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The Lead-Lag Effect of Global Gold Prices on ANTM's Brand Equity: A Cross-Correlation and Prewhitening Approach

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Kata Kunci
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Analisis Deret Waktu

Abstrak

Studi ini secara sistematis menyelidiki hubungan dinamis lead-lag antara harga emas global dan nilai merek berbasis pasar PT Aneka Tambang Tbk (ANTM) untuk menilai stabilitas struktural selama guncangan pasar sistemik. Menggunakan harga penutupan harian yang disesuaikan dan diubah menjadi log return, kestabilan data awalnya dikonfirmasi melalui uji Augmented Dickey-Fuller (ADF). Untuk menghilangkan korelasi palsu dan mengisolasi inovasi stokastik, prosedur prewhitening berbasis ARIMA(0,0,2) yang ketat diterapkan pada pengembalian emas global sebelum memetakan Fungsi Korelasi Silang (CCF). Selain itu, analisis pemutusan struktural sub-sampling dilakukan seputar peringatan transparansi pasar MSCI pada 28 Januari 2026. Temuan empiris selama periode stabilitas pra-kejadian menunjukkan korelasi kontemporer yang kuat (Lag 0) dan efek lead satu hari yang sangat signifikan (Lag -1). Hal ini menunjukkan bahwa harga emas global secara efisien menentukan valuasi ANTM, sehingga mengonfirmasi kekuatan ekuitas merek berbasis keuangan sebagai proxy komoditas yang tepercaya. Namun, analisis pasca-MSCI menggambarkan keruntuhan korelasi yang parah, ditandai dengan struktur lag yang terdistorsi dan pergerakan harga yang tidak teratur dan didorong oleh noise. Studi ini menyimpulkan bahwa meskipun ekuitas merek berbasis sumber daya memberikan landasan fundamental yang kuat dalam kondisi rasional, mekanisme perlindungan ini terputus sementara selama kepanikan institusional. Temuan ini menyoroti kebutuhan kritis untuk mengintegrasikan heterogenitas dinamis dan pemutusan struktural saat memodelkan seri waktu keuangan di pasar emerging.

ABSTRACT

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This study systematically investigates the dynamic lead-lag relationship between global gold prices and the market-based brand equity of PT Aneka Tambang Tbk (ANTM) to assess structural stability during systemic market shocks. Utilizing daily adjusted closing prices transformed into log returns, data stationarity was initially confirmed via the Augmented Dickey-Fuller (ADF) test. To eliminate spurious correlation and isolate stochastic innovations, a rigorous ARIMA(0,0,2)-based prewhitening procedure was applied to the global gold returns prior to mapping the Cross-Correlation Function (CCF). Furthermore, a sub-sample structural break analysis was conducted surrounding the MSCI market transparency warning on January 28, 2026. The empirical findings during the pre-shock stability period reveal a robust contemporary correlation (Lag 0) and a highly significant one-day lead effect (Lag -1). This demonstrates that global gold prices efficiently dictate ANTM's valuation, thereby validating its strong financial-based brand equity as a trusted commodity proxy. However, the post-MSCI analysis illustrates a severe correlation breakdown, characterized by distorted lag structures and erratic, noise-driven price movements. The study concludes that while resource-based brand equity provides strong fundamental anchoring under rational conditions, this protective mechanism is temporarily severed during institutional panic. These findings highlight the critical necessity of integrating dynamic heterogeneity and structural breaks when modeling financial time series in emerging markets.

Keywords
Cross-Correlation Function
Correlation
Time Series
Lead-Lag
Time Series Analysis

1. Introduction

The mining companies in the globalised financial market are fundamentally connected with the price of their commodities by valuing the commodity volatility [1], [2]. As one of the most main Indonesian state-run firms, PT Aneka Tambang Tbk (ANTM) forms a very particular point of interaction between the global commodity markets [3], [4] and the domestic equity performance [3], [5]. Traditional finance considers stock prices to be reflected by fundamental measures only, where as modern marketing-finance literature opines that Financial-Based Brand Equity (FBBE) is also manifested by stock performance [6], [7], [8], [9], [10]. This equity represents the intangible premium that investors would be prepared to pay to a brand that they trust as an LBMA-approved brand like ANTM [11], [12], on top of the actual value of its gold deposits.

Volatility spillovers have been quantified with the help of Vector Autoregression (VAR) [13], [14], [15], Dynamic Conditional Correlation-Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) [16], [17], Baba-Engle-Kraft-Kroner Generalized Autoregressive Conditional Heteroskedasticity (BEKK-GARCH) [18] and Vector Autoregression-Generalized Autoregressive Conditional Heteroskedasticity (VAR-GARCH) [13], [19] models that are widely used in current research on commodity-linked equities. The researchers have shown that the global gold prices have a strong impact on the returns of mining companies [20], [21], [22]. Furthermore, there is a technique called Cross-Correlation Function (CCF) that has been applied and it is a strong econometric tool that can be used to determine the lead-lag dynamics, allowing analysts to find out what

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market initiates the movement, and what is the time lag of the information transmission. This technique has been applied in various fields, including finance [23], [24], [25], [26], signal processing [27], [28], [29], [30], and environmental studies [31]. The global crude oil prices have a dynamic and positive connection with the Jakarta Composite Index (IHSG), indicating that changes in crude oil prices can lead to corresponding changes in the IHSG [32]. The Dow Jones Index and gold prices are also significant predictors of the IHSG, with their fluctuations impacting the IHSG's movements [33], [34].

Although there is extensive literature on this topic, there are still three notable gaps. First, most studies focus on the Jakarta Composite Index (IHSG) and gold prices, with none specifically linking gold prices to ANTM share prices. Second, although there is mention of a correlation between gold and gold company share prices [35], [36], [37], [38], there has been no in-depth discussion of delayed correlations or lead-lag effects. Third, econometric time series analysis and the concept of Brand Equity in the mining industry are not integrated with each other. Most studies do not consider the role of a company's brand reputation as a balancing or reinforcing agent in the event of external shocks, such as Morgan Stanley Capital International (MSCI)'s warning to the IHSG, which could trigger significant market abnormalities and consequently cause what is known as a correlation collapse.

The major aim of the study is to conduct a systematic research to explore the dynamic lead-lag association between global gold prices with ANTM market-based brand equity in an enforced econometric model. In the present study, it is possible to establish the particular temporal lags at which global commodity movements affect local equity returns, and, at the same time, determine how stable such correlations are during divergent market regimes, especially high-volatility events like MSCI index rebalancing. Also, the analysis will attempt to establish the technical justification of a pre-whitening step in the filtering of the internal autocorrelation process, thus, guaranteeing that the lead-lag signals obtained accurately capture external transmission of value as opposed to spurious statistical artefacts.

The originality of this investigation is that it has a dual-approach methodology. In contrast to the traditional approaches where investigations are carried out based on crude price data, the current paper uses a strict Prewhitening CCF model to disband authentic leadlag signals and internal autocorrelation noise. As well, the research proposes the concept of Brand Equity Resilience through the analysis of the development of lead-lag structure in case of crashes. This study provides a new model of how the world commodity shocks can be internalized in the local high-equity brands in the emerging economies by treating the ANTM stock premium as a financial brand equity. This research is therefore urgent because investors, market regulators, and corporate financial managers need empirically grounded evidence on whether ANTM’s valuation remains fundamentally anchored to global gold movements or becomes vulnerable to structural disconnection during institutional shocks. If this gap remains unaddressed, market participants may continue to rely on static commodity-equity assumptions that underestimate delayed transmission effects, misread systemic panic as fundamental weakness, and fail to design timely risk-mitigation strategies in emerging market conditions.

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2. Methods

2.1 *Data Collection and Preparation*

The research utilizes secondary data, which consists of daily adjusted closing price of the global gold futures (GC=F) and stock of PT Aneka Tambang Tbk (ANTM.JK). The data is mined out of Yahoo Finance database between a horizon of 2 years (from January 2, 2024, to February 20, 2026) so as to capture a range of market regimes including structural discontinuities created by index rebalancing. To achieve stationarity and reduce the heteroscedasticity the raw price series are transformed into logarithmic returns as shown below:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

where P_t represents the price at time t. The stationarity of the return series is subsequently verified using the Augmented Dickey-Fuller (ADF) test. The gold return series from the transformation of the gold raw price series using Equation 1 is symbolized by (x_t), while ANTM's return series is symbolized by (y_t).

2.2 *Augmented Dickey-Fuller (ADF) test*

The Augmented Dickey-Fuller (ADF) test is employed to examine whether a time-series contains a unit root, which indicates non-stationarity. In financial time-series analysis, stationarity is essential because non-stationary variables may generate misleading statistical relationships and spurious correlations. The ADF test extends the Dickey-Fuller framework by including lagged differences of the dependent variable, thereby controlling for higher-order serial correlation in the residuals. In this study, the ADF test is applied to the log return series of global gold prices and ANTM stock prices before conducting prewhitening and cross-correlation analysis.

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \, \Delta y_{t-i} + \varepsilon_t \tag{2}$$

In this specification, y_t denotes the observed time-series, $\Delta y_t = y_t - y_{t-1}$ represents the first difference, α is the intercept term, βt captures deterministic time trend effects, γ is the coefficient used to test the presence of a unit root, p denotes the number of lagged difference terms, δ_i represents the short-run adjustment coefficients, and ε_t is the white-noise error term. The inclusion of lagged difference terms ensures that the residuals are not serially correlated, making the unit-root inference more reliable.

$$H_0: \gamma = 0 \quad \text{(the series has a unit root and is non-stationary)}$$

$$H_1: \gamma < 0 \quad \text{(the series is stationary)}$$

The null hypothesis is rejected when the ADF test statistic is smaller than the corresponding critical value or when the p-value is below the selected significance level. Rejection of H_0 implies that the series is stationary and suitable for further time-series

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modeling. Therefore, confirming stationarity through the ADF test provides the statistical foundation for applying ARIMA-based prewhitening and Cross-Correlation Function analysis without relying on non-stationary data patterns.

2.3 *Cross-Correlation Function*

The Cross-Correlation Function is employed to measure the linear relationship between the gold return series (x_t) and ANTM's return series (y_t) at various time lags k. The sample cross-correlation coefficient $\rho_{xy}(k)$ is estimated by [39]:

$$\rho_{xy}(k) = \frac{c_{xy}(k)}{\sqrt{c_{xx}(0)c_{yy}(0)}} \tag{3}$$

where $c_{xy}(k)$ is the sample cross-covariance function. A significant spike at a negative lag $(k < 0)$ indicates that gold price movements lead ANTM returns, whereas a spike at a positive lag $(k > 0)$ suggests a lagging response from the commodity market.

2.4 *Cross-Covariance Function*

The cross-covariance function measures the linear dependence between two stochastic processes, x_t (Gold) and y_t (ANTM), at lag time k. The general formula is:

$$\gamma_{xy}(k) = E\left[(x_t - \mu_x)\left(y_{t+k} - \mu_y\right)\right] \tag{4}$$

where:

$E[\cdot]$: expected value.

μ_x, μ_y: mean from x series dan y series.

k: lag. If k is positive, we see a relationship between the current x and the future y.

2.5 *Sample Cross-Covariance Estimation*

In this research, since we are using historical stock data (samples) from Yahoo Finance, we use the sample estimator $c_{xy}(k)$. The formula is divided into two conditions based on the lag direction:

for $k \geq 0$ (Positive Lag)

$$c_{xy}(k) = \frac{1}{n}\sum_{t=1}^{n-k}(x_t - \bar{x})(y_{t+k} - \bar{y}) \tag{5}$$

for $k < 0$ (Negative Lag)

$$c_{xy}(k) = \frac{1}{n}\sum_{t=1-k}^{n}(x_t - \bar{x})(y_{t+k} - \bar{y}) \tag{6}$$

where:

n: Total number of stock data observations (January 2, 2024 - February 20, 2026).

$\bar{x}, \bar{y}$: The average sample of the log return of each asset.

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$c_{xy}(k)$: This result then becomes the numerator in the CCF formula to produce the correlation coefficient $r_{xy}(k)$.

2.6 *ARIMA-Based Prewhitening Procedure*

A key methodological issue in cross-correlation analysis of financial time series is that each series may contain its own autocorrelation structure. If this intra-series dependence is not removed, the estimated cross-correlation may reflect common persistence or internal momentum rather than genuine inter-series transmission. Therefore, this study applies an ARIMA-based prewhitening procedure before estimating the CCF. The procedure is formalized by first modeling the gold return series as a univariate stochastic process, not as an independent variable in a regression framework.

$$\phi(B)(1-B)^d x_t = c + \theta(B)\varepsilon_t \tag{7}$$

In this specification, x_t denotes the gold return series, B is the backshift operator, $\phi(B) = 1 - \phi_1 B - \cdots - \phi_p B^p$ is the autoregressive polynomial, $\theta(B) = 1 + \theta_1 B + \cdots + \theta_q B^q$ is the moving-average polynomial, d is the order of differencing, c is the constant term, and ε_t represents the innovation or residual series. For the selected ARIMA(0,0,2) model, the fitted equation can be written as:

$$x_t = \mu + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} \tag{8}$$

After estimating the ARIMA model for the gold return series, the fitted ARIMA filter is used to obtain the prewhitened gold innovations, denoted by $\hat{\varepsilon}_{x,t}$. The same linear filter is then applied to the ANTM return series y_t to generate the filtered ANTM series $\hat{\varepsilon}_{y,t}$. The CCF is subsequently computed using these two filtered series rather than the original returns:

$$\rho_{\hat{\varepsilon}_x\hat{\varepsilon}_y}(k) = \frac{\gamma_{\hat{\varepsilon}_x\hat{\varepsilon}_y}(k)}{\sqrt{\gamma_{\hat{\varepsilon}_x\hat{\varepsilon}_x}(0)\gamma_{\hat{\varepsilon}_y\hat{\varepsilon}_y}(0)}} \tag{9}$$

The validity of prewhitening depends on whether the residuals from the fitted ARIMA model behave as white noise. Therefore, this study conducts a Ljung-Box diagnostic test on the ARIMA residuals. The Ljung-Box statistic is defined as:

$$Q(m) = n(n+2)\sum_{k=1}^{m}\frac{\hat{\rho}_k^2}{n-k} \tag{10}$$

where n is the sample size, m is the maximum lag used in the diagnostic test, and $\hat{\rho}_k$ is the sample autocorrelation of the ARIMA residuals at lag k. The null hypothesis is $H_0: \rho_1 = \rho_2 = \cdots = \rho_m = 0$, indicating that the residuals are independently distributed up to lag m. If the Ljung-Box p-value is greater than the selected significance level, the null hypothesis is not rejected, and the residuals can be treated as white noise. Only after this diagnostic condition is satisfied can the prewhitened CCF be interpreted as evidence of lead-lag transmission rather than remaining autocorrelation from the individual time series.

2.7 *Sub-Sample Analysis for Market Shocks*

To evaluate the stability of the lead-lag effect during extreme market volatility, such as MSCI rebalancing events, the dataset is partitioned into sub-samples: the pre-shock period and the post-shock period. This comparative approach allows for the identification of structural breaks in the cross-correlation structure. Significant shifts in the magnitude or position of the CCF spikes across these periods are interpreted as changes in market efficiency and the resilience of ANTM's financial brand equity.

2.8 *Computational Algorithm*

The computational workflow for this study is executed using R programming through the following algorithmic steps:

1) Stationarity Check: Conducting ADF tests on log return series.
2) Model Identification: Utilizing the **auto.arima()** function to determine the stochastic structure of the leading variable.
3) Residual Extraction: Generating prewhitened series for both gold and ANTM.
4) Cross-Correlation Mapping: Computing $\rho_{xy}(k)$ for $k = \pm 20$ days.
5) Significance Testing: Comparing coefficients against the 95% confidence interval, defined as $\pm 2/\sqrt{n}$.

All statistical computations, including the stationarity tests, ARIMA model fitting, and sub-sample analysis, were executed using R programming. To ensure full transparency and reproducibility, the step-by-step computational workflow, raw outputs, and high-resolution diagnostic plots have been documented and published on RPubs, accessible at: https://rpubs.com/anggadwimulyanto/CCFGoldANTM.

3. Result and Discussion

4.1 *Result*

The **getSymbols()** function was used to obtain the data. The symbol for gold is GC=F, while the symbol for ANTM stock prices is ANTM.JK. The head and tail of the data collection can be seen in Table 1.

Table 1. Data Gold and ANTM

Date	Raw Price	
	Gold (USD/oz)	ANTM (IDR/share)
2024-01-02	2064.4	1524.817
2024-01-03	2034.2	1494.057
2024-01-04	2042.3	1480.874
⋮	⋮	⋮
2026-02-18	4986.5	4050.000

2026-02-19	4975.9	4230.000
2026-02-20	5059.3	4220.000

The transformation based on equation 1 was performed on both Gold and ANTM values. The results of the transformation are presented in Table 2.

Table 2. Transformation Gold and ANTM

Date	Transformation	
	Gold	**ANTM**
2024-01-02	-1.473698e-02	-0.020379176
2024-01-03	3.974050e-03	-0.008862693
2024-01-04	4.895125e-05	-0.005952320
⋮	⋮	⋮
2026-02-18	1.976794e-02	0.000000000
2026-02-19	-2.128022e-03	0.043485112
2026-02-20	1.662186e-02	-0.002366865

After the transformation process, the ADF test was conducted using the **adf.test()** function. Because the output provides the p-value directly, the stationarity results are reported in statistical table format rather than as a visual figure.

Table 3. ADF Test Results Based on p-value

Variable	p-value	Decision	Conclusion
Gold log return	0.01	Reject H0	Stationary
ANTM log return	0.01	Reject H0	Stationary

The foundation of this time-series analysis relies on ensuring data stationarity to prevent the detection of spurious correlations. As presented in Table 3, the log returns for both Global Gold Futures (GC=F) and PT Aneka Tambang Tbk (ANTM.JK) yielded a p-value of 0.01 over the 2024–2026 sample period. Since this p-value is below the 5% significance level, the null hypothesis of a unit root is rejected for both variables. This confirms that both log return series are stationary and suitable for subsequent ARIMA-based prewhitening and cross-correlation analysis.

Following the confirmation of stationarity, a rigorous prewhitening procedure was implemented to eliminate the confounding effects of internal autocorrelation within the time series. To achieve this, an autoregressive integrated moving average (ARIMA) modeling approach was applied to the gold log return series as a univariate stochastic process.

Table 4. Summary of the Selected ARIMA Model for Gold Log Returns

Model Component	Value
Selected model	ARIMA(0,0,2) with non-zero mean
Mean	0.0018
MA(1)	-0.0753
MA(2)	-0.1356
sigma²	0.0001763
Log likelihood	1426.74
AIC	-2845.48
AICc	-2845.40
BIC	-2828.70

As shown in Table 4, the ARIMA model selected by the automatic model selection procedure was ARIMA(0,0,2) with a non-zero mean. The raw R console output was not retained in the manuscript; instead, the selected model is reported as a structured statistical summary containing the estimated parameters and information criteria. The model produced AIC = -2845.48, AICc = -2845.40, and BIC = -2828.70. The estimated mean was 0.0018, while the moving-average coefficients were MA(1) = -0.0753 and MA(2) = -0.1356. These coefficients are presented to document the stochastic filter used in the prewhitening procedure rather than to make separate inferential claims about individual ARIMA parameters. Therefore, the interpretation is limited to the adequacy of the selected filter for removing internal autocorrelation before CCF estimation. Because the model was obtained from the automatic selection routine rather than from a manually tabulated comparison of candidate models, the full computational workflow and original R output are documented in the supplementary RPubs material for transparency and reproducibility. The residuals extracted from this fitted ARIMA(0,0,2) model represent stochastic innovations of the gold market only if they pass residual diagnostic testing. Therefore, the adequacy of the selected ARIMA model was evaluated using the Ljung-Box test to confirm that no significant autocorrelation remained in the residuals. After this diagnostic requirement was satisfied, the same ARIMA filter was applied to the ANTM log return series to generate the corresponding filtered series. By isolating the prewhitened components of both series, the subsequent cross-correlation analysis is safeguarded against spurious association and can be interpreted as inter-market transmission rather than shared internal autocorrelation.

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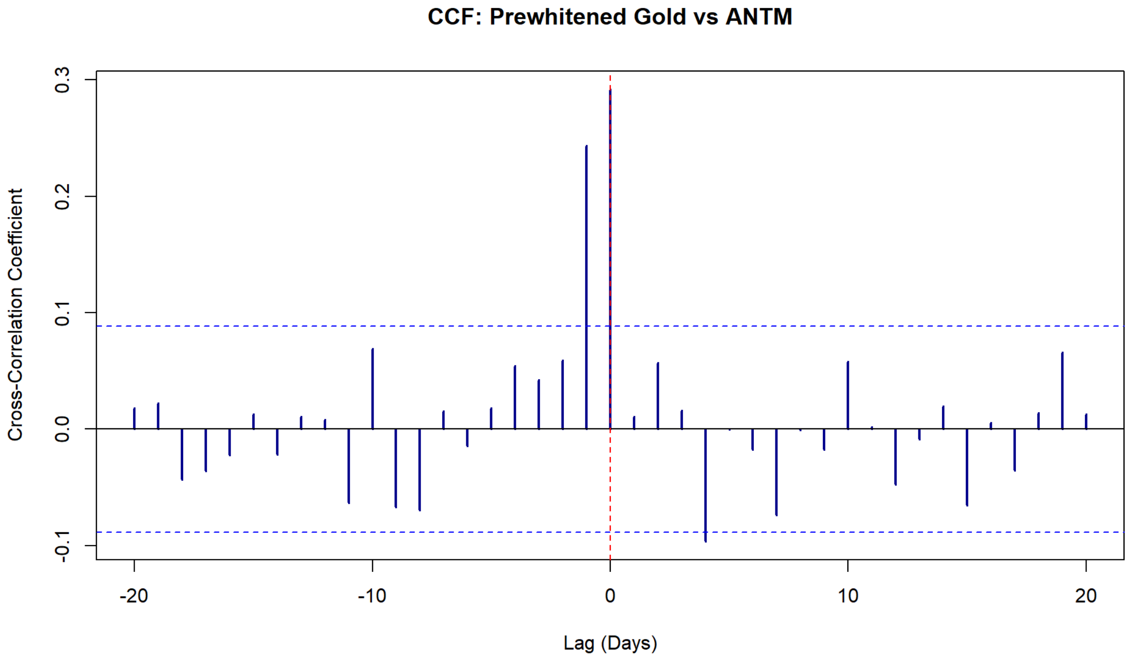

Figure 2. Cross Correlation Function

The empirical findings depicted in the figure of the CCF shows that the market shock propagation between the global commodity index and the domestic equity asset follows a strong temporal hierarchy. The highest statistical impression is the very significant positive spike at lag 0 ($\rho \approx 0.29$) indicating a strong contemporaneous relationship where the market value of ANTM is swift to absorb a large portion of the world gold price fluctuations. However, the most important finding in this study is that the positive correlation that is highly significant at lag -1 ($\rho \approx 0.24$), which provides conclusive evidence of a lead-lag effect, which shows that global gold price variations are systematic determinants of the market value of ANTM with a one-day lag. This time delay of one day is logically consistent with time differences between the closing of the global commodity exchanges and the following opening of domestic market.

Also, there is a spike in marginal negative correlation at lag +4 ($\rho \approx -0.10$) indicating a delayed correcting mechanism in the market, which, presumably, is caused by profit-taking in retailers after the initial fundamental price adjustment. Taken as a whole, these results provide empirical support to the hypothesis of dynamically and predictably anchoring the financial brand equity to the underlying commodity of ANTM as a financial brand.

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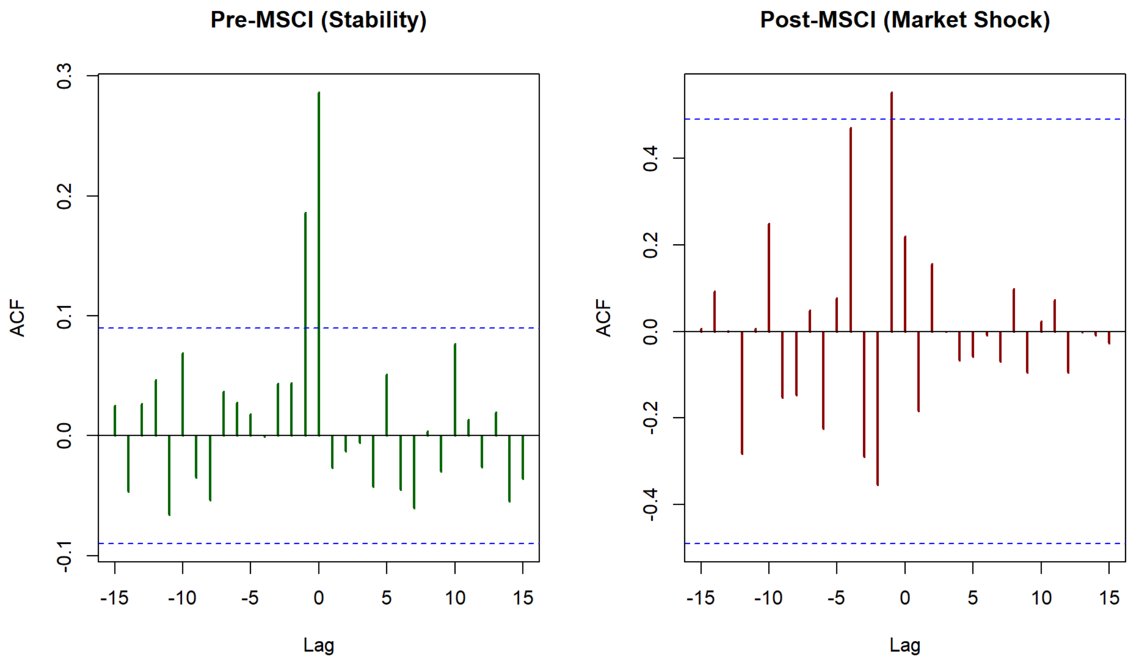

Figure 3. Cross-Correlation Function (Before and After MSCI Warning on January 28, 2026)

To test the resilience of the lead-lag structure to extreme external shocks, the analysis continued by partitioning the data into two subsamples: the period of stability before the MSCI warning (Pre-MSCI) and the period of crisis after the ultimatum (Post-MSCI). On the left panel (Pre-MSCI Chart), the cross-correlation structure shows very consistent stability with rational market conditions. There is a clear significant positive spike in Lag 0 and Lag -1. In this phase, information transmission is efficient; stock valuations strictly follow the fundamental movements of global gold prices. The company's Financial-Based Brand Equity during this period functioned optimally as a proxy for a trusted commodity asset in the eyes of investors.

In contrast, the right panel (Post-MSCI Chart) provides an empirical illustration of the correlation breakdown phenomenon triggered by market panic at the end of January 2026. The previously solid rational structure collapsed instantly. The predictable relationship at Lag 0 and Lag -1 was severely distorted, even swinging sharply in a negative direction. It should be noted that the widening of the confidence interval (blue dotted line) in this panel is purely a mathematical function of the much smaller sample size (n) in the post-shock period. However, despite these widened significance limits, the emergence of very high, random, and irregular correlation spikes at more distant lags (such as Lag -2, Lag -3, and Lag -4) is a visual indicator of high noise in the market. Price movements are no longer driven by gold fundamentals, but rather by blind sell-off pressure.

This structural distortion has profound theoretical implications for the resilience of Brand Equity. When domestic exchanges are hit by systemic risk, in this case a crisis of confidence in the transparency of ownership structures highlighted by MSCI, institutional panic

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sentiment dominates the pricing mechanism. The intrinsic value of global commodities, which should support stock prices, is ignored by the market in the short term. This finding proves that Brand Equity protection has a tolerance limit; the fundamental correlation of an issuer to its underlying commodities can be temporarily severed when there is massive capital flight due to macro market governance issues.

4.2 *Discussion*

The results of the Cross-Correlation Function (CCF) analysis applied to prewhitened residuals provide strong empirical evidence regarding the mechanism of information transmission between global commodity markets and domestic equities. The significant positive correlation found at Lag 0 and Lag -1 confirms that global gold price movements act as a leading indicator that dictates ANTM's stock valuation with a maximum transmission lag of one trading day. This proves that under normal market conditions, ANTM has very solid Financial-Based Brand Equity. Investors rationally position this stock as a direct proxy for gold assets. However, sub-sample analysis of the post-MSCI ultimatum period (January 28, 2026) reveals the vulnerability of this brand equity. Systemic risk shocks related to transparency issues triggered a correlation breakdown phenomenon, where ANTM's valuation was temporarily disconnected from its gold fundamentals due to market panic and irrational sell-off behavior.

Methodologically, this study demonstrates the absolute necessity of using ARIMA-based prewhitening procedures in analyzing financial time series data. If cross-correlations are calculated directly from log returns without isolating the ARIMA(0,0,2) structure in the gold variable, the resulting lead-lag estimates will be biased and prone to spurious correlations due to internal market momentum. Furthermore, the data partitioning approach (structural break analysis) used to capture the effects of the MSCI crisis provides an important theoretical basis regarding the dangers of assuming data homogeneity. The fact that correlation parameters can shift dramatically due to external shocks demonstrates the need for segmentation methods in time series data statistical modeling.

This study enriches the existing literature on commodity financialization and semi-strong form efficiency. While previous studies generally only assume a long-term static relationship between commodity prices and mining stocks, this study fills a gap in the literature by proving that this relationship is dynamic and highly sensitive to macro market governance. The finding regarding the collapse of the lead-lag structure after the MSCI ultimatum provides a new dimension to financial brand equity theory, namely that no matter how strong the perception of a resource-based company's value is, its resilience has a tolerance limit when faced with institutional-scale negative sentiment. Thus, this article offers a more comprehensive perspective for investors and regulators in understanding the interaction between fundamental risk and systemic risk in emerging markets.

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4. Conclusion

This study comprehensively proves the dynamic relationship between global gold price movements and the financial brand equity of PT Aneka Tambang Tbk (ANTM). Through the application of prewhitening procedures based on the ARIMA(0,0,2) model and Cross-Correlation Function (CCF) analysis, the test results reveal that in rational market conditions, global gold consistently acts as a leading indicator of ANTM stock valuation with a lag of one trading day (Lag -1) and a strong contemporary correlation (Lag 0). These empirical findings confirm that ANTM has very solid Financial-Based Brand Equity, where market participants disciplinedly position the company's shares as a proxy for trusted basic commodity assets.

However, this study also concludes that this structural stability is highly vulnerable to macro-level systemic risk shocks. A sub-sample analysis isolating the market transparency ultimatum event by MSCI on January 28, 2026, demonstrates an instant and profound correlation breakdown. Institutional panic over market governance issues caused pricing mechanisms to become distorted and completely disconnected from the fundamental value of the underlying commodities. The essential conclusion of this study is that the equity protection of a commodity issuer's brand has a real tolerance limit. No matter how strong the fundamental correlation is, the relationship can experience a structural break when faced with an aggregate crisis of confidence. Therefore, academics, investors, and policymakers can no longer rely solely on the assumption of static correlation, but must actively integrate market heterogeneity risk in modeling future asset behavior.

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