0.60549 [0.7920]
RESET test: F(1,31) = 0.12655 [0.7244]

** and * indicates rejection of the null hypothesis at the 1 and 5 levels of error margin

As to the diagnostic tests, the Durbin Watson (DW) test statistic is closer to 2 implying that there is no problem of autocorrelation. The null hypothesizes that the error term is normally distributed; no problem of misspecification and no problem of hetroscedasticity are not rejected as implied by the Jacque Bera test for normality, Ramsey's RESET test and the autoregressive conditional hetroscedasticity (ARCH) test respectively at the 1 percent level of significance. Moreover, the coefficient of the one period lagged error correction term (ECT_{t-1}) has a negative sign and is statistically significant at 1 percent level of significance.

The short run result shows that the change in imports is affected positively and significantly by the current income level and the one period lagged foreign exchange level of reserves. As is in the long run, imports are income elastic and FOREX inelastic. That is a one percent change in real domestic income, changes imports by about 1.122 percent; and a one change in reserves changes the demand for imports by about 0.11percent.

As in the long run, the short run coefficients of domestic price level and exchange rate are not statistically different from zero that both variables fail to explain the variation in the demand for imports.

The coefficient of the one period lagged error correction term (ECT_{t-1}) measures the speed at which the disturbances in the short run could be corrected each year in order that import attains its long run equilibrium. This coefficient has a negative sign and is not greater than unity. It suggests a yearly speed of adjustment of about 60 percent towards equilibrium and whilst its being negative and statistically significant confirms the existence of co-integration between imports and its determinants (Gujarati, 2004). This implies that real import adjusts itself to the equilibrium by about 60 percent in one year and the complete adjustment will take about twenty months.

3.6. Model Stability Test Result

Figure 3.1(a) shows that the import demand function remained stable for the sample period for the cumulative sum does not go outside the five percent critical lines. The cumulative sum of squares plot in Figure 3.1(b) too indicates that the residual variance is stable over the sample period since cumulative sum of the recursive residuals squares line lies within the 5 percent critical lines. It is, thus, possible to use the estimated VECM for a policy purpose.

Figure 3.1a: CUSUM

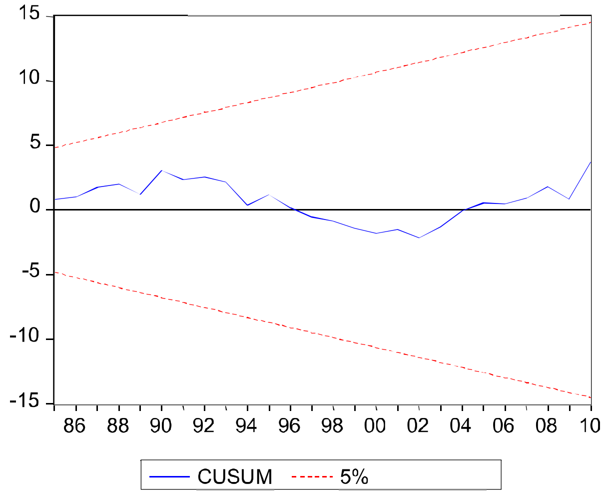


Figure 3.1b: CUSUM of Squares Test

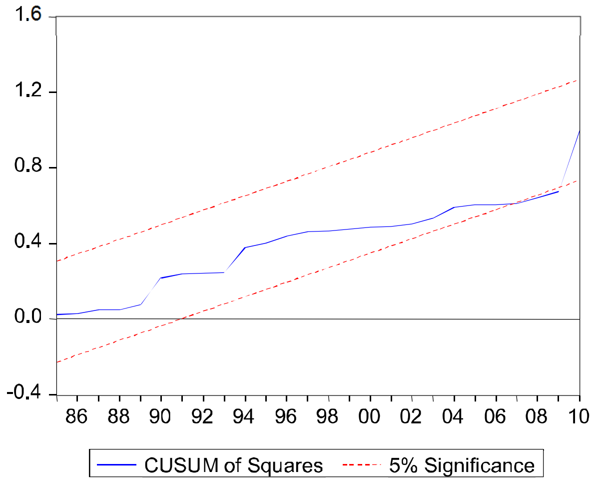


Figure 3.1: VECM Stability Tests Result

3.7. Variance Decompositions and Impulse Response Functions

Variance decompositions (VDCs) and Impulse Response Functions (IRFs) are important to get the relative effect of an explanatory variable's shock on the endogenous variable of a VAR model. Accordingly, the VDCs and IRFs of the VAR, specified in system (2.2), are employed in the following two sub-sections to see the degree of responsiveness of imports to innovations.

3.7.1. Variance Decompositions (VDCs)

Variance decomposition decomposes the sources of variation in an endogenous variable into the component shocks to the VAR variables. That is, VDC provides information about the relative strength of each random innovation or shock in affecting the variables in a VAR model.

The variance decompositions of imports witnesses that a shock to foreign exchange reserve best explains the forecast error variance of imports, next to import itself, up to the fifth period (see Table 4.10 below). From the 5th period onwards, the relative forecast error variance of imports diminishes implying the relative strength of FOREX reserves in the long run. The relative growth in real GDP also is higher in the long run that it explains more than 30 percent of the forecast error variances of import growth from the 9th period onwards. Domestic price level and exchange rates hardly explain the forecast error variance of import growth.

It is important to note that variance decomposition based on Cholesky factor may change dramatically if the order of the variables in the VAR is changed. Thus, an alternative estimation by interchanging the order of the four explanatory variables is carried out to check for the robustness of the results. This attempt also yielded the same results.

Table 3.9: Variance Decomposition of log imports (lnM_t)

Period	S.E.	lnM	LnY	LnP	lnR	LnER
1	0.139488	100.0000	0.000000	0.000000	0.000000	0.000000
2	0.177383	85.35098	2.003318	0.568565	11.86742	0.209717
3	0.208923	67.31901	6.227519	1.378380	24.20671	0.868381
4	0.239473	52.50705	11.38463	2.151728	32.17646	1.780126
5	0.269772	41.58468	16.49614	2.820684	36.42248	2.676013
6	0.299834	33.68010	21.10178	3.392402	38.42000	3.405721
7	0.329620	27.86845	25.07153	3.887922	39.24228	3.929823
8	0.359180	23.47379	28.42637	4.324363	39.50880	4.266683
9	0.388654	20.05101	31.23901	4.712628	39.54308	4.454276
10	0.418237	17.31502	33.59092	5.059121	39.50340	4.531547

3.7.2. Impulse Response Functions

An impulse response function traces the effect of a one standard deviation shock to one of the exogenous variables on the current and future values of the endogenous variables in a VAR. A shock to the i^{th} variable directly affects the i^{th} variable and could also transmit to all of the endogenous variables through a dynamic structure of the VAR (Stock and Watson, 2001).

Imports respond positively and significantly only to itself in the first period (see Table

3.10). From first period onwards, it positively and significantly responds to output and foreign exchange reserve. In the long-run, imports respond more significantly to changes in output growth than to changes in other variables. The Impulse response functions are graphed (see Appendix IV); and the results are similar to the ones in Table 3.10.

The findings from both the variance decomposition and the impulse response functions supplement the short and long run results that growth in domestic output and FOREX exchange reserve are more important for the prediction of import growth in Ethiopia.

Table 3.10: Impulse Responses of log of Imports to one Standard Deviation

Period	lnM	lnY	lnP	LnR	lnER
1	0.139488	0.000000	0.000000	0.000000	0.000000
	(0.01579)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
2	0.086014	0.025107	0.013375	0.061107	0.008123
	(0.02075)	(0.01732)	(0.01183)	(0.01932)	(0.00690)
3	0.050284	0.045694	0.020561	0.082655	0.017693
	(0.02571)	(0.02398)	(0.01696)	(0.02313)	(0.01026)
4	0.026968	0.061729	0.025146	0.088805	0.025334
	(0.02958)	(0.02760)	(0.01976)	(0.02513)	(0.01301)
5	0.012359	0.074004	0.028616	0.089749	0.030441
	(0.03359)	(0.03075)	(0.02192)	(0.02741)	(0.01572)
6	0.003817	0.083458	0.031575	0.089625	0.033380
	(0.03767)	(0.03402)	(0.02408)	(0.02987)	(0.01847)
7	-0.000564	0.090937	0.034270	0.089982	0.034756
	(0.04162)	(0.03744)	(0.02640)	(0.03234)	(0.02123)
8	-0.002157	0.097123	0.036806	0.091290	0.035139
	(0.04540)	(0.04099)	(0.02888)	(0.03479)	(0.02398)
9	-0.001947	0.102538	0.039238	0.093595	0.034983
	(0.04900)	(0.04469)	(0.03144)	(0.03726)	(0.02666)
10	-0.000631	0.107568	0.041605	0.096797	0.034618
	(0.05246)	(0.04864)	(0.03401)	(0.03986)	(0.02927)

3.8. Comparing Forecasts

In this section, the forecasting ability of the conventional partial adjustment and the Johansen approaches of estimating the import demand function are compared. To this end, the OLS estimates to the conventional model for imports are given in Table 3.11.

The estimated partial adjustment model shows that import is responsive only to its lagged values and the current domestic income level. But, it is can also be argued that import has a possibility of responding to lagged values of other explanatory variables as well. Moreover, this model fails to account for the long run speed of adjustment term unlike the vector error correction model.

Table 3:12: The Estimated Conventional Import Model

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	-3.828226	1.913367	-2.000780	0.0540
$\ln M_{t-1}$	0.472015	0.129060	3.657339	0.0009
$\ln Y_t$	0.873346	0.288251	3.029805	0.0048
$\ln P_t$	-0.060216	0.097999	-0.614452	0.5433
$\ln R_t$	0.091023	0.047350	1.922338	0.0635
$\ln ER_t$	0.082178	0.130557	0.629441	0.5335

Table 3.12 reports several objective criteria that could be used to evaluate the forecast performance of the two models. The root-mean-squared error (RMSE), the mean absolute error (MAE), and the Mean Absolute Percentage Error (MAPE) of the conventional import model are higher than that of the Johansen's model. It could, thus, be concluded that that the error-correction model outperforms the conventional model for estimating import demand equation.

Table 3.13: Comparing the conventional and Johansen import models

Criteria	Conventional	Johansen
Root Mean Squared Error	0.145687	0.11403
Mean Absolute Error	0.11309	0.08969
Mean Absolute Percentage Error	0.99114	0.78866

V. POLICY IMPLICATIONS

The Granger causality test reveals that domestic income, domestic price level, and exchange rate and foreign exchange reserves jointly Ganger cause imports in the long run while it is only foreign exchange reserves that Granger causes imports in the short run. VDCs indicate that import of the country is highly sensitive to itself only in the short run; and foreign exchange reserves and domestic income level explain a significant portion of forecast error variances of imports in the long run. Similarly, the plots of IRFs shows that import responds positively and significantly to output and foreign exchange reserves in the long run though it positively and significantly responds to itself in the Short run.

Finally, the conventional partial adjustment model of import demand, where import is regressed on its first lag and on the current values of domestic income level, foreign exchange reserves, domestic price level and exchange rate is estimated and its forecasting performance is compared to the Error-Correction Model. Such an evaluation proved that the error-correction model predicts turning points with a greater degree of accuracy than the conventional partial adjustment model that the estimates obtained from the former are robust.

On the basis of the findings of the study, the following policy implications are drawn. First, the relatively higher long run income elasticity of import demand predicts the dependency of the county on imported inputs of production, especially on capital goods, over longer time horizons. Under such a situation, imports grow at a faster rate than the growth of income of a country and would deteriorate the trade balance of the country unless the growth in imports is accompanied by the growth in exports. This represents a key risk to the balance of payments of the nation for a few exportable commodities are fetching its export earnings. That is, the limited production capacity of the nation along with the rising import demand for imports (especially of consumer goods) places a pressure on the balance of payments of the country. It is, thus, highly advisable to diversify production in order that this reliance on few exports and huge imports would be minimized. In particular, it should be worked to boost the productivity and international competitiveness of the export sector.

Second, the lower short run income elasticity suggests the effective room available for import substitution. The share of consumer goods in the total import value is, on average, not less that 30 percent[5] between 1994/94 and 2009/10 which makes it the second largest component of the country's import; and the foreign exchange reserve is found to have a positive effect on import. It can be inferred from this that a considerable portion of FOREX reserves are being spent on consumer goods which would otherwise be used for the purchase of domestically unavailable production inputs. This shows how important it is to find domestic substitutes so that the share of consumer goods in the total import would at least be minimized.

Another policy option would be that of supplementing devaluation with import restriction. The empirical findings show that devaluation has seldom been effective in reducing imports. This being the case; consumer goods take the lion's share of the country's import volume. To this end, devaluating more may cut imports. But, this can only be achieved at the cost of losing necessary inputs to the production process since the Ethiopian economy is an import dependent one. Thus, it is recommendable to supplement the exchange rate policy with impose restrictions targeting luxury (consumer) items instead of sorting to a more devaluating policy.

[5] See Table 4.1 in Chapter Four

References

Alem, A., 1995. Government Policies, Real Exchange Rates and Agricultural Exports. *Unpublished Msc. Thesis, Addis Ababa University*.

Brown, R., Durbin, J. & Evans, J., 1975. Techniques for Testing the Constancy of Regression Relationships over Time. *Journal of the Royal Statistical Society, Series B, 35*, pp.pp.149-192.

Dickey, D. & Fuller, W., 1981. *Likelihood Ratio Statistics for Autoregressive Time Series with Unit Root.Econometrica, 49, 1057-1072.*

Dike, E., Ogujiuba, K. & Nwogwugwu, U., 2011. Import Substitution Industrialization as Learning Process: Sub Saharan African Experience as Distortion of the "Good" Business Model. *Business and Management Review Vol. 1(6)*, p.08 – 21.

Engle, R. & Granger, C., 1987. *Co-Integration and Error Correction: Representation, Estimation and Testing. Econometrica 55 (2) pp 251-76.*

Girma, E., 1982. An Analysis of the relationship between Ethiopia's foreign Trade and Gross Domestic Product. *Msc. Thesis, Addis Ababa University*.

Granger, C. & Swanson, N., 1996. Impulse Response Functions Based on a Causal Approach to Residual Orthogonalization in Vector Autoregressions.

Gujarati, D., 2004. *Basic Econometrics,4th edition*. New York: McGraw Hill.

Harris, R., 1995. *Using Cointegration Analysis in Econometric Modeling*. Edinburgh Gate,Harlow,England: Prentice Hall.

Hemphill, 1974. The Effect of Foreign Exchange receipts on Imports of Less Developed Countries. *IMF Staff Papers,Vol.21*.

Hong, P., 1999. Import Elasticities Revisited. *Discussion Paper No. 10, Department of Economic and Social Affairs, United Nations*.

Johansen, S. & Juselius, K., 1990. Maximum likelihood estimation and inference on co-integration with application to the demand for money. *Oxford Bulletin of Economics and Statistics, vol. 52*, p.269–270.

Khan, 1974. Import and Export Demand in Developing Countries. *IMF Staff Papers, Vol.21*, pp.pp.678-693.

Khan, M. & Ross, K., 1977. The Functional Form of the Aggregate Import Demand Equation. *Journal of International Economics No. 7*, pp.149-60.

Kilic, E., 2008. An Empirical Analysis of the Relationship between Financial Deepening andEconomic Growth:The Case of Turkey. *A Thesis Submitted to the Graduate School of Social Sciences of Middle East Technical University*.

Kmenta, J., 1986. *Elements of Econometrics. 2nd edition*. New York: Macmillan Publishing Company.

Krugman, P., 1996. *International Economics: Theory and Policy, 4th edition, University of California*. Berkeley.

Maddala, G., 1992. *Introduction to Econometrics, 2nd edition*. New York: Macmillan Publishing Company 866,Third Avenue,New York,New York 10022.

Mah, J., 1997. An Empirical Examination of the Disaggregated Import Demand of Korea: The case of information technology products. *Journal of Asian Economics*, p.pp.230– 240.

Moran, 1989. Imports under a Foreign Exchange Constraint. *World Bank Economic Review, Vol.3, No.2.*.

Muluneh, A., 1982. Analysis of Ethiopian Imports. *unpublished Msc. Thesis, Addis Ababa University*.

Mwega, F., 1993. Import Demand Elasticity's and Stability During Trade Liberalization : A case Study of Kenya. *Journal of African Economics , Vol.2 ,PP.381-416* .

Pesaran, H., 1997. *Generalized Impulse Response Analysis in Linear Multivariate Models*.

Pesaran, H. & Shin, Y., 1997. Generalized Impulse Response Analysis in Linear Multivariate Models. *Economics Letters 58 (1998) 17–29*.

Phlilips, P. & Perron, P., 1988. *Testing for a Unit Root in Time Series Regression. Biometrica, 75, 335-46*.

Rao, B., 1994. *Cointegration: For the Applied Economist*. Macmillan.

Rehman, H., 2007. An Econometric Estimation of Traditional Import Demand Function for Pakistan. *Pakistan Economic and Social Review Volume 45,number 2,* pp.pp.245-256.

Rogers, A., 2000. An analysis of the Determinants of Fiji's Imports. *Working Paper 2000/03,Reserve Bank of Fiji*.

Salvatore, D., 1990. *International Economics,2th ed.* New York: Macmillan Publishing Company.

Senhadji, A., 1998. Time-series estimation of structural import demand equations: A cross-country analysis. *IMF Staff Papers,45*, pp.pp.230-265.

Sewasew, P., 2002. The Relationship between Import and GDP Growth in Ethiopia. *Unpublished MSc. Thesis, Addis Ababa University*.

Sinha, D., 1997. Determinants of Import Dermand in Thailand. *International Economic Journal,Vol.11,Number 4*, pp.pp.2-10.

Stock, J. & Watson, M., 2001. Vector Autoregressions. *Journal of Economic Perspectives*, Vol. 15, No. 4, pp.pp.101-115.

Sultan, Z.A., 2011. Foreign Exchange Reserves and India's Import Demand: A Cointegration and Vector Error Correction Analysis. *International Journal of Business and Management Vol. 6, No. 7; July 2011.*.

Tura, K., 2001. Determinants of International trade Flows: The Case of Ethiopian. *Msc.Thesis, Addis Ababa University*.

Yohaness, B., 2011. The Impact of Foreign Aid on Economic Growth in Ethiopia: Accounting for Transmission Mechanisms. *Unpublished MSc. Thesis, Addis Ababa University* .

Yuan, M. & Kochhar, K., 1994. An Empirical Analysis of China's import Using Johansen's Cointegration Approach. *IMF Working Paper WP/94/145*.

Yue, Y., 2010. An Econometric Estimation of Import Demand Function for Cote D'Ivoire. *International Journal of Business and Management Vol.5,No.2*.

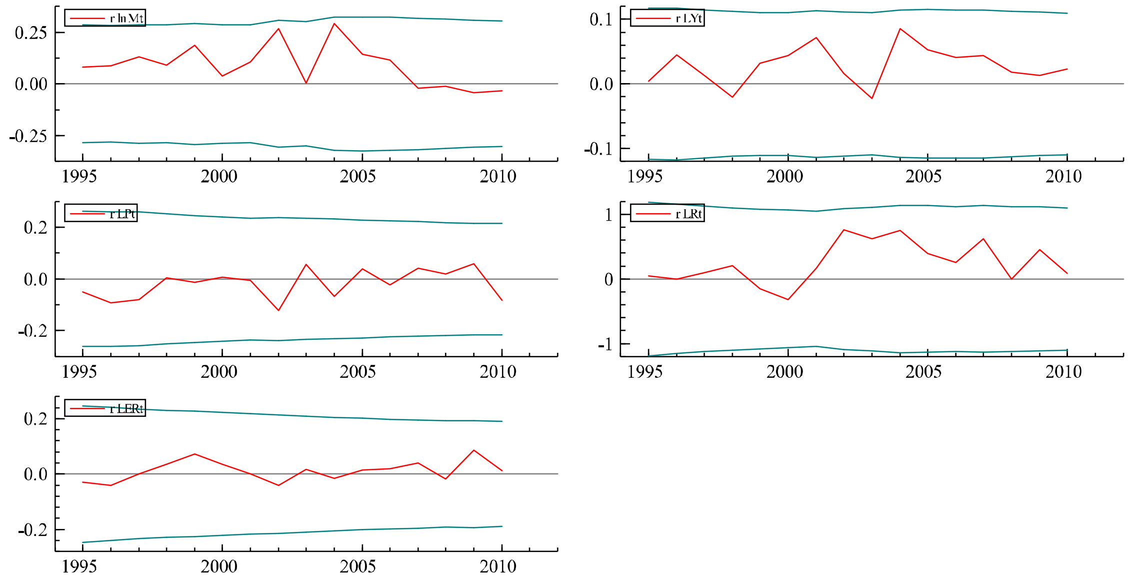
International Journal of Academic Research
ISSN: 2348-7666; Vol.4, Issue-12(2), December, 2017
Impact Factor: 6.023; Email: drtvramana@yahoo.co.in

Appendix I: Long run Model Diagnostic Test Result

lnMt :Normality test: Chi^2(2) = 4.4259 [0.1094] lnYt : Normality test: Chi^2(2) = 3.6565 [0.1607] lnPt : Normality test: Chi^2(2) = 4.8883 [0.0868] lnRt : Normality test: Chi^2(2) = 1.5023 [0.4718] lnER :Normality test: Chi^2(2) = 29.318 [0.00]**	lnMt :AR 1-2 test: F(2,31) = 1.6565 [0.2073] lnYt: AR 1-2 test: F(2,31) = 3.1329 [0.0576] lnPt: AR 1-2 test: F(2,31) = 3.9886 [0.0287]* lnRt : AR 1-2 test: F(2,31) = 0.76071 [0.4759] lnERt: AR 1-2 test: F(2,31) = 0.74410 [0.484]
lnMt: hetero test: F(10,22) = 1.6817 [0.1486] lnYt : hetero test: F(10,22) = 1.0468 [0.4397] lnPt : hetero test: F(10,22) = 0.76207 [0.6622] lnRt : hetero test: F(10,22) = 2.0062 [0.0834] lnERt : hetero test: F(10,22) = 1.0835 [0.4149]	lnMt : ARCH 1-1 test: F(1,31) = 0.54699 [0.465] lnYt : ARCH 1-1 test: F(1,31) =2.5427 [0.1210] lnPt : ARCH 1-1 test: F(1,31) =2.3101 [0.1387] lnRt : ARCH 1-1 test: F(1,31) = 0.44186 [0.511] lnERt : ARCH 1-1 test: F(1,31) = 0.57073 [0.456]
lnMt : hetero-X test: F(20,12) =1.1412 [0.4181] lnYt : hetero-X test: F(20,12) = 1.7218 [0.1675]	lnPt :hetero-X test: F(20,12) =0.8769 [0.0321]* lnRt : hetero-X test: F(20,12) = 1.4882 [0.2420] lnERt : hetero-X test: F(20,12) = 2.6694 [0.042]*

Appendix II: Long Run Stability Test Result [6] (Recursive Graphics)

[6] The fact that the plot of recursive residual stays within the critical lines implies that the VAR is stable


r lnMt
0.25
0.00
-0.25
r LYt
0.1
0.0
-0.1
r LPt
0.2
0.0
-0.2
r LRt
1
0
-1
r LERt
0.2
0.0
-0.2
1995
2000
2005
2010