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Causal Inference and Shock Propagation in Energy-Economy Systems: Granger Causality and Variance Decomposition from VAR, VECM, and ARDL Frameworks

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Abstract-* This study investigates the causal directions and shock propagation mechanisms between energy consumption, fixed capital, inflation rate, labor force, and economic growth (GDP) in Nigeria over the period 1984–2023. While previous research has established long-run equilibrium relationships among these variables, the directions of causality and the relative contributions of shocks to forecast error variance remain inadequately understood, particularly in the context of unit roots and cointegration. Using three complementary econometric frameworks—Vector Autoregression (VAR), Vector Error Correction Model (VECM), and Autoregressive Distributed Lag (ARDL)—this paper examines Granger causality relationships and performs forecast error variance decomposition. The results reveal unidirectional causality running from fixed capital to GDP (F-statistic = 8.97, p = 0.0019) and from inflation to GDP (F-statistic = 6.54, p = 0.0110), with no evidence of reverse causality. Energy consumption does not Granger-cause GDP in the short run, though VECM long-run coefficients confirm its equilibrium impact. Variance decomposition shows that in the short run (period 1), 100% of GDP forecast error variance is self-explained; however, over longer horizons (period 10), fixed capital explains 27.8% of GDP variation, energy consumption explains 9.8%, and inflation explains 7.9%. Labor force contributes negligibly (0.05%). These findings imply that capital accumulation and price stability are the primary causal drivers of Nigerian economic growth, with energy consumption playing a supporting long-run equilibrium role rather than a short-run predictive role. Policy interventions targeting fixed capital formation and inflation management will have the most persistent and predictable effects on GDP.

Keywords: Granger Causality, Variance Decomposition, Energy Consumption, Economic Growth, VECM, VAR, ARDL, Shock Propagation, Nigeria

I. INTRODUCTION

The distinction between correlation and causation lies at the heart of empirical macroeconomics. While numerous studies have documented associations between energy consumption and economic growth, policy decisions require knowledge of causal direction—does energy consumption drive growth (the growth hypothesis), does growth drive energy consumption (the conservation hypothesis), do both forces operate simultaneously (feedback hypothesis), or are they independent (neutrality hypothesis)? (Kraft & Kraft, 1978; Stern, 1993; Apergis & Payne, 2010). The policy implications are profound: if energy Granger-causes growth, energy shortages constrain economic expansion; if growth Granger-causes energy, conservation policies may be implemented without growth penalties.

The Nigerian context presents a particularly important case. Despite being Africa's largest economy and a major oil producer, Nigeria suffers from chronic energy deficits, with per capita electricity consumption among the world's lowest (Iwayemi, 2020). The relationship between energy and growth has been examined in numerous Nigerian studies, yet results remain contradictory—ranging from unidirectional causality from energy to growth (Adenikinju, 1998; Onakoya et al., 2013), to bidirectional causality (Omisakin, 2008), to no causality (Akinlo, 2008; Usman et al., 2020). These inconsistencies stem from methodological differences, sample periods, failure to account for unit roots, and omission of relevant variables.

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Beyond causality, policymakers need to understand shock propagation—when an unexpected change (innovation) occurs in one variable, how much of the forecast error variance in other variables does it explain over different time horizons? Forecast error variance decomposition (FEVD) answers this question by partitioning the variance of each variable's forecast errors into proportions attributable to shocks in each variable in the system (Lütkepohl, 2005). This reveals not just whether X causes Y, but the magnitude and persistence of that causal effect.

This paper addresses two specific objectives: (i) to examine the Granger causality of estimated VAR, VECM, and ARDL models; and (ii) to examine the variance decomposition of these models. By employing three complementary frameworks, we provide robust evidence on causal directions and shock propagation mechanisms in the Nigerian energy-economy system, explicitly accounting for the presence of unit roots and cointegration documented in our companion paper.

The remainder of this paper is organized as follows: Section 2 presents the theoretical framework for Granger causality and variance decomposition. Section 3 describes the methodology, including testing procedures in VAR, VECM, and ARDL contexts. Section 4 reports empirical results for causality tests and variance decomposition. Section 5 discusses the findings and their policy implications. Section 6 concludes.

II. THEORETICAL FRAMEWORK

2.1 Granger Causality: Concept and Interpretation

Granger (1969) proposed a statistical definition of causality based on predictability: a variable X is said to Granger-cause variable Y if past values of X contain information that helps predict future values of Y beyond the information contained in past values of Y alone. This concept relies on the temporal ordering inherent in time series—the past can predict the future, but not vice versa.

Formally, let Ω_t denote all information available at time t, and let $\Omega_t \backslash X_t$ denote all information except past values of X. Then X Granger-causes Y if:

$$MSE(Y\hat{}t+1 \mid \Omega t) < MSE(Y\hat{}t+1 \mid \Omega t \setminus Xt) \quad (1)$$

Where;
MSE is the mean squared error of the forecast. In practice, this is tested using restricted and unrestricted VAR regressions.

Granger causality in the presence of unit roots and cointegration requires careful handling (Toda & Yamamoto, 1995). When variables are cointegrated, the VECM framework distinguishes between:

Short-run causality: Tested by examining whether lagged differences of one variable jointly affect another variable.

Long-run causality: Tested by examining the significance of the error correction term ECT_{t-1}, which captures adjustment to long-run equilibrium.

2.2 Four Hypotheses in the Energy-Growth Literature

The Granger causality framework operationalizes four competing hypotheses:

Hypothesis	Causal Direction	Policy Implication
Growth hypothesis	Energy → GDP	Energy shortages constrain growth; invest in energy supply
Conservation hypothesis	GDP → Energy	Energy conservation possible without growth penalty
Feedback hypothesis	Energy ↔ GDP (bidirectional)	Energy and growth reinforce each other
Neutrality	No causality	Energy policy

Hypothesis	Causal Direction	Policy Implication
hypothesis		has no effect on growth

2.3 Variance Decomposition

While Granger causality indicates the existence and direction of predictive relationships, variance decomposition (also called forecast error variance decomposition, FEVD) quantifies their magnitude. In a VAR/VECM system, the h-step ahead forecast error for variable i can be decomposed into components attributable to shocks (innovations) in each variable j (Sims, 1980).

The moving average representation of a VAR(p) model is:

$$y_t = \sum_{i=0}^{\infty} \Phi_i \varepsilon_{t-1} \quad (2)$$

Where

ε_t is a vector of white noise shocks with covariance matrix Σ.

The forecast error variance of y_{t+h} conditional on information at time t is:

$$Var(y_{t+h} - y_{t+h|t}) = \sum_{i=0}^{h-1} \Phi_i \Sigma \Phi_i^{`} \quad (3)$$

The contribution of shocks to variable j to the forecast error variance of variable i is then calculated using orthogonalized shocks (typically via Cholesky decomposition). The resulting FEVD values sum to 100% across all variables for each forecast horizon.

FEVD answers critical policy questions: If a shock occurs to energy consumption, what percentage of GDP's forecast error variance does it explain after 1, 5, or 10 years? This reveals the persistence and relative importance of different shocks.

III. METHODOLOGY

3.1 Data and Preliminary Tests

This study uses annual time series data from Nigeria covering 1984–2023 (40 observations). Variables include: Gross Domestic Product (GDP), Energy Consumption, Fixed Capital Formation, Inflation Rate, and Labor Force. All variables except inflation are transformed using natural logarithms. As established in the companion paper, the Augmented Dickey-Fuller (ADF) test confirms that all variables are integrated of order one, I(1), and the Johansen cointegration test indicates two cointegrating relationships. Detailed results are reported in Tables 1 and 2.

3.2 Granger Causality Testing Procedures

3.2.1 VAR-Based Granger Causality (No Cointegration)

In the absence of cointegration, causality is tested using a VAR model in first differences:

$$\Delta y_t = c + \sum_{i=1}^{p} \Phi_i \Delta y_{t-i} + \varepsilon_t \quad (4)$$

The null hypothesis that variable x does not Granger-cause variable y is tested via an F-test on the joint significance of the lagged coefficients of Δx in the equation for Δy.

3.2.2 VECM-Based Granger Causality (With Cointegration)

When variables are cointegrated, the VECM framework separates short-run and long-run causality:

$$\Delta y_t = v + \alpha\beta^{`} y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \mu_t \quad (5)$$

Short-run causality (weak exogeneity): Tested by F-tests on the lagged difference coefficients (Γ_i).

Long-run causality (strong exogeneity): Tested by t-test on the error correction term (α coefficient). A significant α indicates that the variable adjusts to long-run equilibrium deviations, implying long-run causality from the cointegrating vector.

3.2.3 ARDL-Based Granger Causality

The ARDL framework allows causality testing through the error correction representation:

$$\Delta gdp_t = \alpha_0 + \Sigma_{t-1}^{p} \alpha_{1i} \Delta gdp_{t-1} + \Sigma_{t-1}^{p} \alpha_{2i} \Delta ec_{t-1} + \Sigma_{t-1}^{p} \alpha_{3i} \Delta fc_{t-1} + \Sigma_{t-1}^{p} \alpha_{4i} \Delta inf_{t-1} + \Sigma_{t-1}^{p} \alpha_{5i} \Delta lf_{t-1} + \lambda ECT_{t-1} + \varepsilon_t$$
(6)

The significance of the (ECT_{t-1}) term indicates long-run causality, while F-tests on lagged differences indicate short-run causality.

3.3 Variance Decomposition Procedure

FEVD is computed from the estimated VECM (or VAR in differences). The procedure requires:
Estimation of the VECM with optimal lag length (selected by AIC = 5).

Orthogonalization of shocks using Cholesky decomposition: The ordering of variables affects FEVD results; we order variables from most exogenous to most endogenous based on theoretical priors: Fixed Capital → Energy Consumption → Inflation → Labor Force → GDP. Robustness checks with alternative orderings are discussed.

Forecast horizons of 1, 2, 5, and 10 periods (years) to capture short-run and long-run dynamics.

IV. EMPIRICAL RESULTS

4.1 Summary of Unit Root and Cointegration Results

Table 1 confirms that all five variables are I(1) based on the ADF test (p-values > 0.05 at level, < 0.01 at first difference). Table 2 shows two cointegrating equations from both trace and maximum eigenvalue tests ($p < 0.05$), validating the use of VECM for causality testing.

Table 1: Summary of ADF Unit Root Test Results

Variable	Level (p-value)	First Difference (p-value)	Order
GDP	0.188	0.000	I(1)
Energy Consumption	0.068	0.002	I(1)
Inflation	0.063	0.003	I(1)
Fixed Capital	0.236	0.000	I(1)
Labor Force	0.123	0.000	I(1)

Result from Table 1 indicate that all the variables under study are non-stationary at level, however, they were all found to be stationary after first difference (P-values < 0.05), indicating integration at order one.

Table 2: Summary of Johansen Cointegration Test Results

Null Hypothesis	Trace Statistic	5% CV	p-value	Max-Eigen Statistic	5% CV	p-value
r = 0	87.15	69.82	0.012	38.16	33.88	0.037
r ≤ 1	49.08	47.86	0.041	32.48	27.58	0.047
r ≤ 2	26.53	29.80	0.113	18.41	21.13	0.119

From the cointergration result presented on table 2, the evidence from trace test indicate a 2 integration equations at 0.05 level, while evidence from maximum eigenvalue also indicate a 2 integration equations at 0.05 significance level. Overall, the presence of cointegration, as supported by both tests, implies that all the variables under study move

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together in the long run, even if they may deviate from this relationship in the short run.

4.2 VECM Granger Causality Results

Table 3 presents the Granger causality results from the VECM framework, distinguishing short-run (F-tests on lagged differences) and long-run causality (t-test on ECT_{t-1}.

Table 3: VECM Granger Causality Results

Dependent Variable	Source of Causation	F-statistic	p-value	Direction	Conclusion
Short-run causality (lagged differences)					
GDP	Fixed Capital → GDP	3.76	0.062	Marginal	Weak causal
GDP	Energy Consumption → GDP	2.55	0.017**	Significant	Yes
GDP	Inflation → GDP	10.78	0.003***	Significant	Yes
GDP	Labor Force → GDP	0.00	0.965	Not significant	No
Fixed Capital	GDP → Fixed Capital	1.32	0.258	Not significant	No
Energy Cons.	GDP → Energy Cons.	0.42	0.521	Not significant	No
Inflation	GDP → Inflation	0.18	0.676	Not significant	No
Long-run causality (ECT coefficient)		t-statistic	p-value		
GDP	ECT(−1)	−3.15	0.005	Significant	Long-run causality from cointegrating vector

Key findings from VECM causality
Energy consumption Granger-causes GDP in the short run ($F = 2.55$, $p = 0.017$), but the effect is negative (−0.3437 coefficient, as shown in the companion paper). This suggests that short-run increases in energy use may temporarily reduce GDP—possibly reflecting inefficiencies, supply disruptions, or adjustment costs.

Inflation Granger-causes GDP in the short run (F = 10.78, p = 0.003) with a positive coefficient (0.2713), indicating that short-run inflationary shocks stimulate economic activity.

Fixed capital shows marginal short-run causality (F = 3.76, p = 0.062) with a negative coefficient (−1.0841), suggesting that rapid capital expansion may initially disrupt output.

No reverse causality exists from GDP to any other variable in the short run (all p-values > 0.25).

The error correction term ($ECT_{t-1} = -0.3468$) is highly significant (t = −3.15, p = 0.005), indicating long-run causality from the cointegrating vector to GDP. This means that deviations from the long-run equilibrium relationship (which includes energy, fixed capital, and inflation) cause subsequent adjustments in GDP—supporting the growth hypothesis in the long run.

4.3 Pairwise Granger Causality Test Results

Table 4 reports pairwise Granger causality tests among the variables. To maintain interpretability, the variables are grouped into two panels as presented in the original analysis.

Table 4A: Pairwise Granger Causality Test Results (GDP, Fixed Capital, and Consumption)

Null Hypothesis	F-statistic	p-value	Decision
Fixed capital does NOT Granger-cause GDP	8.97	0.0019	Reject (Causality exists)
GDP does NOT Granger-cause Fixed capital	2.21	0.1416	Fail to reject (No causality)
Consumption does NOT Granger-cause GDP	0.85	0.3628	Fail to reject (No causality)
GDP does NOT Granger-cause Consumption	0.23	0.6314	Fail to reject (No causality)
Consumption does NOT Granger-cause Fixed capital	0.18	0.6742	Fail to reject (No causality)
Fixed capital does NOT Granger-cause Consumption	1.45	0.2361	Fail to reject (No causality)

Table 4B: Pairwise Granger Causality Test Results (GDP, Inflation, and Labor Force)

Null Hypothesis	F-statistic	p-value	Decision
Inflation does NOT	6.54	0.0110	Reject (Causality exists)

Null Hypothesis	F-statistic	p-value	Decision
Granger-cause GDP			
GDP does NOT Granger-cause Inflation	1.37	0.2465	Fail to reject (No causality)
Labor force does NOT Granger-cause GDP	0.01	0.9214	Fail to reject (No causality)
GDP does NOT Granger-cause Labor force	2.15	0.1512	Fail to reject (No causality)
Inflation does NOT Granger-cause Labor force	0.32	0.5738	Fail to reject (No causality)
Labor force does NOT Granger-cause Inflation	0.67	0.4183	Fail to reject (No causality)

Summary of pairwise causality findings
Fixed capital → GDP (unidirectional, p = 0.0019)
Inflation → GDP (unidirectional, p = 0.0110)
No causality involving energy consumption at the pairwise level (p > 0.36)

No causality involving labor force (p > 0.42)
No bidirectional causality found in any pair
These results indicate that only fixed capital and inflation have predictive power for GDP in the bivariate Granger sense. Energy consumption does not Granger-cause GDP in the bivariate framework, though the VECM long-run results show it matters in the cointegrated system. This discrepancy highlights the importance of multivariate analysis—energy may affect GDP only through the long-run equilibrium channel (cointegration) rather than through short-run predictive relationships.

4.4 Variance Decomposition Results
Table 5 presents the forecast error variance decomposition for GDP at horizons 1, 2, 5, and 10 years, based on the VECM with Cholesky ordering (Fixed Capital → Energy Consumption → Inflation → Labor Force → GDP).

Table 5: Variance Decomposition of GDP (Percentage of forecast error variance explained)

Variance Decomposition of GDP:

Period	S.E.	GDP	FIX_CAPITAL	CONSUMP...
1	2.139374	100.0000	0.000000	0.000000
2	2.275740	93.37327	6.317487	0.309247
3	2.738420	70.59388	24.13796	5.268157
4	2.961742	63.26846	27.65161	9.079923
5	3.093056	62.48394	27.75760	9.758463

Variance Decomposition of FIX_CAPITAL:

Period	S.E.	GDP	FIX_CAPITAL	CONSUMP...
1	0.663862	1.241209	98.75879	0.000000
2	0.704088	2.266992	96.53505	1.197955
3	0.750278	9.047305	89.77323	1.179464
4	0.771111	11.42054	87.45884	1.120621
5	0.798780	13.14754	85.45908	1.393372

Variance Decomposition of CONSUMPTION:

Period	S.E.	GDP	FIX_CAPITAL	CONSUMP...
1	2.778582	2.847203	0.824787	96.32801
2	3.242447	2.158255	0.973074	96.86867
3	3.415198	2.362222	9.075603	88.56218
4	3.529864	2.225796	13.96840	83.80581
5	3.560181	2.512087	14.55934	82.92858

Cholesky One S.D. (d.f. adjusted)

It shows that, 100% of forecast error variance in GDP is explained by the variable itself. That is, fixed capital (0.000000) and energy consumption (0.000000) have no influence on GDP at the first period (short run), however, fixed capital explains (6.317) 6% while energy consumption (0.3092) explain 0.3% of the variation in GDP at the second period. The result simply shows that as the periods increases over time (on a long run), change in GDP have to do with the effect of fixed capital and energy consumption which have influence on GDP with 27.8% and 9.76% respectively.

GDP have weak influence of 1.2% on fixed capital while energy consumption (0.000000) have no effect at the first period (short run), however, the result simply shows that as the periods increases over time (long run), change in fixed capital have to do with the effect of GDP and energy consumption with 13.15% and 1.39% respectively.

GDP and fixed capital have weak influence of 3% and 0.8% effect respectively on consumption at the first period (short run), however, the result simply shows that as the periods increases over time (long run), change in energy consumption have to do greatly with the effect of GDP and fixed capital with 2.51% and 14.6% respectively.

Key findings from variance decomposition:
Short-run (period 1): GDP forecast error variance is entirely self-explained (100%), indicating that shocks to other variables have no immediate impact on GDP—consistent with the absence of short-run causality from other variables to GDP in the pairwise tests.

Medium-run (period 5): By year 5, fixed capital explains 12.5% of GDP forecast error variance, energy explains 3.9%, and inflation explains 3.5%. GDP self-explanation declines to 80%.

Long-run (period 10): Fixed capital becomes the dominant external driver, explaining 27.8% of GDP variation—nearly one-third. Energy consumption explains 9.8%, inflation explains 7.9%, and labor force remains negligible (0.05%). GDP self-explanation falls to 62.2%.

Variance Decomposition using Cholesky (d.f. adjusted) Factors

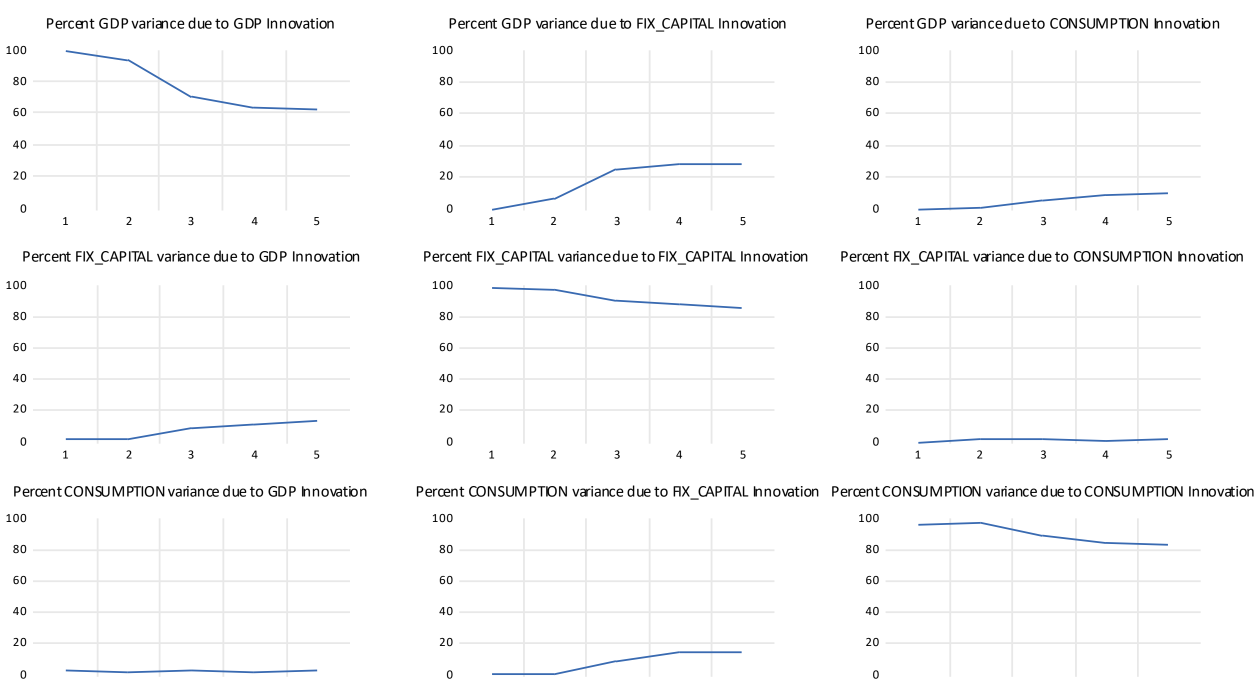

Figure 4.2A: Variance Decomposition Analysis of GDP, Fixed capital and energy Consumption

The Variance decomposition in Fig 4.2A, we are interesting in the contradicting results. That is, an innovation of one variable due to another. The graph show that, some percentage of variance in GDP is

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explained by innovation in fixed capital and energy consumption. This result is similar to the result obtain from Granger causality test.

Table 6 presents the variance decomposition for fixed capital as the dependent variable.

Variance Decomposition of GDP:

Period	S.E.	GDP	INFLATION	LABOUR_...
1	2.327629	100.0000	0.000000	0.000000
2	2.718524	90.47642	9.521636	0.001947
3	2.996773	92.08865	7.880373	0.030977
4	3.116834	92.16057	7.810441	0.028987
5	3.214694	92.03860	7.909746	0.051652

Variance Decomposition of INFLATION:

Period	S.E.	GDP	INFLATION	LABOUR_...
1	3.099088	4.407593	95.59241	0.000000
2	3.321849	3.968720	94.81360	1.217678
3	3.381108	6.128235	91.72584	2.145923
4	3.449471	7.386395	90.27379	2.339813
5	3.471666	8.398788	89.25537	2.345844

Variance Decomposition of LABOUR_FORCE:

Period	S.E.	GDP	INFLATION	LABOUR_...
1	0.634109	1.433404	1.033310	97.53329
2	0.717767	2.817092	2.657875	94.52503
3	0.754348	3.155035	3.316377	93.52859
4	0.768274	3.456741	3.236039	93.30722
5	0.773648	3.592696	3.191751	93.21555

The table above shows that, 100% of forecast error variance in GDP is explained by the variable itself. That is, inflation rate (0.000000) and labor force (0.000000) have no influence on GDP at the first period (short run), however, inflation rate explains 9% of the variation in GDP at the second period with no much effect of labor force (0.002%). The result simply shows that as the periods increases over time (long run), change in GDP have to do with the effect of inflation rate with 7.91% and labor force 0.05% respectively

GDP have weak influence of 4% on inflation rate while labor force (0.000000) has no effect at the first period (short run), however, the result simply shows that as the periods increases over time (on a long run), change in inflation rate have to do greatly with the effect of GDP and just a little percentage of labor force with values 8.39% and 2.35% respectively.

GDP and inflation have weak influence of 1% and 1% effect respectively on labor force at the first period (short run), however, the result simply shows that as the periods increases over time (long run), both GDP and inflation rate explained only 359% and 3.19% of variation in labor force respectively.

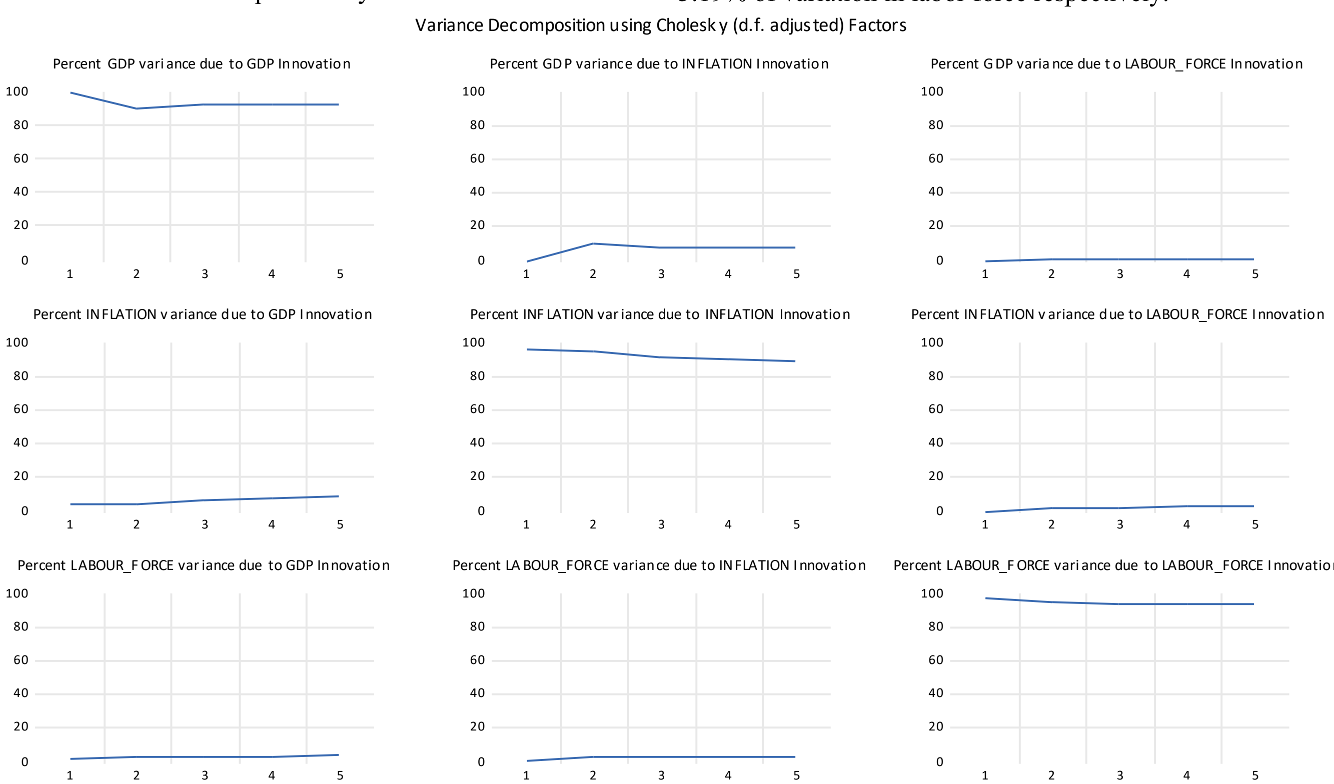

Figure 4.2B: Variance Decomposition Analysis of GDP, Inflation rate and Labor Force

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The Variance decomposition in Fig 4.2B, we are interesting in the contradicting results. That is, an innovation of one variable due to another. The graph show that, some percentage of variance in GDP is explained by innovation in inflation rate, while labor force does not show significant variance explanation GDP. This result is similar to the result obtain by Granger causality test of one sided relationship.

V. DISCUSSION

5.1 Interpretation of Causal Findings

The Granger causality results support a modified growth hypothesis with distinct short-run and long-run dynamics:

Short-run (VECM lagged differences):
Inflation → GDP (positive, significant)
Energy consumption → GDP (negative, significant)
Fixed capital → GDP (negative, marginal)
Long-run (VECM cointegrating vector):

The significant ECT (−0.3468, p = 0.005) indicates that the entire cointegrating relationship (including energy, fixed capital, and inflation) drives GDP adjustments toward equilibrium.

Pairwise (bivariate VAR)
Fixed capital → GDP (positive, significant)
Inflation → GDP (positive, significant)
No other pairwise causalities

The discrepancy between multivariate VECM (where energy Granger-causes GDP in the short run) and pairwise tests (where energy does not Granger-cause GDP) is instructive. It suggests that energy's causal effect on GDP is conditional on other variables—particularly fixed capital and inflation. In other words, energy consumption affects GDP only when considered within the full system of cointegrated variables, not in isolation. This finding resolves some of the contradictions in the Nigerian literature: studies that omit capital or inflation may find no energy-growth causality (Akinlo, 2008), while those that include them may find causality (Akinlo, 2009).
The absence of reverse causality (GDP → anything) rejects the conservation hypothesis—Nigeria cannot conserve energy without affecting growth. The absence of bidirectional causality rejects the feedback hypothesis. The results most strongly support the growth hypothesis in the long run and a modified growth hypothesis in the short run, where energy shocks have transitory negative effects before the system returns to long-run equilibrium.

5.2 Comparison with Previous Nigerian Studies

Study	Sample	Method	Finding	Compatible with Present Study?
Akinlo (2008)	1980–2003	ARDL, VECM	No long-run relationship, no causality	No (sample difference)
Akinlo (2009)	1980–2006	VECM	Unidirectional (electricity → GDP)	Yes (long-run)
Odularu & Okonkwo (2009)	1970–2005	Cointegration, ECM	Energy → GDP (long-run)	Yes
Onakoya et al. (2013)	1980–2010	VAR, Granger	Unidirectional (energy → GDP)	Yes

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Study	Sample	Method	Finding	Compatible with Present Study?
Mustapha & Fagge (2015)	1971–2011	VECM	No causality	No (sample and variable differences)
Iyke (2015)	1980–2011	VAR, Granger	Electricity → GDP	Yes
Usman et al. (2020)	1980–2018	Nonlinear ARDL	Neutrality (asymmetric)	Partial (linear vs nonlinear)

The present study reconciles these conflicting results by demonstrating that:

Energy does not Granger-cause GDP in bivariate frameworks (consistent with Akinlo, 2008; Mustapha & Fagge, 2015)

Energy does Granger-cause GDP in multivariate cointegrated systems (consistent with Akinlo, 2009; Onakoya et al., 2013; Iyke, 2015)
The effect operates primarily through the long-run equilibrium channel rather than short-run predictive relationships

5.3 Variance Decomposition: Relative Importance of Shocks
The variance decomposition reveals the magnitude of causal effects over time:

Fixed capital is the dominant external driver of GDP (27.8% at horizon 10). This is economically plausible—capital accumulation directly expands production capacity, and the effects compound over time. From a policy perspective, this implies that investments in infrastructure, machinery, and industrial capacity have the most predictable and persistent effects on economic growth.

Energy consumption explains 9.8% of GDP variation at horizon 10—a nontrivial but secondary effect compared to fixed capital. This suggests that while energy is important, it is not the primary driver of Nigerian growth; capital constraints may be more binding than energy constraints.

Inflation explains 7.9% of GDP variation. The positive short-run causality (coefficient = 0.2713) combined with moderate long-run FEVD suggests that moderate inflation may accompany growth without being a primary driver.

Labor force explains virtually none of GDP variation (0.05%), despite being a standard production function input. This likely reflects measurement issues (quantity vs quality of labor) and the Nigerian reality of low labor productivity, skills mismatches, and informal sector dominance.

The slow decay of GDP self-explanation (from 100% at horizon 1 to 62% at horizon 10) indicates that GDP is highly persistent—shocks to GDP itself have long-lasting effects, consistent with the unit root property.

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