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ANALYSING THE RELATIONSHIP BETWEEN OIL FUTURES AND CRYPTOCURRENCY MARKETS FROM 2018 TO 2024

Kyrylo Troian
PhD Student, Department of Economics, Finance and Accounting,
European University, Kyiv, Ukraine
ktroyan@e-u.edu.ua

Abstract

This study investigates the complex relationship between oil futures and cryptocurrencies, addressing the growing interest in the integration of digital assets with traditional financial markets. Employing a comprehensive suite of econometric techniques, including correlation analysis, Granger causality tests, Vector Autoregression (VAR), Johansen cointegration testing, and Forecast Error Variance Decomposition (FEVD), we analyse daily price data from January 2018 to May 2024 for four major oil benchmarks and ten cryptocurrencies. Our findings reveal a nuanced interplay characterised by weak short-term correlations but significant long-term cointegration for certain pairs, particularly involving major cryptocurrencies and stablecoins. The study identifies heterogeneous relationships across different cryptocurrency-oil pairs, with Bitcoin and Ethereum showing more consistent significant relationships with oil benchmarks compared to smaller altcoins. While oil prices demonstrate limited predictive power for cryptocurrency movements, the presence of long-term cointegration suggests potential underlying connections. These results have important implications for portfolio diversification, risk management, and market regulation, highlighting the evolving nature of cryptocurrency markets and their gradual integration with traditional financial systems. Our study contributes to the growing body of literature on digital assets and provides valuable insights for investors, policymakers, and researchers navigating the intersection of commodity and cryptocurrency markets.

Keywords: Oil futures, Cryptocurrencies, Market integration, Cointegration, Portfolio diversification

INTRODUCTION

The global financial landscape has undergone significant transformations in recent years, marked by the emergence of cryptocurrencies as a novel asset class and the continued importance of oil as a crucial commodity for an economy. This study aims to investigate the complex interplay between these two distinct markets, exploring potential interdependencies, correlations, and causal relationships that may exist between oil futures and cryptocurrencies.

The oil market has long been a cornerstone of the global economy, with its dynamics influencing a wide range of economic activities. Fattouh (2011) provides a comprehensive analysis of oil pricing mechanisms, emphasizing the role of futures contracts in price discovery and risk management. The author argues that the complexity of the oil market, with its multiple benchmarks and grade differentials, necessitates sophisticated pricing models that account for both physical and financial market factors.

Kilian (2009) delves deeper into the macroeconomic implications of oil price shocks, distinguishing between supply-side and demand-side drivers. This seminal work establishes a framework for understanding how different types of oil price shocks can have varying impacts on the broader economy. Kilian's research underscores the importance of considering the underlying causes of oil price fluctuations when analysing their economic effects.

The advent of cryptocurrencies, starting with Bitcoin in 2009, has introduced a new paradigm in financial markets. Corbet et al. (2018) provide a comprehensive review of the nascent literature on cryptocurrencies, highlighting their unique characteristics as financial assets. The authors note the high volatility of cryptocurrency markets and their potential to act as diversifiers in traditional investment portfolios.

Liu & Tsyvinski (2021) expand on this work by examining the risk-return trade off of cryptocurrencies. Their research suggests that cryptocurrency returns can be predicted by factors specific to momentum and investor attention, distinguishing them from traditional asset classes. This finding has important implications for understanding how cryptocurrencies might interact with other financial markets, including commodities like oil.

The potential relationship between oil and cryptocurrency markets has garnered increasing attention from researchers. Bouri et al. (2017) investigate Bitcoin's role as a hedge and safe haven for commodities, including oil. Their findings suggest that Bitcoin can serve as an effective diversifier for oil price movements, although its effectiveness as a hedge or safe haven is time-varying.

Ismail & Basah (2021) employ cointegration and Vector Error Correction Model analysis to examine the interaction between Bitcoin and macroeconomic variables, including oil prices. Their research indicates a high positive correlation between Bitcoin and oil markets, suggesting a strong relationship between these seemingly disparate asset classes. However, the authors acknowledge limitations in their methodology, particularly the potential for omitted variable bias.

Beckmann et al. (2020) provide a more nuanced view, identifying potential long-term cointegration relationships between oil and major cryptocurrencies. Their study employs a range of econometric techniques, including threshold cointegration models, to capture non-linear dynamics in the relationship. While they find evidence of long-term equilibrium relationships, the authors caution that these relationships are not stable over time and can be influenced by market conditions.

The COVID-19 pandemic provided a unique context for studying market interactions. Ha (2023) applies Bayesian vector heterogeneous autoregressions to study network interactions between crude oil, gold, stock, and cryptocurrency markets during the pandemic. This sophisticated methodological approach allows for a more nuanced understanding of market interdependencies during times of crisis. Ha's findings highlight how shocks in the cryptocurrency market can impact traditional commodity markets, including oil, emphasizing the growing interconnectedness of these markets.

He (2022) investigates the impact of the Russia-Ukraine conflict on crude oil prices and cryptocurrency market fluctuations. This study provides valuable insights into how geopolitical events can influence the relationship between oil and digital assets. He's research suggests that while increases in futures crude oil prices positively affect cryptocurrency yields in the short term, they do not lead to increased daily volatility. These findings challenge simplistic notions of a direct, consistent relationship between oil and cryptocurrency markets.

Novalita et al. (2022) take a different approach, focusing on the role of volatility, liquidity, and oil prices in cryptocurrency market efficiency. Their research suggests that while volatility and liquidity play significant roles in influencing cryptocurrency market efficiency, the oil price index does not have a discernible impact. This study highlights the complexity of factors influencing cryptocurrency markets and cautions against oversimplifying the relationship between oil and digital assets.

Zhou (2022) contributes to this nuanced understanding by examining the time-varying nature of the relationship between oil futures and Bitcoin. Zhou's findings indicate that while there is a significant short-term correlation between futures crude oil prices and Bitcoin yields, this relationship diminishes over time. This research underscores the need for dynamic models that can capture the evolving nature of the oil-cryptocurrency relationship.

An often-overlooked aspect of the oil-cryptocurrency relationship is the energy-intensive nature of cryptocurrency mining, particularly for proof-of-work systems like Bitcoin. Fang et al. (2022) explores this connection, analysing how energy prices, including oil, can influence the cost structure of cryptocurrency production. Their research suggests that energy prices can have a significant impact on the profitability of cryptocurrency mining operations, potentially influencing supply dynamics in the cryptocurrency market.

The existing literature on the relationship between oil futures and cryptocurrencies presents a complex and sometimes contradictory picture. While some studies suggest significant correlations and potential cointegration relationships, others find limited or time-varying connections. The inconsistency in these findings underscores the need for more sophisticated, dynamic models that can capture the evolving nature of these market interactions.

This study aims to contribute to the existing literature by providing a comprehensive analysis of the relationship between oil futures and a diverse set of cryptocurrencies. By employing a range of econometric techniques, including Vector Autoregression (VAR) analysis, Granger causality tests, and cointegration analysis, we seek to uncover both short-term dynamics and long-term equilibrium relationships between these markets (Sims, 1980; Granger, 1969; Johansen, 1991).

Our analysis encompasses four major oil futures contracts: West Texas Intermediate (WTI), Brent, Dubai Fateh, and Urals. This selection provides a comprehensive representation of global oil pricing mechanisms (Fattouh, 2011), including both sweet and sour crude types traded on major exchanges. On the cryptocurrency side, we include a diverse set of digital assets, ranging from major cryptocurrencies like Bitcoin and Ethereum to emerging altcoins and stablecoins. This broad selection allows for a nuanced examination of how different types of cryptocurrencies may interact with oil markets.

The time frame of our study, spanning from January 2018 to May 2024, encompasses several significant events in both oil and cryptocurrency markets. This period includes the COVID-19 pandemic and its aftermath, major fluctuations in oil prices including negative WTI futures prices in April 2020, and several boom-and-bust cycles in the cryptocurrency market. By analysing data across this extended period, we aim to capture the evolving nature of the relationship between these markets under various economic conditions.

Our methodology employs rigorous data preprocessing techniques, including normalisation and stationarity testing, to ensure the reliability of our analyses. We utilise a suite of analytical techniques, including correlation analysis, Granger causality testing, VAR modelling, and cointegration analysis, to provide a broader view of the relationships between oil futures and cryptocurrencies.

The findings of this study have significant implications for various stakeholders. For investors and portfolio managers, understanding the relationship between oil futures and cryptocurrencies can inform diversification strategies and risk management practices. Policymakers and regulators may gain insights into the growing interconnectedness of traditional commodity markets and emerging digital asset markets, potentially informing future regulatory frameworks. For academics, this study contributes to the growing body of literature on the integration of cryptocurrencies into the broader financial system and their relationship with traditional asset classes.

As the global financial landscape continues to evolve, with increasing digitalisation and the emergence of new asset classes, understanding the interplay between traditional commodities like oil and innovative digital assets like cryptocurrencies becomes increasingly crucial. This study aims to shed light on these complex relationships, providing empirical insights that can inform decision-making processes in an increasingly interconnected global financial system.

In the following sections, we will detail our methodology, present our findings, and discuss the implications of our results in the context of existing literature and market dynamics. Through this analysis, we aim to contribute to the ongoing dialogue on the role of cryptocurrencies in the global financial ecosystem and their relationship with traditional commodity markets.

METHODOLOGY

The Study

This study employs a comprehensive quantitative approach to investigate the relationships between oil futures and cryptocurrencies, two distinct asset classes that have garnered significant attention in financial markets. The methodology is designed to capture both short-term dynamics and long-term equilibrium relationships, providing a nuanced perspective on the potential interdependencies between these markets.

Data Selection and Preparation

The dataset comprises daily price series of four major oil futures contracts and ten cryptocurrencies, spanning from January 1, 2018, to May 31, 2024. This extensive time frame allows for the capture of various market cycles and exogenous shocks, enhancing the robustness of our analysis.

The selected oil futures contracts include West Texas Intermediate Crude Oil Futures, Brent Crude Oil Futures, Dubai Fateh Crude Oil Futures, and Urals Crude Oil Futures. These contracts were chosen to represent a diverse array of global oil benchmarks, encompassing both sweet and sour crude types traded on major exchanges. This selection ensures a comprehensive representation of global oil pricing mechanisms, as suggested by Fattouh (2011) in his analysis of the oil pricing system.

The cryptocurrency dataset includes trading pairs Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Dogecoin (DOGE), Solana (SOL), Ripple (XRP), Avalanche (AVAX), Shiba Inu (SHIB), and the stablecoins TrueUSD (TUSD) and USD Coin (USDC) with stablecoin Tether USD (USDT). This diverse selection represents various market capitalisations, use cases, and technological foundations within the cryptocurrency ecosystem, allowing for a broad perspective on the cryptocurrency market dynamics.

Data Preprocessing

The raw price data underwent rigorous preprocessing to ensure its suitability for time series analysis. This process involved several key steps tailored to the specific requirements of our study and the nature of the financial markets under investigation.

Firstly, data cleaning was performed to examine the datasets for missing values, outliers, and inconsistencies. This step ensures the integrity and reliability of the subsequent analyses. Secondly, to address the varying market entry dates of different assets, particularly for series that entered the market after January 1, 2018, we implemented a date intersection approach. This method ensures that only overlapping time periods between two analysed time series are considered, maintaining consistency and comparability in our analyses.

Thirdly, we addressed the issue of non-trading days in traditional markets, which unlike cryptocurrency markets, are closed on certain days. To overcome this discrepancy, we employed a forward-filling technique. For instance, if Friday and Monday prices were 50 and 60 respectively, we assumed Saturday and Sunday's prices to be that of Friday - 50. This approach preserves the last known market price and is consistent with how investors would value their portfolios over non-trading periods.

While using the average of Friday and Monday prices for Saturday and Sunday is a potential alternative, we chose not to implement this method due to several drawbacks. Averaging creates artificial price movements that didn't actually occur in the market, potentially leading to overestimation of volatility. It also assumes a linear price movement over non-trading days, which is not reflective of an actual market behaviour. Moreover, as discussed by Campbell et al. (1997) in 'The Econometrics of Financial Markets', using Monday's price information for weekend data points could introduce a form of look-ahead bias in certain analyses. Furthermore, for the purpose of price prediction, forward-filling is the only viable option, as predictive models cannot be fed with data from the future. This ensures our analysis maintains temporal integrity and avoids inadvertent introduction of future information into historical data points.

Lastly, differencing was applied selectively, depending on the specific analysis requirements. For analyses necessitating data stationarity, we employed the percentage change method as a differencing technique. This approach is widely used in financial analysis and is particularly suitable for comparing assets with different nominal values (Campbell et al., 1997). The percentage change was calculated as:

$$R_t = \left(\frac{P_t - P_{t-1}}{P_{t-1}}\right) \times 100$$

Where:

P_t is the price at time t ,

$P_{t-1}$is the price at time $t-1$

However, it's important to note that this normalisation step was omitted for certain analyses, such as the Johansen Cointegration testing, where the non-normalised price series were utilised.

The stationarity of the transformed series was assessed using the Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979), as many time series analyses, including VAR, assume stationarity in the data. The ADF test was applied with the null hypothesis of a unit root (non-stationarity) against the alternative of stationarity. The lag order for the ADF test was selected using the Akaike Information Criterion (AIC) to ensure optimal model fit (Akaike, 1974).

Analytical Techniques

The study employs a comprehensive suite of analytical techniques to provide a thorough understanding of the relationships between oil futures and cryptocurrencies. It's important to note that these analyses are performed in a pairwise fashion, which, while limiting the scope of each individual test, allows for the examination of a greater number of variables across the dataset.

The analytical process begins with correlation analysis, which forms the foundation of our understanding of asset relationships. Simple Pearson correlation coefficients are calculated to measure the linear relationships between the percentage returns of oil futures and cryptocurrencies. While straightforward, this method provides an initial insight into the co-movement of these assets. To account for potential lead-lag relationships, cross-correlation analysis is conducted, allowing for the examination of correlations at various time lags and potentially revealing delayed effects between markets. The time-varying nature of these relationships is captured through rolling correlations, computed using 30-, 90-, and 180-day windows. This approach, as described by Zivot & Wang (2006), enables the visualisation of how correlations evolve over time, potentially revealing periods of increased or decreased market integration.

To investigate potential predictive relationships between oil futures and cryptocurrencies, the study employs Granger causality testing (Granger, 1969). This test examines whether past values of one series (e.g., oil futures) provide statistically significant information about future values of another series (e.g., cryptocurrencies). The test is conducted using various lag structures to account for different potential delay effects, enhancing the robustness of our findings.

The study further delves into the dynamics of these relationships through Vector Autoregression analysis. A VAR model is constructed to capture the linear interdependencies among the multiple time series (Sims, 1980). This model treats each variable as endogenous and regresses it on its own lags and the lags of all other variables in the system. The optimal lag length for the VAR model is determined using information criteria such as AIC, BIC, and HQC. The VAR model is defined as follows:

$$Y_t = c + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \epsilon_t$$

Where:

Y_t is a vector of endogenous variables at time t ,

c is a vector of constants (intercept),

$A_1, A_2, \ldots, A_p$ are matrices of coefficients for each lag,

ε_t is a vector of error terms at time t

From the estimated VAR model, two key analyses are derived: Impulse Response Functions (IRF) and Forecast Error Variance Decomposition (FEVD). IRFs are computed to trace out the response of cryptocurrencies to a one-time shock in oil futures prices, helping to understand the magnitude, direction, and persistence of market responses to shocks (Koop et al., 1996). FEVD is conducted to determine how much of the forecast error variance of each variable can be explained by exogenous shocks to the other variables in the system, providing insight into the relative importance of different shocks in explaining the variability of the series (Hamilton, 1994).

Lastly, the study incorporates cointegration analysis to investigate the existence of long-run equilibrium relationships between oil futures and cryptocurrency prices. The Johansen cointegration test (Johansen, 1991) is employed, which is particularly suitable for multivariate systems and can detect multiple cointegrating relationships. The test is conducted using both the trace and maximum eigenvalue statistics, with the number of cointegrating relationships determined by sequential testing procedures. It's worth noting that this is the only analysis conducted without differencing the dataset, as cointegration testing requires the use of price levels rather than returns.

This comprehensive analytical approach, while conducted in a pairwise fashion, allows for a nuanced understanding of the complex relationships between oil futures and cryptocurrencies, capturing both short-term dynamics and long-term equilibrium relationships.

Model Diagnostics and Robustness Checks

To ensure the validity and reliability of our results, a comprehensive set of diagnostic tests and robustness checks were performed throughout the analysis. These tests are crucial in validating the assumptions underlying our models and reinforcing the credibility of our findings.

A key component of our validation process involved rigorous residual analysis. The residuals from the VAR model were subjected to a battery of tests to ensure that the model assumptions were not violated. This included the Ljung-Box test for autocorrelation, which examines whether there are any significant correlations in the residual series. Additionally, we employed the ARCH-LM test to check for heteroskedasticity, a common issue in financial time series that can lead to inefficient estimates if not properly addressed. The normality of residuals was assessed using the Jarque-Bera test, which provides insights into the distribution of the error terms and can indicate potential misspecification issues.

The stability of our VAR model was another critical aspect of our diagnostic process. We utilised eigenvalue stability condition tests to ensure that the estimated model remains stable over time. This step, as outlined by Hamilton (1994), is critical for the reliability of our impulse response functions and forecast error variance decompositions, as unstable models can lead to spurious results and unreliable forecasts.

To further bolster the robustness of our findings, we conducted extensive sensitivity analyses. This involved examining how our results changed under different lag specifications and across various sample periods. By doing so, we could assess whether our findings were overly dependent on specific model choices or time frames, thus providing a more comprehensive understanding of the relationships between oil futures and cryptocurrencies.

In cases where the data characteristics or theoretical considerations suggested alternative modelling approaches, we estimated alternative specifications. For instance, in situations where cointegration was detected, we employed Vector Error Correction Models (VECM) as described by Engle & Granger (1987). This approach allowed us to cross-validate our results and capture both short-term dynamics and long-term equilibrium relationships that might be present in the data.

This comprehensive methodology, grounded in established financial econometric techniques, aims to provide a thorough and nuanced understanding of the complex dynamics between oil futures and cryptocurrency markets. By employing a diverse set of analytical tools and rigorous validation procedures, we seek to capture both short-term fluctuations and long-term relationships. Our approach not only ensures the reliability of our results but also contributes valuable insights to the growing body of literature on the intersection of traditional commodities and digital assets.

Descriptive Statistics

Table 1: Descriptive statistics of the data. Key statistics presented include the mean, standard deviation, minimum, and maximum values, as well as the 25th, 50th (median), and 75th percentiles.

Series	Count	Mean	Std Dev	Min	25%	50%	75%	Max
BTC	2480	23202.87	18039.78	3189.02	8169.97	17170.95	36183.77	73072.41
SOL	1390	59.19	59.43	1.20	19.39	32.60	95.69	258.44
ETH	2480	1317.21	1172.77	83.76	246.88	1112.98	1959.37	4807.98
DOGE	1793	0.089	0.094	0.002	0.003	0.070	0.130	0.690
BNB	2399	185.44	186.77	1.49	15.94	165.32	312.25	676.15
XRP	2220	0.493	0.264	0.135	0.305	0.444	0.605	1.835
SHIB	1118	0.000015	0.000011	0.000006	0.000008	0.000011	0.000022	0.000079
AVAX	1348	31.55	26.90	2.90	13.04	19.75	39.56	134.84
TUSD	2193	1.000	0.006	0.960	0.999	0.9998	1.0003	1.056
USDC	1995	0.9999	0.0028	0.9592	0.9994	0.9999	1.0001	1.0318
Brent	2370	72.71	18.39	19.33	62.70	73.85	83.58	127.98
Dubai	2370	71.29	17.94	19.07	61.45	72.28	82.25	122.53
Urals	2179	65.11	14.99	8.40	57.90	66.32	74.59	111.01
WTI	2343	67.66	18.64	-37.63	56.24	68.47	78.90	123.70

As per the table 1, cryptocurrencies exhibit significantly higher standard deviations compared to oil commodities, indicating greater price volatility. Among cryptocurrencies, Shiba Inu and Dogecoin display the highest levels of volatility. The minimum and maximum values from the table reflect substantial fluctuations in price. For instance, Dogecoin reached a maximum price of 0.690 USDT and dipped to a low of 0.002 USDT, illustrating substantial price swings within the observed period. Despite this high volatility, the median values for most cryptocurrencies are closer to their lower quartiles, which suggests that while prices experience notable peaks, they tend to stabilize closer to lower values over the sampled period.

EMPIRICAL RESULTS

Correlation analysis

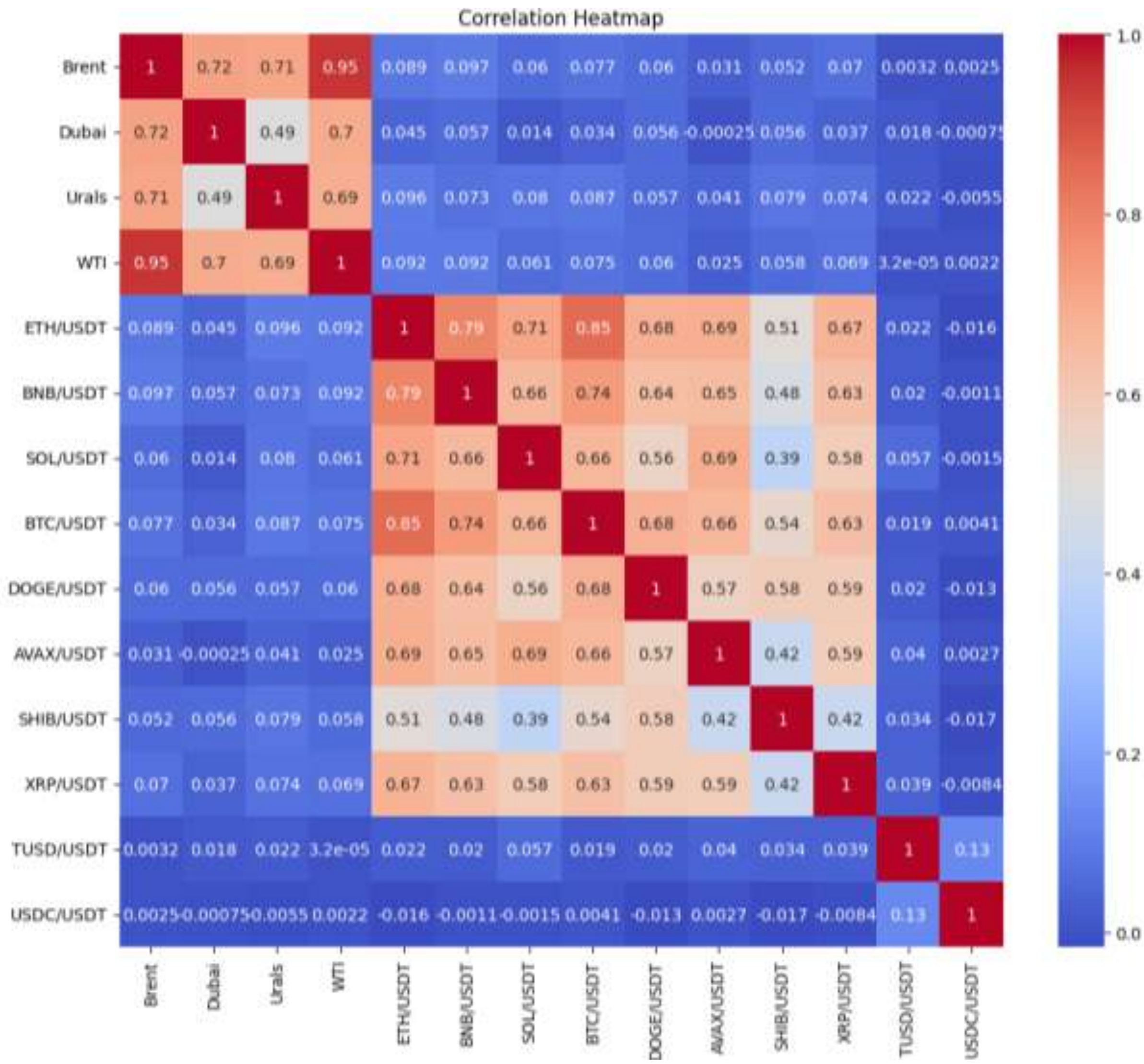

Figure 1: The correlation heatmap visualising the pairwise correlation coefficients between oil futures and cryptocurrencies

Note: The values range from 1 (perfect positive correlation) to -0.1 (slight negative correlation), represented by a colour gradient from deep red to blue.

Strong positive correlations are evident among the oil futures, with particularly high correlations between Brent and WTI (*r = 0.95*), suggesting that movements in the prices of these oil types are closely aligned. Among cryptocurrencies, higher correlations are visible between pairs such as Ethereum and Bitcoin (*r = 0.79*), indicating a significant positive relationship in their daily price movements. The correlations between oil futures and cryptocurrencies generally appear weaker, as evidenced by the lighter colours. However, there are noteworthy mild correlations, such as between WTI and Ethereum (*r = 0.092*), which might suggest a nuanced interplay between commodity markets and digital currency markets.

Across all the pairs analysed, the cross-correlation at zero lag is consistently low, hovering around zero and rarely exceeding a magnitude of 0.02. This indicates a negligible simultaneous linear relationship between the daily price changes of the commodities and the cryptocurrencies.

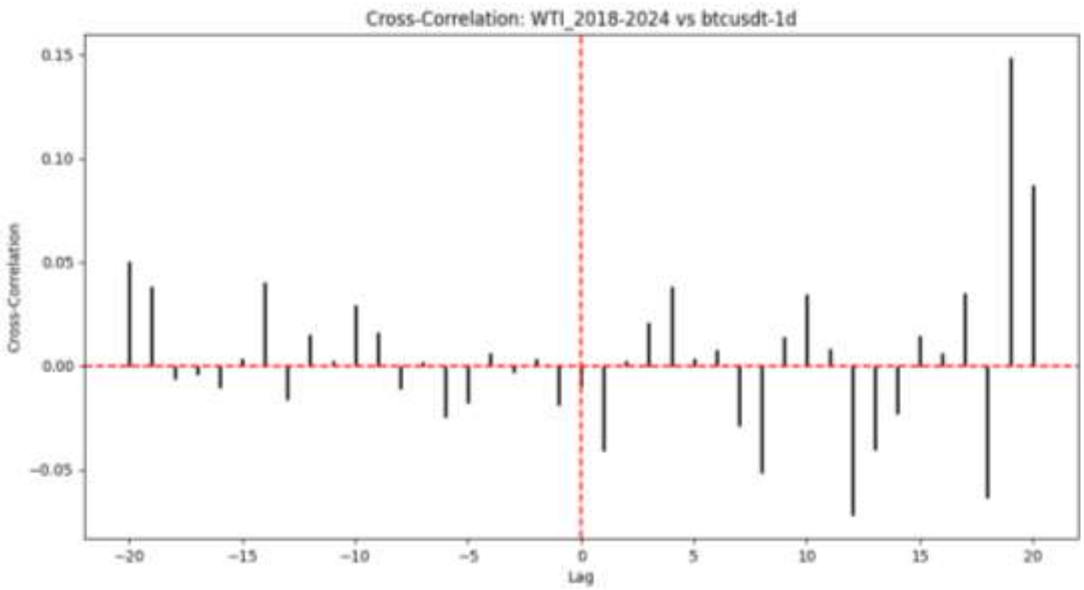

Figure 2: Cross-Correlation Between WTI Crude Oil Prices and Bitcoin Prices

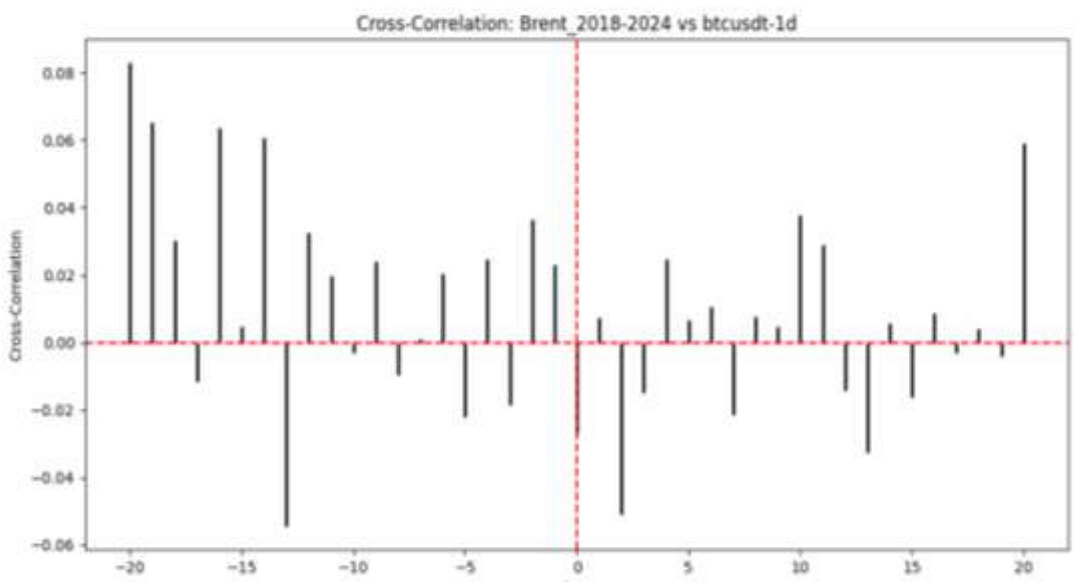

Figure 3: Cross-Correlation Between Brent Crude Oil Prices and Bitcoin Prices

Some mild correlations were observed at various non-zero lags, particularly with lag shifts ranging from +15 to +20 in the case of WTI and Bitcoin (see Figure 2), suggesting that price changes in Bitcoin may follow those in WTI with a delay. However, these correlations were not strong, typically not surpassing 0.10 to 0.15.

No consistent patterns of significant positive or negative correlations were evident across different lags. The correlations exhibited sporadic peaks at different lags without a clear or consistent trend, suggesting the absence of a systematic lead-lag relationship between the commodities and cryptocurrencies.

The variability in correlation coefficients and the general lack of strong correlations suggest that the markets for these commodities and cryptocurrencies operate independently on a day-to-day basis. They appear to be influenced by different factors or market conditions that do not consistently intersect.

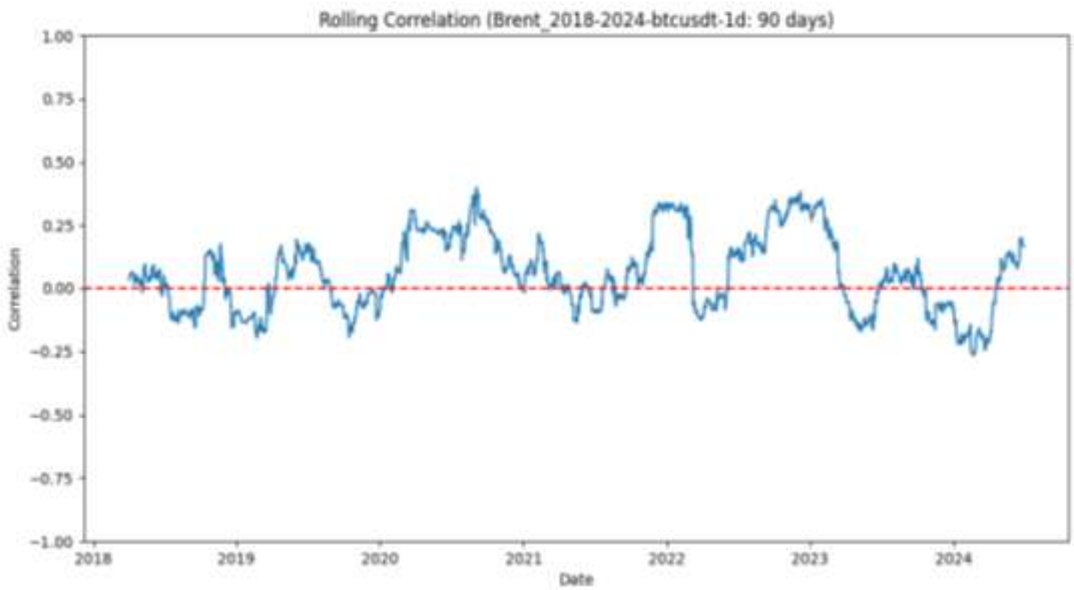

Figure 4: Rolling Correlation Between Brent Crude Oil Prices and Bitcoin Prices with 90-day window

The rolling window analysis shows that correlations fluctuate significantly over time across all commodities and cryptocurrencies, indicating that the relationship between these assets is not stable but varies depending on market conditions, economic factors, and potentially other external influences.

All the plots show correlations frequently crossing the zero line, suggesting that the relationships alternate between positive and negative correlations over the period from 2018 to

2024. This could indicate that the assets are occasionally moving in the same direction and at other times in opposite directions.

None of the plots consistently display strong positive or strong negative correlations. Most correlation values are within a range that suggests a weak to moderate relationship at best.

Johansen Cointegration Testing

Table 2: Johansen cointegration t-statistics between selected oil futures and cryptocurrencies. Critical values: 16.1619 (90% confidence), 18.3985 (95% confidence), and 23.1485 (99% confidence)

	Urals	**WTI**	**Brent**	**Dubai**
USDC/USDT	178.3836	177.5806	176.7663	174.7511
TUSD/USDT	104.6462	105.5130	105.5130	103.5261
XRP/USDT	21.1440	23.7378	22.1789	21.0728
SHIB/USDT	18.9118	14.1883	13.8441	11.2985
ETH/USDT	15.6678	18.5067	16.3318	15.1927
BTC/USDT	13.7726	17.0285	15.2873	14.7881
AVAX/USDT	16.9875	15.0098	15.2390	12.0987
DOGE/USDT	16.2561	15.1004	13.5252	12.8485
BNB/USDT	13.8324	14.3903	12.4269	10.6611
SOL/USDT	12.1127	9.6824	9.4083	7.9790

Johansen Cointegration test results revealed varying degrees of cointegration between cryptocurrency pairs and major global oil benchmarks. The stablecoin pairs USD Coin and TrueUSD exhibited the strongest evidence of cointegration across all tested oil benchmarks. For USD Coin, the test statistics were notably high, with values of *178.38* for Urals, *177.58* for WTI, *176.77* for Brent, and *174.75* for Dubai. Similarly, TrueUSD showed robust cointegration with test statistics of *105.51* for both Brent and WTI, *104.65* for Urals, and *103.53* for Dubai. These values significantly exceeded the critical thresholds at all confidence levels (90%, 95%, and 99%), strongly indicating long-term equilibrium relationships between these stablecoin pairs and oil prices.

A second group of cryptocurrency pairs, including Bitcoin, Ethereum, Dogecoin, Shiba, and Ripple, demonstrated cointegration above the 90% confidence level with various oil benchmarks, albeit not consistently across higher confidence levels. Bitcoin and Ethereum showed moderate to strong evidence of cointegration at the 90% level when paired with WTI and Brent, but failed to meet the 95% or 99% thresholds. Dogecoin and Shiba approached the 90% cointegration threshold when tested against Urals oil. Notably, Ripple crossed the 90% threshold in most cases across all oil benchmarks, suggesting a likely connection to oil price movements.

Some cryptocurrency pairs showed potential for cointegration despite not meeting statistical thresholds. Ethereum, when paired with Urals and Dubai oil, produced test statistics that, while not surpassing critical values at any confidence level, were close to the 90% critical value. This proximity suggests a potential, albeit weak, cointegration relationship that may warrant further investigation or consideration in the context of broader market dynamics.

In contrast, several cryptocurrency pairs showed no evidence of cointegration with oil prices. Binance Coin and Solana consistently produced low test statistics across all oil benchmarks, failing to surpass any critical values. This pattern was mirrored by Avalanche, which also failed to demonstrate any significant relationship with oil prices across all tested benchmarks. These results suggest that the price movements of these cryptocurrencies operate independently of oil market fluctuations, at least in terms of long-term equilibrium relationships as measured by the Johansen cointegration test.

Vector Autoregression

The Vector Autoregression analysis reveals a complex relationship between oil futures and cryptocurrencies, with varying degrees of interaction across different pairs and lag periods. Out of the numerous coefficients examined, only 30 demonstrated statistical significance at the $p < 0.05$ level, indicating that while some relationships exist, they are not uniformly strong or consistent across all pairs and time lags.

Table 3: significant (P < 0.05) VAR coefficients that quantify the impact of oil price changes on various cryptocurrency trading pairs, revealing both positive and negative relationships at different time lags.

Pair	Coefficient	Std. Error	T-value	P-value	lag
Brent/BNB	0.0226298954563250	0.009004041	2.5133042404	0.011960613	4
Brent/ETH	0.0308107878440735	0.009844391	3.1297809623	0.001749366	1
Brent/ETH	0.0246061074108674	0.009866795	2.4938297817	0.012637313	4
Brent/ETH	0.0284614020326960	0.009831960	2.8947840219	0.003794194	6
Brent/ETH	-0.030080271113019	0.009848666	-3.054248006	0.002256254	7
Dubai/ETH	0.022989951369486	0.008553708	2.6877173143	0.007194227	2

Table 3…

WTI/BNB	-0.074306029555563	0.028107638	-2.643624034	0.008202370	7
WTI/BNB	0.0622781277963219	0.028022103	2.2224643944	0.026251937	10
Urals/ETH	0.0593820805496033	0.015512504	3.8280137544	0.000129181	1
Urals/ETH	0.0359604584598780	0.015617159	2.3026248417	0.021299960	6
WTI/ETH	0.0607586749929375	0.030646968	1.9825345717	0.047419442	10
WTI/ETH	-0.114915001203234	0.030730848	-3.739402205	0.000184458	14
Brent/BNB	-0.018615970082252	0.008977883	-2.073536685	0.038122360	7
Brent/BNB	0.0182165749960274	0.008979140	2.0287660354	0.042482126	8
Urals/BNB	0.037644324125075	0.014556476	2.5860877128	0.009707222	4
Urals/SOL	0.0228366152167685	0.009633075	2.3706464608	0.017757007	10
Brent/XRP	0.0233939998854981	0.008497057	2.7531884737	0.005901790	6
Brent/XRP	-0.017058849010640	0.008507328	-2.005194607	0.044942246	7
Urals/XRP	0.0291218846311757	0.012459547	2.3373147724	0.019422822	1
Urals/XRP	0.0254013491801644	0.012486131	2.0343649860	0.041914809	6
Dubai/SHIB	-0.013123370019076	0.006478225	-2.025766095	0.042788759	2
Brent/BTC	0.044234178632542	0.012622496	3.5043922544	0.000457650	1
Brent/BTC	0.03879429642245	0.012602327	3.0783437112	0.002081546	4
Brent/BTC	0.027425333556752	0.012604475	2.1758408668	0.029567161	6
Brent/BTC	-0.035690908851435	0.012598831	-2.832874540	0.004613148	7
Dubai/BTC	0.023875202470823	0.010963168	2.1777647530	0.029423555	1
Dubai/BTC	0.0216818414013016	0.010938804	1.9821034328	0.047467665	4
Urals/BTC	0.07669147341724	0.020132040	3.8094238177	0.000139291	1
Urals/BTC	0.043854611774737	0.020225664	2.1682655328	0.030138489	4
Urals/BTC	0.045877473179222	0.020233891	2.2673579156	0.023368370	6

Brent crude oil shows significant relationships with several cryptocurrencies. Notably, it exhibits a positive relationship with Ethereum across multiple lags (1, 4, 6), with coefficients ranging from *0.024* to *0.031*, though a negative coefficient (-*0.030*) is observed at lag 7. Brent's relationship with Bitcoin is also noteworthy, with positive coefficients at lags 1, 4, and 6 (ranging from *0.027* to *0.044*) and a negative coefficient (-*0.036*) at lag 7. Brent's impact on Binance Coin and Ripple is less pronounced but still significant at certain lags.

The Urals oil benchmark demonstrates significant positive relationships with several cryptocurrencies. Its impact on Ethereum is particularly strong, with coefficients of *0.059* and *0.036* at lags 1 and 2 respectively. Urals also shows significant positive relationships with Bitcoin at multiple lags, with coefficients ranging from *0.044* to *0.077*. Additionally, Urals exhibits significant positive relationships with Binance Coin, Solana, and Ripple at various lags.

West Texas Intermediate crude oil shows fewer significant relationships compared to Brent and Urals. However, it demonstrates a notable impact on Ethereum, with a positive coefficient (*0.061*) at lag 1 and a negative coefficient (-*0.115*) at lag 4. WTI's relationship with Binance Coin is mixed, showing both positive and negative coefficients at different lags.

Dubai Fateh oil futures show significant relationships primarily with Bitcoin, Ethereum, and Shiba. Its impact on Bitcoin is positive at lags 1 and 4, with coefficients of *0.024* and *0.022* respectively. The relationship with Ethereum is also positive (*coefficient 0.023*) at lag 1. Interestingly, Dubai oil shows a small but significant negative relationship with Shiba Inu at lag 2 (*coefficient -0.013*).

Among the cryptocurrencies, Ethereum and Bitcoin show the most consistent significant relationships with oil benchmarks across various lags. Binance Coin and Ripple also demonstrate several significant relationships, albeit with less consistency across oil types and lag periods. Solana and Shiba Inu show the fewest significant relationships with oil prices.

The analysis reveals that while there are statistically significant relationships between oil futures and cryptocurrencies, these relationships vary in strength, direction, and consistency across different cryptocurrency-oil pairs and time lags. The presence of both positive and negative coefficients at different lags suggests a complex dynamic between these asset classes that may involve short-term reactions and subsequent adjustments.

Response of Cryptocurrencies to Oil Price Shocks

Bitcoin typically shows a minimal immediate reaction to shocks in oil prices. If there is a response, it tends to be very slight, reflecting Bitcoin's general insulation from traditional economic factors that heavily influence commodity prices. Over time, the response of Bitcoin may show some fluctuation but generally tends to return to baseline, indicating no long-lasting impact. This suggests that while there might be short-term market sentiment effects, fundamental drivers of Bitcoin prices do not significantly intersect with oil market dynamics.

Similar to Bitcoin, Ethereum also shows a negligible immediate response to oil price shocks. This aligns with the broader narrative that major cryptocurrencies operate independently of traditional commodities. Ethereum's price response may show slightly more variation compared to Bitcoin in some models, possibly due to Ethereum's wider usage in applications that might be indirectly affected by economic shifts impacting oil prices. However, like Bitcoin, these effects do not show a sustained trend and typically diminish over time.

Other cryptocurrencies, including altcoins such as Binance Coin, Solana, and smaller tokens like Doge and Shiba, generally exhibit a weak response to oil price shocks. The IRFs likely indicate that there are no significant or consistent impacts across these cryptocurrencies, reflecting their independence from oil price dynamics. Some cryptocurrencies might show transient volatility in response to oil shocks, possibly due to broader market sentiment or speculative trading behaviours during periods of high volatility in commodity markets. However, these responses are not uniform and do not suggest a direct linkage.

Forecast Error Variance Decomposition

For most assets, especially cryptocurrencies like Bitcoin and Ethereum, a significant portion of the forecast error variance is explained by their own shocks, indicating a high degree of self-driven market dynamics. Among commodities, there are noticeable interactions, with shocks in Brent oil explaining parts of the variance in other oils like WTI, Dubai, and Urals, reflecting the interconnected nature of global oil markets. The influence of oil shocks on cryptocurrencies is minimal, underscoring the decoupled nature of these digital assets from traditional commodity markets. This decomposition highlights the isolated nature of cryptocurrency markets from traditional energy commodities, suggesting that cryptocurrencies may serve as a diversification tool in investment portfolios that include oil and other commodities.

Granger's Causality Test

The Granger causality analysis yielded varying results across different oil benchmarks and cryptocurrencies. For Brent crude, significant Granger causality was observed with Ethereum ($p = 0.0010$) and Bitcoin ($p = 0.0002$), indicating that Brent prices possess predictive power for these cryptocurrencies, with a stronger relationship evident for Bitcoin. However, other cryptocurrencies such as Dogecoin, Binance Coin, and Solana demonstrated weaker or insignificant Granger causality from Brent.

Dubai Fateh oil prices exhibited some level of causality for Ethereum, Binance Coin, and Bitcoin, while showing no significant causality for other cryptocurrencies including Ripple, Shiba Inu, USD Coin, TrueUSD, Dogecoin, Avalanche, and Solana. Urals oil prices demonstrated strong Granger causality for Bitcoin ($p = 0.0004$), suggesting that historical Urals price data could be utilised to forecast Bitcoin prices. However, this causality was not significant for other major cryptocurrencies such as Ethereum, Binance Coin, and Dogecoin.

In contrast, West Texas Intermediate crude oil prices generally showed no significant Granger causality with the examined cryptocurrencies in either direction. This finding suggests that past WTI prices do not consistently predict cryptocurrency prices, nor do cryptocurrency prices predict WTI prices.

These results highlight the complex and varied relationships between different oil benchmarks and cryptocurrencies, with some oil prices demonstrating predictive power for certain cryptocurrencies while others show little to no predictive relationship. This variability underscores the need for nuanced analysis when considering the interplay between oil markets and the cryptocurrency sector.

DISCUSSION

The analysis of the relationship between oil futures and cryptocurrencies reveals a complex and nuanced interplay between these distinct asset classes. This discussion will explore the implications of our findings, contextualise them within the existing literature, and consider their broader impact on financial markets and investment strategies.

Correlation Dynamics

The strong positive correlations observed among oil futures, particularly between Brent and WTI ($r = 0.95$), reinforce the established understanding of the global oil market's interconnectedness. The high correlation suggests these benchmark oils respond similarly to global economic factors and geopolitical events, which is consistent with previous studies (e.g., Fattouh, 2010; Kilian, 2009).

In contrast, the weaker correlations between oil futures and cryptocurrencies, exemplified by the mild correlation between WTI and Ethereum ($r = 0.092$), indicate a degree of market segmentation. This finding aligns with the notion that cryptocurrencies, as a newer asset class, may operate under different market dynamics compared to traditional commodities (Corbet et al., 2018). The stronger correlations observed within the cryptocurrency market, such as between Ethereum and Bitcoin ($r = 0.79$), suggest that crypto assets may be more influenced by factors specific to their ecosystem, such as technological developments or market sentiment within the crypto community (Liu & Tsyvinski, 2021).

Time-Varying Relationships

The results from rolling correlation and cross-correlation analyses highlight the dynamic nature of the relationship between oil and cryptocurrencies. The frequent crossing of the zero line in rolling correlations and the lack of consistent patterns in cross-correlations at different lags suggest any relationships between these assets are not stable over time. This instability could be attributed to the evolving nature of the cryptocurrency market, which has undergone significant changes in terms of market maturity, institutional involvement, and regulatory landscape since its inception (Fang et al., 2022).

The observed time-varying relationships also underscore the challenges in developing consistent trading or hedging strategies that rely on stable correlations between oil and cryptocurrencies. Investors and portfolio managers should be cautious when considering these assets for diversification purposes, as the benefits may not be consistent across different time periods.

Long-term Equilibrium Relationships

Despite the weak short-term correlations, the Johansen cointegration tests reveal varying degrees of long-term equilibrium relationships between oil and cryptocurrency prices across the examined pairs. This finding is particularly intriguing as it suggests that while day-to-day movements may appear uncorrelated, there exists an underlying long-term relationship between these markets, though the strength of this relationship differs significantly among different cryptocurrencies.

The presence of strong cointegration in stablecoin pairs (USD Coin and TrueUSD) with oil benchmarks is especially noteworthy. This robust long-term relationship could indicate that stablecoins, designed to maintain a stable value, are particularly sensitive to the same macroeconomic factors that influence oil prices, such as global economic growth, inflation expectations, or monetary policy (Beckmann et al., 2020). The moderate cointegration observed in major cryptocurrencies like Bitcoin and Ethereum with certain oil benchmarks suggests that as these digital assets become more mainstream, they may be increasingly influenced by broader economic factors that have traditionally affected commodity markets.

Interestingly, the lack of cointegration in some cryptocurrency pairs (e.g., Binance Coin, Solana, Avalanche) with oil prices presents a contrasting picture. This absence of a long-term relationship implies that these particular digital assets may operate more independently of traditional economic indicators, potentially driven by factors unique to the cryptocurrency ecosystem or specific blockchain technologies.

These varied cointegration results have important implications for portfolio management and risk assessment. While the short-term diversification benefits of including both oil and cryptocurrencies in a portfolio may still hold due to weak correlations, the long-term cointegration observed in some pairs suggests that these assets may not provide as much long-term diversification as initially thought, particularly for stablecoins and major cryptocurrencies. Conversely, the lack of cointegration in other cryptocurrencies might offer genuine diversification opportunities, albeit with potentially higher volatility.

Causality and Predictive Power

The Granger causality tests reveal varying degrees of predictive relationships between oil benchmarks and cryptocurrencies. The significant Granger causality observed for Brent crude with Ethereum and Bitcoin suggests that historical Brent prices could have some predictive power for these major cryptocurrencies. This finding challenges the notion of complete independence between traditional commodities and digital assets.

However, the lack of consistent Granger causality across all oil benchmarks and cryptocurrencies, particularly the absence of significant causality for WTI, highlights the complexity of these relationships, suggesting the predictive power of oil prices for cryptocurrencies may depend on the specific benchmark and cryptocurrency pair being considered.

These results have implications for forecasting models and trading strategies. While some oil benchmarks may provide valuable information for predicting certain cryptocurrency movements, the inconsistency across different pairs suggests that a one-size-fits-all approach to using oil prices as predictors for the crypto market would be inappropriate.

Market Interdependence and Interconnectedness

The Vector Autoregression analysis provides further insight into the dynamic relationships between oil and cryptocurrencies. The generally weak and inconsistent relationships between oil futures and cryptocurrencies support the notion of market segmentation. This independence could be seen as a positive attribute for investors seeking diversification, as it suggests that cryptocurrencies may offer portfolio benefits that are not achievable with traditional commodities alone.

However, the more substantial relationships observed within the cryptocurrency market itself, particularly the cross-correlations involving Bitcoin, indicate a high degree of interconnectedness within the crypto ecosystem. This finding aligns with previous research highlighting Bitcoin's dominant role in the cryptocurrency market (Antonakakis et al., 2019). It suggests that while cryptocurrencies may be relatively independent of oil markets, they are not immune to contagion effects within their own asset class.

The lack of statistical significance for many coefficients in the VAR model underscores the challenges in developing reliable predictive models for cryptocurrency prices based on oil market movements. This unpredictability aligns with the efficient market hypothesis, suggesting that current prices already incorporate all available information, making future price movements difficult to predict based on historical data alone (Fama, 1970).

Shock Responses and Variance Decomposition

The Impulse Response Functions and Forecast Error Variance Decomposition results further reinforce the notion of limited direct influence between oil and cryptocurrency markets. The minimal immediate reactions of cryptocurrencies to oil price shocks and the quick return to baseline suggest that cryptocurrency prices are largely driven by factors independent of oil market dynamics.

This independence is further supported by the FEVD results, which show that a significant portion of the forecast error variance for cryptocurrencies is explained by their own shocks. This finding has important implications for risk management and portfolio construction. It suggests that the risks associated with cryptocurrency investments are largely idiosyncratic and may not be easily hedged using traditional commodities like oil.

Implications for Market Participants

For investors and portfolio managers, our findings suggest that while cryptocurrencies may offer diversification benefits when combined with oil-related assets in the short term, these benefits may be less pronounced over longer time horizons due to the observed cointegration. The weak short-term correlations but long-term cointegration imply that the optimal allocation strategy may differ depending on the investment time horizon.

Policymakers and regulators should note the evolving relationship between traditional commodities and digital assets. While cryptocurrencies currently appear to operate relatively independently of oil markets, the presence of long-term cointegration suggests that as the crypto market matures, it may become more integrated with the broader financial system. This potential integration may have implications for financial stability and monetary policy effectiveness in the future.

For traders and analysts, our results highlight the importance of considering multiple timeframes and analytical approaches when examining the relationships between oil and cryptocurrencies. The discrepancies between short-term correlations and long-term cointegration underscore the complexity of these markets and the potential pitfalls of relying on a single analytical framework.

LIMITATIONS AND FUTURE RESEARCH

While our study provides a comprehensive analysis of the relationship between oil futures and cryptocurrencies, several limitations should be acknowledged. First, the rapidly evolving nature of the cryptocurrency market means that historical relationships may not be indicative of future patterns. Second, our analysis focuses on a specific set of cryptocurrencies and may not capture the full diversity of the crypto ecosystem.

Future research could extend this work by examining a broader range of cryptocurrencies, including stablecoins and tokens from different blockchain ecosystems. Additionally, investigating the impact of specific events, such as major oil supply disruptions or significant crypto market developments, could provide further insights into the dynamic relationship between these assets.

CONCLUSION

This study on the relationship between oil futures and cryptocurrencies has revealed a complex and nuanced interplay between these distinct asset classes. Our analysis, employing a range of econometric techniques, has yielded several key insights that contribute to the growing body of literature on the integration of cryptocurrencies into the broader financial system.

First, our findings indicate a clear distinction between short-term dynamics and long-term relationships. While short-term correlations between oil futures and cryptocurrencies are generally weak, suggesting market segmentation, the presence of long-term cointegration in some pairs points to underlying connections that may not be immediately apparent. This dichotomy highlights the importance of considering multiple time horizons when analysing these markets.

Second, the study reveals significant heterogeneity in the relationships across different cryptocurrency-oil pairs. Major cryptocurrencies like Bitcoin and Ethereum showed more consistent significant relationships with oil benchmarks, while smaller altcoins demonstrated fewer significant interactions. This variability underscores the diverse nature of the cryptocurrency market and cautions against generalising findings across all digital assets.

Third, our analysis suggests that while cryptocurrencies may offer short-term diversification benefits when combined with oil-related assets, these benefits may be less pronounced over longer time horizons due to the observed cointegration. This finding has important implications for portfolio construction and risk management strategies, particularly for investors with varying time horizons.

Fourth, the weak predictive power of oil prices for cryptocurrency movements, as evidenced by the Granger causality tests and VAR analysis, reinforces the notion that cryptocurrencies operate under distinct market dynamics. This independence could be viewed positively from a diversification perspective, but it also highlights the challenges in developing reliable forecasting models for cryptocurrency prices based on traditional commodity market indicators.

Lastly, our study underscores the evolving nature of these relationships. The time-varying correlations and the differences in cointegration across various cryptocurrency pairs suggest that the integration of digital assets with traditional financial markets is an ongoing process, likely influenced by factors such as market maturity, regulatory developments, and broader economic conditions.

These findings have significant implications for various stakeholders. For investors and portfolio managers, they highlight the need for dynamic asset allocation strategies that account for both short-term and long-term relationships between oil and cryptocurrencies. Policymakers and regulators should be aware of the potential for increased integration between digital assets and traditional commodities, which could have implications for financial stability and market oversight.

While our study provides valuable insights, it also opens avenues for future research. Further investigation into the factors driving the observed long-term cointegration, particularly for stablecoins, could yield important insights into the evolving role of cryptocurrencies in the global financial system. Additionally, examining how these relationships change during periods of market stress or in response to significant geopolitical events could provide a more comprehensive understanding of the dynamics between oil and cryptocurrency markets.

In conclusion, this study contributes to the growing literature on the interdependencies between traditional commodities and emerging digital assets. As the cryptocurrency market continues to evolve and mature, ongoing research will be crucial in understanding its place within the broader financial ecosystem and its relationships with established asset classes like oil futures.

REFERENCES

Akaike, H. (1974). A new look at the statistical model identification. IEEE Transactions on Automatic Control, 19(6), 716-723. doi.org/10.1109/TAC.1974.1100705

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2019). Cryptocurrency market contagion: Market uncertainty, market complexity, and dynamic portfolios. Journal of International Financial Markets, Institutions and Money, 61, 37–51. https://doi.org/10.1016/j.intfin.2019.02.003

Beckmann, J., Czudaj, R. L., & Arora, V. (2020). The relationship between oil prices and exchange rates: Revisiting theory and evidence. Energy Economics, 88, 104772. https://doi.org/10.1016/j.eneco.2020.104772

Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017). Does bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. Finance Research Letters, 23, 87–95. https://doi.org/10.1016/j.frl.2017.02.009

Campbell, J. Y., Lo, A. W., MacKinlay, A. C., & Whitelaw, R. F. (1998). The econometrics of Financial Markets. Macroeconomic Dynamics, 2(4), 559–562. https://doi.org/10.1017/s1365100598009092

Corbet, et al. (2018). Exploring the Dynamic Relationships between Cryptocurrencies and Other Financial Assets. Economics Letters, 165, 28-34. https://doi.org/10.1016/j.econlet.2018.01.004

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series With a Unit Root. Journal of the American Statistical Association, 74(366), 427–431. https://doi.org/10.2307/2286348

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. The Journal of Finance, 25(2), 383–417. https://doi.org/10.2307/2325486

Fang, F., Ventre, C., Basios, M., Kanthan, L., Martinez-Rego, D., Wu, F., Li, L. (2022). Cryptocurrency trading: a comprehensive survey. Financial Innovation, 8(1), 1–59. https://doi.org/10.48550/arXiv.2003.11352

Fattouh, B. (2010). The dynamics of Crude Oil Price Differentials. Energy Economics, 32(2), 334–342. https://doi.org/10.1016/j.eneco.2009.06.007

Fattouh, B. (2011). An Anatomy of the Crude Oil Pricing System (Publisher's version). Oxford Institute for Energy Studies.

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. Econometrica, 37(3), 424–438. https://doi.org/10.2307/1912791

Ha, L. T. (2023). An application of bayesian vector heterogeneous autoregressions to study network interlinkages of the crude oil and gold, stock, and cryptocurrency markets during the covid-19 outbreak. Environmental Science and Pollution Research, 30(26), 68609-68624. https://doi.org/10.1007/s11356-023-27069-z

Hamilton, J. D. (1994). Time Series Analysis. Princeton University Press. https://doi.org/10.2307/j.ctv14jx6sm

He, S. (2022). The russia-ukraine conflict, crude oil prices, and electronic cryptocurrency market fluctuations. BCP Business &Amp; Management, 24, 173-181. https://doi.org/10.54691/bcpbm.v24i.1459

Ismail, S. and Basah, M. Y. A. (2021). An analysis on cryptocurrencies and macroeconomic variables using vector error correction model (vecm). ASEAN Journal of Management and Business Studies, 3(1), 8-15. https://doi.org/10.26666/rmp.ajmbs.2021.1.2

Johansen, S. (1991). Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. Econometrica, 59(6), 1551–1580. https://doi.org/10.2307/2938278

Kilian, L. and Park, C. (2009). The Impact of Oil Price Shocks on the US Stock Market. International Economic Review, 50, 1267-1287. http://dx.doi.org/10.1111/j.1468-2354.2009.00568.x

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. Journal of Econometrics, 74(1), 119-147. https://doi.org/10.1016/0304-4076(95)01753-4

Liu, Y., & Tsyvinski, A. (2021). Risks and Returns of Cryptocurrency. The Review of Financial Studies, 34(6), 2689–2727. https://doi.org/10.1093/rfs/hhaa113

Novalita, Isfenti Sadalia, Nisrul Irawati. The Impact of Volatility, Liquidity, and Crude Oil Price Index on Cryptocurrency Returns (Testing the WeakForm Market Efficiency). International Journal of Research and Review. 2022; 9(12):630-638. DOI: https://doi.org/10.52403/ijrr.20221272

Sims, C. A. (1980). Macroeconomics and reality. Econometrica, 48(1), 1. https://doi.org/10.2307/1912017

Zhou, Y. (2022). The impact of russian-ukrainian conflict on the dynamics of bitcoin. BCP Business &Amp; Management, 26, 611-618. https://doi.org/10.54691/bcpbm.v26i.2014

Zivot, E., & Wang, J. (2001). Modeling Financial Time Series with S-Plus. https://doi.org/10.1007/978-0-387-32348-0