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LONG-RUN AND SHORT-RUN DYNAMICS OF CRUDE PALM OIL (CPO), WORLD CRUDE OIL (WTI), AND COAL PRICES ON THE INDONESIAN COMPOSITE INDEX (IHSG)

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ABSTRACT

This study analyzes the long-run and short-run dynamic relationships between Crude Palm Oil (CPO) prices, West Texas Intermediate (WTI) crude oil prices, and coal prices on the Indonesian Composite Index (IHSG). The researcher applies an explanatory quantitative design using weekly secondary time-series data from 2024 to 2026. The Autoregressive Distributed Lag (ARDL) Bounds Testing approach and Error Correction Model (ECM) process natural logarithm transformed data following unit root tests that confirm stationarity at first difference $I(1)$. Bounds Testing results prove the existence of cointegration among variables at the 10 percent significance level. In the long run, CPO and WTI prices exert statistically significant negative impacts on the IHSG. Increases in CPO and WTI prices depress domestic stock market performance through higher operational cost transmissions and systematic risk sentiment accumulation. Conversely, coal prices demonstrate a positive but statistically insignificant effect on the IHSG due to sectoral offsetting mechanisms across listed firms. The Error Correction Term (ECT) coefficient of -0.075 confirms a relatively slow speed of adjustment at 7.54 percent per week toward long-run equilibrium. This empirical finding highlights weak-form market inefficiency within the Indonesia Stock Exchange in absorbing global commodity market shocks instantly. Capital market regulators and portfolio managers must actively monitor these commodity risk transmissions to formulate market stabilization policies and design adaptive investment portfolio diversification strategies.

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INTRODUCTION

Indonesia occupies a pivotal position in global commodity trading, particularly as a major producer of Crude Palm Oil (CPO) and coal. Indonesia and Malaysia together

contribute more than 80 percent of global CPO production, with their joint export volume accounting for approximately 90 percent of the world market. Consequently, domestic economic stability remains highly vulnerable to agricultural and energy commodity price shocks (Kiatmanaroach et al., 2015). This dependence extends beyond agricultural markets into the energy sector through biodiesel integration (Palm Methyl Ester/PME), creating tight structural interlinkages between CPO and global crude oil benchmarks such as West Texas Intermediate (WTI). Furthermore, Indonesia has implemented the B50 policy, which escalates CPO-derived biodiesel blending requirements to 50 percent.

As primary pillars of state revenue, simultaneous price movements across CPO, WTI, and coal serve as critical signals for investors on the Indonesia Stock Exchange. Historical data indicate that global commodity market shocks frequently trigger extreme volatility in the Indonesian Composite Index (IHSG). The commodity rally during 2007 and early 2008, followed by a sharp collapse during the Global Financial Crisis, demonstrates that Indonesian equity markets cannot isolate themselves from exogenous commodity shocks (Natanelov et al., 2011).

The Indonesian stock market, proxied by the IHSG, reflects macroeconomic health and investor sentiment regarding national growth prospects. Deepening financial integration accelerates information spillover across asset classes (Manuel et al., 2024; Sadorsky, 2014). Rising WTI crude oil and coal prices increase key energy input costs for manufacturing industries, compressing profit margins. Conversely, higher prices yield substantial windfalls for mining sector firms, which hold significant weight in total market capitalization. Meanwhile, CPO serves as a premier export commodity and primary growth driver for the agricultural sector (Bagirov & Mateus, 2024; Alao, 2023).

When these three commodities encounter unexpected price volatility, investors adjust their portfolios aggressively, directly impacting stock index stability (Samour et al., 2022; Keswani et al., 2024). The financialization of commodities strengthens these interlinkages, as physical assets like crude oil and CPO function as investment assets sensitive to geopolitical shocks and global inflation expectations (Mensi et al., 2013; Arfaoui & Rejeb, 2017).

Four theoretical pillars underpin the transmission mechanisms between commodity and stock markets. First, Ross's (1976) Arbitrage Pricing Theory (APT) posits that asset returns depend on multiple systematic risk factors beyond a single market risk parameter (Alao, 2023; Nordin et al., 2013). Within this framework, fluctuations in CPO, WTI, and coal prices act as systematic risk variables affecting corporate cash flows and stock valuations (Igbinovia, 2019).

Second, Fama's (1970) Efficient Market Hypothesis (EMH) provides the foundation for information efficiency. Under EMH, asset prices rapidly reflect all available public information regarding commodity price dynamics (Alao, 2023). In an efficient capital market, energy and agricultural price shocks integrate into equity prices instantly without leaving prolonged arbitrage opportunities.

Third, Gordon's (1963) Dividend Valuation Model (DVM) details equity valuation mechanics. Gordon (1963) establishes that stock intrinsic value equals the present value of expected future cash flows and dividends (Alao, 2023; Nordin et al., 2013). Commodity price shifts affect valuations through revenue channels for producers

and cost channels for energy consumers. Rising WTI or coal prices increase operational expenses for industrial firms, reducing projected cash flows and lowering current equity prices (Alao, 2023; Samour et al., 2022).

Finally, Sharpe's (1964) Capital Asset Pricing Model (CAPM) explains market risk premium adjustments to external shocks. Sharpe (1964) emphasizes that competitive market equilibrium reflects asset responsiveness to macroeconomic conditions, including primary commodity volatility (Nordin et al., 2013).

Existing empirical literature presents conflicting findings regarding commodity price effects on stock exchanges. The first strand documents stable positive relationships. Nordin et al. (2013) find that palm oil prices boost Malaysian stock market performance. Samour et al. (2022) observe similar positive linkages in South Africa, as do Narayan and Narayan (2010) in Vietnam and Jain and Biswal (2016) in India. Furthermore, Gupta & Modise (2013) and Adaramola (2012) show that higher energy export revenues enhance national income, driving stock market expansion.

The second strand reports pronounced negative impacts. Sadorsky (1999) demonstrates that oil price volatility depresses stock returns (Ghosh & Kanjilal, 2016). Basher and Sadorsky (2006) extend these findings across 21 emerging markets, while Park and Ratti (2008) confirm across 13 European countries that energy price spikes induce inflation and suppress stock performance (Bagirov et al., 2024). Chen (2010) in the United States, Al-hajj et al. (2018) in Malaysia, and Bani and Ramli (2019) corroborates these negative long-run impacts.

The third strand finds weak or conditional relationships. Maghyereh (2004) documents weak connections between oil prices and stock indices across 22 emerging economies. Nandha & Faff (2008) and Apergis and Miller (2009) argue that commodity impacts remain sector-specific without affecting aggregate indices significantly. Jammazi & Aloui (2010), Chang et al. (2013), and Mohaddes & Pesaran (2017) note that causal linkages emerge primarily during crisis periods.

Methodological gaps also persist. Most studies apply linear frameworks despite asymmetric tendencies in financial series (Raza et al., 2016; Salisu & Isah, 2017). In Indonesia, simultaneous empirical investigations integrating CPO, WTI, and coal within a unified cointegration system remain sparse.

The novelty of this study lies in integrating three strategic global commodities – CPO, WTI crude oil, and coal – into a single Autoregressive Distributed Lag (ARDL) cointegration system to evaluate their simultaneous impact on the IHSG. Unlike Nordin et al. (2013), who focus solely on CPO, or Sadorsky (1999), who restricts analysis to crude oil, this research investigates how agricultural and energy commodity interactions affect capital market stability in a resource-dependent emerging economy. Applying the ARDL approach developed by Pesaran et al. (2001) offers technical advantages in capturing concurrent long-run and short-run dynamics without rigid integration order restrictions (Igbinovia, 2019).

Additional novelty stems from analyzing the speed of adjustment using the Error Correction Term (ECT) coefficient (Singhal et al., 2019). This step determines how efficiently the Indonesian stock market corrects price deviations driven by exogenous commodity shocks.

This research aims to provide empirical evidence regarding long-run equilibrium relationships and identify which commodity variable exerts the strongest risk transmission on the IHSG. The findings offer strategic guidance for portfolio managers formulating commodity-based diversification strategies and assist capital market authorities in mitigating systemic risk from global commodity volatility (Pessoa et al., 2024).

METHODS

This study uses an explanatory quantitative research design to test causal relationships and equilibrium dynamics within a cointegrated framework. The analysis examines price transmission from three strategic commodities – Crude Palm Oil (CPO), West Texas Intermediate (WTI) crude oil, and coal – to the Indonesian stock market proxied by the IHSG.

The dataset consists of weekly secondary time-series data. Weekly frequency balances short-run signals and long-run fundamental equilibrium while minimizing daily market noise. IHSG weekly closing values, commodity prices for WTI, CPO, and COAL downloaded from <https://id.investing.com>.

All variables undergo natural logarithm (Ln) transformation prior to estimation. Logarithmic transformation stabilizes variance, mitigates outlier impacts, and allows estimated coefficients to be interpreted as elasticities or percentage changes.

Variable Operationalization

The dependent variable is the log of weekly IHSG closing values (LnIHSG). This aggregate indicator reflects equity market performance and investor macroeconomic expectations (Alao, 2023). The key independent variables are global CPO prices (LnCPO), WTI crude oil prices (LnWTI), and global coal prices (LnCOAL). These commodities drive Indonesia's export earnings and energy sector dynamics (Pessoa et al., 2024).

Theoretical models suggest that higher CPO and coal prices strengthen plantation and mining sector earnings, positively influencing total market capitalization. Meanwhile, WTI serves as a global energy benchmark affecting manufacturing operating costs and global risk aversion (Grigoryan, 2023; Basher et al., 2012).

Autoregressive Distributed Lag (ARDL) Estimation Procedure

This study employs the Autoregressive Distributed Lag (ARDL) Bounds Testing approach introduced by Pesaran et al. (2001). ARDL offers clear advantages over traditional cointegration methods like Johansen-Juselius (Buyuksahin & Robe, 2014; Singhal et al., 2019; Raza et al., 2016). First, ARDL handles mixed integration orders, remaining valid whether variables are stationary at level $I(0)$, integrated at first difference $I(1)$, or mutually integrated.

Second, ARDL exhibits superior small-sample statistical performance. Third, the procedure addresses potential endogeneity through optimal lag structure selection, yielding unbiased long-run parameter estimates. The estimation sequence follows these steps:

1. Unit Root Testing: The ARDL framework requires that no variable be integrated of order $I(2)$. If $I(2)$ variables are present, F-statistics from Bounds Testing become

invalid (Pesaran et al., 2001). This study uses Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to confirm variable integration orders.

2. Optimal Lag Selection: Selecting appropriate lag structures ensures that residuals behave as white noise without serial correlation. The optimal lag selection relies on minimizing the Akaike Information Criterion (AIC).
3. Bounds Testing for Cointegration: Following lag selection, F-tests evaluate long-run equilibrium relationships across lagged level variables. The conditional ARDL model equation is:

$$\Delta \text{LnIHSG}_t = \alpha_0 + \sum (\beta_1 \Delta \text{LnIHSG}_{t-i}) + \sum (\beta_2 \Delta \text{LnCPO}_{t-i}) + \sum (\beta_3 \Delta \text{LnWTI}_{t-i}) + \sum (\beta_4 \Delta \text{LnCOAL}_{t-i}) + \lambda_1 \text{LnIHSG}_{t-1} + \lambda_2 \text{LnCPO}_{t-1} + \lambda_3 \text{LnWTI}_{t-1} + \lambda_4 \text{LnCOAL}_{t-1} + \varepsilon_t$$

where Δ denotes first differences, α_0 represents the intercept, β captures short-run dynamics, λ parameters represent long-run coefficients, and ε_t is the error term.

The null hypothesis asserts no long-run cointegration ($H_0: \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 0$). Calculated F-statistics are compared against Pesaran et al. (2001) critical value bounds. An F-statistic exceeding the upper bound $I(1)$ confirms cointegration, indicating a stable long-run equilibrium relationship between IHSG and CPO, WTI, and coal prices.

4. Long-Run Parameters and Error Correction Model (ECM): Once cointegration is established, long-run parameters and short-run dynamics are estimated within an Error Correction Model framework. The key component is the Error Correction Term (ECT). The ECT measures the speed of adjustment at which the dependent variable returns to equilibrium following short-run shocks. Theoretically, the ECT coefficient must be negative and statistically significant ($p < 0.1$). For example, an ECT value of -0.25 indicates that 25 percent of short-run disequilibrium adjusts toward long-run equilibrium per period.

Diagnostic and Model Stability Tests

To ensure estimation reliability and statistical validity, diagnostic tests are conducted using EViews software:

1. Serial Correlation: Breusch-Godfrey Serial Correlation LM test checks for residual autocorrelation.
2. Heteroskedasticity: Breusch-Pagan-Godfrey and ARCH tests check for homoskedastic residual variance.
3. Normality: Jarque-Bera (JB) test evaluates residual normality.
4. Model Specification: Ramsey RESET test detects functional form misspecifications.

Finally, parameter stability is evaluated using Cumulative Sum of Recursive Residuals (CUSUM) and Cumulative Sum of Squares of Recursive Residuals (CUSUMSQ) plots. The model remains structurally stable if CUSUM and CUSUMSQ paths stay within 5 percent significance bounds.

RESULTS AND DISCUSSION

Empirical Results

Unit Root Test Results. Unit root tests prevent spurious regression in time-series analyses. Augmented Dickey-Fuller (ADF) tests at levels show that all variables, LnCOAL ($p = 0.5481$), LnCPO ($p = 0.0742$), LnIHSG ($p = 0.7380$), and LnWTI ($p = 0.1683$), contain unit roots and are non-stationary at level.

First-difference testing yields probability values of 0.0000 ($p < 0.01$) across all variables. Thus, LnIHSG, LnCPO, LnWTI, and LnCOAL are integrated of order I(1). Table 1 and Table 2 show the results of the stationarity tests at the level and first-difference stages, respectively. These results satisfy ARDL requirements, confirming that no variable is integrated of order I(2).

ARDL Estimation and Cointegration Test. Model selection based on the Akaike Information Criterion evaluated 500 specifications in EViews, identifying ARDL(1, 0, 0, 1) as the optimal structure, as shown in Table 3. Bounds Testing evaluated long-run cointegration, as shown in Table 4. The calculated F-statistic reached 4.273066.

Comparing this result against Pesaran et al. (2001) finite sample ($n = 80$) critical values shows that at a 10 percent significance level, the upper bound I(1) threshold is 3.885. Because the F-statistic (4.273) exceeds the upper bound, the null hypothesis of no cointegration is rejected. This confirms a stable long-run equilibrium relationship between CPO, WTI, coal prices, and the IHSG.

Table 1. Level Stationarity Test

Null Hypothesis: Unit root (individual unit root process)
Series: LNCOAL, LNCPO, LNIHSG, LNWTI

Method	Statistic	Prob.**
ADF - Fisher Chi-square	10.5769	0.2268
ADF - Choi Z-stat	-0.82407	0.2050

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Intermediate ADF test results UNTITLED

Series	Prob.	Lag	Max Lag	Obs
LNCOAL	0.5481	0	12	127
LNCPO	0.0742	0	12	127
LNIHSG	0.7380	0	12	127
LNWTI	0.1683	3	12	124

Table 2. First-Difference Stationarity Test

Null Hypothesis: Unit root (individual unit root process)
Series: LNCOAL, LNCPO, LNIHSG, LNWTI

Method	Statistic	Prob.**
ADF - Fisher Chi-square	240.474	0.0000
ADF - Choi Z-stat	-14.4095	0.0000

** Probabilities for Fisher tests are computed using an asymptotic Chi-square distribution. All other tests assume asymptotic normality.

Intermediate ADF test results D(UNTITLED)

Series	Prob.	Lag	Max Lag	Obs
D(LNCOAL)	0.0000	0	12	126
D(LNCPO)	0.0000	0	12	126
D(LNIHSG)	0.0000	0	12	126
D(LNWTI)	0.0000	2	12	124

Table 3. ARDL Test (Spesification 3: Unrest Constant)

Dependent Variable: LNIHSG

Method: ARDL

Model selection method: Akaike info criterion (AIC)

Dynamic regressors (4 lags, automatic): LNCPO LNWTI LNCOAL

Fixed regressors: C

Number of models evaluated: 500

Selected Model: ARDL(1, 0, 0, 1)

Note: final equation sample is larger than selection sample

HAC standard errors & covariance (Bartlett kernel, Newey-West fixed

bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
LNIHSG(-1)	0.924551	0.028632	32.29055	0.0000
LNCPO	-0.074696	0.026089	-2.863082	0.0049
LNWTI	-0.070531	0.030803	-2.289719	0.0238
LNCOAL	-0.115597	0.099629	-1.160275	0.2482
LNCOAL(-1)	0.143101	0.097953	1.460915	0.1466
C	1.463753	0.379736	3.854662	0.0002
R-squared	0.912670	Mean dependent var	8.899055	
Adjusted R-squared	0.909061	S.D. dependent var	0.092139	
S.E. of regression	0.027786	Akaike info criterion	-4.282512	
Sum squared resid	0.093416	Schwarz criterion	-4.148141	
Log likelihood	277.9395	Hannan-Quinn criter.	-4.227919	
F-statistic	252.9084	Durbin-Watson stat	2.066488	
Prob(F-statistic)	0.000000			

*Note: p-values and any subsequent tests do not account for model selection.

Long-Run Parameter Estimates. Cointegration testing permits long-run parameter estimation. The estimated long-run equation is:

$$\text{LnIHSG}_t = 1.4637 - 0.9900 \text{LnCPO}_t - 0.9348 \text{LnWTI}_t + 0.3645 \text{LnCOAL}_t$$

The results show that LnCPO exerts a statistically significant negative long-run effect on the IHSG, with a coefficient of -0.9900 ($p = 0.0394$). A 1 percent increase in CPO prices reduces the IHSG by 0.99 percent in the long run. Similarly, LnWTI displays a negative coefficient of -0.9348, significant at the 1 percent level ($p = 0.0058$).

Conversely, coal prices (LnCOAL) show a positive coefficient of 0.3645 that is not statistically significant ($p = 0.1614$).

Short-Run Dynamics: Error Correction Model (ECM). Short-run dynamics are captured through the Error Correction Model. The Error Correction Term (CointEq-1) coefficient is negative at -0.075449 and statistically significant at the 1 percent level ($p = 0.0001$), as shown in Table 5.

The negative and statistically significant ECT confirms cointegration validity. The coefficient of -0.075 indicates that the speed of adjustment toward long-run equilibrium is 7.54 percent per week. Short-run deviations induced by commodity shocks correct gradually over time.

Diagnostic and Stability Test Results. Diagnostic tests verify model adequacy. The Breusch-Godfrey test yields an Obs R-squared probability of 0.7033, confirming the absence of serial correlation. The Ramsey RESET test probability of 0.9565 confirms correct functional specification, shown in Table 6.

Heteroskedasticity tests (Breusch-Pagan-Godfrey $p = 0.0003$; ARCH $p = 0.0225$) indicate non-constant residual variance, shown in Table 7 and 8. The presence of heteroskedasticity in high-frequency financial and commodity data is a common phenomenon resulting from volatility clustering. To address this issue and ensure the validity of hypothesis testing, the ARDL estimation in this study incorporates HAC Standard Errors & Covariance adjustments (Bartlett kernel, Newey-West fixed bandwidth = 5.0000) using EViews 12. The Newey-West HAC correction yields standard error estimates that are robust against heteroskedasticity and autocorrelation, thereby ensuring that all t-statistics and p-values obtained during hypothesis testing remain econometrically valid.

Table 4. Cointegration Test: Bounds Testing Approach (Unrestricted Constant)

ARDL Long Run Form and Bounds Test				
Dependent Variable: D(LNIHSG)				
Selected Model: ARDL(1, 0, 0, 1)				
Case 3: Unrestricted Constant and No Trend				
Conditional Error Correction Regression				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.463753	0.423272	3.458182	0.0008
LNIHSG(-1)*	-0.075449	0.031172	-2.420380	0.0170
LNCPO**	-0.074696	0.033922	-2.202031	0.0296
LNWTI**	-0.070531	0.024158	-2.919598	0.0042
LNCOAL(-1)	0.027504	0.024536	1.120966	0.2645
D(LNCOAL)	-0.115597	0.078183	-1.478548	0.1419
* p-value incompatible with t-Bounds distribution.				
** Variable interpreted as $Z = Z(-1) + D(Z)$.				
Levels Equation				
Case 3: Unrestricted Constant and No Trend				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNCPO	-0.990030	0.475393	-2.082553	0.0394
LNWTI	-0.934821	0.332964	-2.807576	0.0058

LNCOAL	0.364546	0.258704	1.409128	0.1614
EC = LNIHSG - (-0.9900*LNCPO -0.9348*LNWTI + 0.3645*LNCOAL)				
F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic k	4.273066 3		Asymptotic: n=1000	
		10%	2.72	3.77
		5%	3.23	4.35
		2.5%	3.69	4.89
		1%	4.29	5.61
Actual Sample Size	127		Finite Sample: n=80	
		10%	2.823	3.885
		5%	3.363	4.515
		2.5%	3.69	4.89
		1%	4.29	5.61
t-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
t-statistic	-2.420380	10%	-2.57	-3.46
		5%	-2.86	-3.78
		2.5%	-3.13	-4.05
		1%	-3.43	-4.37

The Jarque-Bera test ($p = 0.0000$) indicates non-normal residuals, as shown in Table 8. In larger samples, asymptotic properties mitigate normality deviations without biasing coefficient estimates.

Model stability testing was conducted using CUSUM and CUSUM of Squares (CUSUMSQ) tests at a 5% significance level. The CUSUM test results indicate that the cumulative statistic line consistently remained within the 5% critical bounds, confirming that the long-run and short-run regression parameter coefficients in the ARDL(1,0,0,1) model are structurally stable.

Meanwhile, the CUSUMSQ plot reveals that the statistic line briefly dipped below the lower critical bound between mid-2024 and early 2026 before rising again. Based on econometric literature (Brown et al., 1975; Bahmani-Oskooee & Bohl, 2000), this discrepancy between the stable CUSUM results and the fluctuating CUSUMSQ results indicates that the observed instability did not stem from changes in regression coefficients but rather from fluctuations in residual variance (variance instability).

This CUSUMSQ behavior is corroborated by the presence of conditional heteroskedasticity (ARCH) effects in the model's residuals. High volatility in WTI oil and CPO prices during the observation period triggered short-term variance fluctuations in the stock market. Nevertheless, since the parameter coefficients were proven stable via the CUSUM test and the heteroskedasticity effect was addressed using Newey-West Standard Errors (HAC) adjustments, the estimated long-run and short-run relationships of the ARDL model remain valid, reliable, and scientifically interpretable.

Table 5. Result of Error Correction Model Test

ARDL Error Correction Regression

Dependent Variable: D(LNIHSG)

Selected Model: ARDL(1, 0, 0, 1)

Case 3: Unrestricted Constant and No Trend

ECM Regression

Case 3: Unrestricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.463753	0.350150	4.180357	0.0001
D(LNCOAL)	-0.115597	0.071814	-1.609662	0.1101
CointEq(-1)*	-0.075449	0.018027	-4.185217	0.0001
R-squared	0.153477	Mean dependent var		-0.001654
Adjusted R-squared	0.139823	S.D. dependent var		0.029594
S.E. of regression	0.027447	Akaike info criterion		-4.329756
Sum squared resid	0.093416	Schwarz criterion		-4.262571
Log likelihood	277.9395	Hannan-Quinn criter.		-4.302460
F-statistic	11.24073	Durbin-Watson stat		2.066488
Prob(F-statistic)	0.000033			

* p-value incompatible with t-Bounds distribution.

F-Bounds Test

Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
F-statistic	4.273066	10%	2.72	3.77
k	3	5%	3.23	4.35
		2.5%	3.69	4.89
		1%	4.29	5.61

t-Bounds Test

Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
t-statistic	-4.185217	10%	-2.57	-3.46
		5%	-2.86	-3.78
		2.5%	-3.13	-4.05
		1%	-3.43	-4.37

Table 6. Result of Ramsey Test

Ramsey RESET Test

Specification: LNIHSG LNIHSG(-1) LNCPO LNWTI LNCOAL

LNCOAL(-1)

C

	Value	df	Probability
t-statistic	0.054628	120	0.9565
F-statistic	0.002984	(1, 120)	0.9565
Likelihood ratio	0.003158	1	0.9552

F-test summary:

Sum of Sq.	df	Mean Squares
------------	----	--------------

Test SSR	2.32E-06	1	2.32E-06
Restricted SSR	0.093416	121	0.000772
Unrestricted SSR	0.093414	120	0.000778

LR test summary:

	Value
Restricted LogL	277.9395
Unrestricted LogL	277.9411

Unrestricted Test Equation:
 Dependent Variable: LNIHSG
 Method: Least Squares
 Date: 08/09/26 Time: 12:08
 Sample: 1/14/2024 6/14/2026
 Included observations: 127
 HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNIHSG(-1)	1.124831	3.603228	0.312173	0.7555
LNCPO	-0.090734	0.289610	-0.313295	0.7546
LNWTI	-0.086123	0.284334	-0.302892	0.7625
LNCOAL	-0.140330	0.467933	-0.299893	0.7648
LNCOAL(-1)	0.173765	0.568773	0.305509	0.7605
C	0.818212	11.59102	0.070590	0.9438
FITTED^2	-0.012182	0.219193	-0.055578	0.9558

R-squared	0.912672	Mean dependent var	8.899055
Adjusted R-squared	0.908305	S.D. dependent var	0.092139
S.E. of regression	0.027901	Akaike info criterion	-4.266789
Sum squared resid	0.093414	Schwarz criterion	-4.110023
Log likelihood	277.9411	Hannan-Quinn criter.	-4.203097
F-statistic	209.0209	Durbin-Watson stat	2.069459
Prob(F-statistic)	0.000000	Wald F-statistic	322.5734
Prob(Wald F-statistic)	0.000000		

Table 7. Result of Heteroskedasticity Test: Breusch-Pagan-Godfrey

Heteroskedasticity Test: Breusch-Pagan-Godfrey

Null hypothesis: Homoskedasticity

F-statistic	5.531349	Prob. F(5,121)	0.0001
Obs*R-squared	23.62763	Prob. Chi-Square(5)	0.0003
Scaled explained SS	28.49974	Prob. Chi-Square(5)	0.0000

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

HAC standard errors & covariance (Bartlett kernel, Newey-West fixed

bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001575	0.019016	0.082841	0.9341
LNIHSG(-1)	-0.003527	0.001897	-1.859045	0.0655
LNCPO	0.004262	0.001477	2.885033	0.0046
LNWTI	0.000850	0.001084	0.784193	0.4345
LNCOAL	0.004112	0.004093	1.004677	0.3171
LNCOAL(-1)	-0.005927	0.003704	-1.599931	0.1122
R-squared	0.186044	Mean dependent var		0.000736
Adjusted R-squared	0.152410	S.D. dependent var		0.001204
S.E. of regression	0.001108	Akaike info criterion		-10.72582
Sum squared resid	0.000149	Schwarz criterion		-10.59145
Log likelihood	687.0896	Hannan-Quinn criter.		-10.67123
F-statistic	5.531349	Durbin-Watson stat		1.967482
Prob(F-statistic)	0.000127			

Table 8. Result of Heteroskedasticity Test: ARCH

Heteroskedasticity Test: ARCH

F-statistic	5.346881	Prob. F(1,124)	0.0224
Obs*R-squared	5.208529	Prob. Chi-Square(1)	0.0225

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Date: 08/09/26 Time: 12:01

Sample (adjusted): 1/21/2024 6/14/2026

Included observations: 126 after adjustments

HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 5.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000592	0.000129	4.583086	0.0000
RESID^2(-1)	0.203107	0.063628	3.192097	0.0018
R-squared	0.041338	Mean dependent var		0.000741
Adjusted R-squared	0.033606	S.D. dependent var		0.001207
S.E. of regression	0.001187	Akaike info criterion		-10.61949
Sum squared resid	0.000175	Schwarz criterion		-10.57447
Log likelihood	671.0280	Hannan-Quinn criter.		-10.60120
F-statistic	5.346881	Durbin-Watson stat		2.077542
Prob(F-statistic)	0.022408			

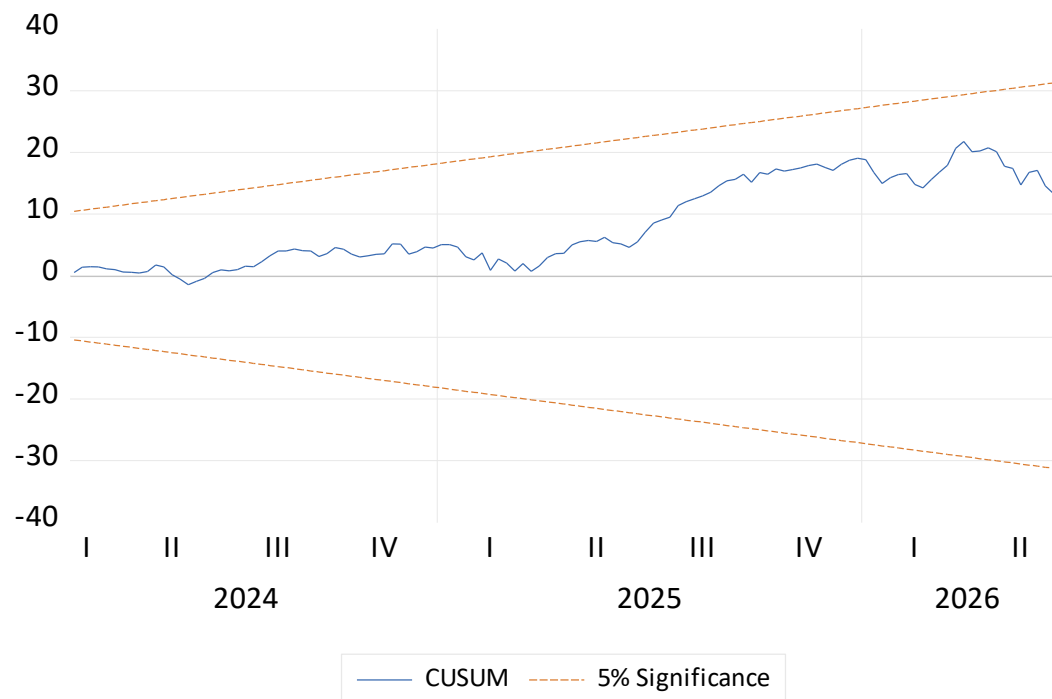


Figure 1. Result of CUSUM Test

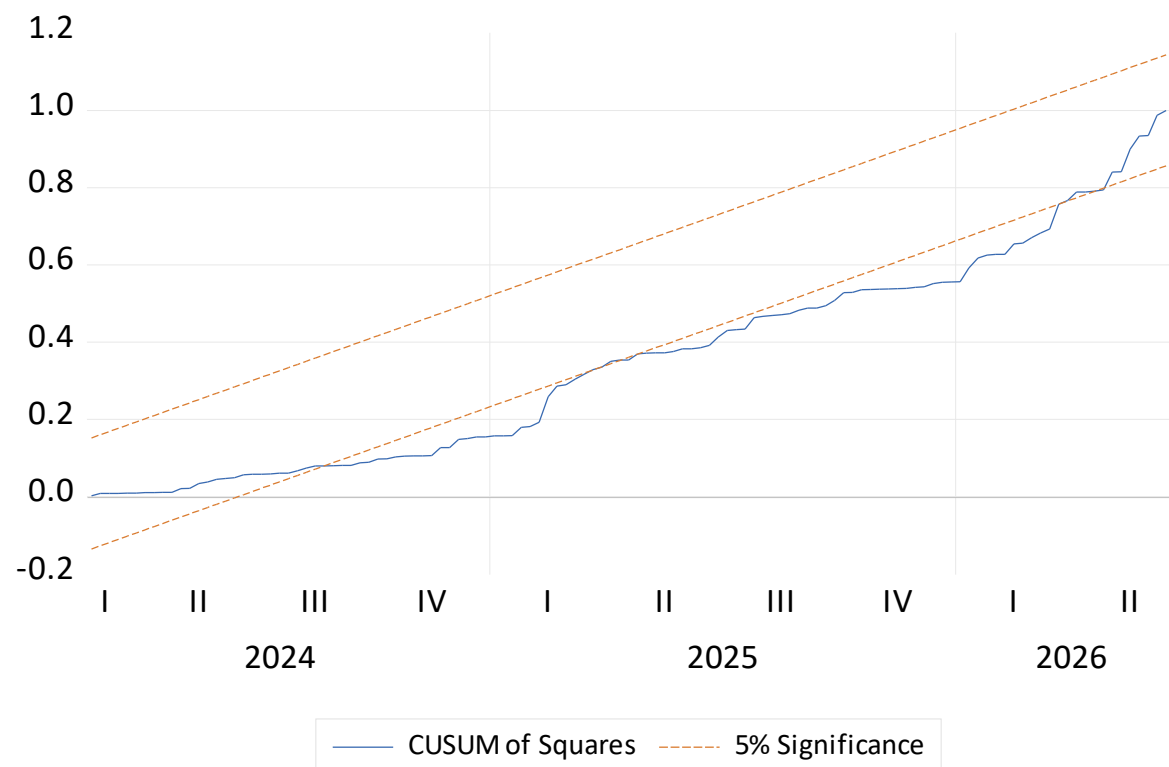


Figure 2. Result of CUSUMSQ Test

These empirical results offer insights into commodity price transmission within the Indonesian capital market. The significant negative impact of CPO prices on the IHSG is notable given Indonesia's position as the world's largest CPO producer. This outcome contrasts with Nordin et al. (2013), who documented a positive relationship between CPO prices and the Malaysian stock market. Difference in market structure and domestic policies explain this divergence. In Indonesia, global CPO price surges often trigger domestic export levies or supply constraints (such as Domestic Market Obligations) that lower market earnings expectations for listed plantation firms.

The negative effect of WTI crude oil prices on the IHSG aligns with Sadorsky (1999) and Basher and Sadorsky (2006), who show that oil price shocks generate negative sentiment across emerging equity markets. Higher global oil prices raise domestic inflation expectations and logistics expenses for industrial firms, lowering intrinsic equity values under the Dividend Valuation Model (Gordon, 1963). Singhal et al. (2019) similarly observe negative equity market responses to energy price shocks due to systemic risk accumulation.

Coal prices exhibit a positive but statistically insignificant effect. Although coal represents a primary export commodity, its transmission to the aggregate IHSG is less pronounced than that of CPO and WTI. Windfall earnings in the mining sector are offset by higher operational energy costs in manufacturing and consumer sectors, resulting in a neutral aggregate effect. The cointegrating relationship coupled with a slow adjustment speed (7.54 percent weekly) indicates that the Indonesia Stock Exchange requires time to process global commodity information, reflecting weak-form market efficiency (Bani & Ramli, 2019).

CONCLUSION

This study evaluated the long-run and short-run dynamics of CPO, WTI, and coal prices on the Indonesian Composite Index (IHSG) for the 2024–2026 period. Bounds Testing confirmed cointegration, establishing a long-run equilibrium among the variables. In the long run, CPO and WTI prices exert statistically significant negative effects on the IHSG. The CPO coefficient of -0.9900 shows that rising global CPO prices depress domestic equity index performance. Similarly, the WTI coefficient of -0.9348 demonstrates that global energy price shocks present systematic risks to Indonesian equities. Conversely, coal prices exhibit a positive but statistically insignificant effect, reflecting sectoral offsetting across market segments.

The empirical novelty of this study lies in identifying a negative relationship between CPO prices and the Indonesian stock market, contrasting with Nordin et al. (2013) findings in Malaysia. This provides empirical evidence that in primary producer countries, agricultural price spikes accompanied by regulatory interventions (such as export levies) can depress equity market valuation. Furthermore, the estimated ECT coefficient of -0.075 demonstrates a slow speed of adjustment (7.54 percent per week), highlighting weak-form market inefficiency on the Indonesia Stock Exchange in absorbing global commodity news.

The findings support Arbitrage Pricing Theory (APT) by establishing CPO and WTI prices as systematic risk factors driving stock market returns. The Dividend Valuation Model (DVM) is also supported, as higher WTI energy costs increase firm operating expenses, lowering dividend expectations and equity values. Additionally,

the 7.54 percent weekly adjustment rate contributes to Efficient Market Hypothesis (EMH) literature by demonstrating persistent price deviations in emerging markets, where information spillovers are absorbed gradually rather than instantaneously.

Monetary authorities and capital market regulators should monitor inflation transmission triggered by CPO and WTI price spikes. Given their negative impacts on the IHSG, policy interventions should prioritize stabilizing domestic energy and food prices to mitigate market risk sentiment. Stock exchange authorities should enhance information transparency and market liquidity to help market participants process global shocks efficiently. Portfolio managers should adopt sector-selective diversification strategies, reducing exposure to energy-sensitive industries during crude oil price uptrends.

This study has limitations that suggest avenues for future research. First, linear ARDL models do not capture potential asymmetric market responses. Future research should apply Non-linear ARDL (NARDL) frameworks to evaluate whether the IHSG reacts differently to commodity price increases versus decreases. Second, future studies should analyze sector-specific indices (such as agriculture versus manufacturing) to trace disaggregated transmission pathways. Finally, incorporating control variables such as foreign exchange rates and global interest rates (e.g., the Fed Funds Rate) would improve model explanatory power regarding emerging market equity volatility.

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