

The Long run and short run impact of GDP and Real Income on Solid Waste in Nigeria using Vector Error Correction Model

Abstract

This study investigates the long-run and short-run impacts of economic growth on solid waste generation in Nigeria using a Vector Error Correction Model (VECM). Analyzing data from 1982 to 2022, the study reveals cointegration among solid waste, GDP, and real income, indicating a long-run equilibrium relationship. Key findings show that economic growth has a statistically significant and positive impact on waste generation in the long run, indicating a potential environmental trade-off associated with economic development. Conversely, resource intensity shows no significant long-run influence on waste generation. In the short run, past waste generation exhibits a positive and significant effect on current levels, highlighting the need for effective waste management practices to combat inertia and prevent further waste accumulation. Interestingly, the short-run impacts of both economic growth and resource intensity are found to be statistically insignificant. Based on these findings, we propose several policy recommendations for sustainable waste management in Nigeria: promoting environmentally friendly production processes, supporting resource recovery and waste-to-energy initiatives, implementing extended producer responsibility, expanding and improving waste collection infrastructure, investing in sorting and recycling facilities, and conducting public awareness campaigns. We further call for further research to explore the nuanced relationship between resource intensity and waste generation across different income groups and sectors.

Keywords: *Solid waste management, Economic growth, Sustainable development, Vector Error Correction Model (VECM), Cointegration analysis, Environmental Kuznets Curve (EKC) hypothesis*

1.0 Introduction

The world is drowning in waste. World Bank estimates show a staggering 2.24 billion tonnes of solid waste generated in 2022, with a projected 73% increase by 2050 (World Bank, 2022). This global avalanche is particularly acute in developing countries like Nigeria, where rapid economic growth and rising incomes strain existing waste management infrastructure. Studies (Al-Khatib et al., 2015; World Bank, 2022) have shown that overburdened waste systems struggle to cope with Nigeria's ballooning waste stream. Overflowing landfills, open dumps, and inadequate collection services threaten environmental and public health, contaminating water and soil, polluting the air, and breeding disease vectors.

Organic waste with high moisture content dominates Nigeria's waste profile. From 17 million tonnes in 2000, the country's annual waste generation has doubled to over 32 million tonnes

in 2020 (World Bank, 2022). Urban areas, especially Lagos, are major contributors, with Nigeria averaging 0.51 kilograms per capita per day (World Bank, 2022). Worryingly, the nature of waste is shifting. Synthetic waste with complex compounds, particularly plastics, glass, and hazardous materials, is rising (Karbassi and Heidari, 2015). Nigeria ranks among the top 20 contributors to land-based plastic waste polluting the oceans (UNIDO, 2022).

The **lack** of a national waste management strategy exacerbates the crisis. Over 200,000 tonnes of Nigerian plastic end up in the Atlantic annually, while over 172.7 million Nigerians live in unclean environments (Aina and Adeola, 2020). This escalating waste generation raises public health concerns and begs the question: why? Studies (Al-Khatib et al., 2015; Xiao et al., 2023) attribute the surge to diverse factors, including rapid population growth, urbanization, and changing consumption patterns. Other empirical works (Guerrero et al., 2013; Lumbreras and Fernández, 2014; Nathanson, 2015) suggest a link between income and waste. As economies expand, production, consumption, and employment rise, generating more waste. Medina (2022) further highlights a positive correlation between income and waste generation, with wealthier individuals consuming and discarding more. Income and household size emerge as key factors influencing household waste generation (Richardson and Havlicek, 1974; Lumbreras and Fernández, 2014; Nathanson, 2015). Visvanathan and Trankler (2013) observed higher daily waste generation rates in families with higher socioeconomic status.

Urbanization, population growth, income increases, and economic growth, while positive indicators of progress, exacerbate waste challenges (Ramachandra et al., 2018; World Bank, 2022). These factors influence lifestyles, preferences, and the volume and nature of both industrial and domestic waste. In view of the above and given the negative environmental impacts of waste, a deeper understanding of the relationship between economic growth (proxied by GDP and real income) and solid waste generation in Nigeria is crucial. Waste reflects environmental health, while GDP measures economic well-being. This link can reveal the ecological consequences of economic growth and inform better environmental and waste management policies. Ultimately, investigating this relationship can contribute to sustainable development goals and predict future economic and ecological trends in Nigeria and beyond.

Comment [U1]: Suggestion;; replace lack with inadequate, poor, or insufficient

The remaining part of the paper is structured into four sections. The second section reviews related literature. These include theoretical and empirical literatures. The third section focuses on the methodology used in the study while data presentation and discussion are contained in the fourth section. The final section concludes and provides some recommendations.

2.0 Review of Related Literature

There is no universally agreed-upon definition of solid waste, as it can be perceived from various perspectives. Its multifaceted and subjective nature leads to diverse interpretations, ranging from the engineer's viewpoint of "materials discarded from residential and commercial sources" (Williams, 2005) to the anthropologist's conceptualization as "factual evidence of a culture" (Rathje, 1992). Despite these differences, a common thread in the literature is that solid waste encompasses discards from residences, businesses, and construction that are not in a liquid or gaseous state. The central tenet is that it is material no longer desired or considered valuable by the owner, often posing significant environmental and public health concerns if not managed properly.

Waste generation patterns exhibit complex relationships with socioeconomic factors. Studies like that by Dikole and Letshwenyo (2020) reveal income-based discrepancies, with wealthier households generating less weekday waste. However, as exemplified by Wang and Qiu's (2013) research in China, the link between income and waste can be non-linear, with rising rural incomes initially increasing waste before promoting sustainable practices. Food waste, further complicating the picture, intertwines with income and consumption patterns (Cusano, 2016; Sarica et al., 2020), emphasizing the need for multifaceted analysis. In this regard, a number of theoretical and empirical studies have been developed to analyse the drivers and impact of solid waste over the years. The first of such work which also provide the theoretical foundation to this paper is the Environmental Kuznets Curve (EKC), initially proposed by Simon Kuznets in the 1950s but later presented by Gene Grossman and Alan Krueger in their seminal 1991 work, "Environmental Impacts of a North American Free Trade Agreement," published in the *Quarterly Journal of Economics*. As income and environmental awareness rise, a transition towards sustainable waste management practices may occur. The EKC theory, despite criticisms oversimplification and pollutant-specificity, offers valuable context for Nigeria's waste management challenges.

Since EKC's time, other studies in Bangladesh, Pakistan, MENA region, and OECD countries have provided empirical support to the the positive long-term impact of economic

growth on solid waste generation. For instance, Nilanthi et al. (2007) investigated the factors influencing solid waste generation and composition in a Sri Lankan suburban area. Utilizing a comprehensive database and a stratified random sampling approach, the study found correlations between waste generation, composition, and socio-economic factors. In a related study, Alajmi (2016) explored the relationship between economic growth and municipal solid waste (MSW) generation in Saudi Arabia. By employing two models, Alajmi identified a turning point where economic growth initially leads to increased MSW generation. The study advocates for new policies and technologies to reduce MSW generation and emphasizes the need for sustainable development.

Grover and Singh (2014) delved into the connection between residential solid waste generation, family size, and income in Dehradun city. The findings highlighted correlations between income, family size, and specific types of waste generation, offering insights into the socio-economic factors influencing waste patterns at the household level. Adzawla et al. (2019) shifted the focus to Ghana, investigating the impact of socio-economic factors on households' choices in solid waste disposal systems. Using Ghana Living Standard Survey data, the study emphasized the crucial role of education and housing characteristics in shaping waste management decisions, providing valuable insights for waste management policies.

Noufal et al. (2020) contributed to the literature by assessing the generation and composition of household solid waste in Homs city, Syria. The study identified the dominant role of organic waste and established correlations with income, household size, and age, enhancing our understanding of the factors influencing waste characteristics. Aina and Ademola (2020) conducted a study in Nigeria evaluating solid waste management techniques in selected markets in Ibadan. Their research revealed inadequacies in waste management practices in both Aleshinloye and Bodija markets, emphasizing the need for awareness campaigns, collaboration between governments and environmental agencies, and the adoption of an urban renewal strategy.

Otumawu-Apreku (2020) investigated the solid waste management issue in Honiara. The study aimed to understand the attitudinal and behavioral challenges, as well as the social and economic costs associated with poor waste management. Descriptive statistics and multivariate regression were employed to analyze the data and draw meaningful conclusions. The findings revealed that poor waste management in developing nations stems from various challenges such as inefficient waste collection methods, inadequate equipment and resources, lack of awareness and education, among others. In the case of the Solomon Islands, limited

awareness, insufficient scientific information for policymaking, lack of cooperation, and poor attitudes at the household and private business levels were identified as significant contributing factors. The research stressed the need for frequent and effective information dissemination to enhance awareness among the population.

Yee et al. (2021) explored the relationship between socio-economic factors and waste generation in the EU-27 countries. The study identified a partial rebound effect, indicating that increased circular material usage was counteracted by factors such as population growth. The researchers developed a predictive model with a lower mean absolute percentage error to enhance waste generation predictions.

Magazzino and Falcone (2022) assessed the relationship between waste generation, wealth, and greenhouse gas emissions in Switzerland. Their study revealed significant impacts of municipal waste and economic growth on GHG emissions, emphasizing the need for sustainable policies. Policy scenario simulations indicated the effectiveness of mission-oriented policy approaches in achieving sustainable outcomes.

Nguyen et al. (2020) conducted a comprehensive study in Taiwan, revealing the influence of socioeconomic factors on municipal solid waste (MSW) composition. The research highlighted safety concerns, economic activities, and lifestyle as primary factors affecting MSW. The study emphasized the role of consumer behavior modification in effective MSW management. Xiao et al. (2023) conducted a study analyzing the interconnections between globalization, green finance, green growth, and carbon dioxide emissions in G7 economies. Their findings indicated a complex relationship between these variables, emphasizing the impact of income growth, globalization, and the potential of green finance and green growth in mitigating carbon dioxide emissions.

In summary, the EKC lays the theoretical foundation for this paper, proposing an inverted U-shaped relationship between economic development and environmental degradation. This provides valuable context for understanding Nigeria's waste management challenges and recognizing the impact of economic growth on waste generation. Overall, the reviewed empirical studies collectively demonstrate the positive long-term impact of economic growth on solid waste generation, offering empirical support for or against the EKC hypothesis in the Nigerian context.

3.0 Methodology

The study utilizes a Vector Error Correction Model (VECM) to comprehensively analyze the long-run and short-run dynamics of the relationship between Gross Domestic Product (GDP),

real income, and solid waste generation in Nigeria. The VECM framework is particularly appropriate in this context due to the presence of non-stationary time series data (Adenomon, et al., 2017), as indicated by unit root tests, and the theoretical underpinnings of the Environmental Kuznets Curve (EKC) hypothesis, which suggests a potential long-run equilibrium relationship between economic growth and environmental degradation. By employing VECM, we are able to capture both the short-run adjustments and the long-run tendencies towards equilibrium within the system, offering a more nuanced understanding of the complex interplay between economic factors and waste generation patterns. This approach provides valuable insights for policymakers and waste management stakeholders in addressing the challenges of sustainable waste management in Nigeria.

Unit Root Test (Stationarity Test)

This study employed the Augmented Dickey-Fuller (ADF) test for stationarity proposed by Dickey and Fuller in 1981, this test aims to determine whether a specific time series variable exhibits stationarity with the following hypothesis:

$H_0: \theta = 0$ i.e., the time series is non-stationary and need to be differenced (has a unit root)

$H_1: \theta < 0$ i.e., the time series is stationary (has no unit root)

The ADF test is expressed by the following ordinary least square (OLS) relationship:

$$\Delta y_t = \alpha_0 + \beta_t + \theta y_{t-1} + \sum_{i=1}^p \delta_i \Delta y_{t-1} + \varepsilon_t \quad (1)$$

Where: Y_t : The time series variable being tested for a unit root (LNSW, LNGDP, and LNRI), ΔY_t : The first difference of Y_t ($Y_t - Y_{t-1}$), α : The intercept term, β : The coefficient on the time trend (t), γ : The coefficient on the lagged value of Y (Y_{t-1}). This is the key parameter for testing the unit root hypothesis, $\delta_1, \dots, \delta_{p-1}$: Coefficients on lagged differences of Y_t , used to control for serial correlation, ε_t : The error term.

If the null hypothesis rejected at level (without differencing), then the order of the stationary series is designated as $I(0)$ whereas if the null hypothesis rejected at first difference then the order of the stationary series is designated as $I(1)$. Similarly, for second difference the order of the stationary series is designated as $I(2)$.

Test for Cointegration

If the time series are non-stationary at level and when the variables are integrated of same order, the Johansen test of cointegration developed by Johansen and Juselius (1990) can be

applied to obtain the number of cointegrating vector(s). Johansen-Juselius (1990) multivariate cointegration model can be expressed as:

$$\Delta y_t = \alpha_0 + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-1} + \varepsilon_t \quad (2)$$

where, Π and Γ_i are the coefficient matrices, Δ is the symbol of difference operator and p is the lag order selected based on Schwarz Bayesian Criterion (SBC). Johansen-Juselius (1990) techniques use two likelihood ratio test statistics to obtain the number of cointegrating vector(s) namely, the Trace test and the Maximum Eigenvalue test which can be computed respectively as:

$$T(r) = -T \sum_{i=r+1}^n \ln(1 - \hat{\lambda}_i) \quad (3)$$

$$\lambda_{max}(r, r+1) = -T \ln(1 - \hat{\lambda}_{i+1}) \quad (4)$$

where, $\hat{\lambda}_i$ is the expected eigenvalue of the characteristic roots and T is the sample size. The null hypothesis of the Trace test (equation 3) investigates the number of r cointegrating vectors against the alternative of n cointegrating vectors. The null hypothesis of the Maximum Eigenvalue test (equation 4) investigates the number of r cointegrating vectors against the alternative of $r+1$ cointegrating vectors. So, if the variables are found to be cointegrated after applying Johansen-Juselius test then it can be concluded that there exists long-run equilibrium relationship between the variables. Further, that long-run equilibrium relationship can be examined by applying VECM scheme.

Vector Error Correction Model

The Vector Error Correction Model (VECM) is a powerful analytical tool that captures the dynamics of adjustment from short-run deviations to long-run equilibrium. By incorporating the error correction term, the VECM allows for the modeling of both short-term dynamics and the long-term relationship among variables. While the Autoregressive Distributed Lag (ARDL) model is an alternate model for VECM (Adenomon&Ojo, 2020).

The inclusion of the error correction term in each equation of the VAR accounts for the disequilibrium between variables in the short run, allowing for the analysis of the adjustments that occur in response to any deviations from the long-run equilibrium.

Theoretically, the VAR model is specified thus:

Let $Y_t = (y_{1t}, y_{2t}, \dots, y_{nt})'$ denote an $(n \times 1)$ vector of time series variables.

The basic p -lag vector autoregressive (VAR(p)) model has the form

$$Y_t = c + \pi_1 Y_{t-1} + \pi_2 Y_{t-2} + \dots + \pi_p Y_{t-p} + \epsilon_t, t = 1, \dots, T \quad (5)$$

Where π_i are $(n \times n)$ coefficient matrix and ϵ_t is an $(n \times 1)$ unobservable zero mean white noise vector process (serially uncorrelated or independent) with time invariant covariance matrix Σ . A bivariate VAR (2) model equation by equation has the form:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} \pi_{11}^1 & \pi_{12}^1 \\ \pi_{21}^1 & \pi_{22}^1 \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} \pi_{11}^2 & \pi_{12}^2 \\ \pi_{21}^2 & \pi_{22}^2 \end{pmatrix} \begin{pmatrix} y_{1t-2} \\ y_{2t-2} \end{pmatrix} + \begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{pmatrix} \quad (6)$$

where $\text{cov}(\epsilon_{1t}, \epsilon_{2t}) = \sigma_{12}$ for $t = s$; 0 otherwise.

From the above, it can be observed that each equation has the same regressors — lagged values of y_{1t} and y_{2t} . Hence, the VAR(p) model is just a seemingly unrelated regression (SUR) model with lagged variables and deterministic terms as common regressors.

In lag operator notation, the VAR(p) is written as:

$$\pi(L)y_t = c + \epsilon_t$$

where $\pi(L) = I_n - \pi_1 L - \dots - \pi_p L^p$.

The VAR(p) is stable if the roots of $\det(I_n - \pi_1 z - \dots - \pi_p z^p) = 0$

The mean-adjusted form of the VAR(p) is then

$$y_{t-\mu} = \Pi_1(y_{t-1-\mu}) + \Pi_2(y_{t-2-\mu}) + \dots + \Pi_p(y_{t-p-\mu}) + \epsilon_t \quad (7)$$

Using the variables for this study, an appropriate VECM model can be formulated as follows

$$\Delta y_t = \alpha \beta' y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-1} + \epsilon_t \quad (8)$$

where:

Δ : Operator differencing, $\Delta y_t = y_t - y_{t-1} - y_{t-i}$: Vector variable endogenous with the 1st lag, ϵ_t : Vector residual, Γ_i : Matrix with order $k \times k$ of coefficient Endogenous of the i -th variable, α : Vector adjustment, matrix with order $(k \times r)$, β : Vector cointegration (long-run parameter) matrix $(k \times r)$

Equation 8 is modified and presented in endogenous variables with Solid Waste (SW) as the dependent variable, explained by economic growth proxied by GDP and Real Income (RI) as stated below:

$$\Delta(SW) = a_0 + a_1SW\phi_{t-1} + \sum_{i=1}^{q_1} a_{2i} \Delta(SW_{t-i}) + \sum_{i=1}^{r_1} \psi_{1i} \Delta(GDP_{t-i}) + \sum_{i=1}^{z_1} \gamma_{1i} \Delta(RI_{t-i}) + \varepsilon_{1t}$$

(9)

Where a_0 is the intercept term, representing the constant or baseline level of Solid Waste Generation when all other variables are zero and $a_1SW\phi_{t-1}$ is the Error correction coefficient, quantifying the speed of adjustment towards equilibrium. Both parameters would be estimated using a seemingly unrelated regressions (SUR) estimation technique. SW, GDP and RI are as previously defined. Δ is operator differencing, and ε_{1t} represents Vector residual.

4.0 Results and Discussion

In this section, we examine the longrun and shortrun correlates of Solid Waste and economic growth, represented by GDP and Real Income (RI) in Nigeria. To provide a contextual foundation for the utilized data, the study conducts a thorough descriptive analysis, as presented below.

4.1 Descriptive Analysis

Table 1: Descriptive statistics of Original Data

	SW	GDP	RI
Mean	2.05E+10	42483.24	39054.13
Median	2.05E+10	11501.45	30745.19
Maximum	4.29E+10	202365.0	74639.47
Minimum	1.31E+08	149.0512	16048.31
Std. Dev.	1.29E+10	56239.14	20892.27
Skewness	0.031876	1.303716	0.489316
Kurtosis	1.798150	3.612143	1.604865
Jarque-Bera	2.474534	12.25459	4.961207
Probability	0.290176	0.002182	0.083693
Sum	8.42E+11	1741813.	1601219.
Sum Sq. Dev.	6.64E+21	1.27E+11	1.75E+10
Observations	41	41	41

Source: Author's computation using Eviews

Table 1 above presents the Descriptive statistics of Nigerian solid waste (SW), Gross Domestic Product (GDP), and Real Income (RI) for the period 1982 to 2022. An analysis of the results in the table reveals intriguing characteristics. The table shows that between 1982 and 2022, Nigeria's SW, GDP, and RI averaged 2.05E+10 tonnes, N 42483.24 million, and N39054.13 million, respectively. The maximum values of 4.29E+10 tonnes, N202365.0 million, and N74639.47 million were all recorded in 2022. Interestingly, positive skewness in GDP and RI hints at right-skewed distributions, with observations clustering towards lower

values. The Jarque-Bera tests suggest normality within a 5% significance level for all the variables except GDP.

4.2 Econometrics Analysis

Building upon the insights gleaned from the descriptive analysis, this subsection (4.2) delves deeper into the relationship between solid waste (SW) and economic growth in Nigeria, represented by GDP and Real Income (RI). Employing the Vector Error Correction Model (VECM), the paper quantifies the long-run and short-run impacts of economic growth on SW generation. To start with, the study performed a cointegration test to determine whether the variables under study share a common stochastic trend. Cointegration is a statistical method that examines the long-run relationship between two or more non-stationary time series. To identify cointegration, two procedures were considered: the Johansen procedure and the Engle Granger single cointegration. The selection of the appropriate cointegration procedure depends on the results of the unit root test, which confirms the stationarity of the variables in first differences. In this study, the Johansen test was adopted as it meets the preconditions of the variables being non-stationary at the level and stationary in first differences, and having the same order of integration. To confirm the order of integration, we employed the Augmented Dickey Fuller (ADF) test to investigate the time series properties of the variables. The results of the ADF test are presented in Table 2

Table.2: Stationarity Test

Variable	ADF Statistics (Levels)	P-value (Levels)	ADF Statistics (at 1 st Difference)	P-Value (at 1 st Difference)
SW	-2.800185	0.0682	-4.612798	0.0007
GDP	-2.620369	0.0985	-3.526377	0.0124
RI	-0.547394	0.8702	-5.351576	0.0001

Source: Author's estimation using Eviews 10

The findings revealed in Table.2 indicate that all the variables under study exhibit non-stationarity at the level of observation. Nevertheless, after being subjected to a transformation into first difference, these variables were found to be stationary, indicating integration at order one. This result further supports the suitability of a VECM to analyze the dynamic relationships between SW, GDP, and RI, as VECM accommodates variables integrated of the same order. In light of this outcome, the subsequent step involves the estimation of long-run

cointegration through the employment of the Johansen procedure. The outcomes of the Johansen test are elaborated in Table 3.

Table 3: Johansen Cointegration Test

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.991798	205.2664	29.79707	0.0001
At most 1 *	0.278571	17.93658	15.49471	0.0210
At most 2 *	0.124877	5.202252	3.841466	0.0226

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 *	0.991798	187.3298	21.13162	0.0001
At most 1 *	0.278571	12.73433	14.26460	0.0860
At most 2 *	0.124877	5.202252	3.841466	0.0226

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

The Johansen Cointegration Test presented in Table.3 reveals strong evidence of cointegration among Solid Waste (SW), GDP, and Real Income (RI) as evidenced by the Trace Test which identifies three cointegrating equations at the 5% significance level, and Maximum Eigenvalue Test, which detects one cointegrating equation. Overall, the presence of cointegration, as supported by both tests, implies that SW, GDP, and RI move together in the long run, even if they may deviate from this relationship in the short run. This aligns with the theoretical framework of the EKC hypothesis and supports the use of a Vector Error Correction Model (VECM) to explore the short-run dynamics and long-run adjustments among these variables.

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Table 4A: Estimated Results of VECM showing Longrun impacts of GDP and Real Income on Solid Waste

Variable	Coefficient	Standard Error	t-Statistic	Significance	Impact
LONG-RUN					
LNGDP(-1)	0.1764	0.0224	7.8621	1%	Positive

LNRI(-1)	0.052	0.0905	0.5743	Not significant	Inconclusive
C	-21.35269				
Estimated Longrun Equation: $LNSW(-1) = 21.35269 + 0.176384LNGDP(-1)^* + 0.051959LNRI(-1)$					

Table 4B: Estimated Results of VECM showing Shortrun impacts of GDP and Real Income on Solid Waste

	Coefficient	Std. Error	t-Statistic	Prob.
ECT _{t-1} (C(1))	-0.146427	0.014264	-10.26582	0.0000
LNSW(-1) (C(2))	0.195736	0.025314	7.732410	0.0000
LNSW(-2) (C(3))	0.005231	0.006374	0.820608	0.4140
LNGDP(-1) (C(4))	-0.022432	0.019572	-1.146149	0.2548
LNGDP(-2) (C(5))	0.003454	0.018369	0.188029	0.8513
LNRI(-1) (C(6))	-0.041194	0.051087	-0.806351	0.4222
LNRI(-2) (C(7))	-0.013533	0.053322	-0.253797	0.8002
Constant (C(8))	0.075643	0.007605	9.946155	0.0000

Estimated Short-run Equation: $D(LNSW) = 0.076 + 0.196D(LNSW(-1)) + 0.0052D(LNSW(-2)) - 0.022D(LNGDP(-1)) + 0.0035D(LNGDP(-2)) - 0.041D(LNRI(-1)) - 0.014D(LNRI(-2)) - 0.146ECM_{t-1} + E_t$

R-squared	0.995497	Mean dependent var	0.100197
Adjusted R-squared	0.994447	S.D. dependent var	0.137661
S.E. of regression	0.010258	Sum squared resid	0.003157
Durbin-Watson stat	2.358862		

Source: Extracted from VECM Results (see appendix)

Table.4 above shows the Longrun and Shortrunimpacts of GDP and Real Income on Solid Waste in Nigeria.

Long-Run Impacts

As shown in the Table, the cointegrating equation reveals a statistically significant positive coefficient for LNGDP(-1), implying that a 1% increase in GDP in the long run leads to an increase in SW generation by 0.1764%. However, the coefficient for LNRI(-1) is not statistically significant, indicating that Real Income may not have a substantial long-run impact on SW generation in the Nigerian context. The positive and significant relationship between long-run GDP growth and solid waste generation is concerning. It suggests that economic development in Nigeria might come at the cost of increased environmental burden. This highlights the need for sustainable development strategies that decouple economic growth from waste generation. The inconclusive impact of real income on waste generation is intriguing. While one might expect rising incomes to lead to more consumption and waste,

the lack of a statistically significant effect suggests that other factors might be at play. Disaggregated data analysis could shed light on this by examining different income groups and their waste generation patterns.

Short-Run Impacts

As shown in the Table, the Error Correction Term (ECT_{t-1}) is 14.64% which means that the corrects to its long-term equilibrium at the previous year at the speed of 14.64% ($P < 0.05$). The lagged value of solid waste generation (LNSW) at lag 1 has a positive and statistically significant impact on current solid waste generation ($P < 0.05$), suggesting persistence of waste generation. Solid Waste Generation at lag 2 is positively related to the current solid waste generation, though not statistically significant ($P > 0.05$). The table further shows that the short-run impacts of GDP and real income are not significant ($P > 0.05$).

Diagnostic Tests

For the validity of the study findings, a number of diagnostic tests were carried out. For Serial Correlation, the p-values for both the LRE and Rao F-statistics are high (greater than 0.05) for both lags 1 and 2. This indicates that we accept the null hypothesis of no serial correlation in the residuals. The Jarque-Bera test rejects the null hypothesis of normality for the residuals of component 2 and jointly for all components. The skewness and kurtosis tests also show some evidence of non-normality in the residuals of component 2. Nevertheless, minor deviations from normality are often not a major concern, especially if the sample size is relatively large. The joint test for heteroskedasticity has a p-value of 0.5727, which is high. This suggests that we accept the null hypothesis of no heteroskedasticity in the residuals. The model imposes 2 unit roots, and all other roots have moduli less than 1, suggesting that the model is stable and does not exhibit explosive behavior. Overall, the diagnostics tests suggest that the VECM is reasonably well-specified. There is no evidence of serial correlation or heteroskedasticity in the residuals, and the model is stable.

5.0 Conclusion and Policy Implication

This study employed a Vector Error Correction Model (VECM) framework to analyze the long-run and short-run impacts of economic growth on waste generation in Nigeria. The findings revealed that GDP has a statistically significant and positive impact on waste

generation in the long run, implying that economic growth may lead to increased environmental burden. However, the impact of Resource Intensity (RI) on waste generation is insignificant. In the short run, past waste generation exhibits a positive and statistically significant influence on current levels, indicating a degree of inertia in the system. Effective waste management practices are crucial to address existing challenges and prevent further waste accumulation. Short-run impacts of GDP and RI on waste generation were found to be insignificant.

Based on these findings, several policy recommendations are made:

- i. Stakeholders in Nigeria should promote and incentivize the adoption of environmentally friendly production processes that minimize waste generation.
- ii. Support initiatives that encourage resource recovery, recycling, and waste-to-energy conversion.
- iii. Implement extended producer responsibility, holding manufacturers accountable for the end-of-life management of their products, encouraging design for recyclability and reduced waste.
- iv. Increase coverage and efficiency of waste collection services, particularly in underserved areas.
- v. Develop and upgrade infrastructure for sorting, composting, and recycling waste streams.
- vi. Conduct educational campaigns to encourage waste reduction, reuse, and responsible waste disposal practices.
- vii. Explore the relationship between RI and waste generation across different income groups and sectors to gain a more nuanced understanding.

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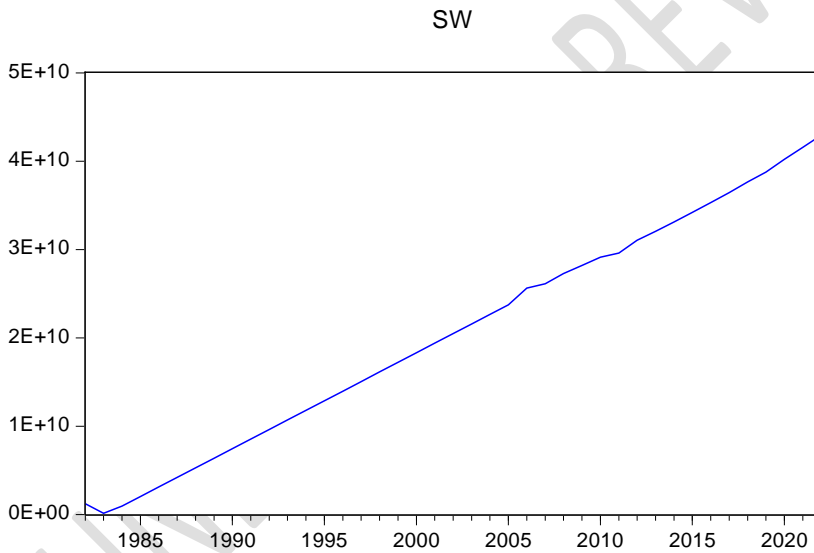
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UNDER PEER REVIEW

Appendix

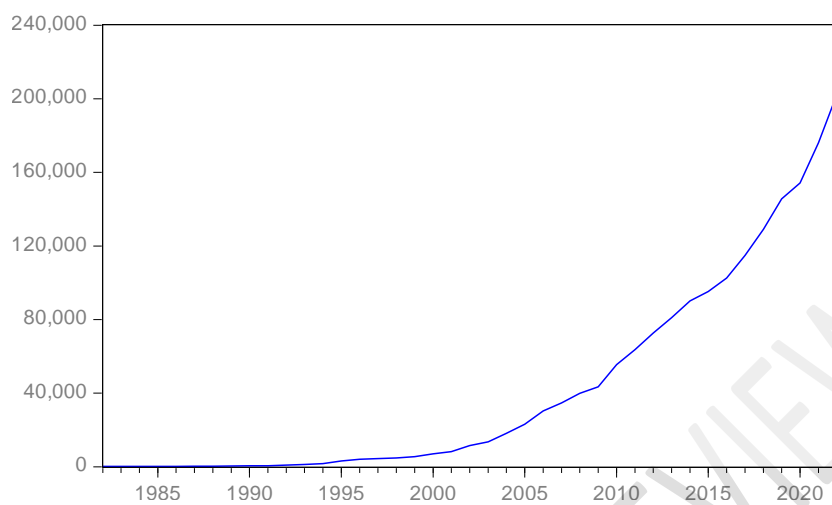
List 1 :Descriptive statistics of Original Data

	SW	GDP	RI
Mean	2.05E+10	42483.24	39054.13
Median	2.05E+10	11501.45	30745.19
Maximum	4.29E+10	202365.0	74639.47
Minimum	1.31E+08	149.0512	16048.31
Std. Dev.	1.29E+10	56239.14	20892.27
Skewness	0.031876	1.303716	0.489316
Kurtosis	1.798150	3.612143	1.604865
Jarque-Bera	2.474534	12.25459	4.961207
Probability	0.290176	0.002182	0.083693
Sum	8.42E+11	1741813.	1601219.
Sum Sq. Dev.	6.64E+21	1.27E+11	1.75E+10
Observations	41	41	41

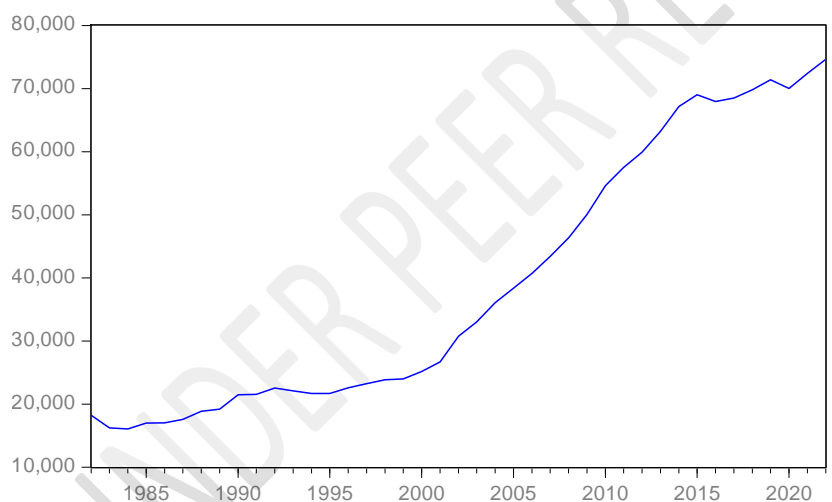


Picture 1 :Graphical presentation showing year wise variation

GDP



RI

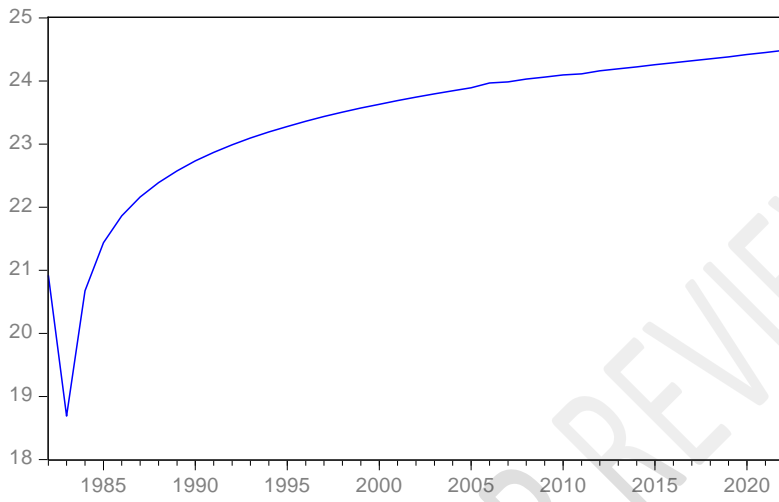


Descriptive statistics of transform Data

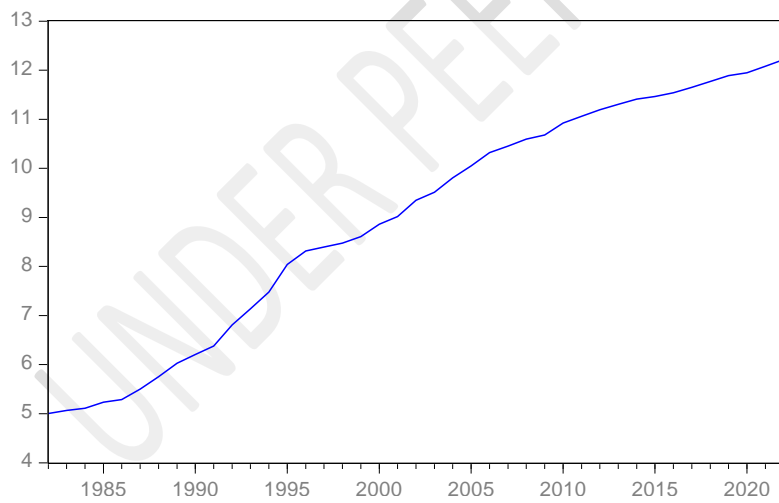
	LNSW	LNGDP	LNRI
Mean	23.34339	8.973736	10.43019
Median	23.74225	9.350228	10.33349
Maximum	24.48321	12.21783	11.22042
Minimum	18.68830	5.004290	9.683359
Std. Dev.	1.214078	2.412751	0.541992
Skewness	-1.902734	-0.329490	0.181810
Kurtosis	6.942576	1.702199	1.453006
Jarque-Bera Probability	51.29354 0.000000	3.619177 0.163721	4.314239 0.115658

Sum	957.0790	367.9232	427.6376
Sum Sq. Dev.	58.95943	232.8546	11.75022
Observations	41	41	41

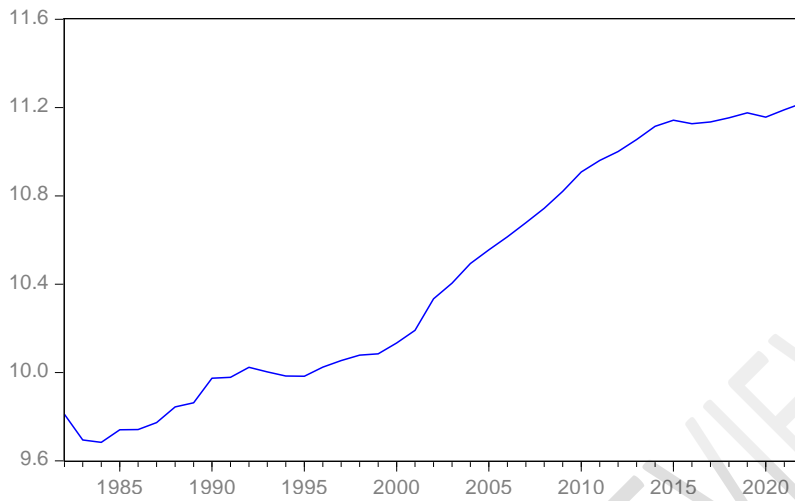
LNSW



LNGDP



LNRI



Null Hypothesis: LNSW has a unit root
 Exogenous: Constant
 Lag Length: 4 (Automatic - based on AIC, maxlag=9)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-2.800185	0.0682
Test critical values:		
1% level	-3.626784	
5% level	-2.945842	
10% level	-2.611531	

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

Null Hypothesis: D(LNSW) has a unit root
 Exogenous: Constant
 Lag Length: 3 (Automatic - based on AIC, maxlag=9)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-4.612798	0.0007
Test critical values:		
1% level	-3.626784	
5% level	-2.945842	
10% level	-2.611531	

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

Null Hypothesis: LNGDP has a unit root
 Exogenous: Constant
 Lag Length: 5 (Automatic - based on AIC, maxlag=9)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-2.620369	0.0985
Test critical values:		
1% level	-3.632900	
5% level	-2.948404	
10% level	-2.612874	

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

Null Hypothesis: D(LNGDP) has a unit root
 Exogenous: Constant
 Lag Length: 0 (Automatic - based on AIC, maxlag=9)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-3.526377	0.0124
Test critical values: 1% level	-3.610453	
5% level	-2.938987	
10% level	-2.607932	

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

Null Hypothesis: LNRI has a unit root
 Exogenous: Constant
 Lag Length: 3 (Automatic - based on AIC, maxlag=9)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-0.547394	0.8702
Test critical values: 1% level	-3.621023	
5% level	-2.943427	
10% level	-2.610263	

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

Null Hypothesis: D(LNRI) has a unit root
 Exogenous: Constant
 Lag Length: 0 (Automatic - based on AIC, maxlag=9)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-5.351576	0.0001
Test critical values: 1% level	-3.610453	
5% level	-2.938987	
10% level	-2.607932	

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

Cointegration test

Date: 10/23/23 Time: 15:24
 Sample (adjusted): 1984 2022
 Included observations: 39 after adjustments
 Trend assumption: Linear deterministic trend
 Series: LNSW LNGDP LNRI
 Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.991798	205.2664	29.79707	0.0001
At most 1 *	0.278571	17.93658	15.49471	0.0210
At most 2 *	0.124877	5.202252	3.841466	0.0226

Trace test indicates 3 cointegratingeqn(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 *	0.991798	187.3298	21.13162	0.0001
At most 1	0.278571	12.73433	14.26460	0.0860
At most 2 *	0.124877	5.202252	3.841466	0.0226

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

VAR Lag Order Selection Criteria

Endogenous variables: LNSW LNGDP LNRI
 Exogenous variables: C
 Date: 10/23/23 Time: 15:26
 Sample: 1982 2022
 Included observations: 36

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-14.33126	NA	0.000526	0.962848	1.094808	1.008905
1	225.0108	425.4970	1.46e-09	-11.83393	-11.30610*	-11.64970
2	236.9751	19.27580*	1.25e-09	-11.99862	-11.07490	-11.67621*
3	246.8875	14.31782	1.23e-09*	-12.04930*	-10.72970	-11.58873
4	252.9024	7.685698	1.53e-09	-11.88346	-10.16799	-11.28472
5	258.6547	6.391519	2.03e-09	-11.70304	-9.591681	-10.96612

* 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

Vector Error Correction Estimates

Date: 10/23/23 Time: 15:28
 Sample (adjusted): 1985 2022
 Included observations: 38 after adjustments
 Standard errors in () & t-statistics in []

Cointegrating Eq:	CointEq1
LNSW(-1)	1.000000
LNGDP(-1)	-0.176384 (0.02243) [-7.86212]
LNRI(-1)	-0.051959 (0.09047) [-0.57434]
C	-21.35269
Error Correction:	D(LNSW) D(LNGDP) D(LNRI)

CointEq1	-0.146427 (0.01426) [-10.2658]	-0.197196 (0.12862) [-1.53313]	-0.004370 (0.04793) [-0.09118]
D(LNSW(-1))	0.195736 (0.02531) [7.73241]	-0.278019 (0.22827) [-1.21795]	0.016430 (0.08506) [0.19316]
D(LNSW(-2))	0.005231 (0.00637) [0.82061]	-0.077035 (0.05748) [-1.34023]	-0.020200 (0.02142) [-0.94312]
D(LNGDP(-1))	-0.022432 (0.01957) [-1.14615]	0.493871 (0.17649) [2.79830]	0.017592 (0.06577) [0.26749]
D(LNGDP(-2))	0.003454 (0.01837) [0.18803]	-0.028439 (0.16565) [-0.17168]	-0.009760 (0.06173) [-0.15812]
D(LNRI(-1))	-0.041194 (0.05109) [-0.80635]	-1.017047 (0.46068) [-2.20771]	0.237310 (0.17167) [1.38239]
D(LNRI(-2))	-0.013533 (0.05332) [-0.25380]	0.835988 (0.48083) [1.73863]	0.365318 (0.17918) [2.03887]
C	0.075643 (0.00761) [9.94616]	0.160747 (0.06858) [2.34390]	0.016075 (0.02556) [0.62901]
R-squared	0.995497	0.445424	0.277946
Adj. R-squared	0.994447	0.316023	0.109467
Sum sq. resids	0.003157	0.256726	0.035649
S.E. equation	0.010258	0.092507	0.034472
F-statistic	947.5388	3.442199	1.649736
Log likelihood	124.5984	41.02964	78.54122
Akaike AIC	-6.136758	-1.738402	-3.712696
Schwarz SC	-5.792003	-1.393647	-3.367941
Mean dependent	0.100197	0.187019	0.040449
S.D. dependent	0.137661	0.111855	0.036529
Determinant resid covariance (dof adj.)	9.53E-10		
Determinant resid covariance	4.69E-10		
Log likelihood	246.3639		
Akaike information criterion	-11.54547		
Schwarz criterion	-10.38192		
Number of coefficients	27		

VEC Residual Serial Correlation LM Tests

Date: 10/23/23 Time: 15:30

Sample: 1982 2022

Included observations: 38

Null
hypothes
is: No
serial
correlati
on at lag
h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
-----	-----------	----	-------	------------	----	-------

1	4.285540	9	0.8916	0.465629	(9, 61.0)	0.8920
2	7.802084	9	0.5542	0.871505	(9, 61.0)	0.5553

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	4.285540	9	0.8916	0.465629	(9, 61.0)	0.8920
2	12.03117	18	0.8456	0.646193	(18, 62.7)	0.8483

*Edgeworth expansion corrected likelihood ratio statistic.

VEC Residual Normality Tests

Orthogonalization: Cholesky (Lutkepohl)

Null Hypothesis: Residuals are multivariate normal

Date: 10/23/23 Time: 15:31

Sample: 1982 2022

Included observations: 38

Component	Skewness	Chi-sq	df	Prob.*
1	0.157568	0.157241	1	0.6917
2	1.327092	11.15409	1	0.0008
3	0.478997	1.453106	1	0.2280
Joint		12.76444	3	0.0052

Component	Kurtosis	Chi-sq	df	Prob.
1	7.241394	28.48325	1	0.0000
2	5.928010	13.57430	1	0.0002
3	3.847742	1.137888	1	0.2861
Joint		43.19544	3	0.0000

Component	Jarque-Bera	df	Prob.
1	28.64049	2	0.0000
2	24.72839	2	0.0000
3	2.590994	2	0.2738
Joint	55.95988	6	0.0000

*Approximate p-values do not account for coefficient estimation

VEC Residual Heteroskedasticity Tests (Levels and Squares)

Date: 10/23/23 Time: 15:32

Sample: 1982 2022

Included observations: 38

Joint test:

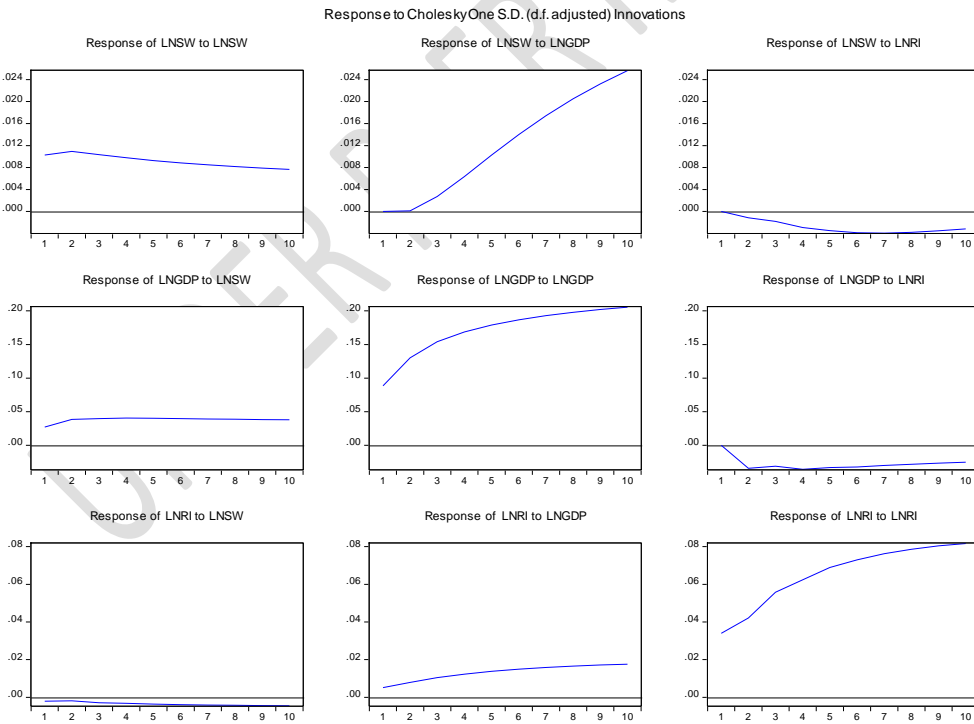
Chi-sq	df	Prob.
80.99213	84	0.5727

Roots of Characteristic Polynomial
 Endogenous variables: LNSW LNGDP
 LNRI

Exogenous variables:
 Lag specification: 1 2
 Date: 10/23/23 Time: 15:33

Root	Modulus
1.000000	1.000000
1.000000	1.000000
0.863641	0.863641
0.733859	0.733859
0.473210	0.473210
-0.452056	0.452056
0.217387	0.217387
-0.010271 - 0.027136i	0.029014
-0.010271 + 0.027136i	0.029014

VEC specification imposes 2 unit root(s).



Variance

Decomposition of LNSW:

Period	S.E.	LNSW	LNGDP	LNRI
1	0.010258	100.0000	0.000000	0.000000
2	0.015030	99.41460	0.007231	0.578168
3	0.018538	96.50064	2.188497	1.310866
4	0.022097	87.49958	9.853979	2.646444
5	0.026299	74.19737	22.17293	3.629700
6	0.031320	60.31066	35.60971	4.079624
7	0.037045	48.36926	47.59937	4.031370
8	0.043292	38.99075	57.29458	3.714677
9	0.049887	31.87954	64.82945	3.291009
10	0.056689	26.52049	70.62221	2.857307

Variance Decomposition of LNGDP:

Period	S.E.	LNSW	LNGDP	LNRI
1	0.092507	8.565694	91.43431	0.000000
2	0.167717	7.887008	87.94064	4.172353
3	0.233251	6.988998	89.06815	3.942855
4	0.292893	6.356920	89.65241	3.990668
5	0.347192	5.861798	90.39313	3.745077
6	0.397515	5.474227	91.01646	3.509311
7	0.444572	5.157137	91.58433	3.258529
8	0.488980	4.893582	92.07803	3.028392
9	0.531151	4.670085	92.51249	2.817420
10	0.571404	4.478322	92.89291	2.628770

Variance Decomposition of LNRI:

Period	S.E.	LNSW	LNGDP	LNRI
1	0.034472	0.342297	2.220314	97.43739
2	0.055034	0.250370	2.974164	96.77547
3	0.079144	0.251227	3.199724	96.54905
4	0.101601	0.249429	3.408932	96.34164
5	0.123580	0.253598	3.549897	96.19651
6	0.144331	0.256842	3.672614	96.07054
7	0.164064	0.260256	3.775096	95.96465
8	0.182720	0.263176	3.865785	95.87104
9	0.200403	0.265809	3.946082	95.78811
10	0.217173	0.268117	4.018365	95.71352

Cholesky Ordering: LNSW LNGDP LNRI

Estimation Proc:

=====
 EC(C,1) 1 2 LNSW LNGDP LNRI

VAR Model:

=====

$$D(LNSW) = A(1,1)*B(1,1)*LNSW(-1) + B(1,2)*LNGDP(-1) + B(1,3)*LNRI(-1) + B(1,4) + C(1,1)*D(LNSW(-1)) + C(1,2)*D(LNSW(-2)) + C(1,3)*D(LNGDP(-1)) + C(1,4)*D(LNGDP(-2)) + C(1,5)*D(LNRI(-1)) + C(1,6)*D(LNRI(-2)) + C(1,7)$$

$$D(\text{LNGDP}) = A(2,1) \cdot B(1,1) \cdot \text{LNSW}(-1) + B(1,2) \cdot \text{LNGDP}(-1) + B(1,3) \cdot \text{LNRI}(-1) + B(1,4) + C(2,1) \cdot D(\text{LNSW}(-1)) + C(2,2) \cdot D(\text{LNSW}(-2)) + C(2,3) \cdot D(\text{LNGDP}(-1)) + C(2,4) \cdot D(\text{LNGDP}(-2)) + C(2,5) \cdot D(\text{LNRI}(-1)) + C(2,6) \cdot D(\text{LNRI}(-2)) + C(2,7)$$

$$D(\text{LNRI}) = A(3,1) \cdot B(1,1) \cdot \text{LNSW}(-1) + B(1,2) \cdot \text{LNGDP}(-1) + B(1,3) \cdot \text{LNRI}(-1) + B(1,4) + C(3,1) \cdot D(\text{LNSW}(-1)) + C(3,2) \cdot D(\text{LNSW}(-2)) + C(3,3) \cdot D(\text{LNGDP}(-1)) + C(3,4) \cdot D(\text{LNGDP}(-2)) + C(3,5) \cdot D(\text{LNRI}(-1)) + C(3,6) \cdot D(\text{LNRI}(-2)) + C(3,7)$$

VAR Model - Substituted Coefficients:

$$D(\text{LNSW}) = -0.146426622566 \cdot (\text{LNSW}(-1) - 0.176383705035 \cdot \text{LNGDP}(-1) - 0.0519588146334 \cdot \text{LNRI}(-1) - 21.3526906648) + 0.195735854797 \cdot D(\text{LNSW}(-1)) + 0.00523060379467 \cdot D(\text{LNSW}(-2)) - 0.0224321143641 \cdot D(\text{LNGDP}(-1)) + 0.00345397569574 \cdot D(\text{LNGDP}(-2)) - 0.0411937566705 \cdot D(\text{LNRI}(-1)) - 0.013532849277 \cdot D(\text{LNRI}(-2)) + 0.0756431387919$$

$$D(\text{LNGDP}) = -0.197195844295 \cdot (\text{LNSW}(-1) - 0.176383705035 \cdot \text{LNGDP}(-1) - 0.0519588146334 \cdot \text{LNRI}(-1) - 21.3526906648) + 0.278018715946 \cdot D(\text{LNSW}(-1)) - 0.0770345410878 \cdot D(\text{LNSW}(-2)) + 0.493870833186 \cdot D(\text{LNGDP}(-1)) - 0.0284385184964 \cdot D(\text{LNGDP}(-2)) - 1.01704682059 \cdot D(\text{LNRI}(-1)) + 0.835988116846 \cdot D(\text{LNRI}(-2)) + 0.160747426418$$

$$D(\text{LNRI}) = -0.00437013247695 \cdot (\text{LNSW}(-1) - 0.176383705035 \cdot \text{LNGDP}(-1) - 0.0519588146334 \cdot \text{LNRI}(-1) - 21.3526906648) + 0.0164300947401 \cdot D(\text{LNSW}(-1)) - 0.0202004123083 \cdot D(\text{LNSW}(-2)) + 0.0175922465765 \cdot D(\text{LNGDP}(-1)) - 0.00976048893583 \cdot D(\text{LNGDP}(-2)) + 0.237309801107 \cdot D(\text{LNRI}(-1)) + 0.365318476197 \cdot D(\text{LNRI}(-2)) + 0.0160748891468$$

System: UNTITLED

Estimation Method: Least Squares

Date: 10/23/23 Time: 15:39

Sample: 1985 2022

Included observations: 38

Total system (balanced) observations 114

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.146427	0.014264	-10.26582	0.0000
C(2)	0.195736	0.025314	7.732410	0.0000
C(3)	0.005231	0.006374	0.820608	0.4140
C(4)	-0.022432	0.019572	-1.146149	0.2548
C(5)	0.003454	0.018369	0.188029	0.8513
C(6)	-0.041194	0.051087	-0.806351	0.4222
C(7)	-0.013533	0.053322	-0.253797	0.8002
C(8)	0.075643	0.007605	9.946155	0.0000
C(9)	-0.197196	0.128623	-1.533135	0.1288
C(10)	-0.278019	0.228269	-1.217945	0.2264
C(11)	-0.077035	0.057479	-1.340227	0.1835
C(12)	0.493871	0.176490	2.798295	0.0063
C(13)	-0.028439	0.165648	-0.171681	0.8641
C(14)	-1.017047	0.460679	-2.207715	0.0298
C(15)	0.835988	0.480832	1.738628	0.0855
C(16)	0.160747	0.068581	2.343899	0.0213
C(17)	-0.004370	0.047930	-0.091178	0.9276
C(18)	0.016430	0.085062	0.193155	0.8473
C(19)	-0.020200	0.021419	-0.943117	0.3481
C(20)	0.017592	0.065767	0.267494	0.7897
C(21)	-0.009760	0.061727	-0.158124	0.8747
C(22)	0.237310	0.171667	1.382388	0.1703
C(23)	0.365318	0.179177	2.038874	0.0444
C(24)	0.016075	0.025556	0.629007	0.5309

Determinant residual covariance 4.69E-10

$$\text{Equation: } D(\text{LNSW}) = C(1) \cdot (\text{LNSW}(-1) - 0.176383705035 \cdot \text{LNGDP}(-1) - 0.0519588146334 \cdot \text{LNRI}(-1) - 21.3526906648) + C(2) \cdot D(\text{LNSW}(-1)) + C(3) \cdot D(\text{LNSW}(-2)) + C(4) \cdot D(\text{LNGDP}(-1)) + C(5) \cdot D(\text{LNGDP}(-2)) + C(6) \cdot D(\text{LNRI}(-1)) + C(7) \cdot D(\text{LNRI}(-2)) + C(8)$$

Observations: 38

R-squared	0.995497	Mean dependent var	0.100197
Adjusted R-squared	0.994447	S.D. dependent var	0.137661
S.E. of regression	0.010258	Sum squared resid	0.003157
Durbin-Watson stat	2.358862		

$$\text{Equation: } D(\text{LNGDP}) = C(9) * (\text{LNSW}(-1) - 0.176383705035 * \text{LNGDP}(-1) - 0.0519588146334 * \text{LNRI}(-1) - 21.3526906648) + C(10) * D(\text{LNSW}(-1)) + C(11) * D(\text{LNSW}(-2)) + C(12) * D(\text{LNGDP}(-1)) + C(13) * D(\text{LNGDP}(-2)) + C(14) * D(\text{LNRI}(-1)) + C(15) * D(\text{LNRI}(-2)) + C(16)$$

Observations: 38

R-squared	0.445424	Mean dependent var	0.187019
Adjusted R-squared	0.316023	S.D. dependent var	0.111855
S.E. of regression	0.092507	Sum squared resid	0.256726
Durbin-Watson stat	2.096964		

$$\text{Equation: } D(\text{LNRI}) = C(17) * (\text{LNSW}(-1) - 0.176383705035 * \text{LNGDP}(-1) - 0.0519588146334 * \text{LNRI}(-1) - 21.3526906648) + C(18) * D(\text{LNSW}(-1)) + C(19) * D(\text{LNSW}(-2)) + C(20) * D(\text{LNGDP}(-1)) + C(21) * D(\text{LNGDP}(-2)) + C(22) * D(\text{LNRI}(-1)) + C(23) * D(\text{LNRI}(-2)) + C(24)$$

Observations: 38

R-squared	0.277946	Mean dependent var	0.040449
Adjusted R-squared	0.109467	S.D. dependent var	0.036529
S.E. of regression	0.034472	Sum squared resid	0.035649
Durbin-Watson stat	1.847947		

UNDER PEER REVIEW