**BULLETIN OF COMPUTER SCIENCE RESEARCH**
**ISSN 2774-3659 (Media Online)**
Vol 6, No 3, April 2026 | Hal 1005-1015
https://hostjournals.com/bulletincsr
DOI: 10.47065/bulletincsr.v6i3.1080

# Dynamic Interdependence Between Altcoin Dominance and Ethereum Price: A Temporal Pattern-Based Analysis

**Diva Ramadhani Ristiaji Putri, Rizky Parlika*, Hendra Maulana**

Faculty of Computer Science, Informatics Study Program, Universitas Pembangunan Nasional "Veteran" Jawa Timur, Surabaya, Indonesia
Email: [1]22081010227@student.upnjatim.ac.id, [2,*]rizkyparlika.if@upnjatim.ac.id, [3]hendra.maulana.if@upnjatim.ac.id
Correspondence Author Email: rizkyparlika.if@upnjatim.ac.id

**Abstract**−The cryptocurrency market exhibits dynamic and time-varying relationships driven by shifts in market structure and investor behavior. This study investigates the dynamic interdependence between altcoin dominance and Ethereum price, addressing the limitations of static correlation analysis by applying a temporal pattern-based approach. Using 1,416 daily observations from 2022 to 2025, the data are segmented into monthly periods to capture time-varying relationships. The analysis combines correlation, trend, and volatility metrics with pattern classification to identify recurring relationship structures across different market conditions. The results reveal a moderate negative correlation ($r = -0.48$) at the aggregate level. However, the monthly analysis shows that this relationship is not stable over time, but instead varies across different market regimes. The relationship is dominated by inverse patterns (40.43%), followed by weak (38.30%) and positive (21.28%) patterns. From an economic perspective, the negative relationship can be explained by capital rotation dynamics within the cryptocurrency market. When altcoin dominance increases, market liquidity tends to shift from major assets such as Ethereum to a broader set of alternative tokens, leading to downward pressure on Ethereum prices. Conversely, during certain bullish periods, capital inflows can simultaneously strengthen both altcoin dominance and Ethereum price, resulting in positive relationships. These findings demonstrate that the relationship between altcoin dominance and Ethereum price is dynamic and context-dependent. The study highlights the importance of temporal segmentation and pattern-based analysis in capturing complex market behavior that cannot be explained by a single aggregate correlation measure.

**Keywords**: Altcoin Dominance, Ethereum Price, Dynamic Interdependence, Cryptocurrency Market, Temporal Patterns

## 1. INTRODUCTION

The rapid development of blockchain technology has led to the emergence of a highly dynamic and complex cryptocurrency market. Since the introduction of Bitcoin, a wide range of alternative digital assets (altcoins) such as Ethereum, Ripple, and Litecoin have emerged, contributing to significant growth in market capitalization and trading activity. This evolution has transformed the cryptocurrency market into an interconnected financial system characterized by high volatility and structural complexity [1], [2].

Within this ecosystem, Bitcoin has historically dominated market capitalization, typically measured through the Bitcoin dominance indicator. However, in recent years, Bitcoin dominance has declined as altcoins, particularly Ethereum, have gained increasing importance due to their role in smart contracts and decentralized applications (dApps) [3], [4]. This shift has led to the emergence of the "altcoin season," where alternative assets outperform Bitcoin [5], [6].

From a market microstructure perspective, this shift reflects a phenomenon known as capital rotation, where investors dynamically reallocate capital across different cryptocurrency assets. When capital flows from major assets such as Bitcoin or Ethereum into a broader set of altcoins, the relative dominance of altcoins increases. This process can exert downward pressure on major assets while simultaneously boosting smaller-cap tokens, indicating that dominance metrics may capture underlying liquidity movements within the market.

While Bitcoin dominance has been widely studied, its complement, altcoin dominance, provides a more direct representation of aggregate capital allocation toward non-Bitcoin assets. Unlike individual price indicators, altcoin dominance reflects the relative share of total market liquidity allocated to the altcoin sector. Therefore, it can serve as a proxy for measuring capital flow dynamics that may influence the price behavior of major altcoins such as Ethereum.

Previous studies have shown that cryptocurrency markets exhibit strong interdependence through price spillovers, volatility transmission, and dynamic correlations [7], [8], with relationships that are highly volatile and evolve across different market conditions, indicating inherently time-varying interdependence [9], [10]. More recent research further confirms that interconnectedness and volatility dynamics can intensify significantly during periods of market stress or uncertainty [11], [12], [13].

These findings suggest that global, aggregate-based analytical approaches are often insufficient to capture the complex and time-varying nature of relationships in cryptocurrency markets. To address this limitation, several studies employ statistical tools such as correlation and volatility measures to quantify the strength and variability of relationships between assets over time [14], [15], [16].

Building upon this perspective, recent research has begun to explore pattern-based approaches for capturing structural dynamics in financial data. For instance, pattern-oriented analysis has been used to map cryptocurrency fluctuations and identify recurring behavioral structures within the market [17]. These approaches emphasize interpretability and temporal dynamics, offering an alternative to traditional econometric models that primarily focus on statistical estimation.

However, even advanced econometric approaches such as Vector Autoregression (VAR) and Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) tend to model relationships continuously over time, often overlooking localized structural changes within shorter time intervals [18],

BULLETIN OF COMPUTER SCIENCE RESEARCH
ISSN 2774-3659 (Media Online)
Vol 6, No 3, April 2026 | Hal 1005-1015
https://hostjournals.com/bulletincsr
DOI: 10.47065/bulletincsr.v6i3.1080

[19]. As a result, these methods may have limited ability to capture context-dependent dynamics in highly volatile markets.

To address this limitation, this study adopts a temporal segmentation approach combined with pattern-based analysis. Instead of modeling relationships solely through global statistical measures, the data are segmented into monthly periods to capture localized dynamics. Each segment is analyzed independently using correlation, trend, and volatility metrics, followed by classification into distinct relationship patterns.

This approach differs from traditional econometric models such as DCC-GARCH by prioritizing interpretability and structural pattern identification over purely statistical estimation. While DCC-GARCH captures continuous time-varying correlations, the proposed approach focuses on identifying discrete, interpretable relationship regimes that reflect changes in market behavior.

Although previous studies have explored relationships between cryptocurrencies, most research focuses on price or return interactions between Bitcoin and altcoins. Limited attention has been given to the role of altcoin dominance as a macro-level indicator of market structure in explaining Ethereum price dynamics. Moreover, few studies explicitly examine how these relationships evolve across segmented time periods. Furthermore, the role of altcoin dominance as a macro-level capital flow indicator remains underexplored within temporally segmented analytical frameworks.

Therefore, this study aims to analyze the dynamic interdependence between altcoin dominance and Ethereum price using a temporal pattern-based approach. By integrating time segmentation with pattern classification, this research seeks to provide a more context-aware understanding of cryptocurrency market dynamics.

The main contribution of this study lies in introducing a pattern-based analytical framework to capture time-varying relationships in the cryptocurrency market. This approach complements existing econometric models by offering a more interpretable representation of dynamic interdependence, thereby providing both theoretical insights and practical implications for market participants.

# 2. RESEARCH METHODOLOGY

## 2.1 Research Stages

This study was conducted through a series of systematically designed stages to analyze the dynamic interdependence between altcoin dominance and Ethereum price using a temporal pattern-based approach. The research stages include data collection, data preprocessing, variable construction, relationship analysis, temporal segmentation, pattern classification, and interpretation of results. Each stage is structured to ensure a consistent analytical process and to produce reliable and interpretable findings. The overall research workflow is illustrated in Figure 1, which presents the sequence of analysis from initial data acquisition to final interpretation.

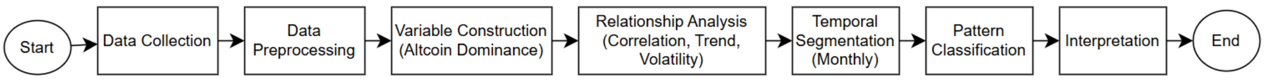


**Figure 1.** Research Flow

As shown in Figure 1, the research begins with the collection of historical cryptocurrency data, including Ethereum price, Bitcoin market capitalization, and total cryptocurrency market capitalization. The data are obtained from multiple digital asset data providers and then standardized into a daily frequency to ensure consistency in time series analysis. The second stage is data preprocessing, which includes data cleaning, time format alignment, and merging datasets from different sources. In this stage, the main research variable, altcoin dominance, is calculated based on the proportion of non-Bitcoin market capitalization relative to the total cryptocurrency market. The third stage involves relationship analysis, where statistical measures such as correlation, trend, and volatility are used to identify the direction, strength, and variability of the relationship between altcoin dominance and Ethereum price.

The next stage is temporal segmentation, where the dataset is divided into monthly periods. Each segment is treated as an independent unit of analysis to capture localized dynamics that may not be visible in aggregate analysis. Following segmentation, a pattern classification process is conducted. For each period, the calculated metrics (correlation, trend, and volatility) are used to classify relationship patterns into structured categories. This approach enables the identification of recurring relationship regimes across different market conditions. The final stage is interpretation and discussion, where the results from all stages are integrated to provide a comprehensive understanding of the dynamic relationship between altcoin dominance and Ethereum price. The findings are then summarized into conclusions and practical implications. This framework emphasizes interpretability and avoids reliance on parametric econometric models, thereby reducing the risk of spurious results associated with non-stationary financial time series data.

## 2.2 Data and Variables

This study utilizes secondary data in the form of historical cryptocurrency market data obtained from several digital asset data provider platforms. The data include Ethereum price, Bitcoin market capitalization, and total global cryptocurrency market capitalization. Ethereum price data were obtained from the Coinbase platform, while Bitcoin market capitalization

ISSN 2774-3659 (Media Online)
Vol 6, No 3, April 2026 | Hal 1005-1015
https://hostjournals.com/bulletincsr
DOI: 10.47065/bulletincsr.v6i3.1080

data were sourced from CoinMarketCap, and total market capitalization data were collected from CoinGecko. The use of multiple data sources aims to ensure broader coverage and improve data reliability.

The observation period spans from January 2022 to November 2025. Initially, Ethereum price data were available at an hourly frequency, whereas Bitcoin market capitalization and total cryptocurrency market capitalization data were available at a daily frequency. To ensure consistency in time series analysis, all data were transformed into daily frequency through a resampling process. Daily Ethereum prices were derived using the closing price for each day.

After preprocessing, the final dataset consists of two primary variables with daily frequency: Ethereum price and altcoin dominance, with a total of 1,416 observations. The main variables used in this study are Ethereum price as the dependent variable and altcoin dominance as the independent variable. The concept of market dominance in cryptocurrency refers to the proportion of an asset's market capitalization relative to the total market capitalization. Bitcoin dominance is commonly defined as the ratio of Bitcoin market capitalization to total cryptocurrency market capitalization [6]. Based on this definition, altcoin dominance is derived as its complement. Altcoin dominance is calculated using the following equation:

$$Alt\ Dominance = \frac{TotalMarketCap - BTCMarketCap}{TotalMarketCap} \times 100 \quad (1)$$

where Total Market Cap represents the total capitalization of all cryptocurrencies, and BTC Market Cap represents the capitalization of Bitcoin. The resulting value reflects the proportion of capital allocated to altcoins within the overall market.

In addition to the primary variables, this study focuses on Ethereum price and altcoin dominance as the main indicators to capture market dynamics. Ethereum price is used to represent asset valuation, while altcoin dominance reflects the proportion of capital allocated to non-Bitcoin assets within the cryptocurrency market. By using these variables, this study examines how changes in market dominance structure relate to Ethereum price dynamics in a time-dependent context.

### 2.3 Data Preprocessing

The data preprocessing stage was conducted to ensure that the dataset is clean, consistent, and suitable for time-based analysis. This process includes data cleaning, time alignment, frequency standardization, dataset integration, and normalization. In the initial step, data completeness was evaluated to identify missing values and potential anomalies. Inconsistent or incomplete records were handled to prevent distortion in subsequent analysis. All time-related variables were then converted into a standardized datetime format to ensure uniformity across datasets.

Since the data were obtained from multiple sources with different time frequencies, a resampling process was performed to align all variables to a daily frequency. Ethereum price data, originally available at an hourly frequency, were aggregated into daily values using the closing price of each day. This step ensures consistency across variables and enables synchronized temporal analysis. After frequency alignment, the datasets were merged using the inner join method based on the timestamp variable. This approach ensures that only observations with complete information across all variables are included, resulting in a fully aligned and integrated dataset.

To address scale differences between variables, normalization was applied using the Min-Max Scaling method, which transforms values into a range between 0 and 1. This normalization is particularly important for visualization and pattern comparison, as it allows both altcoin dominance and Ethereum price to be evaluated proportionally within the same analytical framework. It is important to note that normalization was applied only for visualization and pattern interpretation purposes and does not affect the underlying statistical relationships.

The output of this preprocessing stage is a structured dataset consisting of altcoin dominance and Ethereum price variables at a daily frequency. This dataset serves as the foundation for subsequent temporal analysis and pattern classification.

### 2.4 Time Series Analysis

This study employs a time-based analytical approach to examine the relationship between altcoin dominance and Ethereum price, focusing on three key aspects: relationship direction, strength, and temporal dynamics. Rather than relying on heavy econometric modeling, this approach emphasizes interpretability and the ability to capture dynamic interactions within the cryptocurrency market.

The initial analysis is conducted using the Pearson correlation coefficient to measure the linear relationship between altcoin dominance and Ethereum price. The Pearson correlation coefficient is widely used to quantify the direction and strength of relationships between numerical variables [10]. The coefficient is defined as follows:

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2}} \quad (2)$$

where X represents altcoin dominance, Y represents Ethereum price, and r denotes the correlation coefficient ranging from −1 to 1. A positive value indicates a direct relationship, while a negative value indicates an inverse relationship.

To capture the dynamic nature of the relationship, rolling correlation analysis is applied using a moving time window. This approach allows the correlation between variables to be observed across different time periods, providing insights into how relationships evolve over time [20]. The rolling correlation is expressed as:

$$\rho_t = Corr(X_{t-n:t}, Y_{t-n:t}) \quad (3)$$

where n represents the window size used in the calculation. This method enables the identification of time-varying relationships that cannot be observed through static correlation analysis.

In addition to simultaneous relationships, lag correlation analysis is conducted to examine delayed interactions between variables. This approach evaluates whether changes in altcoin dominance are followed by changes in Ethereum price over subsequent time periods. The lag correlation is defined as:

$$Corr(X_{t-k}, Y_t) \quad (4)$$

where k represents the lag period. In this study, lag values of 1 day, 7 days, and 30 days are used to capture short-term and medium-term temporal dependencies.

By integrating correlation, rolling correlation, and lag correlation analyses, this study provides a comprehensive framework for understanding both static and dynamic relationships between altcoin dominance and Ethereum price. This analytical foundation is subsequently used in temporal segmentation and pattern classification to identify structured relationship patterns across different time periods.

### 2.5 Temporal Pattern Analysis Based on Time Segmentation

Temporal pattern analysis is conducted to capture the dynamic and time-varying relationship between altcoin dominance and Ethereum price. Unlike aggregate analysis, which produces a single global relationship value, this approach enables the identification of localized relationship patterns across different time periods. This approach aligns with prior time-based studies that emphasize segmented analysis to capture structural changes in financial data.

The first step involves segmenting the dataset into monthly periods, where each segment is treated as an independent unit of analysis. This segmentation allows the relationship between variables to be examined within specific temporal contexts. For each monthly segment, three primary metrics are computed: correlation, trend, and volatility. The relationship between altcoin dominance and Ethereum price is measured using the Pearson correlation coefficient, which captures both the direction and strength of the relationship. To evaluate price movement within each period, a linear trend is estimated using a time index:

$$Y_t = \alpha + \beta t + \varepsilon_t \quad (5)$$

where β represents the direction of the trend. A positive β indicates an upward trend, while a negative β indicates a downward trend. Volatility is measured using the standard deviation of Ethereum price within each segment [30], the formula is as follows:

$$\sigma = \sqrt{(\Sigma(Y_i - \bar{Y})^2 / n)} \quad (6)$$

Volatility reflects the degree of price fluctuation within a given period. To ensure consistent classification, volatility levels are categorized relative to the overall dataset, where values above the mean volatility are classified as high volatility, and values below the mean are classified as low volatility.

Market conditions are determined using a normalized price approach. For each segment, Ethereum prices are normalized into a range of 0 to 1 based on the minimum and maximum values within the period. This normalization allows for consistent comparison across different time segments. The classification of market conditions is defined quantitatively as shown in Table 1.

**Table 1.** Market Condition Classification

| Condition | Criteria |
|---|---|
| Bullish | Normalized price > 0.7 |
| Bearish | Normalized price < 0.3 |
| Neutral | 0.3 ≤ normalized price ≤ 0.7 |

This quantitative definition ensures that market condition classification is objective, reproducible, and consistent across all periods. The strength of the relationship between variables is classified based on established statistical interpretation guidelines [16], [17]. The classification is summarized in Table 2.

**Table 2.** Correlation Strength Classification

| Correlation Range | Interpretation |
|---|---|
| r < −0.5 | Strong Inverse |
| −0.5 ≤ r < −0.2 | Moderate Inverse |
| −0.2 ≤ r ≤ 0.2 | Weak |
| 0.2 < r ≤ 0.5 | Moderate Positive |
| r > 0.5 | Strong Positive |

Volatility is used to describe the level of price fluctuation within each segment. To ensure consistent classification, volatility is categorized relative to the overall dataset, as shown in Table 3.

BULLETIN OF COMPUTER SCIENCE RESEARCH
ISSN 2774-3659 (Media Online)
Vol 6, No 3, April 2026 | Hal 1005-1015
https://hostjournals.com/bulletincsr
DOI: 10.47065/bulletincsr.v6i3.1080

**Table 3.** Volatility Classification

| Volatility Level | Criteria |
|---|---|
| High Volatility | σ > mean(σ) |
| Low Volatility | σ ≤ mean(σ) |

Based on these classifications, relationship patterns are constructed by integrating correlation strength, market condition, and volatility level into a unified framework. This multi-dimensional classification enables a more contextual interpretation of the interaction between variables.

To evaluate the consistency of these patterns over time, a distribution analysis is conducted by calculating the frequency of occurrence of each pattern using the following equation:

$$P = (f / N) \times 100\% \quad (7)$$

where *f* represents the number of occurrences of a pattern and *N* is the total number of observed periods. The resulting distribution is used to identify dominant relationship patterns and assess their stability across different temporal segments.

Through this approach, the relationship between altcoin dominance and Ethereum price is interpreted as a dynamic and context-dependent pattern rather than a static statistical relationship. This temporal pattern-based framework provides a more comprehensive and interpretable understanding of cryptocurrency market dynamics.

# 3. RESULT AND DISCUSSION

## 3.1 Descriptive Statistics

Descriptive statistics are used to provide an initial overview of the distribution and variability of the variables analyzed in this study. The analysis includes the mean, minimum, maximum, and standard deviation values of altcoin dominance and Ethereum price during the observation period. The summary of descriptive statistics is presented in Table 4 below.

**Table 4.** Descriptive Statistics of Research Variables

| Variable | Mean | Min | Max | Std |
|---|---|---|---|---|
| Altcoin Dominance | 51.39 | 33.77 | 68.28 | 7.71 |
| Ethereum Price (USD) | 2457.10 | 993.64 | 4831.24 | 879.60 |

Based on Table 4, the average altcoin dominance of 51.39% indicates that, on average, more than half of the total cryptocurrency market capitalization is allocated to altcoins rather than Bitcoin. The wide range between the minimum (33.77%) and maximum (68.28%) values reflects substantial fluctuations in market structure, suggesting that capital allocation between Bitcoin and altcoins changes significantly over time.

Similarly, Ethereum price exhibits a high degree of variability, with values ranging from USD 993.64 to USD 4,831.24 and a relatively large standard deviation of 879.60. This indicates that Ethereum is subject to substantial price volatility, which is a common characteristic of cryptocurrency markets.

From a market dynamics perspective, the variability observed in both altcoin dominance and Ethereum price suggests the presence of continuous shifts in capital allocation within the cryptocurrency ecosystem. These shifts may reflect changing investor preferences, liquidity redistribution, and speculative behavior across different crypto assets.

Importantly, the substantial variation in both variables implies that their relationship is unlikely to be stable over time. Instead, it is more plausible that the interaction between altcoin dominance and Ethereum price evolves across different market conditions. Therefore, relying solely on aggregate statistical measures may be insufficient to capture the underlying dynamics. This motivates the use of time-based analysis and temporal segmentation to better understand the evolving interdependence between the variables.

## 3.2 Time Series Visualization

To examine the temporal movement of the variables, a time series visualization of altcoin dominance and Ethereum price was conducted over the observation period. This visualization provides an initial understanding of how the two variables evolve over time and offers preliminary insight into their dynamic interaction.

Prior to visualization, both variables were normalized using the Min-Max Scaling method to address differences in scale. This transformation allows altcoin dominance and Ethereum price to be displayed within the same range, enabling a clearer comparison of their relative movements.

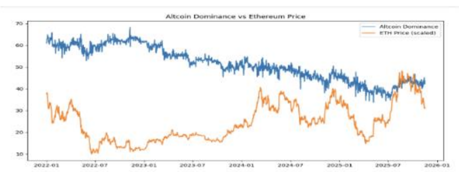


**Figure 2**. Altcoin Dominance and Ethereum Price Movement

BULLETIN OF COMPUTER SCIENCE RESEARCH
ISSN 2774-3659 (Media Online)
Vol 6, No 3, April 2026 | Hal 1005-1015
https://hostjournals.com/bulletincsr
DOI: 10.47065/bulletincsr.v6i3.1080

As shown in Figure 2, both variables exhibit substantial fluctuations throughout the study period, reflecting the inherently volatile nature of the cryptocurrency market. Notably, several periods demonstrate an inverse movement pattern, where increases in altcoin dominance are accompanied by declines in Ethereum price.

From a market dynamics perspective, this inverse pattern may reflect capital rotation behavior, in which investors shift capital allocation from major assets such as Ethereum into a broader set of altcoins. As capital flows into smaller-cap assets, the relative dominance of altcoins increases, while demand for Ethereum weakens, resulting in downward pressure on its price.

However, this inverse relationship is not consistently observed across the entire period. In certain intervals, both variables move in the same direction or exhibit weak and unstable relationships. This indicates that the interaction between altcoin dominance and Ethereum price is not static but varies depending on prevailing market conditions, such as investor sentiment, liquidity distribution, and market cycles.

In addition, Ethereum price demonstrates higher volatility compared to altcoin dominance, suggesting that price movements in Ethereum are more sensitive to short-term market dynamics. In contrast, altcoin dominance tends to change more gradually, as it reflects aggregate capital distribution across the entire market rather than the price of a single asset.

Overall, the visualization highlights that the relationship between altcoin dominance and Ethereum price is time-varying and context-dependent, rather than fixed. This finding reinforces the limitation of relying solely on aggregate analysis and motivates the use of temporal segmentation and pattern-based analysis to capture localized relationship dynamics in subsequent sections.

### 3.3 Global Relationship Analysis

To establish a baseline understanding of the relationship between variables, a global correlation analysis was conducted between altcoin dominance and Ethereum price using the Pearson correlation coefficient. This analysis aims to capture the overall linear relationship between the variables across the entire observation period before examining their temporal dynamics in more detail. The results of the correlation analysis are presented in Table 5.

**Table 5.** Correlation Matrix of Research Variables

| Variable | Altcoin Dominance | Ethereum Price |
|---|---|---|
| Altcoin Dominance | 1.00 | -0.48 |
| Ethereum Price | -0.48 | 1.00 |

Based on Table 5, the correlation coefficient between altcoin dominance and Ethereum price is -0.48, indicating a moderate negative relationship between the two variables. This suggests that, on average, increases in altcoin dominance are associated with decreases in Ethereum price. From a market perspective, this negative relationship can be interpreted as a reflection of capital reallocation within the cryptocurrency ecosystem. When a larger proportion of market capitalization shifts toward altcoins, the relative share of capital allocated to major assets such as Ethereum may decline, potentially exerting downward pressure on its price.

However, it is important to note that this correlation represents an aggregate measure over the entire observation period. As such, it does not capture short-term fluctuations or changes in the relationship under different market conditions. Given the highly dynamic and volatile nature of cryptocurrency markets, the interaction between altcoin dominance and Ethereum price is likely to vary across time. Therefore, while the global correlation provides an important initial indication of an inverse relationship, it remains insufficient for capturing the full complexity of the interaction. This limitation motivates the need for a more granular analysis using time-based approaches, such as rolling correlation and temporal segmentation, which are discussed in the following sections.

### 3.4 Correlation Analysis and Relationship Dynamics

To further investigate the dynamic interaction between altcoin dominance and Ethereum price, a time-based correlation analysis was conducted using rolling correlation and lag correlation approaches. These methods allow the relationship between variables to be examined beyond a single aggregate value, capturing how the interaction evolves over time.

The rolling correlation analysis was performed using a 30-day moving window to observe continuous changes in correlation throughout the study period.

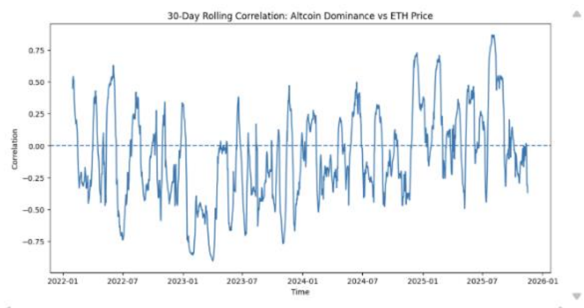


**Figure 3.** Rolling Correlation (30-Day Window)

BULLETIN OF COMPUTER SCIENCE RESEARCH
ISSN 2774-3659 (Media Online)
Vol 6, No 3, April 2026 | Hal 1005-1015
https://hostjournals.com/bulletincsr
DOI: 10.47065/bulletincsr.v6i3.1080

As illustrated in Figure 3, the relationship between altcoin dominance and Ethereum price is not constant, but varies significantly across different time periods. In several intervals, the correlation exhibits strong negative values, while in others it weakens toward zero or becomes less consistent. This confirms that the interaction between the two variables is time-varying and dependent on changing market conditions.

From a market behavior perspective, periods of strong negative correlation can be associated with intensified capital rotation, where investors actively reallocate funds from major assets such as Ethereum into a broader altcoin market. During such periods, increases in altcoin dominance coincide with reduced relative demand for Ethereum, reinforcing the inverse relationship. Conversely, periods of weaker or unstable correlation may reflect transitional market phases, where capital flows are more evenly distributed or influenced by external factors such as macroeconomic sentiment, liquidity shocks, or speculative cycles. This variability indicates that the relationship between the two variables is not governed by a single consistent mechanism, but rather shifts across different market regimes. To complement the dynamic correlation analysis, a lag correlation analysis was conducted to examine potential delayed effects between variables. This approach evaluates whether changes in altcoin dominance are followed by subsequent changes in Ethereum price over different time horizons. The results of the lag correlation analysis are presented in Table 6.

**Table 6.** Lag Correlation Results

| Lag | Correlation |
|---|---|
| 1 Day | -0.508 |
| 7 Days | -0.531 |
| 30 Days | -0.589 |

Based on Table 6, the correlation remains consistently negative across all lag values and becomes stronger as the lag increases. This suggests that the relationship between altcoin dominance and Ethereum price may not occur instantaneously but develops over time.

This pattern indicates a lagged adjustment process, where shifts in market dominance are gradually reflected in Ethereum price movements. In practical terms, changes in capital allocation toward altcoins may take time to fully impact Ethereum price due to market frictions, liquidity distribution, and investor response delays. Overall, the results from both rolling and lag correlation analyses reinforce the notion that the relationship between altcoin dominance and Ethereum price is dynamic, time-dependent, and influenced by evolving market conditions. These findings further support the need for a temporal segmentation approach to capture localized patterns of interaction, which is explored in the following section.

### 3.5 Temporal Pattern Analysis

To understand the dynamics of the relationship between altcoin dominance and Ethereum price in more depth, a temporal pattern analysis was conducted based on monthly segmentation. This approach enables the identification of time-varying relationships that cannot be captured through aggregate analysis. As an initial step, monthly time series visualizations were used to illustrate representative relationship patterns observed during the study period.

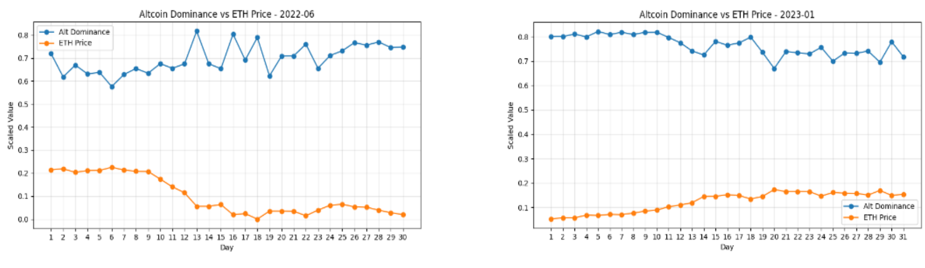


**Figure 5.** Inverse Pattern (June 2022 and January 2023)

Figure 5 shows a condition where altcoin dominance increases while Ethereum price declines. This inverse movement indicates a negative relationship between the two variables within specific periods.

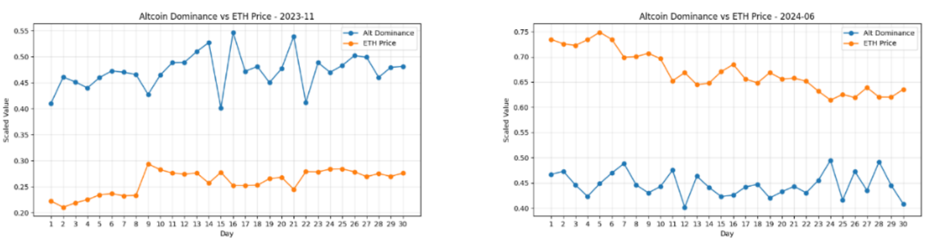


**Figure 6.** Weak Pattern (November 2023 and June 2024)

BULLETIN OF COMPUTER SCIENCE RESEARCH
ISSN 2774-3659 (Media Online)
Vol 6, No 3, April 2026 | Hal 1005-1015
https://hostjournals.com/bulletincsr
DOI: 10.47065/bulletincsr.v6i3.1080

Figure 6 illustrates periods where both variables fluctuate without a consistent directional pattern, indicating a weak relationship.

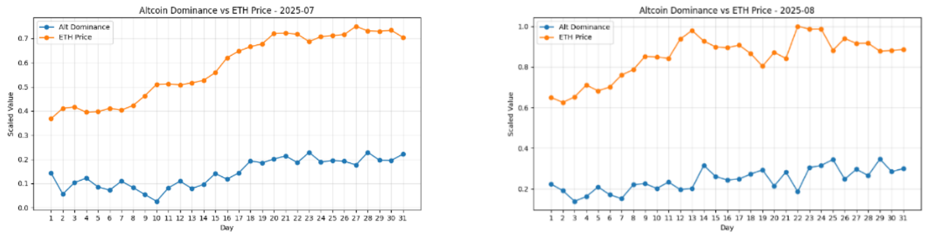


**Figure 7.** Positive Pattern (July 2025 and August 2025)

Figure 7 shows a positive relationship, where increases in altcoin dominance are accompanied by increases in Ethereum price. These visualizations demonstrate that the relationship between altcoin dominance and Ethereum price is not constant, but varies depending on market conditions. To quantify these dynamics, statistical metrics were calculated for each monthly period.

**Table 8.** Monthly Metrics Summary

| month | correlation | eth_trend | dominance_trend | volatility | eth_range |
|---|---|---|---|---|---|
| 2022-01 | 0.47 | -44.64 | -0.10 | 452.95 | 1,416.97 |
| 2022-02 | -0.30 | -11.35 | -0.03 | 202.38 | 677.22 |
| 2022-03 | -0.07 | 23.68 | 0.00 | 280.83 | 910.13 |
| 2022-04 | -0.22 | -21.64 | -0.00 | 210.32 | 796.19 |
| 2022-05 | 0.52 | -35.05 | -0.21 | 364.07 | 1,215.15 |
| 2022-06 | -0.69 | -30.77 | 0.15 | 315.12 | 864.57 |
| 2022-07 | 0.11 | 23.26 | 0.04 | 231.74 | 687.85 |
| 2022-08 | -0.27 | -6.89 | 0.07 | 149.61 | 558.12 |
| 2022-09 | 0.02 | -14.50 | -0.03 | 161.25 | 529.04 |
| 2022-10 | 0.01 | 8.20 | -0.00 | 107.97 | 345.00 |

Based on Table 8, the correlation values vary significantly across periods, ranging from strong negative to positive relationships. In addition, variations in trend and volatility indicate that market conditions differ substantially over time. This confirms that the relationship between the variables is dynamic rather than static. Next, market conditions were classified to provide contextual interpretation of Ethereum price behavior.

**Table 9.** Market Condition Classification

| month | condt | pattern | month | condt | pattern | month | condt | pattern |
|---|---|---|---|---|---|---|---|---|
| 2022-01 | Bearish | Moderate Positive + Bearish (High Volatility) | 2023-05 | Bearish | Strong Inverse + Bearish (Low Volatility) | 2024-09 | Bullish | Weak + Bullish (Low Volatility) |
| 2022-02 | Bearish | Moderate Inverse + Bearish (High Volatility) | 2023-06 | Bullish | Moderate Inverse + Bullish (Low Volatility) | 2024-10 | Bearish | Moderate Inverse + Bearish (Low Volatility) |
| 2022-03 | Bearish | Weak + Bearish (High Volatility) | 2023-07 | Bearish | Moderate Inverse + Bearish (Low Volatility) | 2024-11 | Bullish | Moderate Positive + Bullish (High Volatility) |
| 2022-04 | Bearish | Moderate Inverse + Bearish (High Volatility) | 2023-08 | Bullish | Moderate Inverse + Bullish (Low Volatility) | 2024-12 | Bearish | Moderate Positive + Bearish (High Volatility) |
| 2022-05 | Bearish | Strong Positive + Bearish (High Volatility) | 2023-09 | Bullish | Weak + Bullish (Low Volatility) | 2025-01 | Bearish | Weak + Bearish (Low Volatility) |
| 2022-06 | Bearish | Strong Inverse + Bearish (High Volatility) | 2023-10 | Bearish | Strong Inverse + Bearish (Low Volatility) | 2025-02 | Bearish | Weak + Bearish (Low Volatility) |

BULLETIN OF COMPUTER SCIENCE RESEARCH
ISSN 2774-3659 (Media Online)
Vol 6, No 3, April 2026 | Hal 1005-1015
https://hostjournals.com/bulletincsr
DOI: 10.47065/bulletincsr.v6i3.1080

| month | condt | pattern | month | condt | pattern | month | condt | pattern |
|---|---|---|---|---|---|---|---|---|
| 2022-07 | Bearish | Weak + Bearish (High Volatility) | 2023-11 | Bullish | Weak + Bullish (Low Volatility) | 2025-03 | Bearish | Moderate Inverse + Bearish (Low Volatility) |
| 2022-08 | Bullish | Moderate Inverse + Bullish (Low Volatility) | 2023-12 | Bullish | Weak + Bullish (Low Volatility) | 2025-04 | Neutral | Weak + Neutral (Low Volatility) |
| 2022-09 | Bearish | Weak + Bearish (Low Volatility) | 2024-01 | Bearish | Moderate Positive + Bearish (Low Volatility) | 2025-05 | Bullish | Moderate Positive + Bullish (High Volatility) |
| 2022-10 | Bearish | Weak + Bearish (Low Volatility) | 2024-02 | Bearish | Moderate Inverse + Bearish (High Volatility) | 2025-06 | Bullish | Moderate Positive + Bullish (Low Volatility) |
| 2022-11 | Bearish | Moderate Inverse + Bearish (Low Volatility) | 2024-03 | Bullish | Moderate Inverse + Bullish (High Volatility) | 2025-07 | Bullish | Strong Positive + Bullish (High Volatility) |
| 2022-12 | Bearish | Moderate Positive + Bearish (Low Volatility) | 2024-04 | Bearish | Weak + Bearish (Low Volatility) | 2025-08 | Bullish | Strong Positive + Bullish (High Volatility) |
| 2023-01 | Bullish | Strong Inverse + Bullish (Low Volatility) | 2024-05 | Bearish | Weak + Bearish (High Volatility) | 2025-09 | Bullish | Weak + Bullish (High Volatility) |
| 2023-02 | Bullish | Strong Inverse + Bullish (Low Volatility) | 2024-06 | Bearish | Weak + Bearish (Low Volatility) | 2025-10 | Bearish | Weak + Bearish (High Volatility) |
| 2023-03 | Bullish | Strong Inverse + Bullish (Low Volatility) | 2024-07 | Bullish | Moderate Inverse + Bullish (Low Volatility) | 2025-11 | Bearish | Moderate Inverse + Bearish (High Volatility) |
| 2023-04 | Bearish | Weak + Bearish (Low Volatility) | 2024-08 | Bearish | Weak + Bearish (Low Volatility) | | | |

The classification results show that bearish conditions dominate the early observation period, while bullish conditions become more frequent in later periods, indicating a structural shift in market behavior. By combining correlation strength, market conditions, and volatility levels, a multi-dimensional pattern classification was constructed to better capture the interaction between variables. The results reveal that the relationship between altcoin dominance and Ethereum price is not only dynamic but also structurally dependent on market regimes. The dominance of inverse patterns (40.43%) reflects a systematic mechanism within the cryptocurrency market rather than a purely statistical phenomenon.

From an economic perspective, this inverse relationship can be explained through a capital rotation mechanism. When investors reallocate capital from major assets such as Ethereum into a broader set of altcoins, the relative dominance of altcoins increases. At the same time, reduced capital inflow into Ethereum leads to downward pressure on its price. This mechanism is particularly evident during bearish market conditions, where investors tend to diversify risk and shift capital toward alternative assets. Furthermore, inverse patterns frequently occur under high volatility conditions, suggesting that market uncertainty intensifies cross-asset capital movement. In such environments, portfolio rebalancing becomes more aggressive, reinforcing the negative relationship between dominance and price.

In contrast, positive patterns (21.28%) tend to emerge during bullish market conditions. In these periods, overall market expansion leads to simultaneous increases in both Ethereum price and altcoin dominance. This indicates that capital inflows are distributed across the entire market rather than reallocated between assets, reducing competitive pressure between Ethereum and other altcoins. Meanwhile, weak patterns (38.30%) are generally observed during relatively stable or transitional market conditions. These periods are characterized by lower volatility and less pronounced capital movement, resulting in weaker and less consistent relationships between variables. The distribution of patterns shows that inverse relationships dominate (40.43%), followed by weak patterns (38.30%) and positive patterns (21.28%). This distribution indicates that while the inverse relationship is the most frequent, it is not universally dominant across all market conditions. Instead, the relationship between altcoin dominance and Ethereum price is highly context-dependent and influenced by the interaction between capital flow dynamics, volatility, and market regimes.

ISSN 2774-3659 (Media Online)
Vol 6, No 3, April 2026 | Hal 1005-1015
https://hostjournals.com/bulletincsr
DOI: 10.47065/bulletincsr.v6i3.1080

Overall, the findings demonstrate that the relationship between altcoin dominance and Ethereum price cannot be interpreted as a static correlation. Instead, it reflects a time-varying interdependence driven by capital rotation, market expansion, and volatility conditions. The temporal pattern-based approach used in this study provides deeper insight than aggregate correlation analysis, as it captures not only the direction of the relationship but also the underlying economic mechanisms that govern market behavior across different periods.

## 4. CONCLUSION

This study demonstrates that the relationship between altcoin dominance and Ethereum price is not static, but reflects a time-varying interdependence shaped by market conditions and capital flow dynamics. Rather than relying on a single aggregate correlation, the temporal pattern-based approach reveals that the interaction between the two variables changes across different market regimes, indicating that their relationship is structurally conditional. The findings show that inverse relationships dominate during certain periods, particularly under bearish and high-volatility conditions. This pattern reflects a capital rotation mechanism, where investors reallocate funds from major assets such as Ethereum into a broader set of altcoins, increasing altcoin dominance while exerting downward pressure on Ethereum prices. Conversely, positive relationships tend to emerge during bullish phases, where capital inflows expand across the entire market, allowing both Ethereum and altcoins to grow simultaneously. Weak relationships are typically observed during transitional or low-volatility periods, where no dominant capital flow direction exists. These results indicate that altcoin dominance can serve as a useful proxy for understanding capital allocation behavior within the cryptocurrency market. From a practical perspective, this insight can be applied in trading and portfolio strategies. For instance, an increase in altcoin dominance during volatile or bearish conditions may signal potential downside risk for Ethereum, while synchronized growth between dominance and price may indicate broader market expansion. Therefore, incorporating dominance-based indicators into trading or hedging strategies can help investors better anticipate market shifts and manage risk exposure. Despite these contributions, this study has several limitations. The analysis focuses on a limited set of variables and relies on a pattern-based classification framework, which prioritizes interpretability over predictive precision. Additionally, the temporal segmentation approach captures discrete structural changes but does not model continuous long-term dependencies as in advanced econometric models. As a result, the findings should be interpreted as indicative of market behavior patterns rather than definitive predictive relationships. Future research can extend this study by integrating additional market indicators such as trading volume, investor sentiment, or macroeconomic variables to better capture the complexity of cryptocurrency dynamics. Furthermore, combining temporal pattern analysis with advanced modeling approaches, such as machine learning or volatility-based models, may improve predictive capability while retaining interpretability. Overall, this study highlights that a temporal pattern-based approach provides a more context-aware understanding of cryptocurrency market dynamics compared to traditional aggregate analysis. By revealing how relationships evolve across different market conditions, this approach contributes to both academic research and practical decision-making in digital asset markets.

## REFERENCES

[1] P. Ciaian, M. Rajcaniova, and d'Artis Kancs, "Virtual relationships: Short- and long-run evidence from BitCoin and altcoin markets," *J. Int. Financ. Mark. Inst. Money*, vol. 52, pp. 173–195, Jan. 2018, doi: 10.1016/j.intfin.2017.11.001.
[2] S. Drożdż, L. Minati, P. Oświęcimka, M. Stanuszek, and M. Wątorek, "Competition of noise and collectivity in global cryptocurrency trading: route to a self-contained market," *Chaos Interdiscip. J. Nonlinear Sci.*, vol. 30, no. 2, p. 023122, Feb. 2020, doi: 10.1063/1.5139634.
[3] S. Santos, H. Sebastião, and N. Silva, "Bitcoin and Main Altcoins: Causality and Trading Strategies," *Notas Económicas*, no. 59, pp. 7–33, Aug. 2025, doi: 10.14195/2183-203X_59_1.
[4] Š. Galgauskas, "Modelling the Dynamics of Bitcoin, Ethereum, Ripple Including COVID-19 Impact," Vilnius University, 2021.
[5] A. Kulal, "Followness of Altcoins in the Dominance of Bitcoin: A Phase Analysis," *Macro Manag. Public Policies*, vol. 3, no. 3, pp. 10–18, Sep. 2021, doi: 10.30564/mmpp.v3i3.3589.
[6] T. Suryawijaya, F. A. Laurent, and M. Berger, "Optimizing AltCoin (ETH) Price Synchronization During the Bitcoin Dominance Era: A Comprehensive Phase Analysis with Vector Error Correction Model," *Econ. Bus. Account. Soc. Rev.*, vol. 2, no. 3, pp. 216–229, Oct. 2023, doi: 10.55980/ebasr.v2i3.101.
[7] T. Luu Duc Huynh, "Spillover Risks on Cryptocurrency Markets: A Look from VAR-SVAR Granger Causality and Student's-t Copulas," *J. Risk Financ. Manag.*, vol. 12, no. 2, p. 52, Apr. 2019, doi: 10.3390/jrfm12020052.
[8] T. Kurihara and T. Matsumoto, "Price Transmission from Bitcoin to Altcoins: High-Frequency Evidence and Implications for Trading Strategy," *Asia-Pac. Financ. Mark.*, Dec. 2025, doi: 10.1007/s10690-026-09589-z.
[9] S. Yi, Z. Xu, and G.-J. Wang, "Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency?," *Int. Rev. Financ. Anal.*, vol. 60, pp. 98–114, Nov. 2018, doi: 10.1016/j.irfa.2018.08.012.
[10] S. Kakinaka and K. Umeno, "Exploring asymmetric multifractal cross-correlations of price–volatility and asymmetric volatility dynamics in cryptocurrency markets," *Phys. Stat. Mech. Its Appl.*, vol. 581, p. 126237, Nov. 2021, doi: 10.1016/j.physa.2021.126237.
[11] L. Sebai and Y. Jaber, "Connectedness Between Green Financial and Cryptocurrency Markets: A Multivariate Analysis Using TVP-VAR Model and Wavelet-Based VaR Analysis," *J. Risk Financ. Manag.*, vol. 18, no. 9, p. 483, Aug. 2025, doi: 10.3390/jrfm18090483.
[12] B. Będowska-Sójka, A. Kliber, and A. Rutkowska, "Is Bitcoin Still a King? Relationships between Prices, Volatility and Liquidity of Cryptocurrencies during the Pandemic," *Entropy*, vol. 23, no. 11, p. 1386, Oct. 2021, doi: 10.3390/e23111386.

ISSN 2774-3659 (Media Online)
Vol 6, No 3, April 2026 | Hal 1005-1015
https://hostjournals.com/bulletincsr
DOI: 10.47065/bulletincsr.v6i3.1080

[13] N. Naifar, "Navigating Risk in Crypto Markets: Connectedness and Strategic Allocation," *Risks*, vol. 13, no. 8, p. 141, Jul. 2025, doi: 10.3390/risks13080141.
[14] H. Akoglu, "User's guide to correlation coefficients," *Turk. J. Emerg. Med.*, vol. 18, no. 3, pp. 91–93, Sep. 2018, doi: 10.1016/j.tjem.2018.08.001.
[15] S. N. Papageorgiou, "On correlation coefficients and their interpretation," *J. Orthod.*, vol. 49, no. 3, pp. 359–361, Sep. 2022, doi: 10.1177/14653125221076142.
[16] B. Korkusuz, "Volatility Transmission in Digital Assets: Ethereum's Rising Influence," *J. Risk Financ. Manag.*, vol. 18, no. 3, p. 111, Feb. 2025, doi: 10.3390/jrfm18030111.
[17] R. Parlika, M. Mustafid, and B. Rahmat, "Minimum, Maximum, and Average Implementation of Patterned Datasets in Mapping Cryptocurrency Fluctuation Patterns," *JOIV Int. J. Inform. Vis.*, vol. 8, no. 1, p. 378, Mar. 2024, doi: 10.62527/joiv.8.1.1543.
[18] K. Nakagawa and R. Sakemoto, "Market uncertainty and correlation between Bitcoin and Ether," *Finance Res. Lett.*, vol. 50, p. 103216, Dec. 2022, doi: 10.1016/j.frl.2022.103216.
[19] M. Y. Ahmed, S. A. Sarkodie, and T. Leirvik, "Mutual coupling between stock market and cryptocurrencies," *Heliyon*, vol. 9, no. 5, p. e16179, May 2023, doi: 10.1016/j.heliyon.2023.e16179.
[20] O. Liashenko, B. Adamyk, and O. Adamyk, "Cryptocurrency Market Maturation and Evolving Risk Profiles: A Comparative Analysis of Bitcoin and Ethereum Tail Risk Dynamics," *FinTech*, vol. 5, no. 2, p. 28, Apr. 2026, doi: 10.3390/fintech5020028.
[21] I. Barjašić and N. Antulov-Fantulin, "Time-Varying Volatility in Bitcoin Market and Information Flow at Minute-Level Frequency," *Front. Phys.*, vol. 9, p. 644102, May 2021, doi: 10.3389/fphy.2021.644102.
[22] D. Troop, F. Godin, and J. Y. Yu, "Best-Arm Identification Using Extreme Value Theory Estimates of the CVaR," *J. Risk Financ. Manag.*, vol. 15, no. 4, p. 172, Apr. 2022, doi: 10.3390/jrfm15040172.