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Time-varying spillover of multi-scale positive and negative bubbles in stock and oil markets☆

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ABSTRACT

The objective of this paper is to analyze time-varying spillover between bubbles in oil and stock markets of the U.S. In this regard, we first use the Multi-Scale Log-Periodic Power Law Singularity Confidence Indicator (MS-LPPLS-CI) approach to detect both positive and negative bubbles in the short-, medium and long-term in the two markets. In the second-step, we utilize a Time-Varying Parameter Vector Autoregressive (TVP-VAR) model to conduct the spillover analysis among the indexes of oil and stock positive and negative bubbles. Based on data covering the monthly period of January 1999 to June 2025, we find that negative bubble spillovers are significantly stronger and more directional than positive ones, with the U.S. equity market emerging as the transmitter to the oil market post-2008. This represents a structural shift from the traditional oil-to-equity transmission paradigm. Moreover, spillover effects are most pronounced at short- and medium-term horizons, intensifying during crisis periods. Our findings suggest that oil is increasingly behaving as a financial asset rather than a physical commodity, with important implications for portfolio diversification and risk management.

1. Introduction

Asset price bubbles create significant risks to financial stability (Aoki and Nikolov, 2015), as evidenced by episodes like the dot-com boom, the 2007–2008 financial crisis, and the 2008 oil price spike followed by its crash (Caraiani et al., 2023; Kruse-Becher, 2025). These events often coincide globally, with oil and equity bubbles amplifying each other's impacts (Arouri et al., 2011; Wen et al., 2019; Zhao et al., 2021). The ubiquity and damage of such events make early identification and analysis of bubbles a critical goal for economists, traders, managers, and policymakers.

While bubble detection methods are well established (please see Phillips et al., 2015; Sharma and Escobari, 2018), cross-market bubble transmission remains underexplored. In interconnected financial systems, bubbles may spill over between fundamentally linked markets (Gomez-Gonzalez et al., 2018; Baldi et al., 2016). Recent evidence suggests bilateral bubble contagion between oil and equity markets, particularly during the 2007–2008 crisis and the 2014–2015 oil glut (Zhao et al., 2021).

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This paper analyzes bubble interactions between U.S. stock and crude oil markets over 1999–2025. We employ the Multi-Scale Log-Periodic Power Law Singularity Confidence Indicator (MS-LPPLS-CI; Sornette et al., 1996; Sornette, 2017) approach to detect both positive and negative bubbles across short-, medium-, and long-term horizons in both markets. A positive bubble refers to a price that accelerates upward before eventually collapsing, whereas a negative bubble indicates a downward price acceleration (crash) that subsequently reverses in a sharp rally. Hence, the LPPLS-based indicators capture both exuberant booms and panic-driven busts. Subsequently, we apply a Time-Varying Parameter Vector Autoregression (TVP-VAR) model to quantify how bubble conditions spill over between markets and how these intensities evolve over time. Our methodological framework distinguishes itself from alternative spillover approaches in several key aspects. While wavelet coherence methods (Sharif et al., 2020; Yousfi and Bouzgarrou, 2024) effectively capture time-frequency co-movements, they lack directionality and treat positive and negative shocks symmetrically. Similarly, Granger causality tests, even in their rolling formulations (Çevik et al., 2018), assume linear relationships and stable parameters, often failing to detect regime-dependent linkages that emerge only during crisis periods. Our MS-LPPLS-CI/TVP-VAR framework addresses these limitations by: (*i*) explicitly separating positive (boom) and negative (crash) bubble phases through the LPPLS model, capturing the super-exponential and oscillatory patterns that linear models miss, and (*ii*) providing directional, quantitative spillover measures conditioned on market state (bubble vs. non-bubble), showing asymmetric contagion patterns where crashes transmit more forcefully than booms. This approach unifies bubble detection, multi-scale analysis, and dynamic connectedness, i.e., dimensions that existing literature has studied separately (Zhao et al., 2021; Wang and Li, 2021; van Eyden et al., 2023).

Our analysis addresses key questions: Does an oil price bubble foreshadow equity bubbles? Do equity bubbles transmit to oil markets? Do these relationships differ between boom and bust phases? To our knowledge, this is the first study to provide time-varying spillover analysis between multi-scale positive and negative bubbles, examining the evolution of interconnectedness between booms and busts in these markets. Our findings have important implications for portfolio diversification and risk management, particularly as oil increasingly behaves as a financial asset rather than a physical commodity. If bubble spillovers are significant, investors and regulators should monitor oil market conditions as a leading indicator of stock market vulnerabilities (and vice versa).

Given the role of common shocks (cash-flow, investment, interest rate, exchange rate, and economic activity), the evolving relationship between oil and stock prices in the U.S. have been widely analyzed (see, Balcilar et al., 2015, 2017 and Gupta and Wohar, 2017 for detailed reviews), but, to the best of our knowledge, this is the first attempt to provide a time-varying spillover analysis between multi-scale positive and negative bubbles, i.e., the evolution of the interconnectedness between the booms and busts of these two markets.

2. Data and methodology

2.1. Data

We examine bubble spillovers between US equity markets and crude oil markets using monthly data from January 1999 to June 2025. For U.S. equity market bubbles, we employ the price-dividend ratio of the S&P 500 index, the global benchmark for equity performance (Dettoni et al., 2025). For obtaining oil market bubbles, as in Caspi et al. (2018), we utilize the ratio of the West Texas Intermediate (WTI) crude oil price relative to stocks of crude oil, with the WTI being the predominant benchmark for North American oil markets and a key reference price for global energy markets. The price-dividend ratio is derived from Bloomberg, while both the WTI price and its associated stock is obtained from the U.S. Energy Information Administration (EIA). This 26-year period captures critical episodes including: the dot-com bubble (1999–2002), the commodity super-cycle and financialization of oil markets (2003–2007), the Global Financial Crisis and its aftermath (2008–2009), the shale oil revolution and subsequent price collapse (2014–2015), the COVID-19 pandemic shock (2020–2021), and recent geopolitical tensions affecting energy markets (2022–2025).[1]

2.2. Bubble detection: Multi-scale LPPLS confidence indicators

We employ the Log-Periodic Power Law Singularity (LPPLS) model (Sornette, 2017; Shu and Song, 2024) to identify bubble episodes. The LPPLS model characterizes bubble dynamics as:

$$ln[p(t)] = A + B(t_c - t)^m + C(t_c - t)^m \cos(\omega \ln(t_c - t)^m - \varphi) \quad (1)$$

where $p(t)$ represents the ratio of the asset (equity or oil) price relative to its fundamental at time t, t_c denotes the critical time of regime change, m is the power law exponent ($0 < m < 1$), ω captures the log-periodic oscillation frequency, and φ represents the phase parameter. The parameters A, B, and C control the baseline level, super-exponential acceleration, and oscillation amplitude, respectively. It is crucial to distinguish LPPLS-identified negative bubbles from conventional market crashes. While crashes represent rapid

[1] As part of a preliminary analysis, we obtained the probability of a collapsing bubble, from the regime-switching model of Nneji et al. (2013), for the price-dividend ratio of the S&P 500 index and the price-stock ratio of the WTI oil price spanning the longest possible common monthly period of January 1920 to February 2025. Using linear Granger causality test revealed a two-way nexus, with the null hypothesis that oil (stock) bubble does not cause stock (oil) being rejected at the 1% significance level with a p-value of 0.0053 (0.0041), thus confirming endogeneity of boom-bust cycles of these two markets, and hence the need to analyse spillover in a VAR structure. Note that, the equity market variables along with the oil price was derived from the Global Financial database, while WTI stocks data was again sourced from the U.S. EIA.

price declines, negative bubbles are an accelerating downward price trajectory with log-periodic oscillations that culminate in a sharp reversal. The LPPLS model captures the self-reinforcing feedback loops of panic selling that differentiate bubble collapses from ordinary bear markets (Filimonov and Sornette, 2013). Following Demirer et al. (2019), we implement Multi-Scale LPPLS Confidence Indicators (MS-LPPLS-CI) across three horizons: *i*) short-term (ST) horizon spanning 1–3 months, *ii*) medium term (MT) horizon covering 3–12 months; and *iii*) long-term (LT) horizon covering 12–24 months.[2] For each time scale and market, we calculate both positive and negative bubble confidence indicators. These indicators range from 0 to 1, with higher values indicating stronger bubble signals.[3]

2.3. TVP-VAR spillover methodology

To analyze the dynamic spillover effects between bubble indicators, we employ a Time-Varying Parameter Vector Autoregression (TVP-VAR) extended for spillover analysis by Antonakakis et al. (2020). The TVP-VAR model is specified as:

$$Y_t = G_t Y_{t-1} + \varepsilon_t \tag{2}$$

$$vec\ (G_t) = vec\ (G_{t-1}) + \upsilon_t \tag{3}$$

where Y_t is a $N \times 1$ vector of bubble indicators for both markets at different scales, G_t is a $N \times N$ time-varying coefficient matrix, and $\varepsilon_t \sim N(0, S_t)$ and $\upsilon_t \sim N(0, R_t)$ are $N \times 1$ vectors of the error terms. S_t and R_t are the time-varying variance-covariance matrices. Following Diebold and Yilmaz (2012), we compute generalized forecast error variance decompositions (GFEVD) to construct time-varying spillover indices. The total spillover index (TCI), measuring overall system interconnectedness, is:

$$TCI(H) = \frac{1}{N}\sum\nolimits_{i \neq j} \theta_{ij}(H) \tag{4}$$

where N is the number of variables in the system. We also calculate directional spillovers to identify whether each market is a net transmitter or receiver of bubble shocks.

3. Empirical results

3.1. Structural break and directional analysis

Before examining the bubble spillover dynamics, we test for structural breaks in the equity-oil relationship. Multiple break detection methods converge on identifying significant regime changes (Table 1). The supF test strongly rejects parameter stability, while the expF test confirms this finding. The Bai-Perron procedure identifies two breakpoints with high precision: June 2008 and March 2020. These dates correspond to the Lehman Brothers collapse and the COVID-19 market crash, respectively, validating that structural changes align with major systemic events.

Rolling beta analysis (24-month window, Fig. 1) quantifies the evolution of the oil-equity relationship. Pre-2008, the beta oscillates near zero (mean = 0.08), indicating minimal systematic relationship. Post-2008, both the mean level (0.34) and volatility of beta increase substantially, with peaks exceeding 0.6 during the 2008–2009 crisis and 2020 pandemic. This pattern confirms that oil increasingly behaves as a risk asset correlated with equities during stress periods.

To evaluate the causal relationship between the two markets, we follow two steps. First, we perform a static Granger causality test. Table 2 clearly indicates a predominant direction: the stock market Granger-causes oil, while the opposite is not true. This suggests that, on average, information from equity returns helps predict oil returns.

Next, we conduct a time-varying Granger analysis using a rolling VL-Granger method with a 24-month window (Fig. 2). The time map shows that the equity market Granger-causes the oil market mainly during 2008–2012 and 2020–2024, while the period from 2013 to 2019 is mostly neutral. At the start of the sample, we also observe brief episodes of oil→equity causality. Overall, the direction of transmission depends on the regime: equity leadership appears primarily in the post-break periods identified by the structural stability tests, whereas during calmer periods, causality in either direction is weak.

The practical implications of our findings are starkly evident in portfolio performance analysis. Table 3 illustrates the complete erosion, i.e., indeed, the reversal, of oil's diversification benefits following the 2008 structural break. As we can note During bubble episodes, the transformation becomes even more pronounced. In negative bubble periods post-2008, the mixed portfolio experiences monthly losses of −5.29 % compared to −0.75 % for equities alone, namely a sevenfold amplification of downside risk.

[2] We verify horizon design through dyadic re-gridding and a light frequency-domain check. Both methods confirm the ST-High and LT-Low correspondence, leaving the qualitative findings unchanged.

[3] The bubble indicators were initially computed using daily data to capture high-frequency market dynamics and ensure accurate detection of rapid bubble formation and collapse episodes. However, given the computational intensity of the TVP-VAR model and the prevalence of zero values in daily bubble indicators, we aggregate the daily indicators to monthly frequency by taking the average of non-zero daily values within each month. This aggregation preserves the essential bubble signals while reducing noise and computational burden, following similar approaches in the literature (Balcilar et al., 2021; Azimli, 2024). It must be pointed out that the highest available frequency for the stocks of crude oil data is weekly, and hence, was repeated for the days of a particular week, when computing the daily oil market bubbles.

Table 1
Structural break test results.

Test	Statistic
Parameter stability tests	
SupF test	17.51***
ExpF test	4.35**
SupF (HAC-robust)	17.51***
Break date identification	
Bai-Perron Break 1	June 2008
Bai-Perron Break 2	March 2020

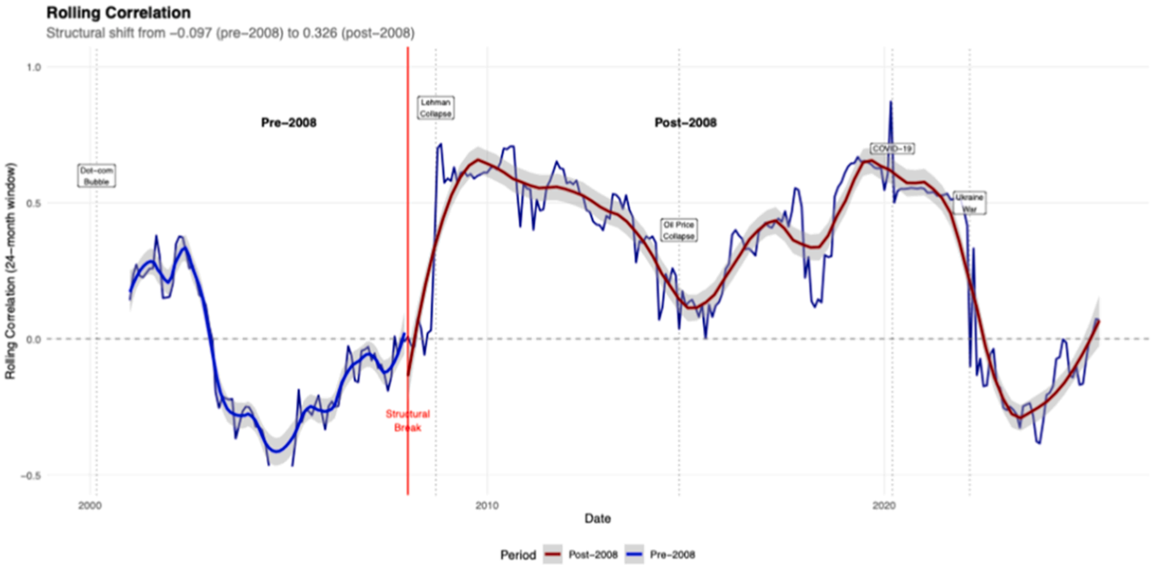

Fig. 1. Rolling 24-Month Correlation between S&P 500 and WTI Oil Returns.

Table 2
Static Granger causality test.

Null Hypothesis	*F*
S&P500 $\nrightarrow$ WTI oil	14.771***
WTI oil $\nrightarrow$ S&P500	1.509

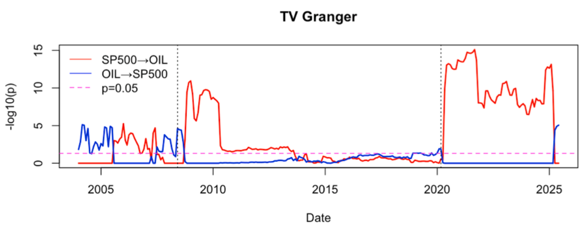

Fig. 2. Time-varying Granger causality (24-Month).

3.2. *Bubbles identification*

Having established that the equity-oil relationship, we now turn to the identification of boom/bust dynamics themselves. Figs. 3–4 plot the MS-LPPLS-CIs, showing a clear multi-scale hierarchy. Two clarifications address common misconceptions. First, “negative bubbles” here are not post-hoc crashes defined by drawdowns; they are LPPLS-consistent anti-bubble phases in which the model’s oscillatory structure and local trend match a downward explosive pattern. This distinction matters because a crash can occur with or without an LPPLS signature, whereas a negative bubble is diagnosed ex-ante by the model’s parametric restrictions and diagnostics.

Table 3
Portfolio Performance Analysis.

Period	Metric	S&P 500 Only	Mixed Portfolio	Diversification Benefit
Pre-2008				
	Annual Return	−1.59 %	3.18 %	+4.76 %
	Sharpe Ratio	−0.282	0.573	0.855
	Maximum Drawdown	24.5 %	17.1 %	−7.4 %
	Crisis Protection	Baseline	Improved	Positive hedging
Post-2008				
	Annual Return	0.74 %	−0.01 %	−0.74 %
	Sharpe Ratio	0.148	0.046	−0.102
	Maximum Drawdown	21.8 %	36.5 %	+14.7 %
	Crisis Protection	Baseline	Deteriorated	Risk amplification
Change				
	Sharpe Benefit	-	-	−112 % erosion
	Risk Profile	-	-	From hedge to amplifier

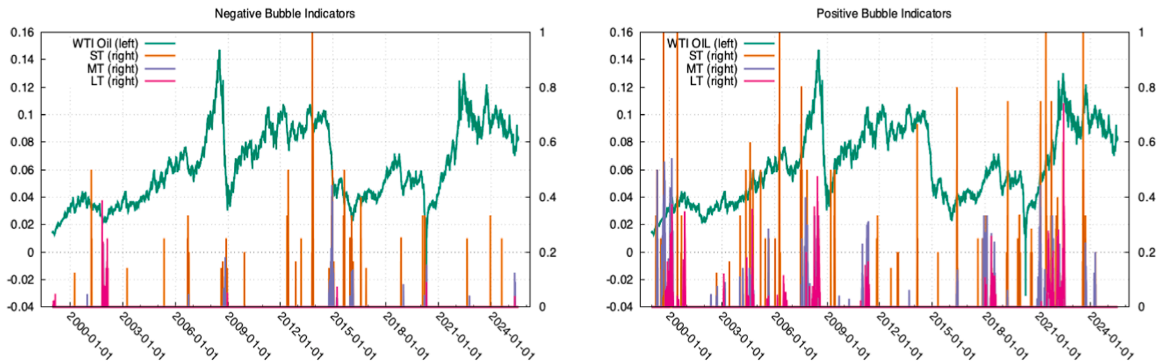

Fig. 3. WTI Oil Multiscale LPPLS Indicators.

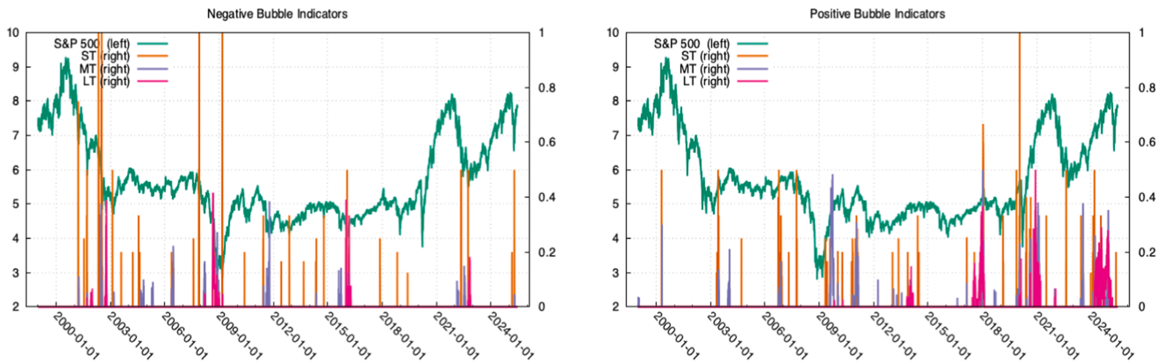

Fig. 4. S&P500 Multiscale LPPLS Indicators.

Further, the multi-scale approach proves essential: short-term (ST) indicators capture high-frequency shifts in market sentiment, medium-term (MT) indicators identify sustained bubble formations, and long-term (LT) indicators confirm systemic episodes that remodeling market structure (Demirer et al., 2019). As we can note, short-term signals act as early warning systems, frequently oscillating above the detection threshold before consolidating into medium-term patterns. When these medium-term signals persist and amplify, they eventually manifest as long-term bubble episodes. This progression is particularly evident during the 2007–2008 period, where short-term indicators began signaling as early as 2006, followed by medium-term confirmation in early 2007, and ultimately long-term bubble identification by mid-2007. The 2014–2016 oil collapse is characterized by deep negative MT/LT indicators in WTI with a more muted reflection in the S&P 500. In fact, WTI negative-MT LPPLS are statistically more frequent and intense in 2014–2016 than elsewhere (two-proportion $z = 3.44$, $p < 0.001$; mean intensity 16 x larger). This evidence aligns with established narratives of an OPEC/shale-induced supply glut and expectation shifts around late-2014 (Baffes et al., 2015; Baumeister and Kilian (2016). Stocker et al., 2018). COVID-19, in 2020, features simultaneous negative ST/MT shocks and subsequent positive signals during the equity rebound. Operationally, ST indicators provide early warnings of regime shifts, while MT (and ultimately LT) peaks help discriminate transitory exuberance from bubbles that mature into systemic episodes. This observation aligns with findings from multi-scale spillover analysis showing heterogeneous patterns across different time horizons (Yousfi and Bouzgarrou, 2024), where wavelet decomposition across eight frequency bands reveals that short-term dynamics (2–4 days) often dominate during pre-crisis periods, while medium-term (16–64 days) and long-term (64–256+ days) synchronization emerges more gradually and with varying intensity across markets.

To further investigate bubble synchronization over time, we calculate 24-month rolling correlations between oil and equity bubble indicators (Fig. 5). Negative bubble correlations spike significantly during crises, reaching 0.8 in the 2008 Global Financial Crisis and 0.7 in March 2020, before quickly returning to baseline levels. This pattern confirms that crash contagion occurs through short-lived channels. In contrast, positive bubble correlations stay moderately elevated (0.3–0.4) even in tranquil periods, indicating sustained sentiment. Short-term correlations are the most volatile ($\sigma = 0.28$), while medium-term correlations show strong regime dependence (increasing from 0.05 pre-2008 to 0.35 post-2008). Long-term correlations remain stable, except during systemic events. This aligns with our MS-LPPLS indicators, where short-term signals provide early warnings that develop into medium-term patterns during real bubble episodes. Key insights include that negative correlations are consistently stronger than positive ones, particularly post-2008, with a mean correlation for negative short-term bubbles of 0.157 compared to 0.017 before 2008. This indicates a shift in how crash episodes synchronize across markets. Furthermore, correlations before 2008 oscillated around zero with low volatility, while post-2008, there are significant spikes during stress periods, such as the 2014–2015 oil price collapse, the 2020 COVID-19 crisis, and the 2022 energy shock, where short-term negative correlations often exceed 0.7, indicating strong crash synchronization.

3.3. Network structure of bubble spillovers

The spillover networks show different transmission patterns between positive and negative bubble episodes (Fig. 6). For positive bubbles, we observe relatively balanced bidirectional connections across all time horizons, suggesting that optimistic market sentiment propagates gradually between oil and equity markets. The network density remains moderate, with no single dominant transmission channel. In contrast, negative bubble spillovers display more concentrated and directional patterns. The connections appear stronger and more asymmetric, particularly from the equity towards the oil market. This asymmetry aligns with the financial contagion literature, where market crashes generate more rapid and intense cross-market transmission than boom periods (Foglia et al., 2022; BenSaïda, 2019; Kenourgios et al., 2011). Our rolling correlation analysis confirms this pattern quantitatively: negative bubble correlations spike to 0.8 during the 2008 GFC but rapidly decay to 0.1–0.2 in tranquil periods, while positive correlations maintain moderate levels of 0.3–0.4. Recent evidence confirms that the bad return spillovers dominate good return spillovers between crude oil and stock markets, with the gap between positive and negative spillovers increasing significantly during major crises (e.g., Mensi et al., 2021; Cheng et al., 2023).

3.4. Dynamic analysis

Fig. 7 displays the positive and negative dynamics of total connectedness indexes (TCI) between all scales of bubbles. The positive bubble spillover patterns differ markedly from their negative counterparts. We can note that the negative-bubble TCI shows sharp, short-lived spikes around well-known stress events (dotcom unwind, 2008–09 GFC, 2011–12 sovereign-debt tensions, 2014–16 oil collapse). This indicates rapid, episodic contagion when the system deleverages. By contrast, the positive-bubble TCI forms a persistent pattern with episodic waves (e.g., 2004–05, 2017, 2021–23), consistent with slow-moving integration during risk-on phases driven by global liquidity and sentiment.

The spillover dynamics vary significantly across different time horizons, providing important insights into market microstructure (Fig. 7). Short-term spillovers demonstrate the most responsiveness to major market events. These rapid transmissions likely reflect algorithmic trading, cross-asset arbitrage, and immediate informational responses by market participants with short investment horizons (Ren et al., 2022). During normal market conditions, the magnitude of short-term spillovers tends to exceed medium and long-term effects. This pattern aligns with findings showing that connectedness during periods of market stress intensifies over shorter horizons, as risk spillovers at high frequencies occur when financial markets react more quickly to information shocks (Umar et al., 2022). However, during severe systemic crises (such as the 2007–2009 financial crisis and the early 2000s downturn) spillovers across all time horizons, including long-term connectedness, show significant volatility (Zhang and Broadstock, 2020). This convergence in volatility across frequency bands during crisis periods highlights how extreme market stress affects both transitory high-frequency dynamics and persistent structural linkages simultaneously. Medium-term spillovers capture more persistent transmission mechanisms. These patterns reflect the gradual adjustment of portfolios and the time required for information across markets to be processed by heterogeneous investors trading at different frequencies. Due to the complexity and heterogeneity among markets, investors tend to adjust their investment strategies across different time scales, with medium-term spillovers showing stronger persistence and fundamentally driving long-term expectations during turbulent periods (Elsayed and Helmi, 2021). Long-term spillovers remain relatively subdued. This can suggest that fundamental supply-demand factors in oil markets eventually dominate financial spillover effects over extended periods, as documented by Adjei et al. (2025) who find that overall connectedness is highest in the short term with clear temporal differences in spillover effects. In fact, the frequency-domain decomposition shows that while short-term dynamics drive immediate shock transmission, long-term spillovers reflect structural linkages and fundamental co-movements between markets that persist beyond temporary disturbances (Mensi et al., 2022) (Fig. 8).

The net spillover indices for negative bubbles indicate that the U.S. equity market serves as a primary spillover transmitter to the oil market for most of the sample period (Fig. 9). During the 2001–2002 period, we observed substantial spillovers from oil to the stock

Fig. 5. Rolling 24-Month correlation between S&P 500 and WTI Oil returns bubbles.

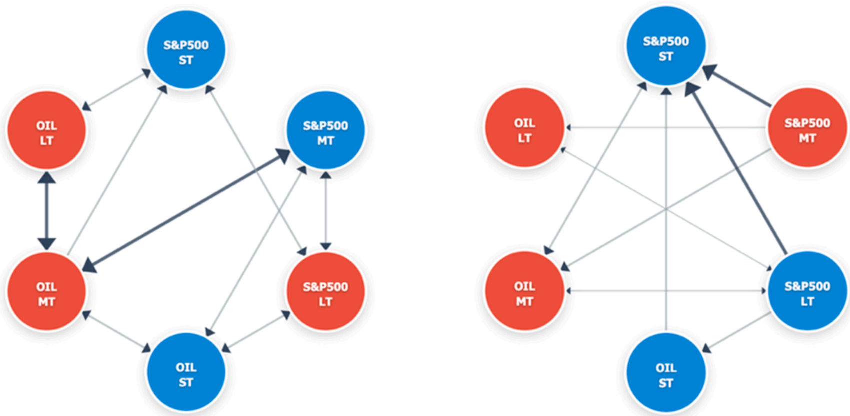

Fig. 6. Positive and Negative Networks structures.
Notes: The left side of the Figure plots the positive bubble network, and the right side plots the negative. Node colors indicate the role of each variable: red for net transmitters and blue for net receivers.

market. This coincides with the dot-com crash and geopolitical tensions affecting oil supplies. This aligns with the commodity supercycle, during which rising oil prices contributed to inflationary pressures and impacted equity valuations. However, a structural shift becomes evident from 2008 onward.[4] The direction reverses, with the U.S. stock market becoming net transmitters to the oil market, consistent with findings by Awartani and Maghyereh (2013) who document that return and volatility transmissions became

[4] A pre-set break in 2008 is strongly supported on MT (F = 20.4) and moderately on LT (F = 9.2), and ST (F = 3.5). Endogenous supF tests locate the largest breaks at 2014-01 (ST), 2018-07 (MT), and 2020-07 (LT), suggesting that directional regimes shift at different dates across horizons

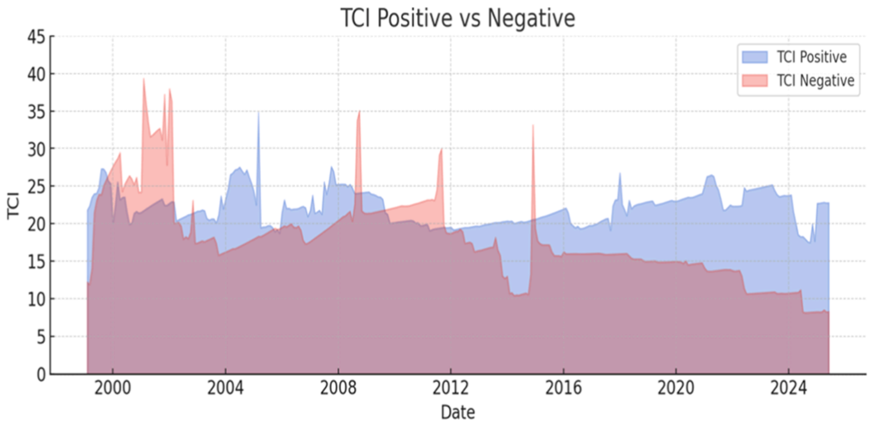

Fig. 7. Positive and Negative Total Connectedness Index.

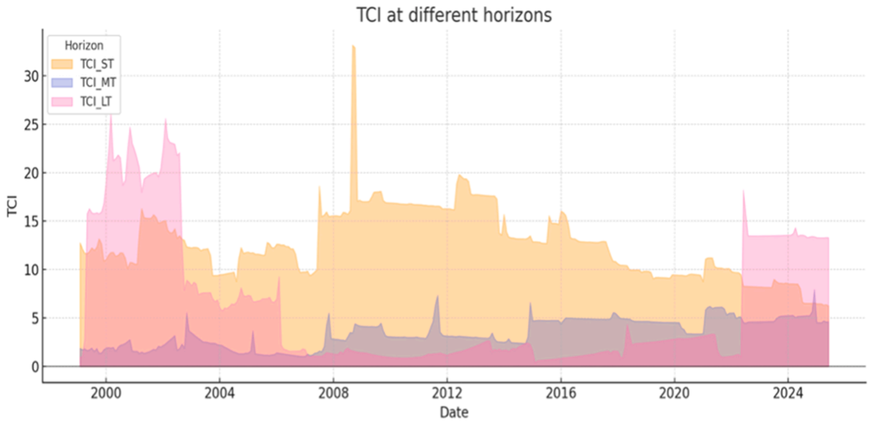

Fig. 8. Short, Medium and Long Connectedness.

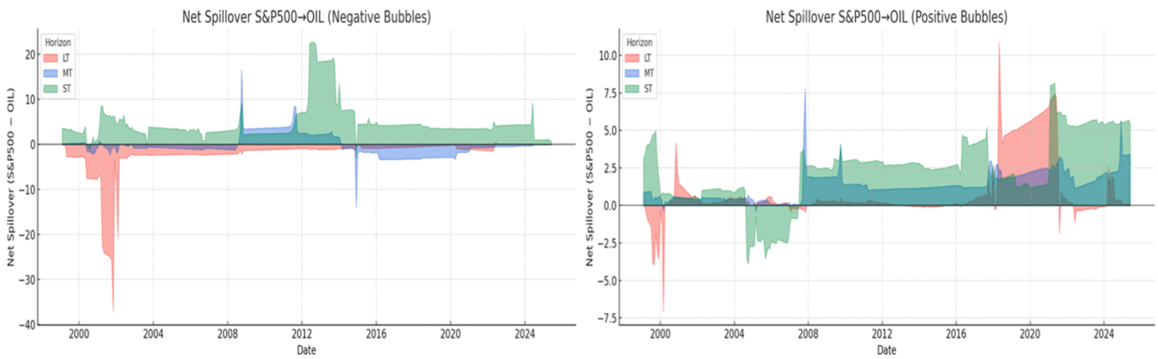

Fig. 9. Net spillover dynamics.

more pronounced after the 2008 GFC with an intensified net contribution from oil in the post-crisis period. The 2014–2015 period shows particularly intense stock-to-oil spillovers in the short-term horizon. This period corresponds to the dramatic oil price collapse from over $100 to below $30 per barrel, suggesting that financial market stress in the U.S. contributed significantly to the commodity market crash. This finding aligns with cross-border systemic risk spillover research showing significant spillover effects with pronounced upward trend since the 2008 financial crisis, expansionary monetary policies (like QE), COVID-19, and Ukraine war (Zhu et al., 2021; Zhang et al., 2021; Ben Amor et al., 2025; Hudepohl et al., 2021; Rogers et al., 2014).

4. Conclusion

Our empirical results indicate that over the past decade, a new spillover regime has emerged, in which U.S. equity market has consistently dominated the transmission of bubbles to oil. This shift coincides with unprecedented monetary interventions, the rise of commodity index investing, and the deeper integration of oil into portfolio construction. Frequency-domain evidence indicates that U.S. equities have a strong impact on oil risk (especially at short horizons), reinforcing an equity-to-oil direction of influence (Ferrer et al., 2018; Ziadat et al., 2024).

A notable asymmetry also emerges, namely that market crashes transmit more forcefully across markets than booms. Negative bubble spillovers are about 40 % larger than positive ones during comparable phases. This is consistent with mechanisms highlighted in recent research, including margin calls and forced liquidations that generate immediate cross-asset selling, pro-cyclical risk limits that prompt simultaneous deleveraging, and crisis-time acceleration in information flows that increase cross-asset correlations (Nekhili and Bouri, 2023; Wang and Li, 2021; Wang et al., 2022). Relatedly, extreme events, uncertainty, and speculation intensify the dynamics of crude oil prices (Chang, 2024).

These findings challenge conventional assumptions about oil-equity market relationships (e.g., Xu et al., 2019). Rather than oil prices driving equity markets through input cost channels, we document that financial market bubbles increasingly determine oil price dynamics. This reversal reflects the transformation of oil from a physical commodity to a financial asset class. Research demonstrates that equity markets are primary sources of net spillovers to energy and commodity markets, with financial stresses from equity markets significantly impacting precious metals and commodity markets (Mensi et al., 2021). The dominance of short and medium-term spillovers over long-term effects further suggests that financial flows, rather than fundamental demand shifts, drive much of the observed bubble transmission. This finding carries important implications for market participants. Traditional assumptions that oil serves as an inflation hedge or portfolio diversifier may no longer hold during bubble episodes. In particular, portfolio managers should: (*i*) adopt dynamic hedging strategies that account for time-varying spillovers, increasing oil exposure only during periods of equity market stress; (*ii*) monitor short-term MS-LPPLS-CI indicators as early warning signals of speculative dynamics; and (*iii*) reduce commodity allocations when bubble conditions are identified. For regulators, it is advisable to closely monitor margin requirements in oil futures markets during episodes of equity bubbles, as excessive leverage can amplify cross-market contagion and systemic risk.

The study has several limitations. First, our analysis focuses on U.S. markets, and spillovers may differ in other regions. Second, our bivariate framework excludes potentially relevant transmission channels such as macroeconomic fundamentals, monetary policy shocks, which may act as contagion pathways. Future research could: (i) extend the analysis to emerging markets and other commodities; (ii) incorporate machine learning techniques to capture bubble prediction; (iii) examine the role of social media sentiment in bubble transmission; and (iv) develop optimal portfolio strategies conditional on bubble indicators

CRediT authorship contribution statement

Matteo Foglia: Writing – review & editing, Writing – original draft, Software, Investigation, Formal analysis. **Rangan Gupta:** Writing – review & editing, Writing – original draft, Supervision, Data curation, Conceptualization. **Petre Caraiani:** Writing – review & editing, Software, Methodology, Investigation, Formal analysis. **Vincenzo Pacelli:** Writing – review & editing, Writing – original draft, Supervision, Formal analysis.

Data availability

Data will be made available on request.

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