VILNIUS TECH
Vilnius Gediminas Technical University

Journal of Business Economics and Management
ISSN 1611-1699 / eISSN 2029-4433
2023 Volume 24 Issue 3: 551–575
https://doi.org/10.3846/jbem.2023.19814

INVESTORS SENTIMENT AND EQUITY MARKETS DURING COVID-19 PERIOD: A QUANTILE REGRESSION APPROACH AND WAVELET ANALYSIS

Ștefan Cristian GHERGHINA [1], Seyed MEHDIAN [2], Ovidiu STOICA [3*]

[1]*Department of Finance, Bucharest University of Economic Studies, Bucharest, Romania*
[2]*School of Management, University of Michigan-Flint, USA*
[3]*Faculty of Economics and Business Administration, Alexandru Ioan Cuza University of Iasi, Romania*

Received 7 March 2023; accepted 24 July 2023

Abstract. The purpose of this study is to investigate the relationship between investor sentiment and leading equity market indices from the U.S., Europe, Asia, and globally between January 2020 and June 2022. The methodological approaches utilized are quantile regression and wavelet analysis. The results of quantile regression suggested that Google Search Volume (GSV) and Twitter-based Market Uncertainty Index (TMU) negatively influenced the equity indices at lower quantiles. The wavelet coherence analysis highlighted that, at lower frequency bands, GSV moves in sync with the S&P 500, NASDAQ Composite, Dow Jones Industrials, and FTSE 100 but not with the DAX, CAC 40, TOPIX, Nikkei 225, or MSCI. Nonetheless, when the TMU was used to measure investors' sentiment, the results revealed that the whole series was out of phase.

Keywords: investors' sentiment, equity markets, COVID-19, quantile regression, wavelet coherence, wavelet cross-correlation.

JEL Classification: C58, G15.

Introduction

The COVID-19 pandemic, which is not a financial-oriented event by nature, was the second event that significantly affected the international financial markets during the last twenty years following the 2007 financial crisis. The pandemic severely distressed the global financial markets and economies. Consequently, the public policymakers in many countries took steps to help the parties affected economically by this event. For instance, the U.S. government implemented a legislative package of about six billion dollars to assist businesses and consumers by easing loans and direct payments. The Fed also put in place various monetary policies to reduce the negative effects of the pandemic. In Europe, as another example, the

*Corresponding author. E-mail: *ostoica@uaic.ro*

European Central Bank initiated several measures, such as cutting the cost of borrowing to fight against the harmful effects of the pandemic. Additionally, the EU response addressing the economic and social impact of the COVID-19 pandemic meant an extraordinary Recovery and Resilience Facility, valued at 672.5 billion EUR. The private sector also plays a role in relieving the pains generated by the pandemic. For example, pharmaceutical companies got involved in developing coronavirus vaccines as soon as possible to provide them to the public. According to Martins and Cró (2022), the market reacted more favourably when the Pfizer-BioNTech COVID-19 vaccine's success was disclosed than it did when the efficacy of other vaccines was recognized. For the Bombay Stock Exchange, Behera et al. (2022) emphasized that immunization has a significant beneficial effect on the stock market and lessens the death rate. Piñeiro-Chousa et al. (2022) found that while market sentiment affected Moderna's returns during the pre-pandemic period, it had a negative impact on Pfizer throughout the COVID-19 period. However, Awijen et al. (2022) reported that the release of the vaccination had sparked widespread anxiety, and people lacked faith in the vaccine's ability to address the Covid-19 issue. Hence, Ho et al. (2022) proved that stocks in different Chinese industries respond to announcements in various ways.

In the academic arena, researchers took part in this challenge by studying the pandemic's psychological, social, and economic impacts on people and suggesting policies to eliminate or mitigate the consequences. Regarding the financial effects of the pandemic, there has been a newly formed remarkable literature, in which a portion has been focused on investigating the investors' reactions and sentiments in equity markets. This literature investigates the impact of investor sentiment changes on the financial markets and stock returns volatilities due to the pandemic.

We review several studies to explain our contribution to the current literature. For example, Dash and Maitra (2022) investigate the impact of generated uncertainty as a result of the pandemic on major equity markets using the wavelet coherence approach. These authors report that uncertainty due to the COVID-19 pandemic results in investors' pessimistic sentiment and high stock return volatility in global equity markets. In line with a similar topic, Huynh et al. (2021) examine the investors' sentiments in the framework of global financial markets during a one-year post-period following the outbreak of the pandemic. These authors provide evidence to indicate that investors' sentiments negatively impact the financial markets, and the sentiment may induce stock return volatility. These authors used six proxies to measure investors' sentiment and seventeen data sets from major economies. Based on the implications of the results, they suggest several policies to be employed to lessen panic and fear during the COVID-19 pandemic.

Costa et al. (2022) use the wavelet methodology and data from the Brazilian equity market to examine investors' reactions to the COVID-19 pandemic. They found the Brazilian equity market reacted intensively to the pandemic's consequences. Debata et al. (2021) examine the relationship between investor sentiment and Indian equity market returns using nonlinear causality, wavelet coherence methodology, and the 2020 data. In addition, they partition their sample semi-annually to further investigate the relationship between investors' sentiment and equity returns. Based on their findings, these authors provide evidence to suggest a significant association between investors' sentiment and stock returns during 2020; however, this correlation declined during the second part of 2020.

Karamti and Belhassine (2022) use wavelet methodology to study the connection between the COVID-19 pandemic and major financial markets in short-term and long-term investors' reactions. They report a strong relationship between COVID-19 and financial markets in the first and second stages of the pandemic. In addition, they document the dissimilarity between long-term investors' attitudes toward the market-related outcome of the pandemic and that of short-term investors. Nian et al. (2021) use a set of American and Chinese daily stock market indices and wavelet coherence to study the effect of the COVID-19 pandemic on investors' sentiments and stock market volatilities. These authors expand their investigation into three phases. Their findings suggest a significant negative correlation with proxies representing the intensity of the pandemic during the first phase. In the second phase, the authors observe a positive response from investors to the pandemic. In the third period, the positive reaction from investors, measured by their sentiment, becomes stronger as the hope for a vaccine develops in a positive sense.

Recently, Gherghina and Simionescu (2022) investigated the interdependence of fifteen equity markets worldwide, which the pandemic has impacted. These authors use the wavelet coherence methodology for their investigation and provide evidence that the stock returns in most countries demonstrate the pandemic's cyclical effects.

Existing theories postulating that people's sentiments and anxiety influence stock market investment decisions served as the rationale for our research. According to Kamstra et al. (2003), cyclic swings in asset values are brought on by seasonal depression, while pessimism and risk-aversion are more prevalent among depressed individuals. Hirshleifer et al. (2020) suggested the mood seasonality hypothesis and contended that upcoming periods of increased sentiment boost high mood beta stocks, while subsequent times of falling attitude underperform them. Chundakkadan and Nedumparambil (2022) suggested that the pandemic altered their emotional state and elevated their fear, which may have an impact on their investing choices.

The present paper's objective is to contribute to the finance literature by examining the investors' sentiments and reactions to the pandemic in equity markets during the COVID-19 period using wavelet models. This study differentiates itself from the previous literature (Gherghina & Simionescu, 2022) by expanding the data worldwide and including other relevant contributory variables into the model used for investigation. Different from earlier literature that explored single markets such as the United States (Chatterjee & French, 2022; Dey et al., 2022; Hasan, 2022; Khoury & Alshater, 2022; Subramaniam & Chakraborty, 2021; H. Wang et al., 2021), China (Gong et al., 2022; Liu et al., 2021; Mezghani et al., 2021; Soltani & Abbes, 2022; H. Wang et al., 2021; Q. Wang & Liu, 2022; Xie et al., 2021), Australia (Maia et al., 2021; Tiwari et al., 2022), Italy (Lazzini et al., 2022; Niu et al., 2021), India (Debata et al., 2021; Sing & Singh, 2023), Saudi Arabia (Wasiuzzaman, 2022), the current study explores several leading equity markets. Additionally, the period was extended to cover the "fear" period, over which the markets were widely affected, and the "hope" period, over which the pharmaceutical companies strived to develop vaccines and remedies for the disease.

Our empirical findings suggest that cyclicality exists between U.S. and U.K. markets and investor sentiment as measured by Google Search Volume (GSV). In contrast, anti-cyclicality occurs in markets in Europe, Japan, and globally. However, when investor sentiment was proxied using the Twitter-based Market Uncertainty index (TMU), the results supported an anti-phase association.

The rest of the paper is organized as follows: Section 1 reviews the literature, Section 2 explains the data and quantitative methodology, Section 3 discusses the empirical results, and the last Section provides the concluding remarks.

1. Literature review

Due to its widespread accessibility to investors, the media has the ability to alter stock valuation and alleviate informational frictions even when it does not provide truthful information (Umar et al., 2021). Even after accounting for prominent risk indicators, Fang and Peress (2009) proved that stocks short of media coverage surpass those with extensive media coverage in terms of returns. Hence, news sentiment is an effective tool that can assist in uncovering the emotions and thoughts of the media, whose opinions subsequently impact others through the headlines (Zhang & Hamori, 2021). Investor sentiment reveals the degree to which an asset's value deviates from its underlying economic fundamentals (Zhou, 2018). Nevertheless, according to Baker and Wurgler (2006), investor sentiment is viewed as an intrinsically vague notion.

The first strand of literature focused on various developed sentiment indices such as the Feverish Sentiment Index (Huynh et al., 2021), Scared COVID-19 Attitude Revealed by Eager Search (SCARES) (Hasan, 2022), New Investor Sentiment Index (NISI) (Zhou, 2018), COVID-19-induced fear sentiment index (Liu et al., 2021). For instance, Salisu and Akanni (2020) created the Global Fear Index (GFI) for the COVID-19 pandemic and showed its appropriateness as an accurate stock return forecast in the OECD and the BRICS countries. Biktimirov et al. (2021) examined media sentiment and hype at the topical level for articles printed in the Wall Street Journal during 2020 and noticed that the S&P 500 index is significantly correlated with the hype scores, which reflect both the range and strength of exposure, rather than the sentiment scores, which reflect polarity. Subramaniam and Chakraborty (2021) designed the COVID-19 fear index based on principal component analysis and revealed a detrimental effect on US market returns that tended to last cumulatively for up to five days. Based on the Shanghai and Shenzhen A-share stock market's discount of closed-end fund and turnover rate, IPO number and first-day return, the number of new investor accounts, and consumer confidence index, Niu et al. (2021) formed an investor sentiment index (ISI) and revealed its leading position throughout the crisis.

Another study focused on indices based on the Google Trends database. Smales (2021) employed Google search volume as a proxy for investor interest and supported a significant association with worldwide stock market returns. According to Costola et al. (2021), stock market activity is associated with Google Trends indexes in Italy, Germany, France, Great Britain, Spain, and the United States. By exploring 59 countries, Chundakkadan and Nedumparambil (2022) claimed that stock markets have been adversely impacted because of market participants' general pessimism brought on by attention to the novel coronavirus. Dey et al. (2022) reinforced that Google search activity has a contemporary association with abnormal stock prices and volatility, as well as prediction accuracy. Szczygielski et al. (2021) proved that heightened investor sentiment, as measured by the index of COVID-19-related internet search volumes, might lead to unexpectedly higher volatility during the pandemic. Hsu and Tang (2022) demonstrated utilizing data from 12 major stock markets that increased investor sentiment as shown by the index of COVID-19-related internet search volumes may result in unanticipated higher volatility during the pandemic. As well, H. Wang et al. (2021) reinforced that the correlation between investor attention and realized and fundamental volatility is positive. However, Cevik et al. (2022) proved that higher levels of optimistic investor sentiment lead stock returns to rise, whereas lower levels of pessimistic investor sentiment drive stock returns to fall. By using Google-based sentiment, Sing and Singh (2023) reinforced that in the first wave of the pandemic, investors' fear diminishes returns, but in the second stage, a shift in attitude increases the predicted return.

Further, examining microblogging platforms like Twitter can be significant for figuring out what individuals are thinking and feeling (Sarirete, 2022). Hence, Twitter sentiment analysis exhibited another area of research. In the early stages of the COVID-19 outbreak, Lazzini et al. (2022) found a significant Granger causality relationship between tweets on a given day and the FTSE MIB closing price. For the Australian stock market, Maia et al. (2021) proved that when analysing market returns and estimating their volatility, a sentiment reflected in topic-related Tweets exerts a crucial role. Based on a sample covering 2000 firms listed on the NASDAQ and daily cumulative Twitter postings on COVID-19, Guan et al. (2022) revealed that the majority of digitally evolved industries are resilient to adverse market sentiments.

Investor mood and various sectors are also the focus of another branch of literature. By examining the spillovers between Twitter uncertainty indexes and ten US sectors, Khoury and Alshater (2022) showed that COVID-19 had a multifold and divergent effect on the examined sectors with a variety of reactions. An event research approach for medical portfolios was taken into consideration by Sun et al. (2021) who noticed that while coronavirus-related news had a negative impact on investor mood in Chinese stock markets, it had a favourable effect on investor sentiment in other markets. Tiwari et al. (2022) examined the constituents of Australia's Overall Consumer Sentiments Index, along with its monthly indexes, and found a substantial association between sentiment and industry stock returns when the market is at steady levels, but this link weakens when consumer perceptions pass through the extreme pessimistic and optimistic periods. Mezghani et al. (2021) found a bidirectional causal link between the Google Investor Sentiment Index and the five sector indices of the Shanghai Stock Exchange, covering the energy, medical and health, utility, travel and leisure, and banking industries, suggesting that both positive and negative financial market returns may have an impact on sentiment. Based on eight measures – turnover rate, trading volume, price-earnings ratio, price/book value ratio, new high-new low index, rate of change, relative strength index and closed-end fund discount – Xie et al., (2021) developed an investor sentiment index and documented its positive impact on Chinese stock market volatility.

Important information concerning shifts in market mood may also be revealed by fluctuations in trade volume. For instance, Ortmann et al. (2020) highlighted that as the COVID-19 outbreak spreads, investors increase their trading activity. In the case of the Chinese stock market, Q. Wang and Liu (2022) proved that buying volume is positively associated with stock prices. However, for the Saudi stock market, Wasiuzzaman (2022) reported that during the pandemic period, trading volume (sentiment) had a noticeably stronger impact on the sectors that witnessed elevated volatility, whereas the impact was insignificant and lower for the indices that registered reduced volatility. Soltani and Abbes (2022) confirmed that the advance-decline ratio, the highest minus and the lowest trading price of the Shanghai stock index, the trading volume, and the relative strength index definitely expose the investor's attitude.

A summary of earlier studies on the effects of investor sentiments and feelings on equity market behaviour during the COVID-19 period is provided in Table 1.

Table 1. Brief review of prior literature on investor sentiments and stock markets during the COVID-19 pandemic

Author(s)	Period	Variables	Empirical methods	Econometric Findings
Chatterjee and French (2022)	January 1, 2011 – August 31, 2020	Twitter-based market uncertainty index (TMU), S&P500 returns, S&P500 index liquidity, VIX	Bayesian vector auto-regression	In the midst of the pandemic, tweets' unpredictability began to provide insightful data on US equities markets
Gong et al. (2022)	February 2003 – February 2021	9 extant market-level investor sentiment indices in the Chinese market, Shanghai Stock Exchange Composite Index	Partial least square	The New Investor Sentiment Index (NISI) can greatly enhance the forecast of stock realized volatility
Hasan (2022)	May 1, 2020 – July 30, 2021	Daily newspaper-based Infectious Disease Equity Market Volatility (EMVID) index, Twitter-based Economic Uncertainty (TEU), news based Economic Policy Uncertainty (EPU), VIX, S&P500 index	Markov switching	Reduced stock market return in lag one is linked to a higher SCARES index
Huynh et al. (2021)	January 1, 2020 – February 3, 2022	RavenPack indices: the panic index, the media hype, the fake news, the media coverage, the Infodemic measure, the sentiment index	Time-varying parameter-vector auto-regression (TVP-VAR)	The stock volatility (return) at the onset of COVID-19 is predicted positively (adversely) by investor sentiment
Liu et al. (2021)	January 1, 2017 – March 31, 2020	COVID-19-induced fear sentiment index, market returns of Shanghai A shares	GARCH with skewness, Granger causality test	Fear-based emotion drives the Chinese stock market meltdown worse
Umar and Gubareva (2021)	January 2022 – June 2020	RavenPack Media Coverage Index, Dow Jones (DJ) Islamic equity indices	Squared wavelet coherence, wavelet coherence phase difference	Overall, there is medium to high coherence between the MCI and the various DJ Islamic equity indices
Yuan et al. (2022)	January 1, 2019 – March 27, 2022	Investor attention (country attention, local attention, and global attention), investor sentiment, investor fear, major emerging and developed markets from America, Asia, and Europe	Regression analysis	The pandemic-driven financial contagion is significantly and adversely related with investor attention, investment sentiment, and investor fear

Following the prior literature, we hypothesize that sentiment and behaviour of investors are impacted by fear due to the violent manifestation of the COVID-19 pandemic.

2. Empirical strategy

2.1. Data and variables

Our dataset includes daily returns sourced from Refinitiv Datastream for leading equity markets such as the U.S. (S&P 500, NASDAQ Composite, Dow Jones Industrials), the U.K. (FTSE 100), Germany (DAX Performance), France (CAC 40), Japan (TOPIX, Nikkei 225 Stock Average), and a global equity index (MSCI World U.S. Dollar), over January 1, 2020 – June 1, 2022, as reported in Table 2. Consistent with Szczygielski et al. (2021); H. Wang et al. (2021), we use the Google Search Volume Index towards investor sentiment. Google Search Volume (GSV) obtained from Google Trends via the R package "gtrendsR" is regarded as a proxy for investor sentiment, with the emphasis on web searches for the keyword "coronavirus" like Costola et al. (2021); Dey et al. (2022); Hsu and Tang (2022); Mezghani et al. (2021); Sing and Singh (2023); Smales (2021), in the category "Finance" similar Yuan et al. (2022) in each selected market and worldwide. We employ investor sentiment because, compared to other metrics such as investor trading behaviour, it typically plays a more significant role in explaining stock market outcomes (Ryu et al., 2017). Further, there are several studies suggesting the Twitter-based Market Uncertainty index (TMU) is helpful in forecasting market volatility during the COVID-19 pandemic. For instance, in line with Chatterjee and French (2022) and Behera and Rath (2022), we employ the TMU retrieved from the Economic Policy Uncertainty website as an alternative measure for investor sentiment. TMU indices include all tweets sent on Twitter that contain keywords related to "uncertainty", as well as "equity markets". TMU-ENG encompasses the total number of daily English-language tweets, TMU-USA reflects the number of tweets that emerged by U.S. users, and TMU-WGT is a weighted index.

Table 2. Variables definitions

Abbreviations	Description	Source
Variables towards leading equity markets		
SP500	Daily returns of Standard and Poor's 500 Composite	Refinitiv Eikon Datastream
NASDAQ	Daily returns of NASDAQ Composite	Refinitiv Eikon Datastream
DJI	Daily returns of Dow Jones Industrials	Refinitiv Eikon Datastream
FTSE100	Daily returns of FTSE 100	Refinitiv Eikon Datastream
DAX	Daily returns of DAX Performance	Refinitiv Eikon Datastream
CAC40	Daily returns of France CAC 40	Refinitiv Eikon Datastream
TOPIX	Daily returns of TOPIX	Refinitiv Eikon Datastream
NIKKEI225	Daily returns of Nikkei 225 Stock Average	Refinitiv Eikon Datastream
MSCIW	Daily returns of MSCI World United States Dollar	Refinitiv Eikon Datastream

End of Table 2

Abbreviations	Description	Source
Variables towards investor sentiment		
Sentiment indexes based on Google searches		
GSV_US	Google search volume in the United States	Google Trends
GSV_GB	Google search volume in the United Kingdom	Google Trends
GSV_DE	Google search volume in Germany	Google Trends
GSV_FR	Google search volume in France	Google Trends
GSV_JP	Google search volume in Japan	Google Trends
GSV_World	Google search volume worldwide	Google Trends
Twitter-based Uncertainty Indices		
TMU_ENG	Twitter-based Market Uncertainty index based on all English tweets	Economic Policy Uncertainty website
TMU_USA	Twitter-based Market Uncertainty index or the United States	Economic Policy Uncertainty website
TMU_WGT	Twitter-based Market Uncertainty weighted index	Economic Policy Uncertainty website

2.2. Quantitative methods

The main advantages of the methodologies used in this paper are twofold. First, the non-parametric nature of the wavelet analysis and its ability to operate in both the time and frequency domains. Second, quantile regression provides the possibility of estimating the whole conditional distribution of the independent variable while no parametric distribution is presumed on the dataset.

In line with Chakraborty and Subramaniam (2020); Khoury and Alshater (2022), the quantile regression approach of Koenker and Gilbert Bassett (1978) is employed in order to examine the impact of each sentiment measure on equity markets' returns. Cevik et al. (2022) argued the need for quantile estimation because the association between investor mood and equity markets may vary throughout various return and volatility circumstances. Also, Sing and Singh (2023) claimed the occurrence of an asymmetric effect in investors' attitudes with reduced (negative) expected return. In this regard, Swamy et al. (2019) emphasized that the connection between the dependent variable and the explanatory measures can be estimated at any selected point in the dependent variable's conditional distribution using the quantile regression method as follows:

$$Q_\tau\left(Return_t, Sentiment_t\right) = \alpha_t\left(\tau\right) + \beta Sentiment_t + e_t, \tag{1}$$

where $Return_t$ denotes daily returns. β highlights the association between daily returns and investor sentiment during the τth quantile.

The wavelet method is employed to investigate the co-movements of stock market returns and investor sentiment as in Debata et al. (2021); Karamti and Belhassine (2022); Niu et al. (2021); Soltani and Abbes (2022); Umar and Gubareva (2021). The continuous wavelet transform of a particular time series $x(t) \in L^2(\mathbb{R})$ in relation to the mother wavelet $\psi(t)$ is described as an inner product of $x(t)$ with the family $\psi_{u,s}(t)$ of wavelet daughters:

$$W_x(u, s) = x(t),\ \psi_{u,s}(t) = \int_{-\infty}^{+\infty} x(t)\psi_{u,s}^{*}(t)dt, \quad (2)$$

where $L^2(\mathbb{R})$ denotes the Hilbert space of square integrable one-dimensional functions, $*$ signifies a complex conjugation, and $\psi_{u,s}(t)$ is derived from $\psi(t)$ during the decomposition:

$$\psi_{u,s}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-u}{s}\right),\ u,s \in \mathbb{R},\ s \neq 0, \quad (3)$$

where u is the translation parameter that controls the wavelet's location in time, s is the scale parameter that determines the wavelet's length, and $\frac{1}{\sqrt{|s|}}$ is the normalization factor, ensuring that the unit variance of the wavelet satisfies $\psi_{u,s}(t)^2 = 1$.

The Morlet mother wavelet introduced by Goupillaud et al. (1984) is utilized, which is defined as:

$$\psi(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{-\frac{t^2}{2}}, \quad (4)$$

where $\pi^{-\frac{1}{4}}$ ensures the unity energy of Morlet ($\left(\int_{-\infty}^{+\infty} \psi^2(t)dt = 0\right)$, $i = \sqrt{-1}$ is an imaginary number, ω_0 is the dimensionless frequency, and t is the dimensionless time.

Following Torrence and Compo (1998), the cross wavelet transform of two time-series $x(t)$ and $y(t)$ with the continuous wavelet transforms $W_x(u, s)$ and $W_y(u, s)$ is defined as follows:

$$W_{xy}(u, s) = W_x(u, s)W_y^{*}(u,s). \quad (5)$$

Further, wavelet coherence can be estimated as follows (Torrence & Webster, 1999):

$$R_{xy}^2(u,s) = \frac{\left|S\left(s^{-1}W_{xy}(u,s)\right)\right|^2}{S\left(s^{-1}\left|W_x(u,s)\right|^2\right)S\left(s^{-1}\left|W_y(u,s)\right|^2\right)}, \quad (6)$$

where S expresses a smoothing operator in both time and scale. The wavelet coherency $R_{xy}^2(u,s) \in [0,1]$, which signifies a weaker to higher co-movement.

The wavelet coherence phase differences defined below show the lead-lag relationships between the two-time series:

$$\Phi_{xy}(u,s) = \tan^{-1}\left(\frac{\Im\left\{S\left(s^{-1}W_{xy}(u,s)\right)\right\}}{\Re\left\{S\left(s^{-1}W_{xy}(u,s)\right)\right\}}\right),\ \varphi_{xy} \in [-\pi, \pi], \quad (7)$$

where $\Im$ and $\Re$ are the imaginary and real parts of smoothed cross-wavelet transform, respectively.

Specifically, the following cases can be distinguished:

– if $\Phi_{xy} = 0$, the two series are in-phase (positive co-movement), and no lead/lag association occurs. The arrow will be pointing to the right $(\rightarrow)$;

– if $\Phi_{xy} \in \left(0, \frac{\pi}{2}\right)$, the two series are in-phase (positive co-movement) with $x(t)$ leading $y(t)$. The arrow will be pointing up and right $(\nearrow)$;

– if $\Phi_{xy} \in \left(\frac{\pi}{2}, \pi\right)$, the two series are out of phase (negative co-movement) with $y(t)$ leading $x(t)$. The arrow will be pointing up and left $(\nwarrow)$;

– if $\Phi_{xy} \in \left(-\frac{\pi}{2}, 0\right)$, the two series are in-phase (positive co-movement) with $y(t)$ leading $x(t)$. The arrow will be pointing down and right $(\searrow)$;

– if $\Phi_{xy} \in \left(-\pi, -\frac{\pi}{2}\right)$, the two series are out of phase (negative co-movement) with $x(t)$ leading $y(t)$. The arrow will be pointing down and left $(\swarrow)$.

3. Empirical results

3.1. Summary statistics

Figure 1 depicts the changes in equity index returns, GSV, and TMU for each market during the pandemic period. The returns series exhibits a similar pattern, with volatility clustering.

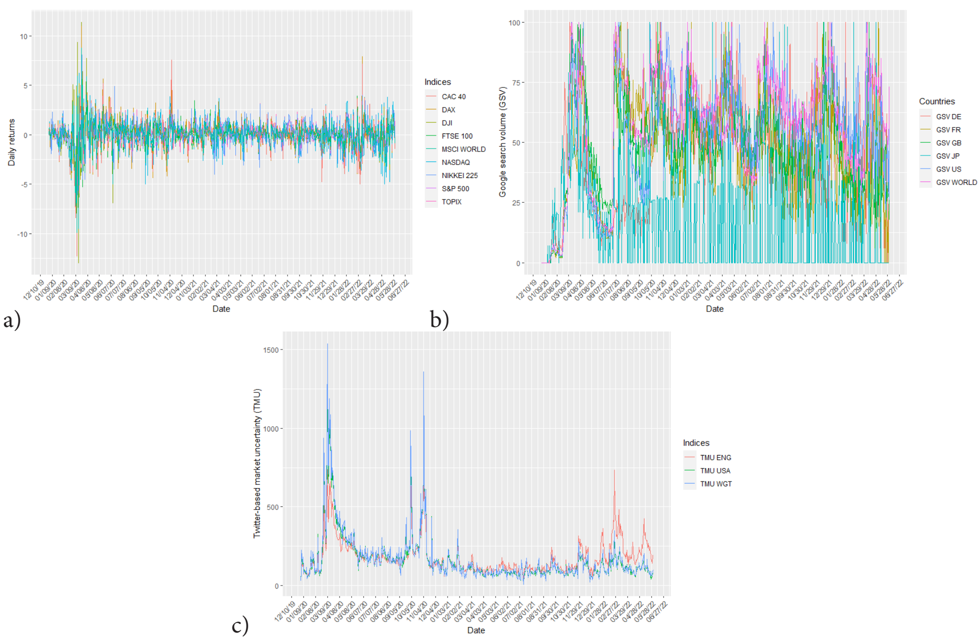


Figure 1. Plots of selected time series: a – Equity returns; b – Google Search Volume; c – Twitter-based Market Uncertainty

For example, the European indices fell sharply on March 12, 2020, while the U.S. indices plunged dramatically on March 16, 2020. GSV follows a similar trajectory over time and selected markets, apart from Japan, which has the highest popularity for the term "coronavirus", with a value of 100, while being recorded 12 times in France, ten times in the U.S. and worldwide, and nine times in the remaining markets. TMU-USA and TMU-WGT rose sharply on March 9, 2020, while all three TMU indices soared swiftly on November 4, 2020.

The summary statistics for the selected data are shown in Table 3. All return series have a positive mean value. In terms of skewness, leading equity markets are left-skewed, except the Japanese market. In terms of kurtosis value, all series are positive, and all data are leptokurtic.

Table 3. Summary statistics

Variables	Mean	Min	Max	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob	Obs
SP500	0.050586	–11.98	9.38	1.592801	–0.596896	15.32652	4032.304	0	631
NAS-DAQ	0.062662	–12.32	9.35	1.809036	–0.573618	9.802295	1251.151	0	631
DJI	0.035293	–12.93	11.37	1.623868	–0.562258	19.16719	6905.308	0	631
FTSE100	0.009049	–10.87	9.05	1.361618	–0.874829	14.56033	3594.135	0	631
DAX	0.025277	–12.24	10.98	1.595677	–0.402423	14.22724	3331.122	0	631
CAC40	0.023788	–12.28	8.39	1.575282	–0.779444	13.23697	2819.143	0	631
TOPIX	0.025927	–5.61	6.87	1.199089	0.033456	6.21289	271.5176	0	631
NIK-KEI225	0.032964	–6.08	8.04	1.374184	0.222347	6.937155	412.7513	0	631
MSCIW	0.034734	–9.915	8.77	1.353545	–0.952859	16.34897	4780.525	0	631
GSV_US	53.41997	0	100	24.11894	–0.41956	2.636903	21.97888	0.000017	631
GSV_GB	48.5309	0	100	21.14302	–0.091535	3.184008	1.771371	0.412431	631
GSV_DE	42.9683	0	100	23.99588	0.249865	2.359001	17.36851	0.000169	631
GSV_FR	45.05705	0	100	23.50022	0.065634	2.60581	4.538391	0.103395	631
GSV_JP	18.40729	0	100	24.60644	1.336289	4.283462	231.1024	0	631
GSV_WORLD	57.69255	0	100	24.22731	–0.689087	2.863503	50.42732	0	631
TMU_ENG	180.8556	23.44252	1173.795	110.7751	2.869426	17.24092	6197.954	0	631
TMU_USA	164.5866	10.70382	1303.19	150.2761	3.69071	21.08283	10029.59	0	631
TMU_WGT	172.5782	10.00646	1536.019	161.9601	3.814238	22.82361	11861.99	0	631

The correlations among the included variables are plotted in Figure 2. The overall correlations between Twitter-based uncertainty indices and returns of the top equity markets are negative, but low. With reference to sentiment indexes based on Google searches, the correlations with return series are mixed but also reduced.

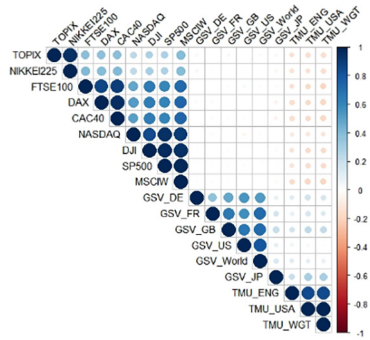


Figure 2. Correlations among selected variables

3.2. Results of quantile regressions

The coefficient estimates from quantile regressions when considering GSV are exhibited in Table 4. The outcomes reveal that at lower quantiles, GSV negatively influences the selected equity indices, but the results are slightly statistically significant only in the case of NASDAQ, TOPIX, NIKKEI225, and MSCIW. This finding is in line with Da et al. (2015), which revealed that the first three days are when FEARS have the greatest impact on asset prices. At higher quantiles, merely GSV in the United Kingdom positively influences the returns of FTSE100. The findings confirm Ryu et al. (2017), which found for the Korean market that high sentiment is associated with greater stock performance. Also, for the Chinese stock market, Chi et al. (2012) found that stocks with high sentiment generate greater returns than those with low sentiment.

Table 4. Results of quantile estimations towards the impact of Google Search Volume on equity markets' returns

	SP500		NASDAQ		DJI	
τ	C	GSV_US	C	GSV_US	C	GSV_US
0.1	−1.661111*** (−3.528063)	0.002222 (0.315911)	−1.774516*** (−4.405332)	−0.005161 (−0.829908)	−1.800000*** (−4.618963)	0.006667 (1.167096)
0.2	−0.517778*** (−3.427718)	−0.004222 (−1.596939)	−0.6475** (−2.321303)	−0.0075 (−1.478716)	−0.573651*** (−3.98543)	−0.001587 (−0.669767)
0.3	−0.28** (−2.170038)	−0.001264 (−0.561355)	−0.094681 (−0.670667)	−0.005745** (−2.281151)	−0.307619** (−2.490217)	−0.000952 (−0.460739)
0.4	0.034211 (0.304991)	−0.002105 (−1.081325)	0.112381 (0.831387)	−0.003095 (−1.351048)	0.000000 (0.000000)	−0.002 (−1.064999)
0.5	0.19* (1.658847)	−0.002069 (−1.049206)	0.334** (2.528863)	−0.004* (−1.761146)	0.108 (0.971121)	−0.001 (−0.517596)
0.6	0.428889*** (3.672689)	−0.002222 (−1.101642)	0.73*** (4.983549)	−0.005* (−1.954141)	0.31*** (2.911486)	−0.000909 (−0.491454)
0.7	0.67*** (5.08492)	−0.001389 (−0.616297)	0.930526*** (6.448339)	−0.003158 (−1.207767)	0.599365*** (4.477008)	−0.000794 (−0.363074)

End of Table 4

0.8	1.133529*** (6.691855)	−0.003235 (−1.17404)	1.318571*** (8.059834)	−0.002381 (−0.818632)	1.16*** (5.174213)	−0.005161 (−1.584949)
0.9	1.635849*** (8.530766)	−0.003019 (−0.981367)	1.890571*** (7.23863)	−0.000857 (−0.191294)	1.771351*** (7.368099)	−0.005946 (−1.282489)
	FTSE100		DAX		CAC40	
τ	C	GSV_GB	C	GSV_DE	C	GSV_FR
0.1	−1.056667*** (−3.288456)	−0.006667 (−1.132769)	−1.422642*** (−5.356245)	−0.001698 (−0.276175)	−1.253146*** (−5.697072)	−0.005169 (−1.277306)
0.2	−0.570714*** (−4.312858)	−0.002321 (−0.821855)	−0.840189*** (−6.570342)	0.003019 (1.192859)	−0.642131*** (−4.347924)	−0.003934 (−1.22387)
0.3	−0.336774*** (−2.729344)	−0.000645 (−0.254511)	−0.464328*** (−4.368293)	0.001791 (0.889185)	−0.304444*** (−2.842567)	−0.001587 (−0.697673)
0.4	−0.14 (−1.214287)	0.000857 (0.353409)	−0.155833 (−1.548125)	0.000833 (0.434734)	−0.094286 (−0.8993)	−0.000357 (−0.16559)
0.5	0.01 (0.091277)	0.001091 (0.473692)	−0.019114 (−0.179253)	0.001139 (0.558881)	0.063333 (0.593425)	0.000476 (0.227708)
0.6	0.06 (0.600565)	0.003947* (1.913765)	0.25** (2.06801)	−6.51E−19 (−2.86E−16)	0.363488*** (3.124822)	−0.000698 (−0.320715)
0.7	0.283377*** (2.793292)	0.004156** (1.982003)	0.747222*** (5.537595)	−0.003889 (−1.559458)	0.738947*** (6.024665)	−0.003158 (−1.398675)
0.8	0.438571*** (3.328449)	0.007857*** (2.700412)	1.040233*** (8.331889)	−0.002791 (−1.009186)	1.02*** (7.630805)	−0.003043 (−1.11469)
0.9	0.85*** (5.291468)	0.011143*** (2.837944)	1.456066*** (8.355316)	0.001639 (0.424677)	1.431579*** (7.663198)	0.001053 (0.249367)
	TOPIX		NIKKEI225		MSCIW	
τ	C	GSV_JP	C	GSV_JP	C	GSV_WORLD
0.1	−1.32*** (−10.57867)	−0.005926 (−1.557425)	−1.58*** (−8.637147)	−0.001587 (−0.367881)	−1.456*** (−4.663857)	0.004 (0.864716)
0.2	−0.68*** (−7.75653)	−0.005455* (−1.673043)	−0.72*** (−8.023467)	−0.007273* (−1.891328)	−0.441773*** (−3.169088)	−0.003742* (−1.700267)
0.3	−0.33*** (−5.460295)	−0.0058** (−2.386538)	−0.38*** (−5.633344)	−0.005556** (−2.075951)	−0.1655* (−1.778301)	−0.00225 (−1.340623)
0.4	−0.05 (−0.977998)	−0.005313*** (−2.62952)	−0.06 (−1.073665)	−0.006*** (−2.847411)	−0.043388 (−0.443567)	−0.000816 (−0.494144)
0.5	0.03 (0.598526)	−0.002371 (−1.346513)	0.03 (0.538276)	−0.001837 (−1.01097)	0.035241 (0.362466)	0.001127 (0.702484)
0.6	0.263158*** (5.092342)	−0.002632 (−1.362996)	0.27*** (4.764448)	−0.0027 (−1.37578)	0.3422*** (3.263438)	−0.00128 (−0.75442)
0.7	0.49*** (7.160714)	0.000375 (0.122063)	0.58*** (7.790118)	−0.002059 (−0.661067)	0.458*** (4.005019)	0.0005 (0.276575)
0.8	0.88*** (9.448105)	0.002462 (0.650083)	0.96*** (9.591279)	−0.0006 (−0.188809)	0.761333*** (5.578686)	0.000667 (0.309221)
0.9	1.46*** (12.1826)	0.002581 (0.521393)	1.67*** (12.66313)	0.002941 (0.557873)	1.360882*** (4.656862)	−0.001376 (−0.309004)

Notes: ***, ** and * represent significant level at 1%, 5% and 10% respectively.

Table 5 exhibits the outcomes of quantile regression models when Twitter-based uncertainty indices are considered as proxies for investor sentiment. The findings provide support that TMU has a negative impact on equities returns at lower quantiles, being confirmed Chakraborty and Subramaniam (2020) since these investors are more likely to react significantly to changes in sentiment because of their high reactivity. At higher quantiles, the whole sentiment measures positively influence equity returns. Hence, the asymmetric effects are confirmed, in line with Sing and Singh (2023), Cevik et al. (2022).

Table 5. Results of quantile estimations towards the impact of Twitter-based Uncertainty on equity markets' returns

	SP500		NASDAQ		DJI	
τ	C	TMU_USA	C	TMU_USA	C	TMU_USA
0.1	−0.103821 (−1.000667)	−0.008372*** (−12.74768)	−0.630376*** (−3.619875)	−0.007832*** (−9.438287)	0.022189 (0.28966)	−0.008911*** (−16.22453)
0.2	0.218932*** (3.040619)	−0.006956*** (−12.66405)	−0.075166 (−0.63878)	−0.006297*** (−7.863515)	0.211295** (2.170856)	−0.00711*** (−8.11003)
0.3	0.268889** (1.992139)	−0.005289*** (−4.191311)	0.242415*** (2.747264)	−0.005647*** (−8.649315)	0.272109* (1.958907)	−0.005352*** (−4.029408)
0.4	0.198462 (0.965964)	−0.002781 (−1.421054)	0.186897 (1.401356)	−0.002666** (−2.25495)	0.159528 (0.842554)	−0.002453 (−1.396683)
0.5	0.194981** (2.063707)	−0.000947 (−1.159943)	0.14202 (1.164293)	−0.000144 (−0.149798)	0.11517 (1.099266)	−0.000663 (−0.731043)
0.6	0.111307 (1.619788)	0.00162*** (3.08956)	0.235913 (1.312914)	0.001585 (1.058784)	0.156269** (2.196797)	0.000937* (1.670463)
0.7	0.302032*** (3.408049)	0.002133*** (3.3883)	0.450339*** (4.833151)	0.002636*** (4.995716)	0.241462*** (2.789974)	0.002211*** (3.354055)
0.8	0.44942 (1.617227)	0.003882 (1.61315)	0.773525*** (6.452545)	0.002792*** (3.669292)	0.340612** (2.311357)	0.004277*** (3.342991)
0.9	0.375208** (2.348968)	0.007511*** (5.418678)	0.688565*** (3.3981)	0.008227*** (4.752804)	0.402767*** (3.779491)	0.007122*** (9.379647)
	FTSE100		DAX		CAC40	
τ	C	TMU_ENG	C	TMU_WGT	C	TMU_WGT
0.1	0.303932 (1.297354)	−0.009858*** (−5.110686)	−0.313817 (−0.651768)	−0.007925* (−1.898797)	−0.300604 (−1.577641)	−0.007261*** (−5.059462)
0.2	0.258383** (2.422581)	−0.006292*** (−8.279874)	0.040048 (0.147252)	−0.005852** (−2.442414)	−0.022811 (−0.31883)	−0.005447*** (−17.5846)
0.3	0.253126 (1.442326)	−0.004165*** (−3.188579)	0.20752** (2.004795)	−0.004621*** (−5.197018)	0.236026* (1.927495)	−0.004954*** (−5.06524)
0.4	0.08123 (0.534638)	−0.001332 (−1.200235)	0.121235 (0.805834)	−0.002161* (−1.661116)	0.167743 (0.915573)	−0.002368 (−1.486752)
0.5	0.050000 (0.504304)	0.000000 (0.000000)	0.105894 (1.220981)	−0.000564 (−0.871718)	0.168337 (1.517173)	−0.00059 (−0.676133)
0.6	0.20093** (2.278267)	0.000286 (0.486888)	0.186007* (1.698903)	0.000573 (0.64031)	0.254338* (1.948552)	0.000529 (0.499255)

End of Table 5

0.7	0.246686*** (3.2952)	0.001367*** (2.778036)	0.323451*** (2.858741)	0.001687* (1.854796)	0.389274*** (5.938366)	0.001495*** (3.787653)
0.8	0.332774*** (2.628427)	0.003235*** (3.860536)	0.616857*** (5.907618)	0.002361*** (3.736349)	0.544898*** (4.446337)	0.002647*** (2.757163)
0.9	0.388197 (1.514448)	0.005407*** (2.929367)	0.983281*** (5.344195)	0.003627*** (2.791541)	0.63175*** (3.616058)	0.005845*** (4.055221)
	TOPIX		NIKKEI225		MSCIW	
τ	C	TMU_WGT	C	TMU_WGT	C	TMU_WGT
0.1	−0.867677*** (−9.080117)	−0.003087*** (−12.59289)	−1.028374*** (−6.869273)	−0.003029*** (−6.376208)	0.094331 (1.295638)	−0.008433*** (−16.7579)
0.2	−0.301916*** (−3.995102)	−0.003225*** (−10.32131)	−0.388666*** (−4.873999)	−0.003048*** (−8.580248)	0.053263 (0.916917)	−0.00488*** (−14.17517)
0.3	−0.074342 (−0.49511)	−0.002572** (−2.242017)	−0.100928 (−1.039309)	−0.002534*** (−4.107938)	0.250151** (2.311537)	−0.004345*** (−4.646298)
0.4	0.134654 (1.525628)	−0.00196*** (−3.331128)	0.096987 (1.005415)	−0.002064*** (−3.286312)	0.199564 (1.628491)	−0.002388** (−2.288015)
0.5	0.104362 (0.978769)	−0.000707 (−0.969278)	0.149635 (1.472132)	−0.000832 (−1.311101)	0.197241** (2.008164)	−0.000952 (−1.155096)
0.6	0.252122*** (2.75518)	−0.000337 (−0.556578)	0.377477*** (3.902887)	−0.001064* (−1.797779)	0.169851 (1.397276)	0.000814 (0.774986)
0.7	0.43661*** (5.132724)	0.000457 (0.933221)	0.65819*** (5.728957)	−0.000759 (−1.045199)	0.255922** (2.207815)	0.001716* (1.759473)
0.8	0.826444*** (6.834217)	0.00064 (1.012376)	0.844817*** (8.976884)	0.000645 (1.482684)	0.385668** (2.226208)	0.002762* (1.847011)
0.9	1.225702*** (7.128016)	0.001777* (1.693348)	1.491017*** (7.233492)	0.001256 (1.075279)	0.452222*** (3.771306)	0.005224*** (5.443893)

Note: ***, ** and * represent significant level at 1%, 5% and 10% respectively.

3.3. Wavelet analysis

The estimated wavelet coherence between stock market returns and GSV is plotted in Figure 3. The frequency bands and investigation period in days are represented by the vertical and horizontal axes, respectively. Each series is decomposed into six-time scales on the y-axis, with the shortest (2–4 days) signifying the highest frequency band and the longest (64–128 days) indicating the lowest frequency band. The colour gradient code of power is placed on the right side of each plot, with dark blue suggesting low power and dark red implying high power. Significant areas are located within the thick black curve, which is significant at the 5% level and was achieved from Monte Carlo simulations using the phase randomized surrogate series. Consistent with Debata et al. (2021), lower frequency bands exhibit stronger coherence. Between January and July 2020, the returns of the S&P 500, NASDAQ Composite, Dow Jones Industrials, and FTSE 100 positively co-move with GSV in the lowest frequency band, but sentiment leads the returns. Hence, investors should be aware of their emotional reactions since it aids in predicting the direction of the stock market. This

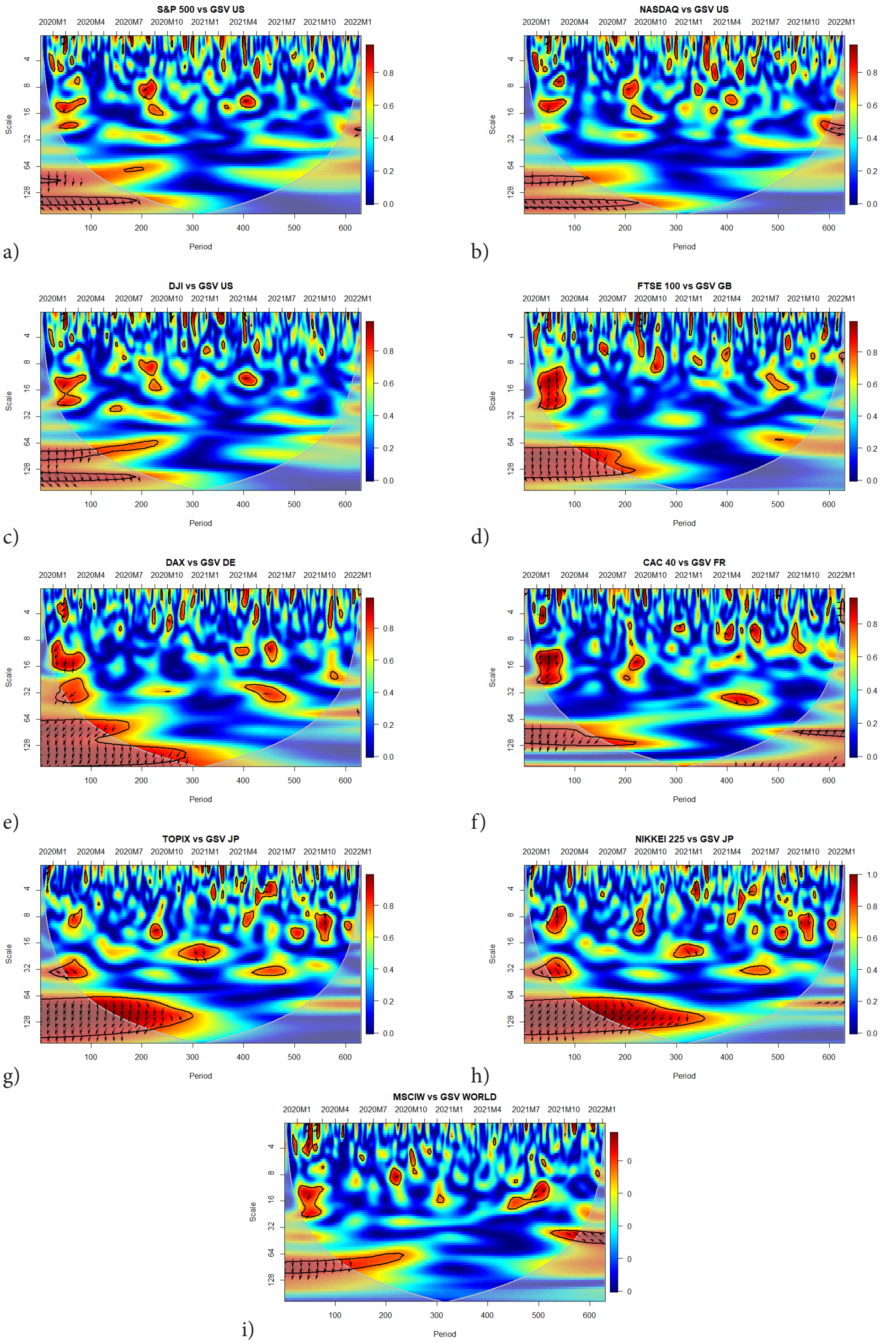
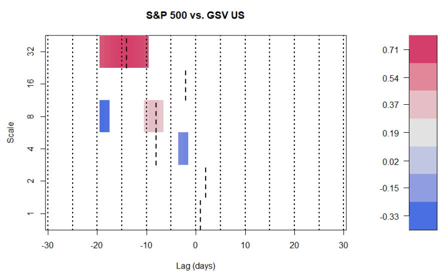


Figure 3. Wavelet coherence plots between equity returns and Google Search Volume

outcome is consistent with Soltani and Abbes (2022), which argued that the attitude of investors can be discerned by sentiment measures. Because of the widespread investor pessimism throughout the pandemic crisis, Niu et al. (2021) reasoned that investors developed a major cognitive bias, and irrational purchasing and selling actions decreased market returns. In line with Dash and Maitra (2022), negative sentiment is more common in the market through the initial spread of the virus. Also, Chundakkadan and Nedumparambil (2022) confirmed that the week that the World Health Organization proclaimed COVID-19 a pandemic has a stronger negative correlation between search volume and market returns. However, throughout the lower frequency band, the returns of the European and Japanese leading equity indices, along with MSCI are anti-phase with GSV, but the returns lead sentiment.

Figure 4 depicts the wavelet cross-correlations between stock returns and GSV. The vertical lines with long dashes show where the strongest wavelet correlation values are in time. On a scale of 32, the S&P 500 and GSV have the highest degree of correlation (0.71). Nonetheless,



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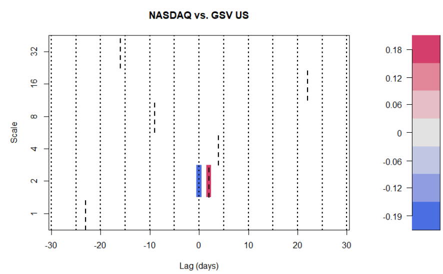

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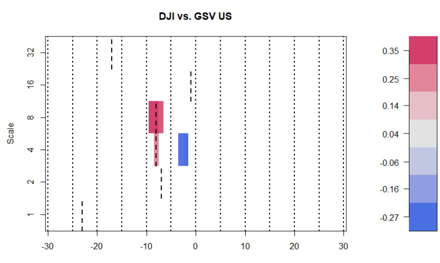

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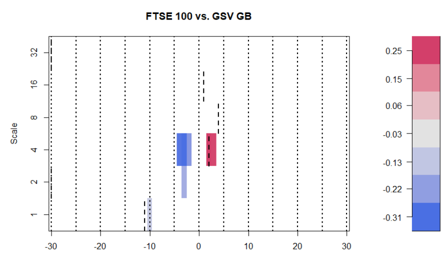

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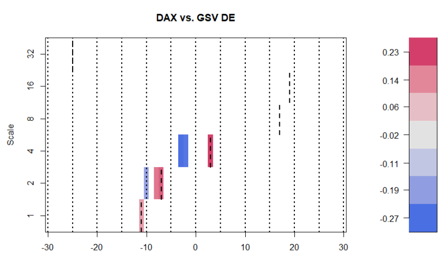

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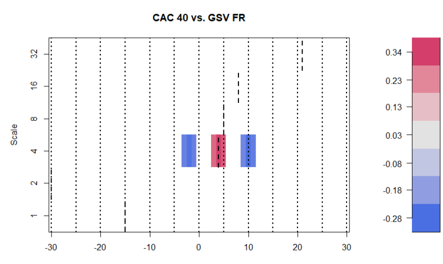
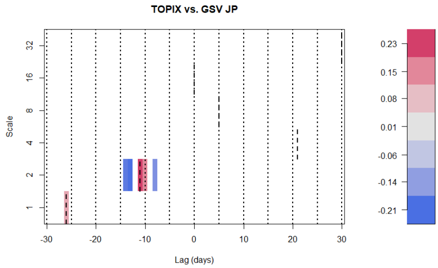


f)

Figure 4. *To be continued*



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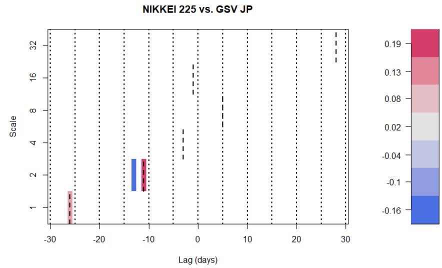

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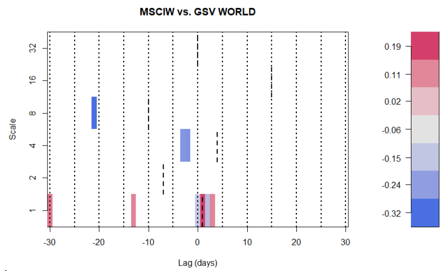
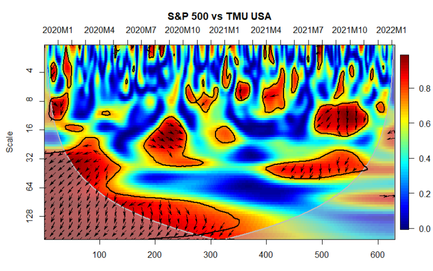


i)

Figure 4. Wavelet cross-correlation plots between equity returns and Google Search Volume

even at low and medium scales, the remaining returns have lower correlations with GSV. MSCI, for example, has a low association (0.19) with GSV worldwide.

Further, to test the robustness of the results, we show the wavelet coherence between equity returns and TMU in Figure 5. Unlike when GSV was used as a measure of investor sentiment, we notice that the entire set of selected stock market returns is out of sync with



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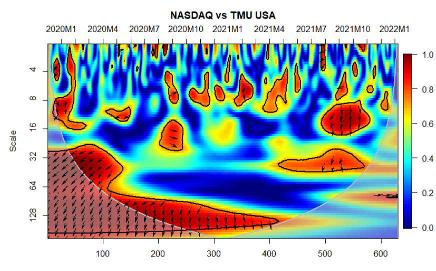

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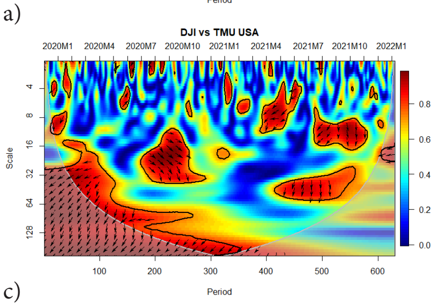

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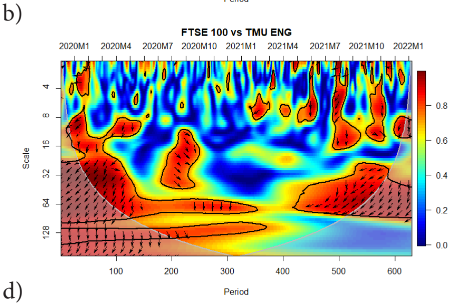

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Figure 5. *To be continued*

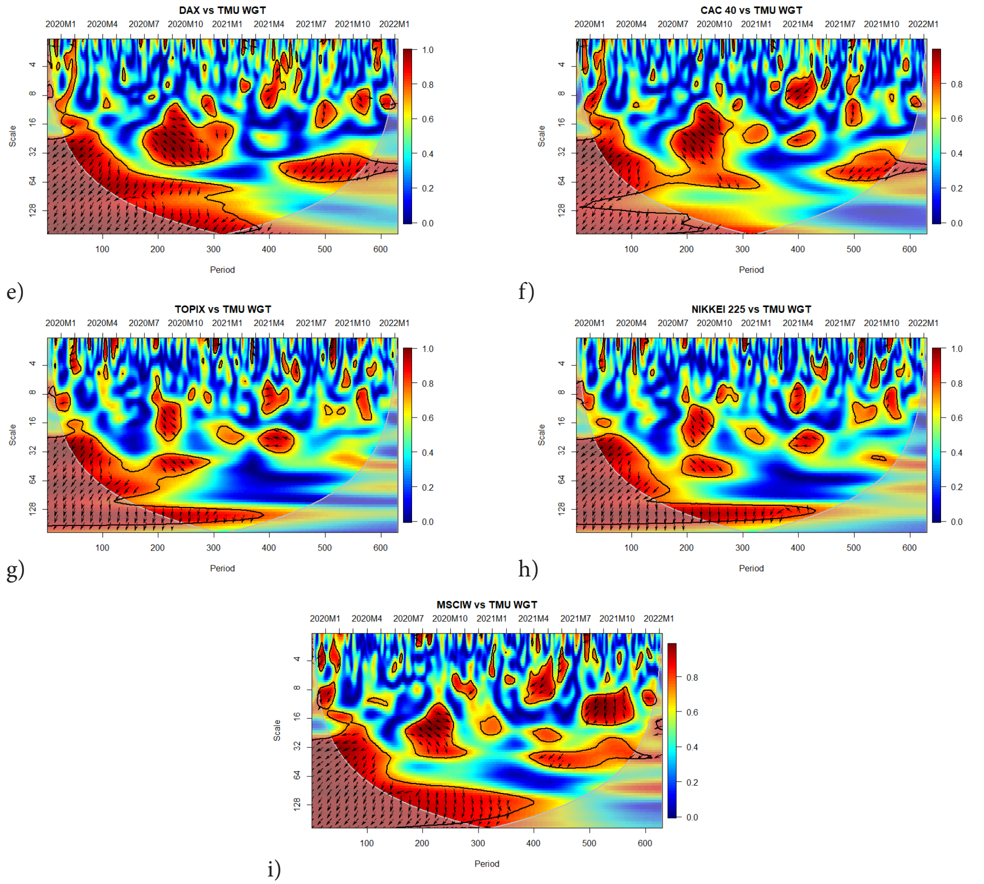
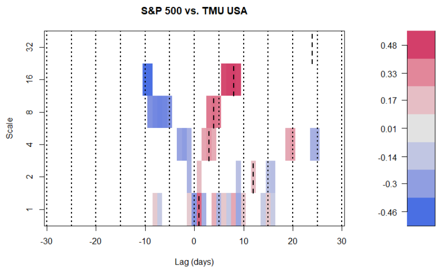


Figure 5. Wavelet coherence plots between equity returns and Twitter-based Market Uncertainty index

the Twitter-based Market Uncertainty indices at both medium and lower frequency bands. This outcome is in line with Subramaniam and Chakraborty (2021), which found an adverse association between retail investors' mood and stock returns. In addition, returns are the leading sentiment argued by the fact that these frequency bands are dominated by fundamental traders (Debata et al., 2021). The outcomes are contrary to Chatterjee and French (2022), which found that markets were a leading indicator of the uncertainty content of tweets before the pandemic. However, the negative co-movement supports the mood sensitivity hypothesis like Chundakkadan and Nedumparambil (2022); Hirshleifer et al. (2020). Hence, the stock markets have plummeted because of the news about COVID-19, creating a negative market attitude.

Figure 6 reveals the wavelet cross-correlations among stock returns and TMU. Overall, we find a medium degree of correlation for all the wavelet scales. For instance, on a scale of 16, all returns except NASDAQ, TOPIX, and Nikkei 225 Stock Average emphasize the highest association.



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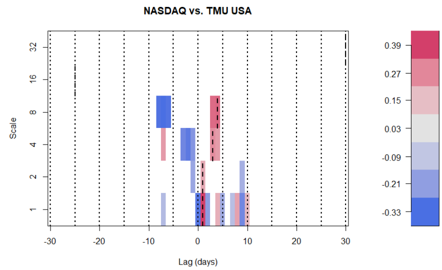

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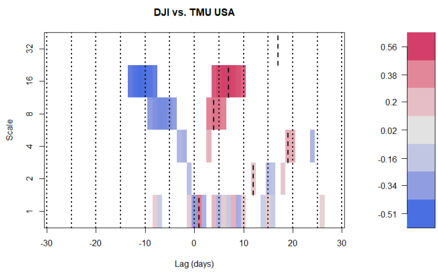

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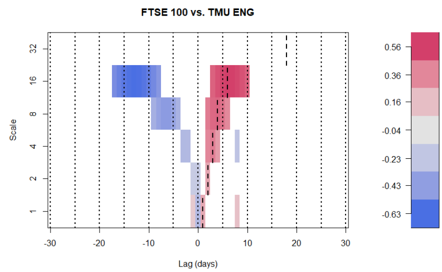
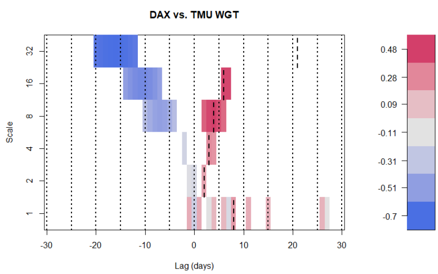
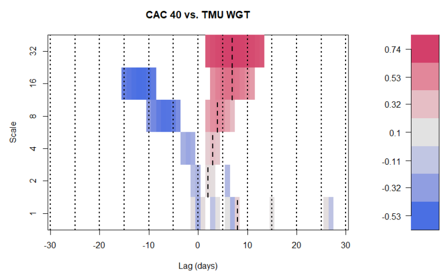


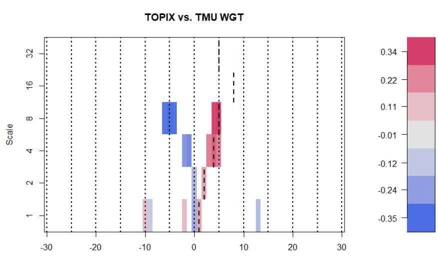
d)



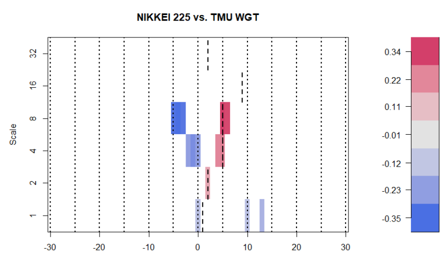
e)



f)

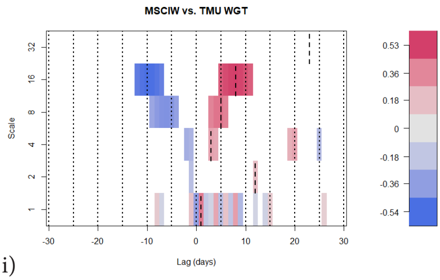


g)



h)

Figure 6. *To be continued*



i)

Figure 6. Wavelet cross-correlation plots between equity returns and Twitter-based Market Uncertainty index

Conclusions

The goal of this study was to investigate the relationship between investor sentiment and leading equity index returns during the COVID-19 pandemic. The estimation of quantile regressions shows that GSV and TMU negatively impacted the equity indices at lower quantiles. The wavelet coherency revealed that markets in the U.S. and the U.K. positively co-move with investor sentiment, but markets in Europe, Japan, and globally were anti-phase when GSV was used. However, when TMU was employed, the whole returns and investor sentiment negatively co-move. COVID-19 substantially affected investor sentiment, particularly during the early stages of the pandemic propagation.

Overall, the empirical results of this paper provide significant theoretical and practical insights. With reference to the theoretical implications, sentiment theory serves as the study's cornerstone. The findings suggest that attention to information derived from Google searches and Twitter-based Uncertainty Indices affects stock returns. Thus, trading strategies can be developed by considering asymmetric relations among Twitter-based uncertainty indices and equity markets' returns. With respect to asset valuation and risk management, during periods of greater insecurity, such as pandemic waves, investors could optimally rebalance their portfolio holdings. Not least, public policymakers could initiate policies to combat the consequences of the pandemic.

The main limitation of our study is illustrated by the inability of sentiment indexes based on Google searches to distinguish between positive and negative sentiment. However, because not all sectors were negatively influenced by the pandemic, future research can be extended by investigating whether sentiment influences particular industries.

Funding

The authors received no specific funding for this work.

Acknowledgements

We would like to thank the Editor and anonymous reviewers for all the insightful comments and suggestions regarding our paper.

Author contributions

All authors contributed equally to this paper.

Disclosure statement

Authors do not have any competing financial, professional, or personal interests from other parties.

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