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Unveiling the Co-Movements and Spillovers in Financial, Cryptocurrency and Commodity Markets: Insights from Googling Investors' Sentiment

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Hayet Soltani[1], Mouna Boujelbène Abbes[2]

Abstract:

Purpose: *This study aims to investigate the interconnectedness patterns between investor sentiment, as reflected in Google search trends, and various asset returns, specifically over the period from 2017 to 2023.To achieve this, we combine two methodologies: wavelet coherence analysis and Diebold–Yilmaz Spillover Indexes.*
Design/Methodology/Approach: *Using wavelet coherence model, we confirm the leading effect of googling investor sentiment, particularly during periods marked by unexpected health and geopolitical crises.*
Findings: *The results indicate that investor sentiment negatively affects the S&P 500, Brent crude oil, wheat, and Hellogold. Specifically, the study reveals that during the COVID-19 and Russian-Ukraine war periods, investor sentiment, MOEX, Nasdaq, Natural-Gas and Bitcoin are net volatility transmitters, whereas S&P 500, US bonds, Brent-oil, wheat and hellogold are net volatility receivers. During the Russian-Ukraine war, the investor sentiment (ISent) shifted from being a net transmitter of volatility to a net recipient of volatility.*
Practical Implications: *The findings offer valuable insights for investors and portfolio managers, aiding them in designing portfolio strategies that align with market dynamics and developing supportive strategies that enhance portfolio resilience and adaptability, especially in volatile market conditions.*
Originality/Value: *This study analyses the dynamic connections between various asset classes and stock prices to better understand the similarities and differences in information transmission across these asset classes.*

Keywords: *Google Trends, Investor sentiment, COVID-19 pandemic, Russia-Ukraine conflict, Diebold–Yilmaz Spillover Index, Wavelet coherence.*

JEL Classification: *G12, G15, C58, E44, G41.*

Paper type: *Research article.*

[1]*Corresponding author, Faculty of Economics and Management of Sfax, Laboratory LEG, University of Sfax, Tunisia, e-mail: hayetsoltani91@yahoo.fr;*
[2]*The same as in 1, e-mail: abbes.mouna@gmail.com;*

1. Introduction

The global economic and financial landscape has experienced significant disruptions since the first quarter of 2020 due to the COVID-19 pandemic, the Russia-Saudi Arabia oil price conflict, and the Russia-Ukraine conflict. These events triggered a remarkable decline in international stock markets, cryptocurrency markets, and crude oil prices, leading to increased volatility and uncertainty worldwide.

Moreover, these global events, including financial crises, health pandemics, and geopolitical conflicts, have generated considerable uncertainty, including market fear. This increased fear has played a major role in the substantial volatility of commodity and cryptocurrency prices, while facilitating the propagation of risks in financial markets (Li *et al.,* 2021; Jiang *et al.,* 2023).

Thoroughly analyzing and understanding the complex relationships and volatility among stock, commodity, and cryptocurrency markets can aid investors, portfolio managers and policymakers in leveraging market movements, crafting more effective investment strategies, and improving portfolio management.

Furthermore, the intensified financialization of commodities has significantly increased spillovers and interconnections across these markets, especially during periods of instability (Kang *et al.,* 2019; Chen *et al.,* 2022). In such times, investors become increasingly concerned about potential disruptions that may negatively impact their portfolios. This concern often drives them to actively search the internet for real-time news and data that could influence asset performance.

Indeed, news updates and Google search trends serve as vital resources for gauging the crisis landscape, thereby guiding investor decisions in stock markets. Particularly during financial crises, investors rely on technology to access accurate, timely information. Access to high-quality data enables investors to perform swift, critical analyses essential for effective asset management, allowing them to respond promptly to rapidly changing market conditions.

Both the COVID-19 pandemic and the Russia-Ukraine conflict have caused severe disruptions in global supply chains, intensifying volatility across financial and commodity markets worldwide. Traditionally, investors mitigate losses by diversifying across different sectors and asset classes. In fact, the primary aim of holding varied asset classes is to reduce risk through diversification, avoiding assets with high correlation.

However, during crises, even assets that appear unrelated often show strong movement, diminishing the effectiveness of diversification, (Conlon and McGee, 2020). Furthermore, declines in stock market indices following terrorist attacks and conflicts indicate that geopolitical risks significantly impact asset prices (Gong and Xu, 2022).

In this context, risk contagion and spillover effects are evident within financial markets, making it essential to identify and mitigate market risk characteristics effectively (Gong *et al.,* 2019). Recent health crises, such as the COVID-19 pandemic, have severely impacted capital markets and economies, with recovery often challenging within a short timeframe as announced by Zihui and Yinggang, 2020).

Analyzing cryptocurrencies, Sarkodie and Owusu (2021) observed significant price volatility in Bitcoin, Bitcoin Cash, Ethereum, and Litecoin during the pandemic. Additionally, Mishra and Mishra (2020) reported that rising COVID-19 case counts and fatalities negatively affected stock returns on both the Hang Seng Index and the Shanghai Composite Index. Qarni et al. (2019) investigate the volatility spillover dynamics between U.S. Bitcoin and financial markets from July 19, 2010, to December 29, 2017. They find insignificant effect of Bitcoin on the US financial markets.

Phochanachan *et al.* (2022) examine whether Bitcoin, gold, oil, and stocks serve as effective hedges against inflation in countries with high cryptocurrency adoption from January 2010 to March 2021, utilizing the Markov Switching Vector Autoregressive model.

Their findings indicate that, in the short term, holding assets such as Bitcoin, gold, stocks, or oil can effectively hedge against inflationary shocks. Notably, they report that Bitcoin proves to be an efficient hedge against inflation. Consequently, investors and portfolio managers are encouraged to consider including Bitcoin and similar assets in their portfolios to mitigate inflation risks.

On another hand, the Russia–Ukraine conflict has triggered significant ripple effects, notably creating turbulence in financial markets. This conflict suggests a period of slower global growth and rising inflation, as growth risks are closely linked to disruptions in Russia's energy supply. In this regard, Liadze *et al.* (2023) report that the Russia–Ukraine conflict has highly affected the economy of the World through energy supply contraction and supply chain disturbances.

Fang and Shao (2022) suggest that the intensification of the Russia-Ukraine conflict significantly increases the volatility of agricultural, metal, and energy markets. Antonakakis et al. (2023) examine the dynamic relationships between oil price implied volatility (OVX) and fourteen other assets across five asset classes: energy commodities, stock markets, precious metals, exchange rates, and bond markets.

They find that the connectedness between OVX and these asset classes varies significantly over time. Bossman et al. (2023) investigate the asymmetric interactions among EU sectoral stock markets, market sentiment, WTI (crude oil), OVX, and Geopolitical Risk (GPR) during periods of intense geopolitical unrest, using VIX, OVX, and GPR as sentiment-driven indices.

Their findings reveal that EU stock markets are asymmetrically affected by GPR, OVX, WTI, and VIX, with VIX and OVX exhibiting certain safe-haven and hedging characteristics for EU stocks. Gökgöz *et al.* (2024) analyze volatility connectedness between BRICS stock markets and various asset price implied volatility indices using a TVP-VAR broadened connectedness approach.

Their results indicate notable dynamic connectedness within BRICS stock markets and across different markets from 31 March 2019 to 31 August 2023, highlighting diverse patterns of connectedness between stock and volatility indices, especially strong during black-swan events.

Nevertheless, understanding connectedness among various asset classes is of paramount importance for risk management, (Diebold and Yilmaz, 2009; Diebold and Yilmaz, 2012). Although connectedness among various asset classes has always been important, studies like Yilmaz (2010) revealed that volatility spillovers among financial markets across the globe increased substantially during the global financial crisis. The burst in volatility spillover indices during crises is not limited to equity markets alone.

There is evidence of increased connectedness among markets for commodities, digital currencies, precious metals, and crude oil. For example, Song *et al.* (2021) report that connectedness among commodities increased more than threefold after the financial crisis. Recently, the crisis induced by the COVID-19 pandemic further strengthened the importance of understanding connectedness across markets and asset classes.

The COVID-19 pandemic and the Russian invasion of Ukraine represent unprecedented financial events, highlighting the necessity to investigate investor sentiment and asset allocation during extreme circumstances. Our study makes significant contributions to the expanding body of literature and has several important policy implications.

First, we introduce a novel proxy for measuring Russian investor sentiment through Google search queries. This article examines a psychological phenomenon, specifically the panic triggered by the COVID-19 pandemic and the Russia-Ukraine conflict, utilizing an investor sentiment index that reflects the anxiety prevalent in commodity, cryptocurrency, and stock markets.

Second, our approach is distinctive, as we focus on asset classes (stocks, commodities, and cryptocurrencies) that are uniquely interrelated and influenced by these significant events. Finally, our study's geographic scope offers a comprehensive perspective on investor sentiment, amplifying its relevance for investors, banks, financial institutions, investment firms, and central banks in the affected countries.

By doing so, we enhance the existing literature on the effects unexpected events on various markets and illuminate the interconnectedness of different asset classes in financial markets.

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature, while Section 3 outlines the methodology used in the study. Section 4 presents the data description, and Section 5 discusses the empirical results. Finally, the concluding section summarizes the study's findings.

2. Literature Review

Recently, there has been a growing body of literature on the impacts of COVID-19, the oil crisis, and the Russia-Ukraine war (Shahzad *et al.,* 2022; Orhan, 2022; Soltani *et al.,* 2024; Soltani and Boujelbène Abbes, 2024a; 2024b). Researchers have shown increasing interest in the relationships between traditional assets, such as equities and commodities, and cryptocurrencies. Previous studies have examined various interactions between cryptocurrencies and stock markets.

For example, Ji *et al.* (2018) analyzed the causal links between Bitcoin and stock, bond, and commodity markets, finding that Bitcoin tends to remain relatively isolated from these traditional assets, though its relationship with them exhibits fluctuations over time. Naeem *et al.* (2022) conduct a study to quantify spillover effects among seven major cryptocurrencies, namely, Bitcoin, Ethereum, Ripple, Litecoin, Monero, Stellar, and NEM.

Their findings reveal that Bitcoin, Litecoin, and Ripple are the primary transmitters of return spillovers, indicating their influential role within the cryptocurrency market. Jian *et al.* (2023) examine the impact of the Russia–Ukraine conflict on return spillover transmission across various assets. Their findings reveal a significant short-term surge in total connectedness, with the oil market becoming increasingly vulnerable to external shocks, shifting from a role as a net transmitter to that of a net receiver.

More importantly, Investor sentiment, a central theme in behavioral finance, examines how emotions and attitudes influence investors' decisions in the stock market (López-Cabarcos *et al.,* 2021). The sentiment is shaped by various factors, including economic data releases, geopolitical developments, corporate news, and financial media coverage (Sapkota, 2022; Kyriazis *et al.,* 2023).

Optimism toward a particular market or asset can increase the likelihood of buying and holding stocks or cryptocurrencies, driving up asset values. Conversely, a more pessimistic outlook may lead investors to sell off assets, which can contribute to price declines (Baker and Wurgler, 2006). For instance, various empirical methods have been applied to measure investor sentiment (Baker and Wurgler, 2006; Yi and Mao, 2009; Soltani and Boujelbène Abbes, 2024a), though this task remains challenging due to the inherent complexity of capturing investor sentiment and the lack of a standardized approach.

Early studies, such as Shen *et al.* (2019), analyzed the impact of Twitter content on Bitcoin trading volume, uncovering a genuine relationship between social media posts and cryptocurrency activity. Building on these findings, Trichilli *et al.* (2018) further contributed to the literature by demonstrating the predictive power of Google-based investor sentiment in forecasting returns in emerging and frontier markets in the MENA region. Their study highlights the critical role of sentiment analysis in understanding and predicting market dynamics.

Nevertheless, previous studies (Cheah and Fry, 2015; Miao *et al.,* 2022; Liu *et al.,* 2024; Seok *et al.,* 2024) have primarily focused on the impact of investor sentiment on individual financial markets, commodities, and other asset classes. However, little research has explored investor sentiment toward a combination of various markets. Namouri *et al.* (2018), using a panel switching transition model to examine the investor sentiment–stock return relationship, investigated this relationship in the G7 countries from June 1987 to February 2014.

Their findings reveal that investor sentiment significantly and nonlinearly influences stock returns, with its effects varying according to market conditions. Similarly, Liston-Perez *et al.* (2018) estimated the dynamic correlation between investor sentiment and Mexican stock market returns, showing that Mexican investor sentiment is a significant predictor of equity returns in Mexico.

Soltani *et al.* (2023) analyzes the connectedness between the Gulf Cooperation Council (GCC) stock market indices and cryptocurrencies. Specifically, they examine the impact of RavenPack COVID sentiment on the dynamics of stock market indices and both conventional and Islamic cryptocurrencies at the onset of the COVID-19 crisis. Their results reveal that COVID-19 significantly affected all cryptocurrency markets, with time variations in stock returns displaying stylized characteristics such as fat tails and volatility clustering across all return series.

Additionally, their findings underscore a substantial spillover of shocks among RavenPack COVID sentiment, Islamic and conventional stock return indices, and cryptocurrencies. Notably, RavenPack COVID sentiment emerged as the primary net transmitter of shocks for all conventional market indices, while most Islamic indices and cryptocurrencies were identified as net receivers.

Using a comprehensive dataset that includes the S&P 500 index, historical Bitcoin prices, the Investor Sentiment Index, the Industrial Production Index, and the US Consumer Price Index, Chowdhury *et al.* (2024) investigate shifts in investor sentiment during the Russia–Ukraine war and its subsequent impact on market volatility. Their findings indicate that investor sentiment has a significant positive influence on returns in both stock and cryptocurrency markets.

Chundakkadan and Nedumparambil (2022) argue that sudden declines in stock prices are largely influenced by shifts in market sentiment. Similarly, Boubaker et al. (2022) observed a significant impact on both stock and cryptocurrency markets stemming from the ongoing conflict between Russia and Ukraine.

Research conducted by Boungou and Yatié (2022) revealed a negative correlation between the Russia–Ukraine war and the overall performance of global financial markets. The conflict particularly adversely affected European stock markets, leading to substantial and notably negative returns (Ahmed *et al.,* 2022).

Table 1 reports some studies that examine the volatility nexus and connectedness among investor sentiment and different asset classes.

3. Methodology Approach

Development of the Russian Investor Sentiment Index through Google Search Trends:
Building on the work of Da *et al.* (2015), we employ the Global Volume Search Index (GVSI) from Google Trends to develop daily investor sentiment index (ISent) for the MOEX stock exchange market. To achieve this, we select a comprehensive set of 149 financial terms sourced from the Harvard IV-4 dictionary and the Lasswell Value Dictionary (Tetlock, 2007).

Given our focus on the search behaviors of local households, we translated these English terms into Russian using Google Translate, including keywords such as “coronavirus” and “war.” Furthermore, we argue that news articles containing at least one of our predefined positive or negative words evoke corresponding optimistic or pessimistic thoughts in readers. This emotional response, in turn, influences their perceptions of the stock market and the broader economy.

The last step of the construction process involves identifying the most relevant search terms linked to returns. To compile a consistent list of terms while addressing outliers, seasonality, and heteroskedasticity in the data, we implement several additional transformations. First, to minimize the impact of outliers, we applied for a winsorization at the 5% level, adjusting both tails by 2.5%. Next, we assessed the presence of intra-annual seasonality by conducting 105 one-factor analysis of variance (ANOVA) tests.

To account for heteroskedasticity in the data and create comparable statistics, we standardize the values based on the quality gap of the statistics. For ease of interpretation, we use the log of the Global Volume Search Index (GSVI), referred to as the Search Volume Index (SVI) for each search term.

Next, we retrieve the daily Search Volume Index (SVI) for the selected terms over our sample period from 2017 to 2023. We then calculate the daily changes in the SVI, denoted as ΔSVI, for each term. Additionally, we derive the adjusted daily changes in search volume, referred to as ΔASVI. This process involved calculating the changes for both positive and negative terms to construct our sentiment proxy. Finally, we develop our sentiment index by measuring the average adjusted Global Search Volume Index (ΔAGSVI) for the top 30 positive and top 30 negative daily search terms.

$$ISent = \sum_{i=1}^{30} \mathrm{R}_{+}^{i}\,(\Delta\mathrm{ASVI}_{i}) - \sum_{i=1}^{30} \mathrm{R}_{-}^{i}\,(\Delta\mathrm{ASVI}_{i}) \tag{1}$$

Where: $\sum_{i=1}^{30} \mathrm{R}_{\pm}^{i}\,(\Delta\mathrm{ASVI}_{i})$: represents the t-statistically weighted average of the top 30 positive and negative search terms, respectively.

Wavelet coherence approach:
To analyze the lead-lag (bi-directional) relationships among googling investor sentiment, commodities, cryptocurrencies, and stock markets across different time scales and frequencies, we utilize the wavelet coherence approach. Utilizing the methodology developed by Torrence and Webster (1999), we define the wavelet coherence coefficient as follows:

$$R^2{}_n(S) = \frac{\left|s\left(s^{-1}W_n^{XY}(s)\right)\right|^2}{s\left(s^{-1}\left|W_n^{X}(s)\right|^2\right)s\left(s^{-1}\left|W_n^{Y}(s)\right|^2\right)} \tag{2}$$

Where:

- S represents a smoothing operator in both time and frequency domains,
- W^X and W^Y denote the wavelets for the series X and Y, respectively.
- W^{XY} represents the cross wavelet, while S^{-1} is used to convert the data to energy density, where s represents the scale and n denotes the time index.

The squared wavelet coherence coefficient, denoted as $R^2{}_n(S)$, ranges from 0 to 1. A value of $R^2{}_n(S)$ close to zero indicates a weak correlation, whereas a value achieving one signifies a strong correlation. To assess the coefficients against the null hypothesis of autoregressive AR(1) noise at the 5% significance level, we utilize Monte Carlo simulation methods.

Spillover index:
To analyze the dynamic interconnectedness across different variables, we apply the spillover connectedness index method developed by Diebold and Yilmaz (2012).

This technique is rooted in the generalized vector autoregressive (VAR) model framework put forth by Pesaran and Shin (1998), which allows for the decomposition of forecast error variances to remain consistent regardless of the order in which the variables are arranged.

In the generalized VAR framework, the H forward forecast error variance (H) input is:θ_{ij}^{g}

$$\theta_{ij}^{g}(\mathrm{H}) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (e_i A_h \Sigma\, e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \;,\; \mathrm{H} = 1,2,\ldots\ldots, \mathrm{N} \tag{3}$$

Where:
- Σ : indicates the covariance matrix for the error vector ε,
- σ_{jj}: is the standard deviation of the error term for the *jth* equation,
- e_i: is the selection vector with 1 as with ith element and zero otherwise.

Since we are employing the Koop Pesaran Potter Shin generalized VAR framework, the variance shares do not have to add to 1: $\sigma_{jj} e_i \sum_{j=1}^{N} \theta_{ij}^{g}(\mathrm{H}) \neq 1$.
At this level, Diebold and Yilmaz (2012) illustrate that $\theta_{ij}^{g}(\mathrm{H})$ should be normalized such that the information contained in the directional connectivity from market *j* to market *i* is that:

At this stage, Diebold and Yilmaz (2012) demonstrate that $\theta_{ij}^{g}(\mathrm{H})$ should be normalized to reflect the information contained in the directional connectivity from market *j* to market *i* is as:

$$\widehat{\theta_{ij}}(H) = \frac{\theta_{ij}^{g}(\mathrm{H})}{\sum_{j=1}^{N} \theta_{ij}^{g}(\mathrm{H})} \tag{4}$$

Note that, by construction $\sum_{j=1}^{N} \widehat{\theta_{ij}}(\mathrm{H}) = 1$ et $\sum_{j=1}^{N} \widehat{\theta_{ij}}(\mathrm{H}) = \mathrm{N}$

The connectedness volatility indices are categorized into three distinct types: total volatility spillover for the entire sample, directional volatility spillover, and net volatility spillover (see Table 1). Furthermore, we can break down the directional spillovers into pairwise directional spillovers. The net pairwise directional connectedness is calculated as the difference between the shocks transmitted from markets *i* to all other markets *j*, defined as follows:

Table 1. *The decomposition of the volatility spillover indices*

$TOTAL(h) = \frac{\sum_{ij=1}^{N} \theta_{ij}^{g}(\mathrm{h})\ i \neq j}{N} * 100$ (5)	- The **Total Spillover Index** is represented by the cumulative spillovers across all market classes.
$TO_i(h) = \frac{\sum_{j=1}^{N} \theta_{ij}^{g}(\mathrm{h})\ i \neq j}{N} * 100$ (6)	- The spillovers from variable i to all other variables $j = 1; \ldots; \mathrm{N}; \mathrm{j} \neq \mathrm{i}$ are captured by the **“Directional spillover index to the remaining assets”.**
$FROM_i(h) = \frac{\sum_{j=1}^{N} \theta_{ij}^{g}(\mathrm{h})\ i \neq j}{N} * 100$ (7)	- The spillovers received by variable i from all other variables $j = 1; \ldots; \mathrm{N}; \mathrm{j} \neq \mathrm{i}$ are reflected in the **“Directional spillover index originating from the other assets”.**
$NET_i(h) = TO_i(h) - FROM_i(h)$ (8)	- The **“Net spillover index”** reflects the spillovers sent from variable iii to all other variables $j = 1; \ldots; \mathrm{N}; \mathrm{j} \neq \mathrm{i}$, minus the spillovers received from these same variables.

Source: *Authors' elaboration.*

The following equation represents the shocks transferred from market *j* to market *i*:

$$(H) = \frac{\tilde{\theta}_{ij}^{g}(H)}{N} \tag{9}$$

4. Data Description and Preliminary Analysis

4.1 Data Description

We utilize daily and monthly price data from the Moscow Exchange Market (MOEX) index as a benchmark for Russia's stock market performance, alongside American indices (NASDAQ and S&P500), three major commodities (Brent Oil, Natural Gas, and Wheat) and two key cryptocurrencies, Bitcoin and HelloGold. Brent Oil and Wheat are selected due to their significant economic impact and pivotal roles in global financial markets.

Data was gathered from CoinMarketCap, Datastream, and ABC Bourse for the period spanning January 2017 to May 2023, capturing both stable phases and crisis periods, including the COVID-19 pandemic and the Russia-Ukraine conflict.

To examine the impacts of the 2020 global pandemic and the Russia-Ukraine conflict, we divide the research period into two sub-periods. The "COVID-19 Outbreak" period covers 01 December 2019 to 23 February 2022, while the "Russia-Ukraine Conflict" period extends from 24 February 2022 to 18 May 2023. For the

Investor Sentiment Index, we use the daily Global Search Volume Index (GSVI), with Russia-specific data sourced from Google Trends[3]. The formula for calculating the rate of return is as follows:

$$R_t = ln\left(\frac{P_t}{P_{t-1}}\right) \tag{10}$$

Where, R_t represents the logarithmic return, and P_t and P_{t-1} are the closing prices on consecutive days.

4.2 Preliminary Analysis

Figure 1 illustrates the impact of the COVID-19 pandemic and the Russia-Ukraine conflict on various assets and markets. The conflict had a more dramatic effect than the pandemic, causing sharp drops in Brent-oil, Natural gas, and stock market returns, especially in Russia (MOEX). American markets (NASDAQ and S&P 500) were more resilient, suggesting a wider impact on the Russian economy.

Bitcoin remained relatively stable, while Hellogold experienced a decline in 2022, indicating potential loss of investor confidence. The spike in wheat returns in 2022 likely resulted from supply chain disruptions caused by the conflict, (Chatziantoniou *et al.,* 2022; Fang and Shao, 2022). In fact, the Russian investor’s sentiment reveals significant fluctuations throughout the period from 2019 to 2022, closely correlated with both the COVID-19 pandemic and the Russia-Ukraine conflict.

In addition, markets during the Russia–Ukraine conflict were significantly impacted by investor sentiment, as demonstrated by the research of Chung (2023), Puscasu (2023) and Derindere Köseoğlu *et al.* (2024). Consequently, these plots highlight the complex interplay of economic and geopolitical events on the global financial landscape, highlighting the diverse responses of various assets and markets to these multifaceted challenges.

Table 2 presents descriptive statistics for daily returns of financial markets (MOEX, NASDAQ and S&P500), three commodities (Brent oil, Natural gas and Wheat), and two cryptocurrencies (Bitcoin and HelloGold). Most assets exhibit significant volatility, particularly during the pandemic health crisis and Russia-Ukraine conflict periods, with high standard deviations and non-normal distributions.

[3]*https://www.google.com/trends/*

Figure 1. *Time series plot of Russian investor sentiment, commodities, cryptocurrencies and stock markets returns*

Source: *Authors' elaboration.*

The Russian stock market (MOEX) shows a dramatic decline in mean return during the conflict, indicating a strong negative impact on the Russian economy, while global markets like NASDAQ and S&P500 experience less significant drops.

Commodity prices like Brent oil and Natural gas exhibit high volatility due to supply disruptions, while wheat shows a positive mean return during the conflict, likely driven by supply chain issues.

Bitcoin remains volatile but stable in terms of mean return, while HelloGold displays significant price fluctuations. These observations highlight the need to consider non-normality and high volatility, particularly during times of uncertainty.

Table 2. *Summary statistics for all variables*

	Mean	Median	Maximum	Minimum	Std,Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
Panel A: All-sample period (from January 04, 2017 to May 31. 2023)									
ISENT	4.6367	0.8248	467.4623	-391.5401	85.7006	0.3436	7.6621	1304.6570	0.0000
MOEX	-0.001	0.0007	0.1826	-0.4047	0.0207	-5.0678	116.5890	764054.6000	0.0000
NASD	0.056	0.1171	9.5966	-13.0032	1.6066	-0.5279	9.3666	2446.8040	0.0000
S&P500	0.031	0.0657	8.9671	-12.7657	1.3214	-0.8257	16.9436	11582.6100	0.0000
GAS	0.000	0.0010	0.0551	-0.1388	0.0169	-0.5468	6.9975	1009.0940	0.0000
OIL	-0.001	0.0010	0.1529	-0.4046	0.0274	-2.5779	38.8826	77205.9200	0.0000
WHEAT	0.000	-0.0007	0.1106	-0.0930	0.0180	0.7559	10.7049	3622.0080	0.0000

BTC	0.000	-0.0003	0.1774	-0.4973	0.0421	-1.2657	18.4209	14347.3800	0.0000
HG	-0.005	-0.0004	11.5247	-9.4751	0.5560	4.5535	273.7038	4310105.0000	0.0000
Panel B: Period of the COVID-19 health crisis (from December 02.2019 to December 31.2021)									
ISENT	4.421	0.9002	467.4623	-391.5401	112.4618	0.2510	4.7383	74.3413	0.0000
MOEX	-0.001	0.0006	0.1826	-0.4047	0.0258	-6.8251	117.3104	300957.9000	0.0000
NASD	0.126	0.2601	9.5966	-13.0032	1.7487	-0.8454	13.4825	2560.1590	0.0000
S&P500	0.079	0.1613	8.9671	-12.7657	1.5841	-1.0949	19.4064	6221.2670	0.0000
GAS	0.000	-0.0003	0.0551	-0.0697	0.0169	-0.0072	3.9013	18.4524	0.0001
OIL	-0.001	0.0017	0.1027	-0.1264	0.0235	-0.6834	6.4621	314.6111	0.0000
WHEAT	0.000	-0.0011	0.1106	-0.0930	0.0204	0.4928	8.5508	721.7394	0.0000
BTC	0.003	0.0020	0.1774	-0.4973	0.0459	-2.2593	29.0040	15819.1900	0.0000
HG	0.004	0.0000	0.4385	-0.5600	0.1230	0.1160	5.5601	150.0525	0.0000
Panel C: Russo-Ukrainian Conflict (from February 24. 2022 to May 31. 2023)									
ISENT	0.334	0.6961	13.3251	-22.6723	3.1088	-2.9912	22.7092	5833.2990	0.0000
MOEX	0.000	0.0005	0.0731	-0.0778	0.0148	-0.7973	9.9466	698.4768	0.0000
NASD	0.011	-0.0617	7.2200	-5.7020	1.8096	-0.0649	3.7302	7.5629	0.0228
S&P500	-0.004	-0.0740	5.3953	-4.4199	1.3627	-0.1025	3.9467	12.9017	0.0016
GAS	0.001	0.0019	0.0494	-0.0529	0.0165	0.0434	3.6107	5.2317	0.0731
OIL	-0.001	0.0008	0.0672	-0.0878	0.0233	-0.3496	3.5137	10.3495	0.0057
WHEAT	0.000	-0.0010	0.1050	-0.0567	0.0180	0.6982	7.0681	254.3609	0.0000
BTC	-0.001	-0.0016	0.1362	-0.1699	0.0351	-0.5151	6.9052	224.2889	0.0000
HG	0.004	0.0000	1.2983	-0.3230	0.1152	8.1247	92.6415	114120.0000	0.0000

Source: *Authors' elaboration.*

5. Empirical Results and Discussion

5.1 Wavelet Coherence

The wavelet coherence analysis enables us to differentiate between short-term and long-term co-movement dynamics between investor sentiment and the returns of various assets. By employing Monte Carlo simulations, we evaluate the significance level of the wavelet coherence. The horizontal axis denotes time intervals, while the vertical axis represents the scale. Areas highlighted in red indicate strong co-movement, whereas those in blue signify weak co-movement, illustrating the relationships across both low and high frequencies.

Furthermore, arrows pointing to the right (→) indicate that the variables are in phase, signifying a cyclical effect on each other. An upward diagonal arrow (↗) and a downward diagonal arrow (↙) denote that investor sentiment is leading, while a downward diagonal arrow (↘) and an upward diagonal arrow (↖) suggest that investor sentiment is lagging. However, arrows pointing to the left (←) signify that the variables are out of phase, reflecting an anti-cyclical effect, as outlined by Pal and Mitra (2019) and Jiang and Yoon (2020).

During the COVID-19 health crisis, Figure 2(a) in Appendix 1, we observe a significant concentration of red areas across low, medium, and high frequencies, indicating a strong correlation between Google searches related to investor sentiment and the returns of various assets, including MOEX, NASDAQ, S&P 500, Brent oil, natural gas, Bitcoin, and HelloGold. In contrast, during the Russia-Ukraine conflict of 2022, Figure 2(b) in Appendix 1, red zones are also evident at low, medium, and high frequencies for most assets, with the exception of HelloGold.

These findings can be attributed to heightened pessimism among American and Russian investors during these stressful events. This prevailing over-pessimism during both crises appears to have influenced investors worldwide, who faced increased uncertainty. Consequently, investors heightened their search behavior for information related to economic, financial, and political conditions.

This trend is further amplified by advancements in technology, such as smartphones, which facilitate mobile web browsing, enabling investors to access new information quickly and at any time. These findings align with the results reported by Arfaoui and Naoui (2022), Naeem *et al.* (2024), and Soltani and Boujelbène Abbes (2024a).

The analysis of the arrows reveals that during the health crisis, the relationship between investor sentiment and asset returns exhibits a cyclical pattern for most indices at both the 16- and 32-month scales, as well as at scales greater than 128 months. Arrows pointing to the right and upward indicate that investor sentiment is leading for the majority of these indices.

Additionally, we observe that investor sentiment is out of phase for Bitcoin, HelloGold, and wheat at the 32- and 64-month scales, while remaining a leading indicator for most other indices. This phenomenon can be attributed to the significant impact of geopolitical instability during the invasion period, which has profoundly affected investor emotions and driven volatility in market indices.

5.2 Total Volatility Spillover between Googling Investor Sentiment, Commodities, Cryptocurrencies and Stock Markets

To gain deeper insights into the spillover effects between the Googling investor sentiment (ISent) and each selected variable during both the COVID-19 pandemic and the Russia-Ukraine conflict, we apply the spillover index methodology developed by Diebold and Yilmaz (2012). Table 3 in Appendix 1 presents the estimated connectedness parameters between investor sentiment (ISent) and various assets. The off-diagonal elements specifically capture the volatility spillovers between ISent and other variables.

Additionally, the off-diagonal values within each column and row represent the contributions of investor i to and from market j. These contributions are summed to determine the directional spillovers transmitted to or received from other variables, termed "*Net transmitter*" and "*Net recipient*," respectively. The difference between the "*To*" and "*From*" values provides the "*Net directional spillovers*". During the COVID-19 pandemic, the total volatility connectedness is 25.3%, reflecting a substantial degree of interconnectedness across markets.

The first value of the last row of the connectedness matrix represents the “Net connectedness” between the Investor’s sentiment and the stock, commodity and cryptocurrency markets. This measure confirms that investor sentiment acts as the primary net transmitter of shocks, exerting greater influence on other variables than it receives. The main recipients of these shocks include S&P 500 (70.7%), Brent oil (17%), wheat (6.5%), and HelloGold (16.8%).

In contrast, during the Russia-Ukraine conflict, total volatility connectedness rises to 37.4%, signaling increased connectedness among these assets. In fact, NASDAQ emerges as the largest net transmitter of spillovers, followed by natural gas. Notably, investor sentiment shifts from being a net transmitter of volatility to a net recipient. The S&P 500 and HelloGold stand out as the two largest net receivers of spillovers during this period.

Therefore, to identify pairs that significantly transmit and receive shocks from one another, we examine the first column and row of Table 3. For instance, investor sentiment transmits the largest shocks from the NASDAQ index (4.7%), suggesting that Russian investor sentiment acts as a net transmitter of shocks originating from the NASDAQ.

In the commodity market, investor sentiment transmits 2.10% of shocks while receiving only 1.90%. Furthermore, the pairwise data reveal that Bitcoin exerts a particularly strong influence on investor sentiment, supporting the notion that the cryptocurrency market, as a virtual market, has a dominant effect on investor sentiment, whereas, investor sentiment acts as a net recipient of volatility, driven by external factors like market movements.

The Russian MOEX index is a net transmitter, highlighting the conflict's strong impact on the Russian economy. NASDAQ and S&P500 also act as net transmitters, influencing global markets. Commodities like natural gas, Brent oil, and wheat are significant drivers of investor sentiment due to their price fluctuations related to the conflict's impact on energy and food security, as announced by Diaconaşu *et al.,* (2023).

HelloGold is a net receiver of volatility, suggesting investors may be seeking safe havens during uncertainty, while Bitcoin is a net transmitter, potentially due to investors exploring alternative investment options. This analysis reveals the complex interplay of geopolitical events, asset prices, and investor sentiment during the conflict, highlighting the importance of understanding these interconnected dynamics for informed decision-making.

These findings are consistent with the work of Fang and Shao (2022), who argue that the intensification of the Russia-Ukraine conflict significantly amplifies volatility across agricultural, metal, and energy markets.

Figure 3. *Total time-varying volatility spillover index during COVID-19 pandemic and Russo-Ukrainian Conflict*

Source: *Authors' elaboration*

Figures 3(a) and 3(b) depict the dynamic total volatility spillovers between investor sentiment and other asset classes during the COVID-19 pandemic and the Russo-Ukrainian conflict.

The analysis reveals that both events significantly increased market connectedness, with the pandemic causing an initial spike in volatility spillovers in early 2020, which then gradually declined as markets adapted to the uncertainty. However, the Russo-Ukrainian conflict triggered a sharp and sustained increase in volatility spillovers, highlighting its ongoing disruption to global markets.

The conflict's impact on investor sentiment appears to be more pronounced and persistent than the pandemic's, signifying a greater level of interconnectedness and uncertainty in the market.

As Adekoya *et al.* (2022) note, the conflict has profoundly affected global financial markets and investor sentiment, while Behnassi and El-Haiba (2022) emphasize its disruptive effect on the export of wheat, corn, and other agricultural commodities, further intensifying market uncertainty.

This analysis underscores the significant influence of major events on market dynamics and the crucial role of investor sentiment in driving volatility spillovers, which is in line with the findings of Elhassan (2021), Shaikh and Huynh (2022), and Cui and Maghyereh (2023), who emphasize that financial asset volatility during the pandemic has had a substantial impact across various asset classes, including equities, bonds, currencies, and commodities.

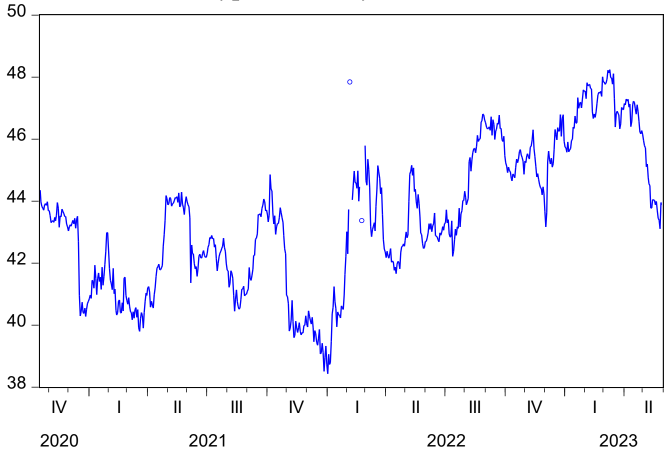
5.2 Robustness Check

To further validate our findings, we incorporate the RavenPack sentiment index (RavenPackSent) as an additional measure of investor sentiment. Additionally, we examine the effects of the COVID-19 pandemic and the Russia-Ukraine conflict on risk spillover between the RavenPack sentiment index and the stock, commodities, and cryptocurrency markets.

Using daily data from January 2020 to May 2023, we also analyze the dynamics of connectedness among these markets. Figures 4 and 5 respectively illustrate the total spillover connectedness index between RavenPack sentiment and the stock, commodity, and cryptocurrency markets. We reveal that the dynamic connectedness between RavenPack sentiment and financial markets exhibits considerable volatility, peaking at approximately 50% in early 2023.

Following this peak, it declined gradually but consistently until mid-2023, when it dropped below 42%. This decrease aligns with the broader developments of the Russia-Ukraine conflict.

Figure 4. *Dynamic of total volatility spillovers between the RavenPackSent index, the stock commodities and cryptocurrency markets*



Source: *Authors' elaboration*

Figure 5 presents the dynamic net pairwise connectedness from the RavenPack sentiment index to the stock, commodities, and cryptocurrency markets. The findings indicate that the Russian RavenPack sentiment index leads net pairwise connectedness, exerting a significant influence on the MOEX, Bitcoin, NASDAQ, and Natural Gas markets.

On the contrary, at the start of 2022, markets such as Brent Oil, HelloGold, and Wheat functioned as persistent net receivers of shocks, making them more susceptible to external influences and less attractive to investors.

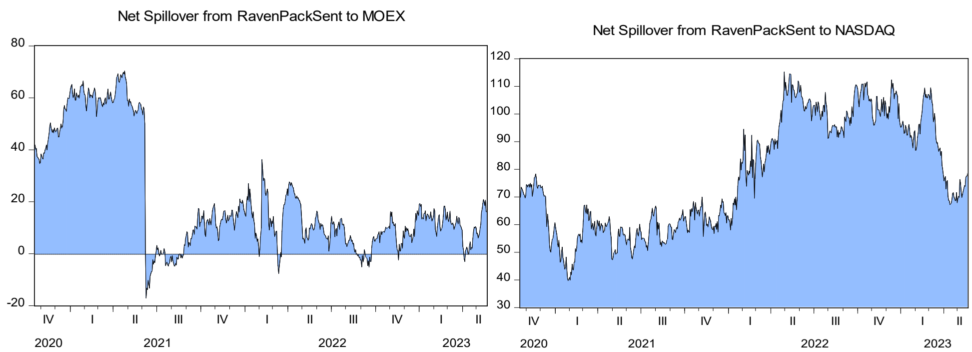
This pattern aligns with the widespread impacts of the COVID-19 pandemic and the Russia-Ukraine conflict, which intensified the connectedness and reactive behaviors within these markets. Accordingly, these results corroborate prior studies, including Soltani et al. (2024), emphasizing that investor sentiment and stock market reactions amplify during periods of heightened stress.

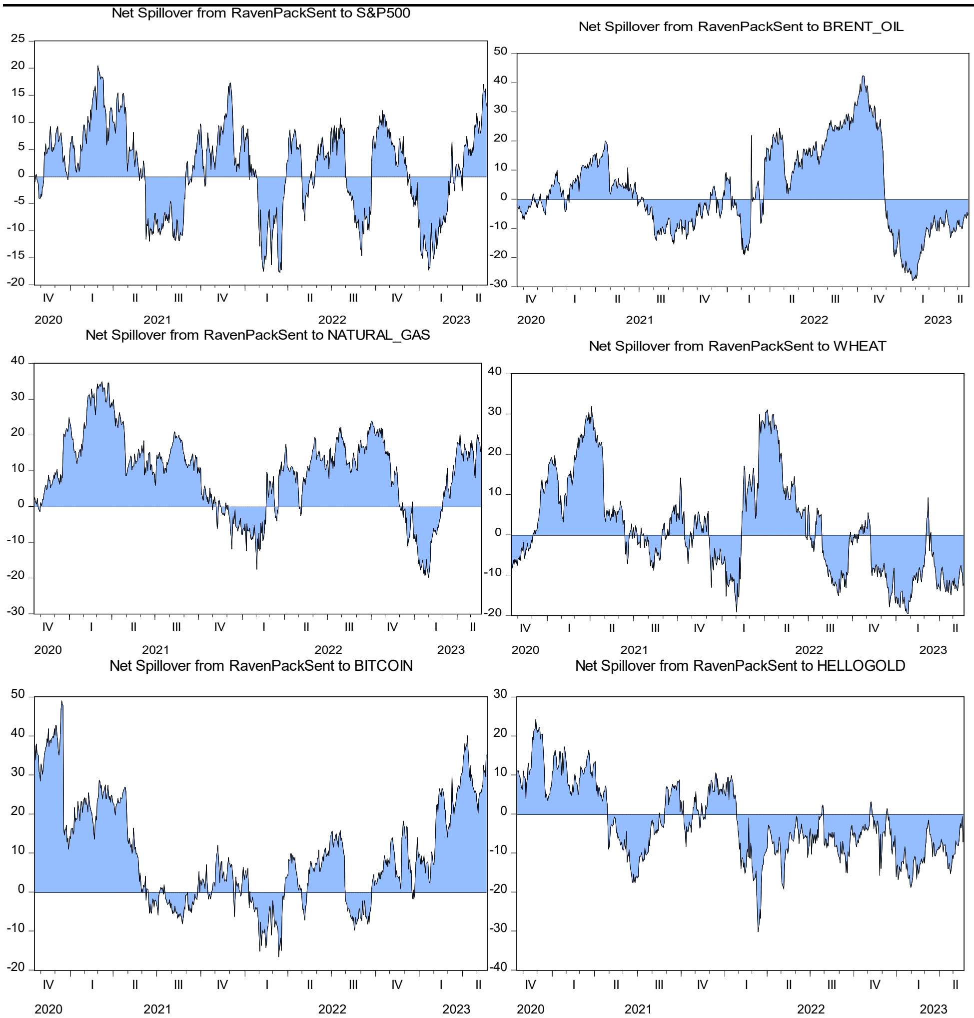
6. Conclusion and Policy Implications

This comprehensive study examines the co-movements and spillovers between investor sentiment and various market returns, particularly in the context of significant global events such as the COVID-19 pandemic and the Russia–Ukraine conflict.

We develop a measure of investor sentiment using social media and internet data, constructing a Russian Google-based investor sentiment index. Then, we rely on the wavelet coherence approach to explore the co-movements between Investor sentiment, commodities, cryptocurrency and stock markets.

Figure 5. *Net pairwise directional connectedness from the RavenPack Sentiment index to the stock, commodities and cryptocurrency market*





Source: *Authors' elaboration*

Then, the methodology of Diebold and Yilmaz (2012; 2014) was applied to construct network-associated measures. To further ensure the robustness of our findings, we incorporate the RavenPack sentiment index as an additional measure of investor sentiment, analyzing daily data spanning from January 2020 to May 2023.

The analysis of the lead–lag relationship reveals notable peaks between 2019 and 2022, suggesting that the dynamic between investor sentiment and asset returns is significantly affected by health crises and geopolitical tensions across various markets. Moreover, using the Diebold and Yilmaz spillover indexes, we reveal significant peaks in connectivity between investor sentiment and asset returns during both the COVID-19 pandemic and the Russia-Ukraine conflict.

The dynamic net pairwise spillover analysis confirms that the S&P 500, Brent oil, wheat, and HelloGold exhibit a net receiving behavior, absorbing more shocks than they transmit. Moreover, during the COVID-19 period, Russian investor sentiment emerges as a net transmitter of shocks across most assets, positioning it as a key channel for volatility spillovers.

This finding supports the notion that Russian investor sentiment, gauged via Google search trends, acts as a primary channel for shock transmission in times of market stress, as highlighted by Soltani and Boujelbene Abbes (2023) and Soltani et al. (2024), whereas, the investor sentiment (ISent) shifted from acting as a net transmitter of volatility to becoming a net recipient of it, during the Russian-Ukraine war.

These insights are valuable for fund managers seeking to adjust portfolio risk exposure by balancing assets sensitive to COVID-19 sentiment with those less affected. The interplay between volatility mechanisms and investor sentiment provides investors with a nuanced understanding of market dynamics, enabling them to optimize asset allocation within their portfolios.

Declarations :

- **Funding:** This research was conducted independently, without any external financial support.
- **Conflict of Interest:** The authors confirm that there are no conflicts of interest associated with this study.

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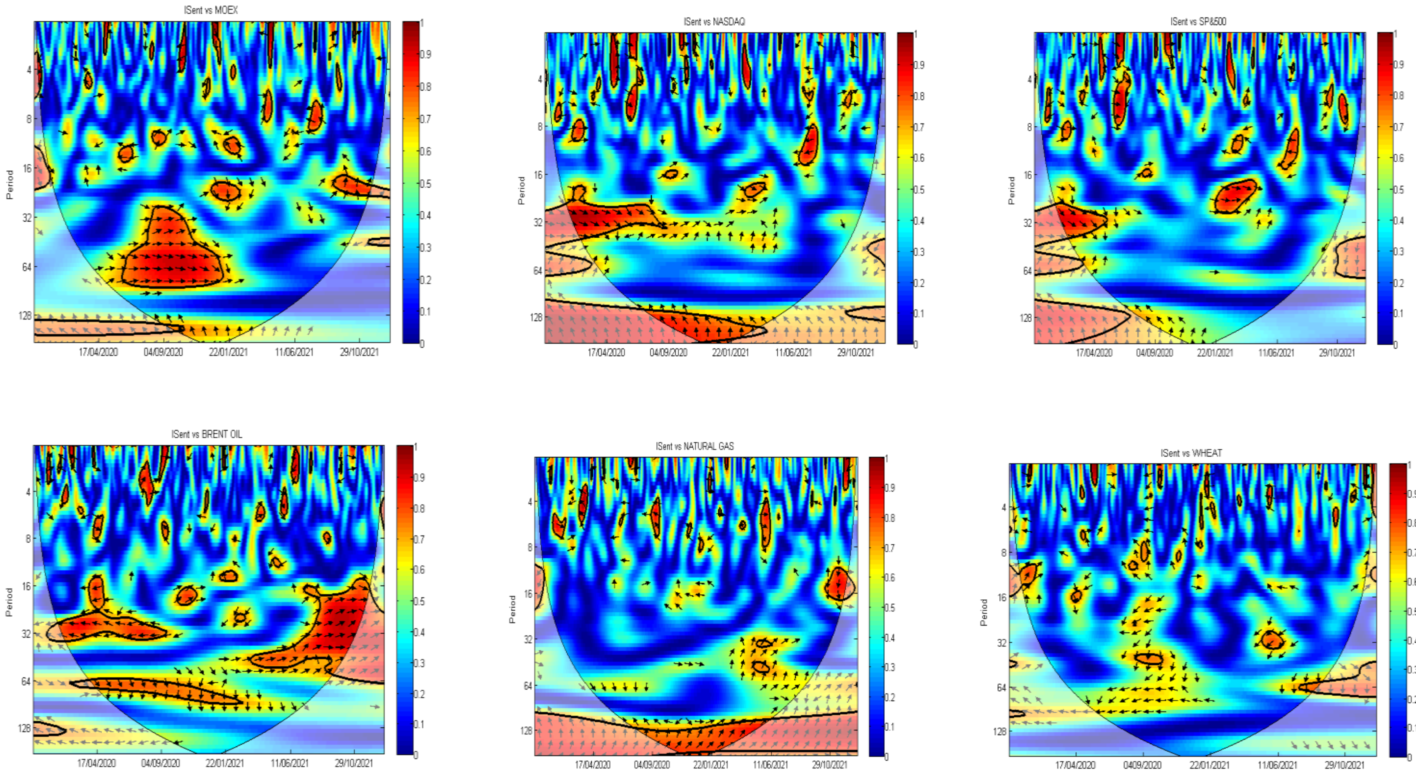
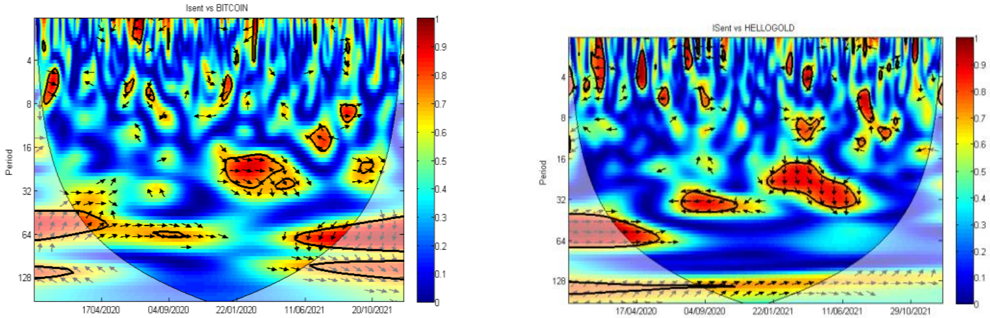
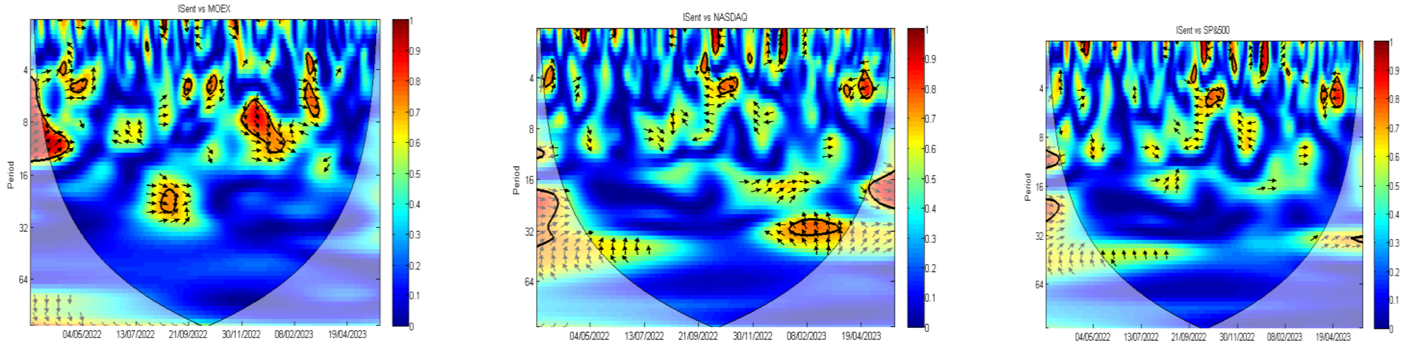
Figure 2. *Wavelet coherece analysis for investor sentiment (ISent) vs other assets*

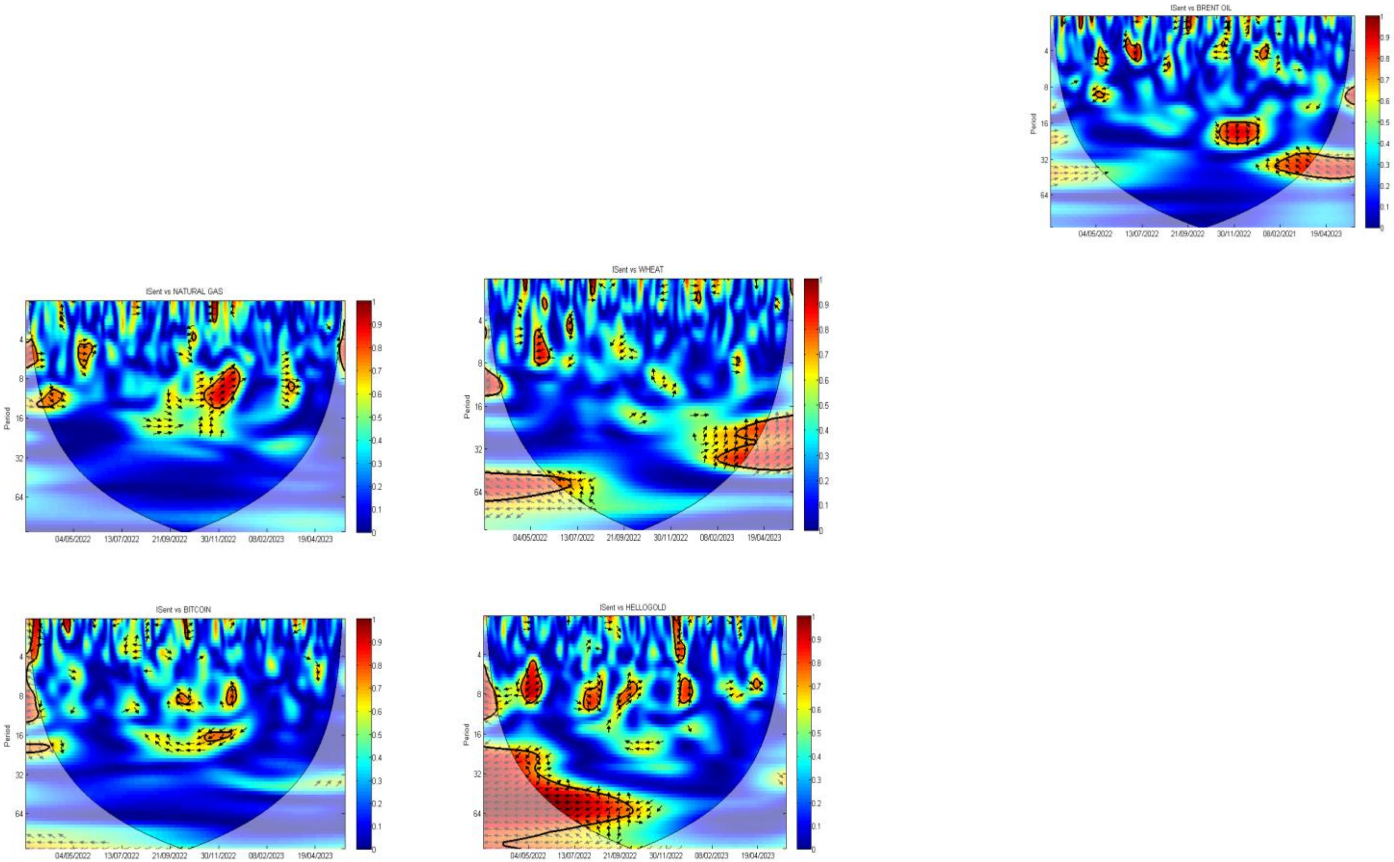
(a) COVID-19 pandemic





(b) Russo-Ukrainian conflict





Source: *Authors' Elaboration.*