Journal of Science and Inclusive Development Vol. 5, No. 1, DOI: 10.20372/jsid/2023-175

An analysis of causal relationship between economic growth, exports, and imports in Ethiopia: Toda Yamamoto Approaches

Tesfaye Denano[1*], Sintayehu Sibera[1] and Tizazu Toma[2]

[1]Department of Statistics (Econometrics), Wolaita Sodo University, Ethiopia.

[2]Department of Statistics (Applied Statistics), Wolaita Sodo University, Ethiopia.

[*]Corresponding author email: tesfustat@gmail.com; https://orcid.org/0000-0002-5815-4454

Received: 22 June 2022; Revised: 17 January 2023; Accepted: 20 February 2023

Abstract

There has been economic growth associated with the increase in exports. Even though figures show a correlation between exports and economic growth in Ethiopia, they cannot guarantee that the export sector has been supporting the Ethiopian economy's double-digit growth rate. Therefore, the main objective of this study was to identify whether there is a short-run or long-run causal relationship between imports, exports, and economic growth. A multivariate Granger causal framework and time series data (1988–2021) were employed. The Johansen Co-integration test is used to determine the presence of a co-integrating vector in the variables. Accordingly, there is a long-run relationship between economic growth, exports, and imports. In the study, the Granger Causality and Toda Ymamoto tests revealed that there is a long run bidirectional causal relationship between imports and economic growth (GDP), as well as a unidirectional causal relationship between economic growth (GDP) and exports in the long-run. This indicates that exports and imports cause economic growth both individually and jointly, lending support to export or import growth. Individual granger economic growth causes imports in both directions. That means GDP granger causes imports, and import granger causes GDP. As a result, the researchers conclude that in Ethiopia, there is a dynamic relationship between imports, exports, and economic growth. To boost Ethiopia's economic growth and development, the government should develop export-led policies and ensure a higher level of exports.

Keywords: Multivariate Granger causality, Toda Yamamoto, Cointegration, Exports, Imports, Economic growth, Ethiopia

Introduction

Trade increases specialization in production, resulting in more efficient production and resource allocation (Md and Suleiman, 2016). According to Solow's neoclassical growth theories, imports and exports are significant determinants of growth and have long-term relationships with economic growth (Solow, 1956). Because every country wants to increase GDP and improve the quality of life for its citizens, the theoretical and empirical relationships between exports, imports, and economic growth have long been a source of debate and interest in international trade literature (Bakari and Mabrouki, 2017). Many economists believe that an increase in exports leads to an increase in economic growth because exports are directly related to economic growth (Saaed and Hussain, 2015). Exports of goods and services increase foreign exchange earnings, which relieves pressure on the balance of payments, reduces unemployment, facilitates capital goods imports, increases production competition, and, as a result, leads to increased productivity and optimal resource allocation. It is also possible that the causality runs from production growth to exports. Domestic demand in these countries is unlikely to develop at the same rate as production from these industries. As a result, these domestic producers will search for sales in international markets. Furthermore, higher production growth may lead to increased investment, some of which may be used to expand export capacity (Ugochukwu and Chinyere, 2013).

In this context, we are looking to see if there is a relationship between Ethiopian exports, imports, and economic growth. In various sectors of the economy, the country has developed various strategies and implemented policy changes. Among these changes, the export promotion strategy takes centre stage. Moreover, as a result of this policy, the country's economy and exports have tangibly improved over time. According to a study published by Tesfa-Amlak (2020), over the past decade, Ethiopia's economy has grown twice as fast as the rest of Africa, averaging 10.6 percent GDP per year between 2004 and 2011, compared to 5.2 percent in Sub-Saharan Africa. Similarly, exports increased by 20% during the same period, with primary commodities in general and coffee in particular accounting for 26.4 percent of total exports. Even though these figures show that there is a correlation between exports and economic growth in Ethiopia, they cannot guarantee that the export sector has been supporting the Ethiopian economy's double-digit growth rate. To this end, some researchers have looked into the relationship between exports and development in Ethiopia.

According to Allaro (2012), annual data from 1974 to 2009 was used to empirically analyse the impact of export-led development on the Ethiopian economy using the causality test, which found unidirectional causality from exports to economic growth in Ethiopia (Granger, 1969). The link between Ethiopian exports, domestic demand, and economic development was studied using time-series data from 1960 to 2011. The findings revealed a complicated link between exports and economic development, as well as between local demand and growth. Exports and domestic demand are critical for economic growth, and economic growth affects both exports and domestic demand in Ethiopia (Jarra, 2013).

However, empirical studies on the impact of exports and imports on economic growth have followed a variety of different paths over the last four decades. As a result, all of the preceding works have flaws. The early research on this topic analyzed the simple correlation coefficient between exports and economic growth (GDP), to put it loosely (Jarra, 2013). Finally, in this research, the impulse response functions test and variance decomposition analysis are used to see whether the independent variables play a role in explaining GDP variation over short and long forecasting horizons. We used Ethiopian annual time series data from 1988 to 2021. This information was obtained from Ethiopia's national bank (NBE). The logarithmic first difference form is used to express all variables.

Research methodology

Types and sources of datasets

This study covered three variables, namely economic growth, exports, and imports. The variables were collected from the National Bank of Ethiopia over the period of 1988–2021. EVIEWS 9.1 software was used to analyse the data.

a. Unit root test

Time series data were used to avoid the pitfall of wrong inferences from the non-stationary regressions. Hence, before proceeding any further, it is very important to ensure that the underlying data-generating processes are stationary at their respective orders of integration. If the variables have a unit root (non-stationary), then the series needs to have differences to achieve stationarity.

b. The Augmented Dickey-Fuller (ADF) test

There are two common problems with performing the ADF test. The first problem is the number of lags to be included. The second problem is whether to include constant terms and time trends in the regression. This choice will be based on equations (1) and (2). The choice here is important because the asymptotic distribution of the t-statistic under the null hypothesis depends on our assumptions regarding these deterministic terms.

Consider the AR (p) model and assume the series does not exhibit any trend and has a non-zero mean in the regression.

$$\Delta X_t = \theta_0 + \theta_1 X_{t-1} + \sum_{i=1}^{p} \prod_i \Delta X_{t-i} + u_t \qquad (1)$$

$$\Delta X_t = \theta_0 + \theta_1 X_{t-1} + \theta_2 t + \sum_{i=1}^{p} \prod_i \Delta X_{t-i} + u_t \qquad (2)$$

Where $\theta = \sum_{i=1}^{p} \vartheta_i - 1 \, and \, \prod_i = \sum_{j=1}^{p} \vartheta_j$

c. Phillips and Perron test

Phillips and Perron (1988) proposed an alternative method of controlling for serial correlation when testing for a unit root. This method estimates the non-augmented DF test and modifies the t ratio coefficient so that serial correlation does not affect the asymptotic distribution of the test statistic. Another advantage of using the Phillips and Perron test for unit root is that it is robust to general forms of heteroskedasticity in the error term and does not have to specify a lag length for testing the regression.

Journal of Science and Inclusive Development Vol. 5, No. 1, DOI: 10.20372/jsid/2023-175

The Phillips and Perron test is based on the statistic:

$$\hat{t}_\alpha = t_\alpha \left(\frac{\gamma_0}{f_0}\right)^{\frac{1}{2}} - \frac{T(f_0 - \gamma_0)(s_e(\hat{\alpha}))}{2 f_0^{\frac{1}{2}} s} \tag{3}$$

where $\hat{\alpha}$ is the estimate, t_α is the t-ratio of μ, $s_e(\hat{\alpha})$ is coefficient standard error and s is the standard error of the test regression. Besides this, γ_0 is a consistent estimate of the error variance calculated as $\frac{(T-K)s^2}{T}$, where K is the number of regressors. The remaining term f_0 is an estimator of the residual spectrum at frequency zero (3).

The Vector Autoregressive (VAR) model

For multivariate time series, VAR models (vector autoregressive models) are utilized (Seifu 2010). Each variable is a linear function of its own past lags as well as the past lags of the other variables. The dynamic multivariate autoregressive model is a natural extension of the univariate autoregressive model. The VAR model has shown to be particularly beneficial for forecasting and understanding the dynamic behavior of economic and financial time series. (Sims, 1980) proposed the VAR model as a method for macroeconomists to define the joint dynamic behavior of a set of variables without requiring the type of severe constraints required to identify underlying structural factors. It has become a popular time-series modelling technique.

$$GDP_t = \alpha_1 + \sum_{i=1}^{m} \beta_{1,i} GDP_{t-i} + \sum_{i=1}^{m} \eta_{1i} Exports_{t-i} + \sum_{i=1}^{m} \xi_{1i} Imports_{t-i} + u_{1t} \tag{4}$$

$$Exports_t = \alpha_2 + \sum_{i=1}^{m} \beta_{2,i} GDP_{t-i} + \sum_{i=1}^{m} \eta_{2i} Exports_{t-i} + \sum_{i=1}^{m} \xi_{2i} Imports_{t-i} + u_{2t} \tag{5}$$

$$Imports_t = \alpha_3 + \sum_{i=1}^{m} \beta_{3,i} GDP_{t-i} + \sum_{i=1}^{m} \eta_{3i} Exports_{t-i} + \sum_{i=1}^{m} \xi_{3i} Imports_{t-i} + u_{3t} \tag{6}$$

A vector autoregressive model system contains a set of n variables, each of which is expressed as a linear function of p lags of itself and all of the other n–1 variables, plus a disturbance term. In a VAR system, it is possible to include exogenous variables such as time trends VAR. In this study, we have used three variables, such as economic growth (GDP), exports, and imports. The mathematical equation for the multivariate VAR model is considered if the three series are stationary, that is, if they are $I(0)$ series.

The Vector Error Correction (VEC) model

The error correction mechanism is a mechanism used to correct any short-run deviation of the variables from their long-run equilibrium. The advantage of utilizing an error correction term to test for causality is that it allows testing for both short-run and long-run causality using the lagged error correction term.

If two variables Y and X are cointegrated, then the long-term or equilibrium relationship that exists between the two can be expressed as ECM (Gujarati, 2003). This means one could go for the construction of an error correction model if and only if the variables are cointegrated. The vector error correction model (VECM) that was used to analyze the short-run relationships between the variables is constructed as follows:

$$GDP_t = \alpha_1 + \sum_{i=1}^{m} \beta_{1,i} GDP_{t-i} + \sum_{i=1}^{m} \eta_{1i} Exports_{t-i} + \sum_{i=1}^{m} \xi_{1i} Imports_{t-i} + \lambda_1 ECT_{t-1} + u_{1t} \tag{7}$$

$$Exports_t = \alpha_2 + \sum_{i=1}^{m} \beta_{2,i} GDP_{t-i} + \sum_{i=1}^{m} \eta_{2i} Exports_{t-i} + \sum_{i=1}^{m} \xi_{2i} Imports_{t-i} + \lambda_2 ECT_{t-1} + u_{2t} \tag{8}$$

$$Imports_t = \alpha_3 + \sum_{i=1}^{m} \beta_{3,i} GDP_{t-i} + \sum_{i=1}^{m} \eta_{3i} Exports_{t-i} + \sum_{i=1}^{m} \xi_{3i} Imports_{t-i} + \lambda_3 ECT_{t-1} + u_{3t} \tag{9}$$

Where, residuals u_t are independently and normally distributed with a mean of zero and constant variance or which is a stochastic error term often called impulse or innovation or shocks. ECT_{t-1} is the error correction term which is lagged value of the residuals obtained from the co-integrating regression of the dependent variable on the explanatory; contains long-run information derived from the long-run co-integration relationship. β_i, η_i *and* ξ_i are short-run dynamic coefficients of the model's adjustment for long-run equilibrium parameters to be estimated. Where, i=1, 2, 3 and λ_i speed of adjustment parameter with a negative sign (7-9).

Toda Yamamoto causality test

In this study, the causality testing procedure (Toda and Yamamoto, 1995) and co-integration tests were used. Cointegration can be defined simply as the long-term, or equilibrium, relationship between two series. This makes cointegration an ideal analysis technique to

Journal of Science and Inclusive Development Vol. 5, No. 1, DOI: 10.20372/jsid/2023-175

ascertain the existence of a long-term relationship between expected economic growth, exports, and imports. The Toda Yamamoto model equation is given as follows (all variables in logarithm first difference form) in equation (10-12)

$$GDP_t = \alpha_1 + \sum_{i=1}^{m}\beta_{1,i}GDP_{t-i} + \sum_{j=m+d}^{m+d_{\max}}\beta_{1j}GDP_{t-j} + \sum_{i=1}^{m}\eta_{1i}EX_{t-i} + \sum_{j=m+d}^{m+d_{\max}}\eta_{1j}EX_{t-j} + \sum_{i=1}^{m}\xi_{1i}\,\mathrm{Im}_{t-i} + \sum_{j=m+d}^{m+d_{\max}}\xi_{1j}\,\mathrm{Im}_{t-j} + u_{1t} \tag{10}$$

$$Ex_t = \alpha_2 + \sum_{i=1}^{m}\beta_{2,i}GDP_{t-i} + \sum_{j=m+d}^{m+d_{\max}}\beta_{2j}GDP_{t-j} + \sum_{i=1}^{m}\eta_{2i}EX_{t-i} + \sum_{j=m+d}^{m+d_{\max}}\eta_{2j}EX_{t-j} + \sum_{i=1}^{m}\xi_{2i}\,\mathrm{Im}_{t-i} + \sum_{j=m+d}^{m+d_{\max}}\xi_{2j}\,\mathrm{Im}_{t-j} + u_{2t} \tag{11}$$

$$\mathrm{Im}_t = \alpha_3 + \sum_{i=1}^{m}\beta_{3,i}GDP_{t-i} + \sum_{j=m+d}^{m+d_{\max}}\beta_{3j}GDP_{t-j} + \sum_{i=1}^{m}\eta_{3i}EX_{t-i} + \sum_{j=m+d}^{m+d_{\max}}\eta_{3j}EX_{t-j} + \sum_{i=1}^{m}\xi_{3i}\,\mathrm{Im}_{t-i} + \sum_{j=m+d}^{m+d_{\max}}\xi_{3j}\,\mathrm{Im}_{t-j} + u_{3t} \tag{12}$$

Where *m* denotes the optimal lag length determined by the usual information criteria such as AIC and SIC and $d_{\max}$ is the maximum order of integration in (10-12).

Johansen Cointegration Test

According to Johansen (1988), trace statistics and the maximum Eigen-value test criteria were employed to conduct co-integration tests generated with the Maximum Likelihood technique. The null hypothesis is that there is no co-integration between the series under examination. If a co-integration test is carried out and the results are shown with a trace statistic and maximum Eigen-value suggest that the null hypothesis of no co-integration should be rejected, then it implies that co-integration exists and, as such, there is a long-run relationship between the variables in the model. Thus, a model for a co-integrating equation may be specified in line with Johansen and Juselius (1990) and Johansen (1988), as below in (13): Tests for co-integration are carried out using Johansen's testing procedure, which involves the estimation of a vector error-correction model (VECM) to obtain the likelihood ratios. To describe this procedure, the researchers consider the ordinary p-dimensional vector autoregressive process with k lags.

$$X_t = \sum_{i=1}^{p}\prod_i X_{t-i} + \Phi d_t + \varepsilon_t \tag{13}$$

Where X_t contains an observation on the p time series at time t, Π_i is the matrix of coefficient describing the dynamics of the system while d_i contains d deterministic trend or dummy variable at time t whose effect on X_t is captured by Φ. Finally, ε_t is a vector of error terms assumed to follow the $N_p(0,\Sigma)$ distributed with independent between periods. Then, an equivalent parameterization of a VAR model of equation (13), better suited for co-integration analysis is the Error Correction Model (ECM) given by:

$$\Delta X_t = \prod X_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta X_{t-i} + \Phi d_t + \varepsilon_t \tag{14}$$

where $\Delta \mathrm{X}_{t-i} = \mathrm{X}_{t-i} - \mathrm{X}_{t-i-1}$, $\prod = \sum_{i=1}^{p} \prod_i - I_p$ and $\Gamma_i = -\sum_{j=i+1}^{p} \Pi_j$

The greatest merit of ECM is that it separates the long-run component of the series from the short run dynamics; a separation simplifies the interpretation of the non-stationary process. The role of co-integration is to link between the relations among a set of integrated (no stationary) series and the long-term equilibrium. The presence of a co-integrating equation is interpreted as a long-run equilibrium relationship among the variables. Suppose β and α are matrices of dimension $p \times r$ and if rank $(\Pi) = r$, we can write $\Pi = \alpha\beta'$ where rank (Π) indicates the number of independent co-integrating vectors, the elements of α are the adjustment parameters in the error-correction model, and β contains the co-integrating vectors. Then, inserting the above decomposition in to equation (14), we obtain:

$$\Delta X_t = \alpha\beta' X_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta X_{t-i} + \Phi d_t + \varepsilon_t \tag{15}$$

Where $\beta' X_{t-1}$ interpreted as a new set of r stationary processes representing departures from the r equilibria while the adjustment coefficient α describes the adjustment back to equilibrium. The columns β are the co-integrating vectors. Johansen's procedure relies on the rank of Π and the roots of its characteristic: If rank $(\Pi) = 0$, the matrix is null (no co-integration) and equation in the vector X_t are common VAR first difference. If rank $(\Pi) = p$, the vector process is stationary and the equation in a vector X_t is modeled in levels-I(0). If rank $(\Pi) = 1$, there is evidence of a single co-integrating vector.

Impulse response functions

Any covariance stationary VAR (p) process has a Wold's representation of the form:

$$y_t = \mu + \varepsilon_1 + \varphi_1\varepsilon_{t-1} + \varphi_2\varepsilon_{t-2} + \varphi_3\varepsilon_{t-3} + ... + \varphi_p\varepsilon_{t-p} \tag{16}$$

where the $(n \times n)$ moving average matrices φ_s are determined recursively. It is tempting to interpret the $(i, j)^{th}$ element $\varphi_{ij}{}^s$ of the matrix φ_s as the dynamic multiplier or impulse response:

$$\frac{\partial Y_{i,t+s}}{\partial \varepsilon_{j,t}} = \frac{\partial Y_{i,t}}{\partial \varepsilon_{j,t-s}} = \varphi^s{}_{ij} \tag{17}$$

However, this interpretation is only possible if $\text{var}(\varepsilon_t) = \Sigma$ is a diagonal matrix so that the elements are uncorrelated.

Forecast Error Variance Decompositions (FEVDs)

The contribution of each type of shock to the prediction error variance is measured by FEVDS. FEVDS determines how much of a change in a variable is attributable to that variable's shock and how much is due to other variables' shocks. The majority of the fluctuation in the SR is attributable to personal shock. However, when the influence of the lagged factors becomes more apparent, the fraction of the effect of other shocks grows with time.

$$Y_{t+n} - \varepsilon_t Y_{t+n} = \varphi_o \varepsilon_{t+n} + \varphi_1 \varepsilon_{t+n-1} + ... + \varphi_{n-1}\varepsilon_{t+1} = \sum_{j=1}^{n-1} \varphi_j \varepsilon_{t+n-j} \tag{18}$$

Consider, y_{1t} for example, the variance of its n-step ahead forecasting error can be expressed as:

Total var(y_{1t})=proportion of variance due to y_{1t} shock plus the proportion of variance due to shocks of other variables in the model.

Granger causality test

The Granger-causality test, introduced by Granger, is the most commonly used approach to examine the causal link between two variables (Granger, 1988; Johansen, 1988). In a range of domains, such as economics, engineering, physical sciences, and biological sciences, analyzing the interrelationships among many concurrently recorded time series is a serious challenge. The dynamic interactions between the series over time are of special relevance since they aid in determining the causal driving processes of the underlying system (Schelter et al., 2006). Three unique strategies for dealing with causality difficulties may be found in contemporary econometrics.

The first is the probabilistic approach to causality, which may be thought of as a simplified form of the probabilistic causality theory, developed by Suppes (1973). Granger causality, a class of probabilistic approach, is defined as a (time series) variable $Exports_{t,}$ *and* $Imports_t$ causes GDP_t if the probability of GDP_t is conditional on its history and the history of $Exports_t$ *and* $Imports_t$ (besides the set of the available information) does not equal the probability of Y_t conditional on its past history alone.

The structural approach to causal analysis is a second technique for causal analysis that is often used in economics. The probabilistic method seeks to reduce causes to regularities (measured by probability), but the structural approach keeps a realist ontology. The assumption is that the existence of economic structures implies that causal relationships between economic variables are not completely reducible to regularities. Given the complexity of economic structures and the limits of the observer, the data generated by economic structures have to be measured with probabilistic tools. In this approach, the existence of economic structures is dictated by economic theory, and the aim of probabilistic methods is to measure causal relations in an identified system of equations (Hoover, 2001).

One of the most essential and challenging challenges in economics is determining causation between variables. The other difficulty arises when two or more completely unrelated variables trend over time and appear to be connected merely because they have the same directionality. In such situations, correlation does not necessarily imply causation in any meaningful sense, which is simply spurious or meaningless (Wells, 1995). Therefore, traditional linear regression and correlation methods cannot be used to establish causal relations among a group of variables. The past and the present may cause the future, but the future cannot cause the past. All causal relationships remain constant in direction throughout time.

When dealing with Granger's causality, it is important to keep the following in mind: The multivariate model that is chosen must be well-defined. That is, the residuals should show no evidence of substantial serial correlations. Granger non-causality is also rejected if the null hypothesis is rejected. To put it another way, the alternative hypothesis is that Granger causality exists. The Wald test, which is chi-square distributed, is used to test for Granger non-causality.

There must be unidirectional or bidirectional Granger causality if there is cointegration. This is a good cross-check on the causality results' validity. In other words, there is a problem if there is cointegration but none of the groups is statistically significant, suggesting no causality. The causality results must indicate a long-term link if one exists. It's conceivable that the data sample size has to be double-checked. It might be too tiny to meet the asymptotic criteria of the cointegration and causality tests.

When testing for Granger non-causality, the model must be expressed in levels and not in first differences. Note that only the VAR and TY models are expressed in levels and are therefore used when testing for Granger non-causality. In other words, the VEC and VAR-in-First Differences must not be used when testing for Granger non-causality.

Results and discussions

It is important to test the presence of unit roots in the variables and thus determine their order of integration before estimating models with time series variables. The variables used in the study must be stationary and co-integrated to infer a meaningful relationship from time series models. The primary goal of unit root tests is to figure out how many extra lags should be applied to the vector autoregressive (VAR) model for the Toda and Yamamoto test. Table 1 shows that all of the variables are not stationary at level, but become stationary after first differing at the 5% level of significance, and p-values are in parenthesis.

Table 1. Unit Root Test

Phillips-Perron Test			Augmented Dickey-Fuller Test		
Variables	Constant, At level	with Trend At level	Constant, At level	with Trend First difference	Order of identification
GDPPC	2.073	-4.942	2.6289	-0.49415	I(1)
	(0.047)	(0.000)*	(1.000)	(0.000)*	
Exports	0.084	-4.862	-0.084	-4.862	I(1)
	(0.934)	(0.000)*	(0.934)	(0.000)*	
Imports	0.469	-5.380	0.469	-5.380	I(1)
	(0.642)	(0.000)*	(0.642)	(0.000)*	

Notes: ** denotes rejection of the null hypothesis of unit root at 5% level.*
Source: Authors calculation, 2022

Final Prediction Error (FPE), Schwarz Information Criterion, and Hannan-Quinn Information Criterion selected the optimal lag length of four out of a maximum of four lag lengths in Table 2.

Table 2. VAR Lag length selection criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-20.641	NA	0.001	1.689	1.831	1.732
1	53.563	127.208	1.04e-05	-2.969	-2.398*	-2.794
2	64.891	16.992	9.02e-06	-3.135	-2.135	-2.829
3	79.661	18.989*	6.38e-06	-3.547	-2.119	-3.111
4	92.014	13.236	5.73e-06*	-3.787*	-1.931	-3.219*

* indicates lag order selected by the riterion;
Source: Authors calculation, 2022

Inverse roots of the characteristic AR polynomial and found that the VAR is well specified; there is no autocorrelation problem at the optimal lag of 5% level; all the inverse roots of the characteristic AR polynomial lie inside the unit circle. In both cases, the modulus values satisfy the stability condition of the VAR model in Table 3.

Table 3: Eigenvalue stability condition

Root	Modulus
0.342085 - 0.870577i	0.935375
0.342085 + 0.870577i	0.935375
0.935228	0.935228
-0.514956 - 0.746317i	0.906735
-0.514956 + 0.746317i	0.906735
-0.692684 - 0.358695i	0.780047
-0.692684 + 0.358695i	0.780047
0.435732 - 0.491880i	0.657121
0.435732 + 0.491880i	0.657121
-0.536167	0.536167
0.074112 - 0.525882i	0.531078
0.074112 + 0.525882i	0.531078

Source: Authors calculation, 2022

We must first ensure that the estimates of the chosen multivariate time series models are accurate before moving on to the causality test, variance decomposition, and impulse response functions. The serial correlation test is the most important post-estimation test for multivariate models using the LM test. The empirical result in Table 4 indicates that there is no serial correlation problem. If there is evidence of serial association, increasing the optimum lag period will help overcome it.

Table 4: Serial correlation LM tests

Lags	LM-Stat	Prob
1	14.796	0.967
2	14.022	0.122
3	2.662	0.976
4	8.266	0.508
5	5.422	0.796

Source: Authors calculation, 2022

Exports and import shocks explain 36 percent and 12 percent of the GDP forecast error variance, respectively, according to the variance decomposition study over a ten-year forecasting period, as figures show in Table 5.

Table 5: Variance Decomposition Analysis Results

Period	S.E.	GDP	Exports	Imports
1	0.074230	100.0000	0.000000	0.000000
2	0.107449	60.82990	23.05614	16.11396
3	0.126269	47.59956	18.41161	33.98883
4	0.133079	42.94032	20.21639	36.84329
5	0.147114	36.60833	29.25286	34.13881
6	0.186532	55.36677	19.83124	24.80199
7	0.234934	64.30906	19.76408	15.92686
8	0.260160	68.03902	16.12872	15.83226
9	0.313264	57.61998	25.68515	16.69487
10	0.365683	51.51491	35.71449	12.77061

Source: Authors calculation, 2022

The trace and maximum Eigen-value methods were used to determine whether or not there is co-integration between variables. We reject the null hypothesis if the trace or maximum Eigenvalue is greater than the critical value. As a result, the findings suggest that there is co-integration and a long-term relationship between GDP, exports, and imports (Table 6). According to Johansen normalization data, exports have a positive effect on economic growth (GDP) in the long run, while imports have a negative impact, ceteris paribus. The coefficients are statistically significant at the 1% level of significance.

Table 6: Johansen Cointgration test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.706	48.154	29.797	0.002
At most 1 *	0.499	17.515	15.495	0.025
At most 2	0.009	0.227	3.841	0.634
Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.706	30.638	21.131	0.001
At most 1 *	0.499	17.288	14.265	0.016
At most 2	0.009	0.227	3.841	0.634
Normalized cointegrating coefficients (standard error in parentheses)				
GDP	Export	Import		
1.000000	-2.345895	5.401335		
	(0.69100)	(1.12752)		

Source: Authors calculation, 2022

Granger causality test: The long-run Granger causality test using the vector error correction model given in Table 7 revealed that economic growth (GDP), exports, and imports have a long run causal relationship. The findings revealed that imports and economic growth have a long-run bidirectional causal relationship. Furthermore, the findings revealed that exports and economic growth have a unidirectional causal relationship. In this study, exports granger cause unidirectional GDP growth and imports granger cause bidirectional economic growth. This indicates that exports and imports generate economic growth both individually and jointly, supporting export or import growth. This study confirms the studies of (Ali et al., 2018; Ashenafi and Getaneh, 2014), but it is not consistent with the study of Bakari (2021) that exports cause bidirectional GDP.

Journal of Science and Inclusive Development Vol. 5, No. 1, DOI: 10.20372/jsid/2023-175

Table 7. Granger causality test

Null Hypothesis:	Obs	F-Statistic	Prob.
GDP does not Granger Cause exports	27	1.732	0.186
Exports do not Granger Cause GDP		2.636	0.068**
Import does not Granger Cause exports	27	1.148	0.366
exports do not Granger Cause imports		0.419	0.792
Imports do not Granger Cause GDP	27	7.644	0.009*
GDP does not Granger Cause imports		2.341	0.094**

Where:,** indicates that statistically significant at 1% and 10% respectively*
Source: Authors calculation, 2022

Toda-Yamamoto Granger causality test: have ascertained that a cointegration relationship exists among exports, imports, and economic growth (GDP). The study results of the Granger causality test based on Toda and Yamamoto (1995) methodology are estimated through the Modified Wald test and reported in Table 8. According to the Modified Wald test estimates, the test output follows a four-degree-of-freedom chi-square distribution with the required lag duration and probability. There is unidirectional causality between imports, exports, and economic growth, according to the Toda-Yamamoto Granger causality test results in Table 8.

Table 8. Toda-Yamamoto Causality (modified WALD) Test Result

Null hypothesis	Chi-sq	p-values	Granger Causality
Exports do not Granger cause GDP	4.7127	0.318	No causality
Imports do not Granger cause GDP	18.383	0.001*	Unidirectional Causality
Export does not granger cause GDP	16.263	0.000*	Unidirectional Causality
Imports do not granger cause exports	4.793	0.309	No causality
Exports do not granger cause imports	7.526	0.111	No causality
GDP does not granger cause imports	4.351	0.361	No causality

*Where * indicates statistically significant at 1% level*
Source: Authors calculation, 2022

Conclusion and recommendation

This study examined the multivariate Granger causality of imports and exports on Ethiopian economic growth (GDP) using annual time series data from 1988 to 2021. The figures for level variables are less than the critical values, meaning that the variables are non-stationary. According to the ADF and the Phillips-Perron test, GDP, exports, and imports are non-stationary at the level. The cointegration results show that GDP, exports, and imports have a long-run relationship, suggesting that all three variables shift together in the long run. As shown by the impulse response functions, when there is a shock to exports, GDP responds positively in the following years, but when there is a shock to imports, GDP responds negatively in the following years. Exports and import shocks explain 36 percent and 12 percent of the GDP forecast error variance, respectively, according to the variance decomposition study over a ten-year forecasting period. As a result, it is vital to streamline import and export processes, create highly skilled export agencies, provide exporters with the knowledge they need to reach global markets, and employ modern technology. Exports have a positive effect on economic growth (GDP), while imports have a negative impact on GDP, ceteris paribus, according to the Johansen cointegration test. At the 5% level, the coefficients are statistically significant. The findings of the vector error correction model (VECM) support the existence of a long-run causal relationship between exports, imports, and economic development (GDP). This means that Ethiopia's exports and imports have a huge effect on the country's economic growth (GDP). Furthermore, the Wald test shows a short-run causality between exports, imports, and economic growth (GDP). In Ethiopia, the Granger Causality Test reveals a long-run bidirectional causal relationship between imports and GDP, as well as a unidirectional causal relationship between exports and GDP in the long run. As a result, we conclude that in Ethiopia, there is a dynamic relationship between imports, exports, and economic growth (GDP). To boost Ethiopia's economic growth and development, the government should develop export-led policies and ensure a higher level of exports.

Availability of data and materials: The data sets generated and/or analyzed during the current study are publically available upon request from corresponding author.

Funding source: There was no specific fund for this work

Competing interests: The authors declare that they have no competing interests.

Aknowlegments: We would like to thank National Bank of Ethiopia for provision of data.

Authors' contribution: TD conceptualized the study, developed the manuscript and analyzed data; **SS** designed the methodology and enterpreted the results; **TT** finalized the write up of the manuscript and all the authors were agreed to publish the manuscript.

References

Ali AA, Ali Yassin SA, Mohamed SD. 2018. The impact of imports and exports performance on the economic growth of Somalia. Int J Econ Finance. 10(1): 110-119.

Allaro HB. 2012. The effect of export-led growth strategy on the Ethiopian economy. Am. J. Econ 2(3): 50-56.

Ashenafi Beyene, Getaneh Benalfew. 2014. Export trade incentives and export growth nexus: Evidence from Ethiopia. J Econ Manag Trade 4(1): 111-128.

Bakari S. 2021. Reinvest the relationship between exports and economic growth in African countries: New insights from innovative econometric methods. MPRA Paper No. 108785, Tunisia. https://mpra.ub.uni-muenchen.de/108785/

Bakari S, Mabrouki M. 2017. Impact of exports and imports on economic growth: new evidence from Panama. J Smart Econ Growth. 2(1): 67-79.

Dey S. 2018. Relationship between export revenue and gross domestic product in Bangladesh: An Econometric Analysis. Asian Bus. Rev 8(1): 1-12.

Tesfa-Amlak Gizaw, Tasew Tadesse. 2020. Sectors' export and economic growth in Ethiopia (VECM Causality Approach). J Econ Sustain Dev. 11(3):43-50.

Granger CWJ. 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica. 37(3): 424-438.

Granger CWJ. 1988. Causality, cointegration, and control. J Econ Dyn Control 12(2-3): 551-559.

Gujarati DN. 2003. Basic Econometrics. 4th edition. McGraw-Hill. USA.

Hoover KD. 2001. Causality in macroeconomics. Cambridge University Press.UK.

Jarra ST. 2013. Exports, domestic demand and economic growth in Ethiopia: Granger causality analysis. J Econ Int Finance 5(9): 357-372.

Johansen S. 1988. Statistical analysis of cointegration vectors. J Econ Dyn Control 12(2-3): 231-254.

Johansen S. 1995. Likelihood-based inference in cointegrated vector autoregressive models. (Oxford, online edn, Oxford Academic), https://doi.org/10.1093/0198774508.001.0001.

Johansen S, Juselius K. 1990. Maximum likelihood estimation and inference on cointegration—with appucations to the demand for money. Oxf Bull Econ Stat 52(2): 169-210.

Lanne M, Lütkepohl H. 2008. Identifying monetary policy shocks via changes in volatility. J Money Credit Bank 40(6): 1131-1149.

Legesse M. 2009. Is the export led growth valid for Ethiopia (Application of Co-Integration and Granger Causality Analysis). MA Thesis. Unity University, Ethiopia.

Md MA, Suleiman N. 2016. The relationship among export, import, capital formation and economic growth in Malaysia. J Glob Econ 4: 186.

Osterwald-Lenum M. 1992. A note with quantiles of the asymptotic distribution of the maximum likelihood cointegration rank test statistics. Oxf Bull Econ Stat. 54(3): 461-472.

Phillips PC, Perron P. 1988. Testing for a unit root in time series regression. Biometrika 75(2): 335-346.

Saaed AAJ, Hussain MA. 2015. Impact of exports and imports on economic growth: Evidence from Tunisia. J Emerg Trends Educ Res Policy Stud. 6(1): 13-21.

Schelter B, Matthias W, Jens T. 2006. Handbook of time series analysis: recent theoretical developments and applications. John Wiley & Sons. USA.

Seifu N. 2010. Multivariate time series analysis of inflation in the case of Ethiopia, MSc Thesis Addis Ababa University. Ethiopia.

Sims CA.1980. Macroeconomics and reality. Econometrica: J Econ Soc 1-48.

Solow M. 1956. A contribution to the theory of economic growth. Q J Econ. 70(1): 65-94.

Suppes P. 1973. A probabilistic theory of causality. Br J Philos Sci. 24(4).

Toda HY, Yamamoto T. 1995. Statistical inference in vector autoregressions with possibly integrated processes. J Econom 66(1-2): 225-250.

Ugochukwu US, Chinyere UP. 2013. The impact of export trading on economic growth in Nigeria. Int J Econ Bus Finance 1(10): 327-341.

Wells M. 1995. Applied econometric time series. J Am Stat Assoc. 90(431): 1135-1135.