# 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 (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 (Zambrano et al., 2021; Xiao et al., 2023) attribute the surge to diverse factors, including rapid raise in population growth, urbanization, and changing consumption patterns. Other empirical works (Sanchez et al., 2020; Nathanson, 2015) suggest a link between GDP 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 (Kala et al., 2020; Gharagozloo&Ghazizade, (2023)) 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 (Zambrano et al., 2021; 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.

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 (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.

Zambrano et al. (2021) delved into the connection between residential solid waste generation, and its determinants in 173 countries worldwide. Their study analyzes the effect that GDP, population density, urbanization, and tourists' flow have on the generation of MSW. They grouped countries according to their income levels to control for heterogeneity between regions. The results show that, during 2016, solid waste generation increased along with GDP increments, mainly in high-income countries. Their findings show that the increase in MSW is also due to the rise in population and urbanization. Tourism also has a positive and significant impact on the generation of waste.

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 (Usman et al., 2022), 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:

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

Where: $Y_t$: The time series variable being tested for a unit root (LNSW, LNGDP, and LNRI), $\Delta Y_t$: The first difference of $Y_t$ ($Y_t$ - $Y_{t-1}$), α: The intercept term, β: The coefficient on the time trend (t), $\gamma$: The coefficient on the lagged value of Y ($Y_{t-1}$). This is the key parameter for testing the unit root hypothesis, $\delta_1, ..., \delta_{p-1}$: Coefficients on lagged differences of $Y_t$, used to control for serial correlation, $\varepsilon_t$: 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, $\Pi$ and $\Gamma i$ are the coefficient matrices, $\Delta$ 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 ad 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 their 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 $Y_t = (y_{1t}, y_{2t}, \ldots, y_{nt})^0$ denote an ($n$ 1) vector of time series variables.

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

$$Y_t = c + \pi_1 Y_{1-t} + \pi_2 Y_{t-2} + \cdots + + \pi_p Y_{t-p} + £_t, \text{ t} = 1, \ldots, \text{T} \qquad (5)$$

Where $\pi_i$ are (n x n) coefficient matrix and $£_t$ is an (n × 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:

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

where cov ($£_{1t}$, $£_{2t}$) = σ12 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:

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

where $\pi(L) = I_\pi - \pi_1 L - \ldots - \pi_p L_p$.

The VAR(p) is stable if the roots of det $(I_\pi - \pi_{1z} - \cdots - \pi p_z^p) = 0$

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

$$y_{t-\mu} = \Pi_1(y_{t-1-\mu}) + \Pi_2(y_{t-2-\mu}) + \cdots + \Pi p(y_{t-p-\mu}) + \varepsilon_t \quad (7)$$

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

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

where:

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

$$\Delta(SW) = a_0 + a_1 \mathrm{SW}\phi_{t-1} + \sum_{i=1}^{q1} a_{2i}\, \Delta(\mathrm{SW}_{t-i}) + \sum_{i=1}^{r1} \psi_{1i}\, \Delta(\mathrm{GDP}_{t-i}) + \sum_{i=1}^{z1} \Upsilon_{1i}\, \Delta(\mathrm{R}I_{t-i}) + \varepsilon_{1t}$$

(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 $a_1 \mathrm{SW}\phi_{t-1}$ 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 $\varepsilon t$ 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 4.1: 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 4.2

**Table 4.2: Stationarity Test**

| Variable | ADF Statistics (Levels) | P-value (Levels) | ADF Statistics (at 1st Difference) | P-Value (at 1st 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 4.2indicate 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 4.3.

**Table 4.3: 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 4.3 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.

**Table 4.4A: 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 4.4B: 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)) - 0.146$ECM_{t-1}$ + $E_t$

| | | | |
|---|---|---|---|
| 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 4.4 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. This disagree with the finding of Kala et al., 2020 in Delhi, India, Their study reported that socio-economic parameters like monthly income of the family is statistically significant predictor.

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 agree with the study of Sanchez et al., 2020 in Medellin, Colombia, they find evidence of cointegration between Colombia's gross domestic product (GDP) and Medellín's solid waste generation. Using different methodologies, they find that there is a long-term equilibrium relationship between the series and that the elasticity between the GDP and solid waste is 0.66%. This result has two implications. First, Colombia is in the growing phase of the Kuznets curve, and second, that one percent increase in GDP increases by 0.66% the generation of solid waste. That is more than one hundred thousand tons of solid waste.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 analysiscould 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 2unit 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. This agrees with the study conducted by Ella et al., (2022) in OECD countries, the result of their findings indicated that GDP has high positive effect on solid waste, which shows that the quantity and composition of solid waste generation is influenced by level of economic development.It also agrees with the findings of Manuel and his team in 2021, they grouped 173 countries according to their income levels to control for heterogeneity between regions. Their results show that, during 2016, solid waste generation increased along with GDP increments, but mainly in high-income countries. 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.

## REFERENCES


Adenomon, M. O. & Ojo, R. O. (2020): Autoregressive Distributed Lag Modeling of the Effects of Some Macroeconomic Variables on Economic Growth in Nigeria. Folia OeconomicaStetinensia, 20(2):1-19 DOI:10.2478/foli-2020-0032 https://sciendo.com

Aina, O. M., & Ademola, A. A. (2020) Evaluation of solid waste management techniques in selected markets in Ibadan, Nigeria. *Journal of Environmental Management*, 269, 110766.

Alajmi, R. G. (2016) Relationship between Economic Growth and Municipal Solid Waste & Testing the EKC Hypothesis: Analysis for Saudi Arabia. *Journal of International Business Research and Marketing*, 1(5).

Dikole, T. N., &Letshwenyo, G. L. (2020). Characterization of household solid waste generation patterns and composition in a middle-income country: A case study of Gaborone, Botswana. Resources, Conservation and Recycling, 154, 104615.

Ella, Danielle & Lim, Dennise & Lu, Bosyong& Cabauatan, Ronaldo. (2022). The Impact of Solid Waste Management to the Economic Growth in selected OECD Countries and Philippines. Journal of Economics, Finance and Accounting Studies. 4. 297-313. 10.32996/jefas.2022.4.1.20.

Gharagozloo, S., &Ghazizade, M. J. (2023). The Influence of Socio-Economic and Psychological Factors on the Composition of Household Solid Waste in Farahzad Neighborhood, Tehran, Iran. *Environmental health insights*, *17*, 11786302231195794. https://doi.org/10.1177/11786302231195794.

Grossman, G. M., & Krueger, A. B. (1991). Environmental impacts of a North American free trade agreement. The Quarterly Journal of Economics, 106(3), 677-725.

Kala, Kaveri & Bolia, Nomesh& Sushil, Professor. (2020). Effects of Socio-Economic Factors on Quantity and Type of Municipal Solid Waste. Management of Environmental Quality An International Journal. ahead-of-print. 10.1108/MEQ-11-2019-0244.

Karbassi, A. R., & Heidari, M. (2015). Sustainable solid waste management: A case study of the city of Shiraz, Iran. Journal of Material Cycles and Waste Management, 17(2), 308-318.

Magazzino, O., & Falcone, P. M. (2022). Waste generation, wealth, and greenhouse gas emissions in Switzerland: An integrated assessment. Resources, Conservation and Recycling, 189, 105156.

Medina, M. (2022). Assessment of solid waste management practices in developing countries: A case study of Nairobi, Kenya. Resources, Conservation and Recycling, 181, 105171.

Nathanson, J. A. (2015). Urbanization, waste management, and human health. Journal of Urban Health, 92(2), 1-5.

Nguyen, T. P., Bui, X. N., & Le, N. H. (2020). Influence of socioeconomic factors on municipal solid waste composition in Taiwan: A case study in Ho Chi Minh City. Journal of Cleaner Production, 260, 121057.

Nilanthi, V., Manage, P. M., &Premarathna, L. (2007). Factors influencing solid waste generation and composition in a Sri Lankan suburban area. Waste Management, 27(12), 1706-1715.

Noufal, D., Al-Khatib, I. A., & Kazmanli, K. (2020). Generation and characterization of household solid waste in Homs city, Syria. Waste Management, 108, 356-363.

Otumawu-Apreku, K. (2020). Solid waste management in Honiara: Attitudinal, behavioral, social and economic challenges. Journal of Solid Waste Technology and Management, 46(2), 147-164.

Rathje, W. L. (1992). Rubbish! The archaeology of garbage. Harper Perennial.

Richardson, H. W., & Havlicek, J. L. (1974). Solid waste management: A systems approach. Ann Arbor, MI: Ann Arbor Science Publishers

Sanchez Gonzalez, Jim & Fernández, Luisa & Ceballos, Hermison. (2020). Solid Waste and GDP: A Cointegration Analysis.

Sarica, K., Selçuk-Kestel, A. S., Karlıdağ, H., & Arslan, F. (2020). Quantitative analysis of food waste in Turkish households: A case study in Kırklareli Province. Journal of Material Cycles and Waste Management, 22, 2149-2157.

UNIDO (United Nations Industrial Development Organization). (2022). Waste management technologies and practices in developing countries. Vienna, Austria: United Nations Industrial Development Organization.

Usman, M., Loves, L., Russel, E., Ansori, M., Warsono, W., Widiarti, W., &Wamiliana, W. (2022). Analysis of Some Energy and Economics Variables by Using VECMX Model in Indonesia. *International Journal of Energy Economics and Policy*, *12*(2), 91–102. https://doi.org/10.32479/ijeep.11897.

Wang, F., & Qiu, J. (2013). Investigation of relationship between socio-economic development and solid waste discharge based on spatial effect analysis: A case study of Liaoning Province in China. Waste Management, 33(4), 988-998.

Williams PT. 2005. Waste Treatment and Disposal. West Sussex, UK: Wiley. 380 pp.

World Bank. (2022). What a waste 2.0: A global snapshot of solid waste management to 2050. Washington, DC: World Bank Group.

Xiao, X., Xi, W., Xiangming, H., Tong, L., & Syed, N. A. (2023). An empirical test of the environmental Kuznets curve hypothesis: Evidence from China's environmental pollution. Environmental Science and Pollution Research, 30(1), 1175-1185.

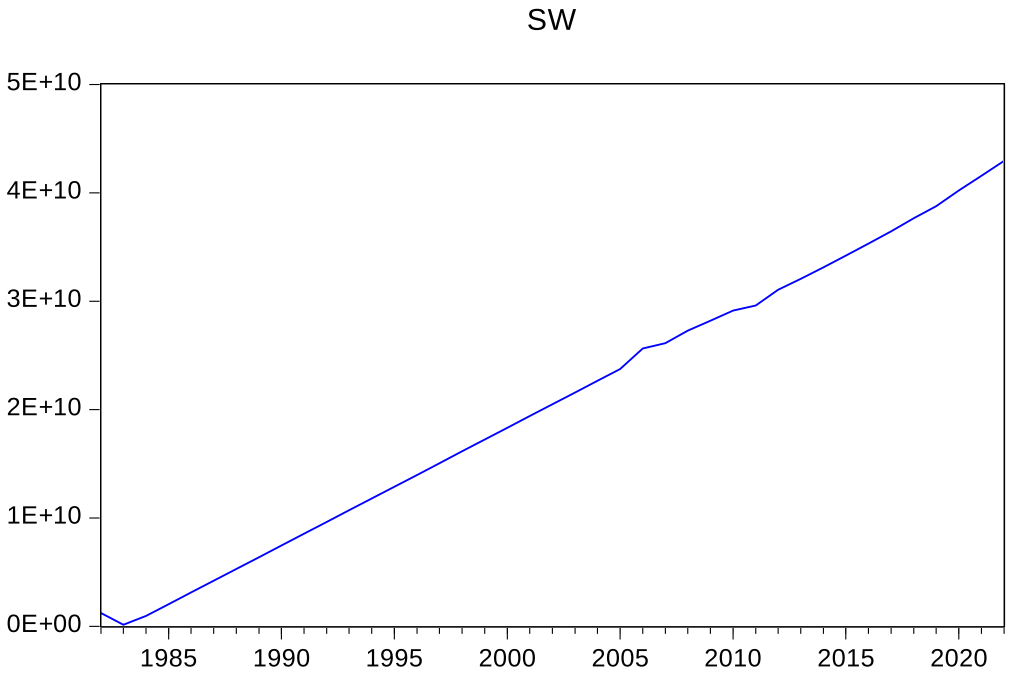
Yee, W. W. D., Hadithsari, N., & Berrueta, P. (2021). Socio-economic factors and municipal solid waste generation in the EU-27: Is there a partial rebound effect? Waste Management, 133, 341-354.

Zambrano-Monserrate, M.A., Ruano, M.A. & Ormeño-Candelario, V. Determinants of municipal solid waste: a global analysis by countries' income level. *Environ Sci Pollut Res* **28**, 62421–62430 (2021). https://doi.org/10.1007/s11356-021-15167-9

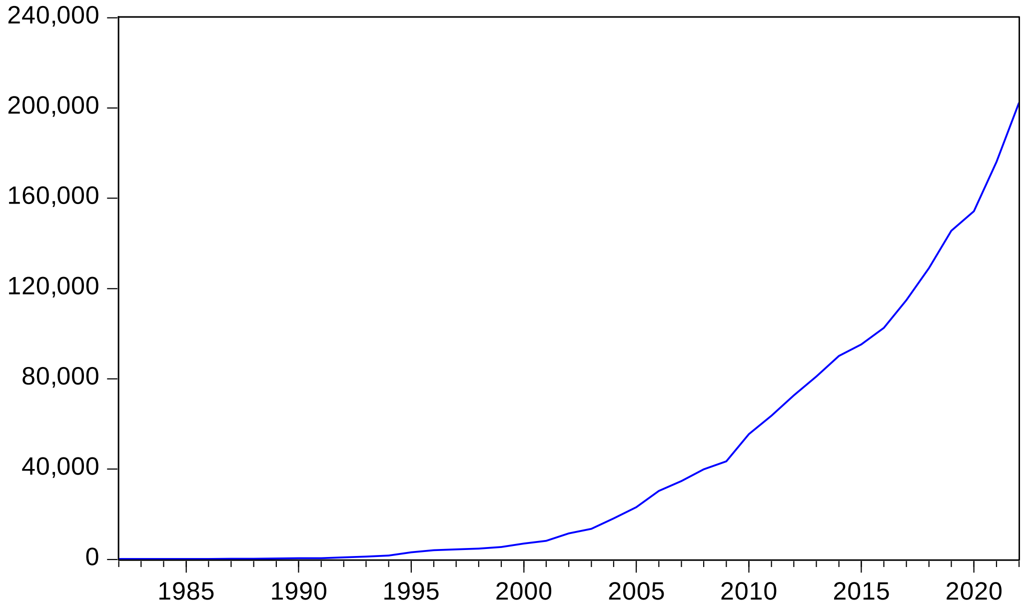
# Appendix

Descriptive statistics of Original Data

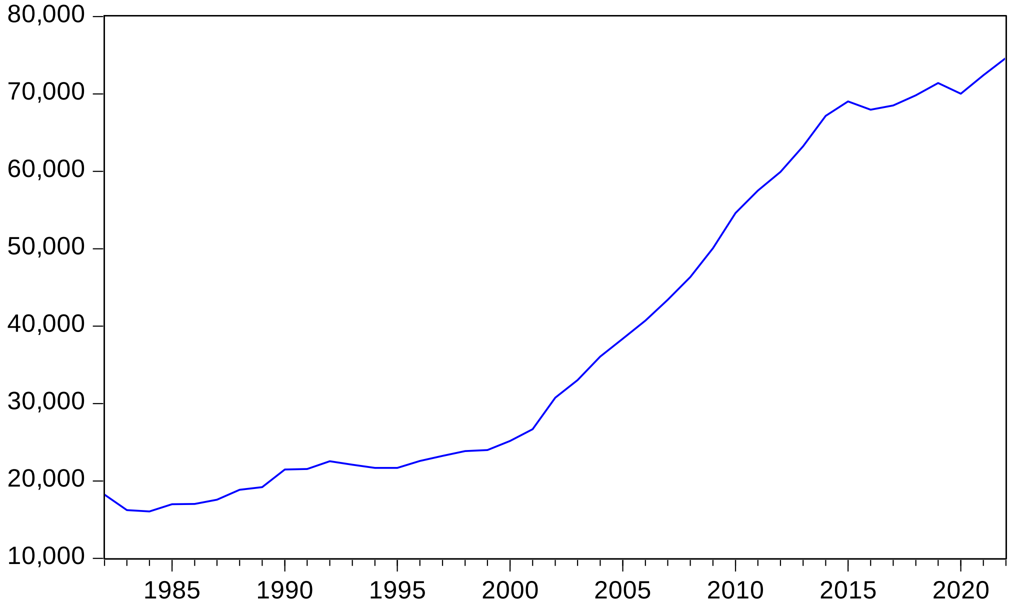
| | SW | GDP | RI |
|---|---|---|---|
| Mean | 2.05E+10 | 42483.24 | 39054.13 |
| Median | 2.05E+10 | 11501.45 | 30745.19 |
| Maximum | 4.29E+10 | 202365.0 | 74639.47 |
| Minimum | 1.31E+08 | 149.0512 | 16048.31 |
| Std. Dev. | 1.29E+10 | 56239.14 | 20892.27 |
| Skewness | 0.031876 | 1.303716 | 0.489316 |
| 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 |



GDP




RI

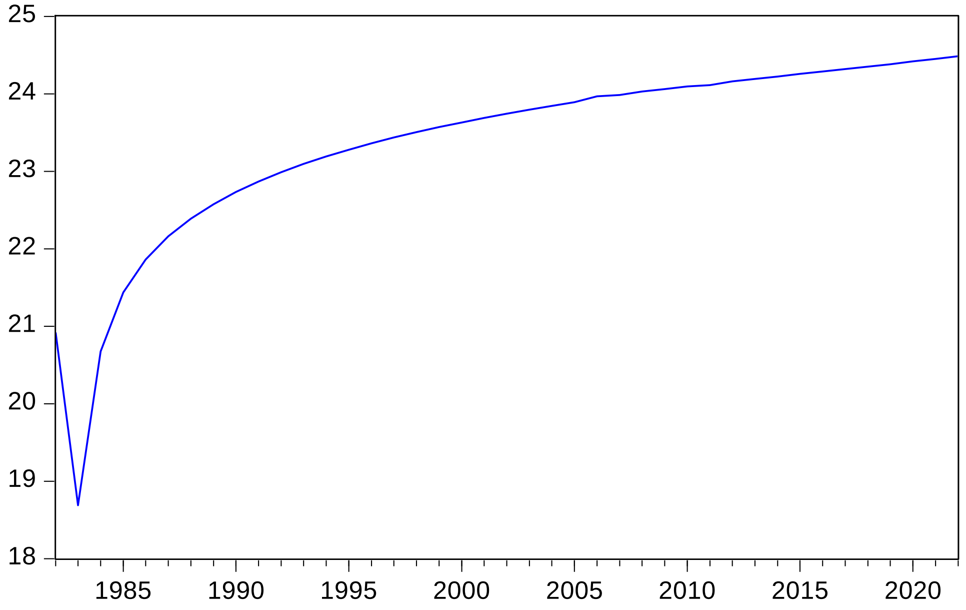



Descriptive statistics of transform Data

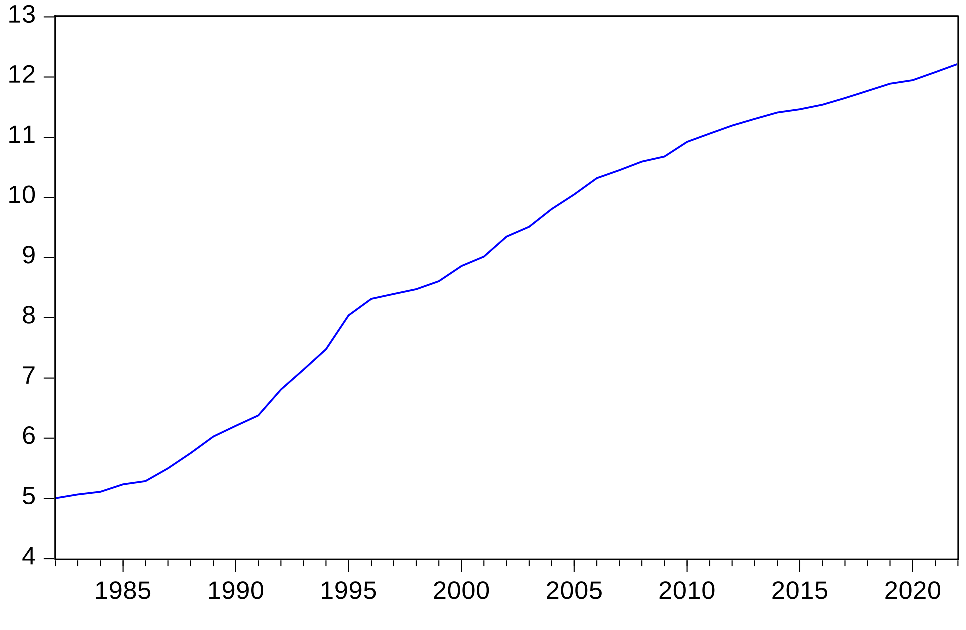
| | LNSW | LNGDP | LNRI |
|---|---|---|---|
| Mean | 23.34339 | 8.973736 | 10.43019 |
| Median | 23.74225 | 9.350228 | 10.33349 |
| Maximum | 24.48321 | 12.21783 | 11.22042 |
| Minimum | 18.68830 | 5.004290 | 9.683359 |
| Std. Dev. | 1.214078 | 2.412751 | 0.541992 |
| Skewness | -1.902734 | -0.329490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

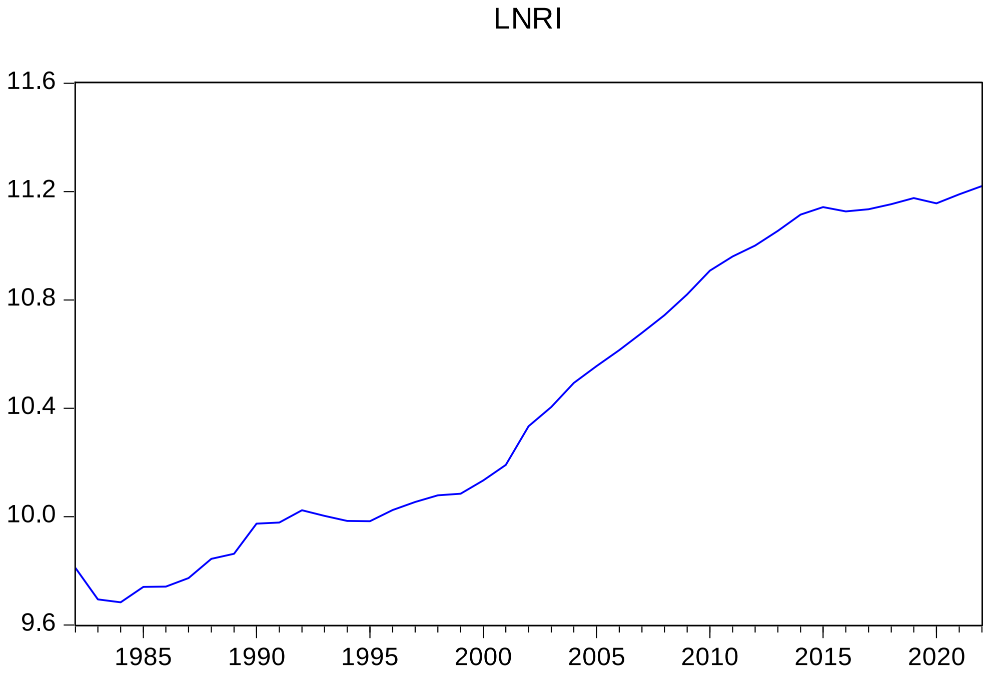
| | | | |
|---|---|---|---|
| Sum | 957.0790 | 367.9232 | 427.6376 |
| Sum Sq. Dev. | 58.95943 | 232.8546 | 11.75022 |
| Observations | 41 | 41 | 41 |

LNSW




LNGDP






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 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

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<br>(0.02243)<br>[-7.86212] | | |
| LNRI(-1) | -0.051959<br>(0.09047)<br>[-0.57434] | | |
| C | -21.35269 | | |
| Error Correction: | D(LNSW) | D(LNGDP) | D(LNRI) |

| | | | |
|---|---|---|---|
| CointEq1 | -0.146427 | -0.197196 | -0.004370 |
| | (0.01426) | (0.12862) | (0.04793) |
| | [-10.2658] | [-1.53313] | [-0.09118] |
| D(LNSW(-1)) | 0.195736 | -0.278019 | 0.016430 |
| | (0.02531) | (0.22827) | (0.08506) |
| | [ 7.73241] | [-1.21795] | [ 0.19316] |
| D(LNSW(-2)) | 0.005231 | -0.077035 | -0.020200 |
| | (0.00637) | (0.05748) | (0.02142) |
| | [ 0.82061] | [-1.34023] | [-0.94312] |
| D(LNGDP(-1)) | -0.022432 | 0.493871 | 0.017592 |
| | (0.01957) | (0.17649) | (0.06577) |
| | [-1.14615] | [ 2.79830] | [ 0.26749] |
| D(LNGDP(-2)) | 0.003454 | -0.028439 | -0.009760 |
| | (0.01837) | (0.16565) | (0.06173) |
| | [ 0.18803] | [-0.17168] | [-0.15812] |
| D(LNRI(-1)) | -0.041194 | -1.017047 | 0.237310 |
| | (0.05109) | (0.46068) | (0.17167) |
| | [-0.80635] | [-2.20771] | [ 1.38239] |
| D(LNRI(-2)) | -0.013533 | 0.835988 | 0.365318 |
| | (0.05332) | (0.48083) | (0.17918) |
| | [-0.25380] | [ 1.73863] | [ 2.03887] |
| C | 0.075643 | 0.160747 | 0.016075 |
| | (0.00761) | (0.06858) | (0.02556) |
| | [ 9.94616] | [ 2.34390] | [ 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 hypothesis: No serial correlation 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

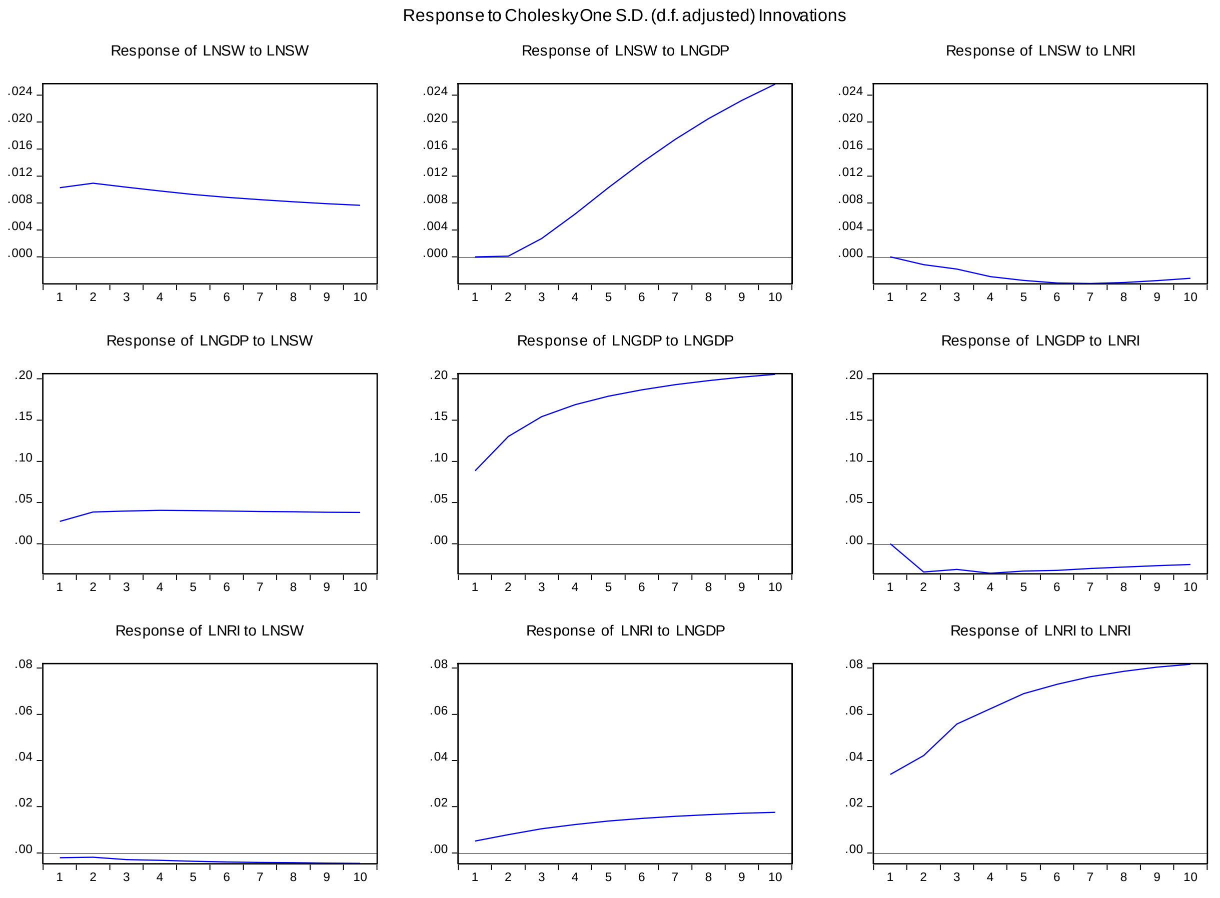
Joint test:

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

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

VAR Model - Substituted Coefficients:
===============================
D(LNSW) = - 0.146426622566*( LNSW(-1) - 0.176383705035*LNGDP(-1) - 0.0519588146334*LNRI(-1) - 21.3526906648 ) + 0.195735854797*D(LNSW(-1)) + 0.00523060379467*D(LNSW(-2)) - 0.0224321143641*D(LNGDP(-1)) + 0.00345397569574*D(LNGDP(-2)) - 0.0411937566705*D(LNRI(-1)) - 0.013532849277*D(LNRI(-2)) + 0.0756431387919

D(LNGDP) = - 0.197195844295*( LNSW(-1) - 0.176383705035*LNGDP(-1) - 0.0519588146334*LNRI(-1) - 21.3526906648 ) - 0.278018715946*D(LNSW(-1)) - 0.0770345410878*D(LNSW(-2)) + 0.493870833186*D(LNGDP(-1)) - 0.0284385184964*D(LNGDP(-2)) - 1.01704682059*D(LNRI(-1)) + 0.835988116846*D(LNRI(-2)) + 0.160747426418

D(LNRI) = - 0.00437013247695*( LNSW(-1) - 0.176383705035*LNGDP(-1) - 0.0519588146334*LNRI(-1) - 21.3526906648 ) + 0.0164300947401*D(LNSW(-1)) - 0.0202004123083*D(LNSW(-2)) + 0.0175922465765*D(LNGDP(-1)) - 0.00976048893583*D(LNGDP(-2)) + 0.237309801107*D(LNRI(-1)) + 0.365318476197*D(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 | | |

Equation: D(LNSW) = C(1)*( LNSW(-1) - 0.176383705035*LNGDP(-1) - 0.0519588146334*LNRI(-1) - 21.3526906648 ) + C(2)*D(LNSW(-1)) + C(3)*D(LNSW(-2)) + C(4)*D(LNGDP(-1)) + C(5)*D(LNGDP(-2)) + C(6)*D(LNRI(-1)) + C(7)*D(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 | | |

Equation: D(LNGDP) = C(9)*( LNSW(-1) - 0.176383705035*LNGDP(-1) - 0.0519588146334*LNRI(-1) - 21.3526906648 ) + C(10)*D(LNSW(-1)) + C(11)*D(LNSW(-2)) + C(12)*D(LNGDP(-1)) + C(13)*D(LNGDP(-2)) + C(14)*D(LNRI(-1)) + C(15)*D(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 | | |

Equation: D(LNRI) = C(17)*( LNSW(-1) - 0.176383705035*LNGDP(-1) - 0.0519588146334*LNRI(-1) - 21.3526906648 ) + C(18)*D(LNSW(-1)) + C(19)*D(LNSW(-2)) + C(20)*D(LNGDP(-1)) + C(21)*D(LNGDP(-2)) + C(22)*D(LNRI(-1)) + C(23)*D(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 | | |