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Analysis of the Influence of Macroeconomic Variables on the Movement of the Composite Stock Price Index using Nonlinear Autoregressive Distributed Lag

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ABSTRACT

The stock market is one of the key indicators reflecting a country's economic conditions. In Indonesia, the Composite Stock Price Index (CSPI) serves as a primary benchmark of domestic stock market performance. Movements in the CSPI are influenced by various macroeconomic variables, including real sector activity as represented by the Industrial Production Index (IPI) and the interest rate. Previous studies suggest that the relationship between the CSPI and macroeconomic variables is not always linear, but may exhibit asymmetric behavior in both the short run and the long run. In this context, asymmetry refers to differences in the effects of positive and negative changes in macroeconomic variables on the CSPI. To capture such nonlinear relationships, this study employs the Nonlinear Autoregressive Distributed Lag (NARDL) approach. The optimal lag selection based on the Akaike's Information Criterion (AIC) identifies NARDL(12,12,11) as the preferred model specification. The estimation results indicate that the CSPI has a long-run relationship with both the IPI and the interest rate, as evidenced by the bound cointegration test. Furthermore, the relationship among these variables is asymmetric. Increases and decreases in the IPI have different effects on the CSPI, with strong evidence of long-run asymmetry, while short-run asymmetry remains present but weaker. Dynamically, declines in the IPI tend to trigger stronger and more volatile responses in the CSPI compared to increases in the IPI, whose effects generally materialize with a time lag. In contrast to the IPI, the interest rate does not exhibit long-run asymmetry. However, significant short-run asymmetry is observed. Decreases in the interest rate have a positive and significant effect on the CSPI after several periods, whereas increases in the interest rate do not show a significant short-run impact. Overall, decreases in industrial activity and decreases in the interest rate have a stronger effect on the CSPI than increases in these variables. This shows that the CSPI responds differently to positive and negative changes in both industrial activity and interest rates.

Keywords: Asymmetric Relationship; Long-Run Relationship; Nonlinear Model; Stock Market

1. Introduction

In recent years, global and domestic economic uncertainties have increasingly influenced financial market dynamics. Slowing global economic growth, persistent inflationary pressures, geopolitical tensions, and fluctuations in energy prices have created a challenging environment for both developed and emerging economies. As an emerging market that is increasingly integrated into the global financial system, Indonesia is particularly exposed to external shocks, including changes in global interest rates and international capital flows. These factors can significantly affect domestic financial markets, especially the stock market.

In Indonesia, stock market performance is commonly represented by the Composite Stock Price Index (CSPI), which reflects the aggregate movement of stock prices listed on the Indonesia Stock Exchange. The CSPI serves as an important indicator for investors in assessing market performance, risk, and expected returns. As a forward-looking indicator, stock prices incorporate expectations about future economic conditions, making the CSPI a valuable proxy for both current sentiment and future economic prospects.

Macroeconomic variables play a crucial role in shaping stock market dynamics. Among these, the interest rate and the Industrial Production Index (IPI) are particularly important. Interest rates, as a key monetary policy instrument, influence investment decisions and asset allocation by affecting borrowing costs and discount rates. Empirical studies generally find a negative relationship between interest rates and stock prices, as higher interest rates tend to reduce corporate profitability and shift investor preferences toward fixed-income assets.

Meanwhile, the Industrial Production Index reflects real economic activity and serves as an indicator of economic growth. An increase in industrial production is often associated with improved corporate performance and stronger stock market outcomes. Prior studies, such as Chen et al. (1986) and Mukherjee and Naka (1995), provide evidence of a positive relationship between industrial activity and stock market returns.

Given the dynamic nature of economic relationships, the interaction between macroeconomic variables and stock market performance is not always instantaneous and may involve lagged effects. In addition, time series data often exhibit different orders of integration and potential long-run relationships, known as cointegration. The Autoregressive Distributed Lag (ARDL) model provides a suitable framework for analyzing such relationships, as it allows for the estimation of both short-run dynamics and long-run equilibrium without requiring all variables to have the same integration order.

However, the standard ARDL model assumes symmetric relationships, which may not fully capture real-world financial dynamics. In practice, stock market responses to macroeconomic changes can be asymmetric, meaning that positive and negative changes in economic variables may have different impacts. Ignoring such asymmetry may lead to biased or incomplete conclusions.

To address this limitation, this study employs the Nonlinear Autoregressive Distributed Lag (NARDL) model developed by Shin et al. (2014), which allows for the decomposition of explanatory variables into positive and negative changes. This approach enables a more comprehensive analysis of asymmetric effects in both the short run and long run.

Therefore, this study aims to examine the dynamic and asymmetric relationship between the Composite Stock Price Index (CSPI), the Industrial Production Index (IPI), and the interest rate in Indonesia using monthly data from January 2015 to January 2025. Specifically, the study investigates the existence of cointegration, the presence of asymmetric effects, and the differences in stock market responses to positive and negative changes in macroeconomic variables.

2. Theoritical Framework

2.1 Stock Market and Macroeconomic Variables

The stock market is a key financial instrument that enables firms to raise capital and investors to obtain returns through ownership claims on corporate earnings and assets (Indonesia Stock Exchange, 2023). Stock prices reflect not only firm-specific performance but also broader economic conditions. Stock market performance in Indonesia is proxied by the Composite Stock Price Index (CSPI), which represents the overall price movements of all listed companies on the Indonesia Stock Exchange. The CSPI serves as a benchmark for market performance and reflects overall investor sentiment. It is widely used as an indicator of market returns, systematic risk, and portfolio performance.

Macroeconomic variables play an important role in influencing stock market movements. One of the key variables is the interest rate, defined as the cost of borrowing expressed as a percentage (Huda et al., 2019). The interest rate set by Bank Indonesia acts as a benchmark for financial institutions and serves as a primary monetary policy tool to control inflation and economic growth (Khoirul, 2009).

Changes in interest rates affect investment and consumption decisions, thereby influencing corporate earnings and stock prices. Generally, higher interest rates tend to reduce stock prices, while lower interest rates stimulate economic activity and support stock market growth (OCBC, 2023).

Another important macroeconomic indicator is the Industrial Production Index (IPI), which measures changes in industrial output over time (OECD, 2023). The IPI reflects the level of economic activity, particularly in the manufacturing sector, and is often used as a leading indicator of economic performance. An increase in industrial production indicates economic expansion and is associated with improved corporate performance and rising stock prices, while a decline suggests economic slowdown (Moody's Analytics, 2023).

2.2 Time Series Properties and Stationarity

A stochastic process $\{Y_t\}$ is said to be strictly stationary if the joint distribution of $(Y_{t_1}, Y_{t_2}, \dots, Y_{t_n})$ is identical to that of $(Y_{t_1+k}, Y_{t_2+k}, \dots, Y_{t_n+k})$ for all time indices and any lag k. A common example of a strictly stationary process is white noise, which consists of independently and identically distributed random variables with zero mean and constant variance.

In empirical applications, a weaker form known as weak (or covariance) stationarity is more commonly used. A time series is weakly stationary if it satisfies three conditions: (i) a constant mean over time, (ii) constant variance, and (iii) an autocovariance that depends only on the lag between observations rather than on time itself (Cryer, 2008).

However, many macroeconomic and financial time series are non-stationary, often due to the presence of trends or structural changes. To address this issue, the concept of integration is used. A time series is said to be integrated of order zero, denoted as $I(0)$, if it is stationary in levels. If it becomes stationary after first differencing, it is classified as $I(1)$, and similarly, if second differencing is required, it is $I(2)$. In general, a time series is integrated of order d, denoted as I(d), if it becomes stationary after being differenced d times (Verbeek, 2017).

2.3 Cointegration

Cointegration refers to a situation where two or more non-stationary time series, typically integrated of order one $I(1)$, form a linear combination that is stationary $I(0)$. This implies that although the individual series exhibit stochastic trends, they move together in the long run and maintain a stable equilibrium relationship. The existence of cointegration indicates a long-run equilibrium between variables. While individual variables may deviate from this equilibrium in the short run, such deviations are temporary and tend to be corrected over time. This property ensures that the relationship among variables is not spurious, even when the series themselves are non-stationary. In a simple bivariate case, the long-run relationship can be expressed as:

$$Y_t = \alpha + \beta x_t \tag{1}$$

where β represents the long-run coefficient. The deviation from equilibrium, often referred to as the equilibrium error, measures how far the system is from its long-run path. If this error term is stationary, it confirms the presence of cointegration and implies that the variables are tied together in the long run.

According to the Granger Representation Theorem, if variables are cointegrated, their relationship can be represented through an Error Correction Model (ECM). The ECM captures both short-run dynamics and long-run adjustments, allowing the system to gradually return to equilibrium after a shock. The general form of the ECM can be expressed as:

$$\Delta Y_t = \delta + \phi \Delta x_{t-1} - \gamma(Y_{t-1} - \alpha + \beta x_{t-1}) + \varepsilon_t \tag{2}$$

where the term $(Y_{t-1} - \alpha + \beta x_{t-1})$ represents the equilibrium error, and γ measures the speed of adjustment toward long-run equilibrium. A negative and statistically significant adjustment coefficient confirms the existence of a stable long-run equilibrium, where deviations are corrected over time (Verbeek, 2017).

2.4 Autoregressive Distributed Lag (ARDL) Model

The Autoregressive Distributed Lag (ARDL) model is an econometric approach used to capture the dynamic relationship between a dependent variable and its explanatory variables through their lagged values. The model combines autoregressive components of the dependent variable with distributed lag effects of independent variables, allowing it to simultaneously estimate short-run dynamics and long-run relationships. One of the key advantages of the ARDL framework is its flexibility in handling variables with different orders of integration, specifically a mixture of I(0) and I(1), without requiring all variables to be integrated of the same order. In its general form, an ARDL (p,q) model with one explanatory variable can be expressed as:

$$y_t = \alpha + \sum_{i=1}^{p} \lambda_i y_{t-i} + \sum_{j=0}^{q} \beta_j x_{t-j} + u_t \tag{3}$$

where p and q denote the lag orders of the dependent and independent variables, respectively, and u_t is the error term.

The ARDL model can be reparameterized into an Error Correction Model (ECM), which explicitly distinguishes between short-run dynamics and long-run equilibrium. The ECM representation can be written as:

$$\Delta y_t = \alpha + \sum_{i=1}^{p-1} \lambda_i \Delta y_{t-i} + \sum_{j=0}^{q-1} \beta_j \Delta x_{t-j} - \gamma(y_{t-1} - \theta x_{t-1}) + u_t \tag{4}$$

where $(y_{t-1} - \theta x_{t-1})$ represents the long-run equilibrium relationship, and γ is the adjustment coefficient. A negative and statistically significant γ indicates that deviations from the long-run equilibrium are corrected over time. The parameter θ represents the long-run coefficient, which captures the long-term effect of changes in the independent variable on the dependent variable. Meanwhile, the differenced terms reflect short-run adjustments (Pesaran, 2015).

2.5 Bound Test

The bounds testing (Pesaran, 2015) approach provides an alternative method for testing the existence of cointegration within the ARDL framework. One of its main advantages is that it does not require pre-testing for the order of integration, as it can be applied when variables are a mixture of I(0) and I(1). The approach is based on estimating an Error Correction Model (ECM) derived from the ARDL specification. In this framework, cointegration is tested by examining the joint significance of the lagged level variables. The general form of the ECM can be written as:

$$\Delta y_t = \alpha + \sum_{j=1}^{p} \psi_j \Delta y_{t-j} + \sum_{j=0}^{q} \phi_j \Delta x_{t-j} + \delta_1 y_{t-1} + \delta_2 x_{t-1} + u_t \tag{5}$$

The null hypothesis of no cointegration is defined as:

$$H_0: \delta_1 = \delta_2 = 0 \tag{6}$$

against the alternative hypothesis that at least one of the coefficients is non-zero, indicating the presence of a long-run relationship.

The test is conducted using an F-statistic based on a Wald test for the joint significance of the lagged level variables. The calculated F-statistic is then compared with two sets of critical values: the lower bound (F_L) and the upper bound (F_U). The decision rules are as follows:

- If $F > F_U$, the null hypothesis is rejected, indicating the presence of cointegration.
- If $F < F_L$, the null hypothesis cannot be rejected, implying no cointegration.
- If $F_L < F < F_U$, the result is inconclusive.

2.6 Diagnostic Tests

To ensure the reliability of the estimated ARDL model, several diagnostic tests are conducted, including tests for normality, homoskedasticity, autocorrelation, and parameter stability.

First, the normality test is used to examine whether the residuals are normally distributed. In this study, residual normality is assessed using the Jarque–Bera test, where the null hypothesis states that the residuals follow a normal distribution. A probability value greater than 0.05 indicates that the null hypothesis cannot be rejected, suggesting that the residuals are normally distributed.

Second, the heteroskedasticity test is applied to determine whether the variance of the residuals remains constant across observations. The Breusch–Pagan–Godfrey test is employed for this purpose. A probability value greater than 0.05 indicates the absence of heteroskedasticity, implying that the residual variance is constant.

Third, the autocorrelation test is conducted to examine whether the residuals are correlated across time. Since time series data are often prone to serial correlation, this study uses the Breusch–Godfrey LM test. A probability value greater than 0.05 indicates that the null hypothesis of no autocorrelation cannot be rejected, meaning that the residuals are free from serial correlation.

Finally, the stability test is used to assess whether the model parameters remain stable over the sample period. In this study, stability is evaluated using the CUSUM test. If the CUSUM plot remains within the critical bounds at the 5% significance level, the estimated parameters are considered stable over time.

3. Methods

3.1 Data and Variables

This study uses monthly time series data covering the period from January 2015 to January 2025, resulting in 121 observations for each variable. The analysis focuses on the relationship between stock market performance and selected macroeconomic indicators in Indonesia.

The dependent variable is the Composite Stock Price Index (CSPI), which is used as a proxy for overall stock market performance in Indonesia. The independent variables consist of the Industrial Production Index (IPI) and the interest rate. IPI is employed to represent real economic activity, while the interest rate reflects the monetary policy stance. The CSPI data are obtained from Investing Indonesia, the interest rate data are sourced from the official publications of Badan Pusat Statistik (BPS), and the IPI data are obtained from ECONDB.

To improve interpretability and reduce scale differences, the CSPI and IPI variables are transformed into natural logarithms, denoted as ln(CSPI) and ln(IPI). This transformation allows the estimated coefficients to be interpreted more meaningfully in relative terms and helps stabilize variation in the data. In contrast, the interest rate is maintained in level form because its economic interpretation is more appropriate in percentage-point changes rather than proportional changes. In addition, monthly dummy variables are included to control for possible seasonal patterns in monthly economic time series. This is intended to ensure that recurring seasonal fluctuations do not distort the estimated relationship between the main variables.

3.2 Nonlinear Autoregressive Distributed Lag (NARDL) Model Specification

To capture potential nonlinear and asymmetric relationships, this study employs the Nonlinear Autoregressive Distributed Lag (NARDL) model (Shin, Yu, & Greenwood-Nimmo, 2014). The NARDL model extends the conventional ARDL framework by allowing positive and negative changes in the explanatory variable to have different effects on the dependent variable. For a single explanatory variable x_t, the NARDL model is specified by decomposing the variable into positive and negative partial sums:

$$x_t = x_0 + x_t^+ + x_t^- \tag{7}$$

where x_t^+ and x_t^- represent cumulative positive and negative changes, respectively.

The NARDL (p,q) model can be written as:

$$y_t = \alpha + \sum_{j=1}^{p} \phi_j y_{t-j} + \sum_{j=0}^{q} (\theta_j^+ x_{t-j}^+ + \theta_j^- x_{t-j}^-) + \varepsilon_t \tag{8}$$

For estimation purposes, the model is reparameterized into the Unrestricted Error Correction Model (UECM) form:

$$\Delta y_t = \alpha + \rho y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + \sum_{j=1}^{p-1} \gamma_j \Delta y_{t-j} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta x_{t-j}^+ + \pi_j^- \Delta x_{t-j}^-) + \varepsilon_t \tag{9}$$

The UECM specification allows the simultaneous estimation of short-run dynamics and long-run relationships. All parameters are estimated using Ordinary Least Squares (OLS), while the optimal lag structure is selected based on the Akaike Information Criterion (AIC).

The existence of a long-run relationship is tested using the bounds testing approach, by examining the joint significance of the lagged level variables. If cointegration is confirmed, the model can be expressed in the Error Correction Model (ECM) form. The long-run asymmetric coefficients are defined as:

$$\beta^+ = \frac{-\theta^+}{\rho} \qquad \beta^- = \frac{-\theta^-}{\rho} \tag{10}$$

The equilibrium error term is given by:

$$\xi_t = y_t - \beta^+ x_t^+ - \beta^- x_t^- \tag{11}$$

Thus, the ECM specification becomes:

$$\Delta y_t = \alpha + \rho \xi_{t-1} + \sum_{j=1}^{p-1} \gamma_j \Delta y_{t-j} + \sum_{j=0}^{q-1} (\pi_j^+ \Delta x_{t-j}^+ + \pi_j^- \Delta x_{t-j}^-) + \varepsilon_t \tag{12}$$

The coefficient ρ represents the speed of adjustment, which is expected to be negative and statistically significant.

The NARDL framework also allows formal testing of asymmetry in both the long run and short run. Long-run asymmetry is tested using a Wald test with the null hypothesis:

$$H_0: \beta^+ = \beta^- \tag{13}$$

Short-run asymmetry is tested by evaluating whether for at least one *j*:

$$H_0: \pi_j^+ = \pi_j^- \tag{14}$$

Rejection of these hypotheses indicates the presence of asymmetric effects in the relationship.

In this study, the model is extended to include two explanatory variables: the Industrial Production Index (IPI) and the interest rate. The dependent variable is specified as ln(CSPI), while IPI is transformed into logarithmic form and decomposed into positive and negative changes. The final model can be written as:

$$y_t = \alpha + \sum_{j=1}^{p} \phi_j y_{t-j} + \sum_{j=0}^{q_1} (\theta_{1j}^{+\prime} x_{1,t-j}^+ + \theta_{1j}^{-\prime} x_{1,t-j}^-) + \sum_{j=0}^{q_2} (\theta_{2j}^{+\prime} x_{2,t-j}^+ + \theta_{2j}^{-\prime} x_{2,t-j}^-) + \sum_{m=1}^{11} \delta_m D_{m,t} + \varepsilon_t \tag{15}$$

where:
$y_t = ln(CSPI)$
$x_{1,t} = ln(IPI)$
$x_{2,t} = interest\ rate$
$D_{m,t} = monthly\ dummy\ variables$

4. Results and Discussion

4.1 Stationarity Tests

Prior to model estimation, unit root tests are conducted to determine the order of integration of each variable and to ensure that none of the variables are integrated of order two, which would violate the assumptions of the NARDL framework. The Augmented Dickey–Fuller (ADF) test is applied to all variables in level form. The results indicate that ln(IPI) is stationary at level, while ln(CSPI) and the interest rate are non-stationary, as the null hypothesis of a unit root cannot be rejected at conventional significance levels.

Table 1. ADF Unit Root Test Results (Level)

Variable	ADF Statistic	Critical Value (5%)	p-value	Result
ln(CSPI)	-1.308	-2.886	0.624	Non-stationary
ln(IPI)	-3.168	-2.886	0.024	Stationary
Interest Rate	-2.224	-2.886	0.199	Non-stationary

After applying first differencing, both Δln(CSPI) and Δinterest rate become stationary, indicating that these variables are integrated of order one $I(1)$. Therefore, the variables used in this study are a mixture of $I(0)$ and $I(1)$, satisfying the requirement for the application of the NARDL approach.

Table 2. ADF Unit Root Test Results (First Differenced)

Variable	ADF Statistic	Critical Value (5%)	p-value	Result
Δln(CSPI)	-9,690	-2.886	0.0000	Stationary
Δinterest rate	-4,611	-2.886	0.0002	Stationary

4.2 Optimal Lag Selection

The optimal lag determination based on the Akaike's Information Criterion (AIC) identifies the lag combination that yields the lowest AIC value. The best model specification is NARDL(12,12,11) with an AIC value of -4.192. This notation indicates that the model uses 12 lags for the dependent variable CSPI, 12 lags for the independent variable IPI, and 11 lags for the independent variable interest rate.

Table 3. Best NARDL Models Based on AIC

Model Specification	AIC
NARDL(12,12,11)	-4.192
NARDL(12,12,12)	-4.177
NARDL(12,11,11)	-4.172
NARDL(12,12,9)	-4.163
NARDL(12,11,12)	-4.155

4.3 Cointegration Test

After the optimal lag specification is determined and the NARDL model is transformed into the UECM form, the next step is to test the existence of a long-run relationship among variables using the bound test. The F-statistic obtained is 7.269, which exceeds the critical value upper bound of 4.010 and lower bound of 2.860 at the 5% significance level. Therefore, the null hypothesis stating no long-run relationship is rejected, indicating that the variables in the NARDL model have a long-run relationship or cointegration.

Table 4. Bound Cointegration Test Results

	Value
F-Statistic	7.269
Lower Bound (5%)	2.860
Upper Bound (5%)	4.010

4.4 Error Correction Model results

The ECM estimation results show that the error correction term (ECT) coefficient is -0.039 and significant at the 5% level, satisfying the cointegration requirement in the NARDL model. The negative sign indicates the existence of an adjustment mechanism toward long-run equilibrium, while the magnitude indicates that approximately 3.9% of the deviation of ln(CSPI) from the long-run relationship in the previous period is corrected in the current period.

The estimation results show that positive changes in IPI have a positive and significant effect on the CSPI, particularly at lag one and lag three. This indicates that increases in IPI are not immediately reflected in the CSPI in the same period but only have an impact after several periods. Conversely, negative changes in IPI show a more complex response pattern. A decline in IPI in the current period has a negative and significant effect on the CSPI, reflecting the market's initial response to worsening economic conditions. However, in several subsequent periods, the negative change has a positive and significant effect on the CSPICSPI before showing a negative impact again at longer lags.

Unlike IPI, the results show that positive changes in the interest rate do not have a significant effect on the CSPICSPI in the short run. Conversely, negative changes in the interest rate have a positive and significant effect on the CSPI at several lags. This finding shows that monetary policy easing has a role in driving CSPI increases, although the effect does not appear instantly. The CSPI response that is only significant to interest rate decreases indicates asymmetry in monetary policy transmission.

Table 5. NARDL-ECM Estimation Results

Variable	Coefficient	Std. Error	t-Statistic	p-value
ρ	-0,039	0,006	6,373	0,000
ΔY_{t-3}	-0,527	0,135	-3,896	0,000
ΔY_{t-6}	0,400	0,156	2,569	0,014
ΔY_{t-7}	0,500	0,154	3,243	0,003
ΔY_{t-8}	0,592	0,167	3,546	0,001
ΔY_{t-9}	0,270	0,139	1,946	0,059
ΔY_{t-10}	0,451	0,139	3,257	0,002
ΔY_{t-11}	0,2858	0,139	2,056	0,047
$\Delta X^{+}{}_{1,t-1}$	0,968	0,271	3,576	0,001
$\Delta X^{+}{}_{1,t-3}$	0,508	0,208	2,448	0,019
$\Delta X^{-}{}_{1,t}$	-0,299	0,135	-2,220	0,033
$\Delta X^{-}{}_{1,t-1}$	-1,062	0,221	4,797	0,000
$\Delta X^{-}{}_{1,t-2}$	-0,837	0,255	3,278	0,002
$\Delta X^{-}{}_{1,t-6}$	-0,591	0,211	-2,806	0,008
$\Delta X^{-}{}_{1,t-7}$	-0,663	0,231	-2,871	0,007
$\Delta X^{-}{}_{1,t-10}$	-0,596	0,199	-2,993	0,005
$\Delta X^{-}{}_{2,t-3}$	-0,057	0,026	2,244	0,031
$\Delta X^{-}{}_{2,t-4}$	-0,076	0,027	2,820	0,008
$\Delta X^{-}{}_{2,t-5}$	-0,094	0,029	3,263	0,002
$\Delta X^{-}{}_{2,t-6}$	-0,059	0,027	2,187	0,035
$D_{2,t}$	-0,053	0,022	-2,400	0,021
$D_{3,t}$	-0,082	0,025	-2,288	0,002
$D_{4,t}$	-0,091	0,025	-2,619	0,001
$D_{5,t}$	-0,109	0,027	-4,046	0,000
$D_{6,t}$	-0,139	0,028	-5,031	0,000
$D_{7,t}$	-0,089	0,028	-3,210	0,003

Table 5. NARDL-ECM Estimation Results (Contiued)

Variable	Coefficient	Std. Error	t-Statistic	p-value
$D_{8,t}$	-0,089	0,026	-3,351	0,002
$D_{9,t}$	-0,089	0,027	-3,241	0,003
$D_{10,t}$	-0,053	0,023	-2,306	0,027
$D_{11,t}$	-0,035	0,019	-1,832	0,075
α	0,585	0,085	6,877	0,0000

4.5 Long-run Coefficients

Based on the estimation output, both the positive and negative components of IPI have negative coefficients toward the CSPI. Meanwhile, for the interest rate variable, both positive and negative components have positive coefficients toward the CSPI. However, the estimated long-run coefficients are not statistically significant individually. This does not mean that the long-run relationship among variables does not exist, as the existence of the long-run relationship has been confirmed through the significant bound test.

Table 6. Estimated Long-Run Coefficients

Variable	Coefficient	Std. Error	t-Statistic	p-value
lnIPI+	-21.781	162.701	-0.134	0.894
lnIPI-	-23.612	174.743	-0.135	0.893
Rate+	0.115	1.069	0.107	0.915
Rate-	0.881	6.032	0.146	0.884

4.6 Asymmetry Tests

In the long run, the IPI variable has a p-value of 0.039. Thus, the null hypothesis is rejected at the 5% significance level, and it can be concluded that long-run asymmetry exists for IPI. In the short run, the IPI p-value is 0.082, which is greater than 0.05 but below 0.10, indicating weak short-run asymmetry evidence. This finding is consistent with previous research from Tiryaki et al. (2018) and Alqaralleh (2020).

The interest rate variable has a long-run p-value of 0.175, thus failing to reject the null hypothesis at the 5% significance level, indicating no evidence of long-run asymmetry. For the short run, the interest rate p-value is 0.020, so the null hypothesis is rejected, and it can be concluded that short-run asymmetry exists. This finding is consistent with Moussa and Delhoumi (2021).

Table 7. Asymmetry Test Results

Variable	LR F-stat	LR p-value	SR F-stat	SR p-value
IPI	4.610	0.039	3.222	0.082
Interest Rate	1.917	0.175	5.937	0.020

4.7 Diagnostic Tests

To ensure the validity of the estimated model, several diagnostic tests are conducted, including tests for normality, heteroskedasticity, and autocorrelation. The results are summarized in Table X.

Table 8. Diagnostic Test Results

Test	Statistic	p-value	Conclusion
Jarque–Bera (Normality)	1.553	0.460	Residuals are normal
Breusch–Pagan (Homoskedasticity)	1.140	0.343	No heteroskedasticity
Breusch–Godfrey (Autocorrelation)	1.286	0.294	No autocorrelation

As shown in Table 8, all p-values exceed the 5% significance level, indicating that the model satisfies the assumptions of normality, homoskedasticity, and absence of autocorrelation.

Furthermore, parameter stability is evaluated using the CUSUM test. The results in Figure 1, shows that the CUSUM statistic remains within the 5% critical bounds throughout the sample period, indicating that the estimated parameters are stable and no structural break is detected.

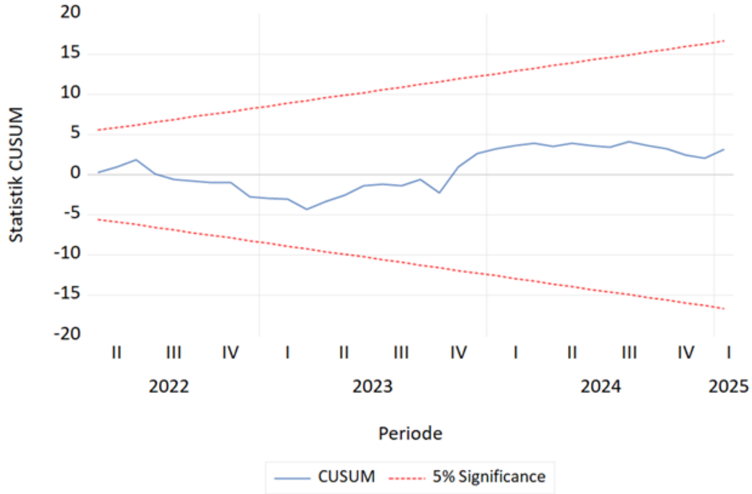

Figure 1. CUSUM Stability Test Result

5. Conclusion

Based on the series of analyses using the NARDL approach with optimal lag selection through AIC, yielding the best model NARDL(12,12,11), this study demonstrates that the CSPI has a long-run relationship with the macroeconomic variables examined, namely IPI and the interest rate. The bound test confirms that the long-run relationship is statistically proven.

The relationship between these variables and the CSPI is not entirely symmetric. For IPI, there is strong evidence that the long-run relationship is asymmetric. In the short run, asymmetry in IPI persists although with a weaker level of significance. The interest rate does not show long-run asymmetry but shows significant asymmetric patterns in short-run dynamics.

The CSPI responds to positive and negative changes in macroeconomic variables with different patterns. IPI increases are associated with significant CSPI increases after some time, while IPI declines are followed by CSPI decreases in the initial period with more volatile movements subsequently. Interest rate decreases are significantly associated with CSPI increases in subsequent periods, while interest rate increases do not show a significant relationship with the CSPI in the short run.

These results carry important policy implications. Maintaining stability in industrial activity is crucial to avoid adverse market reactions, while accommodative monetary policy may support stock market performance during periods of economic slowdown.

Despite its contributions, this study has several limitations. The analysis is limited to a specific set of macroeconomic variables and monthly data frequency, which may not fully capture broader economic dynamics or high-frequency market adjustments.

Future research may extend this study by incorporating additional macroeconomic variables, such as exchange rates, inflation, or consumer confidence indices, to provide a more comprehensive analysis. Furthermore, advanced approaches such as MT-NARDL or QARDL can be explored to capture more complex forms of asymmetry. The inclusion of structural break models or regime-switching frameworks may also help to better understand how relationships change during periods of economic crisis or heightened volatility. Finally, the use of higher-frequency data, such as weekly or daily observations, could provide deeper insights into short-term market dynamics.

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