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Quantile connectedness between sentiment and financial markets: Evidence from the S&P 500 twitter sentiment index

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ABSTRACT

We examine the quantile connectedness of returns between the recently developed S&P 500 Twitter Sentiment Index and various asset classes. Rather than a mean-based connectedness measure, we apply quantile-connectedness to explore connectedness of means and, especially, extreme left and right tails of distributions. Using mean-based connectedness measures, the level of return connectedness between the twitter sentiment index and all financial markets is a modest 46%. However, when applying a novel quantile-based connectedness approach, we find that levels of tail-connectedness are much stronger, up to 82%, at extreme upper and lower tails. This suggests that the impact of sentiment on financial markets is much stronger during extreme positive/negative sentiment shocks. Moreover, return connectedness measures are less volatile during extreme events. Net connectedness analysis shows that the Twitter sentiment index acts as a net transmitter of return spillovers, highlighting the leading role of investor sentiment on predicting other financial markets.

1. Introduction

Following considerable research in behavioral finance, we consider that bounded rationality (Conlisk, 1996) will lead to investor sentiment impacting asset prices (Baker & Wurgler, 2006; Hughen & McDonald, 2005; Shleifer & Summers, 1990).[1] In this context, a stream of empirical research examines the impact of investor sentiment on both returns and volatility of various financial assets (Baker, Wurgler, & Yuan, 2012; Black, 1986; Bouri, Demirer, Gabauer, & Gupta, 2022; Corbet, Larkin, Lucey, Meegan, & Yarovaya, 2020; De Long, Shleifer, Summers, & Waldmann, 1990; Frugier, 2016; Li, Guo, & Park, 2017; Suardi, Rasel, & Liu, 2022; Yarovaya, Brzeszczyński, Goodell, Lucey, & Lau, 2022). Such research uses various proxies for investor sentiment. In the literature, three proxies are employed to depict investor sentiment. First, many studies use stock market-related proxies, including trading volume, turnover rate (Baker & Stein, 2004), and dividend premiums. A second stream of research uses survey-related sentiment measures, such as investor intelligence as early proposed by the American Association of Individual Investors (Lee, Jiang, & Indro, 2002), the UBS/Gallup survey (Qiu & Welch, 2006) and the investor sentiment by animusX (Lux, 2011). Thirdly, social media platforms provide a more recent opportunity for academic researchers to investigate investor attention, investor sentiment; and investor behavior (Anamika Chakraborty & Subramaniam, 2021; Corbet, Goodell, & Günay, 2022; Gan, Alexeev, Bird, & Yeung, 2020; Hu, Li, Goodell, & Shen, 2021; Li, Goodell, & Shen, 2021a; Liang, Tang, Li, & Wei, 2020; Long, Lucey, & Yarovaya, 2021; Pham & Cepni, 2022; Piñeiro-Chousa, López-Cabarcos, Caby, & Šević, 2021). We reason that by using different social media platforms individuals are more able to discuss views, opinions, and information (Tan & Tas, 2020). Recently, social media such as Twitter and chatting tools have been identified as playing a major role in making financial decisions (Bouri et al., 2022; Dash & Maitra, 2022; Huynh, 2021; Li et al., 2021a; Piñeiro-Chousa, López-Cabarcos, & Šević, 2022; Umar, Gubareva, Yousaf, & Ali, 2021).

Twitter is one of the largest social media platforms, where the most discussed topics are about stock markets. Many investors, financial analysts, regulators and news agency share tweets containing information about stock markets (such as suggestions, rumors and commentaries). Stockholders rely on news events posted by different tweets in making trading decisions. A number of studies explore the impact of tweets-contents and stock market performance, finding that Twitter information significantly impacts financial markets (Critien, Gatt, & Ellul, 2022;

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[1] In fact, Baker and Wurgler (2007) show that investor sentiment may provide useful information to predict future stock returns.

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Gu & Kurov, 2020; Li et al., 2021a; Piñeiro-Chousa, López-Cabarcos, Pérez-Pico, & Ribeiro-Navarrete, 2018; Shen, Urquhart, & Wang, 2019; Suardi et al., 2022; Sul, Dennis, & Yuan, 2017; Valle-Cruz, Fernandez-Cortez, López-Chau, & Sandoval-Almazán, 2022; Zhang & Zhang, 2022).

Recently, academics and researchers have been motivated to develop new proxies to gauge investor sentiment. These include the Twitter happiness index and the S&P500 Twitter Sentiment Index. Many studies explore the relationship between the Twitter happiness index and financial markets (e,g., Zhang, Li, Shen, and Teglio (2016), You, Guo, and Peng (2017), Li, Shen, Xue, & Zhang, 2017, Zhao, 2020, Naeem, Farid, Balli, & Shahzad, 2020; Li, Goodell, & Shen, 2021b)), results from these studies reveal that the Twitter sentiment index significantly causes the returns of various international markets. A second index, the recently created S&P500 Twitter sentiment index measures the performance of 200 S&P500 companies with high sentiment scores.

We extend the literature on linkages between financial market and the investor sentiment originating from social media platforms by exploring, for the first time, the relationship between different financial markets and the newly developed S&P500 Twitter Sentiment Index. More specifically we aim to explore the time-varying quantile connectedness between the S&P500 Twitter Sentiment Index and various financial markets including, metals, cryptocurrencies, fiat currencies, energy, and equity markets. To do so, we use the VAR-quantile-based method as a recent extension of the average-based vector autoregressive (VAR) approach of Diebold and Yilmaz (2012).

We apply this methodology to the daily returns of the S&P500 Twitter Sentiment Index and five financial markets including, gold, Bitcoin, the EUR/USD exchange rate, the S&P500, and developed and emerging stock market indices for the period running from February 07, 2018 to November 26, 2021. Our analysis aims to examine return spillovers paths not only in static state, but also in dynamic settings, in both average and across upper and lower extreme quantiles.

We follow Diebold and Yilmaz (2012) by applying quantile-VAR models at extreme lower, median and extreme upper percentiles via the quantile regression methodology of Koenker and Bassett Jr (1978). This permits us to depict connectedness measures at extreme tails of the distribution. This analysis is more convenient and useful than focusing only on the middle quantile through application of mean-based models (e.g., Meng & Huang, 2019; Pandey & Sehgal, 2018; Yousaf, Ali, & Shah, 2018). When applying this new approach for the connectedness process, we discern the structure of tail-return spillovers paths between the Twitter Sentiment Index and the considered financial markets, which helps understanding of the tail-risk transmission between social media news and financial markets, notably, this important concern has not been considered by previous studies.

According to efficient market theory, the asset prices reflect all available information and investors are rational in efficient markets (Fama, 1970). Further, any new information adjusts quickly into asset prices, i.e., if any good (bad) news arrives related to asset, then asset price should increase (decrease) instantly. In contrast, in real life, investors overreact, especially in extreme market conditions, to the new information which ultimately create the larger than appropriate/normal effect on the asset's price (Piccoli & Chaudhury, 2018). Overreaction "is an emotional response to news about an asset, led by either greed or fear, which causes it to become either overbought or oversold". The overreaction of investors provides the evidence of inefficiency of the market as well due to two reasons, firstly overreaction is emotional response which is not expected from rational investor, secondly if overreaction results in overbought/oversold then it reflects those emotions/sentiments are useful in predicting the markets. Therefore, the information shared through tweets regarding any asset may lead the investors toward overreaction in extreme positive or negative market conditions. Hence, we can expect greater impact of investor sentiment at the tails. The findings of current study also confirm that the impact of investors sentiment on financial markets is higher at tails compared to the median quantile.

We contribute to our understanding of sentiment spillovers among financial markets and investor sentiment in several ways. First, we use the newly S&P500 Twitter Sentiment Index as a proxy of investor sentiment to examine the connectedness between the developed S&P 500 Twitter Sentiment Index and financial markets. Further, we use five different markets including, energy, metal, cryptocurrency, fiat currency, S&P500 and emerging and developed stock market indices. We use various categories of the markets because there is a possibility of heterogeneous impacts of sentiment on differing markets.

Additionally, rather than just focusing on the average measure-based connectedness, we examine the quantile (extreme upper and extreme lower) connectedness between Twitter index and several financial markets. For this purpose, we apply the recent quantile-based approach proposed by Ando, Greenwood-Nimmo, and Shin (2022) to explore the dynamics of return spillovers on the extreme upper and extreme lower tails of the shock distribution. This approach can capture the information contained in the conditional distribution of financial asset returns. Unlike the connectedness mean-based approach, the newly quantile-based approach allows to capture the dynamic of return spillovers between the Twitter Sentiment Index and the financial markets under bearish, normal and bullish market conditions, including the COVID-19 crisis period.

We evidence dissimilarities in return spillovers under bearish, normal and bullish market states, with higher return spillovers occurring in the upper and lower tails compared to those at the median. Furthermore, higher return spillovers are observed in the upside return distribution rather than those at the downside return distribution. Additionally, our approach allows detection of return transmitters and the return receivers under different market conditions. Our results show that the S&P500 Twitter Sentiment Index dominates, acting as a net transmitter of return shocks to other financial markets for the majority of the whole sample period. We show that extreme upside/downside shocks are not only major factors that derive the dynamics of extreme return spillovers, but also can cause a structural reversal of the return spillovers. Our findings have important implications for individual investors, portfolios managers and policy makers.

The remaining paper is arranged as follow. Section 2 consists of literatures. Section 3 presents the data and methodology. Section 4 presents empirical results, and Section 5 concludes.

2. Background

Literature evidences the role of bounded rationality (CONLISK) in influencing asset prices (Baker & Wurgler, 2007; Ho & Hung, 2009; Lee et al., 2002; Lee, Shleifer, & Thaler, 1991). In this context, Baker and Wurgler (2006) construct a sentiment index, showing that investor sentiment has a strong effect on securities that are highly subjective valuated and difficult to arbitrage. A large strand of literature investigates the effects of media or news tone (Tetlock, 2011; Tetlock, Saar-Tsechansky, & Macskassy, 2008). Recently, social media platforms, as alternatives to traditional media sources, have been examined. Social media platforms permit gathering of direct aggregate data related to human factors (Tan & Tas, 2020). Recent research analyzes the effect of index level sentiment on the U.S market. Zhang, Fuehres, and Gloor (2011) and Bollen, Mao, and Zeng (2011) find that Twitter-related moods are key determinants of U.S stock indexes.

A stream of research explores the relationship between Twitter sentiment and individual stock returns and trading activity. Sprenger, Sandner, Tumasjan, and Welpe (2014) use computational linguistics on stock-related daily messages to analyze S&P 100 companies. Their results reveal tweet sentiment significantly affects stock returns, while message volume significantly causes trading volume. They also evidence association between disagreement and volatility. Yu, and J., and Yuan Y. (2012) explore the impact of investor sentiment on a broad set of anomalies on cross-sectional stock returns, establishing that investor sentiment has asymmetric effects on stock returns, particularly high sentiment being more likely to produce overpricing than low sentiment.

Ranco, Aleksovski, Caldarelli, Grčar, and Mozetič (2015) scrutinize Dow Jones Industrial Average firms, revealing that Twitter sentiment significantly impacts abnormal returns at the peaks of Twitter volume. Using Twitter volume as a residual methodology for proxying investor attention, Wu (2019) show that, after earnings announcements, social media attention positively affects the cumulative abnormal returns even after bad news if the attention is high. Gu and Kurov (2020) construct the twitter index based on the firm specific twitter news and examine its impact on the equity returns. They report that Twitter sentiment provides useful information in predicting the stock returns. Umar et al. (2021) explore the factors which hugely increase the stock prices of GameStop and conclude that the twitter sentiment is the one of the important factors which play important role in hugely increasing the prices of GameStop stocks at the start of 2021. Behera and Rath (2021) examine the linkages between Twitter uncertainty index and volatility of G7 stock markets and find that Twitter market uncertainty is the net recipient of the spillover from the few stock markets, majorly the German stock market. Bouri et al. (2022) find that Twitter-based-investor happiness index significantly influence the connectedness between international equity markets. Chatterjee and French (2022) investigate the impact of Twitter-based-market uncertainty (TMU) on the US stock market and report the significant effect of the TMU on equity markets only during the COVID-19 pandemic. Several studies examine the impact of the Twitter Happiness index on stock market performance, finding a significant association between Twitter happiness and stock market returns (Bouri, Demirer, Gabauer, & Gupta, 2021; Li, Shen, et al., 2017; You et al., 2017; Zhang et al., 2016). Naeem et al. (2020) and Li et al. (2021b) examine the ability of Twitter Happiness index to predict the future stock market volatility, finding that Twitter happiness index significantly affects the future volatility of different country's stock market under study.

Another stream of the empirical literature investigates the relationship between investor sentiment and cryptocurrency market. Pant, Neupane, Poudel, Pokhrel, and Lama (2018) analyze how Twitter as a proxy of investor sentiment predicts Bitcoin prices using a neural network model. Karalevicius, Degrande, and De (2018) evidence that media sentiment accurately predicts and drives the short-term price movement of Bitcoin. Vidal-Tomás, Ibáñez, and Farinós (2018) analyze the existence of herding behavior in the cryptocurrency markets. Karaa, Slim, Goodell, Goyal, and Kallinterakis (2021) evidence feedback looping in cryptocurrencies markets. Shen et al. (2019) and Li et al. (2021b) find that Twitter affects the variance of returns. Likewise, using a textual technique analysis, Kraaijeveld and Smedt (2020), find that Twitter bots significantly predict returns of main cryptocurrencies including Bitcoin, Litecoin, and Bitcoin cash.

More recently, Naeem et al. (2020) examine the predictive ability of Twitter Happiness Index for six major cryptocurrencies using quantile-quantile QQ analysis. They find a significant nonlinear relationship between Twitter happiness sentiment and cryptocurrencies, indicating that high and low sentiment peaks predict returns of considered cryptocurrencies. Moreover, Naeem, Mbarki, and Shahzad (2021) investigate the ability of online investor sentiment to predict future returns of six major cryptocurrencies. Using two proxies of investor sentiment: the Fear index of Da, Engelberg, and Gao (2015) and Twitter Happiness sentiment, along with the bivariate cross-quantilogram framework of Han, Linton, Oka, and Whang (2016), they find that happiness sentiment is a robust predictor for most cryptocurrency returns. The FEARS index also shows significant ability to predict returns of most cryptocurrencies, but with less predictive power over short-term horizons. Huynh (2021) report the significant effect of Donald Trump tweets and Bitcoin's volume and price. Zhang and Zhang (2022) explore the sensitivity of cryptocurrencies to the Twitter-issuer-sentiment and find that Twitter-issuer-sentiments are positively linked to the cryptocurrencies. Critien et al. (2022) report that the twitter sentiment is useful in forecasting the two elements of Bitcoin, namely the magnitude in price change and direction of price.

In the context of commodity markets, several studies show that investor sentiment significantly causes return and volatility of commodity markets (Bahloul & Bouri, 2016; Bahloul & Gupta, 2018; Qadan & Nama, 2018; Shahzad, Raza, Balcilar, Ali, & Shahbaz, 2017; Shen, Li, & Zhang, 2017; Smales & Yang, 2015). Omura and Todorova (2019) investigate the effect on news sentiment on commodity future returns under different market states, they show that markets respond asymmetrically to positive and negative news sentiment, and changes in period of financial distress. More recently, Maghyereh and Abdoh (2020) investigate the dynamic quantile-dependence among investor sentiment and major commodities. Using the quantile cross-spectral dependence approach and the non-parametric causality-in-quantiles test, they show that the dependency between investor sentiment and commodities varies according to return quantiles and time-horizon. In the same context, Su and Li (2020) employed the time-frequency spillover index methods to explore the sentiment spillover among various financial markets including energy, metal and cryptos markets. Their findings prove that the magnitude of sentiment spillover among crude oil, gold and Bitcoin markets varies across time and is greatly influenced by major market events.

We extend Su and Li (2020) by investigating the spillover of sentiment to various financial markets including energy, cryptocurrency, fiat currency and global stock markets. Using the novel S&P500 Twitter Sentiment index we examine extreme upper and extreme tail sentiment spillovers among markets using a quantile-based spillover index rather than the more usual mean-based connectedness approach.

3. Data and methodology

3.1. Data

We use daily data of metal (gold), cryptocurrency (Bitcoin), currency (EUR/USD), energy (Brent WTI oil), and stock markets (S&P 500, Dow Jones developed stock market-excluding US index, emerging stock market index). Moreover, we collect the daily data of newly developed S&P 500 Twitter Sentiment Index from the website of S&P Global.[2] Data of equity and energy markets are obtained from the website of S&P Global and the US Energy Information Administration, respectively. Data regarding gold and Bitcoin is gathered from the website of the London Bullion Market Association and Capitalmarket.com, respectively. The sample period is 07 February 2018–26 November 2021. All indices are denominated in US dollars, while returns and growth rate are calculated by us.

Fig. 1 depicts the price distributions of the S&P500 Twitter Sentiment Index and the different financial assets. We observe that the values of the S&P500 Twitter Sentiment Index were relatively low during the first part of the sample period, with a rise toward the end of 2021. Regarding gold, we note that prices were increasing continuously from the beginning of the sample period then slightly decreased during the first quarter of 2020, after which price increased and reach a peek during the third quarter of 2020. After this, prices remained at a high level. Similarly, Bitcoin prices were approximately stable and at a low level from the beginning of the sample period until the third quarter of 2020. After this, Bitcoin prices began to increase sharply, reaching a peak in mid-2021.

Regarding the EUR/USD exchange rate, we notice a sharp decline of EUR/USD prices from the beginning of the study period, with prices reaching their lowest at the first quarter of the year 2020, This coincides with the outbreak of the COVID-19 pandemic. After this, the price recovers rapidly, reaching its maximum. Regarding oil prices we notice a deep decline of both Brent and WTI oil prices during our period after

[2] Source:"https://www.spglobal.com/spdji/en/indices/strategy/sp-500-twitter-sentiment-index/#overview".

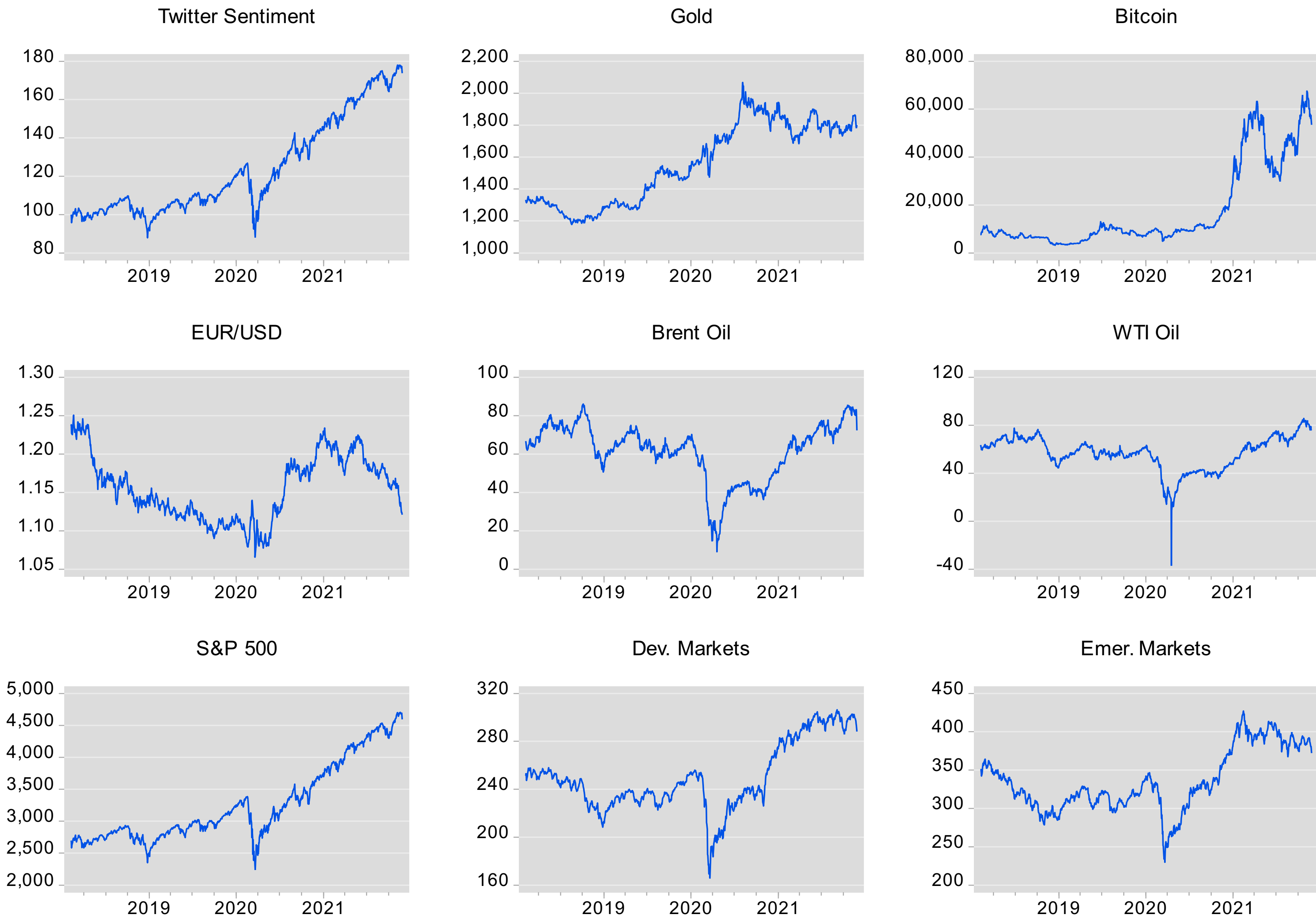


Fig. 1. Twitter sentiment and market price indices.

that date prices increased continuously and recover to their first level. This movement in WTI oil, particularly in April 2020 has been well highlighted before (Corbet, Goodell, & Günay, 2020; Yousaf, 2021). Regarding stock market indices, their prices increase and decreased dramatically during the onset of the COVID-19 pandemic.

Fig. 2 illustrates the return series of the S&P500 Twitter Sentiment Index, as well as the asset series of our study. The returns paths show high volatility and volatility clusters during the first quarter of the year 2020, coinciding with the outbreak of the recent COVID-19 outbreak. Table 1 reports summary statistics and preliminary tests of daily returns of different series under study. Mean return values differ across the series considered. Bitcoin exhibits the highest mean returns (0.0031), while the lowest average return is observed for the WTI oil prices (−0.0027). Standard deviations preliminarily indicate that the different considered series exhibit differing levels of risk. The riskiest assets being WTI oil, Bitcoin and Brent oil. Results of normality tests reveal that the return distributions are asymmetric and exhibit fat tails as indicated by skewness and kurtosis excess values. The null hypothesis of normality is strongly rejected at 1% significance level for all return series as shown by the Jarque-Berra statistics. Preliminary analysis results support the use of the quantile-based analysis in this study.

To test the presence of unit roots in our series, we apply the Augmented Dickey Fuller unit root test. Results support the rejection of the null hypothesis of unit root for all returns series.

3.2. Methodology

To investigate the quantile connectedness for pairs of twitter sentiment with financial markets, we use the quantile-connectedness technique of Ando et al. (2022). In order to compute metrices of the quantile spillover, the infinite order-based vector moving average specifications of QVAR are defined as:

$$y_t = \mu(\tau) + \sum_j^p \Phi_j(\tau) y_{t-j} + u_t(\tau) = \mu(\tau) + \sum_{i=0}^{\infty} \Omega_i(\tau) u_{t-i} \tag{1}$$

We follow Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998) for the generalized forecast error variance decomposition (GFEVD) with forecast horizon of H, which is defined as follows:

$$\Theta_{ij}^g(H) = \frac{\sum(\tau)_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Omega_h(\tau) \sum(\tau) e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Omega_h(\tau) \sum(\tau) \Omega_h(\tau)' e_i\right)} \tag{2}$$

e_i denotes a zero vector with the unity on ith position. In the decomposition matrix, the normalization of elements is given as:

$$\widetilde{\Theta}_{ij}^g(H) = \frac{\Theta_{ij}^g(H)}{\sum_{j=1}^k \Theta_{ij}^g(H)} \text{with} \sum_{j=1}^k \widetilde{\Theta}_{ij}^g .1 \text{and} \sum_{i,j=1}^k \widetilde{\Theta}_{ij}^g(H) = 1, \tag{3}$$

GFEVD based spillover measures are defined below following Diebold and Yilmaz (2012):

$$TO_{j,t} = \sum_{i=1, \ i \neq j}^k \widetilde{\Theta}_{ij,t}^g(H) \tag{4}$$

$$FROM_{j,t} = \sum_{i=1, i \neq j}^k \widetilde{\Theta}_{ji,t}^g(H) \tag{5}$$

$$NET_{j,t} = TO_{j,t} - FROM_{j,t} \tag{6}$$

$$TCI_t = \frac{\sum_{i,j=1, i \neq j}^k \widetilde{\Theta}_{ij}^g(H)}{k-1} \tag{7}$$

$TO_{j,\ t}$ indicates the effect of variable j on variable I. $FROM_{j,\ t}$ represents the impact of i on j. $NET_{j,\ t}$ shows the disparity between TO and FROM, with a the negative (positive) value referring to the net recipient (transmitter) of spillover. TCI_t represents average level of total connectedness.

4. Empirical analysis

4.1. Static quantile connectedness

To explore the dynamic connectedness between the Twitter S&P500 Sentiment Index and selected financial markets under different market states, we apply the quantile-based autoregressive vector methodology (QVAR) proposed by Ando et al. (2022). This method extends the mean-based measures of Diebold and Yilmaz (2012, 2014). This approach is applied for three quantiles to consider the median or normal ($\tau = 0.5$), the bearish ($\tau = 0.05$) and to account for the bullish ($\tau = 0.95$) market conditions.

Using the return series, QVAR modeling, Eq. (1), is estimated. Following this, related connectedness measures are computed such as the Total Connectedness Index (TCI) (Eq. (7)), directional FROM (Eq. (5)), directional TO (Eq. (4)), and Net Connectedness (Eq. (6)), under median, bearish and bullish market conditions.

4.1.1. Conditional median connectedness (median quantile ($\tau = 0.5$))

We first consider the conditional median connectedness ($\tau = 0.5$) which is used as reference to compare the results of the conditional connectedness at upper and lower tails. The estimation results of the conditional median connectedness are reported in panel (A) of Table 2. We notice that at a normal market state ($\tau = 0.5$), total connectedness index (TCI) between the Twitter S&P 500 index and all considered markets is relatively high (46.90), highlighting high conditional connectedness between the different variables in the system even in period of stable markets.

In contrast, we notice that the S&P500, as well as other developed markets stock indices, and the Twitter index receives (transmits) the returns spillovers from (to) the system, 65.52%, 65.39%, 64.60% (85.14%, 74.45%, 81.43%,), respectively. The latest row of the panel (A) of Table 2 reports the net conditional connectedness measured as the difference between the amounts of transmitted and received shocks. Results show that the Twitter sentiment Index, WTI oil, the S&P 500, and other developed markets stock indices exhibit positive net conditional connectedness values which indicate that these assets act as net transmitters of returns shocks to the system under normal market state. These results demonstrate that in period of stable markets Twitter Sentiment Index, WTI oil, S&P 500, and other developed markets stock indices are useful in predicting the remaining financial markets, provide the evidence of inefficiency of few markets in the normal market conditions. These findings are consistent with Bouri et al. (2021) who apply a quantile-on-quantile framework and show that investor happiness significantly affects the return and volatility spillovers among global stock markets. Our findings are also consistent with Tan and Tas (2020) who find that trading value and returns are significantly affected by Twitter activity and sentiment, particularly, their findings show that the firm-specific twitter sentiment contains predictive information of stock returns and this predictive ability continue significant after controlling news sentiment.

Conditional connectedness at lower (($\tau = 0.05$)) and upper ($\tau = 0.95$) (quantiles)

To explore extreme sentiment spillovers emanating from downside shocks and upside shocks, we estimate the connectedness measures at the extreme right and left tails. Estimation results are reported in Panel (B) (extreme lower quantile) and Panel (C) (extreme upper quantile) of Table 2. First, it's clear from the results in Panels (B) and (C) that the return spillovers in both right and left tails exceed return spillovers in the median. The total connectedness index at the extreme left tail ($\tau = 0.05$) is 84.21%, and 82.82% at the extreme right tail ($\tau = 0.95$) compared to only 46.90% in the median quantile.

These results underscore the strong effect of the extreme shocks on the system of return spillover and justify the application of the quantile-

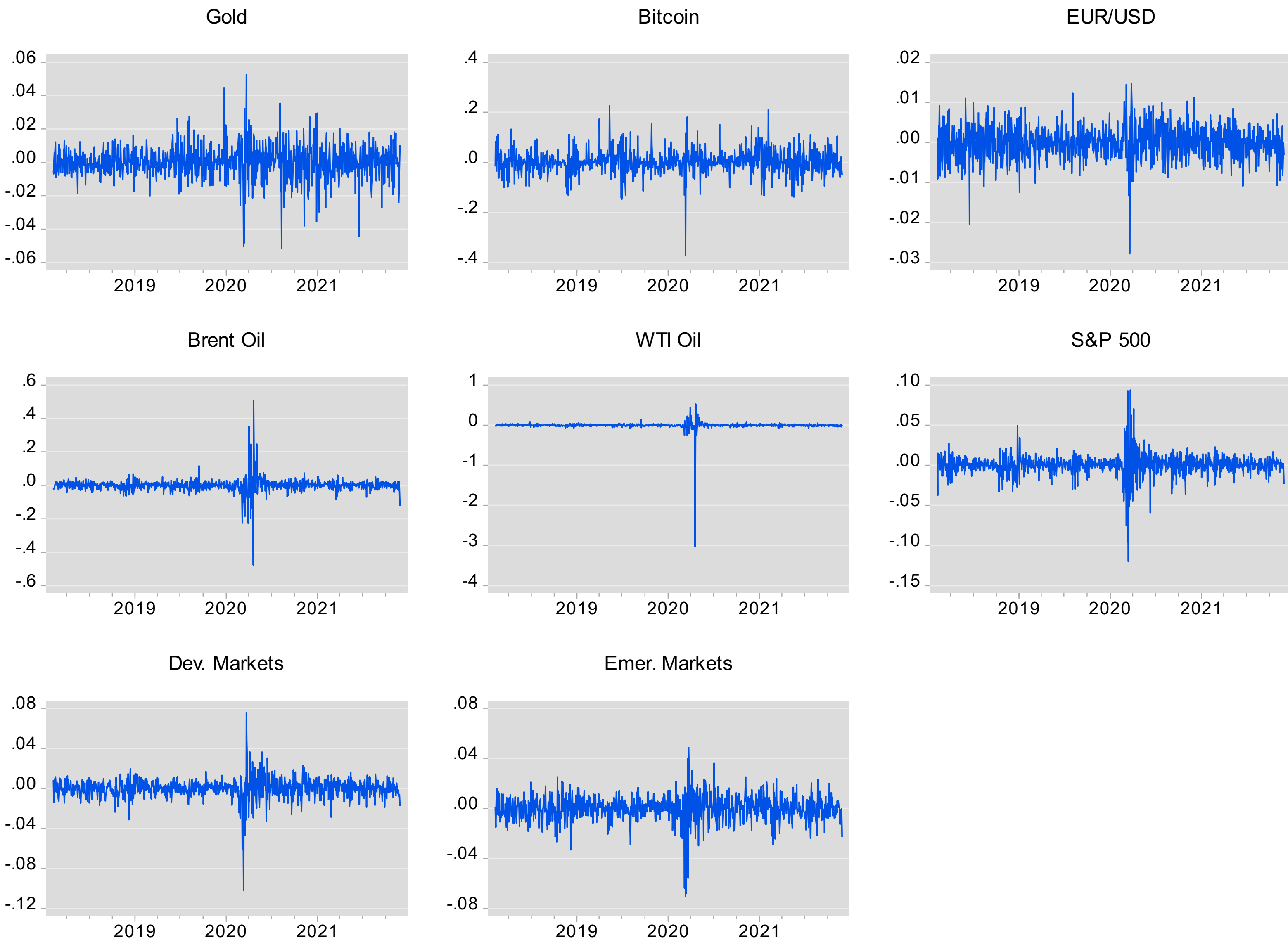


Fig. 2. Returns of markets.

Table 1
Summary statistics.

	Mean	Max	Min	Std. Dev.	Skew	Kurt	J-B	ARCH	ADF
Gold	0.0004	0.0527	−0.0513	0.0095	−0.2926	7.7826	927.6[a]	13.707 [a]	−31.196 [a]
Bitcoin	0.0031	0.2251	−0.3717	0.0460	−0.2621	9.3997	1647.5 [a]	6.931[b]	−32.108 [a]
EUR/USD	−0.0001	0.0146	−0.0278	0.0041	−0.3706	5.8168	339.0 [a]	9.191 [a]	−30.183 [a]
Brent Oil	0.0009	0.5099	−0.4747	0.0409	0.9227	57.7242	119,800.8 [a]	66.782 [a]	−5.589 [a]
WTI Oil	−0.0027	0.5309	−3.0197	0.1134	−20.860	540.283	1,160,447 [a]	22.244 [a]	−22.904 [a]
S&P 500	0.0006	0.0938	−0.1198	0.0135	−0.6691	19.9020	11,486.7 [a]	109.095 [a]	−9.105 [a]
D. Markets	0.0002	0.0756	−0.1016	0.0096	−1.1874	22.9632	16,149.9 [a]	26.347 [a]	−17.782 [a]
E. Markets	0.0001	0.0489	−0.0701	0.0104	−0.9431	9.9572	2076.3 [a]	82.920 [a]	−18.686 [a]

Notes: "Max-Maximum, Min-Minimum, Std. Dev.-Standard deviation, Kurt-Kurtosis, J-B-Jarque Bera test, ADF-Augmented Dicky Fuller test. [a, b, c] indicates the level of significance at 1, 5, and 10%, respectively."

Table 2
Static return connectedness.

	Twitter.Sentiment	Gold	Bitcoin	EUR/USD	Brent.Oil	WTI.Oil	S&P.500	Dev..Markets	Emer..Markets	From others
Panel A. Quantile (median τ = 0.50)										
Twitter.Sentiment	35.40	1.35	2.11	0.41	2.08	1.92	34.12	12.60	10.00	64.60
Gold	3.53	76.30	3.68	1.74	2.02	1.03	3.33	4.60	3.76	23.70
Bitcoin	4.38	3.68	78.14	0.66	1.23	0.42	4.56	4.08	2.86	21.86
EUR/USD	4.54	9.78	1.56	65.16	1.44	1.16	4.66	7.38	4.31	34.84
Brent.Oil	3.62	1.29	1.25	0.53	52.61	27.33	3.88	5.39	4.10	47.39
WTI.Oil	2.81	0.65	0.76	0.67	24.17	60.97	3.05	4.19	2.73	39.03
S&P.500	33.53	1.22	2.14	0.38	2.21	2.00	34.61	13.75	10.15	65.39
Dev..Markets	16.26	2.27	2.11	0.80	3.60	3.27	18.27	34.48	18.94	65.52
Emer..Markets	12.75	2.01	2.18	1.35	3.09	2.63	13.28	22.45	40.25	59.75
TO others	81.43	22.25	15.80	6.54	39.84	39.77	85.14	74.45	56.86	422.08
Inc. own	116.83	98.55	93.94	71.70	92.45	100.73	119.75	108.93	97.12	TCI
NET	16.83	−1.45	−6.06	−28.30	−7.55	0.73	19.75	8.93	−2.88	46.90
Panel B. Quantile (extreme lower quantile τ = 0.05)										
Twitter.Sentiment	14.55	8.97	8.86	9.12	10.09	8.96	14.51	12.63	12.31	85.45
Gold	10.17	16.82	11.02	10.73	10.01	8.39	10.12	11.10	11.64	83.18
Bitcoin	10.40	11.23	16.99	9.65	10.24	8.79	10.47	10.92	11.32	83.01
EUR/USD	10.60	11.04	9.49	16.13	9.89	8.65	10.67	11.65	11.89	83.87
Brent.Oil	10.58	9.48	9.36	9.18	15.55	12.17	10.74	11.39	11.55	84.45
WTI.Oil	10.29	9.15	8.89	9.03	12.96	17.41	10.49	10.84	10.92	82.59
S&P.500	14.41	8.76	8.73	9.15	9.99	8.93	14.74	12.87	12.42	85.26
Dev..Markets	12.51	9.07	9.00	9.25	10.33	9.05	12.88	14.67	13.24	85.33
Emer..Markets	11.85	9.65	9.30	9.60	10.21	8.96	12.04	13.16	15.22	84.78
TO others	90.82	77.35	74.66	75.73	83.72	73.89	91.91	94.56	95.29	757.92
Inc. own	105.36	94.16	91.65	91.86	99.27	91.30	106.66	109.23	110.52	TCI
NET	5.36	−5.84	−8.35	−8.14	−0.73	−8.70	6.66	9.23	10.52	84.21
Panel C: Quantile (Extreme upper quantile τ = 0.95)										
Twitter.Sentiment	16.51	8.83	9.45	8.20	8.66	7.73	16.14	12.14	12.34	83.49
Gold	10.41	18.44	11.65	11.00	8.67	7.88	9.98	11.05	10.92	81.56
Bitcoin	10.73	10.89	18.59	9.70	9.41	8.44	10.65	10.87	10.74	81.41
EUR/USD	10.38	12.08	10.86	16.98	8.87	8.57	10.20	11.15	10.92	83.02
Brent.Oil	10.40	8.96	9.86	8.72	16.95	13.72	10.55	10.29	10.56	83.05
WTI.Oil	10.05	8.77	8.86	8.41	14.21	19.13	10.22	10.07	10.29	80.87
S&P.500	16.16	8.57	9.28	8.47	9.01	7.90	16.40	12.05	12.17	83.60
Dev..Markets	12.33	9.80	9.82	9.07	9.42	8.48	12.58	15.21	13.28	84.79
Emer..Markets	12.14	9.28	9.71	9.08	9.41	8.67	12.26	13.04	16.41	83.59
TO others	92.62	77.18	79.48	72.65	77.65	71.39	92.57	90.65	91.20	745.38
Inc. own	109.13	95.62	98.07	89.63	94.60	90.52	108.96	105.86	107.61	TCI
NET	9.13	−4.38	−1.93	−10.37	−5.40	−9.48	8.96	5.86	7.61	82.82

Notes: Twitter.Sentiment-Twitter sentiment, Brent.oil-Brent oil, WTI.Oil-WTI oil, Dev..Markets-Developed markets, Emer.. Markets-Emerging markets.

VAR approach instead of the mean-VAR approach in which the level of connectedness is found to be invariant regardless the market conditions. Similarly, the amounts of spillovers emitted (received) to (from) others in both the right and left tails are more pronounced than those on the median. Moreover, the net recipients and emitters of spillovers differ from those shown in panel (A). For example, at bearish market state, the Twitter Sentiment Index and developed markets stock indices are the net transmitters of spillovers to the system, whereas at bullish market condition we find that emerging markets stock index turn to the net transmitter side. As twitter sentiment is the net transmitter at both tails, showing the twitter sentiment as useful predictor for most of the financial markets, implying the inefficiency of majority of financial markets at extreme market conditions. Further, it shows that investors can get abnormal returns through using the information of twitter to predict markets in the extreme market conditions. The huge spillover from Twitter sentiment to financial markets (system) in extreme market conditions can also destabilize the markets which is the major concern of policymakers and regulators, as previously happened in case of GameStop episode through Reddit and Twitter platforms (Umar et al., 2021). Moreover, the variation of the total connectedness level between lower, upper and median quantiles underscores that the level of connectedness strengthens with the size of shock for extreme downside and extreme upside shocks. This finding supports previous empirical studies in contagion which suggest the spillover of extreme shocks in both right and left tails (Londono, 2019).

Fig. 3 depicts the network visualition of the of pairewise return spillovers at median, lower and upper quantiles among the Twitter Sentiment Index and the considred financial markets under study. Examining Fig. 3, we notice that the network of the returns spillovers between the Twitter Sentiment Index and the considered financial markets have different structural charcteristics at differet quantiles. Fig. 3a graphs the network of returns spillovers at the middle quantiles, highlighting a weak system connectedness level. Notably, return spillover are weak among the Bitcoin, gold and brent oil which act as net receivers of returns shocks from the system, wheras the EUR/USD exchange market is the greater receiver of returns spillovers from the system. The Twitter Sentiment Index and the S&P500 stock index are the main emmitters of return spillovers to the system, with developed markets stock indices contributing weakly to return shocks emmitted to the system.

Under bullish market sentiment (Fig. 3c) and bearish market sentiment (Fig. 3b) the network of return spillovers are more complicated compared to those under normal market state (Fig. 3a). We notice that the contribution of the developed and emerging stock market indices in the return spillovers to the system become more prononced under bearish and bullish market conditions. Additionally, the exposures of oil, gold and Bitcoin markets to negative returns shocks emmanating from the system become greater under bearish market states. In contrast, when the market is relatively high (bullish market) the Twitter Sentiment Index play a major role in leading the system, acting as the main emmitter of positive return shocks to the system.

Overall, findings are consistent with previous studies examining the tail connectedness between investor sentiment and financial markets. Maghyereh and Abdoh (2020) and Omura and Todorova (2019) apply different methodologies (the quantile cross-spectral dependence approach and the non-parametric causality in quantile test and the quantile regression, resppectively), showing that inter-dependence between sentiement and commodities differs during bullish, normal and bearish investors sentiment periods. Moreover, Naeem et al. (2021) show that Happiness sentimement index significantly predicts Bitcoin retuns as well as other major cryptocurrencies at both bearish and bullish market conditions and for extreme levels of sentiment. In contrast, our findings are consistent with Naeem et al. (2020) who find that the happiness sentiment predicts currency returns during normal market conditions, but this predictive power weakens during bearish and bullish states of the market.

4.2. Dynamic quantile connectedness

4.2.1. Dynamic analysis of directional connectedness index

The previous analysis of the return spillovers, reported in Table 2, evidence return spillovers between the Twitter Sentiment Index and all considered financial markets at different quantiles of the return distribution, providing preliminary evidence of quantile connectedness between the Twitter Sentiment Index and other financial markets during the whole sample period. However, these static analyses provide limited information about the dynamic evolution of return spillovers. To better understand the return spillovers process we estimate dynamic quantile connectedness using the previous quantile spillover index combined with a rolling-window technique to detect the trajectory of time-varying return spillovers between variables of the system under different market conditions.

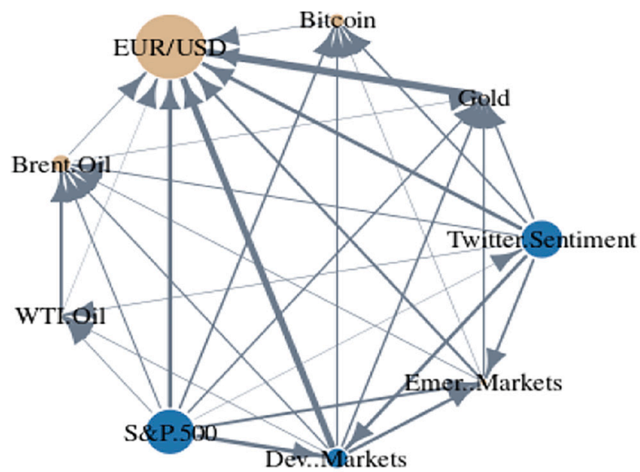
Fig. 4 depicts the time-varying total spillover index (TCI) between Twitter Sentiment Index and all markets under median, extreme upper and extreme lower quantiles. The blue trajectory presents the evolutions of total returns spillovers in the median of the distribution ($\tau = 0.50$). We can see that the TCI varies considerably in response to different economic events occurring during the full sample period, ranging from 39% to 61%. However, the TCI at both right and left tails (red and green curves, respectively shown in Fig. 4) is much stronger, with the range of fluctuations much lower, ranging between 75% and 90%. Notably, the great level of connectedness at both left and right tails underscores the high sensitivity of the considered financial markets to both extreme positive and extreme negative shocks to the returns of the Twitter Sentiment Index. These results suggest that investor and portfolio managers should consider extreme tails as well while constructing portfolios, instead of only focusing on the median quantile. Our results are inconsistent with Maghyereh and Abdoh (2020) who find that the sentiment-commodity markets dependencies are lower at highest quantiles compared to medium and low quantiles, especially for gold. However, our results are consistent with Naeem et al. (2021) who find that the Twitter Happiness Index impacts the returns of Bitcoin as well as major currencies under the extreme bullish market and for extreme levels of sentiment.

Fig. 5 provides the net total connectedness between the Twitter Sentiment Index and all financial markets at median, extreme upper and extreme lower quantiles. The red curve in Fig. 5 presents net total return spillovers at conditional median quantile. Based in the trajectories of spillovers, we notice that in the center of the distribution during the fill-sample period, the Twitter Sentiment Index acts as a net emitter of return spillovers to all financial markets, while all financial markets act as net recipients of return shocks from the Sentiment Index. This result underscores that, in stable period, the Twitter sentiment Index dominants the system and affect all other financial markets. Whereas the green curve presents the net conditional spillover index at the extreme upper tail ($\tau = 0.95$) and the red curve depicts net conditional spillovers at the extreme lower tail ($\tau = 0.05$). The graphs show that, at bullish or bearish market sentiment, the paths of net extreme spillover are mixed. In fact, the Twitter Sentiment Index sometimes acts as net emitter of return spillovers while at other times acts as net recipient of return spillovers.

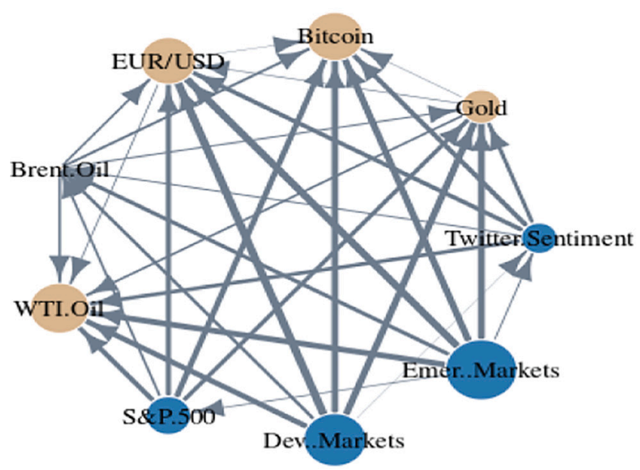
Specifically, under extreme positive return shocks, we observe that the Twitter Sentiment Index acts as net receiver of return spillovers from other financial markets. However, at the end of the first quarter of the year 2020 it turns to net emitter of return shocks, with the magnitude of return spillovers increasing dramatically and reaching a high point during this period. After this, the Twitter Sentiment Index moves to being a net recipient of return spillovers for the latest quarter of the year 2020 and the year 2021. Regarding the net spillover of negative return shocks, we find that net spillovers of negative shocks are much stronger than positive shocks during the whole sample period. Furthermore, the Twitter Sentiment Index acts as net receiver of negative return spillover during two periods: mid-2019, and during the first quarter of the year-2020. However, it turns to being a transmitter during other periods.

In summary, under extreme events, the patterns of spillovers at left and right tails differ from those at medians. This finding may be attributed to investor responses to bad or good news emanating from different financial markets. Consequently, under extreme events, investors, market participants and policy makers should continuously monitor the patterns of net spillovers of sentiment between different financial markets. Our findings are in line with Smales and Yang (2015) who show that the interconnection between disaggregated market sentiment and gold's daily returns increased during the most recent recession in the U.S, but largely recovered during the onset of the GFC.

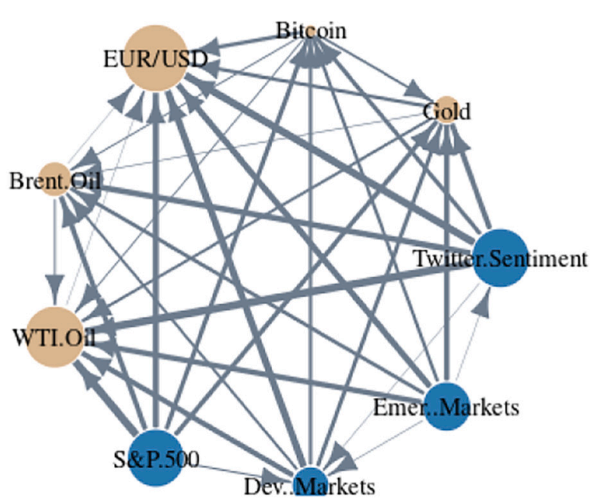
Moreover, Smales and Yang (2015) shows that asymmetric responses to differing components of the sentiment measure intensify during period of market turmoil. Our results concord with findings of Smales and Yang (2015) particularly for both gold and oil. Similarly, our findings are consistent with Naeem et al. (2020) who find that the investor sentiment acts as a leader of stock market volatility. Their results show that the Twitter Happiness index provides functional predictive information for the future volatility of stock markets. Thus, our findings suggest that investors should prudently control the information content in the S&P500 Twitter Sentiment Index to adjust quickly their



(a) Median $\tau = 0.50$



(b) Extreme lower quantile $\tau = 0.05$



Extreme upper quantile $\tau = 0.95$

(caption on next column)

Fig. 3. Net pairwise directional spillover network [Blue (yellow) nodes illustrate net transmitter (receiver) of shocks. Vertices are weighted by averaged net pairwise directional connectedness measures. Size of nodes represents weighted average net total directional connectedness.] (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

investment decisions and cover against bearish and bullish Twitter Sentiment Index episodes.

4.2.2. Dynamic analysis of net pairwise directional connectedness

In this section we investigate net pairwise directional connectedness between the S&P500 Twitter Sentiment Index and each financial market considered separately, as depicted in Fig. 6 (Figs. 6a to 6h). Different pictures of shock return spillover are visualized in Fig. 6. In fact, at stable periods (median quantiles) we find that the Twitter Sentiment Index acts as net transmitter of return spillovers for all considered financial markets, highlighting the dominant role of the Twitter Sentiment Index in leading the system regarding return spillovers transmissions.

Under bullish markets (upper quantile 0.95) we observe a mixed picture of return spillovers. Examining all graphs in Fig. 6 we see that the Twitter sentiment index acts as net transmitter of return volatility spillovers to other financial markets during most of the sample periods, with some exceptions for which the Twitter Sentiment Index turn to net receiver of return spillovers from other financial markets.

For example, the first quarters of 2019 and mid-2020 the Twitter Sentiment Index receives return shocks from the cryptocurrency market. Moreover, during the first part of the sample-period until the end of the first quarter of the year 2020 the Twitter Sentiment Index acts as net receiver of returns spillovers from the WTI oil market. Additionally, during the third quarter of the years 2020 and 2021 the Twitter Sentiment Index is affected by return shocks emanating from oil markets (both Brent and WTI) and acts as net recipient of return shocks spillovers from those markets. Additionally, Twitter Sentiment Index receives shocks of returns from stock market indices during some periods, including from the S&P500 index during the last quarter of the year 2020, and from the developed and emerged stock market indices during the first part of the sample period until the first quarter of the year 2020, and during the end of the year 2021. Moreover, in period of downside returns (at lower quantile 0.05), the conditional connectedness between Twitter sentiment index and all other markets is generally weak compared to period of high returns.

In summary, Twitter Sentiment Index dominants the system and acts as net emitter of negative return shocks to all financial markets, with some exceptions for which the Twitter Sentiment Index moves to the recipient side and receives return shock spillovers emanated from other financial markets. Hence, portfolio investors should adjust timely their portfolio in accordance with the market sentiment state, rather than limit their allocations to safe-haven assets (Naeem et al., 2021). These results support previous findings suggesting that economic and financial events are closely related to financial markets.

Overall, we offer new insights to investors, market participants and policy makers to better understand the extreme return spillovers between sentiment index and financial markets. Our findings reveal new evidence concerning sentiment return spillovers connectedness between tails. We extend the literature related to the investor sentiment spillovers among financial markets (Zhang et al., 2016), You et al., 2017), Li, Shen, et al., 2017, Zhao, 2020, Naeem et al., 2020), by considering the tail-connectedness approach based on a Quantile-VAR framework and using the S&P500 Twitter sentiment index.

Our results are consistent with prior research (Bouri et al., 2021; Bouri, Lucey, Saeed, & Vo, 2020; Maghyereh & Abdoh, 2020; Naeem et al., 2020; Naeem et al., 2021; Tan & Tas, 2020), and evidence that a mean-based connectedness approach does not suitably identify the degree of connectedness spillovers related to large downside/upside

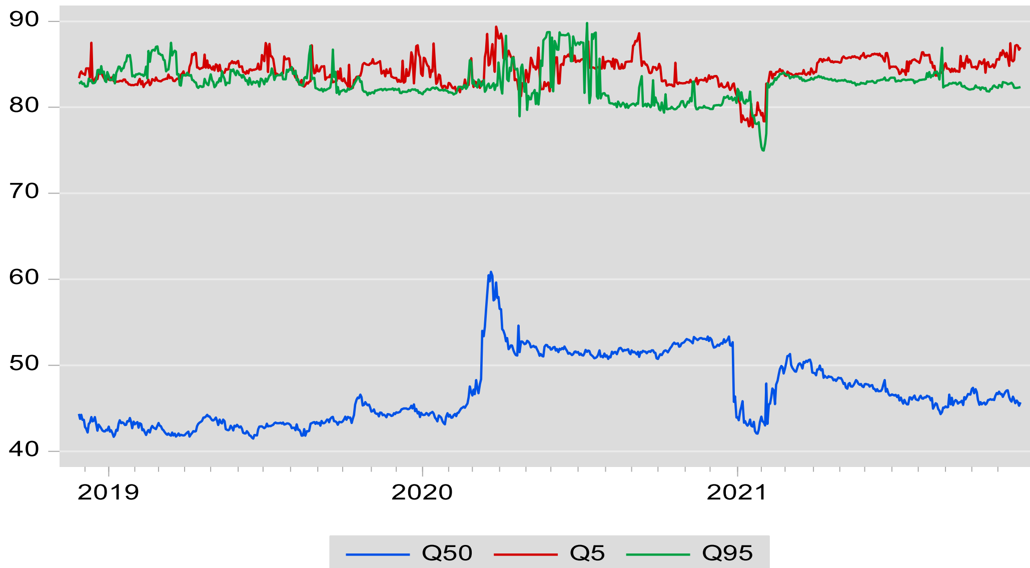


Fig. 4. Time-varying total spillover index between Twitter sentiment and all markets at various quantiles [Median (Q50), Extreme lower (Q5), Extreme upper (Q95)].

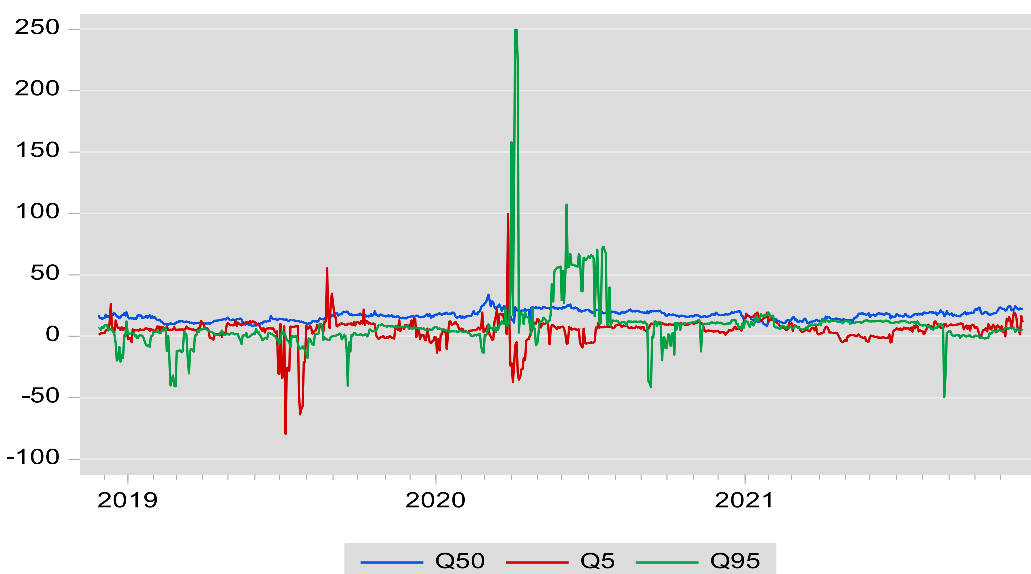


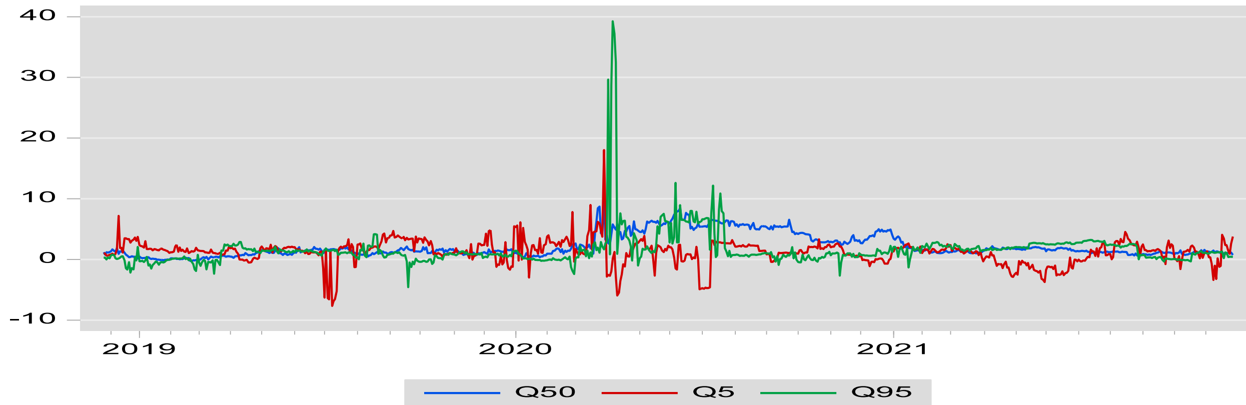
Fig. 5. Time-varying net spillover between Twitter sentiment and all markets at various quantiles [Median (Q50), Extreme lower (Q5), Extreme upper (Q95)].

shocks. That spillovers across the Twitter Sentiment Index and other financial markets are strengthening during turmoil periods is evidenced in other assets, even with different methods. For example, Betz, Hautsch, Peltonen, and Schienle (2016) highlight that tail-based dependency provide useful information for banker in terms of making prudential regularity and surveillance mechanism.

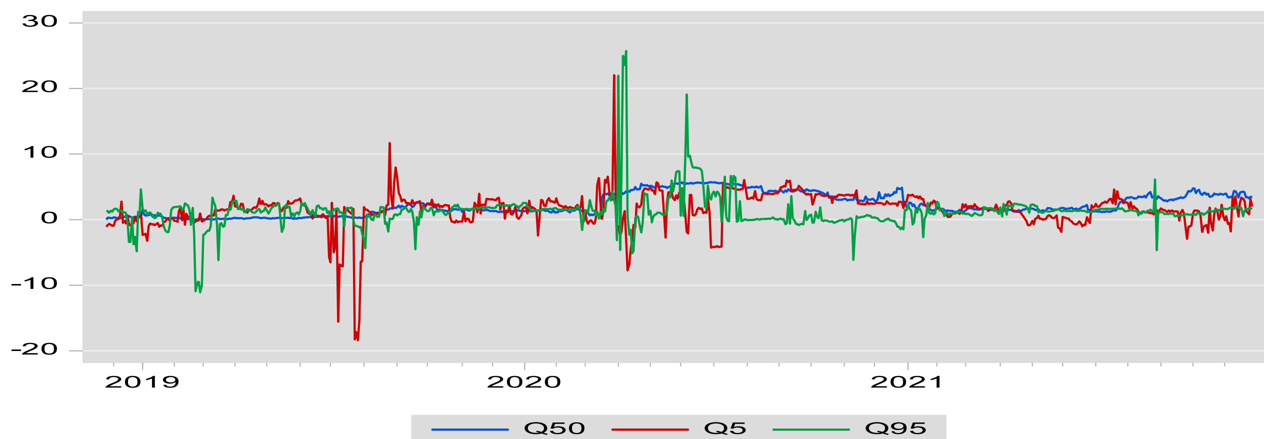
5. Conclusions

Given the growing role of social media platforms in exchanging ideas and information, researchers and academicians have implemented many investor sentiment proxies based on news shared on social media platforms. This study uses the newly developed S&P500 Twitter Sentiment Index to investigate investor sentiment spillovers among various financial markets. We apply a recent methodology, the quantile-VAR connectedness measures following Ando et al. (2022) and Diebold and Yilmaz (2014). This allows differentiating between connectedness patterns in the upper, median, and lower quantiles. We use daily data for five financial markets including, metal (gold), energy (WTI crude oil), cryptocurrency (Bitcoin), fiat currency (EUR/USD) and equity markets (S&P 500, Dow Jones developed stock market-excluding US, emerging stock market), for February 7, 2018–November 26, 2021, include the COVID-19 period.

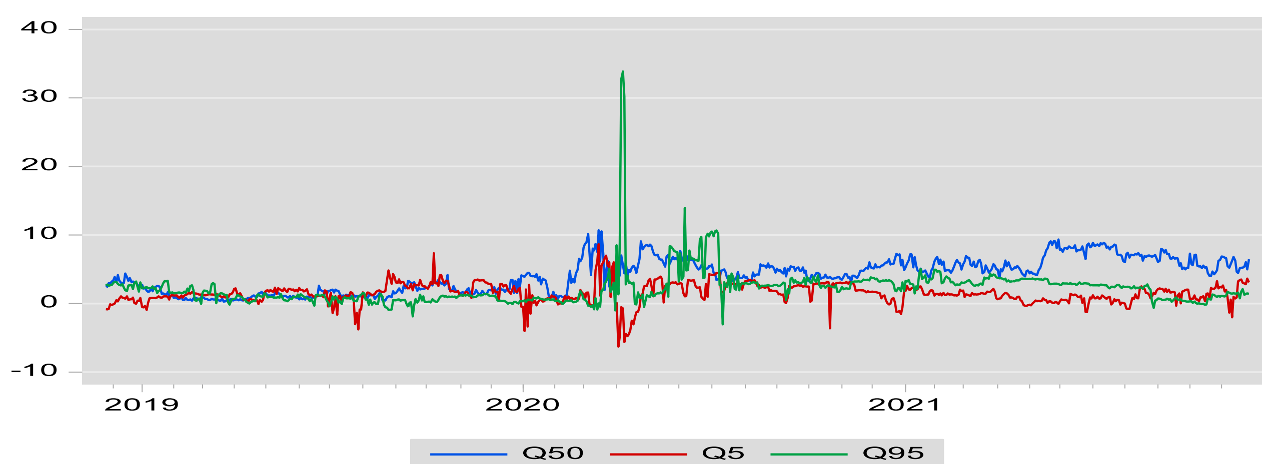
We evidence that the S&P500 Twitter Sentiment Index significantly affects returns of the studied financial markets, with spillover from Twitter sentiment time varying and highly affected by economic and financial events. Moreover, our results offer important new evidence regarding connectedness in extreme lower quantile, median and extreme upper quantiles of the conditional distribution. Twitter Sentiment Index spillovers are stronger at both extreme upper and extreme lower tails compared to those in the median. Specifically, results from the dynamic quantile connectedness approach show that tail-dependences between the Twitter Sentiment Index and the financial markets are time-varying, with the tail sentiment spillovers in lower



(a) Twitter sentiment and gold

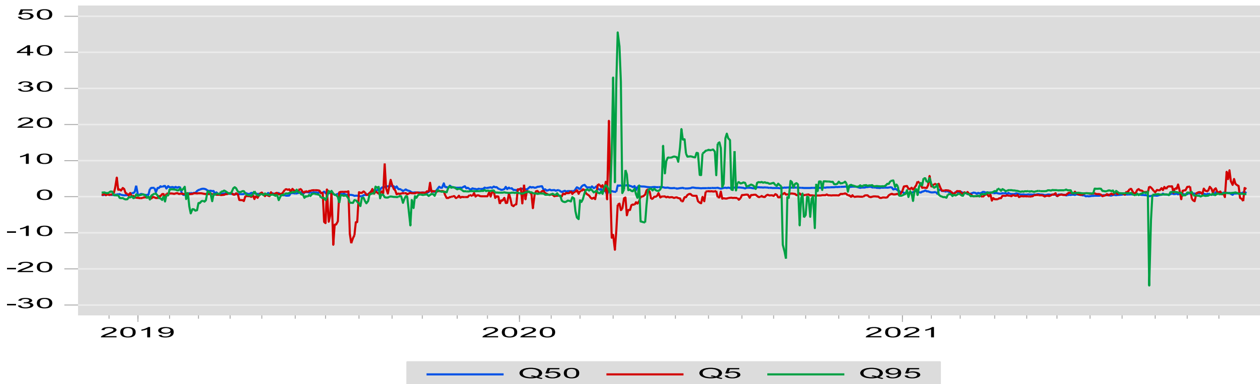


(b) Twitter sentiment and Bitcoin

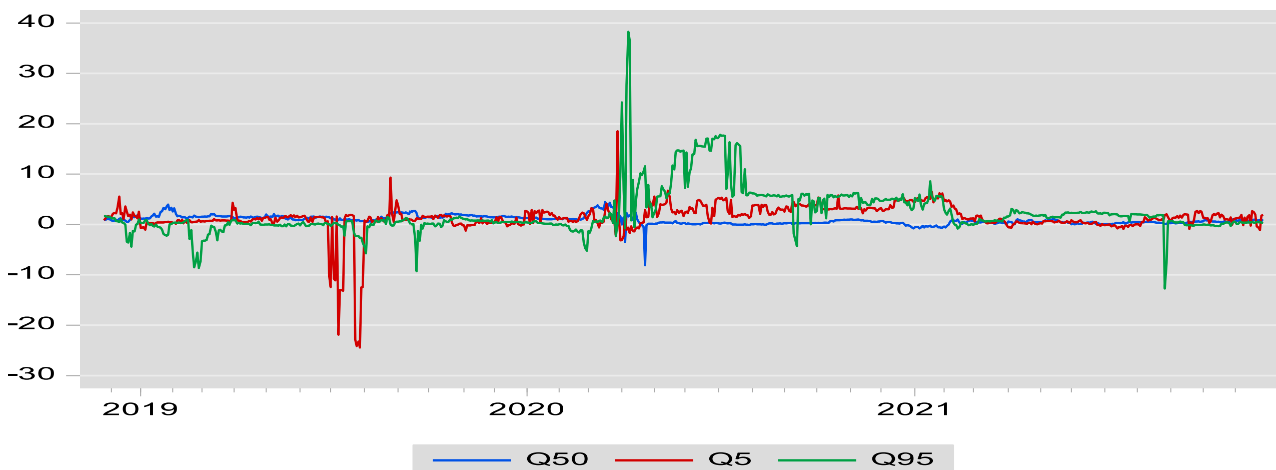


(c) Twitter sentiment and EUR/USD

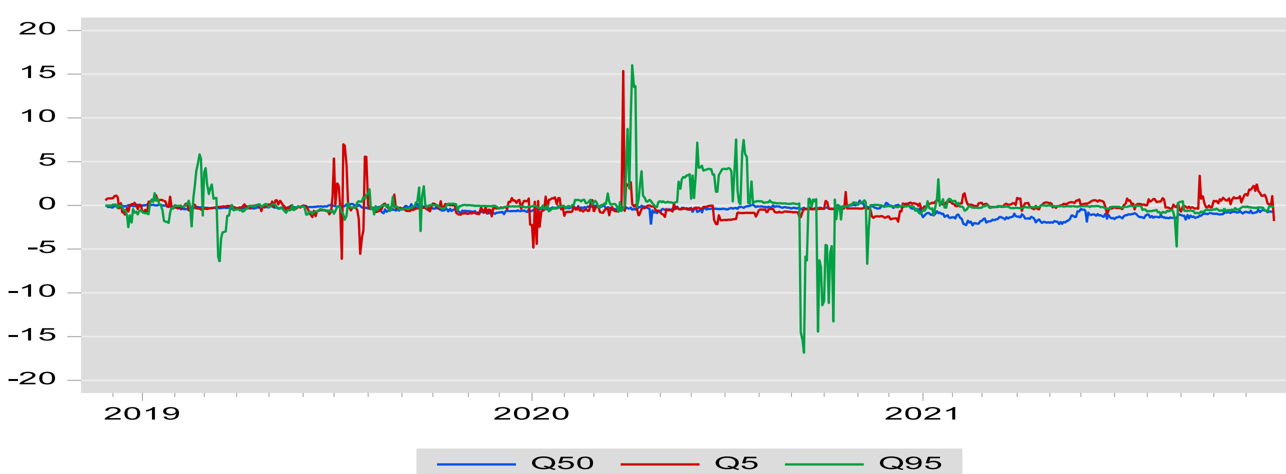
Fig. 6. Time-varying pairwise spillover between Twitter sentiment and each market at various quantiles [Median (Q50), Extreme lower (Q5), Extreme upper (Q95)].



(d) Twitter sentiment and Brent oil

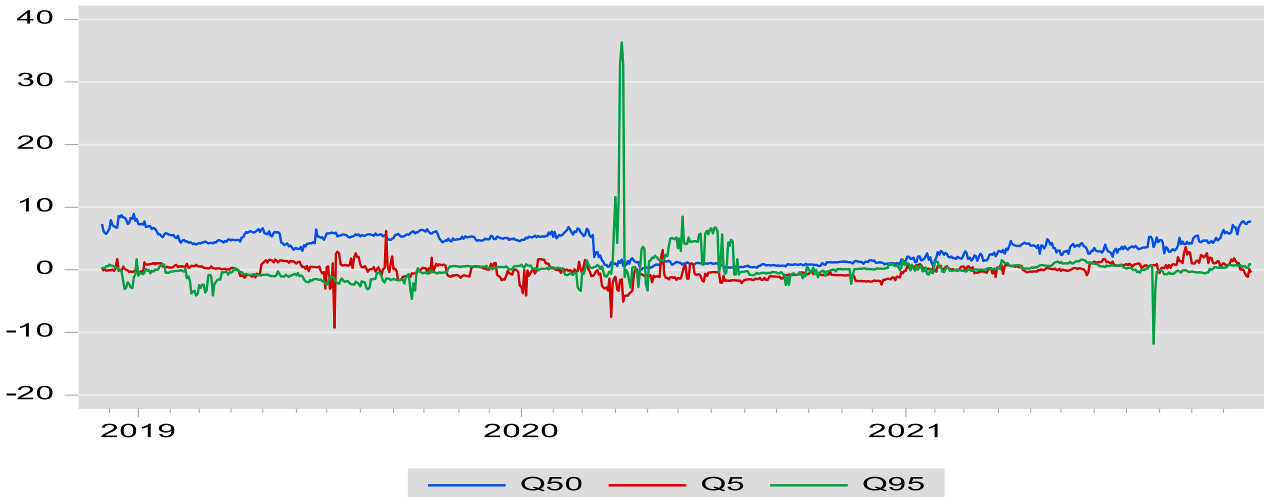


(e) Twitter sentiment and WTI oil

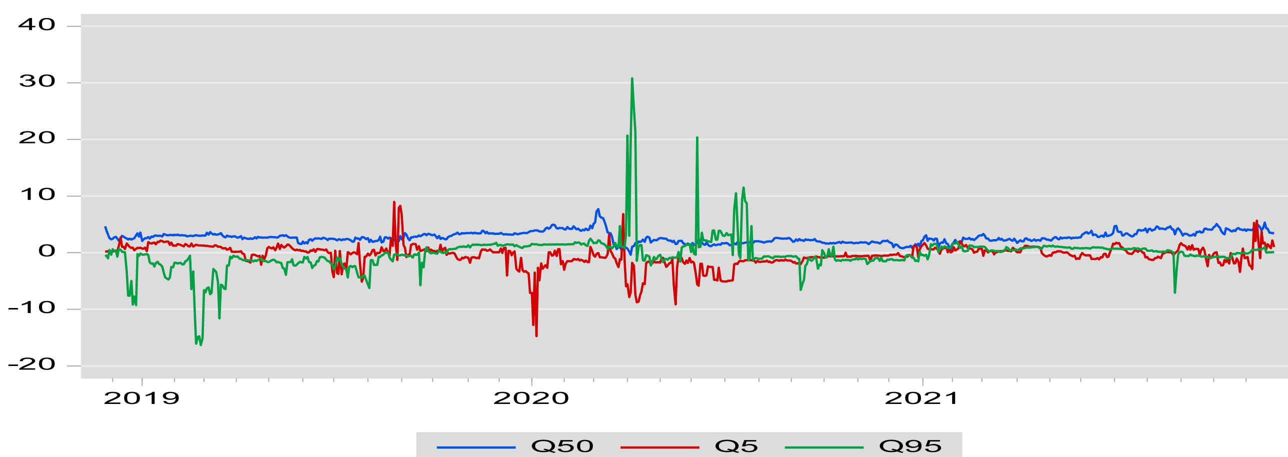


(f) Twitter sentiment and S&P 500

Fig. 6. (*continued*).



(g) Twitter sentiment and Development markets



(h) Twitter sentiment and Emerging markets

Fig. 6. (*continued*).

quantile generally changing concomitantly with changes in upper-tail sentiment spillovers. Therefore, extreme downside events are closely interconnected to an increase in right-tail connectedness disturbance. Furthermore, the patterns of sentiment spillovers among financial markets in both left and right tails are wide different to those obtained in the center of the distribution, indicating that the patterns of tails-sentiment spillovers are masked when using only mean-based connectedness measures. Accordingly, the quantile-based spillover index is highly recommended as a relative framework of the traditional mean-based spillover measures.

Another advantage of the quantile connectedness approach is that it allows specifying the role of each variable as whether a net transmitter or receiver of return spillovers. Our results show that, in the static state, the Twitter Sentiment Index acts generally as a net transmitter of return spillovers to other financial markets in upper, median and lower quantiles. This result highlights the leading role of the S&P500 Twitter Sentiment Index in the whole system, underscoring the preeminence of Twitter platform compared to other social media platforms such as Google, in formulating online investor sentiment proxies and forecasting financial market's returns.

Similarly, dynamic sentiment spillovers patterns show that the Twitter Sentiment Index mainly acts as a net emitter of spillovers to other markets, with role changes in some specific periods where the Twitter index turns to net receiver of return spillovers from other markets. Finally, we notice an unprecedented upsurge in the magnitude of sentiment spillovers in both upper and lower tails during the recent COVID-19 crisis, consistent with the effect of investor's sentiment is more prominent during period of market turmoil. These results underscore that the effect of investor's sentiment on financial markets varies in direction and intensity responding to the global economic and financial state.

Our findings provide important new information for investors, portfolio managers and policy makers. In fact, understanding the direction and intensity of the sentiment spillovers in the connectedness system will help investors maximize their benefits from well diversified portfolios by allocating funds across markets according to sentiment changes. Results from tail-sentiment spillovers offer particularly functional information for portfolio allocation regarding positions in each market under bearish or bullish market conditions. Investors can adjust their strategies and risk exposures during extreme distress episodes (extreme upside/extreme downside shocks) in response to the extreme negative and positive return shocks. Furthermore, time-varying net spillovers between sentiment index and financial markets provide new insights for traders and portfolio managers to timely adjust their positions in response to market conditions. Further, findings on the extreme tail-sentiment spillovers suggest the importance of tail-sentiment propagation among financial markets. Portfolio managers are also suggested to continuously watching the relevant twitter trends to gauge the sentiment of investors and then design portfolios accordingly. As Twitter sentiments are net transmitter, therefore policy makers are suggested to consider the investor's sentiments through Twitter to make/adjust policies or regulations to stabilize the financial markets.

The current study uses only the twitter sentiment index as the proxy of investor sentiments, however, google trends can also be the alternate proxy of the investor's sentiments, therefore, for future studies, we suggest using both investor's sentiment proxies to examine its impact on financial markets.

Author statement

The authors assert that this project is a genuine collaboration of all authors and that this work is not published or under consideration elsewhere.

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