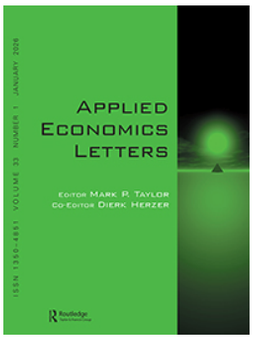

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Examining time-varying causality: investor sentiment and asset spreads across in COVID, and Ukraine War periods

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ABSTRACT

This article investigates the dynamic causal relationships between investor sentiment, measured through Twitter mentions of uncertainty, CBOE volatility index, the spreads of key assets, S&P 500, oil, gold, and Bitcoin, during the COVID crisis and the Ukraine War. The results reveal significant bidirectional causality between investor sentiment and S&P 500 spreads during the COVID era, contrasting with minimal causality during the Ukraine War Other of the hand, the relationship between the VIX and the S&P 500 is unidirectional, during COVID period, while, no causality is observed for the period of the Ukraine War. Moreover, a bidirectional causality appears between the VIX and Bitcoin at distinct times, While, for the period of the war in Ukraine, there is a small one-way causality from bitcoin to the VIX in May 2022 and in June. Gold spreads demonstrated a reciprocal influence with sentiment, while no significant relationships were found for oil and Bitcoin spreads. These findings underscore the variability of market-sentiment interactions across different crises, providing insights for investors and policymakers.

KEYWORDS

Investor sentiment; time-varying causality; S&P500; COVID crisis; Ukraine War

JEL CLASSIFICATION

D84; C32; G15; G01

I. Introduction

The relationship between economic policy uncertainty and capital markets has been a focal point of academic research. Several studies have demonstrated how economic policy uncertainty affects capital market performance (T. Li et al. 2020; Megaritis, Vlastakis, and Triantafyllou 2021), volatility (Liu and Zhang 2015; Baker et al. 2016; Zeng et al. 2024), and commodities or currency markets. For instance, research by Lu and Lang (2023) indicates that both traditional indices and Twitter-derived metrics can predict economic policy uncertainty in China, with Twitter metrics often surpassing conventional measures.

In the context of commodities, previous research has extensively studied the impact of political and economic uncertainty on gold prices (Bilgin et al. 2018; Tiwari, Gupta, and Gkillas 2020), while Jones and Sackley (2016) find a positive relationship between uncertainty and higher gold prices. However, the effect of uncertainty on oil prices remains inconclusive, with conflicting findings ranging from positive, negative, or neutral impacts. For example, Q. Li, Cheng, and Yang (2015) suggest that heightened uncertainty encourages financial actors to reduce their long positions in oil futures, which can lead to price drops. Conversely, Bakas and Triantafyllou (2018) argue that declining oil futures amplify volatility in both demand and supply expectations, thereby increasing market fluctuations.

The role of uncertainty in stock market volatility has also been widely studied (Liu and Zhang 2015; Baker et al. 2016; Zeng et al. 2024). The COVID-19 pandemic brought renewed focus to market behaviour under crisis conditions, with many studies examining the pandemic's impact on global stock markets (Behera, Gunadi, and Rath 2023). Additionally, Bartov, Faurel, and Mohanram (2018) highlight the predictive power of Twitter sentiment for corporate performance, while Behera, Gunadi, and Rath (2023) examine its relationship with G7 stock market movements, emphasizing its role in reflecting global trends.

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Table 1. Descriptive of variables.

Variable	Database	Description
LnTEU	Own preparation	$\ln(TEU)$
Spread_S&P500	Own preparation	$\ln(\frac{S\&P500}{S\&P500\,t-1}) - Risk\ free\ rate$
Spread_Oil	Own preparation	$\ln(\frac{Oil}{Oil\,t-1})$ - *Risk free rate*
Spread_Gold	Own preparation	$\ln(\frac{Gold}{Gold\,t-1})$ - *Risk free rate*
Spread_Bitcoin	Own preparation	$\ln(\frac{Bitcoin}{Bitcoin\,t-1})$ - *Risk free rate*
VIX (index)	Own preparation	*nominal index value*

LnTEU is the logarithm of the investor sentiment in the Twitter*, Spread_S&P500 represent the spread S&P 500, Spread_Oil represent the oil spread, Spread_Gold represent the gold spread, Spread_Bitcoin represent the Bitcoin spread and VIX (index) represent the nominal index of VIX.

This study is, to our knowledge, the first to provide investors with a comparative perspective on the performance of various assets during periods of uncertainty. By examining the spread of each asset relative to a risk-free rate, it allows for a more nuanced understanding of profitability without the security of guaranteed returns (Table 1).

The remainder of this article is structured as follows: Section II presents the data and methodology. Section III outlines the main results. Section IV concludes.

II. Data and variables

The COVID era spans 1 January 2020 – 21 February 2022, beginning with the WHO's December 2019 alert on a pneumonia-like outbreak in Wuhan and the identification of a new virus on 7 January 2020. The Ukraine War period covers 22 February 2022 – 21 April 2023, marking Russia's invasion of Ukraine. The key variable, LnTEU, measures the daily U.S. Twitter frequency of the term 'uncertainty' (Baker et al. 2021). Market behaviour is analysed using spreads for the S&P500, Oil, Gold, and Bitcoin, defined as each asset's excess return over the risk-free rate (Pastor & Veronesi 2013).

Daily data for these assets were obtained from Invest.com. These spreads reflect deviations from risk-free returns, capturing market performance under uncertainty.

III. Time-varying causality approach

This study employs the time-varying causality test, as developed by Shi, Phillips, and Hurn (2018), to identify the direction of causality between the variables in the econometric model. The methodology is based on the Lag-Augmented VAR (LA-VAR) framework, which allows for dynamic analysis of causal relationships over time.

The LA-VAR model, applied to two variables Y_{it} and X_{2it}, can be expressed as follows:

$$Y_{it} = \alpha_{10} + \alpha_{11t} + \sum_{i=1}^{k+d} \beta_{1i} Y_{1i-t} + \sum_{i=1}^{k+d} \delta_{1i} Y_{2i-t} + \varepsilon_{1t} \quad (1)$$

$$X_{2it} = \alpha_{20} + \alpha_{21t} + \sum_{i=1}^{k+d} \beta_{2i} X_{2i1t-i} + \sum_{i=1}^{k+d} \delta_{2i} X_{2t-i} + \varepsilon_{2t} \quad (2)$$

Here k represents the lag length, and d denotes the maximum order of integration, as specified by (Raifu 2022). This approach is well suited for examining casual links between variables evolve over time, particularly during periods of uncertainty.

Time-varying LA-VAR granger causality test including trend

To estimate the VAR model and perform time-varying causality tests, we first determined the order of integration using the BIC criteria, with a maximum lag length of 12, as recommended by Shi, Phillips, and Hurn (2018). Next, we conducted the time-varying dynamic causality tests for each period using Stata's TGVC module, following the approach outlined by

Baum et al. (2022) and applied in Fromentin et al. (2022).

Time-varying LA-VAR granger causality test including trend

We conducted the Ditzen, Karavias, and Westerlund (2021) unit root test (see Appendix A), which accounts for multiple structural breaks such as those caused by the COVID-19 pandemic and the Ukraine War. The results indicate that, for most of the series, the null hypothesis of a unit root is rejected, suggesting stationarity once structural breaks are considered. Only a few variables (such as Bitcoin and Gold returns in some specifications) show weaker evidence against non-stationarity. Overall, these results support the application of the time-varying causality framework, as the majority of the series are stationary or become stationary after accounting for structural breaks.

The procedure for estimating the VAR model and performing time-varying causality tests involved several steps. First, we determined the appropriate order of integration for the VAR model using BIC criteria, with a maximum lag length of 12, as suggested by Shi, Phillips, and Hurn (2018). We then applied time-varying dynamic causality tests for each period, using Stata's TGVC module, a method recently employed

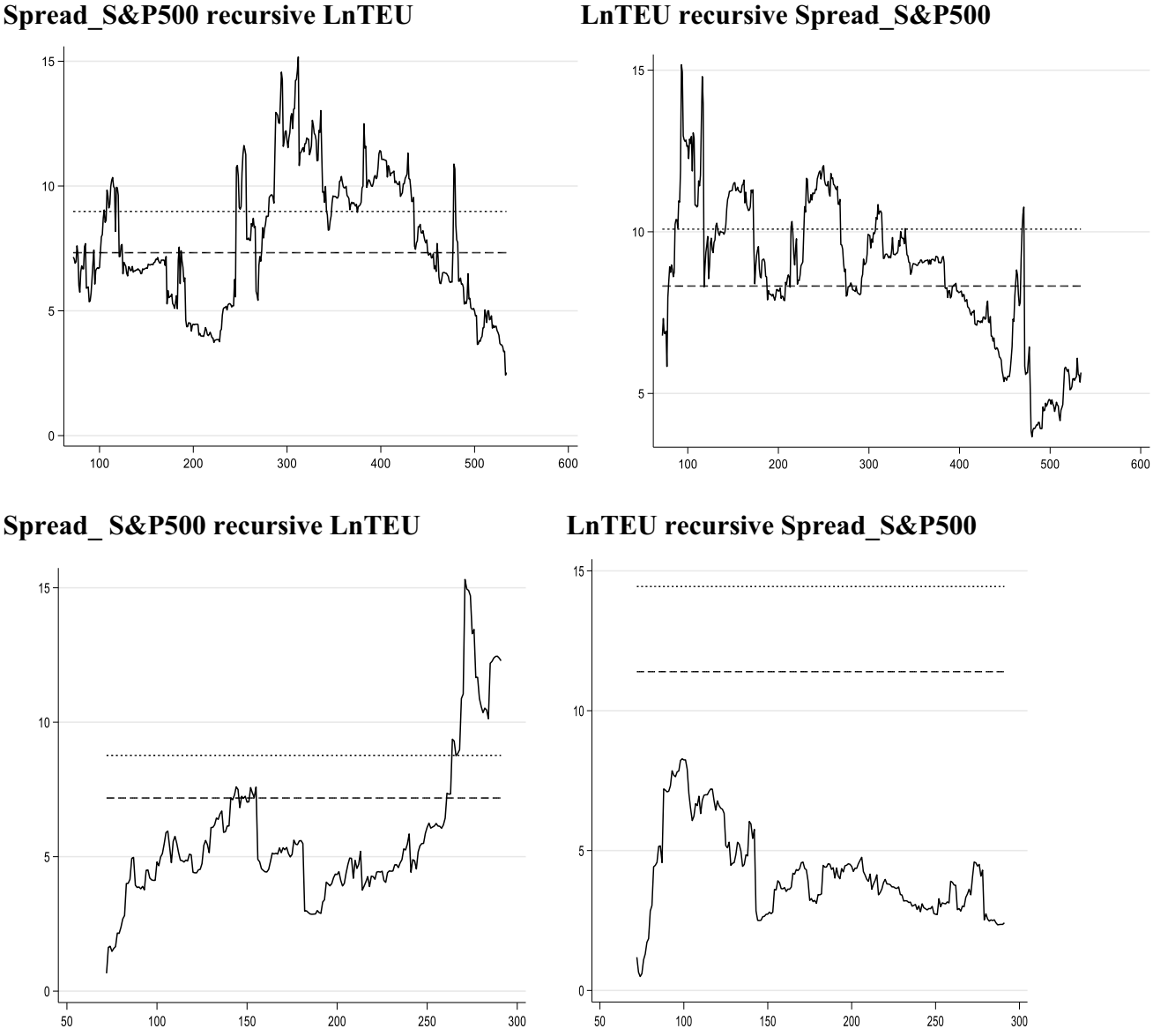

Figure 1. Dynamic causal relationships between Spread_S&P500 and LnTEU.

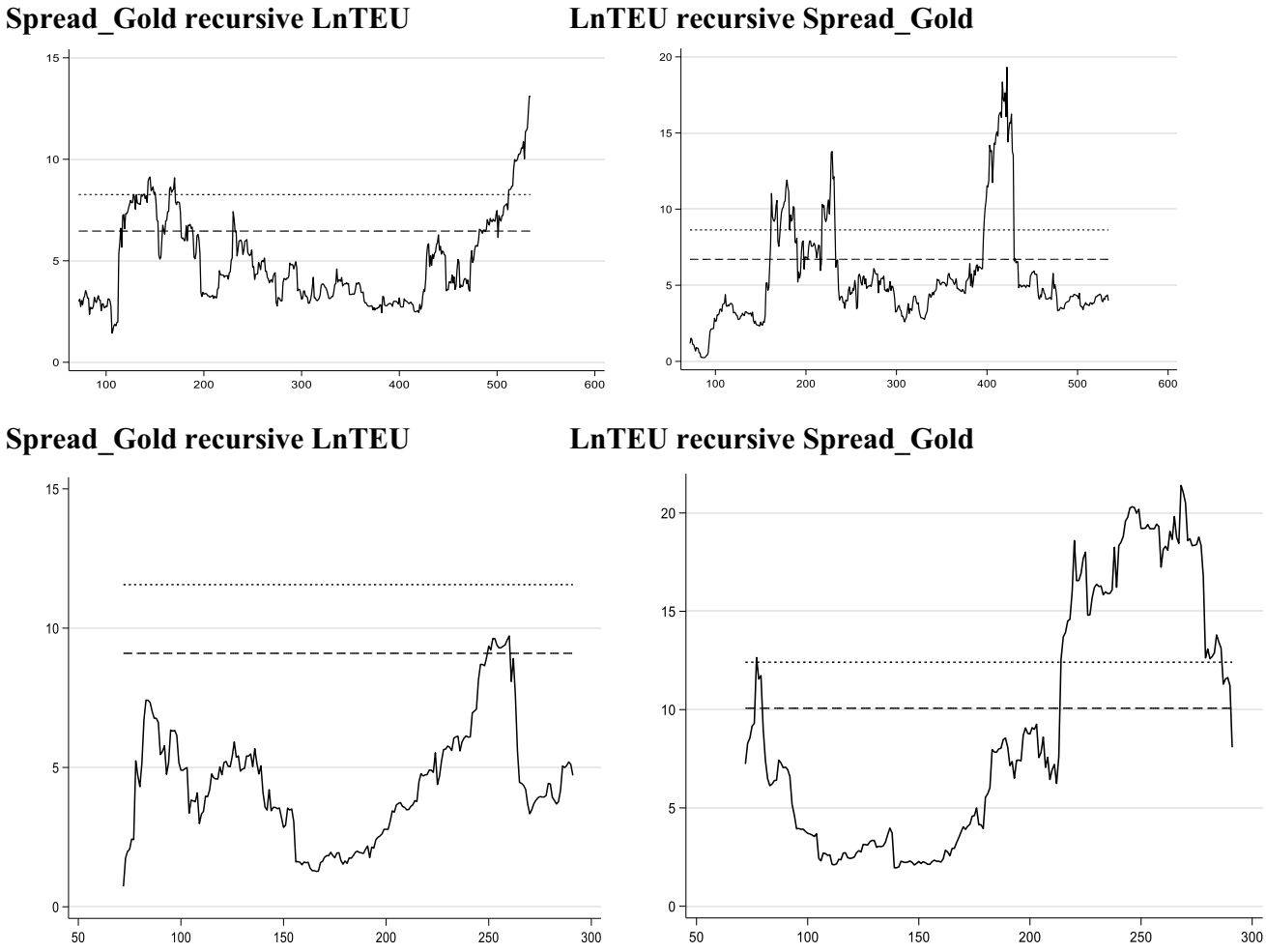

Figure 2. Dynamic causal relationships between Spread_Gold and LnTEU.

by Mohamad and Fromentin (2023), among others.

Time-varying causality in the pandemic crisis

For the LA-VAR Granger causality analysis during the pandemic crisis, the results are presented in the accompanying Figure 1. The first two graphs illustrate findings from the COVID period, while the subsequent two correspond to the Ukraine War period, highlighting key causal relationships during these phases.

Causal links between the S&P500 spread and the LnTEU sentiment index were analysed across the pandemic and the Ukraine War.

During the pandemic, strong bidirectional causality emerged, with the S&P500 spread predominantly influencing investor sentiment, reflecting their close interdependence.

In contrast, the Ukraine War showed little causality for most of the period; only near the end did a unidirectional effect appear, where the S&P500 spread affected sentiment.

Overall, the results reveal that market – sentiment dynamics vary by crisis – interactive during the pandemic but largely independent during the Ukraine War.

The graphs in Figure 2 examine the time-varying causality between Spread_Gold and the LnTEU uncertainty sentiment index during the pandemic. The findings primarily reveal a lack of bidirectional causality on most days, with only few instances of significant causality. In the war period, no causal relationship was found. However, after day 220, a unidirectional causality from the LnTEU index

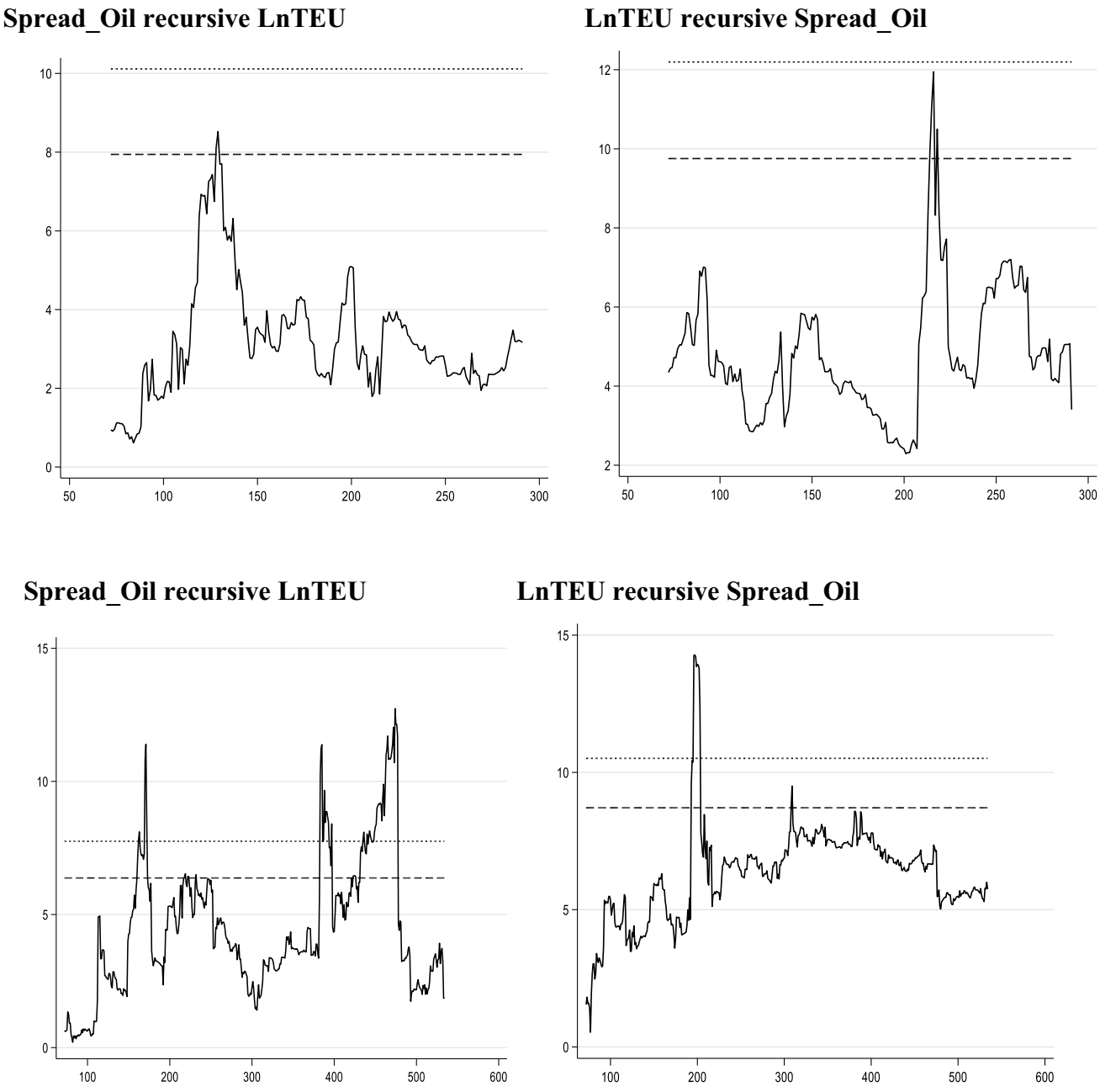

Figure 3. Dynamic causal relationships between Spread_Oil and LnTEU.

to Spread_Gold emerged, lasting until the end of the analysis, although its significance was greater before day 220. Overall, the results indicate a general absence of causality in both directions for most of the period.

Figure 3 shows no consistent bidirectional causality between Oil spreads and the LnTEU sentiment index. Only brief unidirectional effects appear, confirming a weak and largely insignificant relationship between the two variables across most periods

Figure 4 shows little significant bidirectional causality between Bitcoin's excess spread return and the LnTEU sentiment uncertainty index during COVID, except on a few days. Between days 100–180, causality ran from LnTEU to

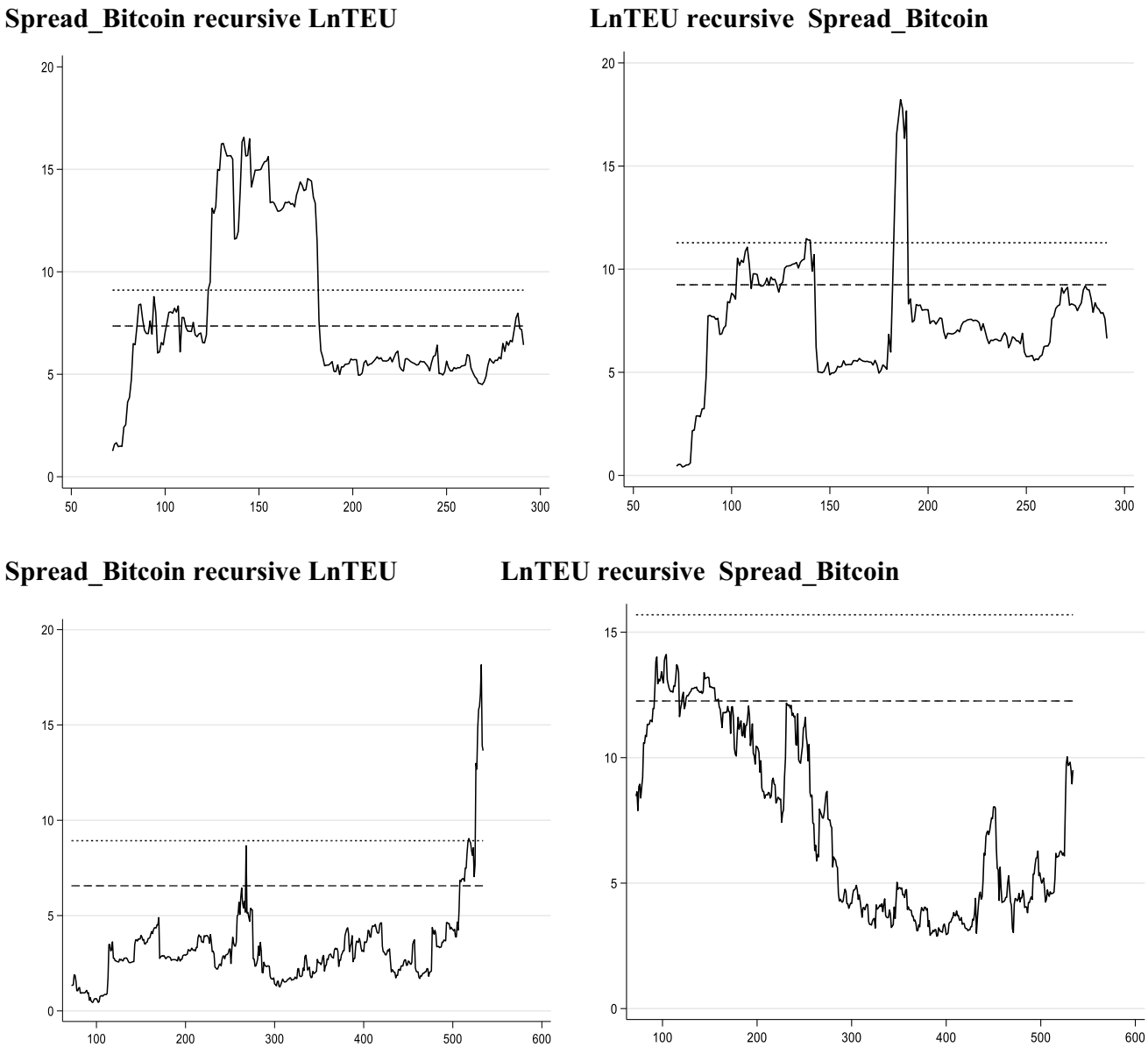

Figure 4. Dynamic causal relationships between Spread_Bitcoin and LnTEU.

Bitcoin returns, while scattered days between 120 and 185 showed the reverse. Overall, evidence of any causal link between the two variables remains minimal across most of the period.

IV. Conclusions

During COVID, sentiment regarding the pandemic not only influenced the S&P500 spread but was also shaped by it, confirming Baker et al. (2016), who highlighted sentiment's strong role in market behaviour during crises.

In contrast, during the Ukraine War, the S&P500 spread showed little dependence on sentiment. For Gold, the relationship reversed – its spread moved contrary to sentiment, consistent with gold's role as a hedge against stock market volatility. No causal links emerged between Oil or Bitcoin spreads and the LnTEU index in either period.

These patterns indicate that the S&P500 and Gold spreads act as mutual barometers of Twitter-based sentiment, alternating in influence as noted by Fromentin et al. (2022). While the LnTEU index generally did not affect S&P500 excess returns, a late unidirectional effect appeared, with returns

influencing sentiment uncertainty, echoing Bartov, Faurel, and Mohanram (2018).

Overall, the results underscore the crisis-dependent and dynamic interplay between market spreads and investor sentiment, offering implications for investors and policymakers alike.

Author contributions

CRediT: **Vitor Moutinho:** Data curation, Formal analysis, Investigation, Methodology, Software; **Renato Heitor Correia Domingues:** Conceptualization, Data curation, Investigation, Methodology, Software, Supervision, Validation, Visualization, Writing – original draft; **Giulia Fantini:** Conceptualization, Data curation, Formal analysis, Investigation, Validation, Visualization, Writing – review & editing; **Michelle Moraes:** Conceptualization, Data curation, Formal analysis, Investigation, Resources, Validation, Writing – original draft.

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