International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2026, 16(2), 494-507.

Macroeconomic Indicators and Market Index Interactions in the United States: An Empirical Analysis

Ahmad Monir Abdullah[1]*, Syahidah Hanis Meor Rithuan[1], Hamdy Abdullah[2]

[1]Universiti Kebangsaan Malaysia, Malaysia, [2]Universiti Sultan Zainal Abidin, Malaysia.

*Email: ahmadmonirabdullah@ukm.edu.my

Received: 26 August 2025 **Accepted:** 28 December 2025 **DOI:** https://doi.org/10.32479/ijeep.22331

ABSTRACT

This study investigates the dynamic interactions among the major United States (US) equity indices (NYSE, NASDAQ, and S&P 500), key macroeconomic indicators (Gross Domestic Product and Consumer Price Index), and West Texas Intermediate (WTI) crude oil prices over 2005-2024. Using descriptive statistics, correlation analysis, and Wavelet Transform Coherence (WTC), the research captures both linear relationships and time–frequency comovements across economic regimes, including the 2008 Global Financial Crisis, the COVID-19 pandemic, and the post-pandemic recovery. The results show strong coherence among the equity indices but weak and unstable linkages with macroeconomic fundamentals, especially GDP. WTI demonstrates persistent medium- to low-frequency coherence with CPI and equity indices during crisis periods, highlighting its role as a major macro-financial transmission channel. These findings reveal that US financial markets have become increasingly decoupled from real-sector performance while remaining sensitive to energy-price shocks and inflation dynamics. By applying a continuous wavelet approach to a long-horizon, multi-indicator dataset, this study provides a richer view of how systemic events reshape market–macro relationships. The evidence offers new insights for policy formulation, portfolio diversification, and risk management, underscoring the need for frequency-sensitive, nonlinear frameworks for analysing macro-financial interdependence.

Keywords: Macroeconomic Indicators, Financial Market Indices, Wavelet Transform Coherence, Time-Frequency Dynamics, Oil Price Shocks
JEL Classifications: E44, G12, Q43, C22, C58

1. INTRODUCTION

Financial markets act as a real-time barometer of a nation's economic health, responding rapidly to both anticipated and unforeseen macroeconomic developments (Humpe and McMillan, 2020). In the United States, the New York Stock Exchange (NYSE), the NASDAQ Composite, and the Standard & Poor's 500 (S&P 500) serve as critical benchmarks for investor sentiment and economic performance. Complementing these, macroeconomic indicators such as Gross Domestic Product (GDP) and the Consumer Price Index (CPI) capture broader trends in output, inflation, and purchasing power. Understanding how these financial and economic indicators interact is essential for informed investment decisions, effective policy design, and accurate macroeconomic forecasting.

Over the past two decades, the global financial system has undergone repeated episodes of instability that have reshaped market–macro relationships. The 2008 global financial crisis, the COVID-19 pandemic, and recent geopolitical tensions have each disrupted conventional linkages among financial, energy, and real-sector variables. These shocks were accompanied by dramatic shifts in oil prices, supply-chain disruptions, and aggressive monetary and fiscal responses, all of which challenge the classical assumption that markets efficiently reflect economic fundamentals (Bekaert et al., 2013). In this evolving context, time-varying and frequency-dependent approaches, such as Wavelet Transform

Coherence (Rua and Nunes, 2009), offer a more robust framework for analysing nonlinear interactions. The role of oil, particularly West Texas Intermediate (WTI), adds further complexity, as it serves simultaneously as a production input, an inflation driver, and a financial asset that influences investor sentiment (Kilian and Park, 2009; Degiannakis et al., 2018).

Despite a vast body of literature exploring individual relationships between stock markets and economic variables (for example, Gan et al., 2006; Ho and Odhiambo, 2018; Bhuiyan and Chowdhury, 2020), there is a noticeable gap in studies that offer a holistic, updated, and time-frequency-based analysis that includes oil prices as a central factor. Most prior research has focused either on static correlations or on limited time horizons, failing to capture nonlinear dependencies, structural breaks, and evolving market conditions over extended periods encompassing crisis and recovery phases (Dong, 2019; Sharif et al., 2020).

While numerous studies have explored oil–stock and macro–market relationships, few have provided a long-horizon, multi-frequency examination that integrates post-pandemic dynamics. This study contributes by (i) extending the wavelet-based framework to the 2005-2024 period, (ii) jointly analysing macro, energy, and equity channels, and (iii) empirically demonstrating how structural crises alter macro-financial coherence patterns.

This study aims to fill the gap by empirically analysing the comovement and interactions among key US financial market indices (NYSE, NASDAQ, and S&P 500), macroeconomic indicators (GDP and CPI), and oil prices (WTI) over the period from March 2005 to September 2024. The main objectives of this study are as follows:

1. To identify and visualise the time-frequency comovement patterns among these indicators using the Wavelet Transform Coherence (WTC) technique.
2. To evaluate whether US financial markets reflect underlying macroeconomic fundamentals and whether oil prices serve as a transmission channel between market activity and economic performance.
3. To explore how these relationships change across different economic regimes - crises, recovery, and expansion - thereby providing insights for both policymakers and investors.

The contribution of this study lies in its comprehensive, frequency-domain assessment of market-macro dynamics using high-resolution, post-2010 data that includes both stable periods and significant economic disruptions. By integrating multiple indicators within a unified framework, this research enhances the understanding of systemic risk, market efficiency, and the predictive power of macroeconomic signals. The findings are expected to offer valuable implications for investment strategy, risk management, and policy formulation in increasingly complex and interconnected economic systems.

In addition, this study is also grounded in the Portfolio Diversification Theory introduced by Markowitz (1952). This theory emphasises the importance of holding a diversified portfolio of assets to reduce overall risk, provided the assets are not perfectly correlated. In a macroeconomic context, understanding the relationships among indicators such as GDP, inflation, stock market indices, and oil prices is crucial, as their correlations can significantly influence investment strategies and the level of risk borne by investors.

The structure of this article is as follows: Section 2 reviews the relevant literature; Section 3 details the research methodology; Section 4 presents and interprets the empirical findings; and Section 5 concludes with key insights, implications, and directions for future research.

2. LITERATURE REVIEW

The relationship between macroeconomic indicators and stock market performance has long been a central theme in financial economics. Seminal work by Chen et al. (1986) established that macroeconomic variables, such as industrial production, the term structure, inflation, and market risk premiums, significantly influence asset pricing. Fama (1981) emphasised the role of real activity in shaping stock returns, while Geske and Roll (1983) highlighted the indirect channels through which fiscal and monetary dynamics affect equity markets via inflation.

Building on these foundations, subsequent research has increasingly examined how external shocks, particularly from commodity markets, interact with financial systems. Hamilton (2009) reaffirmed the importance of oil price shocks as precursors to economic recessions, tracing their impact through supply disruptions and increased production costs. Kilian and Park (2009) distinguished the effects of oil supply shocks, aggregate demand shocks, and oil-specific demand shocks on equity returns, emphasising that the source of oil volatility shapes market interpretation. Baumeister and Hamilton (2019) extended this narrative by modelling oil market dynamics more accurately through the structural decomposition of demand and supply influences.

In recent years, the nuanced relationship between oil prices and equity markets has garnered renewed interest, particularly during periods of heightened volatility. Liu and Zhang (2020) found that GDP growth in the US tends to correlate more strongly with broad market indices, such as the S&P 500, whereas tech-heavy indices, such as the NASDAQ, react more sharply to interest rate movements and investor sentiment. Arouri et al. (2012) further found that oil price volatility affects equity sectors asymmetrically, depending on their energy intensity.

The COVID-19 pandemic marked a turning point in understanding financial-macro linkages. Altig et al. (2020) documented unprecedented market responses to policy shocks and health-related uncertainty during the COVID-19 pandemic, demonstrating how traditional macroeconomic signals were temporarily overridden by investor panic and liquidity concerns. Their analysis utilised various forward-looking uncertainty indicators, including stock market volatility, newspaper-based economic uncertainty, and subjective uncertainty from business expectation surveys, to quantify the surge in economic uncertainty. This period challenged conventional models and underscored the necessity for advanced time-frequency techniques to analyse financial dynamics. One of the most promising approaches for capturing the evolving nature of macro-financial interactions is the wavelet transform, which enables the simultaneous analysis of time and frequency domains. Diebold and Yilmaz (2014) introduced connectedness measures for financial markets that quantify volatility transmission across asset classes. Apergis and Payne (2022) applied machine learning tools to explore how oil price shocks propagate through financial systems, revealing nonlinear and time-varying effects that standard linear models miss.

Several recent studies from 2021 to 2024 have expanded the application of wavelet coherence methods to account for post-pandemic structural changes. Sharif et al. (2020) analysed the oil price–stock market relationships in the US, China, and Malaysia using wavelet coherence across pre-, during-, and post-COVID periods, highlighting strong time-varying comovements and lagging effects. Similarly, Choi et al. (2024) investigated systemic risk-sharing between natural gas, oil, and stock markets in top energy-producing and consuming countries, revealing increased comovement during crisis episodes. Other wavelet-based research (e.g., Marín-Rodríguez et al., 2023) linked oil price fluctuations to macroeconomic indicators such as CO_2 emissions and green bond returns, demonstrating that commodity shocks extend to environmental and financial domains.

In addition, studies have focused on the role of economic policy uncertainty (EPU) as a key variable that interacts with oil shocks and macroeconomic indicators. For instance, Alola et al. (2024) demonstrated that economic policy uncertainty (EPU) significantly modulates the strength and frequency of oil-stock linkages, suggesting that investor confidence and policy ambiguity must be incorporated into modern forecasting models.

Despite these advancements, the literature still lacks a holistic, post-2010 empirical evaluation that concurrently examines US equity indices, oil prices, and macroeconomic indicators using high-resolution time-frequency techniques. Most existing studies focus either on short-term volatility, static correlations, or single-country frameworks, overlooking the interconnected evolution of financial and macroeconomic systems over extended time horizons.

In summary, previous studies have established the significance of oil and uncertainty shocks but have often been limited by static or single-period analyses. Few have integrated frequency-domain methods with multiple macroeconomic indicators over extended post-crisis horizons. This study addresses that gap by combining WTC with correlation and descriptive analysis to reveal both transient and persistent macro–market linkages in the US context.

3. RESEARCH METHODOLOGY

This study adopts a quantitative and time-series econometric approach to examine the interactions between macroeconomic indicators and financial market indices in the US from Q1 2005 to Q3 2024. The methodology integrates descriptive statistics, correlation analysis, and time-frequency domain techniques, particularly the WTC, to uncover both linear and nonlinear relationships across time and scale.

3.1. Data Collection

The dataset comprises 78 quarterly observations for six key variables: the NYSE Composite Index, the NASDAQ Composite Index, the S&P 500 Index, WTI crude oil prices, the Consumer Price Index (CPI), and Gross Domestic Product (GDP). Data were sourced from reputable databases, including the US Bureau of Economic Analysis (BEA), Federal Reserve Economic Data (FRED), and Refinitiv Eikon. All financial indices and WTI prices were converted to natural logarithmic returns to standardise the scale and reduce heteroskedasticity. CPI and GDP were converted to quarterly growth rates using log differences to ensure comparability and consistency across macroeconomic time series.

3.2. Descriptive Statistics

Descriptive statistics, including mean, standard deviation, skewness, and kurtosis, were computed for each variable to summarise their statistical properties and assess distributional characteristics. This preliminary analysis provides a foundation for understanding volatility dynamics, asymmetry, and tail risk inherent in the data.

3.3. Correlation Analysis

Pearson correlation coefficients were calculated to examine linear relationships among the variables. A correlation matrix was developed to explore the degree of comovement between financial market indices, oil prices, and macroeconomic indicators. Although useful for detecting initial associations, Pearson correlation captures only contemporaneous linear dependence and does not account for potential lag effects or dynamic interactions. Therefore, more advanced techniques were subsequently employed.

3.4. Volatility Calculation

The volatility analysis in Figure 1 shows fluctuations in the log returns of selected variables over the study period. To compute volatility, the standard deviation of log returns is calculated using a rolling window of a specified length (e.g., a 4-quarter window for annualised volatility). This method effectively captures both short-term and long-term fluctuations within the data series. Log returns are calculated using the following formula:

$$R_t = \ln(\frac{P_t}{P_{t-1}})$$

where:

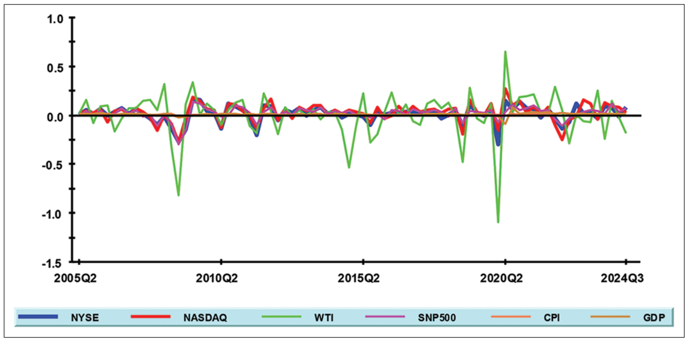
R_t = Log return at time t

P_t = Value in the current period

P_{t-1} = Value in the previous period

The computed log returns are then used to derive the rolling standard deviation, which provides a time-varying measure of volatility. This approach is commonly applied to detect volatility clustering. However, this method does not capture time- and frequency-dependent interactions, thereby motivating the use of the WTC method in this study.

Figure 1: Volatility of log return of variables



3.5. Wavelet Transform Coherence (WTC) Analysis

This study applies the WTC methodology to effectively examine the time-frequency dynamics between macroeconomic indicators and financial indices. WTC enables a two-dimensional analysis of time series data, offering localised views of correlations across varying frequencies and time intervals. It is particularly suitable for non-stationary data, which is common in financial and macroeconomic datasets.

Unlike discrete wavelet transforms such as Discrete Wavelet Transform (DWT) or Maximal Overlap Discrete Wavelet Transform (MODWT), WTC does not require predefined decomposition levels, and its continuous nature provides a more redundant and detailed view of time-frequency structures. This redundancy enhances pattern detection and enables smoother visualisation of temporal changes. The wavelet filter used in this study is the least asymmetric wavelet of length 8, denoted as LA(8), first introduced by Daubechies (1992). This filter provides high resolution in both time and frequency domains and has been shown to perform effectively in economic and financial analyses (Gençay et al., 2001; In and Kim, 2013).

The interpretation of the WTC output is conducted using the wavelet coherence map, where red regions indicate strong correlations between the two variables during a specific time period, blue regions denote weak correlations, and yellow regions represent moderate correlations. The direction of the arrows in the wavelet coherence map provides insight into the phase relationship between the variables. A rightward arrow (→) indicates that both time series move together, or are in-phase, suggesting a positive correlation. A leftward arrow (←) denotes that the series move in opposite directions, or are anti-phase, reflecting a negative correlation. When arrows tilt upward-right (↗) or downward-right (↘), the first series leads the second. Conversely, upward-left (↖) or downward-left (↙) arrows signify that the second series leads the first.

The WTC technique of Torrence and Compo (1998) is adopted to capture both time- and frequency-domain interactions among variables. WTC is preferred over conventional VAR or MGARCH models because it simultaneously reveals transient and long-run comovements without requiring stationarity. The LA(8) wavelet, following Daubechies (1992), provides an optimal balance between time and frequency localisation. To assess directional influence, phase-difference analysis (Grinsted et al., 2004) identifies leading–lagging effects between oil and macro-financial variables. The mathematical expression for WTC is presented as follows:

$$R^2(u,s) = \frac{\left|S(s^{-1}W_{xy}(u,s))\right|^2}{S\left(s^{-1}\left|W_x(u,s)\right|^2\right).S(s^{-1}\left|W_y(u,s)\right|^2)}$$

In this formula, the symbol 'S' denotes the dual-smoothing parameter, which plays a crucial role in influencing both the time and scale dimensions of the analysis. Subsequently, $R^2(u, s)$ measures the comovement between two data series, with values ranging from 0 to 1, as explained by Rua and Nunes (2009). An $R^2(u, s)$ value approaching 1 indicates a strong correlation between the two series, whereas a value approaching 0 suggests a weak or negligible relationship. By analysing the contour plots of this metric, regions within the time–frequency space where both series move together can be identified. This method provides a comprehensive examination of comovements, including fluctuations and variations across different time scales and frequencies. In this study, the Wavelet Phase Difference approach introduced by Bloomfield et al. (2004) is employed to examine directional interactions and causality among the variables. This method calculates the phase difference between m(t) and n(t), offering insights into the timing and causal dynamics of their interactions. The equation for the phase difference is expressed as follows:

$$\varnothing_{mn}(u,s) = tan^{-1}\left(\frac{\Im\{W_{mn}(u,s)\}}{\Re\{W_{mn}(u,s)\}}\right)$$

with: $\varnothing_{mn} \in [-\pi,\pi]$

The Least Asymmetric Wavelet Filter of Length 8 (LA(8)) introduced by Daubechies (1992) is employed. This filter generates eight coefficients that are highly suitable for time series analysis, as noted by Gençay et al. (2001) and In and Kim (2013). Compared to other filters, such as the Haar filter, the LA(8) filter produces more detailed wavelet coefficients, thereby enhancing the accuracy and precision of the analysis.

The WTC method is deemed appropriate for this study, as it has been widely applied in modern financial research, including by Rua and Nunes (2009), Goodell and Goutte (2021), and Dowling (2022), to analyse comovement dynamics in contexts such as stock markets, cryptocurrencies, and non-fungible tokens (NFTs).

4. FINDINGS AND DISCUSSION

This section presents the empirical findings from the analysis of quarterly data spanning from March 2005 to September 2024. The variables analysed include NYSE, NASDAQ, S&P 500, WTI crude oil prices, Consumer Price Index (CPI), and Gross Domestic Product (GDP). Descriptive statistics, correlation analysis, and WTC techniques were applied to evaluate the nature of interactions and comovements among the selected financial and macroeconomic indicators.

4.1. Descriptive Statistics

Figure 2 illustrates the time series trajectories of six key economic and financial variables (NYSE, NASDAQ Composite Index, S&P 500 Index, WTI crude oil prices, CPI, and GDP) from Q1 2005 to Q3 2024 (March 2005-September 2024). Each series exhibits distinct temporal patterns, reflecting underlying macroeconomic conditions and sectoral dynamics.

The NYSE index demonstrates a pronounced upward trend over the sample period, interrupted by noticeable declines during the 2008 global financial crisis and the COVID-19-induced market shock in early 2020. Despite these downturns, the NYSE rebounded strongly, particularly after 2020, driven by expansive monetary policy and a surge in investor confidence. This recovery trajectory highlights the resilience of large-cap industrial and financial equities (Altig et al., 2020; Sharif et al., 2020).

The NASDAQ Composite Index shows exponential growth, especially since 2015, with marked volatility. Its pronounced ascent and subsequent corrections around 2022 underscore its sensitivity to technology-sector valuations and speculative investor behaviour (Liu and Zhang, 2020). The index's sharp fluctuations make it a leading indicator of sentiment within growth-oriented sectors.

WTI crude oil prices, in contrast, exhibit substantial cyclicality and volatility. Sharp price escalations around 2008 and 2011 are attributable to geopolitical tensions and global supply shocks, while the significant collapse in early 2020 reflects unprecedented demand destruction amid pandemic-related lockdowns. Post-2020, WTI recovered steadily but remains susceptible to global market fluctuations and energy policy shifts.

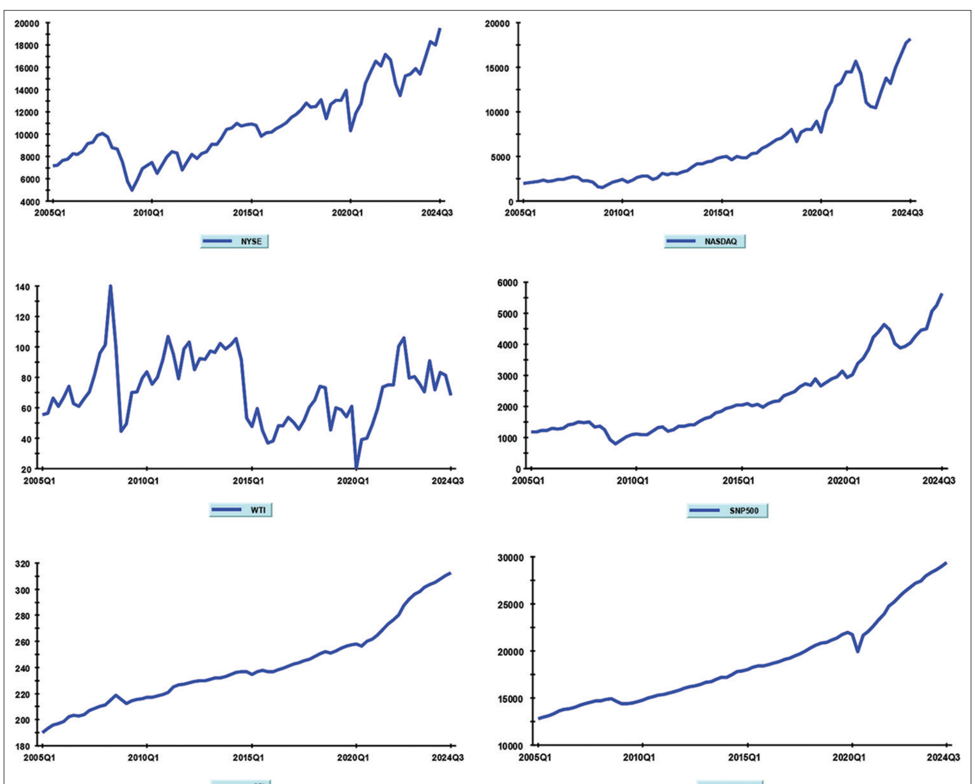
The S&P 500 Index displays a relatively smoother, more persistent growth pattern than the NASDAQ, with downturns synchronised with macroeconomic crises. Its broad sectoral composition makes it a reliable barometer of the overall health of the US corporate sector. Following the 2020 crisis, accelerated growth coincided with record corporate earnings and fiscal stimulus.

The CPI series follows a stable upward trajectory, reflecting long-term inflation trends in the US economy. While generally smooth, a noticeable acceleration in price levels emerges after 2021, likely due to supply chain disruptions and higher energy costs. Nonetheless, CPI remains the least volatile series, serving as a critical gauge of purchasing power stability.

Similarly, the US GDP series registers consistent expansion over the period, with a prominent contraction in early 2020, corresponding to the pandemic-induced recession. The subsequent rebound is swift and robust, reflecting both policy interventions and economic reopening. Overall, GDP demonstrates steady long-term growth with minimal structural breaks.

In summary, while equity indices exhibit strong upward trends with varying degrees of volatility, macroeconomic indicators such as CPI and GDP remain comparatively stable. Oil prices, represented by WTI, show the most pronounced cyclical behaviour. These descriptive patterns substantiate the relevance of applying time-frequency analytical tools, such as the WTC, to explore the

Figure 2: Dynamics of original data series



evolving interdependencies and lead-lag dynamics among these variables.

4.1.1. US data

Table 1 summarises the descriptive statistics for the six core variables analysed in this study (NYSE, NASDAQ, S&P 500, WTI crude oil prices, CPI, and GDP) based on 78 quarterly observations from March 2005 to September 2024. The NYSE returns have a mean of 0.013 and a standard deviation of 0.087, indicating moderate volatility over the sample period. The distribution is negatively skewed (−1.345), reflecting a longer left tail, and slightly platykurtic (kurtosis = 2.645), suggesting a flatter shape than the normal distribution with only mild deviation from normality. The NASDAQ shows a higher mean return of 0.028, consistent with its growth-oriented composition and slightly higher volatility (standard deviation = 0.095). Its skewness (−0.898) and kurtosis (1.774) suggest a distribution that is moderately left-skewed and slightly platykurtic, indicating fewer extreme returns than in a normal distribution. WTI crude oil prices exhibit the highest volatility (standard deviation = 0.239) among all variables, with a minimal mean return (0.003). The distribution is highly negatively skewed (−1.720) and strongly leptokurtic (kurtosis = 6.682), reflecting the presence of extreme negative shocks in oil prices, particularly during geopolitical tensions and the COVID-19 crisis. The S&P 500 Index displays a smoother return profile with a mean of 0.020 and the lowest standard deviation among the equity indices (0.065). However, it is the most negatively skewed (−1.907) and highly leptokurtic (6.710), indicating rare but severe negative return episodes, which is characteristic of crisis periods like early 2020. The CPI return series is the most stable among the macroeconomic indicators, with a mean of 0.006 and a very low standard deviation of 0.007. It is nearly symmetric (−0.253 skewness) and platykurtic (kurtosis = 1.681), reflecting a consistent inflation trend with limited deviations over time. The GDP growth rate also displays stability with a mean of 0.011 and a standard deviation of 0.016. However, it shares the same high negative skewness (−1.720) as WTI and exhibits extreme leptokurtosis (22.128), highlighting the presence of a few large deviations from the mean, primarily driven by the 2020 pandemic recession. The descriptive statistics confirm substantial variability in return profiles across the financial and macroeconomic indicators. Equity indices, particularly NASDAQ and NYSE, show moderate volatility and negative skewness. WTI and GDP demonstrate the most extreme non-normal characteristics, suggesting the influence of external shocks and systemic risks. These distributional features warrant further investigation through time-frequency analysis, such as the WTC, to better understand comovement dynamics across different time horizons (Rua and Nunes, 2009; Degiannakis et al., 2018).

4.2. Correlation Analysis

Table 2 presents the Pearson correlation coefficients among the six key variables: NYSE, NASDAQ, S&P 500, WTI crude oil prices, CPI, and GDP. This analysis provides initial insights into the linear relationships and potential comovements between financial market indices, oil prices, and macroeconomic indicators over the sample period. As expected, the three major equity indices (NYSE, NASDAQ, and S&P 500) exhibit strong positive correlations with each other, similar to the finding by Rua and Nunes (2009). The NYSE highly correlates with the NASDAQ (r = 0.864) and the S&P 500 (r = 0.812), suggesting a consistent comovement across broad market segments. Similarly, the NASDAQ and S&P 500 are positively correlated (r = 0.780), reflecting synchronised investor sentiment and economic outlook among large-cap and technology-focused stocks. The WTI crude oil price is moderately correlated with the stock indices, particularly the NYSE (r = 0.635) and NASDAQ (r = 0.510), indicating that oil market fluctuations can influence equity returns (Kilian and Park, 2009; Arouri et al., 2012), albeit to a lesser extent. The correlation between WTI and the S&P 500 is relatively weak (r = 0.478), suggesting differentiated exposure to oil price shocks across the sectors represented in the indices. In terms of macroeconomic variables, the CPI shows weak correlations with financial indices, including the NYSE (r = 0.116), NASDAQ (r = −0.029), and S&P 500 (r = 0.272), suggesting that inflationary trends are not immediately reflected in short-term stock returns. However, CPI exhibits a moderate positive correlation with GDP (r = 0.505), indicating that price levels and output growth tend to move together over time, as expected from economic theory. The GDP variable is weakly correlated with all three stock indices: the NYSE (r = 0.122), the NASDAQ (r = −0.012), and the S&P 500 (r = 0.314), highlighting the well-documented disconnect between financial markets and real economic activity in the short run. Notably, the negative correlation between GDP and NASDAQ may reflect the sensitivity of high-growth technology stocks to monetary policy changes and speculative dynamics rather than fundamental macroeconomic performance. Overall, the correlation matrix suggests that while equity markets are closely interconnected, their links to macroeconomic fundamentals such as inflation and GDP growth are relatively weak or inconsistent. The moderate correlations between oil prices and stock indices highlight the partial transmission of commodity shocks into financial markets. These results justify the application of more sophisticated time-frequency-domain techniques, such as the WTC, to capture potential nonlinear and time-varying dependencies.

4.3. Volatility of Log Return of Variables

Figure 1 illustrates the quarterly log-return volatility of the six observed variables from Q2 2005 to Q3 2024. The chart visually

Table 1: Descriptive Statistics

Variables	No of Observation	Minimum	Maximum	Mean	Std. Deviation	Skewness	Kurtosis
NYSE	78	−0.301	0.171	0.013	0.087	−1.345	2.645
NASDAQ	78	−0.283	0.267	0.028	0.095	−0.898	1.774
WTI	78	−1.092	0.651	0.003	0.239	−1.720	6.682
S&P500	78	−0.295	0.139	0.020	0.065	−1.907	6.710
CPI	78	−0.014	0.026	0.006	0.007	−0.253	1.681
GDP	78	−0.086	0.084	0.011	0.016	−1.720	22.128

Table 2: Correlation analysis

	NYSE	NASDAQ	WTI	S&P500	CPI	GDP
NYSE	1	0.864	0.635	0.812	0.116	0.122
NASDAQ		1	0.510	0.780	−0.029	−0.012
WTI			1	0.478	0.248	0.006
S&P500				1	0.272	0.314
CPI					1	0.505
GDP						1

depicts dynamic changes in return magnitudes, highlighting periods of heightened market turbulence and economic shocks. A key observation from the figure is the pronounced volatility of WTI crude oil prices (light green line) compared to all other variables. The WTI series exhibits frequent and large fluctuations throughout the sample, with extreme volatility spikes around 2008-2009 and again in early 2020. These spikes align with the global financial crisis and the COVID-19 pandemic, both triggering substantial disruptions in oil demand and supply dynamics. In contrast, the equity indices (with NYSE in blue, NASDAQ in red, and S&P 500 in purple) exhibit relatively smoother volatility patterns, though brief spikes are visible during the same crisis periods. Notably, the volatility spike around Q1 2020 reflects the rapid market reaction to pandemic-induced uncertainty. Among the three, NASDAQ appears slightly more volatile, consistent with its exposure to high-growth, high-risk technology stocks. The CPI (orange) and GDP (light brown) lines remain close to the zero axis throughout the sample period, reinforcing their nature as low-volatility macroeconomic indicators. This reflects the structural and gradual nature of inflation and economic growth, which typically do not exhibit the rapid, large fluctuations seen in financial or commodity markets. The volatility analysis reveals that financial market indices and oil prices are significantly more reactive to global events and economic shocks, whereas macroeconomic variables exhibit stability and inertia. These contrasting characteristics further justify the use of time-frequency tools like the WTC to capture both the high-frequency volatility of financial variables and the low-frequency trends in macroeconomic fundamentals.

4.4. Wavelet Transform Coherence (WTC) Analysis

To analyse the evolving time–frequency relationships between macroeconomic indicators and financial market indices, this study applies the WTC technique using the least-asymmetric wavelet filter of length 8 [LA(8)], as introduced by Daubechies (1992). The WTC enables the decomposition of time series into both time and frequency domains, thereby facilitating the detection of localised and scale-specific correlations which traditional time-domain or spectral techniques often fail to uncover. Significance contours at the 5% level were obtained via Monte-Carlo against AR(1) red-noise surrogates; the cone of influence (COI) bounds regions affected by edge effects. Only regions within the COI and above the 5% contour are interpreted (Rua and Nunes, 2009).

The wavelet coherence analysis reveals several distinct patterns of comovement across the sample period from June 2005 to September 2024. Table 3 lists the reference dates for the horizontal axes in Figures 3-16, covering June 2005-September 2024. The timeline starts in June 2005 rather than March 2005 because the first quarter is used to construct log returns (first-differencing), which removes the initial observation. This table lists specific dates corresponding to the numerical values along the horizontal axis, allowing for a more accurate interpretation of the graphical representation of relationships among macroeconomic variables over time. The selected dates are spaced roughly every 2 years to capture major economic changes and trends throughout the study period.

Table 3: Date for horizontal axis

Horizontal axis	Date
0	June 2005
10	September 2007
20	March 2010
30	September 2012
40	March 2015
50	September 2017
60	March 2020
70	September 2022
78	September 2024

Figure 3: NYSE versus WTI

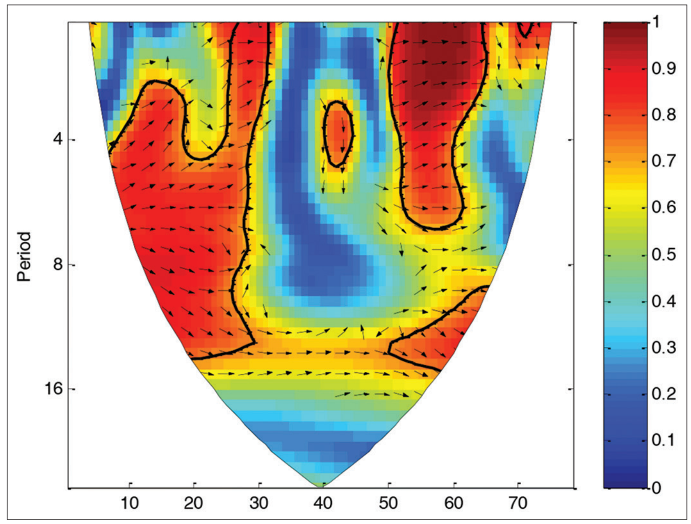


Figure 4: S&P500 versus WTI

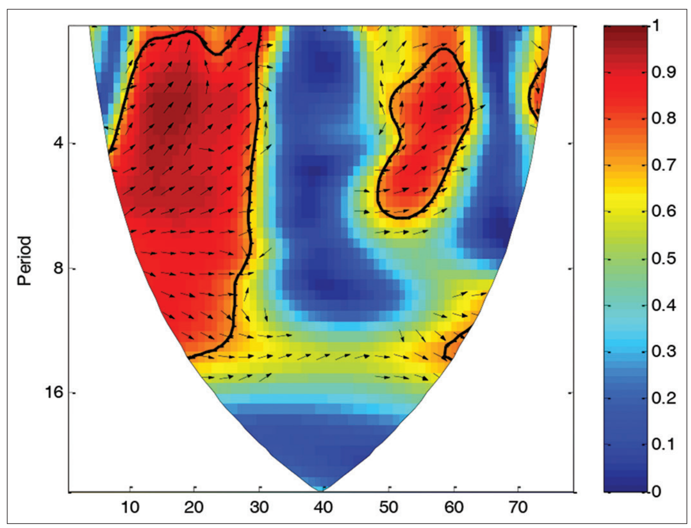


Figure 5: NASDAQ versus WTI

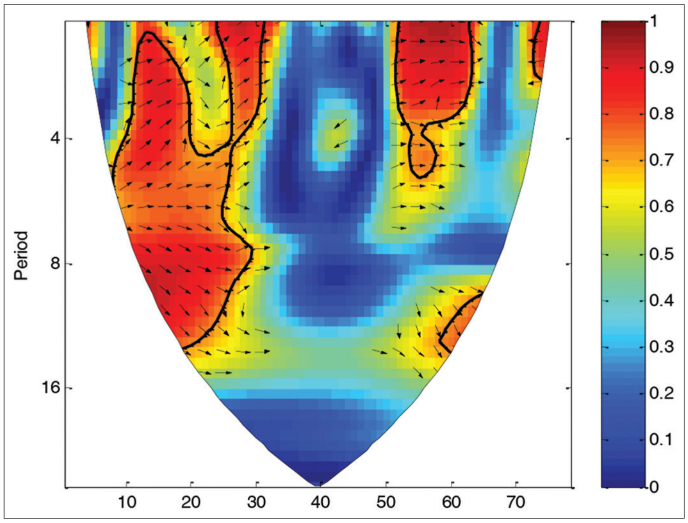


Figure 6: NYSE versus S&P500

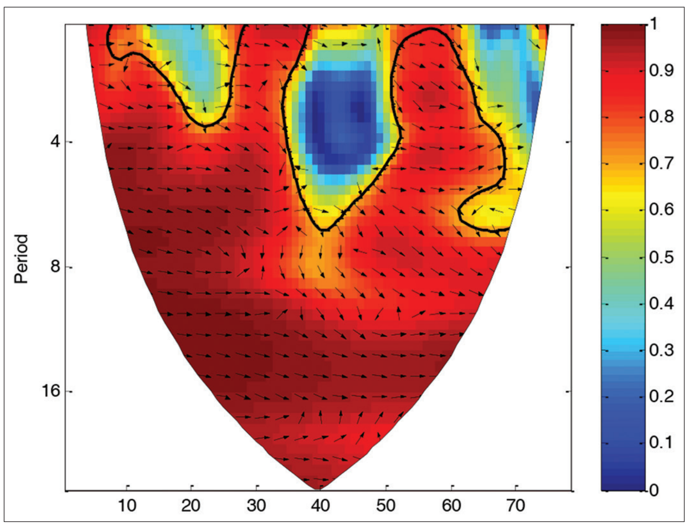


Figure 7: NASDAQ versus NYSE

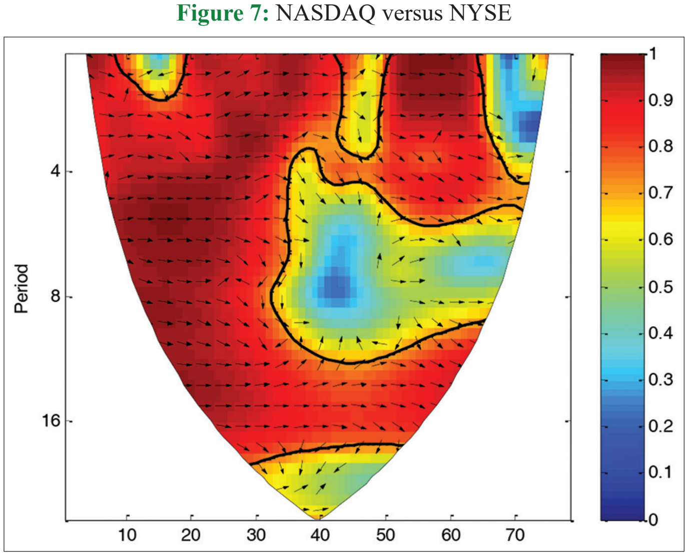


Figure 8: NASDAQ versus S&P500

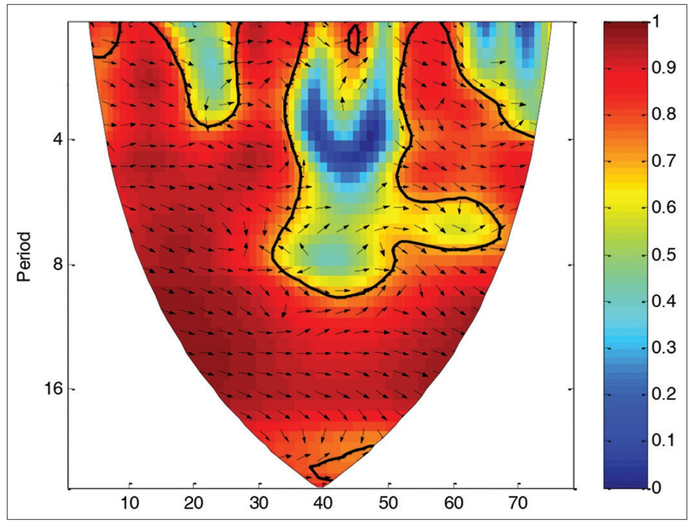


Figure 9: GDP versus NASDAQ

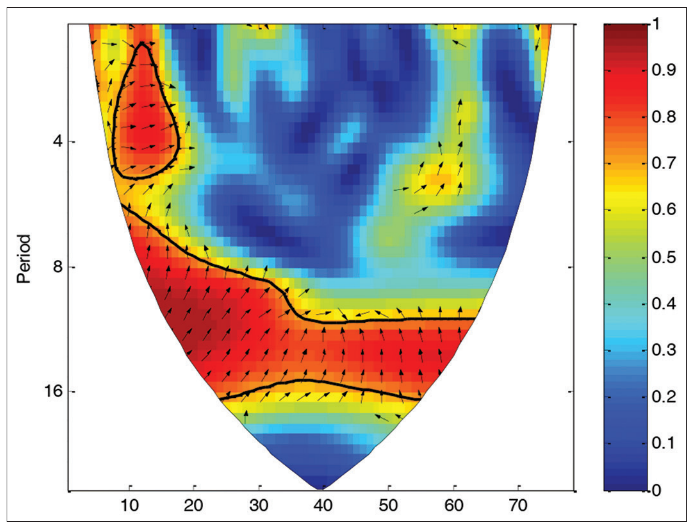


Figure 10: GDP versus NYSE

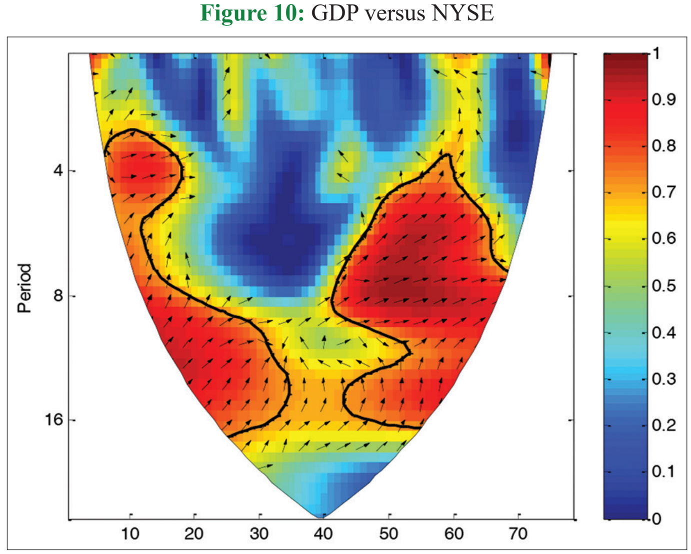


Figure 11: GDP versus WTI

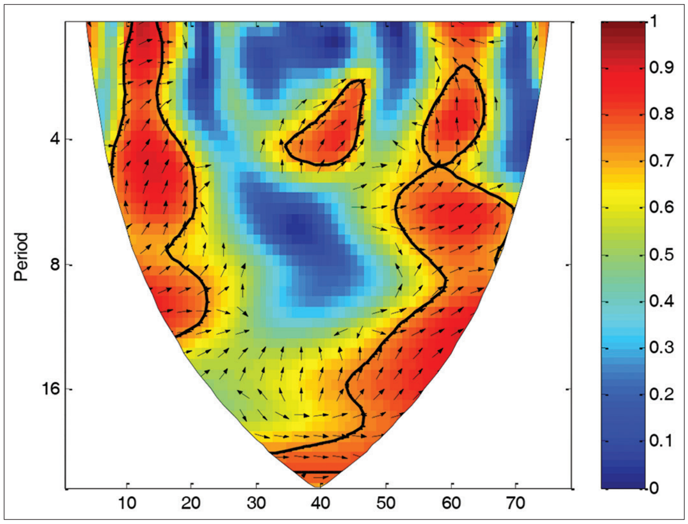


Figure 14: CPI versus WTI

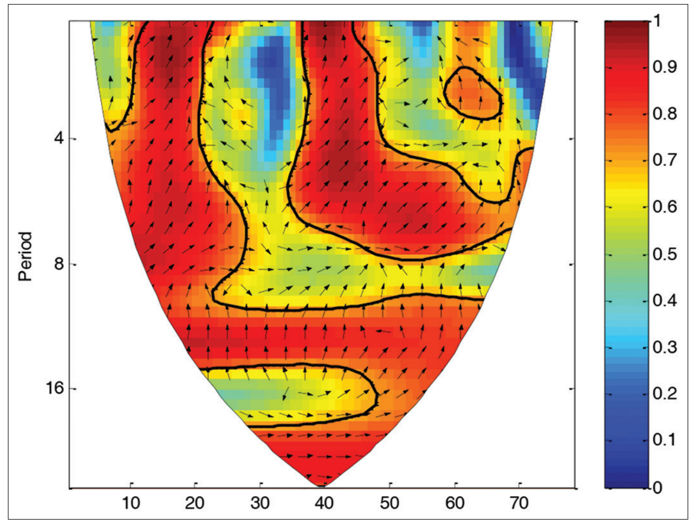


Figure 12: CPI versus GDP

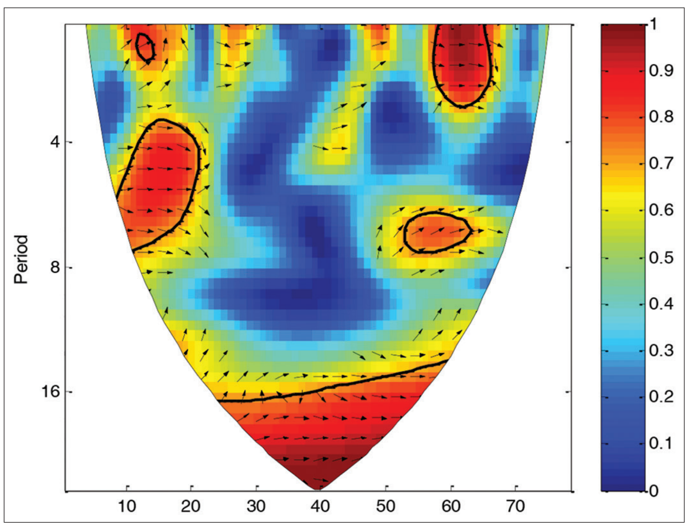


Figure 15: CPI versus NYSE

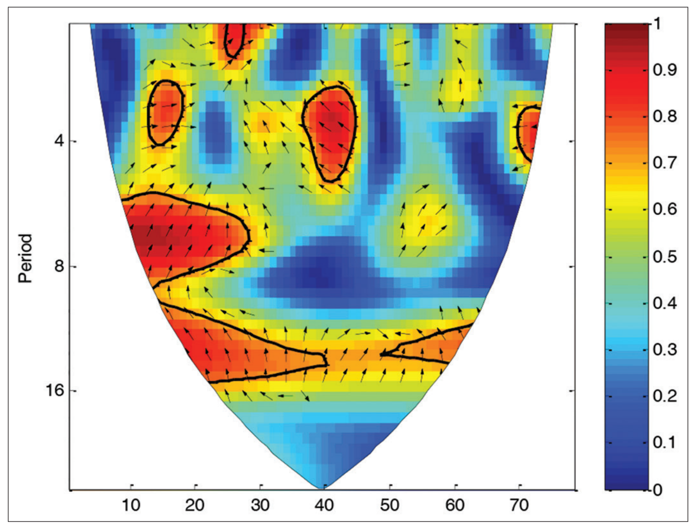


Figure 13: CPI versus NASDAQ

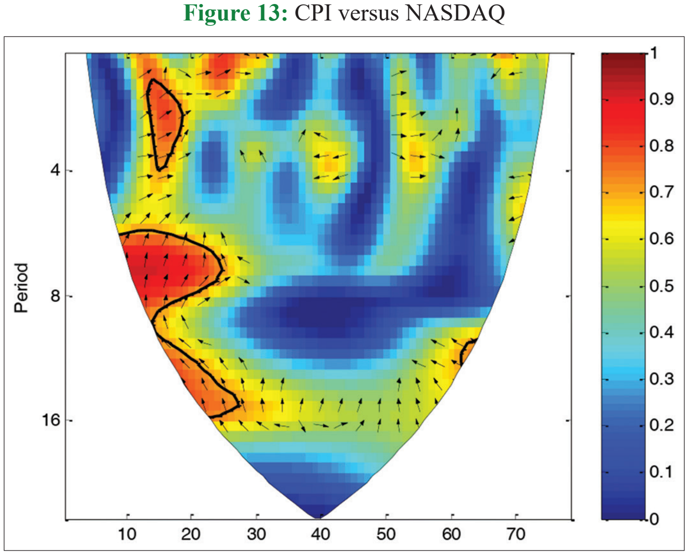
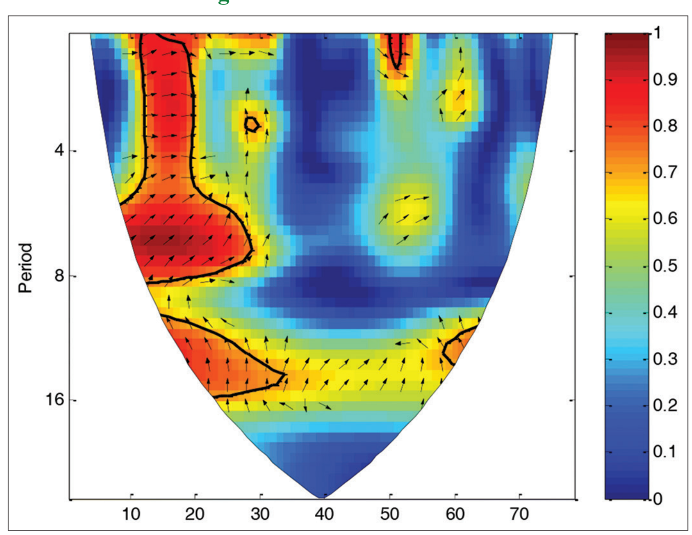


Figure 16: CPI versus S&P500



4.4.1. Figure 3: NYSE versus WTI

The wavelet coherence analysis between NYSE and WTI returns from June 2005 to September 2024 shows that their relationship is time- and frequency-dependent. Strong in-phase coherence occurs during major crises, notably around 2008-2009 (the global financial crisis) and 2020-2021 (the COVID-19 pandemic), indicating synchronised movements driven by systemic shocks and recovery efforts. A moderate coherence zone is also observed during 2016-2017, as oil prices stabilised post-collapse, with arrows pointing diagonally upward (↗), suggesting that the NYSE led WTI at certain frequencies. After 2022, coherence weakens with inconsistent phase directions, reflecting diverging market drivers. These findings confirm that oil–equity dynamics vary across regimes and time scales, aligning with prior evidence that market sentiment can sometimes precede oil-price adjustments (Kilian and Park, 2009; Arouri et al., 2012).

4.4.2. Figure 4: S&P 500 versus WTI

The wavelet coherence analysis of S&P 500 and WTI returns from June 2005 to September 2024 reveals several moderate-to-strong comovement episodes, primarily at high to medium frequencies. Notably, high coherence appears during the 2007-2009 financial crisis, with right-pointing in-phase arrows indicating that both oil prices and equity markets moved together under systemic stress. Following the oil-price recovery, another coherence cluster emerges around 2016-2017, again showing an in-phase relationship, while arrows in some regions point diagonally upward (↗), suggesting that the S&P 500 led WTI at certain medium-term frequencies. A strong but narrower coherence zone also arises during 2020-2021 (COVID-19 period), reflecting synchronised rebound patterns. Compared with the NYSE, the coherence with the S&P 500 is less persistent and more fragmented, consistent with the index's broader sectoral coverage that includes industries less directly tied to oil. After 2022, coherence declines, with scattered arrows and lower magnitudes, indicating weaker, less stable linkages as post-pandemic dynamics and policy divergence shaped market behaviour. Overall, these results confirm that the oil-equity relationship for the S&P 500 is conditional, event-driven, and scale-specific, consistent with prior evidence on oil–stock market interdependence (Kilian and Park, 2009; Arouri et al., 2012).

4.4.3. Figure 5: NASDAQ versus WTI

The wavelet coherence analysis of NASDAQ and WTI returns from June 2005 to September 2024 reveals weak and sporadic comovement, with only short bursts of moderate coherence observed primarily at high-to-medium frequencies. Unlike the NYSE and S&P 500, the NASDAQ index displays less persistent and more fragmented coherence zones, reflecting its structural concentration in technology and growth-oriented sectors that are less directly influenced by oil-price dynamics. Small patches of in-phase coherence emerge during the 2008-2009 financial crisis and again briefly around 2016-2017, but neither is strong nor sustained. A narrow coherence zone appears during the 2020-2021 COVID-19 period, though limited in scale and duration, further underscoring the index's relatively weak sensitivity to oil-market fluctuations. After 2022, coherence further diminishes, with scattered, low-magnitude patches, indicating minimal alignment between oil and NASDAQ performance during recent macro-financial adjustments. Overall, the results confirm that the NASDAQ–WTI relationship is infrequent, short-term, and event-specific, largely driven by external shocks rather than structural dependence, consistent with earlier findings on the asymmetric and nonlinear transmission of oil-price shocks to equity markets (Kilian and Park, 2009; Arouri et al., 2012; Degiannakis et al., 2018).

4.4.4. Figure 6: NYSE versus S&P500

The wavelet coherence analysis between NYSE and S&P 500 returns from June 2005 to September 2024 reveals a consistently strong and persistent comovement across nearly all frequencies and time periods, as indicated by the dominant red-shaded regions covering most of the cone of influence. The coherence remains high at both high (top) and low (bottom) frequencies, demonstrating that the linkage between these two major US equity indices operates across both short- and long-term horizons. Throughout the sample period, the phase arrows are predominantly rightward, indicating a stable in-phase relationship in which both indices move together over time. This high and enduring coherence reflects the structural similarity between the NYSE Composite and the S&P 500, which broadly represent the US stock market and share overlapping constituent firms. Minor short-term fluctuations occur intermittently around 2010 and 2018 but do not significantly disrupt the overall synchrony. These findings confirm the existence of a highly synchronised, robust relationship between the NYSE and S&P 500 across market regimes, consistent with prior evidence of integrated equity-market behaviour (Rua and Nunes, 2009; Grinsted et al., 2004).

4.4.5. Figure 7: NASDAQ versus NYSE

The wavelet-coherence analysis of NASDAQ and NYSE returns from June 2005 to September 2024 reveals a high degree of persistent, multi-frequency coherence, with dominant red-shaded regions spanning most of the time and scale domains. This indicates a strong and stable comovement between the two indices across both short-term (high-frequency) and long-term (low-frequency) horizons. Right-pointing in-phase arrows dominate the plot, particularly at medium to low frequencies, confirming that both indices move in the same direction over time. Even during major disruptions, such as the 2008-2009 global financial crisis and the 2020-2021 COVID-19 pandemic, coherence remains robust, though small blue patches suggest brief divergences at specific frequencies. The sustained alignment reflects the structural and behavioural linkages between the NASDAQ and NYSE, driven by shared macroeconomic factors, investor sentiment, and financial policy conditions. Overall, the findings highlight the systemic interconnectedness of US equity markets and validate the presence of long-run synchronisation across indices, consistent with prior evidence of integrated financial-market dynamics (Rua and Nunes, 2009; Vácha and Barunik, 2012).

4.4.6. Figure 8: NASDAQ versus S&P500

The wavelet-coherence analysis between NASDAQ and S&P 500 returns from June 2005 to September 2024 reveals a consistently high and stable comovement across most time and frequency domains. The plot is dominated by red-shaded regions, particularly at medium-to-low frequencies, indicating strong and persistent long- to medium-term coherence. The phase arrows are predominantly rightward, signifying an enduring in-phase relationship in which both indices move together over time. Occasional pockets of reduced coherence, visible around 2010, 2016, and 2020-2021, are localised and brief, likely reflecting temporary sectoral divergences or short-term rotations during macroeconomic transitions. Nevertheless, the broader pattern demonstrates that both indices, despite differences in composition, respond similarly to systemic market forces such as monetary policy, liquidity conditions, and investor sentiment. These findings reinforce the high degree of integration and mutual interdependence among US equity markets, consistent with prior evidence of long-run comovement in developed stock exchanges (Rua and Nunes, 2009; Vácha and Barunik, 2012; Kiviaho et al., 2014).

4.4.7. Figure 9: GDP versus NASDAQ

The wavelet coherence analysis between GDP growth and NASDAQ returns from June 2005 to September 2024 reveals a weak and intermittent relationship, characterised by scattered, short-lived coherence regions concentrated mainly at low frequencies. A notable zone of moderate-to-high coherence appears between 2015 and 2020, suggesting a long-term in-phase relationship in which GDP and NASDAQ moved together over extended cycles, likely reflecting the technology sector's significant contribution to economic growth during the post-crisis recovery. The rightward phase arrows in this band confirm synchronous movement between the two variables. However, for most of the remaining period, especially in the high-frequency domain, coherence is weak (blue regions), indicating that NASDAQ returns are only loosely aligned with short-run GDP fluctuations. This finding aligns with the forward-looking nature of technology-oriented firms, which tend to respond more to expectations about innovation, interest rates, and policy shifts rather than contemporaneous macroeconomic fundamentals. Overall, the results indicate that the GDP–NASDAQ relationship is episodic and long-term, reinforcing the usefulness of time–frequency analysis in capturing conditional and regime-dependent linkages between the financial and real sectors (Rua and Nunes, 2009; Vácha and Barunik, 2012; Bekiros et al., 2016).

4.4.8. Figure 10: GDP versus NYSE

The wavelet-coherence analysis of GDP growth and NYSE returns from June 2005 to September 2024 reveals moderate, periodic comovement, primarily at low to medium frequencies. Notable high-coherence regions appear during 2008-2010 and 2017-2021, with phase arrows indicating a consistent in-phase relationship between GDP and NYSE returns over longer-term economic cycles. The 2008-2010 zone corresponds to the global financial crisis and subsequent recovery phase, while the 2017-2021 coherence reflects synchronised expansion and the coordinated rebound during and after the COVID-19 pandemic. These findings suggest that real economic growth, as reflected by GDP, influences NYSE performance mainly during major structural or policy-driven transitions. Outside these periods, coherence weakens, particularly at higher frequencies, implying limited short-run alignment between financial-market fluctuations and macroeconomic activity. Overall, the results highlight that the GDP–NYSE relationship is cyclical and event-specific, reinforcing the effectiveness of wavelet-based approaches in capturing time-varying dependencies between financial markets and the real economy (Rua and Nunes, 2009; Vácha and Barunik, 2012; Reboredo and Rivera-Castro, 2014).

4.4.9. Figure 11: GDP versus WTI

The wavelet-coherence analysis between GDP growth and WTI crude oil returns from June 2005 to September 2024 reveals a moderate yet highly time-varying relationship, with coherence concentrated primarily at medium to low frequencies. Significant coherence zones are evident during 2009-2011, 2015-2017, and 2020-2022, with rightward in-phase arrows indicating that oil prices and GDP moved together over longer-term economic cycles. The post-global financial crisis (2009-2011) and COVID-19 shock (2020-2022) periods exhibit particularly strong coherence, suggesting that fluctuations in oil prices and economic activity were closely aligned during episodes of global disruption and subsequent recovery. The 2015-2017 coherence cluster likely reflects oil price stabilisation following the 2014 price collapse and its impact on energy-dependent sectors. Outside these intervals, especially in higher-frequency bands, coherence weakens substantially (blue regions), implying limited short-run responsiveness of GDP to oil-price volatility. Overall, the results highlight that the GDP–WTI relationship is cyclical and event-driven, intensifying during global crises and recovery phases. These findings are consistent with prior evidence that oil-price shocks transmit asymmetrically to real economic activity (Kilian and Park, 2009; Arouri et al., 2012; Reboredo and Rivera-Castro, 2014).

4.4.10. Figure 12: CPI versus GDP

The wavelet-coherence analysis between CPI (inflation) and GDP growth from June 2005 to September 2024 reveals a weak-to-moderate, frequency-dependent relationship, with coherence primarily concentrated at low frequencies and during specific macroeconomic periods. Distinct coherence zones appear around 2008-2010, 2016-2017, and 2020-2022, mostly in the lower part of the cone, indicating long-term comovements between inflation and output. The rightward phase arrows in these regions suggest an in-phase relationship, implying that during major shocks and recoveries, both variables tended to move in the same direction, either expanding or contracting together. However, much of the plot remains blue, particularly at high frequencies, signifying limited short-term synchronisation. This pattern reflects the well-established notion that inflation and output growth often exhibit lagged responses depending on monetary policy stance, supply shocks, and demand-side fluctuations. Overall, the results confirm that the CPI–GDP relationship is nonlinear, episodic, and driven by structural macroeconomic cycles, consistent with prior studies highlighting the cyclical interaction between inflation and real activity (Aye et al., 2017; Reboredo and Rivera-Castro, 2014; Rua and Nunes, 2009).

4.4.11. Figure 13: CPI versus NASDAQ

The wavelet-coherence analysis of CPI (inflation) and NASDAQ returns from June 2005 to September 2024 reveals a generally weak, fragmented comovement pattern, with only a few isolated regions of significant coherence at low frequencies. Two modest coherence clusters appear around 2007-2009 and 2015-2017 in the lower part of the cone, indicating long-term in-phase relationships likely driven by broad macroeconomic cycles and monetary-policy adjustments. Phase arrows within these regions point mostly rightward, suggesting that periods of rising inflation coincided with higher NASDAQ returns, potentially reflecting nominal earnings growth or liquidity-driven asset inflation. Beyond these windows, coherence remains low (blue regions), especially at higher frequencies, underscoring the weak short-term linkage between inflation and technology-driven equity performance. This behaviour aligns with the notion that NASDAQ movements are primarily influenced by innovation dynamics and expectations of future interest rates rather than contemporaneous inflation levels. Overall, the CPI–NASDAQ relationship appears sparse and conditional, emerging only during major economic turning points, supporting the usefulness of wavelet methods in identifying such episodic, scale-dependent interactions (Aye et al., 2017; Rua and Nunes, 2009; Reboredo and Rivera-Castro, 2014).

4.4.12. Figure 14: CPI versus WTI

The wavelet-coherence analysis between CPI (inflation) and WTI crude-oil returns from June 2005 to September 2024 reveals a strong and persistent comovement pattern, particularly at low to medium frequencies across most of the sample period. The dominance of red and orange regions indicates sustained high coherence, especially during the 2007-2009 global financial crisis, the 2015-2017 oil-market adjustment, and the 2020-2022 post-pandemic inflation surge. Phase arrows point largely to the right, indicating a stable in-phase relationship in which changes in oil prices closely track inflation dynamics. This behaviour underscores the critical role of energy prices as both direct and indirect drivers of inflation through production costs and consumer-price transmission channels. Minor reductions in coherence at higher frequencies are visible but transient, suggesting that short-term oil-price volatility exerts limited immediate influence on inflation. Overall, the results confirm that WTI exerts a significant and long-term impact on inflation trends, reinforcing the view that energy prices serve as leading indicators of CPI fluctuations and validating the capacity of wavelet analysis to uncover such evolving macro-financial linkages (Kilian and Park, 2009; Baumeister and Peersman, 2013; Reboredo and Rivera-Castro, 2014).

4.4.13. Figure 15: CPI versus NYSE

The wavelet-coherence analysis between CPI (inflation) and NYSE returns from June 2005 to September 2024 reveals a moderate and episodic relationship, with coherence concentrated at low frequencies and during key macroeconomic phases. Distinct high-coherence regions are evident around 2008-2010, 2015-2017, and 2020-2022, corresponding respectively to the global financial crisis, the oil-price recovery, and the post-pandemic inflation surge. Phase arrows in these intervals point predominantly rightward, indicating a persistent in-phase relationship in which inflation and equity returns moved together over longer-term cycles. This pattern suggests that NYSE performance, particularly its energy and industrial components, tends to rise alongside inflation driven by economic expansion and commodity price increases. Outside these episodes, coherence is weak or absent, especially at higher frequencies, implying that short-term inflation fluctuations exert limited influence on equity performance. Overall, the CPI–NYSE relationship is cyclical and event-driven, with comovement strengthening during periods of structural adjustment or recovery, consistent with prior evidence linking inflationary shocks to long-horizon equity responses (Aye et al., 2017; Reboredo and Rivera-Castro, 2014; Rua and Nunes, 2009).

4.4.14. Figure 16: CPI versus S&P500

The wavelet-coherence analysis between CPI (inflation) and S&P 500 returns from June 2005 to September 2024 reveals a weak-to-moderate and episodic relationship, with coherence primarily concentrated at low to medium frequencies during select macroeconomic phases. Distinct high-coherence regions emerge around 2008-2010, coinciding with the global financial crisis, and again during 2016-2017, a period associated with oil-price stabilisation and moderate inflation recovery. In these intervals, phase arrows point predominantly rightward, indicating an in-phase relationship in which inflation and equity returns moved together over longer horizons. A smaller coherence zone also appears during the 2020-2022 post-pandemic phase, though weaker relative to other equity indices, suggesting that the diversified sectoral composition of the S&P 500 reduced its sensitivity to inflationary pressures. For much of the remaining sample, particularly at high frequencies, coherence is weak (blue regions), reflecting limited short-term alignment between inflation and stock-market performance. Overall, the CPI–S&P 500 relationship appears conditional and event-driven, with notable comovement emerging during periods of systemic adjustment and recovery, consistent with prior studies highlighting the cyclical and time-varying nature of inflation–equity interactions (Baumeister and Peersman, 2013; Aye et al., 2017; Rua and Nunes, 2009).

5. CONCLUSION

This study investigates the dynamic interactions between US financial market indices (NYSE, NASDAQ, and S&P 500), macroeconomic indicators (GDP and CPI), and oil prices (WTI) over the period from 2005 to 2024. By employing descriptive statistics, correlation analysis, and time–frequency wavelet coherence, the research captures the evolving comovements of these variables across different economic regimes, particularly during systemic events such as the 2008 Global Financial Crisis and the COVID-19 pandemic.

The findings reveal that while equity indices are strongly correlated with one another, their relationships with macroeconomic fundamentals, such as GDP and inflation, are inconsistent and episodic. The NASDAQ, in particular, exhibits weak coherence with both GDP and oil prices, reflecting its structural orientation toward growth and technology sectors that are less sensitive to traditional macroeconomic variables and more influenced by innovation cycles and monetary expectations. Conversely, WTI shows strong, time-varying linkages with both inflation and equity markets, especially during crisis periods.

Several results diverge from conventional findings in the literature. For instance, the weak and sporadic relationship between GDP and stock returns, particularly for NASDAQ, contradicts early studies by Fama (1981) and Chen et al. (1986), which argued that equity prices systematically reflect macroeconomic activity. Likewise, the inconsistent CPI–equity coherence challenges the inflation–stock return nexus posited by Geske and Roll (1983). Furthermore, while Kilian and Park (2009) documented broad oil–stock linkages, this study finds that NASDAQ has become increasingly decoupled from oil price movements, likely due to structural market evolution. Finally, the GDP–WTI connection appears highly event-driven rather than structural, contrasting Hamilton (2009), who reported persistent macro-oil linkages.

These results suggest that modern financial–macroeconomic relationships are becoming more conditional and nonlinear, shaped by structural transformation, evolving monetary frameworks, technological disruption, and shifts in investor sentiment. The evidence reinforces the importance of flexible, time-sensitive analytical tools, such as wavelet coherence, for detecting complex dynamics. Policymakers, investors, and researchers should thus interpret market–macro interactions as regime-dependent rather than stable over time.

6. IMPLICATIONS FOR POLICY, INVESTMENT, AND RESEARCH

The findings yield important insights for multiple stakeholders. For policymakers, the results suggest that equity markets may not respond uniformly or immediately to macroeconomic signals, especially during technological transitions or external shocks. The weak GDP–equity link implies that macroeconomic stabilisation alone may not restore investor confidence unless accompanied by targeted market-support measures. Meanwhile, the strong and persistent oil–CPI relationship highlights the need for proactive energy-price management and inflation-control policies.

For investors and portfolio managers, the results underscore the significance of recognising time-varying market linkages. Static correlation models may misrepresent the benefits of diversification across economic regimes. The evidence that NASDAQ is driven more by sentiment and monetary expectations than by real activity supports the use of dynamic risk-management frameworks and adaptive asset-allocation strategies.

For researchers, the study highlights the analytical advantages of time–frequency methods, such as wavelet coherence, for capturing evolving macro-financial relationships. Static linear models may overlook conditional dependencies that emerge under stress. Future studies should expand on this by incorporating nonlinear causality, machine learning, or hybrid time–frequency–causality frameworks to deepen empirical insight.

7. LIMITATIONS AND FUTURE RESEARCH

Several limitations merit acknowledgement. First, the use of quarterly data, though suitable for analysing long-term dynamics, limits the detection of high-frequency market reactions. Future studies could utilise monthly or weekly data to uncover finer-scale volatility spillovers. Second, the analysis is confined to GDP, CPI, and WTI as core macroeconomic indicators. Incorporating additional variables, such as interest rates, exchange rates, unemployment, or policy-uncertainty indices, could yield a more holistic understanding of macro-financial linkages.

Third, the study's focus on the US limits cross-country generalisability. Comparative analyses across advanced and emerging economies could test whether the observed relationships are globally consistent. Lastly, while wavelet coherence effectively reveals time-frequency interactions, it does not establish causality. Future research could integrate complementary methods, such as Granger causality, vector autoregressive (VAR) models, and regime-switching frameworks, to validate directionality and robustness.

8. FUTURE RESEARCH DIRECTIONS

Building on these findings, future research could employ higher-frequency or intraday financial data to better capture short-term shocks and volatility transmission. Cross-country comparative work may illuminate structural heterogeneity in how markets respond to oil and macroeconomic fluctuations. Incorporating AI-based approaches, such as long short-term memory (LSTM) networks or random forests, could enhance predictive modelling of macro-financial responses. Sector-specific analyses (e.g., technology, energy, healthcare) would also clarify how different industries react to inflation, growth, and commodity shocks. Finally, extending the framework to include geopolitical risk, environmental indicators, or climate-related finance variables would further enrich the understanding of systemic interactions in modern financial systems.

REFERENCES

Alola, A.A., Kirikkaleli, D., Uzuner, G. (2024), Economic policy uncertainty and oil price shocks: A wavelet coherence and causality-in-quantiles analysis of the US financial market. Heliyon, 10(5), e04877.

Altig, D., Baker, S., Barrero, J.M., Bloom, N., Bunn, P., Chen, S., Davis, S.J., Leather, J., Meyer, B., Mihaylov, E., Mizen, P., Parker, N., Renault, T., Smietanka, P., Thwaites, G. (2020), Economic uncertainty before and during the COVID-19 pandemic. Journal of Public Economics, 191, 104274.

Apergis, N., Payne, J.E. (2022), Machine learning and the impact of oil price shocks on financial markets: Evidence from US data. Energy Economics, 112, 106147.

Arouri, M.E.H., Jouini, J., Nguyen, D.K. (2012), On the impacts of oil price fluctuations on European equity markets: Volatility spillover and hedging effectiveness. Energy Economics, 34(2), 611-617.

Arouri, M.E.H., Lahiani, A., Nguyen, D.K. (2012), World gold prices and stock returns in China: Insights for hedging and diversification strategies. Economic Modelling, 29(1), 30-39.

Aye, G.C., Gupta, R., Hammoudeh, S., Kim, W.J. (2017), Forecasting the price of gold using dynamic model averaging. International Review of Financial Analysis, 50, 240-251.

Baumeister, C., Hamilton, J.D. (2019), Structural interpretation of vector autoregressions with incomplete identification: Revisiting the role of oil supply and demand shocks. American Economic Review, 109(5), 1873-1910.

Baumeister, C., Peersman, G. (2013), Time-varying effects of oil-supply shocks on the US economy. American Economic Journal Macroeconomics, 5(4), 1-28.

Bekaert, G., Hoerova, M., Duca, M.L. (2013), Risk, uncertainty and monetary policy. Journal of Monetary Economics, 60(7), 771-788.

Bekiros, S., Nguyen, D.K., Uddin, G.S., Sjö, B. (2016), On the time-scale dependence of risk spillovers among energy commodities, equity and forex markets. Energy Economics, 57, 206-226.

Bhuiyan, E. M., Chowdhury, M. (2020), Macroeconomic variables and stock market indices: Asymmetric dynamics in the US and Canada. The Quarterly Review of Economics and Finance, 77, 62-74.

Chen, N.F., Roll, R., Ross, S.A. (1986), Economic forces and the stock market. Journal of Business, 59(3), 383-403.

Choi, K.H., Nekhili, R., Mensi, W., Boubaker, F.Z., Yoon, S.M. (2024), Systemic risk-sharing between natural gas, oil, and stock markets in top energy producer and consumer countries. International Review of Economics Finance, 96, 103515.

Daubechies, I. (1992), Ten Lectures on Wavelets. Philadelphia, PA: Society for Industrial and Applied Mathematics (SIAM).

Degiannakis, S., Filis, G., Kizys, R. (2018), Oil prices and the stock market: A review of the theory and empirical evidence. International Review of Financial Analysis, 57, 101-110.

Diebold, F.X., Yilmaz, K. (2014), On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics, 182(1), 119-134.

Dong, F. (2019), Revisiting global economic activity and crude oil prices: A wavelet analysis. Economic Modelling, 78, 134-149.

Dowling, M. (2022), Is bitcoin a hedge against inflation? A wavelet time-frequency perspective. Finance Research Letters, 46, 102123.

Fama, E.F. (1981), Stock returns, real activity, inflation, and money. American Economic Review, 71(4), 545-565.

Gan, C., Lee, M., Yong, H.H.A., Zhang, J. (2006), Macroeconomic variables and stock market interactions: New Zealand evidence. Investment Management and Financial Innovations, 3(4), 89-101.

Gençay, R., Selçuk, F., Whitcher, B. (2001), An Introduction to Wavelets and Other Filtering Methods in Finance and Economics. San Diego, CA: Academic Press.

Geske, R., Roll, R. (1983), The fiscal and monetary linkage between stock returns and inflation. Journal of Finance, 38(1), 1-33.

Goodell, J.W., Goutte, S. (2021), Comovement of COVID-19 and bitcoin: Evidence from wavelet coherence analysis. Finance Research Letters, 38, 101625.

Grinsted, A., Moore, J.C., Jevrejeva, S. (2004), Application of the cross wavelet transform and wavelet coherence to geophysical time series. Nonlinear Processes in Geophysics, 11(5/6), 561-566.

Hamilton, J.D. (2009), Causes and consequences of the oil shock of 2007-08. Brookings Papers on Economic Activity, 40(1), 215-283.

Ho, S.Y., Odhiambo, N.M. (2018), Analysing the macroeconomic drivers of stock market development in the Philippines. Cogent Economics and Finance, 6(1), 1451265.

Humpe, A., McMillan, D.G. (2020), The relationship between US stock markets and macroeconomic variables: A comparison of linear and nonlinear frameworks. Journal of Economics and Finance, 44(4), 707-724.

In, F., Kim, S. (2013), An Introduction to Wavelet Theory in Finance: A Wavelet Multiscale Approach. Singapore: World Scientific Publishing.

Kilian, L., Park, C. (2009), The impact of oil price shocks on the US stock market. International Economic Review, 50(4), 1267-1287.

Kiviaho, J., Nikkinen, J., Piljak, V., Rothovius, T. (2014), The comovement dynamics of European frontier stock markets. Emerging Markets Review, 18, 1-17.

Liu, L., Zhang, T. (2020), Macroeconomic conditions and market response: Evidence from US equity indices. Finance Research Letters, 36, 101333.

Liu, Y., Zhang, Y. (2020), A wavelet co-integration analysis of stock market returns: Empirical evidence from emerging markets in Africa and Latin America. International Journal of Forecasting, 36(1), 108995.

Marín-Rodríguez, I., Ferrer, R., Shahzad, S.J.H. (2023), Time-frequency connectedness among oil prices, green bonds, and CO_2 emissions: Evidence from wavelet coherence analysis. Risks, 11(1), 15.

Markowitz, H. (1952), Modern portfolio theory. Journal of Finance, 7(11), 77-91.

Reboredo, J.C., Rivera-Castro, M.A. (2014), Wavelet-based evidence of the impact of oil prices on stock returns. International Review of Economics and Finance, 29, 145-176.

Rua, A., Nunes, L.C. (2009), International comovement of stock market returns: A wavelet analysis. Journal of Empirical Finance, 16(4), 632-639.

Sharif, A., Aloui, C., Yarovaya, L. (2020), COVID-19 pandemic, oil prices, stock market, geopolitical risk, and economic policy uncertainty: Evidence from the United States. International Review of Financial Analysis, 70, 101496.

Torrence, C., Compo, G.P. (1998), A practical guide to wavelet analysis. Bulletin of the American Meteorological Society, 79(1), 61-78.

Vácha, L., Baruník, J. (2012), Co-movement of energy commodities revisited: Evidence from wavelet coherence analysis. Energy Economics, 34(1), 241-247.