

What Explains the Trends of Wheat Imports in Kenya; A Cointegration Analysis Using ARDL-ECM Modelling

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Abstract
This study aims to determine the cointegration of wheat imports and its determinants in Kenya. To achieve this objective, annual time series secondary data from 2000 to 2019 was utilized. The time frame was considered because it was during this period that wheat imports in Kenya skyrocketed. Data was collected from national and international published sources. The findings of the Auto-Regressive Distributed Lag-Error Correction Model (ARDL-ECM) analysis shows that wheat imports in Kenya are determined by the tariff, relative prices and ending stock in the long run. In the short run relative price was the main determinant that influenced wheat imports in Kenya. It was also realized that wheat imports in Kenya are inelastic to its determinants. Therefore, the study recommends that policymakers should embrace policies that increase the competitiveness of domestic wheat production in Kenya to tap the multiplier benefits that can be realized from the wheat sector. This can be done by embracing modern and efficient production technologies.
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1. INTRODUCTION

Grains are presently the foremost necessary contributor to human food provided globally and it is estimated that 21% of food in the world is dependent on the annual wheat crop harvests (Enghiad *et al*., 2017). According to previous research by FAO (2015), cereals represent the highest commodities imported to Africa, accounting for 43% of total imports, whereby wheat leads followed by rice. In Africa, the wheat economy[1] is characterized by an increasing gap between domestic wheat supply and consumption. The widening gap is progressively making Africa be dependent on imports for staple grains, especially wheat and rice. According to evidence of an increase in Africa's wheat import bill, it is exacerbated by high and volatile wheat prices, climate change, and export restrictions imposed by world major producers such as Russia (Enghiad *et al*., 2017; Mason *et al*., 2012; Negassa *et al*., 2013). The statistics indicate that in 2017 Africa produced 25000 metric tonnes (MT) of wheat on 10 million hectares out of the total demand of 61000 MT. This created a food deficit of approximately 36000 MT (59%) of wheat that was imported. On average, over the past decade, Sub Saharan Africa (SSA) has produced 7500 MT on a total area of 2.9 million hectares and imported 12700 MT (Negassa *et al*., 2013; Tadesse *et al*., 2019). A clear indication that most African nations import more than what they can produce.

Wheat consumption in Africa increased by 55% over the last two decades, the expansion was attributed to rising income levels, an increase in population, as well as convenience associated with wheat products which have made it more popular (Meyer *et al*., 2016). The rapid change in SSA wheat consumption has been reported as part of changing food preferences linked to urbanization (Morris & Byerlee, 1993). As observed by Enghiad *et al*. (2017), consumption by developing countries contributes 77% of total global wheat production and the majority being net importers are at the mercy of global wheat prices. Despite the increase in demand, most African countries have continued to import wheat instead of increasing their domestic production. Therefore, low wheat supply in Africa countries necessitates import of wheat to bridge the deficit.

Wheat in Kenya is an important cereal crop and ranks second after maize in its cereal crop priority. In Kenya, wheat production contributes significantly to food security, poverty reduction and job creation in agriculture (Kamwaga *et al*., 2016). Kenya domestic production of wheat is highly volatile and deficit in meeting the demand of wheat while consumption has been increasing at an average rate of 80% in the last two decades as shown in Table 1. In a nutshell, it can be concluded that there is a stagnation in Kenya wheat sector as average production and consumption diverge over the two decades. Therefore, measures need to be put in place to help in narrowing the yield gap as it occasioned that stem rust disease among other factors has been causing devastation in Kenya wheat production (Macharia & Ngina, 2017).

It is estimated by 2024, Kenya annual consumption of wheat will be 2700 MT against 400 MT that will be produced and Kenya will have to import approximately 2300 MT (Elsheikh *et al*., 2015; Meyer *et al*., 2016; Monroy *et al*., 2013). In the short term, wheat imports to fill domestic supply shortages would be inevitable (Negassa *et al*., 2013). This is because it benefits consumers by lowering the market price of wheat products.

[1]Wheat economy entails production, trading, and consumption of wheat crop.

Hence, importing wheat to Kenya benefits consumers more than domestic producers.

Table 1: Average production and consumption of major staples in Kenya over the past two decades between 1996-2005 and 2006-2016

Staples	Average production in MT			Average consumption in MT		
	1996-2005	2006-2016	% Δ	1996-2005	2006-2016	% Δ
Maize	2,474	3,227	30	2,800	3,440	23
Wheat	295	337	14	787	1,418	80
Rice	47	88	87	155	439	183

Source: (Gitau, 2019)

Kenya is an import-dependent nation with its account deficit expanding driven by increased imports and sluggish production. An increase in trade openness can increase economic efficiency, access to capital and investment, and wide technological knowledge transfer. However, it can lead to crowding out of domestic producers. This leads to resource relocation affecting economic growth in other sectors (Muluvi *et al*., 2014). Considering the Kenya wheat sector, wheat imports could significantly impact domestic wheat production, food security, government revenues and balance of payments. Since there is little up-to-date empirical knowledge of how wheat imports affect domestic production. As a result, policy debates on wheat trade and the effects caused to the domestic sector are often based on conventional ways despite dynamic changes resulting from globalization. Therefore, this study endeavoured to provide empirical evidence of whether there exists a long run relationship between wheat imports and its determinants in Kenya, using annual time series data from 2000 to 2019. This period of analysis was purposively selected because this is the time wheat importation in Kenya surged.

The rest of the paper is structured as follows; in section two, literature review is presented followed by section three that provides materials and methods. In the fourth section, results and discussions were presented and lastly, the fifth section presents the conclusion and policy recommendations.

2. LITERATURE REVIEW

In literature, most determinants of import demand functions include real income, relative price and dummy variables to account for unusual circumstances such as devaluation and policy changes. Furthermore, much of the research on import demand is based on the imperfect substitutes model developed by Goldstein and Khan (1985), with the critical assumption that imports are not perfect substitutes for domestic goods. Therefore, the principle behind international trade is the need to improve economic efficiency by promoting specialization (Nguyen & Jolly, 2013).

A study in South Africa (SA) to estimate import demand of wheat using time series data from 1971 to 2007. Found that wheat consumption increased more than production thus SA remained a net importer of wheat. Also, they noted that urbanization cause consumers to require ready-to-eat food for instance bread. In addition, there are macroeconomic variables that influence production as well as importation and consumption. Among these variables are; real rate of interest, foreign exchange and inflation. Adjustments in these variables can have a positive or negative effect on the amount of imported wheat, based on their impact on real income and real prices. The high cost of production explains the move towards importing wheat in developing countries, as world trade is driven by the comparative advantage possessed by different countries in wheat production (Baiyegunhi & Sikhosana, 2012). As a result, the policy emphasis should be on balancing the development of domestic production while providing an enabling environment for wheat imports under appropriate long-term goals of increasing domestic output to a competitive level with imported wheat.

According to Goldstein and Khan (1985), the import demand function of imported goods to a country is determined by income, price of domestic goods and price of the imported goods. A study by (Çulha *et al*., 2019) in their findings suggested that changes in imports are mainly explained by both income and relative price changes. A study by Uzunoz and Akcay (2009), analyzed factors affecting import demand for wheat in Turkey and found real prices of wheat, Gross National Product (GNP), exchange rate, production value of wheat, domestic demand and trend factor to be statistically significant.

A study in Ghana to understand crude oil import demand behaviour in Africa tried to estimate the short-run and long-run import demand model over the period 1980-2012. The study used the Auto-Regressive Distribution Lag (ARDL) approach. Results show that demand for crude oil is price inelastic in the short-run but elastic in the long run (Marbuah, 2018). Also, a study to examine an import demand function for Cambodia employed the ARDL model and time series data from 1993 to 2015. The findings of the study show that relative prices and exchange rates have a negative effect on import demand in Cambodia for both the long and short-run. While export volume has a positive effect on import demand. But Foreign Direct Investment (FDI), final consumption expenditure and foreign exchange reserve have an insignificant impact on import demand in Cambodia (Hor *et al*., 2018). To estimate Jordanian aggregate import demand, a bounds testing approach was employed to test cointegration, while the ARDL approach was used to analyze long-run elasticities. The results show a cointegration among variables when import volume is a dependent variable. Estimated long-run elasticity for income and relative prices were elastic, thus stable foreign exchange market because elasticities are greater than one in absolute terms. The understanding of import demand behaviour is crucial for significant import forecasts, international trade planning and exchange rate policy designing (Mugableh, 2017). Due to the importance of trade on the economy monitoring imports is key in controlling the trade deficit.

In a study to examine the role of the import demand function for Tunisia from 1990 to 2009 utilized the ADRL bound testing approach for cointegration. The results show that a long-run relationship exists between import demand, exports and household consumption in Tunisia. More so, the import demand of Tunisia is highly elastic for the final consumption of households and exports of Tunisia, but it is inelastic with investment and relative prices in the long run. In the short run, import demand reveals inelastic behaviour with the final consumption of a household, exports, domestic investment and relative prices in Tunisia (Mehmood *et al*., 2013).

A study by Kang *et al*. (2009), in examining import demand model and welfare effects in rice importing countries used Ordinary Least Squares (OLS), Instrumental Variables (IV) with Generalized Method of Moments (GMM) and Seemingly Unrelated Regression (SURE) to specify world rice import demand function. The outcome suggests that FDI, economic growth and importing countries' population positively affect national income (GDP as a proxy variable) hence, positively affecting rice consumption. The oil price has a strong effect on the domestic rice prices in importing countries because oil prices influence the transport costs of rice. Price elasticity of demand and income elasticity are inelastic in regard to rice imports.

The study of Muluvi *et al*. (2014) investigated Kenya aggregated and disaggregated import using the Error Correction Model (ECM) technique. The results indicate existence of cointegration in import demands. Whereby imports was elastic for income and inelastic for price. The finding of Musyoka, (2009) in estimating wheat import demand and welfare effects of import controls in Kenya shows that import prices and real income explains wheat imports and exhibit inelastic characteristics.

From the literature reviewed, it can be summarized that import demand factors include; income, prices and other country-specific factors. This was extended to this study on wheat imports in Kenya. The study hypothesized that wheat imports in Kenya are determined by GDP per capita, tariff, yields, ending stock, relative price, foreign exchange rate and lagged imports. Due to the lagged component in the hypothesized variables, ARDL modelling was preferred because of its advantages over other models in handling lagged values.

3. MATERIALS AND METHODS

3.1 Data collection

In the study, secondary annual time series data from 2000 to 2019 was utilized. This time frame was selected because of the burgeoning of wheat imports in Kenya and data availability over this period. The data were obtained from national and international sources, such as the statistical abstracts of Kenya, Kenya National Bureau of Statistics (KNBS), Ministry of Agriculture, Livestock, Fisheries and Co-operatives (MoALFC), World Integrated Trade Solution (WITS), World Bank database (WB), United Nations Commodity Trade Statistics Database (UN COMTRADE), Food and Agriculture Organization Corporate Statistical Database (FAOSTAT) and International Monetary Fund (IMF). Annual quantitative data was collected for six variables and one qualitative categorical variable (trade instrument). These include; wheat import, GDP per capita, foreign exchange rate, yield of wheat production, relative price of wheat imports, ending stock of wheat and tariff on wheat imports (dummy). The details of these variables are summarized in Table 2.

Table 2: Variables used in analyzing wheat imports in Kenya (2000-2019)

Variable	Symbol	Source	Definitions	Expected Sign
Wheat import	Mt	WITS and FAOSTAT	Quantity of wheat imported in Kenya in MT	+
GDP per capita	GDPTAt	WB	Proxy for income measured by United States of America dollar (US$)	+
Foreign exchange rate	FOREXt	IMF	Represents the foreign exchange rate in US$	-/+
Yield of wheat production	YLDS	FAOSTAT	Domestic wheat yields measured in Hectogram/Hectare (Hg/Ha)	-
Relative price of wheat imports	RPt	UN COMTRADE	Price of wheat imports divided by the price of domestic wheat in US$	-
Ending stock of wheat	STKt	FAOSTAT	Wheat reserve at the end of the year in MT	-/+

Variable	Symbol	Source	Definitions	Expected Sign
Tariff on wheat import	TARt	Statistical abstracts of Kenya, KNBS and MoALFC	This represents tariff on wheat imports in Kenya captured as a dummy variable	-
Lagged wheat import	LMt	Generated	Lagged quantity of wheat imports in Kenya in MT	-/+

3.2 Unit root test

Most time-series data are non-stationary (have unit root). This indicates that their mean, variance and covariance are not constant over time. The regression of a non-stationary time series on another non-stationary time series may produce spurious regression results. A random process Y_t is labelled stationary if it is time-invariant in the first and second moments (mean and variance). The first condition implies that time series data should fluctuate around its mean value. The second condition means that the variance is independent of the time factor (Engle & Granger, 1987).

The Augmented Dickey-Fuller (ADF) and Phillips–Perron (PP) tests are mostly used in testing stationarity. However, the ADF test is becoming more criticized for its often problematic application because it requires carrying out embedded tests and constitutes a framework that is not well-suited to series with a trend (Nishiwaki, 2017). Therefore, PP and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests were employed. This is because PP is non-parametric with consideration of the deterministic trend and the existence of residue autocorrelations (Shrestha & Bhatta, 2018). The PP is modelled as follows;

$$\Delta Y_t = \pi Y_{t-1} + \beta D_{t-1} + e_t \quad \text{……………………..…………………..………………………………………i}$$

e_t is I(0) with zero mean and D_{t-1} *is* deterministic trend component

While in contrast with the other conventional tests, KPSS tests the null hypothesis of level stationarity against the alternative hypothesis of a unit root. Another reason why this test was preferred is because the classical methods are biased toward accepting the null hypothesis (Shrestha & Bhatta, 2018). Kwiatkowski–Phillips–Schmidt–Shin test is intended to complement other unit root tests that is why this study combines with PP to test the unit root of the time series (Nishiwaki, 2017). The KPSS test is modelled as follows;

$$Y_t = X_t + \varepsilon_t \quad \text{hence} \quad X_t = X_{t-1} + u_t \quad \text{……………………………………….………………………......ii}$$

In the KPSS model hypothesis testing is carried out on the u_t whereby the KPSS critical value test statistic is obtained from the formulated Langrage Multiplier test statistic (Shrestha & Bhatta, 2018).

3.3 Cointegration analysis

3.3.1 ARDL bound testing approach for cointegration

If two-time series data Y_t and X_t are integrated of the same order, that is, $Y_t \sim I(1)$ and $X_t \sim I(1)$, then Y_t and X_t are said to be cointegrated. This means they drift in short run but in the long run they converge. This shows that there is a long-run equilibrium relationship between the two variables and the series move together over time or I (0). On the other hand, if Y_t and X_t are not cointegrated, they can drift apart from each other over time in a regression. This means, there is no long-run equilibrium relationship between them. Therefore, regressing Y_t on X_t will yield spurious results (Engle and Granger, 1987).

The ARDL bound test approach is based on OLS estimation of conditional Unrestricted Error Correction Model (UECM) for cointegration analysis (Thao and Hua, 2016). This study employed ARDL bound testing approach in testing cointegration developed by (Pesaran *et al.*, 2001). This procedure has advantages over the classical cointegration tests. First, the model approach can be used irrespective of whether the time series data is stationary or not (I (0) or I (1)) or mixed. Second, UECM can be derived from it through simple linear transformation and this model has both short-run and long-run dynamics in a single equation. Lastly, empirical results of the approach provide superior and consistent results for a small sample size.

The generalized ARDL model is specified as follows;

$$Y_t = \gamma_{0j} + \Sigma_{i=1}^{p} \delta_j Y_{t-1} + \Sigma_{i=0}^{q} \beta_k' X_{t-1} + \varepsilon_{jt} \quad \text{…………………..……………………………………..……iii}$$

Where Y_t is vector and variables in X_t are allowed to be purely I (0) or I (1) or mixed. β and δ are coefficients, γ is constant j = (1…. k); p and q are optimal lag orders and ε_{jt} is a vector of error terms (serially uncorrelated).

The empirical model for ARDL bound test for cointegrations is specified as follows;

$$\Delta logM_t = \alpha_0 + \Sigma_1^{20} \alpha_1 \Delta logM_{t-1} + \Sigma_1^{20} \alpha_2 \Delta logGDPTA_{t-1} + \Sigma_1^{20} \alpha_3 \Delta TAR_{t-1} + \Sigma_1^{20} \alpha_4 \Delta logFOREX_{t-1} + \Sigma_1^{20} \alpha_5 \Delta logYLDS_{t-1} + \Sigma_1^{20} \alpha_6 \Delta logRP_{t-1} + \Sigma_1^{20} \alpha_7 \Delta logSTK_{t-1} + \beta_1 logM_{t-1} + \beta_2 logGDPTA_{t-1} + \beta_3 logTAR_{t-1} + \beta_4 logFOREX_{t-1} + \beta_5 logYLDS_{t-1} + \beta_6 logRP_{t-1} + \beta_7 logSTK_{t-1} + \varepsilon_{it} \quad \text{……..….iv}$$

If the result of the ARDL bound test is greater than the upper bound, the null hypothesis[1] is rejected following the t and F test statistics. Hence, the presence of a long run relationship. But if it is less than the lower bound there is no cointegration.

3.3.2 Error Correction Model

According to Granger's representation model, if the variables are in a long-term equilibrium relationship, then the best short run representation of the long-term relationship is the ECM (Engle and Granger, 1987).
After testing for bound cointegration in the model. If there is no cointegration, short run function is only estimated, simplified as follows;

$$\Delta Y_t = \alpha_0 + \Sigma_i^t \alpha_1 \Delta Y_{t-1} + \Sigma_i^t \alpha_1 \Delta X_{t-1} + \varepsilon_{it} \quad \ldots\ldots\text{v}$$

If there is cointegration both the long-run model and short-run model is estimated specified as follows;

$$\Delta Y_t = \alpha_0 + \Sigma_i^t \alpha_1 \Delta Y_{t-1} + \Sigma_i^t \alpha_2 \Delta X_{t-1} + \alpha_3 Y_{t-1} + \alpha_4 X_{t-1} + \varepsilon_{it} \quad \ldots\ldots\text{vi}$$

Equation vi can be re-written as follows;

$$\Delta Y_t = \alpha_0 + \Sigma_i^t \alpha_1 \Delta Y_{t-1} + \Sigma_i^t \alpha_2 \Delta X_{t-1} + \lambda ECM_{t-1} + \varepsilon_{it} \quad \ldots\ldots\text{vii}$$

The ECM model is empirically stated as follows;

$$\Delta \log M_t = \alpha_0 + \Sigma_1^{20} \alpha_1 \Delta \log M_{t-1} + \Sigma_1^{20} \alpha_2 \Delta \log GDPTA_{t-1} + \Sigma_1^{20} \alpha_3 \Delta TAR_{t-1} + \Sigma_1^{20} \alpha_4 \Delta \log FOREX_{t-1} + \Sigma_1^{20} \alpha_5 \Delta \log YLDS_{t-1} + \Sigma_1^{20} \alpha_6 \Delta \log RP_{t-1} + \Sigma_1^{20} \alpha_7 \Delta \log STK_{t-1} + \lambda ECM_{t-1} + \varepsilon_{it} \quad \ldots\ldots\text{viii}$$

Where; ECM shows long-run model estimation. λ is the extent of the adjustment of $\Delta Y_t/\Delta \log M_t$ to the preceding period explained by residuals. While t is the period from 2000 to 2019. α_3 and α_4 are the individual impacts of long-term elasticity for equation (vi). Δ is the first difference operator. α_0 is constant and $\alpha_1, \alpha_2 \ldots \alpha_7$ are the impact of short-term elasticity. ε_{it} is the error term.

The extent of the adjustment should have a negative sign and be significant to confirm the existence of a long run equilibrium relationship between the variables (Engle and Granger, 1987). Following Fatukasi and Awomuse (2011); Gujarati (1995); Uzunoz and Akcay (2009), the study adopted a regression analysis of using a double logarithmic linear function in estimating the import demand function because it generates elasticities that are easier to interpret.

4. RESULTS AND DISCUSSIONS

4.1 Introduction

In this section, descriptive statistics are presented followed by unit root tests, cointegration test, lag selection criteria and then ARDL-ECM analysis. Lastly, the post estimation diagnostic tests of the model are discussed.

4.2 Descriptive statistics

Table 3: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Minimum	Maximum
Mt (000') (MT)	20	1018.81	510.05	404.06	1998.80
TARt (Dummy)	20	.4	.503	0	1
FOREXt (US$)	20	84.155	11.55	67.318	103.411
YLDS (000') (Hg/Ha)	20	22.46	5.69	12.58	31.00
STKt (MT)	20	174.3	106.433	43	449
GDPTAt (US$)	20	966.246	460.772	389.543	1816.547
RPt (US$)	20	1.503	.266	1.063	2.184
LMt(000') (MT)	19	967.23	467.38	404.07	1854.95

The results in Table 3 show the descriptive statistics of the variables used in modelling wheat imports (Mt) in Kenya. The data used in the analysis was quantitative time series data with one dummy variable. The variables used for wheat imports in Kenya followed the works of (Hor *et al.*, 2018; Musyoka, 2009). From the data, in the last two decades our dependent variable which is wheat imports to Kenya have an average of 1018.81 MT with the highest value of 1998.80 MT while a minimum value of imports was 404.06 MT (units are in thousands). Gross Domestic Product per capita (GDPTAt) was 966.25 US$ on average in the last two decades with the highest value of 1816.55 US$ and minimum value of 460.77 US$. A tariff dummy representing government policy was used with 0 representing period with tariff in place and 1 representing time in which the government does not impose any tariff on wheat imports in Kenya.

The data in Table 3 data was transformed into logarithms (log to base 10). According to Pek *et al*. (2017), the applicability of data transformation help to address non-normality issues usually associated with small sample sizes. The transformation addressed non-normality and serial correlation problems that could arise since

[1] Ho: no levels relationship

the sample size was small (20 observations). After transformation, the results of all the variables were normally distributed as captured by the Jarque Bera test statistics in Table 9. This is because the Jarque Bera p-values are greater than 0.05 and therefore the null hypothesis cannot be rejected implying the is normality in the time series data.

4.3 Unit root test

In performing the unit root test, PP and KPSS were used and the results are presented in Table 4 and Table 5 respectively.

Table 4: Phillips Perron stationarity results

variable	Level				First difference				Summary
	Intercept(constant)		Intercept and trend		Intercept(constant)		Intercept and trend		
	t- test	p-value	t- test	p-value	t- test	p-value	t- test	p-value	
logMt	-0.154	0.9438	-3.393	0.0523	-5.713	0.0000*	-5.889	0.0000*	I(1)
TARt	-0.742	0.8356	-2.122	0.5340	-4.245	0.0006*	-4.126	0.0058*	I(1)
logFOREXt	-0.470	0.8977	-1.734	0.7357	-3.723	0.0038*	-3.807	0.0162*	I(1)
logYLDSt	-3.665	0.0046*	-3.709	0.0218*	-6.805	0.0000*	-6.555	0.0000*	I(0)
logSTKt	-5.602	0.0000*	-6.121	0.0000*	-10.357	0.0000*	-10.122	0.0000*	I(0)
logLMt	-0.368	0.9153	-3.283	0.0691	-5.462	0.0000*	-5.620	0.0000*	I(1)
logGDPTAt	-0.413	0.9079	-1.939	0.6344	-2.859	0.0504*	-2.763	0.2110	I(1)
logRPt	-7.544	0.0000*	-7.182	0.0000*	-10.043	0.0000*	-9.550	0.0000*	I(0)

In the PP test, the null hypothesis is stated as non-stationary while the alternative is stationary. The outcome of the PP test in Table 4 shows that log of yields, log of ending stock and log of relative price are stationary around intercept at original level. The log of wheat imports, tariff dummy, log of foreign exchange, log of lagged wheat imports and log of GDP per capita was stationary around intercept at first difference.

Table 5: KPSS stationarity results

Variable	Level		First difference		Summary
	C @5%=0.463	C and T @5%=0.146	C @5%=0.463	C and T @5%=0.146	
logMt	.7	.126*	.177*	.088*	I(0)
TARt	.624	.119*	.113*	.0921*	I(0)
logFOREXt	.585	.157	.155*	.0757*	I(1)
logYLDSt	.13*	.109*	.123*	.117*	I(0)
logSTKt	.215*	.0617*	.0779*	.0682*	I(0)
logLMt	.659	.129*	.165*	.094*	I(0)
logGDPTAt	.742	.12*	.0835*	.0815*	I(0)
logRPt	.17*	.0758*	.173*	.102*	I(0)

Note, C=Constant, T=Trend, I(0) is stationary at level and I(1) stationary at first difference.

Testing hypothesis was carried out by the use of t-test statistics and critical value in Table 5. The findings of unit root tests show that log of yields, log of ending stock and log of relative prices are stationary around the intercept at original level. While the log of wheat imports, dummy tariff on wheat imports, log of lagged wheat imports and log of GDP per capita are all stationary around intercept and trend at original level. Log of foreign exchange rate is the only variable that was stationary around intercept at the first difference in the analysis of root tests[1]. The results are captured and summarized in Table 5.

The outcome of PP and KPPS tests on unit roots show with robustness that none of the variables tested was integrated of order two I (2). Therefore, the results of variables being either stationary at level or first difference meets the requirement of ARDL modelling. Hence the long run cointegration of the variables was tested using ARDL bound test[2].

4.4 ARDL Bounds Test for Cointegration

Table 6: Pesaran/Shin/Smith (2001) ARDL Bounds Test for cointegration

	Test statistic	Lower bound [I_0]	Upper bound [I_1]
F-statistic	10.596	2.750	3.990
t-statistic	-5.976	-3.130	-4.660

The results of the bound test in Table 6 shows that there is long run cointegration because the F test statistic

[1] In the KPSS test, the null hypothesis signifies the existence of stationary of the time series while the alternative hypothesis shows the presence of unit root in the data being tested.

[2] To estimate ARDL bound test, lag selection was done using Akaike Information Criterion (AIC) and Schwartz Bayesian Information Criterion, in both maximum lag level selected was 1.

(10.596) is greater than the I(1) upper bound (3.990). Therefore the null hypothesis[6] is rejected in favour of the alternative hypothesis[1]. This is confirmed by the t-test statistic (-5.976) being absolutely greater than I(1) upper bound (-4.660). The confirmation of the cointegration in the time series data makes it possible to estimate both the short run and the long run estimates of the ARDL model by estimating the ECM together with the ARDL model in the single equation form.

4.5 ARDL-ECM analysis

Table 7: Lag selection-order criteria

Sample: 2002 - 2019 Number of observations = 18

lag	LL	LR	df	p	FPE	AIC	HQIC	SBC
0	1.95707	-	-	-	052649	-.10634	-.099521	-.056876
1	15.7266	27.539*	1	0.000	012751*	-1.52518*	-1.51154*	1.42625*
2	16.4964	1.5395	1	0.215	.013111	-1.4996	-1.47914	-1.3512

LR: Likelihood Ratio FPE: Final Predictor Error HQ: Hannan-Quinn criterion * optimal lag length

The optimal lag selection structure was carried out using Schwartz Bayesian Information Criterion (SBC). This information criterion was preferred to ensure that the lag level could handle the serial correlation occurrence and its ability to choose a more parsimonious model in the lag structure (Kripfganz & Schneider, 2018). This is because too many lag levels lead to loss of degrees of freedom which can cause multicollinearity, misspecification of errors terms and serial correlation in the model being analyzed. Since annual time series data was utilized, the maximum lag length preferred was 2 (Narayan & Smyth, 2006). With help of SBC and a maximum lag length set to 2 for the annual data, the following ARDL (1,1,0,0,0,1,1) optimal lag lengths were obtained. The number of observations after adjustments was 18 as stated in Table 7.

Table 8: ARDL-ECM model showing long run and short run results for wheat imports in Kenya for ARDL (1,1,0,0,0,1,1) regression, with logMt as the dependent variable.

Independent variables	Coef.	Std.Err.	t-statistic	P>t	[95%Conf	Interval]	sign
Long run effects							
logGDPTAt	0.078	0.110	0.710	0.503	-0.183	0.338	
TARt	-0.112	0.053	-2.130	0.070	-0.237	0.012	*
logFOREXt	-0.728	0.433	-1.680	0.137	-1.752	0.297	
logYLDSt	-0.202	0.131	-1.540	0.167	-0.512	0.108	
logRPt	-0.987	0.356	-2.770	0.028	-1.829	-0.145	**
logSTKt	0.163	0.082	1.980	0.088	-0.032	0.358	*
Short run effects							
ECM_{t-1}	-1.593	0.281	-5.660	0.001	-2.259	-0.927	***
D1.logGDPTAt	1.097	0.776	1.410	0.200	-0.738	2.932	
D1. logRPt	0.794	0.359	2.210	0.062	-0.054	1.643	*
D1. logSTKt	-0.149	0.099	-1.500	0.177	-0.385	0.086	
Constant	-1.397	1.951	-0.720	0.497	-6.010	3.216	
R-squared							0.9279
Adjusted R-squared							0.8248
Jarque-Bera normality test probability value							0.5196
Ramsey RESET test for omitted variables probability value							0.2359
Serial correlation							
Durbin Watson statistic							2.1927
Breusch-Godfrey LM test for autocorrelation probability value							0.1719
Heteroscedasticity							
White's test probability value							0.3888
Cameron and Trivedi's decomposition of IM-test probability value							0.3425
Breusch-Pagan / Cook-Weisberg test for heteroscedasticity probability value							0.6538
LM test for autoregressive conditional heteroscedasticity (ARCH) probability value							0.5247

Note *, ** and *** denotes 10%, 5% and 1% significance level (sign) respectively.

The ARDL (1,1,0,0,0,1,1) model was used to explain the surging wheat importation in Kenya for both the short run and the long run. The null hypothesis of the ARDL-ECM model shows that there is no statistical significance level over the alternative hypothesis of existence of statistical significance level. When the probability value (p-value) is less than the significance level, we reject the null hypothesis and accept the

[1] Ha: levels relationship

alternative hypothesis. But when the p-value is greater than the significance level we don't reject the null hypothesis. Following the works of (Hor *et al*., 2018) the significance levels adopted for the study entails 1%, 5% and 10% in testing the hypotheses.

The results of the ARDL-ECM model analysis are captured in Table 8.The model variables jointly explain 82.48% of the total variation in wheat imports as captured by the Adjusted R^2. The goodness of fit from this study is close to those of Narayan and Narayan, (2010) in estimating import demand elasticities of South Africa with the value of 83.31%. The finding is also close to the results of Musyoka (2009), whereby the R-squared are 85.15% and 85.24% when dynamic instrumental variable two-stage least squares and OLS regression methods were used respectively. This confirms that our model estimation performed quite well.

The variables that are statistically significant in the single equation model are the adjustment coefficient of wheat imports (ECM_{t-1}) which is strongly significant at 1% level, tariff which is a dummy of government policy is significant at 10% level, Relative price is significant at 5% level and ending stock is significant at 10% level for the long run effects. Relative price is the only significant variable in the short run at 10% significance level.

According to the theoretical aspects, the sign of the adjustment coefficient should be negative and significant when there is cointegration in time series data. The findings of our study show that the adjustment coefficient is -1.593 and significant at 1% significance level which is true according to theory. The adjustment coefficient of 1.59 indicates how the deviation from the long-term equilibrium is corrected. The deviations of the wheat import from the long run equilibrium are corrected by 159% in the next period. The disequilibrium of wheat import will take approximately 6 months (1/1.59=0.63) to be fully adjusted to its equilibrium in an oscillatory manner. This is due to a higher adjustment coefficient hence shorter adjustment period is expected. The results show that wheat imports are overcorrected in the coming period by over 59% because the deviations get cleared at 100% level. This may explain why Kenya wheat imports have been surging in the last two decades with no sign of slowing down soon assuming all factors remain constant. This study confirms the previous work of Musyoka, (2009) who found that wheat imports have faster adjustment within a year, implying there is over-importation of wheat in Kenya.

When the lagged error correction term coefficient is somewhere between -1 and -2 in the regression, the error correction term causes dampening oscillations. This indicates that the error correction process varies around the long-run value in a dampening approach, rather than uniformly converging to the equilibrium level. After this process is done, then convergence to the equilibrium path is faster (Narayan & Smyth, 2006). Therefore, it can be deduced that wheat imports are over-adjusted in Kenya because of the dampening nature of wheat imports in Kenya causing a persistent increase in the imports.

From the results, tariff which is a government policy (dummy in this case) on wheat imports in Kenya is significant at 10% significant level. This indicates that whenever the government of Kenya imposes tariffs on wheat imports, the level of wheat imports declines by 11.2% at *ceteris paribus* conditions. This is true based on theory. The study confirms the findings of Alizadeh *et al*. (2019) that tariffs have a negative influence on imports. Additionally, the study corroborates to findings of (Elsheikh *et al*., 2015) that a decrease in wheat import tariff leads to an increase in wheat imports and a decline in domestic production of wheat and *vice versa*. The use of tariffs as a government policy to regulate wheat importation in Kenya has an impact on reducing the quantity of wheat imports in the country. This is a policy that can be varied following how the wheat sector performs. However, according to Musyoka (2009), when the government imposes tariffs on wheat imports, it has far-reaching implications on other agricultural commodities in which Kenya exports. As it happens that the nations that Kenya exports its coffee and tea[1] are the major exporters of wheat to Kenya. He added that import controls[2] make imported wheat less affordable by increasing the price. Therefore, policies that are related to tariffs imposition and are directed to wheat markets have to deal with trade agreements that advocating for free trade in the global economy (Liu, 2017). The use of tariff dummy also indicates trade liberalization based on works of (Monroy *et al*., 2013). In Kenya, wheat imports have continued soaring after tariffs were removed from wheat imports, a possible indication of improvement of the trading terms for wheat importers in Kenya. This is because Kenya is a member of several trading blocs for example World Trade Organization (WTO), Common Market for Eastern and Southern Africa (COMESA) and East Africa Community (EAC) who advocate for free and fair trade.

The finding of relative price is inelastic and significant at 5% level because the p-value of 0.028 is less than the 5% significance level. Therefore, we reject the null hypothesis and accept the alternative hypothesis. The results indicate that when relative price increase by one percent, wheat imports decline by 0.987% at *ceteris paribus* conditions. Even though the result was inelastic, it had a high magnitude level (0.987), which may imply relative price is critical in determining wheat imports in Kenya. The possible explanation is that relative prices indicate substitution effect, in this case domestically produced commodities become substituted for wheat

[1] Coffee and tea are Kenya key foreign exchange earner crops.
[2] Import controls refers to trade instruments that reduce level of imports for example imposing import tariffs.

imports when the price of wheat imports goes up. This reasoning is basically that, when wheat imports become more expensive, more income is devoted to available domestic products for consumption. It can be further explained that international wheat prices are transmitted to the domestic sector lowering domestic wheat prices in the long run. This however creates a dampening effect in the domestic wheat sector. In consequence, it lowers domestic production causing stagnation of Kenya wheat sector as farmers are discouraged to engage in wheat production due to low price incentives and high competition from wheat imports. This finding corroborates with the works of (Hor *et al*., 2018; Kavaz, 2020; Matlasedi, 2017; Mehmood *et al*., 2013; Mugableh, 2017; Musyoka, 2009) who found that relative price to be statistically significant and have a negative impact on import demand empirically and theoretically. However, for (Matlasedi, 2017) the relative price was elastic in the import function. But for (Hor *et al*., 2018; Kavaz, 2020; Mehmood *et al*., 2013; Mugableh, 2017; Musyoka, 2009) the relative price was inelastic in the long run and consistent with the findings of this study. The inelasticity of the relative price could be due to the availability of alternative products that can be used as substitutes for wheat imports in Kenya. Therefore, wheat import demand is less responsive to the changes in the relative prices in Kenya.

In the long run, the ending stock elasticity of wheat was inelastic and statistically significant at the 10% level. Therefore, with a one percent increase in ending stock Kenya wheat imports increase by 0.16% at *ceteris paribus* conditions. This implies that with ending stock being more available more wheat is going to be imported holding other factors constant. This perhaps can be linked to wheat importers using wheat reserves to project wheat importation planning with other factors at their disposal. This argument is supported by the fact that imported products are habit-forming in the long-term and therefore when stock is incorporated in the demand system of a product the impact that it causes is greater than zero. This finding supports the work of Houthakker and Taylor (1970), who proposed that the stock parameter being greater than zero is interpreted as a sense of habit. This is confirmed by their finding with a coefficient estimated in the dynamic food model with a positive value of (0.12) and close to the results of our study (0.16). It is further claimed that higher demand of a commodity in the current period increases the potentiality of consumers to willingly purchase more of that product in the future inclined to the force of habitual nature at the *ceteris paribus* conditions (Mukherjee *et al*., 2017). Based on wheat consumption, it can be argued that wheat imports to Kenya have been changing our food preference from domestic wheat towards wheat imports in the long term with the influence of other factors as supported by the study of (Morris & Byerlee, 1993).

In the short run relative prices of wheat is inelastic and statistically significant at 10% level. The short run effect only occurs after differencing of the variables in the regression analysis. From the results, when relative price increase by one percent in the short run wheat imports increase by 0.794% at *ceteris paribus* conditions. This is consistent with Mehmood *et al*. (2013) on the inelastic properties of imports in the short run. This finding contradicts with theory as it is expected for demand to have an inverse relationship with prices. However, this shows the short-term effect of wheat prices on wheat imports in Kenya, an implication that many factors of the economy cannot be changed at that moment. The underlying reason may be the effect of relative price correlate with income (GDP per capita) in the short run even though not significant it has a positive sign. Implying further when income improves people buy more of a commodity than before. Therefore, when relative prices increase instantaneously, wheat importers take the advantage of importing more wheat at their current capacity to maximize their gain in trade during such periods.

4.6 Post estimation diagnostic tests of the ARDL-ECM model

Post estimation tests were done to ensure there were no violations of Central Limit Regression Model (CLRM) assumptions. The Durbin Watson test was used to check for spurious regression based on the rule of thumb[1] (Shrestha & Bhatta, 2018). Since our regression R^2 output (0.9279) was not greater than the Durbin Watson statistic (2.19), there was no spurious regression. Also, the Durbin Watson statistic provided a clue on the serial correlation[2]. The results of the Breusch-Godfrey LM test for serial correlation of all orders, confirm that there is no serial correlation in the model. This is because the null hypothesis[3] is accepted since the p-value of 0.17 is greater than the 0.05 significance level as recorded in Table 8.

This study employed the following tests to test for heteroscedasticity; White's test, Cameron and Trivedi's decomposition of IM-test, Breusch-Pagan and LM test for Auto-Regressive Conditional Heteroscedasticity (ARCH). In all of the above tests, the null hypothesis[4] was accepted with the following p-values; 0.39, 0.34, 0.65 and 0.52 respectively being greater than the 0.05 significance level as captured in Table 8.

Multicollinearity check was done by use of variance inflation factors (VIF) check. Any value that is greater than or equal to 10 is an indicator of the existence of multicollinearity (Franke, 2010). The results of VIF from this study are tabulated in Table 10 and there was no multicollinearity because all of the VIF values of the

[1] The rule of thumb is where when R^2>Durbin Watson statistic, it indicates the regression is spurious
[2] Durbin Watson statistic being closer to 2 imply no serial correlation
[3] Ho: no serial correlation
[4] Ho: Constant variance

variables did not exceed 10.

In this study, the central tendency and dispersion characteristics of the various variables were calculated as expressed in Table 9. The normality test of the residuals in the regression was tested using JB statistics. The finding confirms that the residuals of the ARDL-ECM regression were normally distributed with a p-value of 0.5196 as captured in Table 8.Therefore, the null hypothesis was accepted[1].

The Ramsey RESET test shows that the model has no omitted variables. This is because the p-value (0.24) is greater than the significance level (0.05) and therefore the null hypothesis[2] is accepted as the alternative hypothesis is rejected in the hypothesis testing as stated in Table 8

The cumulative sum of squared recursive residuals (CUSUMSQ) is used to show if the parameter estimates are stable in the estimated models. The finding of this research established parameter stability for the ARDL-ECM analysis because the CUSUMSQ plot bands around the null hypothesis of parameter stability at 5% significance level as captured in Figure 1.

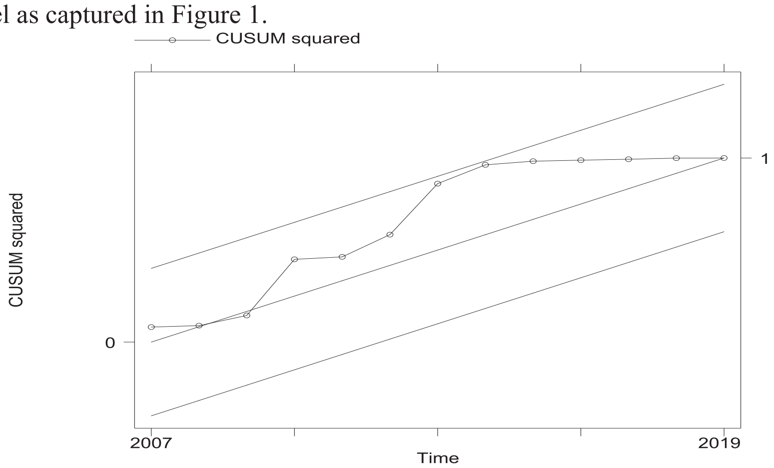

Figure 1: Cumulative Sum of Squared Recursive Residuals

The post estimation tests of the ARDL-ECM model show that there were no violations. This ascertains the dynamic properties of the time series data that was analyzed. Therefore, the output of the study is reliable for making inferences and policy recommendations

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusions

The study explored the cointegration of wheat import and its determinants in Kenya from 2000 to 2019. Secondary data from international and national sources was used to understand why wheat imports skyrocketed in Kenya over the last two decades. The study used PP and KPSS tests to carry out unit root tests for the time series data. All the variables were stationary either at level or first difference and none of these variables was stationary at the second difference. An ARDL bound test was used to test cointegration. The findings of the study indicate existence of long run equilibrium when wheat import is the dependent variable. This made it possible to estimate short run and long run effects using the single equation model (ARDL-ECM technique).

The findings of the study reveal an inelastic response of relative prices and ending stock of wheat in the long run on wheat imports in Kenya. In the short run relative price was inelastic and the only variable that affects wheat importation in Kenya. This indicates that prices play a critical role in influencing the amount of wheat imported in Kenya. Thus a lot of emphases should be placed on scrutinizing the price to understand if the prices are reflecting the actual cost of production in both importing and exporting countries. The inelasticity of relative prices on wheat imports suggests that the consumers of wheat should shift their consumption whenever the prices of wheat imports increase to domestically produced commodities to enhance the agricultural sector in Kenya. Ending stock was inelastic and statistically significant with a positive sign. It thus follows that wheat imports affect the changing habits of its consumers in the long run. Due to the nature in which wheat imports have a high influence on food preference Kenyans should however embrace other locally produced products to increase rural-urban synergies in Kenya. The effect of government tariff was also significant in the long run. This suggested that tariff has the potential of reducing wheat imports in Kenya. But owing to the fact that globalization is necessary for trade, Kenya should embrace those policies that will competitively improve wheat production. This may entail training farmers through extension officers, planting wheat varieties that meet the Kenya market needs and pilot projects such as planting wheat on irrigation to boost wheat availability and reduce overreliance on wheat imports. However, this can have cost implications for such investments.

[1] Ho: normality
[2] Ho: model has no omitted variables

It can be concluded that tariff, relative price and ending stock are the key determinants that affect wheat imports in Kenya. Therefore, policies that target wheat imports should revolve around these three variables with relative price having the greatest impact on wheat importation. The findings are empirically consistent with some of the previous studies and conform to the theory.

The study was limited by the data availability. Hence this research resort to use secondary annual time series data. Therefore, more frequency data should be availed. Future research works on this field should consider using quarterly or monthly data to produce more robust results. The study used tariff to check on trade liberalization and hence in the future dumping of wheat imports in Kenya could be considered.

5.2 Policy recommendations

To ensure that Kenya can feed its population wheat imports are only necessary in short term but leads to growing import bills in the long run. Therefore, this study recommends the following:

i. Our findings propose that due to the high demand for wheat and its alternative uses the government should strive to sustain our domestic wheat production and come up with policies that promote competitive wheat production.
ii. Because of the habitual nature of wheat products, Kenya should utilize their fast land to massively produce the crop as it will create a multiplier effect benefits in the economy in the long run.
iii. Wheat producers should be guided by the government to produce those varieties that are in high demand by the wheat milling companies. This will be a demand-driven production mechanism and it can help alleviate the high imports reliance as well as reducing the wheat import bills in Kenya.

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REFERENCES

Alizadeh, P., Mohammadi, H., Shahnoushi, N., Saghaian Nejad, S. H., & Pooya, A. (2019). Investigating Factors Affecting Import Demand of Meat and Livestock Inputs in Iran. *Agricultural Economics*, *13*(3), 1–28. https://dx.doi.org/10.22034/iaes.2019.114832.1727

Baiyegunhi, L. J. S., & Sikhosana, A. M. (2012). An estimation of import demand function for wheat in South Africa: 1971-2007. *African Journal of Agricultural Research*, *7*(37). https://doi.org/10.5897/ajar11.2053

Çulha, O. Y., Eren, O., & Öğünç, F. (2019). Import demand function for Turkey. *Central Bank Review*, *19*(1), 9–19. https://doi.org/10.1016/j.cbrev.2019.03.001

Elsheikh, O. E., Elbushra, A. A., & Salih, A. A. A. (2015). Economic impacts of changes in wheat's import tariff on the Sudanese economy. *Journal of the Saudi Society of Agricultural Sciences*, *14*(1), 68–75. https://doi.org/10.1016/j.jssas.2013.08.002

Enghiad, A., Ufer, D., Countryman, A. M., & Thilmany, D. D. (2017). An Overview of Global Wheat Market Fundamentals in an Era of Climate Concerns. *International Journal of Agronomy*, *2017*. https://doi.org/10.1155/2017/3931897

Engle, R. F., & Granger, C. W. J. (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing Published by: The Econometric Society Stable URL: http://www.jstor.org/stable/1913236. *Econometrica*, *55*(2), 251–276.

FAO. (2015). *The State of Food and Agriculture 2015 | FAO | Food and Agriculture Organization of the United Nations*. http://www.fao.org/publications/sofa/2015/en/

Fatukasi, B., & Awomuse, B. O. (2011). determinants of import in Nigeria: Application of error correction model. *Centrepoint Journal, Humanities Edition*, *14*(1), 52–72.

Franke, G. R. (2010). Multicollinearity. *Wiley International Encyclopedia of Marketing*. https://doi.org/10.1002/9781444316568.wiem02066

Gitau, R. (2019). Modelling trends in spatial market integration in the post-liberalized era: A case of maize markets in Kenya. *Αγαη*, *8*(5), 55.

Goldstein, M., & Khan, M. S. (1985). Income and price effects in foreign trade. In *Handbook of International Economics* (Vol. 2, Issue C, pp. 1041–1105). Elsevier Science Publishers B.V. https://doi.org/10.1016/S1573-4404(85)02011-1

Gujarati, D. N. (1995). Basic Econometrics. 3rd edn McGraw-Hill. *Inc., New York*.

Hor, C., Keo, K., & Suttiprapa, C. (2018). An empirical analysis of Cambodia's import demand function. *Journal of Management, Economics, and Industrial Organization*, *2*(1), 1–12.

Houthakker, H. S., & Taylor, L. D. (1970). *Consumer demand in the United States*.

Kamwaga, J., Macharia, G., Boyd, L., Chiurugwi, T., Midgley, I., Canales, C., Marcheselli, M., & Maina, I. (2016). Kenya Wheat Production Handbook. *Kenya Agricultural and Livestock Research Organization:*

Nairobi, Kenya, 78.
Kang, H., Kennedy, P. L., & Hilbun, B. M. (2009). *An empirical estimation of the import demand model and welfare effects: The case of rice importing countries*.
Kavaz, İ. (2020). Estimating the Price and Income Elasticities of Crude Oil Import Demand for Turkey. *International Econometric Review*, *12*(2), 98–111. https://doi.org/10.33818/ier.754989
Kripfganz, S., & Schneider, D. C. (2018). ardl: Estimating autoregressive distributed lag and equilibrium correction models. *Proceedings of the 2018 London Stata Conference*.
Liu, P. (2017). *The future of food and agriculture: Trends and challenges. Fao*.
Macharia, G., & Ngina, B. (2017). *Wheat in Kenya: Past and Twenty-First Century Breeding | IntechOpen*. https://www.intechopen.com/chapters/54079
Marbuah, G. (2018). Understanding crude oil import demand behaviour in Africa: The Ghana case. *Journal of African Trade*, *4*(1–2), 75–87. https://doi.org/10.1016/j.joat.2017.11.002
Mason, N. M., Jayne, T. S., & Shiferaw, B. (2012). Wheat consumption in sub-Saharan Africa: Trends, drivers, and policy implication. *MSU International Development Working Paper*, *127*, 1–29.
Matlasedi, T. N. (2017). The influence of the real effective exchange rate and relative prices on South Africa's import demand function: An ARDL approach. *Cogent Economics & Finance*, *5*(1), 1419778. https://doi.org/10.1080/23322039.2017.1419778
Mehmood, H., Ali, A., & Chani, M. I. (2013). Determination of Aggregate Imports Function: Time Series Evidence for Tunisia. *International Journal of Economics and Empirical Research (IJEER)*, *1*(6), 74–82.
Meyer, F., Traub, L. N., Davids, T., Kirimi, L., Gitau, R., Mpenda, Z., Chisanga, B., Binfield, J., & Boulanger, P. (2016). *Modelling wheat and sugar markets in Eastern and Southern Africa; Regional Network of Agricultural Policy Research Institutes (ReNAPRI)*. https://doi.org/10.2788/437123
Monroy, L., Mulinge, W., & Witwer, M. (2013). *Analysis of incentives and disincentives for wheat in Kenya. Technical notes series, MAFAP, FAO, Rome.* http://www.fao.org/3/at561e/at561e.pdf
Morris, M. L., & Byerlee, D. (1993). Narrowing the wheat gap in Sub-Saharan Africa: A review of consumption and production issues. *Economic Development and Cultural Change*, *41*(4), 737–761.
Mugableh, M. I. (2017). Estimating elasticity function of Jordanian aggregate import demand. *Applied Economics and Finance*, *4*(2), 33–37. https://doi.org/10.11114/aef.v4i2.2085
Mukherjee, P., Mukherjee, V., & Das, D. (2017). Estimating elasticity of import demand for gold in India. *Resources Policy*, *51*, 183–193.
Muluvi, A., Kamau, P., & Gitau, C. (2014). *Discussion Paper No. 162 of 2014 on Import Structure and Economic Growth in Kenya*. http://repository.kippra.or.ke/handle/123456789/2535
Musyoka, P. M. (2009). *Wheat Import Demand and Welfare Effects of Import Controls in Kenya*. Kenya Institute for Public Policy Research and Analysis.
Narayan, P. K., & Smyth, R. (2006). What determines migration flows from low-income to high-income countries? An empirical investigation of Fiji–Us migration 1972–2001. *Contemporary Economic Policy*, *24*(2), 332–342. https://doi.org/doi:10.1093/cep/byj019
Narayan, S., & Narayan, P. K. (2010). Estimating import and export demand elasticities for Mauritius and South Africa. *Australian Economic Papers*, *49*(3), 241–252. https://doi.org/doi: 10.1111/j.1467-8454.2010.00399.x
Negassa, A., Shiferaw, B., Koo, J., Sonder, K., Smale, M., Braun, H. J., Gbegbelegbe, S., Guo, Z., Hodson, D. P., Wood, S., Payne, T. S., & Geleta, A. B. (2013). *The potential for wheat production in Africa: Analysis of biophysical suitability and economic profitability* (Issue July).
Nguyen, G. V., & Jolly, C. M. (2013). A cointegration analysis of seafood import demand in Caribbean countries. *Applied Economics*, *45*(6), 803–815. https://doi.org/10.1080/00036846.2011.613771
Nishiwaki, M. (2017). An empirical analysis of the determinants of collusion. In *Competition, Innovation, and Growth in Japan*. African Economic Research Consortium. https://doi.org/10.1007/978-981-10-3863-1_3
Pek, J., Wong, O., & Wong, A. C. (2017). Data transformations for inference with linear regression: Clarifications and recommendations. *Practical Assessment, Research, and Evaluation*, *22*(1), 9. https://doi.org/10.7275/2w3n-0f07
Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*(3), 289–326.
Shrestha, M. B., & Bhatta, G. R. (2018). Selecting appropriate methodological framework for time series data analysis. *The Journal of Finance and Data Science*, *4*(2), 71–89. https://doi.org/10.1016/j.jfds.2017.11.001
Tadesse, W., Bishaw, Z., & Assefa, S. (2019). Wheat production and breeding in Sub-Saharan Africa: Challenges and opportunities in the face of climate change. *International Journal of Climate Change Strategies and Management*, *11*(5), 696–715. https://doi.org/10.1108/IJCCSM-02-2018-0015
Thao, D., & Hua, Z. (2016). ARDL Bounds Testing Approach to Cointegration: Relationship International Trade Policy Reform and Foreign Trade in Vietnam. *International Journal of Economics and Finance*, *8*, 84.

https://doi.org/10.5539/ijef.v8n8p84
Uzunoz, M., & Akcay, Y. (2009). Factors affecting the import demand of wheat in turkey. In *Bulgarian Journal of Agricultural Science* (Vol. 15, Issue 1).

APPENDICES

Table 9: Description of transformed data

Variable	Obs	Mean	Std. Dev.	Min	Max	S	K	Jb statistic	Jb chi^2 p-value
logMt	20	5.956	.218	5.606	6.301	.1554	1.6444	1.612	.4467
logGDPTAt	20	2.932	.229	2.591	3.259	-.2840	1.7116	1.652	.4378
TARt	20	.4	.503	0	1	.4082	1.1667	3.356	.1867
logFOREXt	20	-1.921	.058	-2.015	-1.828	.3187	1.9395	1.276	.5284
logYLDSt	20	4.337	.117	4.1	4.505	-.4718	2.2199	1.249	.5355
logRPt	20	.171	.076	.027	.339	.0875	3.0807	.0309	.9846
logSTKt	20	2.161	.282	1.633	2.652	-.3327	2.4991	.578	.749
logLMt	19	5.938	.208	5.606	6.268	.1986	1.6842	1.496	.4734
DlogMt	19	.026	.102	-.15	.24	.4614	2.5886	.808	.6676

Jb- Jarque Bera
S-Skewness
K-Kurtosis

Table 10: Variance inflation factors

Variable	**VIF**	**1/VIF**
TARt	7.55	0.132400
logSTKt D1.	7.54	0.132595
logFOREXt	7.29	0.137196
logRPt D1.	6.03	0.165744
--.	5.90	0.169551
logSTKt	5.57	0.179570
logGDPTAt	4.70	0.212633
DlogMt L1.	2.93	0.341427
logGDPTAt D1.	2.05	0.486658
logYLDSt	1.70	0.589542
Mean VIF	5.13	