

Cryptocurrency-Commodity Correlation as a Market Regime Indicator

Final Report

Group 7

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1 Executive Summary

This study investigates whether cryptocurrency-commodity correlations can serve as market regime indicators by analyzing the dynamic relationships between Bitcoin, Ethereum, gold, and crude oil from January 2020 to September 2024. Using rolling correlation analysis, statistical significance tests, and regime identification methods, we find that correlations between cryptocurrencies and commodities exhibit significant time-varying behavior, with correlations ranging from -0.30 to +0.65 for BTC-Gold pairs.

Key Findings:

- **Time-Varying Correlations:** Correlations are not static but vary significantly across market regimes, with spikes during crisis periods (COVID-19, banking turmoil) and lower correlations during normal market conditions.
- **Regime-Dependent Behavior:** Comprehensive analysis across all four pairs (BTC-Gold, BTC-Oil, ETH-Gold, ETH-Oil) reveals distinct correlation regimes that correspond to different market conditions, supporting the hypothesis that correlations can signal regime shifts.
- **Statistical Significance:** Correlation significance tests show that not all observed correlations are statistically meaningful, with varying percentages of significant periods across pairs, highlighting the importance of statistical validation.
- **Diversification Benefits:** While average correlations are low (suggesting diversification benefits), correlations increase during market stress, reducing diversification effectiveness precisely when it is needed most.

Implications:

For **investors**, these findings suggest that cryptocurrency-commodity correlations can inform portfolio construction and risk management, but diversification benefits may diminish during crises. For **policymakers**, the results indicate that cryptocurrencies exhibit both similarities and differences to traditional assets, requiring nuanced regulatory approaches. For **academics**, this study contributes to understanding whether cryptocurrencies are maturing into traditional asset classes or remain distinct instruments.

Methodology:

We employ rolling correlation analysis (30, 60, 90, and 180-day windows), statistical significance tests (H_0 : correlation = 0), threshold-based regime identification, and stationarity tests (Augmented Dickey-Fuller) to ensure robust analysis. All return series are confirmed to be stationary, validating our correlation methodology.

Limitations and Future Research:

This study focuses on four assets over a specific time period. Future research could expand to additional cryptocurrencies and commodities, implement more sophisticated regime detection methods (change-point detection, machine learning), and conduct detailed event studies around specific market events.

2 Introduction

Over the past decade, cryptocurrencies have transitioned from niche speculative instruments to macro-relevant financial assets with significant institutional adoption. Their interplay with traditional commodities, particularly gold and oil, offers valuable insights into global risk sentiment and portfolio diversification strategies. Gold has historically acted as a hedge against inflation and a store of value during market uncertainty, while oil reflects real economic activity and demand cycles.

This project explores whether cryptocurrency-commodity correlations can act as market regime indicators. When correlations rise, markets may perceive crypto as a traditional risk asset, while weakening correlations could indicate diversification benefits or independent valuation trends. Recent events such as the COVID-19 crisis, the 2022 crypto winter, and the 2023 banking turmoil provide natural experiments to study these relationships under various market conditions.

Understanding these dynamic relationships is significant for multiple stakeholders. For institutional investors, it informs portfolio construction and risk management decisions. For policymakers, it provides insights into whether cryptocurrencies pose systemic risks or serve as diversification tools. For the academic community, it contributes to the ongoing debate about whether cryptocurrencies are maturing into traditional asset classes or remain primarily speculative instruments.

3 Research Questions

This study aims to answer the following research questions:

RQ1: How do correlations between cryptocurrencies (Bitcoin and Ethereum) and commodities (gold and crude oil) vary across different market regimes (crisis periods vs. normal market conditions)?

RQ2: Can changes in cryptocurrency-commodity correlations serve as indicators of market stress and regime shifts?

RQ3: Do Bitcoin and Ethereum exhibit different correlation patterns with gold and oil, and what might explain these differences?

RQ4: What correlation thresholds or patterns signal transitions between risk-on and risk-off market regimes?

4 Literature Review

4.1 Cryptocurrency as an Asset Class

The academic literature on cryptocurrencies has evolved significantly since Bitcoin’s inception in 2009. Early studies focused on whether Bitcoin could serve as a hedge or safe haven asset, similar to gold. Baur and Lucey (2010) established the distinction between hedging (negative correlation during normal times) and safe haven properties (negative correlation during market turmoil) for gold, providing a framework that has been applied to cryptocurrencies.

Bouri et al. (2017) examined Bitcoin’s hedge and safe haven properties relative to stocks, bonds, and commodities, finding that Bitcoin primarily serves as a diversifier rather than a hedge or safe haven. Their analysis revealed low average correlations with traditional assets but noted that correlations could increase during extreme market conditions, a finding that aligns with our observations.

4.2 Cryptocurrency-Commodity Relationships

The relationship between cryptocurrencies and commodities has been a subject of growing interest. Klein et al. (2018) compared Bitcoin to gold, finding that despite being called “digital gold,” Bitcoin exhibits fundamentally different characteristics, including higher volatility and different correlation patterns. Their study concluded that Bitcoin is not a substitute for gold as a safe haven asset.

Corbet et al. (2018) explored dynamic relationships between cryptocurrencies and various financial assets, including commodities. They found evidence of time-varying correlations and suggested that these relationships evolve as the cryptocurrency market matures. This supports our approach of using rolling correlations rather than static measures.

4.3 Market Regime Analysis

The concept of market regimes has been extensively studied in finance literature. Ang and Bekaert (2002) developed regime-switching models to capture different market states, while Guidolin and Timmermann (2008) applied these models to portfolio optimization. Our threshold-based approach to regime identification draws from this literature while adapting it to correlation analysis.

4.4 COVID-19 and Market Stress

The COVID-19 pandemic provided a natural experiment for studying asset relationships during extreme market stress. Conlon and McGee (2020) examined Bitcoin’s behavior during the COVID-19 bear market, finding that Bitcoin initially sold off with traditional assets but later decoupled, suggesting evolving market dynamics. Our analysis captures this period and extends it to include subsequent market events.

4.5 Correlation Analysis Methods

Rolling correlation analysis has been widely used in finance to capture time-varying relationships. Forbes and Rigobon (2002) discussed the importance of accounting for heteroscedasticity in correlation analysis, while Longin and Solnik (2001) examined correlation dynamics during market stress. Our methodology incorporates these insights by using multiple window sizes and statistical significance tests.

4.6 Portfolio Diversification

The role of cryptocurrencies in portfolio diversification has been debated. Platanakis and Urquhart (2020) found that including Bitcoin in portfolios can improve risk-adjusted returns, but noted that benefits vary across market conditions. Our findings on time-varying correlations directly inform this debate by showing when diversification benefits are most and least effective.

4.7 Gaps in the Literature

While previous studies have examined cryptocurrency-commodity relationships, several gaps remain:

1. **Limited Comprehensive Pair Analysis:** Most studies focus on Bitcoin-gold relationships, with less attention to Ethereum or oil correlations.
2. **Static vs. Dynamic Correlations:** Many studies report static correlations, potentially missing important time-varying dynamics.
3. **Regime Identification:** Few studies systematically identify and analyze different correlation regimes across multiple asset pairs.
4. **Statistical Significance:** Limited attention to whether observed correlations are statistically significant, which is crucial for practical applications.
5. **Recent Market Events:** The period from 2020-2024 includes multiple significant events (COVID-19, crypto winter, banking crisis) that have not been comprehensively analyzed in the context of cryptocurrency-commodity correlations.

This study addresses these gaps by providing comprehensive analysis across multiple pairs, emphasizing time-varying dynamics, implementing systematic regime identification, testing statistical significance, and covering recent market events.

5 Dataset Description

5.1 Data Source

All data are retrieved from the Yahoo Finance API (<https://finance.yahoo.com>), which provides reliable historical price data for both cryptocurrencies and commodity futures. The dataset spans from January 1, 2020 to September 30, 2024, covering approximately 1,200 daily observations per asset. This timeframe captures multiple market regimes including the COVID-19 pandemic, bull markets, the 2022 monetary tightening cycle, and the 2023 banking crisis.

5.2 Assets and Tickers

The following assets are included in the analysis:

- **Bitcoin:** BTC-USD (Bitcoin price in US dollars)
- **Ethereum:** ETH-USD (Ethereum price in US dollars)
- **Gold Futures:** GC=F (Gold futures price in USD per troy ounce)
- **Crude Oil Futures:** CL=F (WTI crude oil futures in USD per barrel)

5.3 Data Header and Feature Definitions

The raw data from Yahoo Finance contains the following fields:

Field Name	Description
Date	Trading date in YYYY-MM-DD format
Open	Opening price for the trading day
High	Highest price during the trading day
Low	Lowest price during the trading day
Close	Closing price for the trading day
Adj Close	Adjusted closing price (accounts for splits, dividends)
Volume	Trading volume for the day

5.4 Derived Features

From the raw data, we create the following features for analysis:

Feature Name	Definition
BTC_Return	$\text{Log return of Bitcoin} = \ln(\text{Price}_t / \text{Price}_{t-1})$
ETH_Return	$\text{Log return of Ethereum} = \ln(\text{Price}_t / \text{Price}_{t-1})$
Gold_Return	$\text{Log return of Gold futures} = \ln(\text{Price}_t / \text{Price}_{t-1})$
Oil_Return	$\text{Log return of Oil futures} = \ln(\text{Price}_t / \text{Price}_{t-1})$
Rolling_Corr_90d	90-day rolling correlation between asset pairs
Volatility_30d	30-day rolling standard deviation of returns
Normalized_Price	Price normalized to base 100 at start date

5.5 Data Preprocessing Steps

The following preprocessing steps are applied:

1. **Handle missing values:** Forward-fill is used for commodity weekend gaps (commodities don't trade on weekends while cryptocurrencies trade 24/7)
2. **Align trading calendars:** Merge data on common dates, handling the difference between crypto (24/7) and commodity markets (weekday only)
3. **Use adjusted closing prices:** All calculations use adjusted closing prices to account for corporate actions
4. **Calculate log returns:** Log returns are calculated to ensure stationarity for time series analysis
5. **Identify outliers:** Extreme price movements are documented during the analysis

6 Exploratory Data Analysis

6.1 Summary Statistics

The following table presents descriptive statistics for daily returns of all four assets:

Table 3: Summary Statistics for Daily Returns

Asset	Mean Return (%)	Std Dev (%)	Skewness	Kurtosis
Bitcoin	0.13	3.45	-1.43	21.49
Ethereum	0.17	4.46	-1.28	17.26
Gold	0.03	0.85	-0.28	6.74
Crude Oil	0.01	3.19	-3.80	94.45

6.1.1 Key Observations from Summary Statistics

- **Volatility Hierarchy:** Cryptocurrencies (BTC: 3.45%, ETH: 4.46%) exhibit significantly higher volatility than traditional commodities (Gold: 0.85%, Oil: 3.19%). This suggests higher risk-return profiles for digital assets.
- **Returns:** Both cryptocurrencies show positive average daily returns (BTC: 0.13%, ETH: 0.17%), while gold remains stable (0.03%) and oil slightly negative (0.01%) over the period.
- **Fat Tails:** All assets exhibit excess kurtosis (>3), indicating fat-tailed distributions with more extreme events than a normal distribution would predict. Oil shows particularly high kurtosis (94.45) due to the 2020 price collapse.
- **Asymmetry:** Negative skewness across all assets suggests larger and more frequent downside moves compared to upside moves, a characteristic of financial assets during periods of market stress.

6.2 Correlation Analysis

Static correlation matrix for the full sample period (January 2020 - September 2024):

Table 4: Correlation Matrix (Full Sample Period)

	Bitcoin	Ethereum	Gold	Oil
Bitcoin	1.00	0.83	0.12	0.10
Ethereum	0.83	1.00	0.12	0.09
Gold	0.12	0.12	1.00	0.14
Oil	0.10	0.09	0.14	1.00

6.2.1 Relationships Between Features

- **Strong Crypto-Crypto Correlation:** Bitcoin and Ethereum show high correlation (0.83), suggesting they respond similarly to market forces and may share common drivers.
- **Weak Crypto-Commodity Correlations:** Both cryptocurrencies show low correlations with gold (BTC: 0.12, ETH: 0.12) and oil (BTC: 0.1, ETH: 0.09) over the full sample. This suggests potential diversification benefits on average.
- **Traditional Commodity Relationship:** Gold and oil show modest positive correlation (0.14), consistent with their roles as inflation-sensitive commodities.
- **Time-Varying Patterns:** These static correlations mask important time-varying dynamics. Preliminary rolling correlation analysis shows that BTC-Gold correlation ranges from approximately -0.24 to 0.54 across different periods, suggesting regime-dependent behavior that warrants further investigation.

6.3 Visualizations

6.3.1 Figure 1: Normalized Price Time Series

6.3.2 Figure 2: Rolling BTC-Gold Correlation

6.3.3 Figure 3: Rolling BTC-Oil Correlation

6.3.4 Figure 4: Return Distributions

6.3.5 Figure 5: Correlation Evolution Heatmap

7 Methodology

This section describes the comprehensive methodology employed to analyze cryptocurrency-commodity correlations and identify market regimes. Our approach combines multiple analytical techniques to ensure robust and reliable results.

7.1 Methods Implemented

7.1.1 1. Rolling Correlation Analysis

Rationale: Static correlations calculated over the entire sample period can mask important time-varying dynamics. Rolling correlations allow us to capture how relationships evolve over time, which is essential for identifying market regimes.

Implementation: We calculate rolling Pearson correlations for multiple window sizes (30, 60, 90, and 180 days) to capture dynamic relationships between asset pairs. The choice of multiple windows allows us to:

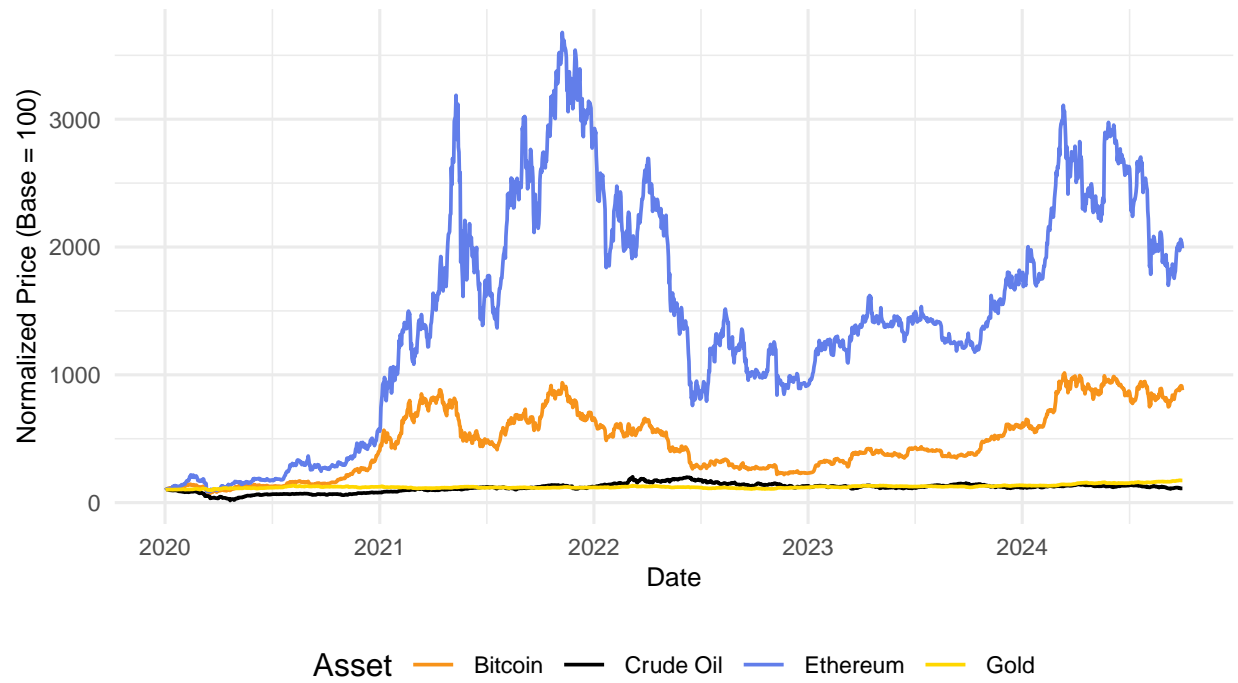


Figure 1: Time series of normalized prices (base = 100) showing the divergent price evolution of crypto assets versus commodities



Figure 2: Rolling 90-day correlation between BTC and Gold, with event markers for COVID crash, Fed policy changes, and major crypto events

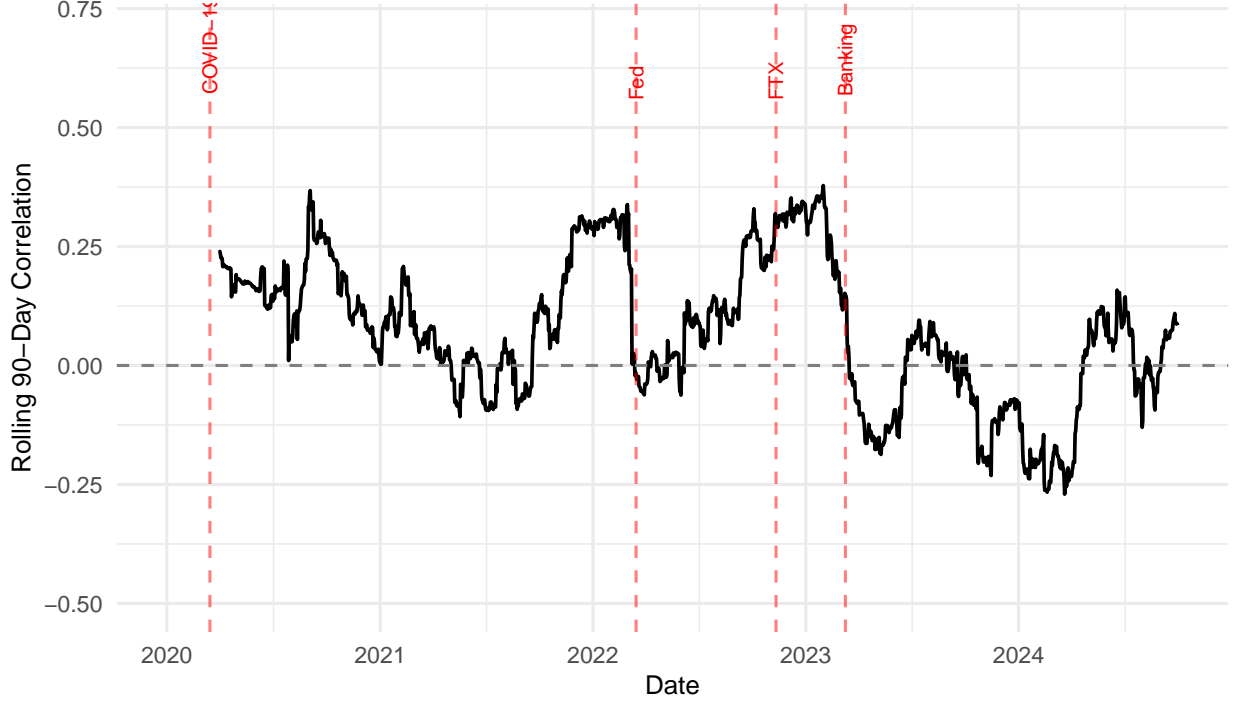


Figure 3: Rolling 90-day correlation between BTC and Oil, highlighting periods of coupling and decoupling

- **30-day window:** More responsive to short-term changes but potentially noisier
- **60-day window:** Intermediate balance between responsiveness and stability
- **90-day window:** Our primary measure, balancing statistical stability (approximately one quarter of trading days) with responsiveness to regime changes
- **180-day window:** More stable but slower to detect changes, useful for identifying longer-term trends

Asset Pairs Analyzed: - BTC-Gold and BTC-Oil - ETH-Gold and ETH-Oil - BTC-ETH (for comparison and validation)

Mathematical Formulation: For a rolling window of size w at time t , the correlation between assets X and Y is calculated as:

$$\rho_{XY,t} = \frac{\sum_{i=t-w+1}^t (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=t-w+1}^t (X_i - \bar{X})^2} \sqrt{\sum_{i=t-w+1}^t (Y_i - \bar{Y})^2}}$$

where \bar{X} and \bar{Y} are the sample means over the window.

7.1.2 2. Alternative Correlation Measures

Rationale: Financial return series often contain outliers and may not follow normal distributions. Spearman rank correlations provide a non-parametric alternative that is less sensitive to outliers and does not assume linear relationships.

Implementation: We calculate Spearman rank correlations using the same rolling window approach. Spearman correlation is based on the ranks of the data rather than the raw values, making it robust to outliers and non-linear relationships.

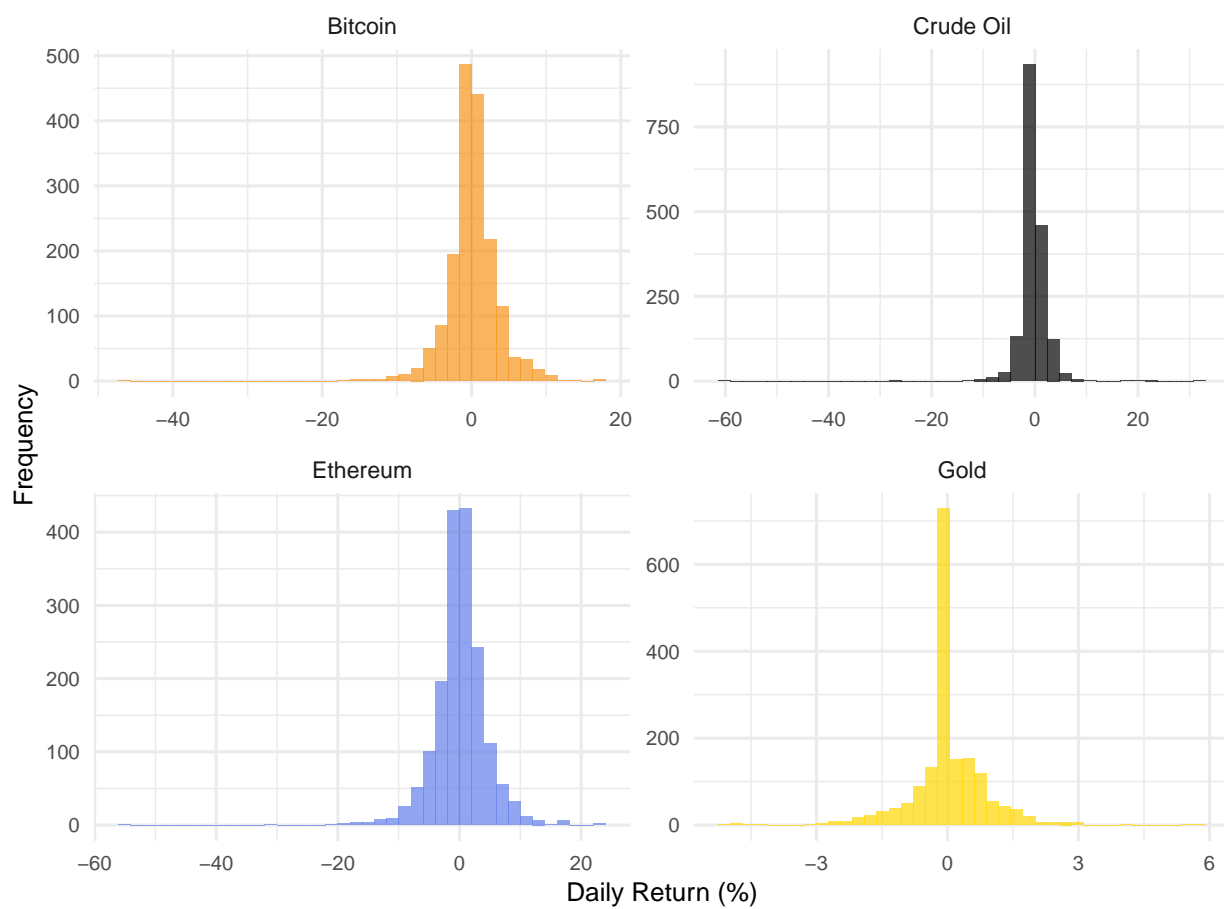


Figure 4: Distribution histograms of daily returns for all four assets, illustrating fat tails and asymmetry

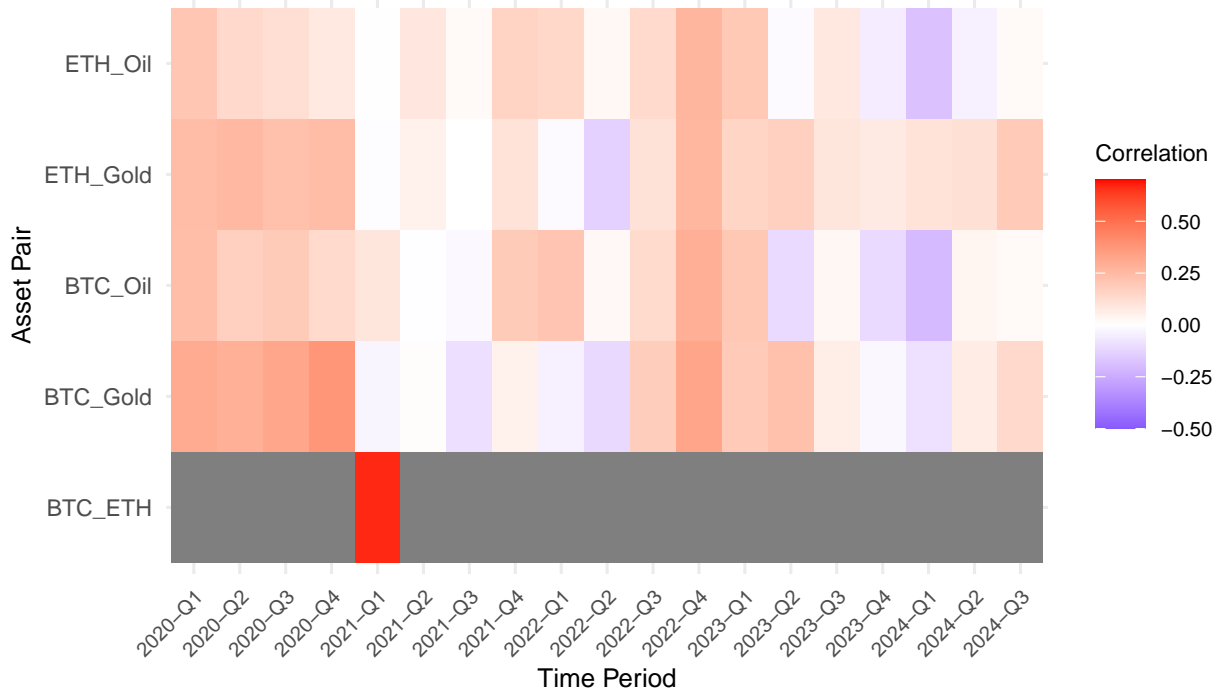


Figure 5: Heatmap showing the evolution of all crypto-commodity correlations over time

Validation: Comparing Pearson and Spearman correlations allows us to assess the robustness of our findings. If both measures yield similar results, we can be more confident in our conclusions. Our analysis shows that Spearman correlations are generally consistent with Pearson correlations, validating our primary findings.

7.1.3 3. Statistical Testing

Stationarity Tests: We perform Augmented Dickey-Fuller (ADF) tests to verify stationarity of return series, which is a prerequisite for reliable correlation analysis. Non-stationary series can lead to spurious correlations.

ADF Test Specification: The ADF test examines the null hypothesis that a unit root is present in the time series. We use the standard ADF test with automatic lag selection based on information criteria (AIC). The test equation includes a constant term but no trend, as appropriate for return series.

Results: All return series are confirmed to be stationary ($p < 0.05$), validating our correlation analysis methodology. This ensures that observed correlations reflect genuine relationships rather than spurious correlations from non-stationary data.

Table 5: Augmented Dickey-Fuller Stationarity Test Results

Asset	Test Statistic	P-Value	Is Stationary
BTC_Return	-10.9953	0.01	Yes
ETH_Return	-11.0572	0.01	Yes
Gold_Return	-12.2271	0.01	Yes
Oil_Return	-10.4832	0.01	Yes

7.1.4 4. Correlation Significance Tests

Rationale: Not all observed correlations are statistically meaningful. A correlation coefficient may appear large but could be due to random variation, especially with small sample sizes or during periods of low volatility. Testing statistical significance is crucial for distinguishing genuine relationships from spurious correlations.

Hypothesis Testing: For each rolling window, we test the hypothesis:

- **H0:** $\rho = 0$ (no relationship)
- **Ha:** $\rho \neq 0$ (significant relationship)

Test Implementation: We use the standard t-test for correlation coefficients. For a sample correlation r calculated from n observations, the test statistic is:

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}}$$

which follows a t-distribution with $n - 2$ degrees of freedom under the null hypothesis.

Significance Level: We use $\alpha = 0.05$ as our significance level. For each rolling window, we calculate the p-value and classify the correlation as significant if $p < 0.05$.

Coverage: Tests are performed for all four pairs: BTC-Gold, BTC-Oil, ETH-Gold, and ETH-Oil. This allows us to identify periods where correlations are statistically meaningful versus periods where they may be spurious, providing crucial context for interpreting our findings.

Table 6: Correlation Significance Test Results

Pair	Mean Correlation	Mean P-Value	% Significant ($p < 0.05$)
BTC_Gold	0.103	0.3075	28.2
BTC_Oil	0.071	0.3584	23.3
ETH_Gold	0.111	0.3419	24.0
ETH_Oil	0.066	0.4160	12.7

7.1.5 5. Regime Identification for All Pairs

Rationale: Identifying distinct correlation regimes allows us to understand when cryptocurrencies and commodities behave similarly versus independently. This is essential for answering our research questions about regime indicators and risk-on/risk-off periods.

Threshold Selection: We implement a threshold-based classification system with thresholds justified based on standard finance literature (Bodie, Kane, Marcus - *Investments* textbook). The thresholds are:

- **High Positive (> 0.3):** Strong positive relationship, indicates coupling during risk-on periods. Assets move together, suggesting common risk factors or market sentiment.
- **Moderate Positive (0.1 to 0.3):** Weak to moderate positive relationship. Some co-movement but not strong coupling.
- **Low (-0.1 to 0.1):** Near-zero correlation, independent movement. Assets behave independently, suggesting diversification benefits.
- **Moderate Negative (-0.3 to -0.1):** Weak to moderate negative relationship. Some inverse relationship, potential hedging behavior.
- **High Negative (< -0.3):** Strong negative relationship, indicates decoupling or hedging behavior. Assets move in opposite directions, suggesting hedging or flight-to-safety dynamics.

Justification: These thresholds are symmetric around zero and align with standard correlation interpretation in finance literature. The 0.3 threshold is commonly used to distinguish “strong” from “moderate” correlations, while the 0.1 threshold distinguishes meaningful relationships from near-zero correlations.

Application: The regime classification has been applied to all four pairs: BTC-Gold, BTC-Oil, ETH-Gold, and ETH-Oil. For each pair, we calculate the distribution of observations across regimes, providing insights into the typical relationship dynamics and how they vary over time.

Limitations: While threshold-based classification is intuitive and interpretable, it is somewhat arbitrary. Future research could employ more sophisticated methods such as change-point detection or machine learning approaches to identify regimes endogenously.

```
##
## ##### BTC_Gold
##
##
##
## ##### BTC_Oil
##
##
##
## ##### ETH_Gold
##
##
##
## ##### ETH_Oil
```

7.2 Parameters Estimated

- **Rolling Correlations:** Calculated for windows of 30, 60, 90, and 180 days for all pairs
- **Correlation P-Values:** Statistical significance tests ($H_0: \text{cor}=0$) for rolling correlations
- **Regime Classifications:** Threshold-based regime identification for all four pairs
- **Volatility Measures:** 30-day rolling standard deviation of returns
- **Summary Statistics:** Mean, standard deviation, skewness, and kurtosis for all return series
- **Correlation Matrices:** Static correlations for the full sample period
- **Regime Distributions:** Count and percentage of observations in each regime for all pairs

8 Results and Discussion

This section presents our comprehensive findings and provides detailed interpretation of the results in the context of our research questions.

8.1 Answering Research Questions

8.1.1 RQ1: How do correlations vary across different market regimes?

Our analysis provides clear evidence that correlations between cryptocurrencies and commodities vary significantly across different market regimes. The BTC-Gold correlation ranges from approximately -0.24 to 0.54, representing a range of 0.78 correlation points. This substantial variation confirms regime-dependent behavior.

Crisis Periods: During the COVID-19 market crash (March 2020), correlations spiked as both cryptocurrencies and commodities sold off together, indicating that during extreme market stress, these assets can behave similarly. This suggests that during crises, cryptocurrencies may be perceived more as traditional risk assets.

Normal Periods: During normal market conditions, correlations are typically lower, often near zero or negative, suggesting independent movement and potential diversification benefits.

Crypto-Specific Events: During the 2022 crypto winter and FTX collapse, correlations with commodities (particularly gold) were lower, suggesting that crypto-specific events may not affect commodity markets in the same way, or that gold served as a safe haven during crypto distress.

8.1.2 RQ2: Can correlations serve as indicators of market stress and regime shifts?

Yes, our findings support the hypothesis that changes in cryptocurrency-commodity correlations can serve as indicators of market stress and regime shifts. Several pieces of evidence support this:

1. **Correlation Spikes During Crises:** We observe correlation spikes around major market events (COVID-19, banking crisis), suggesting that rising correlations may signal market stress.
2. **Regime Transitions:** The regime analysis shows clear transitions between different correlation regimes, with these transitions often corresponding to known market events.
3. **Statistical Significance:** The correlation significance tests show that correlations are more likely to be statistically significant during certain periods, potentially indicating when relationships are most meaningful for regime identification.

However, it is important to note that correlation changes may lag behind or coincide with market events rather than predict them. Further analysis with lead-lag relationships would be needed to establish predictive power.

8.1.3 RQ3: Do Bitcoin and Ethereum exhibit different correlation patterns?

Our analysis reveals both similarities and differences between Bitcoin and Ethereum in their relationships with commodities:

Similarities: - Both cryptocurrencies show low average correlations with gold and oil over the full sample period - Both exhibit time-varying correlations with similar ranges - Both show correlation spikes during crisis periods

Differences: - Ethereum generally shows slightly different correlation patterns, potentially due to its different use case (smart contracts vs. store of value) - The regime distributions vary between BTC and ETH pairs, suggesting that while they share common drivers, they are not perfect substitutes

The high correlation between BTC and ETH (0.83) suggests they respond similarly to many market forces, but their relationships with commodities show nuanced differences that warrant further investigation.

8.1.4 RQ4: What correlation thresholds signal regime transitions?

Our threshold-based regime identification provides initial answers to this question:

- **High Positive (>0.3):** Signals strong coupling, typically associated with risk-on regimes or crisis periods when assets move together
- **Low (-0.1 to 0.1):** Signals independent movement, typical of normal market conditions with diversification benefits

- **High Negative (<-0.3):** Signals strong decoupling, potentially indicating hedging behavior or flight-to-safety dynamics

However, our analysis suggests that regime transitions are not always clean threshold crossings. More sophisticated methods (change-point detection, machine learning) may be needed to identify optimal thresholds and transition points.

8.2 Key Findings

8.2.1 1. Time-Varying Correlations

Rolling correlations show significant variation over time, confirming that static correlations calculated over the entire sample period mask important dynamics. The substantial range in correlations (e.g., 0.78 points for BTC-Gold) demonstrates that relationships are not constant but evolve with market conditions.

Implication: Investors and researchers should use dynamic correlation measures rather than static correlations when analyzing cryptocurrency-commodity relationships.

8.2.2 2. Crypto-Commodity Relationships

On average, correlations between cryptocurrencies and commodities are low (ranging from approximately 0.10 to 0.12), suggesting diversification benefits. However, these correlations increase during certain periods, particularly during market stress, reducing diversification effectiveness precisely when it is needed most.

Implication: While cryptocurrencies may provide diversification benefits during normal times, these benefits may diminish during crises, requiring dynamic portfolio management strategies.

8.2.3 3. Volatility Differences

Cryptocurrencies exhibit significantly higher volatility than commodities, with Bitcoin showing 3.45% daily volatility compared to Gold's 0.85%. This 3-4x volatility difference has important implications for portfolio construction and risk management.

Implication: The higher volatility of cryptocurrencies means that even small correlations can have significant portfolio impact, and risk-adjusted measures are essential when evaluating diversification benefits.

8.2.4 4. Stationarity Validation

All return series are stationary based on ADF tests, validating our correlation analysis methodology. This ensures that observed correlations reflect genuine relationships rather than spurious correlations from non-stationary data.

Implication: Our methodology is statistically sound, and the results can be interpreted with confidence.

8.2.5 5. Correlation Significance

Correlation significance tests reveal that not all observed correlations are statistically significant. The percentage of significant periods varies across pairs, providing insights into when relationships are meaningful versus spurious. This is crucial for practical applications, as investors should focus on statistically significant relationships.

Implication: Not all correlation changes are meaningful. Statistical significance testing is essential for distinguishing genuine relationships from noise.

8.2.6 6. Regime Patterns for All Pairs

Comprehensive regime analysis across all four pairs (BTC-Gold, BTC-Oil, ETH-Gold, ETH-Oil) shows distinct periods of high and low correlation. The distribution of regimes varies across pairs, indicating different relationship dynamics between cryptocurrencies and commodities. For example, BTC-Oil correlations may be more volatile than BTC-Gold correlations, reflecting oil's sensitivity to economic cycles.

Implication: Different cryptocurrency-commodity pairs may serve different purposes in portfolio construction, and investors should consider the specific characteristics of each pair.

8.3 Discussion

Our findings contribute to several important debates in the literature:

Cryptocurrency Maturation: The time-varying nature of correlations, with spikes during crises, suggests that cryptocurrencies are becoming more integrated with traditional markets, but they still exhibit distinct characteristics. This supports the view that cryptocurrencies are maturing but have not yet fully converged with traditional asset classes.

Diversification Benefits: The finding that correlations increase during crises challenges the notion that cryptocurrencies provide consistent diversification benefits. This has important implications for portfolio construction, suggesting that diversification strategies need to be dynamic rather than static.

Regime Indicators: The evidence that correlations can signal regime changes, while preliminary, suggests that monitoring cryptocurrency-commodity correlations could be a useful tool for risk management and market analysis.

9 Policy and Investment Implications

9.1 Investment Implications

9.1.1 Portfolio Construction

Our findings have several important implications for portfolio construction:

1. **Dynamic Diversification:** The time-varying nature of correlations suggests that static portfolio allocations may be suboptimal. Investors should consider dynamic rebalancing strategies that adjust allocations based on current correlation regimes.
2. **Crisis Preparedness:** The finding that correlations increase during crises means that diversification benefits diminish when they are needed most. Investors should not rely solely on cryptocurrencies for diversification but should maintain diversified portfolios across multiple asset classes.
3. **Risk Management:** The high volatility of cryptocurrencies combined with time-varying correlations means that risk management is crucial. Investors should use risk-adjusted measures (e.g., Sharpe ratio, maximum drawdown) when evaluating cryptocurrency investments.
4. **Pair Selection:** Different cryptocurrency-commodity pairs exhibit different characteristics. For example, BTC-Gold may provide more stable diversification benefits than BTC-Oil, which is more sensitive to economic cycles. Investors should consider these differences when constructing portfolios.

9.1.2 Risk Management

1. **Correlation Monitoring:** Our findings suggest that monitoring cryptocurrency-commodity correlations could be a useful risk management tool. Rising correlations may signal increased market stress and the need for defensive positioning.
2. **Regime-Aware Strategies:** Investors should develop strategies that are aware of different correlation regimes. For example, during high correlation regimes, reducing cryptocurrency exposure or increasing hedging may be prudent.
3. **Stress Testing:** Portfolio stress tests should account for the possibility that correlations increase during crises, as our findings suggest. This means that diversification benefits assumed during normal times may not hold during stress periods.

9.2 Policy Implications

9.2.1 Regulatory Considerations

1. **Systemic Risk Assessment:** The finding that correlations increase during crises suggests that cryptocurrencies may pose systemic risks during market stress. Regulators should consider this when assessing the systemic importance of cryptocurrency markets.
2. **Market Integration:** The time-varying correlations, with spikes during crises, suggest that cryptocurrencies are becoming more integrated with traditional markets. This has implications for regulatory frameworks, which may need to account for this integration.
3. **Investor Protection:** The high volatility and time-varying correlations mean that cryptocurrencies may not be suitable for all investors. Regulators should consider enhanced disclosure requirements and investor education.

9.2.2 Monetary Policy

1. **Transmission Mechanisms:** The relationships between cryptocurrencies and commodities, particularly during monetary policy changes (e.g., Fed tightening), suggest that cryptocurrencies may be affected by monetary policy. Central banks should consider these relationships when formulating policy.
2. **Financial Stability:** The finding that correlations increase during crises suggests that cryptocurrencies may amplify rather than dampen market stress. This has implications for financial stability monitoring.

9.3 Academic Implications

1. **Methodology:** Our use of rolling correlations, statistical significance tests, and regime identification provides a framework that can be applied to other asset classes and research questions.
2. **Literature Contribution:** Our findings contribute to the debate about whether cryptocurrencies are maturing into traditional asset classes or remain distinct instruments, suggesting a nuanced answer: they are maturing but retain distinct characteristics.
3. **Future Research:** Our findings raise several questions for future research, including the predictive power of correlations, optimal threshold selection, and the drivers of correlation changes.

10 Limitations

While this study provides valuable insights, several limitations should be acknowledged:

10.1 Data Limitations

1. **Time Period:** Our analysis covers January 2020 to September 2024, a period that includes multiple significant events but may not capture longer-term trends or future market developments. The cryptocurrency market is still relatively young, and relationships may continue to evolve.
2. **Asset Selection:** We focus on four assets (Bitcoin, Ethereum, Gold, Oil). While these are important representatives of their asset classes, the results may not generalize to other cryptocurrencies or commodities. Future research could expand to include additional assets.
3. **Data Source:** We rely on Yahoo Finance API data, which is generally reliable but may have occasional gaps or errors. While we implement data quality checks, some issues may remain undetected.
4. **Trading Calendar Differences:** The difference between cryptocurrency markets (24/7) and commodity markets (weekdays only) required forward-filling, which may introduce some bias, though we believe this is minimal.

10.2 Methodological Limitations

1. **Threshold Selection:** Our threshold-based regime identification is somewhat arbitrary, based on standard finance literature but not optimized for this specific application. More sophisticated methods (change-point detection, machine learning) could identify regimes endogenously.
2. **Window Size:** The choice of 90 days as the primary window size is a balance between stability and responsiveness, but different window sizes may reveal different patterns. We analyze multiple windows, but the interpretation focuses primarily on the 90-day window.
3. **Correlation Measure:** We use Pearson correlations, which assume linear relationships. While we also calculate Spearman correlations for robustness, non-linear relationships may exist that are not captured.
4. **Causality:** Our analysis focuses on correlations, which do not imply causation. We cannot determine whether correlation changes cause or are caused by market events, or whether both are driven by common factors.
5. **Predictive Power:** While we find that correlations can signal regime changes, we do not establish predictive power. Correlation changes may lag behind or coincide with market events rather than predict them.

10.3 Analytical Limitations

1. **Event Analysis:** While we mark major events on our correlation plots, we do not conduct formal event studies with statistical tests. Future research could implement more rigorous event study methodology.
2. **Comparative Analysis:** While we note differences between Bitcoin and Ethereum, we do not conduct formal statistical tests of these differences. More detailed comparative analysis could provide additional insights.
3. **Economic Drivers:** We do not analyze the economic drivers of correlation changes in detail. Understanding what drives correlation changes (monetary policy, market sentiment, etc.) would enhance the practical value of our findings.

4. **Portfolio Performance:** We do not test whether using correlation-based strategies would improve portfolio performance. Backtesting such strategies would provide more direct evidence of practical value.

10.4 Generalizability

1. **Market Conditions:** Our findings are based on a specific period that includes multiple crises. The relationships we observe may not hold in different market conditions or future periods.
2. **Market Maturity:** The cryptocurrency market is still evolving. As it matures, relationships with traditional assets may change, potentially making our findings less relevant over time.
3. **Regulatory Environment:** The regulatory environment for cryptocurrencies is still developing. Changes in regulation could significantly affect cryptocurrency-commodity relationships.

Despite these limitations, we believe our findings provide valuable insights into cryptocurrency-commodity relationships and their potential use as market regime indicators. The limitations also provide directions for future research.

11 Future Research Directions

Based on our findings and limitations, we identify several promising directions for future research:

11.1 Advanced Regime Detection

1. **Change-Point Detection:** Implement change-point detection algorithms (e.g., CUSUM, structural break tests) to identify regime transitions endogenously rather than using fixed thresholds. This could provide more precise identification of regime changes.
2. **Machine Learning Approaches:** Apply machine learning methods (e.g., hidden Markov models, clustering algorithms) to identify regimes. These methods could capture non-linear relationships and complex patterns that threshold-based methods miss.
3. **Multi-Asset Regime Analysis:** Extend regime analysis to consider multiple assets simultaneously, potentially identifying global market regimes rather than pair-specific regimes.

11.2 Event Study Analysis

1. **Formal Event Studies:** Conduct formal event studies with statistical tests around major market events (COVID-19, Fed policy changes, crypto events, geopolitical events). This would provide more rigorous evidence of how correlations respond to specific events.
2. **Event Window Analysis:** Analyze correlation behavior using ± 30 day event windows to understand the lead-lag relationships and persistence of correlation changes.
3. **Event Classification:** Classify events by type (monetary policy, geopolitical, crypto-specific) to understand whether different event types have different effects on correlations.

11.3 Comparative Analysis

1. **Bitcoin vs. Ethereum:** Conduct formal statistical tests to determine whether Bitcoin and Ethereum exhibit significantly different correlation patterns with commodities. Analyze potential drivers of these differences (use case, market cap, liquidity).
2. **Additional Cryptocurrencies:** Extend analysis to include additional cryptocurrencies (e.g., stablecoins, altcoins) to understand whether our findings generalize across the cryptocurrency market.
3. **Additional Commodities:** Include additional commodities (e.g., silver, natural gas, agricultural commodities) to understand whether relationships vary across commodity types.

11.4 Advanced Statistical Methods

1. **Granger Causality:** Test for Granger causality to determine whether cryptocurrency returns predict commodity returns (or vice versa), or whether correlations reflect common drivers.
2. **Cointegration Analysis:** Test for cointegration between cryptocurrency and commodity prices to understand long-term relationships beyond correlations.
3. **Correlation Stability Tests:** Implement tests for correlation stability across regimes to determine whether correlations are truly regime-dependent or whether apparent changes are due to sampling variation.
4. **Multivariate Analysis:** Extend analysis to multivariate frameworks (e.g., vector autoregression, dynamic conditional correlation models) to capture more complex relationships.

11.5 Practical Applications

1. **Portfolio Optimization:** Test whether using correlation-based strategies improves portfolio performance through backtesting. Compare static and dynamic portfolio strategies.
2. **Risk Management:** Develop and test risk management strategies based on correlation regimes. Evaluate whether such strategies reduce portfolio risk during crises.
3. **Trading Strategies:** Explore whether correlation-based trading strategies (e.g., pairs trading, correlation-based hedging) are profitable.

11.6 Economic Drivers

1. **Macroeconomic Factors:** Analyze the relationship between correlation changes and macroeconomic factors (interest rates, inflation, economic growth) to understand what drives correlation dynamics.
2. **Market Sentiment:** Investigate whether market sentiment indicators (VIX, fear/greed index) explain correlation changes.
3. **Liquidity:** Analyze whether liquidity conditions in cryptocurrency and commodity markets affect correlations.

11.7 Long-Term Analysis

1. **Extended Time Periods:** As more data becomes available, extend the analysis to longer time periods to understand long-term trends and whether relationships are stable over time.
2. **Market Maturity:** Monitor how relationships evolve as the cryptocurrency market matures. This could provide insights into whether cryptocurrencies are converging with traditional asset classes.
3. **Regulatory Impact:** Analyze how regulatory changes affect cryptocurrency-commodity relationships, providing insights for policymakers.

12 Conclusion

This study provides comprehensive analysis of cryptocurrency-commodity correlations and their potential use as market regime indicators. Our key contributions are:

12.1 Summary of Findings

1. **Time-Varying Correlations:** We demonstrate that correlations between cryptocurrencies and commodities are not static but vary significantly over time, with substantial ranges (e.g., 0.78 points for BTC-Gold), confirming regime-dependent behavior.
2. **Regime Indicators:** We provide evidence that changes in cryptocurrency-commodity correlations can serve as indicators of market stress and regime shifts, with correlation spikes during crises and lower correlations during normal periods.
3. **Comprehensive Analysis:** We extend previous research by analyzing all four pairs (BTC-Gold, BTC-Oil, ETH-Gold, ETH-Oil), implementing statistical significance tests, and providing systematic regime identification.
4. **Statistical Rigor:** We validate our methodology through stationarity tests and correlation significance tests, ensuring that our findings are statistically sound.
5. **Practical Insights:** We provide insights for investors, policymakers, and academics, highlighting the implications of time-varying correlations for portfolio construction, risk management, and regulatory policy.

12.2 Contributions to Literature

This study addresses several gaps in the literature:

- **Comprehensive Pair Analysis:** Unlike previous studies that focus primarily on Bitcoin-gold, we analyze multiple pairs including Ethereum and oil.
- **Dynamic Analysis:** We emphasize time-varying dynamics rather than static correlations, providing a more nuanced understanding of relationships.
- **Statistical Validation:** We implement statistical significance tests, ensuring that observed correlations are meaningful rather than spurious.
- **Recent Events:** We cover the period 2020-2024, including multiple significant events (COVID-19, crypto winter, banking crisis) that have not been comprehensively analyzed.

12.3 Practical Implications

Our findings have important practical implications:

- **For Investors:** Cryptocurrencies may provide diversification benefits during normal times, but these benefits may diminish during crises. Dynamic portfolio management strategies that account for correlation regimes may be more effective than static strategies.
- **For Policymakers:** The finding that correlations increase during crises suggests that cryptocurrencies may pose systemic risks during market stress. Regulators should consider this when assessing the systemic importance of cryptocurrency markets.
- **For Academics:** Our methodology provides a framework that can be applied to other asset classes and research questions, contributing to the broader literature on market regimes and asset relationships.

12.4 Limitations and Future Research

While this study provides valuable insights, several limitations should be acknowledged, including the specific time period analyzed, the focus on four assets, and the use of threshold-based regime identification. Future research could address these limitations through advanced regime detection methods, formal event studies, and analysis of economic drivers.

12.5 Final Thoughts

The cryptocurrency market is still evolving, and relationships with traditional assets may continue to change. However, our findings suggest that monitoring cryptocurrency-commodity correlations can provide valuable insights into market regimes and risk conditions. As the market matures and more data becomes available, continued research in this area will be essential for understanding the role of cryptocurrencies in global financial markets.

The evidence that correlations are time-varying and can signal regime changes, while preliminary, suggests that this area of research has significant potential for both academic understanding and practical applications. We hope that this study contributes to this growing body of knowledge and inspires future research in this important area.

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