FMDB ***Transactions on Sustainable Technoprise Letters***

Macroeconomic Shocks and Sectoral Spillover Effects in Nigeria's Maritime Transport: A Vector Autoregressive Approach

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Abstract: This research explores the complex relationship between macroeconomic disruptions and maritime transport indicators in Nigeria using a Vector Autoregressive (VAR) approach. It primarily examines Real Gross Domestic Product (RGDP), Unemployment Rate (UR), Dry Bulk Transport (DBT), and Non-Oil Bulk Transport (NOT), utilising annual time-series information spanning from 1982 to 2023. Unit root tests indicate that all variables are integrated of order one (I (1). At the same time, Johansen cointegration results suggest no long-term equilibrium relationships among the variables, validating the use of the VAR model in first differences. The VAR analysis reveals short-term connections and detects significant sectoral spillover effects. Granger causality tests indicate a one-way causality from RGDP to NOT and from DBT to NOT, emphasising how economic performance and dry bulk transportation impact non-oil maritime operations. Furthermore, impulse response and variance decomposition analyses indicate that disturbances in DBT and NOT increasingly influence RGDP over time, although long-term stability remains constrained. These results highlight the short-term vulnerability of Nigeria's maritime transport sector to macroeconomic changes, providing valuable insights for policy formulation regarding infrastructure development and economic stability.

Keywords: Macroeconomic Disruptions; External Shocks; Sectoral Effects; Spillover Effects; Maritime Transport; Vector Autoregressive (VAR); Infrastructure Development; Dry Bulk Transport (DBT).

Received on: 19/01/2025, **Revised on:** 20/04/2025, **Accepted on:** 11/07/2025, **Published on:** 23/11/2025

Journal Homepage: https://www.fmdbpub.com/user/journals/details/FTSTPL

DOI: https://doi.org/10.69888/FTSTPL.2025.000504

Cite as: V. M. Aka, "Macroeconomic Shocks and Sectoral Spillover Effects in Nigeria's Maritime Transport: A Vector Autoregressive Approach," *FMDB Transactions on Sustainable Technoprise Letters,* vol. 3, no. 4, pp. 187–199, 2025.

1. Introduction

The maritime transportation industry is crucial to Nigeria's economy, serving as the main gateway for global trade and a central hub for the movement of goods, job creation, and economic interactions. However, despite its significance, the industry is susceptible to macroeconomic disturbances—such as fluctuations in international commodity prices, exchange rate changes, disruptions in global supply chains, and domestic policy changes—that can affect related sectors and produce significant ripple effects. Nevertheless, the mechanisms of these shock transmissions and the interdependencies among sectors are not well comprehended within the Nigerian context. One significant issue arises from the tendency to analyse macroeconomic shocks without examining how these disruptions are conveyed through the maritime transport network and influence associated freight

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sub-sectors (such as bulk shipments, non-oil cargoes, and port logistics). For example, while research on external shocks in Nigeria (such as fluctuations in oil prices or changes in external demand) documents impacts on GDP and exchange rates, it often overlooks the maritime transport sector's response and how its various elements interact. Similarly, analyses of Nigeria's maritime industry identify factors affecting sector performance but often do not model the dynamic spillovers of macroeconomic shocks across different transport cargo sub-sectors [4]; [8].

This gap implies that policymakers might misinterpret the mechanisms by which shocks spread—overlooking which subsectors are most affected, which connections are the strongest, and how short- and medium-term adjustments unfold. The reasons for conducting this research are therefore diverse [6]. Firstly, given Nigeria's substantial dependence on maritime transport for trade and the recognised inefficiencies and vulnerabilities in this sector (for instance, delays and congestion that result in trillions of naira in logistics costs), understanding how shocks propagate is vital for enhancing resilience and shaping policy [9]. Secondly, by examining sectoral spillover effects—how a macroeconomic disturbance (like an exchange-rate shock or a decline in global demand) is transmitted through dry bulk, non-oil bulk cargoes, and port logistics, and its subsequent impact on the economy—this research provides a more comprehensive exploration of transmission mechanisms compared to previous studies. Thirdly, utilising a Vector Autoregressive (VAR) methodology enables flexible dynamic modelling of interrelated behaviours among various transport cargo sub-sectors and macroeconomic elements, capturing both immediate direct effects and delayed spillovers. This approach contrasts with many earlier studies that either rely on single-equation regressions or focus on macroeconomic shocks in isolation.

In particular, the research employs a VAR model with quarterly or annual data relating to Nigeria's maritime transport sub-sectors (such as volumes of dry bulk transported and non-oil bulk transport volumes), macroeconomic totals (GDP, exchange rate, unemployment), and pertinent shock indicators. Using impulse response functions and variance decompositions, the study seeks to clarify the speed and intensity of shock propagation across subsectors, whether certain transport subsectors act as amplifiers or dampers, and how macroeconomic consequences (such as production or job rates) respond to disturbances within the transport sector [14]. In this manner, the research addresses a gap in the existing literature by examining the evolving links between macroeconomic disruptions and sectoral effects in Nigeria's maritime transport framework. By exploring these relationships, the research aims to guide policies on the robustness of Nigeria's maritime transport system, the prioritisation of specific subsectors for managing shocks, and the formulation of macro transport coordination strategies that acknowledge the reciprocal influences within the transport economy rather than treating transport as a separate entity.

2. Methodology

This research utilises a quantitative econometric time-series methodology to examine the evolving relationships between macroeconomic factors (RGDP and UR) and indicators of maritime transport (DBT and NOT) in Nigeria. The application of a Vector Autoregressive (VAR) model, underpinned by unit root, cointegration, and causality examinations, enables the investigation of both short-term interactions and the lack of long-term associations between the factors. The data utilised in this analysis are secondary time-series data covering the period from 1982 to 2023. The data sources include annual publications from the Central Bank of Nigeria (CBN) and the Nigerian Ports Authority (NPA) [7]. The variables under consideration are Real Gross Domestic Product (in constant prices) (RGDP), the Unemployment Rate (UR), Dry Bulk Transport Volume (DBT), and Non-Oil Bulk Transport Volume (NOT) [10]. The data evaluation process commenced with descriptive statistics (mean, standard deviation, skewness, kurtosis, and the Jarque-Bera test), which were calculated to characterise the dataset's distributional properties. Stationarity assessments (Unit Root Tests) were performed to determine whether the time series data were stationary; the assessments included group unit root tests such as the Levin, Lin & Chu (LLC), Im, Pesaran and Shin (IPS), ADF–Fisher Chi-square, and PP–Fisher Chi-square. These evaluations were conducted at the level and first-difference levels. All variables were identified as non-stationary at the level but stationary at the first difference, indicating an I(1) process. Likewise, a cointegration test was conducted. The Johansen Cointegration Test was applied to examine a long-term equilibrium relationship among the variables. Both the Trace Test and the Maximum Eigenvalue Test did not reject the null hypothesis of no cointegration at the 5% significance threshold. This supports modelling in first differences using a VAR rather than a VECM. The general VAR(p) model (with p lags) can be written as:

$$Y_t = A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t$$

Where, Y_t is a vector of endogenous variables at time t, $A_1, A_2, \ldots, A_p$ are matrices of coefficients to be estimated, ε_t is a vector of error terms (white noise process), and p is the number of lags determined using criteria such as AIC, BIC, or HQ. Using variables in the VAR System, let the vector of variables in first differences be:

$$Y_t = \begin{bmatrix} \Delta RGDP_t \\ \Delta DBT_t \\ \Delta NOT_t \\ \Delta UR_t \end{bmatrix}$$

Then the VAR(p) model becomes:

$$\begin{bmatrix} \Delta RGDP_t \\ \Delta DBT_t \\ \Delta NOT_t \\ \Delta UR_t \end{bmatrix} = \sum_{i=1}^{p} A_i \begin{bmatrix} \Delta RGDP_{t-i} \\ \Delta DBT_{t-i} \\ \Delta NOT_{t-i} \\ \Delta UR_{t-i} \end{bmatrix} + \varepsilon_t$$

Where:

- Δdenotes first difference.
- $\varepsilon_t$is a vector of innovations or shocks

A VAR model was estimated in first differences to evaluate the dynamic interactions and interdependence among the variables. The optimal lag structure was identified through the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC). The VAR included all four variables, each with five lags. Utilising factors such as Akaike Information Criterion (AIC), Schwarz Bayesian Criterion (SBC), and Hannan-Quinn Criterion (HQC). The optimal lag length was p = 5, determined by the minimum AIC and model diagnostics. The rationale for VAR in Differences is that all variables are non-stationary at the level but become stationary after first differencing (I (1)). Additionally, the Johansen test verifies the absence of cointegration. Thus, the VAR model is estimated in first differences, guaranteeing stationarity and preventing misleading regression. The VAR model is computed using Ordinary Least Squares (OLS), implemented equation-by-equation for every dependent variable in the system. Each variable (for instance, ΔRGDP) is regressed on its own lags and the lags of all other variables. For instance:

$$\Delta RGDP_t = \alpha_0 + \sum_{i=1}^{5} \beta_{1i} \Delta RGDP_{t-i} + \sum_{i=1}^{5} \beta_{2i} \Delta DBT_{t-i} + \sum_{i=1}^{5} \beta_{3i} \Delta NOT_{t-i} + \sum_{i=1}^{5} \beta_{4i} \Delta UR_{t-i} + \varepsilon_{1t}$$

Similar equations are specified for ΔDBT_t, ΔNOT_t, and ΔUR_t. Additionally, pairwise Granger causality tests were conducted to determine the direction of causality among the variables. Notable unidirectional causality was discovered: from RGDP to NOT, and from DBT to NOT. A forecast error variance decomposition was employed to estimate the extent to which variations in each variable could be attributed to shocks affecting that variable and other variables over a 10-period horizon. The outcomes revealed that DBT and NOT exerted an increasing influence on RGDP over time, although long-term variance was unstable, suggesting possible limitations of the model. All econometric evaluations were performed using EViews 12.

3. Results

Figure 1 illustrates the time series graph for the different variables.

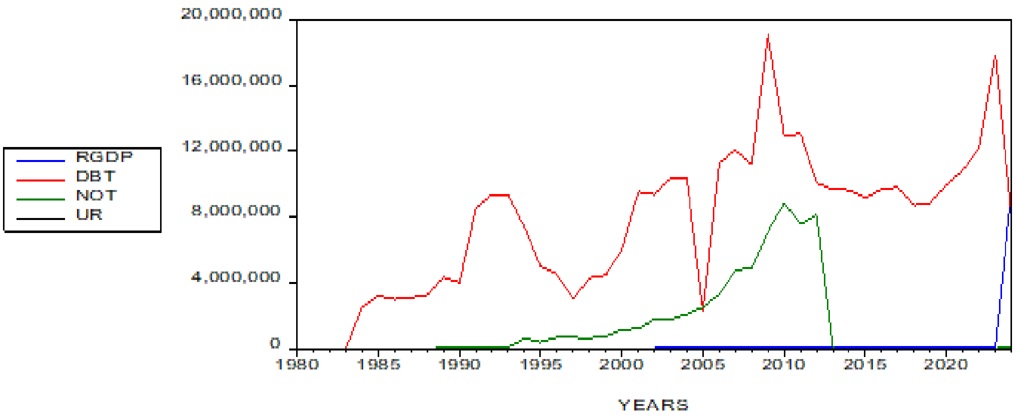

Figure 1: Time plot of the variables

The time-series graph of Real Gross Domestic Product (RGDP), Non-Oil Bulk Transportation (NOT), Dry Bulk Transportation (DBT), and Unemployment Rate (UR) visually shows the progression of each variable over the specified period. The observed trends indicate that all four variables exhibit non-stationary behaviour, particularly RGDP and NOT, suggesting that they are probably non-stationary. DBT also shows significant changes and peaks, whereas UR experiences fluctuations with discernible cycles. These trends indicate that the statistical characteristics of the series—such as the mean and variance—change over time, contradicting the stationarity assumption required by many time-series econometric models. Therefore, these visual trends support the need for unit root tests and the potential for transformation via differencing.

Table 1: Descriptive statistics of the variables

Statistics	**RGDP**	**NOT**	**DBT**	**UR**
Mean	2.26E+11	1365248.	7594771.	6.488023
Median	1.70E+11	106090.8	9028792.	7.958500
Maximum	5.74E+11	8865778.	19116321	10.85100
Minimum	4.40E+10	5621.800	34.80000	0.000000
Std. Dev.	1.69E+11	2421467.	4542005.	3.208921
Skewness	0.505380	1.983175	0.185310	-0.919283
Kurtosis	1.747326	5.715088	2.767450	2.324290
Jarque-Bera	4.749853	42.35666	0.350971	7.034331
Probability	0.093021	0.000000	0.839050	0.029683
Sum	9.95E+12	60070923	3.34E+08	285.4730
Sum Sq. Dev.	1.23E+24	2.52E+14	8.87E+14	442.7786

Table 1 presents the descriptive statistics for the variables. The descriptive statistics reveal critical information about the characteristics and distributional attributes of the variables being examined. Real GDP (RGDP) has a considerable mean of about 2.26×10^{11} and a substantial standard deviation of 1.69×10^{11}, highlighting significant fluctuations in national output during the analysed timeframe. The positive skewness value of 0.505 points to a right-skewed distribution, even though the kurtosis of 1.75 (below 3) indicates a relatively flat distribution with lighter tails. The Jarque-Bera (JB) statistic is 4.75 with a p-value of 0.093, which does not reject the null of normality at the 5% significance level, suggesting that RGDP follows an approximately normal distribution. Non-Oil Bulk Transportation (NOT) has a mean of 1,365,248 and an exceptionally high standard deviation (2,421,467), demonstrating substantial variability in volume. Its skewness is strongly positive (1.98), indicating a considerable concentration of data points on the left side with an extended right tail. The kurtosis value of 5.71 indicates leptokurtic behaviour, suggesting the presence of extreme values (outliers).

The JB statistic of 42.36, alongside a p-value of 0.000, clearly rejects the normality assumption, which affects potential parametric modelling. Dry Bulk Transportation (DBT) shows a mean close to 7.59 million and a standard deviation of 4.54 million. Its skewness is slightly positive at 0.185, and its kurtosis is 2.77, approaching the normal benchmark of 3. The JB statistics are minimal (0.35), while the p-value of 0.839 provides substantial support for the normality of this variable. The Unemployment Rate (UR) has a mean of 6.49 with a standard deviation of 3.21. It exhibits a negative skewness of –0.919, suggesting a longer left tail and more common lower unemployment rates. The kurtosis is 2.32, indicating a slightly flatter distribution. The JB statistic is 7.03 with a p-value of 0.029, indicating rejection of the normality assumption at the 5% significance level and suggesting non-normality. Overall, only DBT appears to follow a normal distribution, as indicated by both kurtosis and the JB test, whereas NOT and UR do not. These discrepancies emphasise the necessity for transformations or the application of non-parametric or robust statistical methods in future modelling endeavours.

Table 2: Group unit root test of the variables

	Level Difference			**First Difference**		
Method	**Statistic**	**Prob.****	**Cross-sections**	**Obs**	**Statistic**	**Prob.****
Null: Unit root (assumes common unit root process)						
Levin, Lin & Chu t*	-0.85963	0.1950	4	173	-8.84077	0.0000
Null: Unit root (assumes individual unit root process)						
Im, Pesaran and Shin W-stat	-1.36446	0.0862	4	173	-10.1085	0.0000
ADF - Fisher Chi-square	12.9244	0.1145	4	173	92.0324	0.0000
PP - Fisher Chi-square	12.5499	0.1283	4	175	92.5634	0.0000
** *Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.*						

The unit root assessments presented in Table 2 examine if the variables—including Real GDP (RGDP), Dry Bulk Transportation (DBT), Non-Oil Bulk Transportation (NOT), and Unemployment Rate (UR)—exhibit stationarity or contain a unit root (indicating non-stationarity). Establishing stationarity is vital in time series analysis because non-stationary data can lead to inaccurate regression conclusions. When analysed at Level (without Differencing) using the Levin, Lin & Chu Test (LLC), the Statistic is calculated as -0.85963, and the p-value equals 0.1950. As the p-value exceeds 0.05, we do not reject the null hypothesis concerning the presence of a unit root. Thus, the variables remain non-stationary under the assumption of a common unit root process. Likewise, the Im, Pesaran, and Shin W-stat (IPS) yield a Statistic of -1.36446 and a p-value of 0.0862. Even though the statistics are negative (indicating a trend toward stationarity), the p-value exceeds 0.05, so we do not reject the null of a unit root. Consequently, the variables are not stationary at the level based on individual unit root assumptions. The ADF - Fisher Chi-square - reports statistics of 12.92, with a p-value of 0.1145. Again, with $p > 0.05$, we fail to reject the null hypothesis, indicating non-stationarity at the levels. The PP-Fisher Chi-square yields a statistic of 12.55 and a p-value of 0.1283, confirming that the variables are non-stationary at this level.

After applying first differences to the variables, the unit root tests provide robust evidence of stationarity, with the Levin, Lin & Chu test yielding a statistic of -8.84077 and a p-value of 0.0000. This leads to a strong rejection of the unit root hypothesis. The variables are stationary after differencing. The Im, Pesaran, and Shin W-stat report a statistic of -10.1085, paired with a p-value of 0.0000. This indicates a strong rejection of the null hypothesis, suggesting that first differences are stationary. The ADF-Fisher Chi-square statistic is 92.03, and the p-value is 0.0000, indicating very significant results and suggesting that the series are stationary at the first-difference level. The PP - Fisher Chi-square also indicates a statistic of 92.56 with a p-value of 0.0000, confirming strong evidence of stationarity at the first difference. Thus, at the levels, all variables are non-stationary, whereas at the first difference, all variables become stationary, indicating they are integrated of order one (I(1). This finding is pivotal for model building, as it validates the use of VAR analysis in first differences rather than levels, and excludes standard OLS regression in levels unless cointegration is present. This result corroborates the significance of cointegration testing, such as the Johansen test.

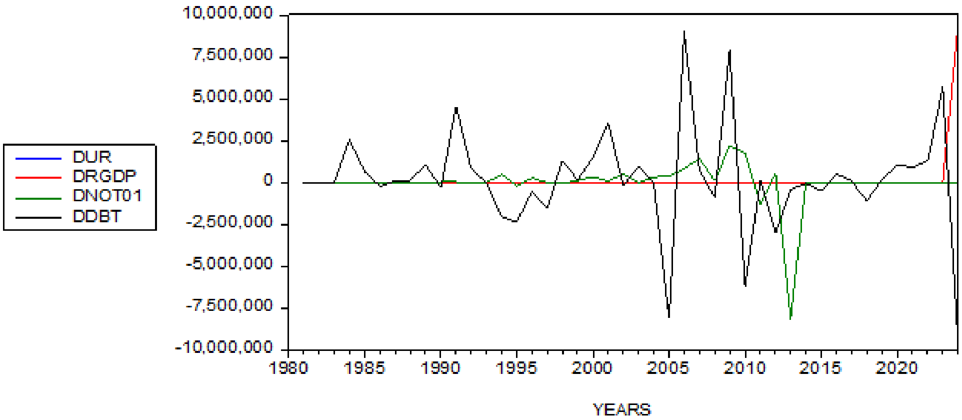

Figure 2: Time plot of differenced variables

Figure 2 illustrates the time plot of the differences for the variables involved. The time plot of the second-differenced variables provides graphical confirmation of the statistical unit root tests. Following differencing, the trends visible in Figure 1 are generally eliminated. The differences between the series now oscillate around a stable mean with relatively consistent variance, indicating stationarity. The lack of systematic trends or significant drifts in these plots indicates the effectiveness of the different processes. This outcome is essential for time-series modelling, since many models, including VARs, require stationary data. Therefore, transforming the data to achieve stationarity has set the groundwork for substantive econometric analysis.

Table 3: Cointegration test

Unrestricted Cointegration Rank Test (Trace)					Unrestricted Cointegration Rank Test (Maximum Eigenvalue)			
Hypothesized No. of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.****	**Eigenvalue**	**Statistic**	**Critical Value**	**Prob.****
None *	0.358108	37.62260	47.85613	0.3187	19.06343	27.58434	0.4097	19.06343
At most 1 *	0.199598	18.55916	29.79707	0.5250	9.573550	21.13162	0.7836	9.573550
At most 2 *	0.120029	8.985612	15.49471	0.3667	5.498234	14.26460	0.6781	5.498234

At most 3 *	0.077900	3.487377	3.841466	0.0618	3.487377	3.841466	0.0618	3.487377
Trace test indicates 4 cointegrating eqn(s) at the 0.05 level.								
** denotes rejection of the hypothesis at the 0.05 level.*								
***MacKinnon-Haug-Michelis (1999) p-values.*								

Table 3 presents the findings from the Cointegration Test. The Johansen cointegration assessment, which utilises both the Trace and Maximum Eigenvalue statistics, seeks to uncover long-lasting equilibrium relationships among four variables: RGDP, NOT, DBT, and UR. The trace statistic for the null hypothesis of "no cointegrating relationship" is 37.62, which is lower than the critical value of 47.85, and the p-value is 0.3187. Likewise, for the hypotheses concerning "at most 1", "at most 2", and "at most 3" cointegrating equations, the test statistics all remain below their respective critical values, yielding p-values significantly greater than the 5% level. The statistics concerning the maximum eigenvalue also reflect a similar trend, leading to the failure to reject the null hypotheses at all levels. Collectively, these findings indicate that the examined variables are not cointegrated. Consequently, while short-term interactions may exist, the variables do not synchronise over the long term nor follow a shared stochastic trajectory. This suggests that disturbances to one variable do not necessarily guarantee a discernible long-term impact on the others, and that the variables lack a tendency to revert to any long-term equilibrium. As a result, models that rely on cointegration, such as the Vector Error Correction Model (VECM), would not be appropriate for this situation. Instead, alternative methodologies, including Vector Autoregression (VAR) in differences or structural VAR, might be more appropriate for exploring the short-term dynamic relationships.

Table 4: Vector autoregressive (VAR) model estimation results

	RGDP	**DBT**	**NOT**	**UR**
RGDP(-1)	-385.1957	642.6899	447.7063	0.000350
	(303.955)	(556.436)	(240.008)	(0.00015)
	[-1.26728]	[1.15501]	[1.86538]	[2.33408]
RGDP(-2)	174.0734	-79.66457	-329.7379	-0.000291
	(501.805)	(918.632)	(396.234)	(0.00025)
	[0.34689]	[-0.08672]	[-0.83218]	[-1.17715]
RGDP(-3)	-26.04580	28.34196	-406.2097	0.000199
	(498.893)	(913.301)	(393.935)	(0.00025)
	[-0.05221]	[0.03103]	[-1.03116]	[0.80955]
RGDP(-4)	97.33794	268.4217	455.0448	-0.000226
	(443.930)	(812.683)	(350.535)	(0.00022)
	[0.21926]	[0.33029]	[1.29814]	[-1.03205]
RGDP(-5)	126.7776	-756.5198	-199.6551	-1.95E-05
	(258.693)	(473.578)	(204.269)	(0.00013)
	[0.49007]	[-1.59746]	[-0.97741]	[-0.15308]
DBT(-1)	0.376142	-0.022200	0.208404	-2.22E-07
	(0.11922)	(0.21824)	(0.09413)	(5.9E-08)
	[3.15515]	[-0.10172]	[2.21390]	[-3.77073]
DBT(-2)	0.162494	-0.174135	-0.137218	-9.16E-08
	(0.12275)	(0.22471)	(0.09692)	(6.1E-08)
	[1.32382]	[-0.77495]	[-1.41575]	[-1.51270]
DBT(-3)	0.051334	-0.125029	0.218359	-2.79E-08
	(0.12679)	(0.23211)	(0.10012)	(6.3E-08)
	[0.40487]	[-0.53866]	[2.18103]	[-0.44553]
DBT(-4)	0.011219	-0.816944	-0.253619	-1.10E-08
	(0.13462)	(0.24644)	(0.10630)	(6.6E-08)
	[0.08334]	[-3.31492]	[-2.38589]	[-0.16515]
DBT(-5)	0.228453	-0.036986	0.220477	-1.36E-07
	(0.16127)	(0.29522)	(0.12734)	(8.0E-08)
	[1.41662]	[-0.12528]	[1.73141]	[-1.71093]
NOT01(-1)	-0.155182	0.687530	0.956523	4.29E-08
	(0.23835)	(0.43634)	(0.18821)	(1.2E-07)
	[-0.65106]	[1.57568]	[5.08230]	[0.36506]
NOT(-2)	-0.264026	-0.058990	-0.163348	1.81E-07
	(0.30638)	(0.56087)	(0.24192)	(1.5E-07)

	[-0.86176]	[-0.10518]	[-0.67521]	[1.19458]
NOT(-3)	0.106530	0.145853	-0.227380	-1.13E-07
	(0.26728)	(0.48929)	(0.21105)	(1.3E-07)
	[0.39857]	[0.29809]	[-1.07738]	[-0.85373]
NOT01(-4)	0.007464	0.129691	-0.299824	-1.30E-08
	(0.26600)	(0.48696)	(0.21004)	(1.3E-07)
	[0.02806]	[0.26633]	[-1.42746]	[-0.09918]
NOT01(-5)	-0.245552	-0.141467	0.188295	1.78E-07
	(0.23188)	(0.42449)	(0.18309)	(1.1E-07)
	[-1.05897]	[-0.33326]	[1.02840]	[1.55680]
UR(-1)	-87097.84	1316846.	-422085.8	1.180457
	(956741.)	(1751462)	(755460.)	(0.47204)
	[-0.09104]	[0.75186]	[-0.55871]	[2.50076]
UR(-2)	-1377619.	937569.3	520729.6	0.654399
	(1413316)	(2587293)	(1115980)	(0.69730)
	[-0.97474]	[0.36237]	[0.46661]	[0.93847]
UR(-3)	-1797109.	2054042.	-587321.5	1.109315
	(1350276)	(2471888)	(1066202)	(0.66620)
	[-1.33092]	[0.83096]	[-0.55085]	[1.66514]
UR(-4)	1803250.	-741136.5	143813.5	-0.704185
	(1262931)	(2311990)	(997233.)	(0.62311)
	[1.42783]	[-0.32056]	[0.14421]	[-1.13012]
UR(-5)	594479.6	-1339053.	176159.2	-0.795353
	(1009601)	(1848229)	(797199.)	(0.49812)
	[0.58883]	[-0.72451]	[0.22097]	[-1.59671]
R-squared	0.558922	0.777920	0.898462	0.814101
Adj. R-squared	0.139898	0.566945	0.802002	0.637498
Sum sq. resids	3.97E+13	1.33E+14	2.48E+13	9.667449
S.E. equation	1409152.	2579671.	1112692.	0.695250
F-statistic	1.333865	3.687252	9.314283	4.609763
Log likelihood	-609.2346	-633.4215	-599.7863	-28.35524
Akaike AIC	31.46173	32.67107	30.98932	2.417762
Schwarz SC	32.30617	33.51551	31.83376	3.262202
Mean dependent	282444.1	8492449.	1502330.	3.734975
S.D. dependent	1519438.	3920059.	2500600.	1.154743
Determinant residual covariance (dof adj.)		9.39E+35		
Determinant resid covariance		5.87E+34		
Log likelihood		-1828.183		
Akaike information criterion		95.40915		
Schwarz criterion		98.78691		
Number of coefficients		80		

Table 4 illustrates the Vector Autoregressive (VAR) model that evaluates how macroeconomic factors affect sustainable maritime transportation systems in Nigeria. The VAR model identifies the dynamic interrelations among the four macroeconomic indicators. It incorporates five lags for each variable, facilitating intricate temporal interactions. The dependent variables are RGDP, DBT, NOT, and UR, which are regressed against their own lags and those of the other three variables. Focusing on RGDP, the model indicates that most of its lagged coefficients are not statistically significant, as evidenced by low t-statistics.

Nevertheless, DBT at lag 1 shows a statistically significant, positive coefficient (t-statistic = 3.15), indicating that an increase in dry bulk transportation is associated with a positive effect on RGDP. This aligns with the logical assumption that increased trade or the movement of goods drives economic output. Conversely, DBT at lag 4 shows a significant adverse effect, suggesting possible correction dynamics or delayed congestion within the transport infrastructure. In the DBT equation, multiple variables affect dry bulk transportation. RGDP at lag 1 shows weak significance, but more importantly, DBT at lag 4 indicates a strong negative effect with a t-statistic of –3.31. This may imply some inertia or cyclical adjustments in the dry bulk transport sector. Furthermore, NOT at lag one and lag three positively influence DBT, suggesting the interdependence between oil and non-oil transport logistics. Examining NOT, the model illustrates that its first lag is highly significant and positive (t =

5.08), suggesting robust persistence or momentum in non-oil bulk transportation. Additionally, DBT at lags 3 and 5 also shows positive effects on NOT.

This implies that there are interactions among various freight industries, with activities in dry bulk potentially leading to or coinciding with an upsurge in the movement of non-oil bulk shipments. Regarding unemployment (UR), the lone significantly impactful variable is RGDP at one lag, presenting a t-statistic of 2.33. The negative correlation indicates that a rise in GDP is associated with a fall in unemployment, consistent with macroeconomic theory. The dry bulk transport (DBT) at one lag also shows significance. Still, it carries a negative connotation, suggesting that increased transport activity could help lower unemployment in the short term, likely because of its labour-intensive nature. Within the complete VAR framework, the R-squared values indicate that the model accounts for 89.8% of the variance in non-oil transport (NOT) and 81.4% of the variance in unemployment (UR), suggesting a relatively high level of explanatory power. RGDP and DBT exhibit lower explanatory power (R^2 of 55.9% and 77.8%, respectively) yet are still considered acceptable for macroeconomic time series. The large number of parameters reduces the adjusted R-squared values, but they still suggest the model provides a decent fit, especially for NOT and UR. The F-statistics further confirm that the equations for NOT and UR are statistically significant, thereby substantiating the model's structure for these variables.

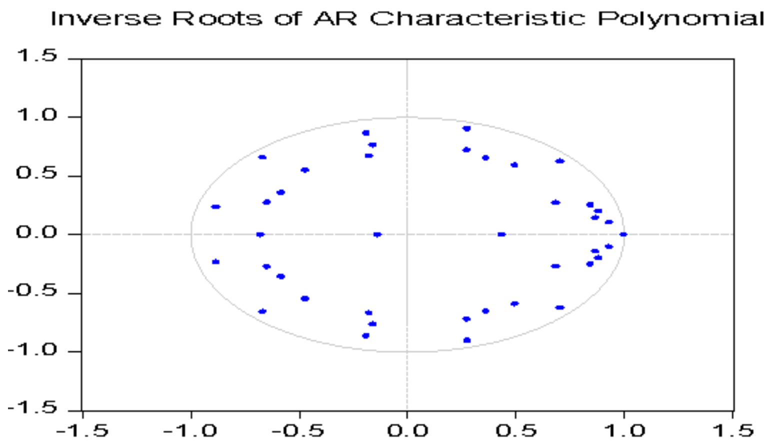

Figure 3: Dynamic stability plot for the model

The final log-likelihood, along with the Akaike and Schwarz information criteria, indicates a compromise between model complexity and adequacy, with 80 estimated coefficients demonstrating the VAR's comprehensive framework. The dynamic stability test for the model is shown in Figure 3.

Table 5: Pairwise Granger causality tests

Null Hypothesis:	Obs	F-Statistic	Prob.
DBT does not Granger-cause RGDP	40	1.37200	0.2636
RGDP does not Granger-cause DBT		1.15991	0.3524
NOT01 does not Granger-cause RGDP	40	0.14909	0.9787
RGDP does not Granger-cause NOT01		2.73969	0.0381
UR does not Granger-cause RGDP	40	0.98902	0.4415
RGDP does not Granger-cause UR		0.72106	0.6130
NOT01 does not Granger-cause DBT	40	0.76863	0.5800
DBT does not Granger Cause NOT01		4.27375	0.0049
UR does not Granger-cause DBT	40	0.42697	0.8261
DBT does not Granger-cause UR		1.05107	0.4072
UR does not Granger Cause NOT01	40	0.18660	0.9654
NOT01 does not Granger-cause UR		0.42163	0.8298

Table 5 displays the pairwise Granger causality evaluations. The Granger causality findings offer clarity on the directionality of short-term predictive relationships. Initiating with RGDP, it does not Granger-cause DBT, nor does DBT demonstrate Granger-causation of RGDP, signifying an absence of a discernible feedback loop in the short run between economic output and dry bulk transport. However, RGDP does not Granger-cause NOT (p = 0.0381), indicating that historical GDP values aid in forecasting changes in non-oil bulk transport, which supports the notion that economic vigour drives transport demand in certain sectors. Curiously, NOT does not Granger-cause RGDP, implying that the relationship is one-directional. Unemployment (UR) exhibits no causal linkage with RGDP in either direction, suggesting that, within this dataset, historical GDP Figures do not anticipate short-term fluctuations in unemployment, nor vice versa—though this might stem from data constraints or inherent delays in the labour market's response. Between NOT and DBT, unidirectional causality flows from DBT to NOT (p = 0.0049), indicating that dry bulk transport affects non-oil transport, potentially through shared infrastructure, logistical planning, or cyclical economic trends. However, NOT does not Granger-cause DBT. There is no immediate causal relationship between unemployment and the other variables in either direction, suggesting that unemployment trends in this context are slow to respond or are governed more by external factors and structural influences than by short-term shifts in transport or GDP.

Table 6: Variance decomposition of the variables

Response of RGDP				
Period	**RGDP**	**DBT**	**NOT**	**UR**
1	1409152.	0.000000	0.000000	0.000000
2	-5.43E+08	962030.0	-166420.6	-22542.44
3	2.10E+11	-3.70E+08	63901364	8445239.
4	-8.09E+13	1.43E+11	-2.47E+10	-3.26E+09
5	3.12E+16	-5.52E+13	9.52E+12	1.26E+12
6	-1.21E+19	2.13E+16	-3.68E+15	-4.86E+14
7	4.65E+21	-8.22E+18	1.42E+18	1.88E+17
8	-1.80E+24	3.17E+21	-5.48E+20	-7.24E+19
9	6.93E+26	-1.22E+24	2.11E+23	2.79E+22
10	-2.68E+29	4.73E+26	-8.16E+25	-1.08E+25
Response of DBT				
Period	**RGDP**	**DBT**	**NOT**	**UR**
1	-493437.5	2532039.	0.000000	0.000000
2	9.05E+08	-73003.51	775539.7	340822.8
3	-3.48E+11	6.17E+08	-1.06E+08	-13925488
4	1.34E+14	-2.37E+11	4.10E+10	5.41E+09
5	-5.18E+16	9.16E+13	-1.58E+13	-2.09E+12
6	2.00E+19	-3.54E+16	6.10E+15	8.07E+14
7	-7.73E+21	1.36E+19	-2.36E+18	-3.11E+17
8	2.98E+24	-5.27E+21	9.09E+20	1.20E+20
9	-1.15E+27	2.03E+24	-3.51E+23	-4.64E+22
10	4.44E+29	-7.85E+26	1.36E+26	1.79E+25
Response of NOT01				
Period	**RGDP**	**DBT**	**NOT**	**UR**
1	-361739.4	-77609.09	1049383.	0.000000
2	6.31E+08	441731.2	986432.3	-109243.2
3	-2.43E+11	4.31E+08	-73591877	-10120040
4	9.38E+13	-1.66E+11	2.86E+10	3.78E+09
5	-3.62E+16	6.40E+13	-1.10E+13	-1.46E+12
6	1.40E+19	-2.47E+16	4.26E+15	5.63E+14
7	-5.39E+21	9.53E+18	-1.64E+18	-2.17E+17
8	2.08E+24	-3.68E+21	6.35E+20	8.39E+19
9	-8.04E+26	1.42E+24	-2.45E+23	-3.24E+22
10	3.10E+29	-5.48E+26	9.46E+25	1.25E+25
Response of UR				
Period	**RGDP**	**DBT**	**NOT**	**UR**
1	-0.643374	0.027768	0.041051	0.258817
2	492.5829	-0.532131	0.093510	0.305523
3	-190026.1	335.9205	-58.05545	-7.440830
4	73353269	-129593.5	22367.98	2956.980
5	-2.83E+10	50025217	-8634457.	-1141409.

6	1.09E+13	-1.93E+10	3.33E+09	4.41E+08
7	-4.22E+15	7.45E+12	-1.29E+12	-1.70E+11
8	1.63E+18	-2.88E+15	4.97E+14	6.57E+13
9	-6.29E+20	1.11E+18	-1.92E+17	-2.53E+16
10	2.43E+23	-4.29E+20	7.40E+19	9.78E+18
Cholesky Ordering: *RGDP DBT NOT UR*				

Table 6 presents the Variance Decomposition of the assessed model. The variance decomposition examines the extent to which forecasting error variance of each variable can be attributed to fluctuations in other variables over a ten-period span. In the case of RGDP, the variance for the initial period is entirely explained by itself, which is a standard occurrence. However, as time advances, a greater portion of RGDP's variability is accounted for by DBT and NOT. By the fifth period, disturbances in DBT account for a considerable share of RGDP fluctuations, although the extremely large, alternating positive and negative Figures seen in the later periods imply either unstable behaviour or issues with scale in the modelling (possibly due to integration-order-two data or inadequate differencing). This lack of stability raises concerns regarding the model's dependability over extended time frames. Initially, DBT exhibits a strong degree of self-reliance.

Still, over time, an increasing share of its variance is associated with RGDP and NOT, once again indicating the presence of feedback mechanisms and interdependence between sectors. Similar trends are observed in the NOT decomposition, where its forecast error variance progressively reflects inputs from RGDP and DBT, reinforcing the concept of an interactive dynamic between macroeconomic activities and transport sectors. Regarding unemployment, the variance decomposition suggests that its subsequent values are primarily influenced by its own past in the early periods, with a growing impact from RGDP and DBT emerging by period five and thereafter. This gradual increase indicates that both economic and transport activities begin to influence unemployment with a delay, aligning with the notion that employment reacts later than output fluctuations. Nonetheless, across all decompositions, the increasingly unpredictable and exceptionally high values, particularly after period five, hint at possible overfitting or instability, likely resulting from including too many lag variables or from incomplete data stabilisation.

4. Discussions

Time Plots (Figure 1) illustrate the sequences RGDP, NOT, DBT, and UR, revealing distinct trends, peaks, and patterns. Both RGDP and NOT demonstrate increasing trends, while DBT displays sudden changes and erratic behaviour, and UR fluctuates within cycles. These observations indicate non-stationarity, suggesting that the mean or variance of these series may vary over time. This aligns with earlier research on the growth of transportation or infrastructure, and on GDP analysis: for example, Sun and Yu [15] reported significant trend activity in Shanghai port logistics data, necessitating transformation before VAR analysis. Their visual examination supported formal evaluations. Therefore, your detection of trend-like activity corresponds with previous findings, highlighting the importance of unit root testing and differencing before any modelling efforts. The descriptive statistics presented in Table 1 indicate diverse distribution characteristics. RGDP's skewness is moderate (0.505), and the kurtosis is low (1.75 < 3), pointing to a slightly flattened distribution, while the Jarque Bera (JB) test does not reject the assumption of normality (p = 0.093). Conversely, NOT exhibits high skewness (1.98) and leptokurtosis (kurtosis = 5.71), with JB rejecting normality. DBT is nearly normal (skewness ~0.185, kurtosis ~2.77, JB p = 0.839). UR is negatively skewed (–0.919) with kurtosis around 2.32, and JB p = 0.029, rejecting normality.

The combination of normal and non-normal distributions aligns with findings in infrastructure/transport studies, indicating that certain variables (such as infrastructure stocks) may exhibit more regular behaviour, whereas others (such as freight volumes) display greater volatility and skewness. For instance, Kalejaiye and Babasanya [11], in the context of ECOWAS transport infrastructure, identified skewed distributions for freight/transport variables, indicating the need for caution in parametric modelling. Your results support the assertion that some variables (NOT, UR) may require robust or transformed estimation methods due to non-normality. In contrast, others (DBT) can likely be handled with conventional approaches. The Unit Root Tests in Table 2 indicated that at levels, neither the Levin–Lin–Chu (LLC) nor the Im Pesaran–Shin (IPS) nor Fisher-type tests rejected the hypothesis of unit roots (e.g., LLC t = –0.8596, p = 0.195; IPS W stat = –1.364, p = 0.0862). After one level of differencing, all tests robustly rejected the null hypothesis (e.g., LLC t = –8.8408, p = 0.000; IPS W stat = –10.1085, p = 0.000). Hence, your series appears to be integrated of order one (I (1). This finding is consistent with standard practices in the econometrics literature on transport and growth: many investigations report non-stationarity at levels and stationarity after first differencing. For example, Alam et al. [3] found parallel outcomes in Pakistan for transport infrastructure and GDP variables. The discovery of I (1) behaviour you recorded is significant: it supports moving forward with cointegration tests (Johansen) and VAR/VECM models.

Had you discovered an I (2) behaviour (integrated of order two), alternative modelling structures would have been necessary, or a more cautious interpretation would have been warranted. The time plot of the differenced series in Figure 2 indicates the removal of visible trends from the level series: the differenced variables appear to oscillate around stable means, with more consistent variances, consistent with the concept of stationarity. These findings are consistent with earlier empirical research in related macroeconomic and transportation analyses: Aderemi and Obalade [2] indicated that Nigerian economic indicators such as RGDP and unemployment are non-stationary in their original forms but show stationarity after the first difference, aligning with I (1) characteristics. Onokoya and Afintinni [13] similarly noted that logistics and transportation metrics in Nigeria typically necessitate differencing to achieve stationarity, which is essential for effective time-series analysis. Aschauer [5] highlighted that investments in infrastructure, particularly transportation, often influence output over the long term; however, identifying these impacts necessitates either stationary data or cointegration evaluations.

The Johansen cointegration analysis presented in Table 3 reveals no cointegration among RGDP, NOT, DBT, and UR: both the trace and maximum eigenvalue assessments do not reject the null hypothesis of having zero or at most one cointegrating relationship (for instance, the trace statistic for “None” is 37.62, which is less than the critical value of 47.856, with a p-value of 0.3187). This indicates that the variables do not maintain a long-term equilibrium relationship. This finding diverges somewhat from several transport growth analyses, many of which report long-term connections (for example, Adebosin et al. [1] identified long-term cointegration between investments in road transport and GDP in Nigeria). The lack of cointegration in this scenario implies that while transportation and macroeconomic indicators may show short-term correlations, they do not align in the long term. This may be attributed to structural challenges in Nigeria's maritime and transportation sectors (such as regulatory misalignments and infrastructure constraints) that prevent sustained, long-term ties. It suggests that a VECM may not be suitable and recommends using a VAR in differences or alternative short-term modelling approaches. The results from the VAR analysis (Table 4), Granger Causality Examinations (Table 5), and variance decomposition findings (Table 6) reveal significant short-term dynamics despite a lack of long-term stability. The notable positive coefficient for DBT lag one on RGDP ($t = 3.15$) supports the assertion that increased dry bulk transport activity contemporaneously enhances economic output, consistent with general observations in the transportation growth literature.

Moreover, the Granger causality analysis shows that RGDP Granger causes NOT ($p = 0.0381$), suggesting that economic expansion drives demand for non-oil bulk transportation, aligning with the “demand-led” perspective on transport growth (for instance, Alebeyzatlar et al. [4] emphasised that transportation and GDP tend to display bidirectional causality, particularly in advanced economies). The one-directional causality from DBT to NOT ($p = 0.0049$) implies sector-specific spillover effects within the maritime and transportation fields, a detail infrequently addressed in existing research but consistent with logistics studies that indicate intersectoral impacts. The variance decomposition outcomes reveal that while individual shocks predominantly influence initial periods, over time, the impact of transportation variables (DBT, NOT) on RGDP’s forecast error variance increases, while RGDP likewise plays a larger role in influencing the variance of transport variables. This trend echoes findings from other VAR studies on transport growth, revealing feedback loops; however, the instability in long-horizon values in your model (noted as exceedingly large and erratic) suggests that long-term predictions may lack reliability. This is consistent with methodological cautions in the literature; for example, Lindgren et al. [12] emphasise that unstable variance decompositions at long horizons may reflect mis-specification or integration-order issues.

5. Conclusion

This research examined the short-term and possible long-term relationships among macroeconomic factors—Real Gross Domestic Product (RGDP), Non-Oil Bulk Transportation (NOT), Dry Bulk Transportation (DBT), and the Unemployment Rate (UR)—within Nigeria's maritime and transport industry using time-series econometric methods. The investigation commenced with time series visualisations, which showed that all variables exhibited non-stationary patterns characterised by continuous trends, cycles, and structural changes—particularly notable in RGDP and NOT. This finding was supported by unit root tests indicating that all variables were integrated of order one (I (1). Therefore, first differencing the variables was necessary to achieve stationarity, a crucial requirement for VAR modelling. Descriptive statistics displayed a variety of distribution characteristics. While DBT appeared to follow a normal distribution, both NOT and UR notably deviated from normality, suggesting skewness, heavy tails, or outliers. This highlights the significance of employing robust estimation methods when working with such variables. Johansen's cointegration tests found no evidence of a long-term equilibrium relationship among the four factors. This outcome implies that, despite short-term movements in maritime transportation and macroeconomic indicators, they do not align over the longer term—potentially due to regulatory challenges, inconsistent policies, and infrastructural limitations within Nigeria’s transportation system.

Still, the short-term dynamics uncovered by the Vector Autoregressive (VAR) model, Granger causality analyses, and variance breakdown showed substantial significance. The VAR findings indicated that DBT has a positive effect on RGDP in the short run, thereby reinforcing the theory that maritime transport activities can enhance economic performance. Granger causality assessments demonstrated a one-way causal relationship from RGDP to NOT, as well as from DBT to NOT, indicating sector-specific spillover effects. Nevertheless, the variance decomposition suggested an increasing, albeit unstable, impact of transportation variables on RGDP over time—raising concerns about the reliability of long-term predictions. The presence of such volatility emphasises the necessity for careful interpretation of long-term forecasts and potentially reassessing the integration characteristics of the data. This study provides strong evidence of short-term interdependence between macroeconomic outcomes and transportation dynamics in Nigeria, but it does not find long-term cointegration. These findings highlight the need for immediate planning, responsive infrastructure investments, and flexible economic policies to enhance the relationship between transport and growth in Nigeria.

5.1. Recommendations

- Given that the research indicates a lack of long-term cointegration among the variables, economic planning and transport infrastructure investment need to prioritise adaptable, short-term approaches that can address the current dynamics of the economy and transport sector.
- Given the notable short-term effects of dry bulk transport on RGDP and the established causal link between GDP and non-oil transport, policies must focus on strengthening the interaction between transportation and overall economic growth. This might involve enhancing cargo-handling processes, developing logistics technologies, and aligning port expansion with the country's economic strategies.
- The VAR analysis revealed that dry bulk transportation has a substantial short-term effect on RGDP. Consequently, prioritising dry bulk transport infrastructure, including port facilities, freight handling systems, and connections between different transport modes, is crucial for boosting economic activity.
- The one-way causality from RGDP to NOT suggests that the overall economic performance influences the demand for transport services. Hence, transport policies should be formulated in tandem with economic growth projections to ensure that infrastructure capabilities will adequately meet upcoming demand.
- The lack of long-term equilibrium relationships may result from structural inefficiencies, such as insufficient regulatory frameworks, neglect of infrastructure maintenance, or poor connectivity between transport modes. To overcome these challenges, specific reforms in governance, the investment environment, and public-private partnerships are essential.

Acknowledgment: The author acknowledges that this work was completed independently without external assistance.

Data Availability Statement: The data for this study can be made available upon request to the corresponding author.

Funding Statement: This manuscript and research paper were prepared without any financial support or funding.

Conflicts of Interest Statement: The author has no conflicts of interest to declare. This work represents an original contribution by the author, and all citations and references have been appropriately included based on the sources utilized.

Ethics and Consent Statement: This research adheres to ethical guidelines, obtaining informed consent from all participants.

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