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A Study On The Relation Of Exports And Imports On Real Gdp For Ghana Using Time Series Analysis

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ABSTRACT

This paper examines the role of trade, that is exports and imports, on economic growth, represented through real GDP and provides policy recommendations. For this purpose, time-series data from 1959 to 2019 collected in Ghana is used, where the export driven growth model is stressed on, and the structural adjustment policy is considered a success. We have conducted two types of computations in order to better discern the data: three separate univariate analyses and thereafter a VAR and VECM.

According to our analysis, the results from the univariate time-series indicate that the future values of GDP could, to a limited degree, be predicted by their past values. However, the same cannot be concluded for exports and imports that had badly fitting models, violating normality in the residuals requirements and suffering from autocorrelation. A multivariate analysis was thus used to better understand the relationship between exports, imports and real GDP. A VAR was utilised, subsequently leading to the application of the VECM due to there being cointegration.

The results from multivariate analysis indicated that GDP was negatively dependent on its previous value when the lagged values were jointly taken into consideration. Unlike the univariate analysis, the VAR model observes normality, homoscedasticity and no serial autocorrelation. The cointegration test establishes a relationship between Real GDP, exports and imports, with results being significant at 5% level. The test shows that imports have a negative long-run impact on GDP and exports have a positive impact on GDP. The granger causality test shows two things - first, we can predict the value of Real GDP based on the value of exports and second, we can predict the value of imports based on the value of exports. Further, when we conduct VECM analysis, we observe the speed of adjustment for Real GDP to be -28%, which indicates that our model will recover from shocks pretty soon.

Thus, Ghana needs to take advantage of its natural resources and train its labour force to develop local production capacity. Export diversification is crucial, and incorporating small enterprises that are drivers in the economy can be used to reduce a reliance on imports.

Keywords: Exports, Imports, Real GDP, Ghana, Time-series.

INTRODUCTION

Economic growth, a continuous process, refers to the increase in the productive capacity of an economy, linked to rising levels of income and a flow of goods and services. A prominent view advanced by economists was the causal factor that international trade, especially export heavy trade, could play as a stimulus for economic growth. Export promotion was argued as superior to import substitution strategies, especially in developing economies. Export growth opens producers to more competitive markets leading to better productivity and efficient allocation of resources. It includes greater specialisation which improves productivity gains and better utilisation of the economies of scale. Effective export strategies allow for improved quality of goods and services, adoption of newer technologies, and provide foreign exchange for integration into the world economy. (Asafu-Adjaye & Chakraborty, 1999)

Several studies have been conducted to provide strong empirical support for this argument. While some studies have attempted to show a correlation between economic growth and exports; others have considered exports as an additional input to capital and labour in the production function. Time-series data analysis has also found a positive relationship between exports and economic growth. This is however context-specific and can change based on the examination of different countries and existing trade networks. A lot of research on this has focused on large economies with data more easily available. East Asian countries such as South Korea and Taiwan are viewed as successes of the rapid export-driven growth hypothesis, with ramped up production in manufacturing and consumer goods, with extensive diversification of exports. Alternatively, studies have also observed a negative impact of exports on economic growth, associated with less developed economies. This can be attributed to reliance on the export of primary goods and the drainage of natural resources, limiting the human capital potential in the economy. (Dodaro, 1993; Njikam, 2003)

In the past few decades, there has been a greater emphasis on exports as a driver for economic development in African countries. The Sub-Saharan African region faces geographical disadvantages, infrastructural shortcomings, high transport costs, and difficult-to-access market intelligence, all of which contribute to weak integration into global and regional value chains. Long distances include a lack of transport infrastructure and low road density, with landlocked countries implying higher transport costs and delays in processing time. The region has faced a low density of economic activity in an area, where highly skilled workers migrate to other continents. Institutional framework, political will, and capacity building are necessary for trade facilitation. (Seck, 2016)

Ghana is a developing country in Africa, with an open economy, a relatively small market, dependent on external trade for its economic growth. Similar to most countries across the world, Ghana underwent extensive trade liberalisation in the 1980s and implemented market-oriented reforms. According to the World Bank, exports accounted for about 32% of GDP in 2020 in Ghana, with imports at 35% in the same year.

The main exports from Ghana include timber products, cocoa beans, coal, crude petroleum, and cola nuts, suggesting a high dependence on primary goods to drive up exports. (Enu et al., 2013) Ghana also has a high reliance on imports with its top imports including refined petroleum, rice, iron, cars, trucks, and other industrial and consumer goods. (Harvey & Sedegah, 2009)

Using time-series data, this paper examines the relationship between trade balance and economic growth in Ghana. The dynamics between exports, imports, and economic output are examined to contribute to the existing literature on export-driven growth. Strong criticism of export-oriented growth studies causes difficulties in identifying causality, with no tests for the direction of that causality. Exports, being a component of GDP, can also be driven up by an increase in GDP. Since there exists this bidirectional relation between exports and GDP, in our analysis we include the Vector Autoregressive Model (VAR) in our Statistical analysis section of the paper.

LITERATURE REVIEW

Numerous studies have indicated the positive relationship between exports and economic growth. Farahane and Heshmati (2020) investigated the contribution of trade to economic growth as well as the impact of regional integration agreements in the Southern African Development Community. The study tested the hypothesis of a positive relationship between trade-related variables including FDI, trade openness, and exports, through a balanced panel data analysis. The study also tested the hypothesis of a negative relationship between economic growth and trade variables including total debt service, effective exchange rate, and terms of trade. The findings of the study supported the view of trade operation as an engine for growth and recommended the promotion of international trade through export expansion for Southern African countries.

Asafu-Adjaye and Chakroborty (1999) employed cointegration techniques to test for intertemporal causality between exports, imports, and real output in less developed countries. An error correction model was used to Evaluate the causal direction, to indicate a representation of the relationship of the variables through the incorporation of feedback mechanisms between them. The study established causality from exports to real output. However, super-exogeneity tests questioned the strength of the causal relationship and indicated the influence of structural changes in the economy as well as political shifts.

In contrast, Dodaro (1993) presents a study involving the application of time series analysis using ordinary least squares to test the relationship between exports and economic growth in less developed countries. The study covers a wide range of countries, including the poorest ones, while accounting for the heterogeneity of the dataset through individual country time series. The paper's causality test provided very weak support for the hypothesis that export growth promotes GDP growth. As evidence is weak, a re-examination of policies towards exports and growth is suggested, especially in the context of less developed countries.

Mensah & Okyere (2020) examined the causal relationship between exports and economic growth for the period 2010 to 2019, based on monthly data in Ghana. They found evidence of bidirectional causality between export and growth, as well as a rapid adjustment to equilibrium between exports and real GDP. The paper focused on a decade where the Ghanian government focussed on ramping up international trade.

Lee and Huang (2002) examined the causal relation between exports and output in five Asian countries (Hong, Kong, Taiwan, Philippines, Korea, and Japan) employing the multivariate Granger causality methodology. The success of newly industrialised economies in Asia was attributed to their adoption of outwardly oriented development strategies. Using the two-regime multivariate TAR model, the results indicated, with the exception of Hong Kong, evidence of export-led growth under certain regimes.

Kalaitzi and Chamberlain (2020) re-examined the validity of the export-led growth hypothesis in the context of the United Arab Emirates. It applies short-range Granger causality tests which support the existence of causality from merchandise export to economic growth in the short run. However, there is a lack of evidence for long-run causality in the UAE, likely due to the country's reliance on oil, subject to oil-price shocks. The majority of UAE's exports include oil and oil-related goods, indicating the need for policymakers to target new export sectors to foster future economic growth. Similarly, Panta, Devkota & Banjade (2022) using the vector error correction model investigated the export-led growth hypothesis in Nepal, and found no evidence to support the hypothesis, either in the short run or long run.

Njikam (2003) examines whether agricultural and manufactured exports caused economic growth or vice versa, utilising the stepwise Granger-causality technique to analyse the direction of causation in Sub-Saharan African countries. The results indicated that, during the export promotion period, agricultural exports unidirectionally caused economic growth for 9 out of 21 countries. However, manufactured exports drove up GDP in only 3 out of 21 countries. This questions the emphasis of export promotion policies, especially with regard to manufacturing in African nations.

Taylor (2015) postulates that the notional 'rise' of Africa, with a comparative advantage as primary commodity exports, contributes to the continent being pushed further into dependency and underdevelopment. The current growth model has been ineffective in establishing sustainable development outcomes and industrial growth is not associated with economic growth. Instead, there has been a greater dependency on primary products, linked with de-industrialisation as a driver of economic growth. This does not lend itself to sustainable economic development, especially in light of shifting prices for primary commodities in the global market.

OBJECTIVES

The Objectives of Our Study are To :

- Conduct statistical analysis (univariate and multivariate) on Real GDP
- To determine the relationship between Real GDP and Exports
- To determine the relationship between Real GDP and Imports
- To study the long-run relationship between Real GDP and Exports
- To study the long-run relationship between Real GDP and Imports

HYPOTHESES

To achieve our objectives, we need the following hypothesis:

- **H1:** Real GDP, Exports, and Imports are expected to have significant trends and unit-roots when considered in levels.
- **H2:** Exports are positive in the VAR model as a significant independent variable.
- **H3:** Imports are negative in the var model as a significant independent variable.
- **H4:** Real GDP is cointegrated with exports in the long run.
- **H5:** Real GDP is cointegrated with imports in the long run.
- **H6:** Exports are cointegrated with imports in the long run.

RESEARCH QUESTIONS

Given our objectives and hypothesis, we formulate the research question as follows :

- Can exports sufficiently explain the variation in real GDP?
- Should imports be considered when explaining variations in the real GDP?

METHODOLOGY

In order to answer the research questions and to prove the hypothesis, we have collected data from the Penn World Table, which is a database of relative levels of income, input-output, and productivity covering 183 countries. Data on exports, imports, and GDP in Ghana have been extracted to examine their relationship. The data covers the time period of 1959 to 2019 in Ghana. Real GDP in Ghana observed very little increase from the 1960s until the 2000s[1]. In the last two decades, GDP rose rapidly with extreme vulnerability to external shocks such as the 2008 financial crisis.

Firstly we will start by looking at the three time series individually by conducting univariate analysis independently on all three series to determine the ARMA model and forecasts. Next, we will look at the relation of the series through multivariate analysis using VAR, Cointegration tests, and Vector Error Correction Model (VECM). Initial data cleaning process was done in Excel and the data was imported to Eviews12 for further computations.

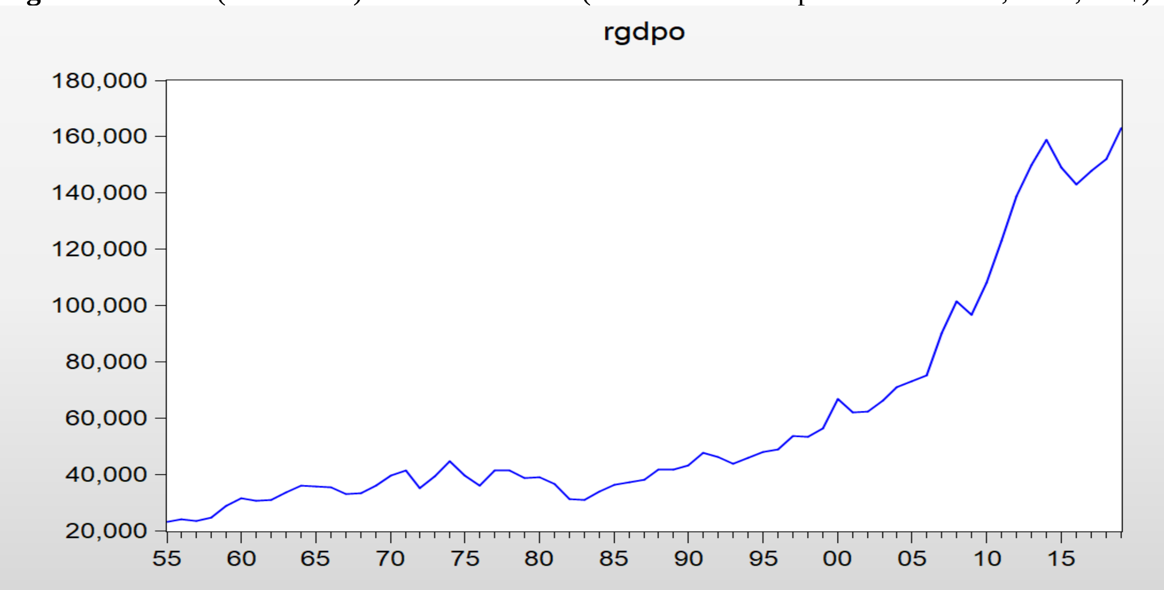
STATISTICAL ANALYSIS

I Descriptive Statistics and Data

Our series will use Real GDP as the dependent variable, with imports and exports representing the explanatory variables. To do this we are going to apply a two-pronged approach. First, we will do 3 univariate analyses on real GDP, exports and imports to see whether these variables can be explained well by only their past values. Thereafter because issues arose, we conducted a VAR with all three variables to see if a joint series is more accurate.

Figure 1 shows how Ghana's GDP has fluctuated significantly with a large peak in the early 2000s. A possible reason for this could be the HIPC (highly indebted poor countries) and MDRI (multilateral debt relief) initiatives that saw debt become null and void, which in turn opened the route to international borrowing, trade and economic growth.[2] (IMF Factsheet, 2021.)An initial sign of the importance of trade can be seen by the drop in 2014/15. As explained in the World Bank article "Commodity Prices Expected to Drop Across the Board in 2015" trade would have dropped and so would have GDP as a consequence.[3]

Figure 1: Annual (1955-2019) Real GDP Ghana (constant national prices in millions, 2017, US$)



For all three variables, we decide to transform them and take the natural logarithm to smoothen our findings. The change in GDP is shown in the histograms below. The skewness decreases by 1 meaning that the data is far more symmetrical, and this does not affect the spread in the tails as the Kurtosis scores remain close to three (the kurtosis score for a standard normal distribution).[4] The distribution was formerly slightly less normal but after the log transformation, visually speaking it comes close to normality. We also take the natural logarithm for Imports and Exports and show their graphs and histograms in the Annex (Annex figures 3 & 6).

Figure 2: Histogram RGDP

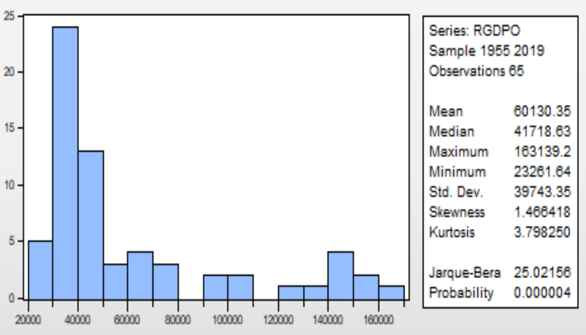
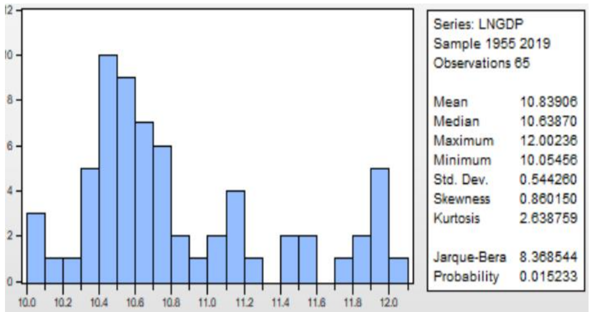


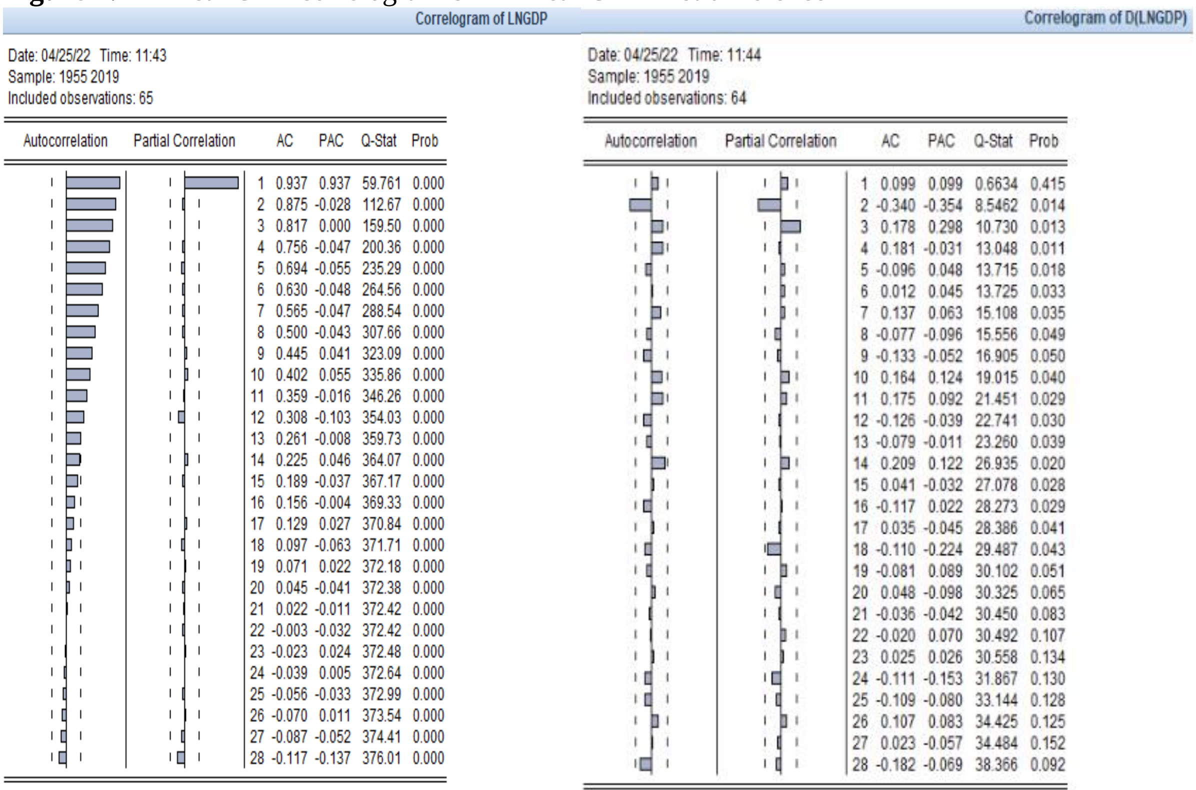
Figure 3: Histogram LNRGDP



2 Stationarity Testing and ARIMA Estimation

Figure 4 first (left) shows the correlogram for LN GDP. From it, we can draw 3 main possibilities. Firstly, the gradual declining slope of the ACF hints toward there possibly being non-stationarity (non-constant mean/variance), which prevents our ability to forecast. Secondly, the high PAC 1 score hints toward possibly being able to use the first difference to make the series stationary. Thirdly, this appears to be an ARMA(p,q) model with many significant MA components (up to MA(13)).

Figure 4: LN Real GDP correlogram & LN Real GDP first difference



Correlogram of LNGDP

Date: 04/25/22 Time: 11:43
Sample: 1955 2019
Included observations: 65

	AC	PAC	Q-Stat	Prob
1	0.937	0.937	59.761	0.000
2	0.875	-0.028	112.67	0.000
3	0.817	0.000	159.50	0.000
4	0.756	-0.047	200.36	0.000
5	0.694	-0.055	235.29	0.000
6	0.630	-0.048	264.56	0.000
7	0.565	-0.047	288.54	0.000
8	0.500	-0.043	307.66	0.000
9	0.445	0.041	323.09	0.000
10	0.402	0.055	335.86	0.000
11	0.359	-0.016	346.26	0.000
12	0.308	-0.103	354.03	0.000
13	0.261	-0.008	359.73	0.000
14	0.225	0.046	364.07	0.000
15	0.189	-0.037	367.17	0.000
16	0.156	-0.004	369.33	0.000
17	0.129	0.027	370.84	0.000
18	0.097	-0.063	371.71	0.000
19	0.071	0.022	372.18	0.000
20	0.045	-0.041	372.38	0.000
21	0.022	-0.011	372.42	0.000
22	-0.003	-0.032	372.42	0.000
23	-0.023	0.024	372.48	0.000
24	-0.039	0.005	372.64	0.000
25	-0.056	-0.033	372.99	0.000
26	-0.070	0.011	373.54	0.000
27	-0.087	-0.052	374.41	0.000
28	-0.117	-0.137	376.01	0.000

Correlogram of D(LNGDP)

Date: 04/25/22 Time: 11:44
Sample: 1955 2019
Included observations: 64

	AC	PAC	Q-Stat	Prob
1	0.099	0.099	0.6634	0.415
2	-0.340	-0.354	8.5462	0.014
3	0.178	0.298	10.730	0.013
4	0.181	-0.031	13.048	0.011
5	-0.096	0.048	13.715	0.018
6	0.012	0.045	13.725	0.033
7	0.137	0.063	15.108	0.035
8	-0.077	-0.096	15.556	0.049
9	-0.133	-0.052	16.905	0.050
10	0.164	0.124	19.015	0.040
11	0.175	0.092	21.451	0.029
12	-0.126	-0.039	22.741	0.030
13	-0.079	-0.011	23.260	0.039
14	0.209	0.122	26.935	0.020
15	0.041	-0.032	27.078	0.028
16	-0.117	0.022	28.273	0.029
17	0.035	-0.045	28.386	0.041
18	-0.110	-0.224	29.487	0.043
19	-0.081	0.089	30.102	0.051
20	0.048	-0.098	30.325	0.065
21	-0.036	-0.042	30.450	0.083
22	-0.020	0.070	30.492	0.107
23	0.025	0.026	30.558	0.134
24	-0.111	-0.153	31.867	0.130
25	-0.109	-0.080	33.144	0.128
26	0.107	0.083	34.425	0.125
27	0.023	-0.057	34.484	0.152
28	-0.182	-0.069	38.366	0.092

When we take the first difference (right) we directly observe that the series seems to now be stationary (sinusoidal P/ACF with no significant large peaks). Moreover, both an ARMA(2,2) and ARMA (3,2) seem to be plausible models as the ACF and PCF scores are significant at these values. To confirm our suspicions of stationarity in the first difference we also perform an Augmented Dickey-Fuller (ADF) unit root test. We know that if a unit root is present, the series is not stationary. We perform the unit root tests with a trend and constant as the graph of LNGDP indicates their possible existence (figure 1).

Taking the first difference (figure 6) results in the unit root no longer being significantly present as the P-score becomes 0.000 (no longer 0.121 - figure 5). Moreover the trend and constant, with P-scores of 0.9 & 0.5 (figure 6) respectively, are not significantly present after taking the 1st difference. We then repeat this process for Imports and Exports in the Annex (Annex figure 8 & 9) to conclude that we will also take the LN first differences here.

Figure 5: ADF for LN Real GDP (level)

Augmented Dickey-Fuller Unit Root Test on LNPL_X

Null Hypothesis: LNPL_X has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.074500	0.1212
Test critical values:	1% level	-4.107947	
	5% level	-3.481595	
	10% level	-3.168695	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNPL_X)
Method: Least Squares
Date: 04/25/22 Time: 12:13
Sample (adjusted): 1956 2019
Included observations: 64 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNPL_X(-1)	-0.257579	0.083779	-3.074500	0.0032
C	-0.521668	0.179401	-2.907835	0.0051
@TREND("1955")	0.007452	0.002666	2.794960	0.0069

R-squared	0.134579	Mean dependent var	0.017992
Adjusted R-squared	0.106205	S.D. dependent var	0.197211
S.E. of regression	0.186445	Akaike info criterion	-0.475622
Sum squared resid	2.120462	Schwarz criterion	-0.374424
Log likelihood	18.21990	Hannan-Quinn criter.	-0.435755
F-statistic	4.742975	Durbin-Watson stat	1.761525
Prob(F-statistic)	0.012174		

Figure 6: ADF LN Real GDP (first difference)

Augmented Dickey-Fuller Unit Root Test on D(LNPL_X)

Null Hypothesis: D(LNPL_X) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.761156	0.0000
Test critical values:	1% level	-4.113017	
	5% level	-3.483970	
	10% level	-3.170071	

*MacKinnon (1996) one-sided p-values.

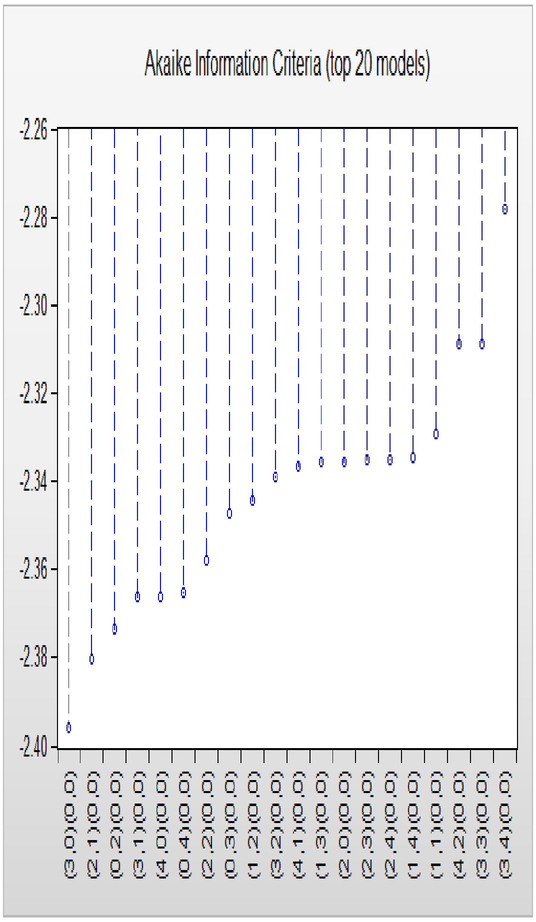
Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNPL_X,2)
Method: Least Squares
Date: 04/25/22 Time: 12:14
Sample (adjusted): 1958 2019
Included observations: 62 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNPL_X(-1))	-1.341326	0.172826	-7.761156	0.0000
D(LNPL_X(-1),2)	0.342294	0.121913	2.807696	0.0068
C	0.032205	0.051519	0.625109	0.5344
@TREND("1955")	-0.000112	0.001354	-0.082952	0.9342

R-squared	0.560527	Mean dependent var	0.000731
Adjusted R-squared	0.537795	S.D. dependent var	0.280591
S.E. of regression	0.190761	Akaike info criterion	-0.413247
Sum squared resid	2.110613	Schwarz criterion	-0.276012
Log likelihood	16.81065	Hannan-Quinn criter.	-0.359365
F-statistic	24.65874	Durbin-Watson stat	2.058163
Prob(F-statistic)	0.000000		

After making the series stationary, the next step is estimating the form of the model. ARIMA(p,d,q) models are in essence ARMA(p,q) models with a differencing/integration element "d." In our model, we are using a first difference and d=1. Under the Eviews function "Automatic ARIMA forecasting" we intend to determine p,q based on the AIC comparisons - although comparing the Schwarz or Hannan-Quinn criteria are also model comparisons. As seen in Figure 7, Eviews tests all possible models to find that for LN GDP, the most likely model is an ARIMA(3,1,0). Both the constant and each of the AR components are significant. We also conduct the same tests for LN Imports and LN Exports in the Annex (Annex figures 10 & 11) to determine that their respective ARIMA models are: ARIMA(4,1,4) & ARIMA(2,1,0).

Figure 7: ARIMA forecasting and equation output for LN GDP (first difference)



Equation Output

Dependent Variable: D(LNGDP)
Method: ARMA Maximum Likelihood (BFGS)
Date: 04/25/22 Time: 12:19
Sample: 1956 2019
Included observations: 64
Convergence achieved after 8 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.030782	0.010130	3.038637	0.0035
AR(1)	0.240911	0.109692	2.196252	0.0320
AR(2)	-0.388987	0.144800	-2.686378	0.0094
AR(3)	0.292884	0.120437	2.431848	0.0181
SIGMASQ	0.004357	0.000774	5.633064	0.0000

R-squared	0.215015	Mean dependent var	0.030434
Adjusted R-squared	0.161796	S.D. dependent var	0.075092
S.E. of regression	0.068749	Akaike info criterion	-2.433392
Sum squared resid	0.278859	Schwarz criterion	-2.264729
Log likelihood	82.86854	Hannan-Quinn criter.	-2.366947
F-statistic	4.040164	Durbin-Watson stat	1.962560
Prob(F-statistic)	0.005811		

Inverted AR Roots	.54	-.15+.72i	-.15-.72i

The **LN GDP Model** becomes therefore: DLN_GDP(t) = 0.03 + 0.24 * DLN_GDP(t-1) - 0.38 * DLN_GDP(t-2) + 0.29 * DLN_GDP(t-3) + ϵt

3 Checking the Model

From the equation output in figure 7 (right), we first look to test for autocorrelation between the residuals. use the Durbin Watson score.[5] Our score is precisely 1.96 and close to 2 meaning autocorrelation is unlikely. To double-check we also look at the Q-Q residual correlogram (figure 8) and perform an LM test (figure 9). The Q-Q plot does not show any significant peaks and furthermore, the null hypothesis of no autocorrelation in the LM test is not rejected.[6] there is no autocorrelation.

Figure 8: DLN_GDP QQ residual correlogram

Sample: 1955 2029
Included observations: 61
Q-statistic probabilities adjusted for 3 dynamic regressors

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.001	-0.001	3.E-05	0.995
		2	-0.018	-0.018	0.0209	0.990
		3	0.020	0.020	0.0485	0.997
		4	-0.038	-0.039	0.1484	0.997
		5	0.065	0.066	0.4396	0.994
		6	0.046	0.045	0.5893	0.997
		7	0.001	0.005	0.5894	0.999
		8	-0.052	-0.055	0.7847	0.999
		9	-0.037	-0.034	0.8878	1.000
		10	0.092	0.090	1.5198	0.999
		11	0.081	0.079	2.0287	0.998
		12	-0.004	-0.006	2.0297	0.999
		13	-0.059	-0.060	2.3058	0.999
		14	0.172	0.189	4.7188	0.989
		15	0.032	0.033	4.8051	0.994
		16	-0.094	-0.119	5.5655	0.992
		17	0.077	0.056	6.0864	0.993
		18	-0.198	-0.178	9.5913	0.944
		19	-0.080	-0.078	10.174	0.949
		20	0.081	0.053	10.787	0.952
		21	-0.044	-0.055	10.975	0.963
		22	0.012	0.011	10.988	0.975
		23	-0.010	0.036	10.998	0.983
		24	-0.089	-0.103	11.819	0.982
		25	-0.097	-0.149	12.817	0.979
		26	0.061	0.080	13.220	0.982
		27	0.023	0.026	13.278	0.987
		28	-0.136	-0.182	15.430	0.974

Figure 9: LM test for DLN_GDP

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.105810	Prob. F(2,55)	0.8998
Obs*R-squared	0.233806	Prob. Chi-Square(2)	0.8897

Thereafter we perform a test on the residuals to test whether they are normally distributed (figure 10). The null hypothesis is that the residuals are normally distributed and with a P-score of 0.45, this is not rejected.[7] Finally, looking at the inverse roots shows whether the model is invertible (and it can be seen as an additional check for stationarity). Our results in figure 11 show that all of the roots are invertible as they are not out of the unit circle. In the Annex (Annex figures 12 &13), we perform the same checks for Imports and Exports.

Figure 10: Histogram residuals DLN_GDP

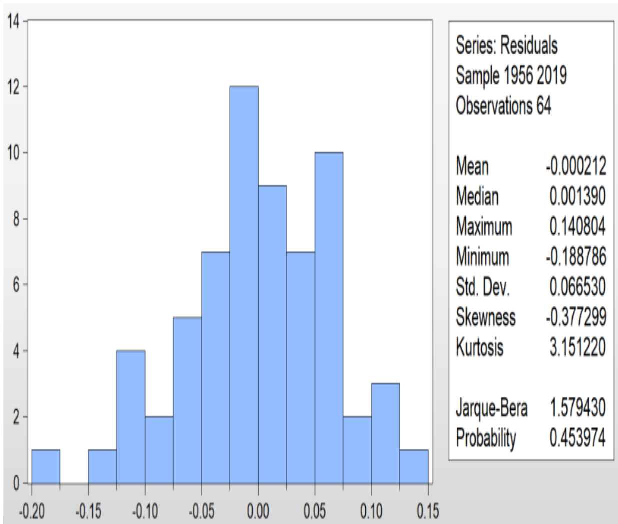
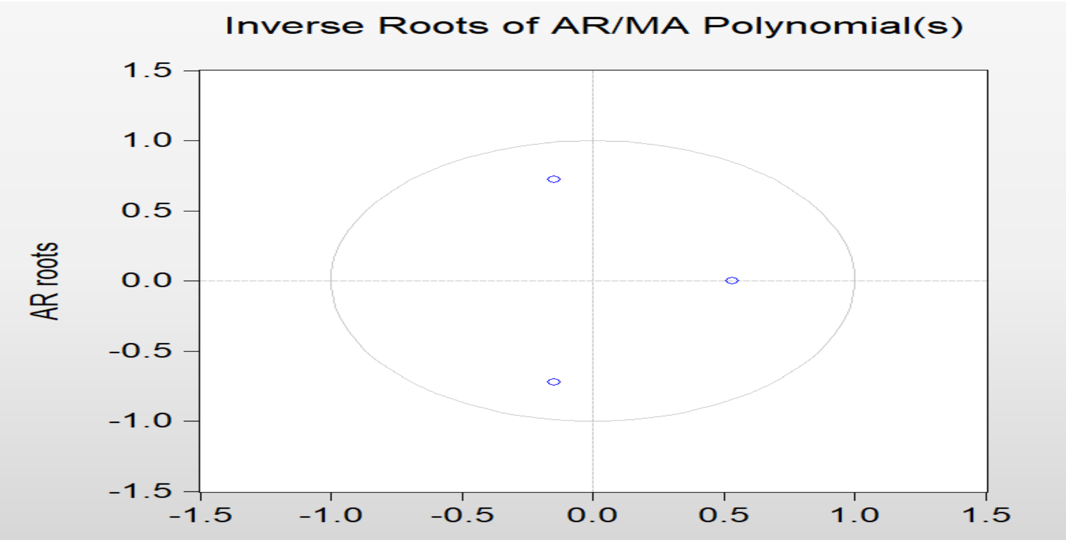
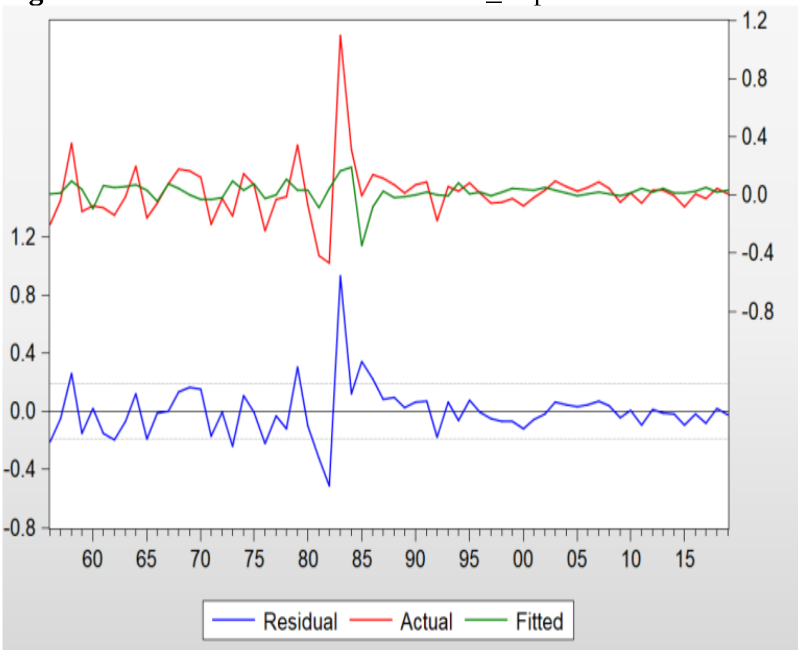


Figure 11: Inverse roots of DLN_GDP



When performing the same tests for Imports and Exports in the Annex (Annex figures 12 & 13) we encounter the first signs that imports and exports cannot be explained by only their own past values. Starting with Exports, the adjusted R-squared is 0.07 (compared to 0.3 and 0.16 for Imports and GDP) and the F-statistic is low. It is only significant at the 10% level (P-score of 0.052) meaning that we are less sure that the model fits the data. An issue from Figure 11 can be shown to come from major residuals in the early 1980s past values of Exports alone do not explain later exports well in this time period. Moreover, the residuals for both Exports and Imports are not normally distributed, and finally, the LM test for Imports indicates that we would reject the null hypothesis of not serial/autocorrelation at a 12% level of significance. Forecasting is unlikely to be reliable for these two variables and we have our first concrete indication that a VAR model may be a better approach.

Figure 11: Actual and fitted values DLN_Exports



4 Forecasting

There are two types of forecasting: static and dynamic. Static uses the actual values to forecast a one-step-ahead forecast. Dynamic on the other hand then uses forecasted (non-actuals) to predict the next values in a multi-step forecast.[8] Figures 12-14 show the dynamic forecasts for GDP, Imports, and Exports. The "S.E." green line represents the absolute value of 2 Standard Errors. The most noteworthy conclusion is that the S.E. is especially large for dynamic imports. Imports are least likely to be a convincing univariate series.

Figure 12: Dynamic (left) and static (right) forecasts DLN_GDP

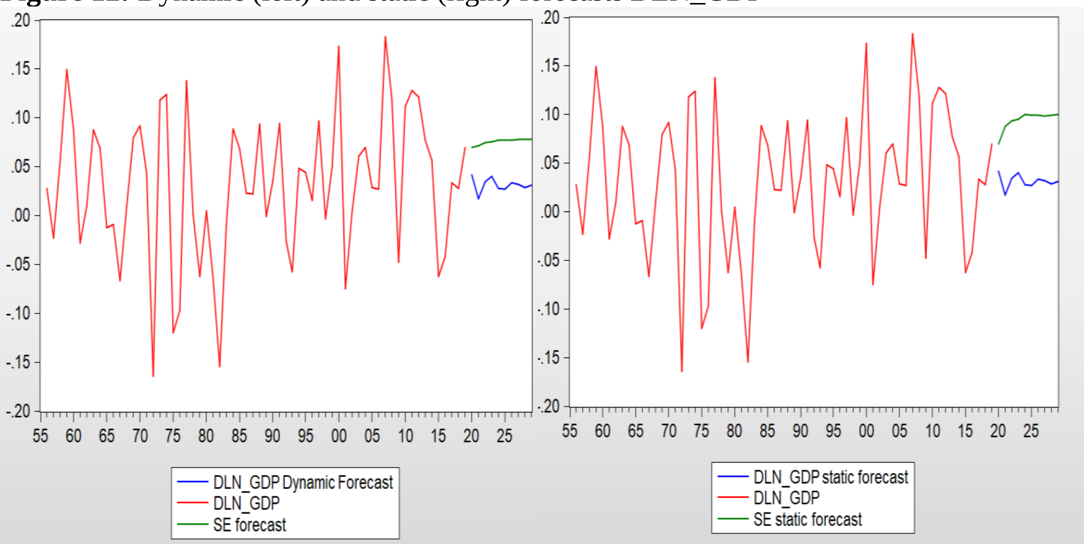


Figure 13: Dynamic (left) and static (right) forecasts DLN_Imports

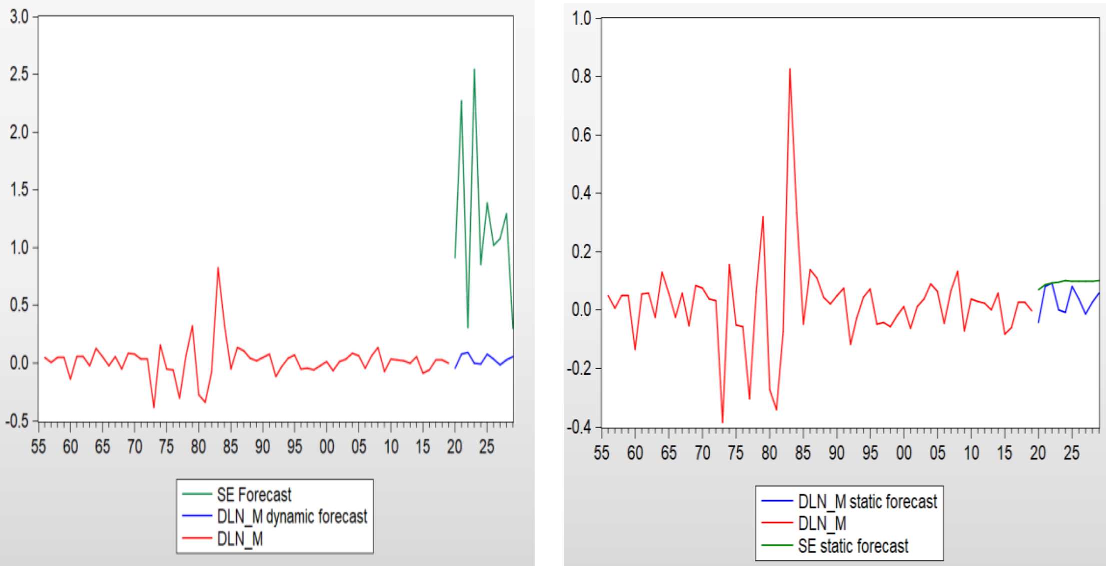
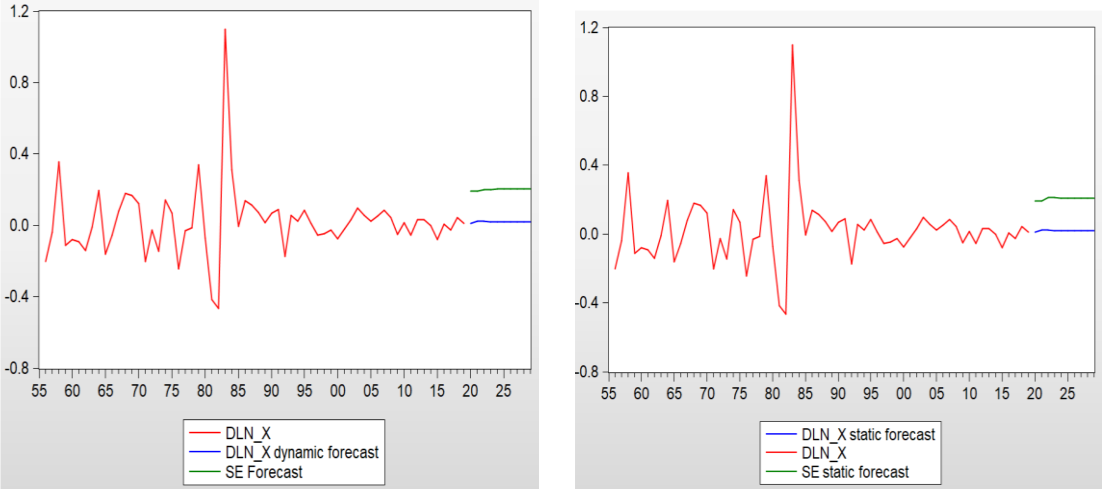


Figure 14: Dynamic (left) and static (right) forecasts DLN_Exports



5 Conclusion of the Three Univariate Tests

When looking at the univariate time series we were able to create a series that will predict Real GDP, Imports, and Exports individually on their past values alone. The models were all transformed into their natural logarithms and the first difference was needed for stationarity. The resulting models became ARIMA (3,1,0), (4,1,4) and (2,1,0) respectively.

For Real GDP most of the checks needed to be able to forecast were convincingly met and a forecast with a respectable SE is created. The resulting model with an R^2 of 21% (adjusted R^2 of 16%) does indicate however that there is room for improvement in explaining/fitting the data.

The more pressing issues are present in the Exports and Imports series. Taking a look at the graph of the smoother LN versions shows the first hint of the issues we found: for both series, there are large peaks of the early 80s that could even start to question the stationarity found. Specifically, for exports the residuals are not normally distributed, the R^2 value of 0.7% is starkly small and this lacking fit is emphasised in the F-statistic that is not significant at the 5% level as well as figure 11 which shows how the peaks of the 80s are not well fitted in the model. Imports on the other hand also do not have normally distributed residuals but more worryingly the LM score suggests that autocorrelation is present at the 12% level. Two worrying issues that are best seen in Imports having by far the largest and most irregular SE intervals for (dynamic) forecasting. All in all, the issues in Imports and Exports are expressed by the best ARIMA model not having all the AR(p) and MA(q) coefficients at the 5% significance level.

In other words, we end up finding that for imports and exports specifically there need to be extra variables that explain the variation. The current best univariate series are not adequate. Secondly, for GDP, although a prediction is possible, an improved prediction is likely one that includes additional variables as well to increase the model fit. Hence we finish this analysis by conducting a VAR.

6 MULTIVARIATE MODELLING

6.1 Vector Autoregressive Regression

Since we are interested in predicting multiple time series variables using a single model, we are in the case of a VAR. In VAR, each variable is a linear function of its past lags as well as the past lags of other variables. Here we regress the vector of time series variables on lagged vectors of these variables. In order to do that, first, we will see how many lags to include:

Figure 15

VAR Lag Order Selection Criteria
Endogenous variables: DLN_RGDPO DLN_PL_X DLN_PL_M
Exogenous variables: C
Date: 05/02/22 Time: 15:37
Sample: 1955 2019
Included observations: 59

Lag	LogL	LR	FPE	AIC	SC	HQ
0	138.7338	NA	2.02e-06	-4.601146	-4.495509*	-4.559910*
1	147.7777	16.86142	2.01e-06	-4.602633	-4.180083	-4.437686
2	158.2834	18.51866	1.92e-06	-4.653676	-3.914214	-4.365020
3	166.1346	13.04086	2.01e-06	-4.614731	-3.558356	-4.202365
4	179.0524	20.14300*	1.78e-06*	-4.747538*	-3.374250	-4.211462
5	187.6317	12.50553	1.84e-06	-4.733279	-3.043080	-4.073494

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

According to AIC criterion, we must include 4 lags to do the VAR and cointegration as follows:

Figure 16

Vector Autoregression Estimates
Date: 05/02/22 Time: 17:20
Sample (adjusted): 1960 2019
Included observations: 60 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	DLN_RGDPO	DLN_PL_X	DLN_PL_M
DLN_RGDPO(-1)	0.176948	0.192180	0.583664
	(0.15289)	(0.34105)	(0.28070)
	[1.15736]	[0.56349]	[2.07929]
DLN_RGDPO(-2)	-0.336773	-0.877461	-0.594833
	(0.14478)	(0.32296)	(0.26581)
	[-2.32615]	[-2.71698]	[-2.23782]
DLN_RGDPO(-3)	0.329150	-0.549966	-0.392419
	(0.14474)	(0.32288)	(0.26575)
	[2.27404]	[-1.70333]	[-1.47667]
DLN_RGDPO(-4)	-0.013052	-1.074468	-1.216935
	(0.15896)	(0.35460)	(0.29186)
	[-0.08211]	[-3.03005]	[-4.16962]
DLN_PL_X(-1)	0.052663	-0.771517	-0.443114
	(0.09729)	(0.21702)	(0.17862)
	[0.54132]	[-3.55510]	[-2.48081]
DLN_PL_X(-2)	-0.050975	-0.740662	-0.582674
	(0.10205)	(0.22764)	(0.18736)
	[-0.49952]	[-3.25365]	[-3.10991]
DLN_PL_X(-3)	-0.117379	-0.405459	-0.334431
	(0.09942)	(0.22178)	(0.18254)
	[-1.18062]	[-1.82821]	[-1.83214]
DLN_PL_X(-4)	-0.056479	-0.097287	0.041723
	(0.08564)	(0.19103)	(0.15723)
	[-0.65953]	[-0.50928]	[0.26537]
DLN_PL_M(-1)	0.012302	0.819014	0.366843
	(0.10645)	(0.23745)	(0.19543)
	[0.11557]	[3.44921]	[1.87707]
DLN_PL_M(-2)	0.102021	0.511973	0.303959
	(0.11736)	(0.26180)	(0.21548)
	[0.86928]	[1.95558]	[1.41064]
DLN_PL_M(-3)	0.120744	0.342316	0.266773
	(0.11427)	(0.25490)	(0.20980)
	[1.05665]	[1.34292]	[1.27156]
DLN_PL_M(-4)	0.094885	0.407962	0.266261
	(0.10468)	(0.23352)	(0.19220)
	[0.90641]	[1.74704]	[1.38536]
C	0.022036	0.090432	0.071883
	(0.01246)	(0.02779)	(0.02287)
	[1.76888]	[3.25418]	[3.14281]
R-squared	0.287608	0.472716	0.478614
Adj. R-squared	0.105721	0.338090	0.345495
Sum sq. resids	0.240350	1.195990	0.810183
S.E. equation	0.071511	0.159520	0.131293
F-statistic	1.581246	3.511332	3.595369
Log likelihood	80.46385	32.32480	44.00888

The above regression table gives us the VAR till lag 4 with adjusted R^2 value of 10%.

Figure 17

Dependent Variable: DLN_RGDPO
Method: Least Squares (Gauss-Newton / Marquardt steps)
Date: 05/02/22 Time: 11:21
Sample (adjusted): 1958 2019
Included observations: 62 after adjustments
DLN_RGDPO = C(1)*DLN_RGDPO(-1) + C(2)*DLN_RGDPO(-2) + C(3)
*DLN_PL_X(-1) + C(4)*DLN_PL_X(-2) + C(5)*DLN_PL_M(-1) + C(6)
*DLN_PL_M(-2) + C(7)

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.119911	0.132388	0.905755	0.3690
C(2)	-0.318890	0.128388	-2.483804	0.0161
C(3)	0.053728	0.086425	0.621670	0.5367
C(4)	-0.063465	0.081295	-0.780672	0.4383
C(5)	-0.000362	0.100281	-0.003614	0.9971
C(6)	0.121089	0.100152	1.209049	0.2318
C(7)	0.034895	0.010507	3.321072	0.0016

R-squared	0.192729	Mean dependent var	0.031343
Adjusted R-squared	0.104663	S.D. dependent var	0.075996
S.E. of regression	0.071909	Akaike info criterion	-2.320828
Sum squared resid	0.284399	Schwarz criterion	-2.080668
Log likelihood	78.94567	Hannan-Quinn criter.	-2.226535
F-statistic	2.188465	Durbin-Watson stat	1.841575
Prob(F-statistic)	0.057844		

Here only the second lag of GDP and constant are significant. This implies that the current GDP is a function of the negative lagged value of GDP in the second lag. We need to test for joint significance of variables using the Wald test to see if there are significant joint relations between the lags:

Figure 18

Lag one and two of GDP are jointly significant in determining GDP which is clear from the table below :

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	3.270098	(2, 55)	0.0455
Chi-square	6.540196	2	0.0380

Null Hypothesis: C(1)=C(2)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(1)	0.119911	0.132388
C(2)	-0.318890	0.128388

Restrictions are linear in coefficients.

Lag three and four are jointly non-significant from the table below :

Figure 19

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	0.709800	(2, 55)	0.4962
Chi-square	1.419601	2	0.4917

Null Hypothesis: C(3)=C(4)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(3)	0.053728	0.086425
C(4)	-0.063465	0.081295

Restrictions are linear in coefficients.

Lag five and six are again not significant jointly from table below:

Figure 19

Wald Test:
Equation: Untitled

Test Statistic	Value	df	Probability
F-statistic	0.764157	(2, 55)	0.4706
Chi-square	1.528315	2	0.4657

Null Hypothesis: C(5)=C(6)=0
Null Hypothesis Summary:

Normalized Restriction (= 0)	Value	Std. Err.
C(5)	-0.000362	0.100281
C(6)	0.121089	0.100152

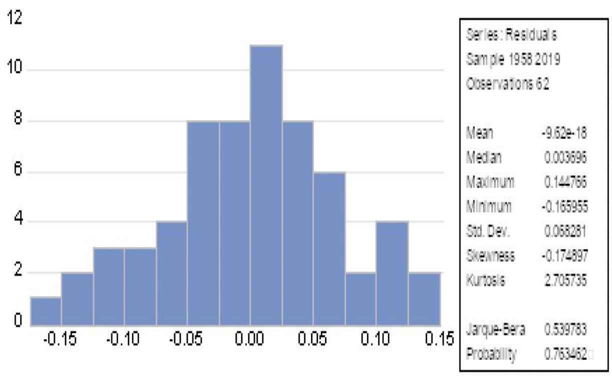
Restrictions are linear in coefficients.

This just means that GDP is a negative function of its previous value in the second lag and does not necessarily depend on previous values of imports and exports even when they are jointly considered.

6.2 Post-Estimation Tests on VAR

Now, we shall conduct some post-estimation tests on the VAR namely - normality, correlation and heteroskedasticity tests to check for the quality of VAR. Normality test for the VAR:

Figure 20



P-val is not significant, so the distribution is normal.

Now we look at correlation using LM test for the VAR:

Figure 21

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

F-statistic	1.470381	Prob. F(2,53)	0.2391
Obs*R-squared	3.259290	Prob. Chi-Square(2)	0.1960

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 05/02/22 Time: 11:32
Sample: 1958 2019
Included observations: 62
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.629739	0.391637	-1.607969	0.1138
C(2)	-0.036328	0.278406	-0.130484	0.8967
C(3)	0.036947	0.088367	0.418103	0.6776
C(4)	0.105180	0.101440	1.036877	0.3045
C(5)	-0.030729	0.101086	-0.303993	0.7623
C(6)	-0.069698	0.107328	-0.649396	0.5189
C(7)	0.019568	0.017646	1.108922	0.2725
RESID(-1)	0.686971	0.400610	1.714812	0.0922
RESID(-2)	0.098953	0.316159	0.312986	0.7555

R-squared	0.052569	Mean dependent var	-9.62E-18
Adjusted R-squared	-0.090439	S.D. dependent var	0.068281
S.E. of regression	0.071302	Akaike info criterion	-2.310313
Sum squared resid	0.269448	Schwarz criterion	-2.001536
Log likelihood	80.61972	Hannan-Quinn criter.	-2.189080
F-statistic	0.367595	Durbin-Watson stat	1.955144
Prob(F-statistic)	0.933037		

P-value is not significant, so there is no serial correlation.

Next we look at heteroskedasticity test for standard errors in VAR:

Figure 22

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.366910	Prob. F(6,55)	0.8968
Obs*R-squared	2.386137	Prob. Chi-Square(6)	0.8810
Scaled explained SS	1.601471	Prob. Chi-Square(6)	0.9525

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/02/22 Time: 11:33
Sample: 1958 2019
Included observations: 62

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.004684	0.000911	5.139447	0.0000
DLN_RGDPO(-1)	0.002523	0.011483	0.219745	0.8269
DLN_RGDPO(-2)	-0.001242	0.011136	-0.111550	0.9116
DLN_PL_X(-1)	-0.003679	0.007496	-0.490767	0.6255
DLN_PL_X(-2)	-0.001638	0.007051	-0.232258	0.8172
DLN_PL_M(-1)	-0.003579	0.008698	-0.411472	0.6823
DLN_PL_M(-2)	0.002156	0.008687	0.248246	0.8049

R-squared	0.038486	Mean dependent var	0.004587
Adjusted R-squared	-0.066406	S.D. dependent var	0.006040
S.E. of regression	0.006237	Akaike info criterion	-7.210590
Sum squared resid	0.002140	Schwarz criterion	-6.970430
Log likelihood	230.5283	Hannan-Quinn criter.	-7.116297
F-statistic	0.366910	Durbin-Watson stat	1.817046
Prob(F-statistic)	0.896779		

Since the observed R^2 p-value is not significant, we can say that the errors are Homoskedastic. All in all, the VAR has a normal distribution, no serial correlation and no heteroskedasticity in its standard errors.

6.3 Cointegration Test

Now we will look at long-term relation between the series to see if they are integrated in the long run using cointegration test:

Figure 23

Date: 05/02/22 Time: 17:22
Sample (adjusted): 1961 2019
Included observations: 59 after adjustments
Trend assumption: Linear deterministic trend
Series: DLN_RGDPO DLN_PL_X DLN_PL_M
Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.500983	61.05653	29.79707	0.0000
At most 1 *	0.178302	20.04477	15.49471	0.0096
At most 2 *	0.133557	8.458195	3.841465	0.0036

Trace test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.500983	41.01177	21.13162	0.0000
At most 1	0.178302	11.58657	14.26460	0.1272
At most 2 *	0.133557	8.458195	3.841465	0.0036

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

In the above, if any one of the p-values are less than 0.05, we can reject the null hypothesis and conclude that there is co-integration in our data. We can see that we have at least 2 cointegrating series. We need to understand the direction of this cointegration:

Figure 24

1 Cointegrating Equation(s): Log likelihood 177.6094

Normalized cointegrating coefficients (standard error in parentheses)

DLN_RGDPO	DLN_PL_X	DLN_PL_M
1.000000	1.738753	-1.401736
	(0.25499)	(0.25426)

Adjustment coefficients (standard error in parentheses)

D(DLN_RGD...	-0.129916
	(0.20121)
D(DLN_PL_X)	-2.434078
	(0.38136)
D(DLN_PL_M)	-1.179739
	(0.34039)

The table above shows imports have a negative long-run impact on GDP and exports have a positive impact on GDP and are significant at 5% level. This means that an increase in exports will lead to an increase in GDP and a decrease in imports will lead to an increase in GDP.

6.4 Granger Causality

Now, we need to test to see if there is any causality between the series, basically we will see if we can predict one series based on data from other series using the Granger-causality test:

Figure 25

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 05/02/22 Time: 17:39
Sample: 1955 2019
Included observations: 60

Dependent variable: DLN_RGDPO

Excluded	Chi-sq	df	Prob.
DLN_PL_X	2.127881	4	0.7123
DLN_PL_M	1.872108	4	0.7593
All	5.146191	8	0.7418

Dependent variable: DLN_PL_X

Excluded	Chi-sq	df	Prob.
DLN_RGDPO	18.69651	4	0.0009
DLN_PL_M	15.97629	4	0.0031
All	29.81559	8	0.0002

Dependent variable: DLN_PL_M

Excluded	Chi-sq	df	Prob.
DLN_RGDPO	24.17055	4	0.0001
DLN_PL_X	12.19882	4	0.0159
All	26.46158	8	0.0009

The null on hypothesis 1 is rejected based on the large p-value which is greater than 0.05, hence we conclude that exports and imports do not granger cause Real GDP. The null on hypotheses 2 and 3 cannot be rejected at 5% level of significance as the calculated p-value is smaller than the actual p-value at 5%. Hence, we conclude from hypothesis 2 that Real GDP granger causes exports and imports granger causes exports. As for hypothesis 3, we conclude that Real GDP granger causes imports and exports granger causes imports. Since there is the presence of causality on our model, we should look at how quickly the model will return to its forecasted path if it undergoes a shock in the next section.

6.5 Vector Error Correction Model

Since we evidently have cointegration in our multivariate time series, we will look at VECM. Here we are applying a VAR to our multivariate integrated time series. Error correction gives us the speed of adjustment within which the model will restore its equilibrium following any disturbances. We shall calculate this figure based on the table below:

Figure 26

Vector Error Correction Estimates
Date: 05/02/22 Time: 15:51
Sample (adjusted): 1958 2019
Included observations: 62 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
DLN_RGDPO(-1)	1.000000
DLN_PL_X(-1)	1.516415
	(0.20343)
	[7.45412]
DLN_PL_M(-1)	-1.373726
	(0.23714)
	[-5.79282]
C	-0.036516

Error Correction:	D(DLN_RG...	D(DLN_PL_X)	D(DLN_PL_M)
CointEq1	-0.285885	-1.268327	-0.398968
	(0.08881)	(0.20253)	(0.20451)
	[-3.21890]	[-6.26244]	[-1.95081]
D(DLN_RGDPO(-1))	-0.044580	0.919980	0.469210
	(0.14022)	(0.31976)	(0.32290)
	[-0.31792]	[2.87709]	[1.45313]
D(DLN_PL_X(-1))	0.329711	0.285430	0.216471
	(0.08218)	(0.18740)	(0.18923)
	[4.01213]	[1.52313]	[1.14393]
D(DLN_PL_M(-1))	-0.315053	-0.455447	-0.482151
	(0.09767)	(0.22272)	(0.22490)
	[-3.22580]	[-2.04498]	[-2.14386]
C	8.34E-05	-0.000565	-0.001174
	(0.01142)	(0.02604)	(0.02630)
	[0.00731]	[-0.02171]	[-0.04463]
R-squared	0.275562	0.501506	0.125773
Adj. R-squared	0.224724	0.466524	0.064424
Sum sq. resids	0.460391	2.394066	2.441234
S.E. equation	0.089872	0.204942	0.206951
F-statistic	5.420410	14.33611	2.050113
Log likelihood	64.01303	12.90419	12.29936
Akaike AIC	-1.903646	-0.254974	-0.235463
Schwarz SC	-1.732103	-0.083431	-0.063920
Mean dependent	0.001499	0.000731	-0.000140
S.D. dependent	0.102070	0.280591	0.213958

Speed of Adjustment

GDP = 1 x -0.28 = - 0.28 = - 28%

Exports = 1.516 x - 1.269 = -1.92 = - 192%

Imports = - 1.37 x - 0.39 = 0.54 = 54%

If the speed of adjustment products is positive as is the case for Imports, it means that VECM continues to move away from long-run equilibrium after experiencing a shock, instead of converging back to it. However, the most important one to look at here is the dependent variable which is real GDP which seems to be converging back at 28%. Moreover, all these variables are significant at 5% level. Here, the adjusted R^2 value is 22.4% which is small and says that some variation in real GDP is captured by exports and imports but there are other factors too that are not considered in the model. The worrying part is about the imports which do not seem to be converging in the long run after the series has experienced a shock.

HYPOTHESIS TESTING:

- H1: Real GDP, Exports, and Imports are expected to have significant trends and unit-roots when considered in levels is accepted.

Reason: Unit roots were observed in real GDP, exports and imports, leading to taking the LN 1st difference where the trend was insignificant, for further analysis, on the basis of Figure 4, 5 and 6. Taking the first difference removed the otherwise significant trend (Annex figures 8 & 9).

- **H2:** Exports are positive in the VAR model as a significant independent variable is rejected.

Reason: Exports are positive only for the first lagged value of GDP but are negative for the other three lagged values of GDP. Moreover, the results are not significant as per Figure 16.

- **H3:** Imports are negative in the VAR model as a significant independent variable is rejected.

Reason: Imports are indeed negative for all lagged values except for the first lag of real GDP and the results are not statistically significant as per Figure 16.

- **H4:** Real GDP is cointegrated with exports in the long run is accepted.

Reason: The results indicate that cointegration exists between real GDP and exports in the long run, as per Figure 24 & 23.

- **H5:** Real GDP is cointegrated with imports in the long run is accepted.

Reason: The results indicate that cointegration exists between real GDP and imports in the long run as per Figure 24 & 23.

- **H6:** Exports are cointegrated with imports in the long run.

Reason: Exports are cointegrated with imports in the long run as we can see from figures 24 & 23.

LIMITATIONS

This research has a few limitations. The study does not explore the relationship between exports, imports, and growth at a sectoral level.[9] This is relevant, especially due to the concentration of exports and imports in specific sectors, which can indicate different degrees of impact. Thus, future research could focus on more sector-specific studies, to allow for clarity on the relevance of different industries and production units.

Another limitation is that the study is based on the data from a single country, and thus indicates very context-specific results. To thoroughly investigate the role of trade in economic growth, future research could use data from multiple countries with similar characteristics, such as other economies of a similar scale in the African continent.

Our univariate analyses had resulted in poor forecasting models for exports and imports, with imports indicating highly irregular SE intervals and models that did not meet all the criteria necessary for forecasting. The irregularities in the export and import data could not be captured by our model, indicating the influence of other variables. The influence of foreign aid on imports can be explored, as a variable of interest, to understand these irregularities. Ghana was a country highly dependent on foreign aid, which observed a drop in recent years. Future research can examine the relationship between aid, trade, and growth, and whether a dependency on aid exists.

The Covid-19 pandemic resulted in huge economic shocks across the world, including both developed and less developed economies. There were huge disruptions in the global supply chain, directly affecting trade and exchange values. This data is limited since it ends at the year 2019, and cannot account for the impact of such an external shock on its economic growth. Further research can analyse the effects of the Covid-19 pandemic, and if that disruption and change in exports and imports led to a positive or negative causal relationship with GDP.

CONCLUSION

Addressing our two research questions, exports and imports cannot sufficiently explain the variation in real GDP, and other variables which are omitted from the model seem to influence real GDP to a greater extent.

The results thus do not validate the hypothesis of export-led growth. It contradicts the results of Enu et al. (2013) who found that exports had a positive impact on real GDP in the long run, with an increase in exports leading to an increase in real GDP in Ghana.

Addressing the research question of considering imports to explain variation in GDP, the results indicate that imports do not have a significant effect on growth. This aligns with findings of

Okyere & Jilu (2020) that found that imports cannot drive Ghana's economic growth.

Moreover, the strength of the model for a causality relationship for real GDP on exports and imports is not very high, implying the relevance of other variables not captured in the model. This is supported by other research on export-led growth, such as Panta et al.'s (2022) research on the lack of evidence on the impact of trade on the small developing economy of Nepal which is similar to Ghana as a small emerging economy, with a relatively recent rise in GDP levels, and thus exports levels.

POLICY RECOMMENDATIONS

Since the results of the study indicate that GDP unidirectionally causes exports and imports, efforts to build up local production capacity are necessary. Non-traditional export industries should be encouraged with less focus on raw material production, with greater labour specialisations in processing such raw materials to intermediate of finished goods before export. Ghana should utilise its abundant natural resources for national production. Its human capital is currently underutilised hence policies to train the labour force will go a long way to add to the progress of the country.

Ghana also shows a high reliance on imports, especially for consumer goods, resulting in a low positive or a negative balance of payments. Sustainable industry development is required to replace imports at a local level. Ghana has a large informal sector, with commerce and entrepreneurship relegated there, to avoid monopolies in the formal sector. Cooperative measures, subsidies by the government, are necessary to incorporate small and medium enterprises, to support their survival, and scale them up to compete in the international market. A stable macroeconomic environment is crucial to encourage greater foreign investment in local manufacturing and service sectors, away from resource-intensive industries.

As indicated in the model, export, import rates and Real GDP are highly interlinked with bidirectional causality. Thus, export success in the country should be developed through the success of domestic industries, which can only be feasible through the support of local production, skill up-gradation of labour, and shifting away from extractive industries. The government should import capital goods to develop its production capacity, with an emphasis on greater industrialisation. Private sector investment should also be boosted to build up the production capacity of finished goods.

ANNEX

Figure 1: Imports histogram

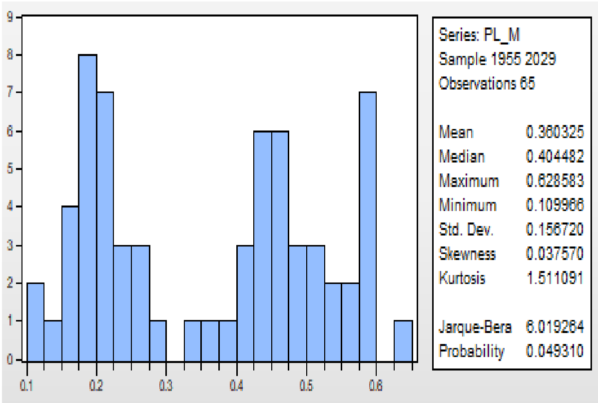


Figure 2: LN Imports histogram

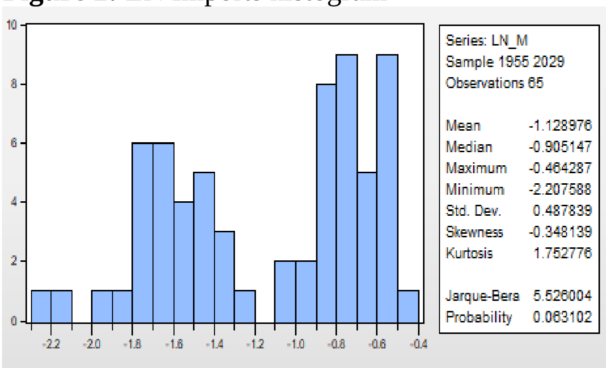


Figure 3: LN Imports graph

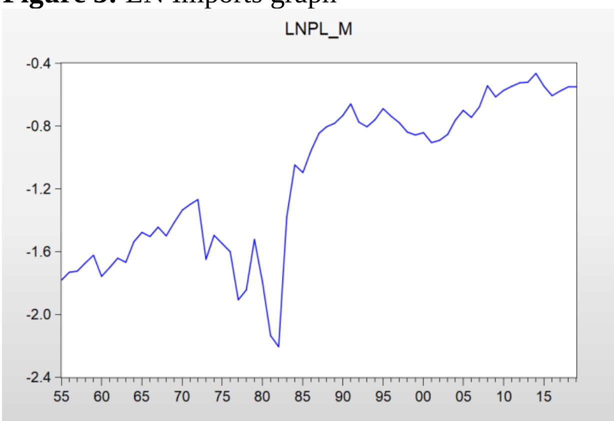


Figure 4: Histogram Exports

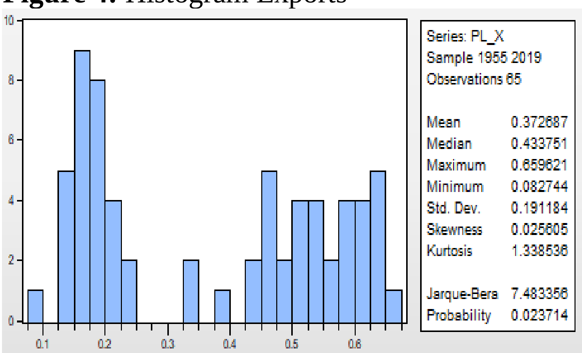


Figure 5: Histogram LN Exports

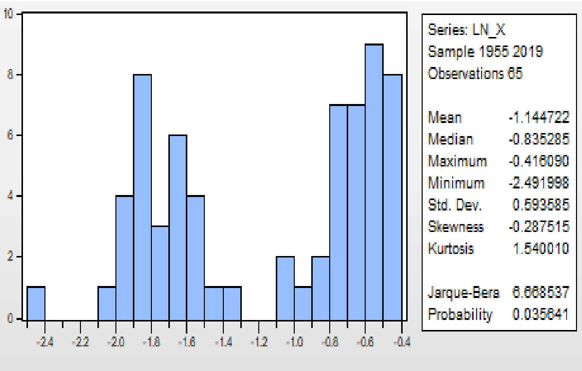


Figure 6: LN Exports graph.

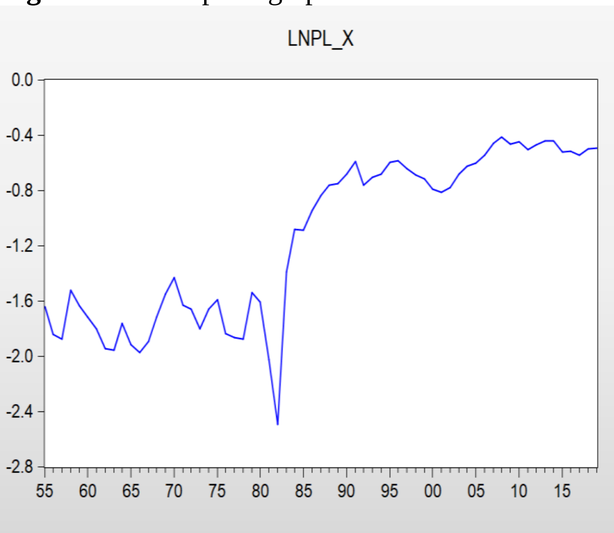


Figure 7: LN RGDP

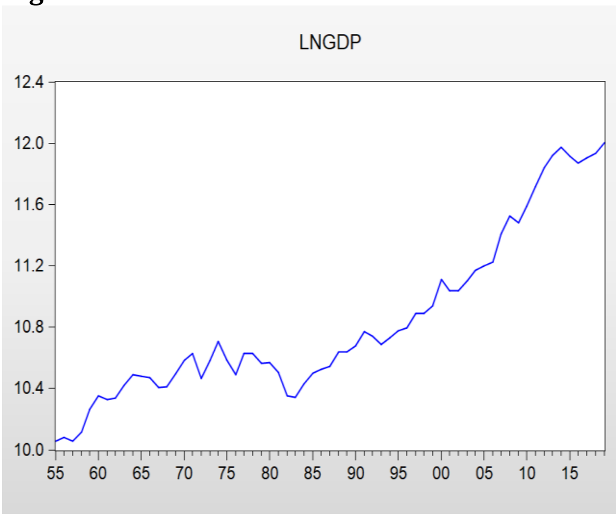


Figure 8: ADFs LN Exports

Augmented Dickey-Fuller Unit Root Test on LNPL_X

Null Hypothesis: LNPL_X has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.074500	0.1212
Test critical values:	1% level	-4.107947	
	5% level	-3.481595	
	10% level	-3.168695	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNPL_X)
Method: Least Squares
Date: 04/25/22 Time: 12:13
Sample (adjusted): 1956 2019
Included observations: 64 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNPL_X(-1)	-0.257579	0.083779	-3.074500	0.0032
C	-0.521668	0.179401	-2.907835	0.0051
@TREND("1955")	0.007452	0.002666	2.794960	0.0069

R-squared	0.134579	Mean dependent var	0.017992
Adjusted R-squared	0.106205	S.D. dependent var	0.197211
S.E. of regression	0.186445	Akaike info criterion	-0.475622
Sum squared resid	2.120462	Schwarz criterion	-0.374424
Log likelihood	18.21990	Hannan-Quinn criter.	-0.435755
F-statistic	4.742975	Durbin-Watson stat	1.761525
Prob(F-statistic)	0.012174		

Augmented Dickey-Fuller Unit Root Test on D(LNPL_X)

Null Hypothesis: D(LNPL_X) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.761156	0.0000
Test critical values:	1% level	-4.113017	
	5% level	-3.483970	
	10% level	-3.170071	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNPL_X,2)
Method: Least Squares
Date: 04/25/22 Time: 12:14
Sample (adjusted): 1958 2019
Included observations: 62 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNPL_X(-1))	-1.341326	0.172826	-7.761156	0.0000
D(LNPL_X(-1),2)	0.342294	0.121913	2.807696	0.0068
C	0.032205	0.051519	0.625109	0.5344
@TREND("1955")	-0.000112	0.001354	-0.082952	0.9342

R-squared	0.560527	Mean dependent var	0.000731
Adjusted R-squared	0.537795	S.D. dependent var	0.280591
S.E. of regression	0.190761	Akaike info criterion	-0.413247
Sum squared resid	2.110613	Schwarz criterion	-0.276012
Log likelihood	16.81065	Hannan-Quinn criter.	-0.359365
F-statistic	24.65874	Durbin-Watson stat	2.058163
Prob(F-statistic)	0.000000		

Figure 9: ADFs LN Imports

Augmented Dickey-Fuller Unit Root Test on LNPL_M

Null Hypothesis: LNPL_M has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.578491	0.2913
Test critical values:	1% level	-4.107947	
	5% level	-3.481595	
	10% level	-3.168695	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNPL_M)
Method: Least Squares
Date: 04/25/22 Time: 12:15
Sample (adjusted): 1956 2019
Included observations: 64 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNPL_M(-1)	-0.198572	0.077011	-2.578491	0.0124
C	-0.347942	0.148871	-2.337213	0.0227
@TREND("1955")	0.004345	0.002011	2.160539	0.0347

R-squared	0.098446	Mean dependent var	0.019239
Adjusted R-squared	0.068887	S.D. dependent var	0.157210
S.E. of regression	0.151698	Akaike info criterion	-0.888109
Sum squared resid	1.403750	Schwarz criterion	-0.786911
Log likelihood	31.41948	Hannan-Quinn criter.	-0.848242
F-statistic	3.330487	Durbin-Watson stat	1.639036
Prob(F-statistic)	0.042388		

Augmented Dickey-Fuller Unit Root Test on D(LNPL_M)

Null Hypothesis: D(LNPL_M) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=10)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-7.386266	0.0000
Test critical values:	1% level	-4.113017	
	5% level	-3.483970	
	10% level	-3.170071	

*MacKinnon (1996) one-sided p-values.

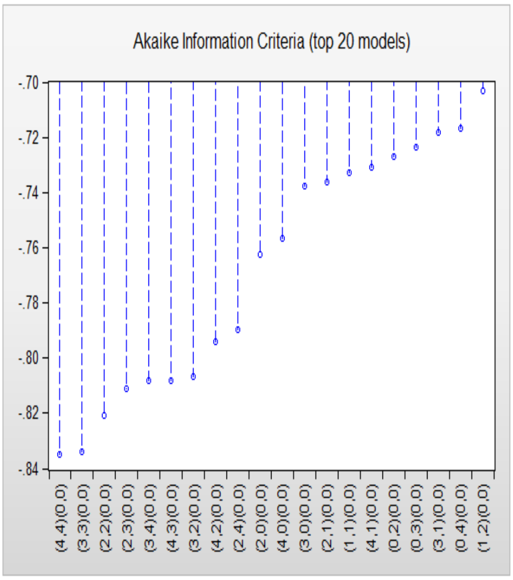
Augmented Dickey-Fuller Test Equation
Dependent Variable: D(LNPL_M,2)
Method: Least Squares
Date: 04/25/22 Time: 12:15
Sample (adjusted): 1958 2019
Included observations: 62 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LNPL_M(-1))	-1.215237	0.164527	-7.386266	0.0000
D(LNPL_M(-1),2)	0.353967	0.122776	2.883034	0.0055
C	0.027295	0.041223	0.662120	0.5105
@TREND("1955")	-0.000124	0.001081	-0.114398	0.9093

R-squared	0.517837	Mean dependent var	-0.000140
Adjusted R-squared	0.492897	S.D. dependent var	0.213958
S.E. of regression	0.152362	Akaike info criterion	-0.862779
Sum squared resid	1.346416	Schwarz criterion	-0.725544
Log likelihood	30.74614	Hannan-Quinn criter.	-0.808897
F-statistic	20.76373	Durbin-Watson stat	2.031903
Prob(F-statistic)	0.000000		

Figure 10: ARIMA forecasting and equation output for LN Imports (first difference)

ARMA Criteria Graph



Equation Output

Dependent Variable: DLN_M
Method: ARMA Maximum Likelihood (BFGS)
Date: 04/28/22 Time: 15:08
Sample: 1956 2019
Included observations: 64
Convergence achieved after 132 iterations
Coefficient covariance computed using outer product of gradients

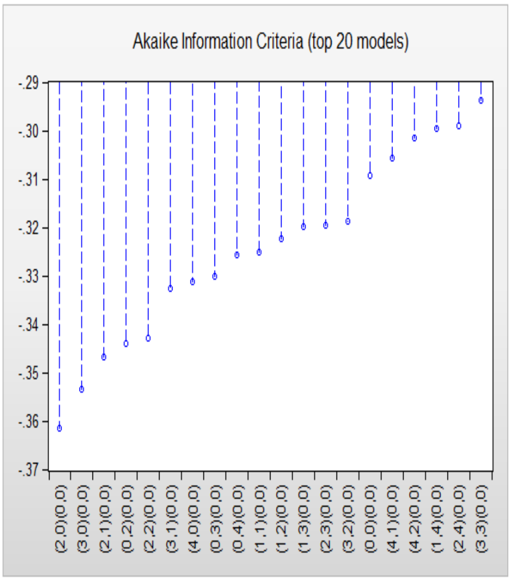
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.021270	0.007600	2.798564	0.0071
AR(1)	-0.384929	0.159214	-2.417677	0.0190
AR(2)	-0.186846	0.137306	-1.360799	0.1792
AR(3)	0.177584	0.191068	0.929429	0.3568
AR(4)	0.526586	0.174632	3.015406	0.0039
MA(1)	0.650913	4514.716	0.000144	0.9999
MA(2)	-2.84E-06	0.005343	-0.000532	0.9996
MA(3)	-0.650913	6902.766	-9.43E-05	0.9999
MA(4)	-0.999997	17540.94	-5.70E-05	1.0000
SIGMASQ	0.014028	10.56600	0.001328	0.9989

R-squared	0.423395	Mean dependent var	0.019239
Adjusted R-squared	0.327294	S.D. dependent var	0.157210
S.E. of regression	0.128941	Akaike info criterion	-0.978624
Sum squared resid	0.897794	Schwarz criterion	-0.641298
Log likelihood	41.31596	Hannan-Quinn criter.	-0.845734
F-statistic	4.405735	Durbin-Watson stat	2.118111
Prob(F-statistic)	0.000239		

Inverted AR Roots	.78	-.17-.89i	-.17+.89i	-.83
Inverted MA Roots	1.00	-.33+.95i	-.33-.95i	-1.00

Figure 11: ARIMA forecasting and equation output for LN Exports (first difference)

ARMA Criteria Graph



Equation Output

Dependent Variable: DLN_X
Method: ARMA Maximum Likelihood (BFGS)
Date: 04/28/22 Time: 15:06
Sample: 1956 2019
Included observations: 64
Convergence achieved after 8 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019015	0.023205	0.819421	0.4158
AR(1)	0.004530	0.112487	0.040269	0.9680
AR(2)	-0.339159	0.089561	-3.786900	0.0004
SIGMASQ	0.033701	0.003569	9.442673	0.0000

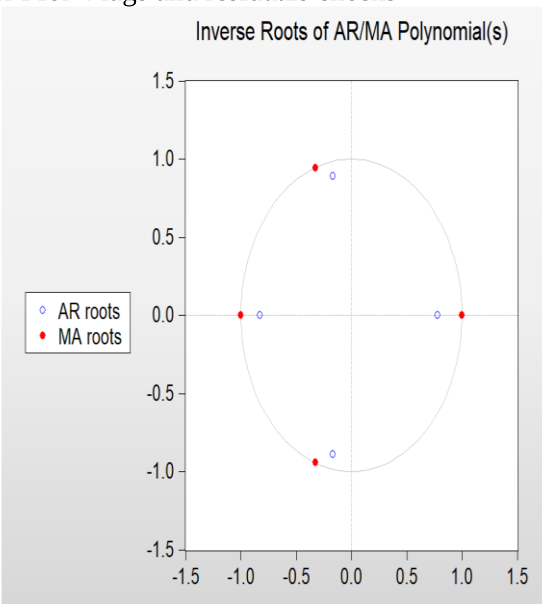
R-squared	0.119733	Mean dependent var	0.017992
Adjusted R-squared	0.075720	S.D. dependent var	0.197211
S.E. of regression	0.189598	Akaike info criterion	-0.423544
Sum squared resid	2.156838	Schwarz criterion	-0.288613
Log likelihood	17.55340	Hannan-Quinn criter.	-0.370388
F-statistic	2.720383	Durbin-Watson stat	2.076946
Prob(F-statistic)	0.052297		

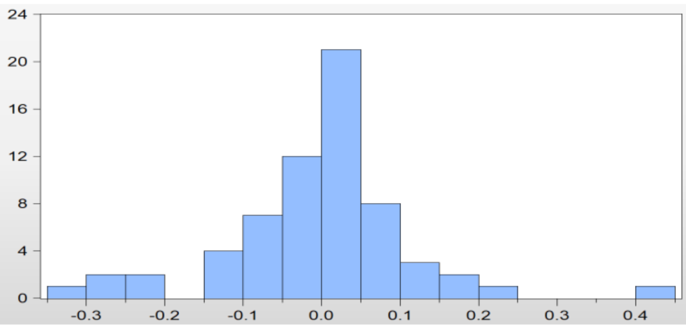
Inverted AR Roots	.00+.58i	.00-.58i

Figure 12: DLN_Imports invertibility, LM for 4 lags and residuals checks

Sample: 1955 2029
Included observations: 64
Q-statistic probabilities adjusted for 8 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.060	-0.060	0.2448	
		2	0.022	0.019	0.2789	
		3	0.019	0.021	0.3029	
		4	0.137	0.139	1.6189	
		5	0.108	0.127	2.4577	
		6	-0.138	-0.132	3.8360	
		7	0.028	-0.002	3.8925	
		8	-0.148	-0.175	5.5443	
		9	-0.004	-0.055	5.5453	0.019
		10	-0.163	-0.148	7.6314	0.022
		11	-0.161	-0.163	9.7070	0.021
		12	-0.032	-0.031	9.7911	0.044
		13	-0.070	-0.022	10.197	0.070
		14	-0.054	-0.044	10.444	0.107
		15	-0.061	0.015	10.766	0.149
		16	-0.048	-0.072	10.970	0.203
		17	0.037	0.010	11.096	0.269
		18	-0.082	-0.121	11.721	0.304
		19	0.125	0.067	13.191	0.281
		20	-0.025	-0.052	13.253	0.351
		21	0.124	0.072	14.764	0.322
		22	0.056	0.028	15.080	0.373
		23	-0.115	-0.161	16.448	0.353
		24	0.043	-0.080	16.640	0.409
		25	0.121	0.109	18.216	0.375
		26	-0.107	-0.237	19.499	0.362
		27	-0.004	0.054	19.501	0.425
		28	0.033	0.024	19.632	0.481





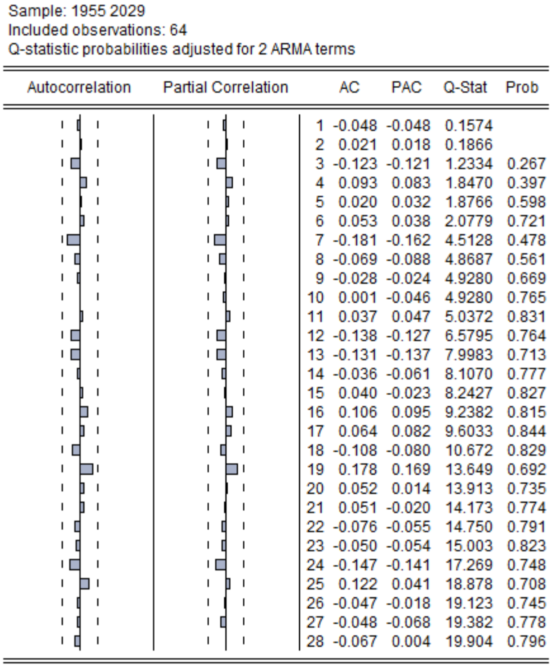
Series: Residuals
Sample 1956 2019
Observations 64

Mean	-0.001044
Median	0.010389
Maximum	0.449323
Minimum	-0.338896
Std. Dev.	0.119498
Skewness	0.101249
Kurtosis	6.224217
Jarque-Bera	27.83088
Probability	0.000001

Breusch-Godfrey Serial Correlation LM Test:

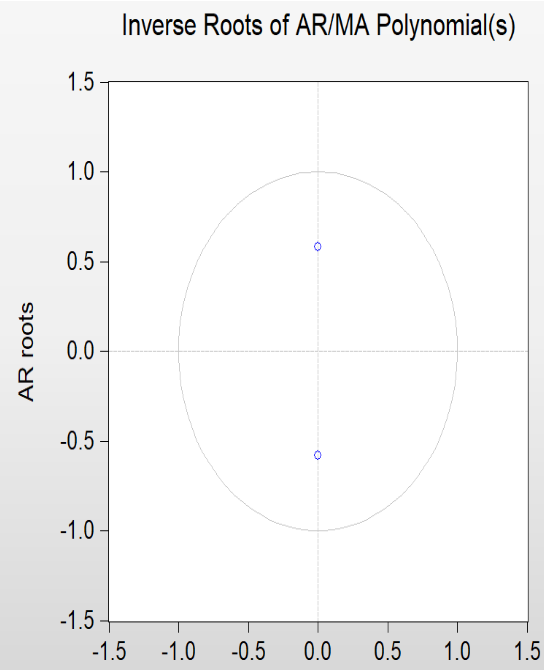
F-statistic	1.971291	Prob. F(2,53)	0.1494
Obs*R-squared	4.154271	Prob. Chi-Square(2)	0.1253

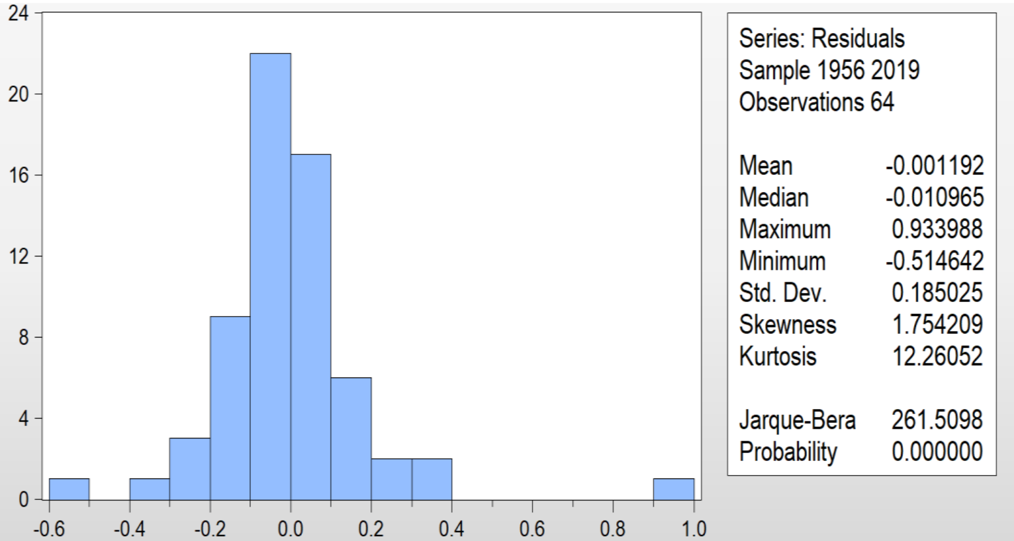
Figure 13: DLN_Exports invertibility, LM test for 2 lags and residuals checks



Sample: 1955 2029
Included observations: 64
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.048	-0.048	0.1574	
		2	0.021	0.018	0.1866	
		3	-0.123	-0.121	1.2334	0.267
		4	0.093	0.083	1.8470	0.397
		5	0.020	0.032	1.8766	0.598
		6	0.053	0.038	2.0779	0.721
		7	-0.181	-0.162	4.5128	0.478
		8	-0.069	-0.088	4.8687	0.561
		9	-0.028	-0.024	4.9280	0.669
		10	0.001	-0.046	4.9280	0.765
		11	0.037	0.047	5.0372	0.831
		12	-0.138	-0.127	6.5795	0.764
		13	-0.131	-0.137	7.9983	0.713
		14	-0.036	-0.061	8.1070	0.777
		15	0.040	-0.023	8.2427	0.827
		16	0.106	0.095	9.2382	0.815
		17	0.064	0.082	9.6033	0.844
		18	-0.108	-0.080	10.672	0.829
		19	0.178	0.169	13.649	0.692
		20	0.052	0.014	13.913	0.735
		21	0.051	-0.020	14.173	0.774
		22	-0.076	-0.055	14.750	0.791
		23	-0.050	-0.054	15.003	0.823
		24	-0.147	-0.141	17.269	0.748
		25	0.122	0.041	18.878	0.708
		26	-0.047	-0.018	19.123	0.745
		27	-0.048	-0.068	19.382	0.778
		28	-0.067	0.004	19.904	0.796





Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.932029	Prob. F(2,57)	0.3997
Obs*R-squared	1.963365	Prob. Chi-Square(2)	0.3747

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