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Spillover between investor sentiment and volatility: The role of social media

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ABSTRACT

We examine the spillover effects between social media sentiments and market-implied volatilities among stock, bond, foreign exchange, and commodity markets. We find that information mainly spillovers from volatility to sentiment indices, with the VIX being the most significant net transmitter. Within each asset class, there is a more pronounced spillover from volatility to sentiment compared to the reverse, implying that a significant portion of investor sentiment is volatility-driven. This relationship intensifies in turbulent economic periods, such as during the Global Financial Crisis, Brexit, the US-China trade war, and the COVID-19 pandemic. Our analysis also reveals that sentiment indices can transition from net receivers to net transmitters of shocks during turbulent periods. This can be explained by the echo chamber effect, where social media echo prevailing news signals, and some investors interpret repeated signals as genuinely new information.

1. Introduction

It has been well documented that sentiment extracted from traditional news media influences financial markets (see, e.g., Fang & Peress, 2009; Engelberg & Parsons, 2011; Dougal et al., 2012). Over the last decade, however, social media has become investors' leading source of information. The Reuters Institute digital news survey (Newman et al., 2021) documents that 56 % of the respondents worldwide use social media to access news and information. In line with this technological change, recent academic literature has highlighted the importance of social media sentiment for the equity markets (see, e.g., Rakowski et al., 2021; Al-Nasseri et al., 2021), bonds (Alomari et al., 2021), foreign exchange (Goddard et al., 2015; Sibande et al., 2023), and commodities (Fan et al., 2023; Han et al., 2017).

Despite the extant studies on social media and financial markets, whether social media sentiment spillovers across different asset classes remains underexplored. The literature has shown that different asset classes are interconnected. For example, the safe haven literature finds a relationship between equity and gold markets (see, e.g., Baur & McDermott, 2016; Triki & Maatoug, 2021). The investor fear and attention literature finds a link between equity and foreign currency markets (Smales & Kininmonth, 2016) or equity and commodity markets (Fernandez-Perez et al., 2020; Gao & Süss, 2015). In the current study, we posit that linkages between various asset classes can be further explained by sentiment spillover, i.e., how investors' sentiment from one asset influences the sentiment of other asset classes. Whether such sentiment transmission exists remains an empirical question. Our study sheds light on the dynamic interplay between market sentiment and volatility through the lens of social media sentiment. Specifically, it explores how investor sentiment in one asset class can influence both the sentiment and volatility of other asset classes, revealing the interconnectedness across markets.

Understanding sentiment spillover is crucial when disentangling the underlying relation among asset classes. Existing studies mainly focus on volatility spillover, and as such, the linkage between two assets often revolves around the transmission of uncertainty (Andrada-Félix et al., 2018; Bouri et al., 2021; Mensi et al., 2021; Sharif et al., 2020). Andrada-Félix et al. (2018), for instance, argue that volatility reflects the extent to which the market evaluates and assimilates new information. Thus, volatility spillover captures how perceptions of uncertainty about economic fundamentals are manifested in prices across various asset classes. Instead, we argue in this paper that linkages between assets can also be explained through a behavioral explanation. That is, during periods of heightened uncertainty about fundamentals, investors consider social

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media as an additional source of information. They exchange their opinions via social platforms and are influenced by other investors' sentiments. A recent study by Umar et al. (2021) demonstrates the sentiment-driven pricing in the case of meme stocks, such as the GameStop stock. Understanding the interdependence between market sentiment and financial volatility is critical for regulators and investors, as it directly impacts market stability and portfolio diversification strategies, particularly during times of turmoil. Collective social media sentiment can influence investor expectations, potentially driving irrational trading behavior, increasing market volatility, and destabilizing multiple asset classes through sentiment spillovers.

Going beyond the interplay of sentiments, we delve into the spillover dynamics between sentiment and volatility across diverse asset classes. Existing studies mainly examine sentiment and volatility spillover independently (Andrada-Félix et al., 2018; Audrino & Tetereva, 2019).[1] However, recognizing the inherent interconnectedness, we can expect cross-linkages between sentiment and volatility. For instance, findings in the crude oil literature indicate that oil price volatility significantly impacts stock market sentiment. The uncertainty in oil prices prompts delays in investment decisions (Elder & Serletis, 2010) and triggers increases in the unemployment rate (Kocaaslan, 2019), consequently dampening investor sentiment in the equity markets (Bennani, 2020; Chalmers et al., 2013). While studies such as Da et al. (2015) and Goddard et al. (2015) explore the linkages between sentiment and volatility, these are predominantly within the confines of a single asset class.[2] To the best of our knowledge, our study is the first to examine the effects of social media sentiment on asset volatility across various asset classes, representing a unique contribution to the sentiment literature.

In this study, we assess the relationship between sentiment and implied volatility across a spectrum of asset classes, encompassing equities, bonds, precious metals, energy, and foreign exchange. We employ Diebold & Yılmaz (2012, 2014) (hereafter, DY) measure of connectedness, which measures the shares of forecast-error variation in an asset due to shocks arising elsewhere. A distinguishing feature of our work compared to the previous studies is that we consider investor sentiment tailored specifically to each asset class. Our work also extends the literature on spillover effects by integrating sentiment measures directly into the DY approach via a vector autoregression (VAR) model, mitigating potential endogeneity issues and revealing intriguing dynamics between sentiment and implied volatility indices.

We leverage the LSEG MarketPsych Analytics (RMA) sentiment, which has been widely used in recent studies as a proxy of investor sentiment (see, e.g., Papakyriakou et al., 2019; Gan et al., 2020; Eierle et al., 2022). The RMA provides sentiment scores in three categories: News, Social, and News&Social. We focus on the sentiment from the social category but also use the other two categories in the robustness tests. The RMA analyzes millions of real-time social media references from thousands of global media outlets daily and measures investor sentiment scores for each asset. The social media sentiment indices we use include those for the stock market, bond market, Euro/USD, gold, and oil.

As volatility measures, we utilize implied volatility indices from the Chicago Board Options Exchange (CBOE) to measure investors' expectations regarding future volatility (Whaley, 2009). The forward-looking nature of implied volatility indices makes them superior to historical volatility (see, e.g., Blair et al., 2001; Jiang & Tian, 2005). To deepen our analysis, we further measure the connectedness between the sentiment block and volatility indices using the generalized connectedness framework developed by Greenwood-Nimmo et al. (2016, 2021).

Measuring connectedness over the sample period from August 2008 to May 2020, we obtain several key findings. First, our sentiment and volatility indices are interconnected, with a total connectedness of 30.4 %. There is a stronger spillover from volatility to the sentiment of the same market but a marginal effect in the opposite direction. Second, informational spillover comes mainly from volatility indices to sentiment indices, with the VIX being the most significant net transmitter to other assets. Third, the connectedness between market sentiment and volatility increases during turbulent economic periods, such as the Global Financial Crisis (GFC), Brexit, the US-China trade war, and the COVID-19 pandemic. However, the sentiment indices can transition from net receivers to net transmitters of shocks during turbulent periods. Our main findings hold up under several robustness tests, including variations in the rolling window length of the time-varying connectedness measures. Our results remain consistent even when accounting for the potential influence of business cycles, market fundamentals, and traditional news media sentiment.

We contribute to several strands of literature. First, this study sheds light on social media sentiment spillover across financial markets. Existing research often concentrates on the influence of one market's sentiment on a specific market type (Long et al., 2023) or explores how general market sentiment affects different asset classes (Zhang et al., 2022). In contrast, our approach involves extracting sentiment for each distinct asset class, allowing for a systematic examination of spillover effects between them. Hence, our findings provide a better understanding of the importance of social media irrespective of the asset classes, depicting the spillover effect across diverse segments of the financial markets.

Second, we show that, in general, social media sentiment is a net receiver rather than a net trigger of market volatility. However, during market turmoil, social media sentiment can become a net shock transmitter. This observation aligns with the *echo chamber* effect (Jiao et al., 2020), where social media echoes existing signals from traditional news media. However, some investors interpret repeated signals as genuinely new information. This mechanism explains why, on average, social media sentiment is a net receiver of shocks but shifts to triggering them during turbulent market periods.

Third, we demonstrate that the linkages among financial markets are not solely attributable to volatilities. Instead, we explain such connectedness from a behavior perspective, showing that social media sentiment also contributes to the interconnections among asset classes. Investors contribute to variations in sentiment, influencing corresponding volatilities. These influences originate from social media platforms, particularly during market turbulence.

Finally, our findings align with Umar et al. (2021), who emphasize the importance of monitoring social media sentiment for market stability. We highlight the significance of social media sentiment in driving excessive price movements, particularly during market turmoil periods. Social media sentiment can become a net transmitter of shocks, amplifying investor irrationality (Hirshleifer, 2001) and influencing market uncertainty dynamics (Baker & Wurgler, 2006). This underscores the broader impact of social media sentiment on market behavior and stability during challenging economic conditions, an area of interest for the regulators. Our study also holds significance for investors with cross-asset portfolios from the risks associated with multi-market sentiment risks. Additionally, it offers practical insights for hedge funds to identify factors influencing market anomalies, particularly those driven by sentiment-induced volatilities.

The remainder of the paper proceeds as follows. Section 2 reviews the literature and motivates our hypotheses. Section 3 presents the methodology. Section 4 introduces the volatility and sentiment datasets and provides descriptive statistics. In Section 5, we report our empirical

[1] Andrada-Félix et al. (2018) investigate the interconnection between implied volatility indices for five different asset classes such as stock, energy, currency, metal and bond. Audrino and Tetereva (2019) study the sentiment spillover effects for US and European companies.

[2] Da et al. (2015), for instance, show that investor sentiment proxied using internet search volume predicts temporary increases in stock market volatility. Goddard et al. (2015) find that investor attention in the foreign exchange markets comoves with contemporaneous foreign exchange market volatility and predicts subsequent volatility.

findings and robustness tests. Section 6 concludes.

2. Literature review and hypotheses development

Since De Long, Shleifer, Summers, & Waldmann, 1990 document that investor sentiment is a factor that can drive excessive price movements, many studies have investigated the effects of sentiment on volatility. The general conclusion is that investor sentiment is associated with volatility in the financial markets (see, e.g., Da et al., 2015; Behrendt & Schmidt, 2018; Liang et al., 2020; Gan et al., 2020). For instance, Lee et al. (2002) empirically show that sentiment is negatively associated with stock market volatility, while negative sentiment induces higher stock market volatility. Da et al. (2015) document that low sentiment (proxied using Google searches of keywords such as 'recession' and 'crisis') predicts short-term return reversals and temporary increases in volatility. Behrendt and Schmidt (2018) and Liang et al. (2020) find that stock market social media sentiment has a pronounced impact on individual stock volatility and can forecast stock market volatility. Gan et al. (2020) show that stock market volatility is more sensitive to social media than news sentiment. A separate study by Sprenger et al. (2014) finds a reverse causality where high stock volatility leads to an increased relevant discussion on social media as uncertainty causes investors to exchange information and consult their peers, which is reflected in the social media sentiment. Long et al. (2023) extract Reddit's social media platform's posts and show that social media sentiment drives the meme stock GameStop's excessive and abnormal price volatility intraday.

The linkage between investor sentiment and volatility has also been documented in assets other than stocks. Karagozoglu and Fabozzi (2017), for instance, show that a signal constructed from social media sentiment can be used to predict VIX-related ETFs. In commodities, Gao and Süss (2015) demonstrate that commodity futures with high volatility are more likely to be exposed to general market sentiment.

In recent studies, Wang et al. (2022) examine the connection between Chinese stocks and sentiment measures using a multi-layer network consisting of a stock return layer and an investor sentiment layer. They find that the investor sentiment layer is weaker than the stock return sentiment layer. This finding aligns with our results, where we observed that the social media sentiment block connectedness is smaller than that of the implied volatility block. However, our research differs from theirs in several key aspects. Firstly, Wang et al. (2022) focus on an emerging market (China) and a single asset class (equities), whereas we consider five asset classes from developed markets. Secondly, their study seeks indirect links between sentiment and equity returns through quantile regressions. The approach we take in our study, on the other hand, allows the system to reveal the connections between all variables (social media sentiment and implied volatilities), uncovering more interesting relationships.

Wang et al. (2023) investigate the interconnectedness between different stock markets and foreign exchange markets following the DY approach. The finding shows that stock markets act as net spillover transmitters, with spillovers signaling financial instability during periods of turmoil, such as the pandemic. However, while their focus is limited to two asset classes, i.e., equities and foreign exchange across different countries, our study expands upon this by providing new insights through an investigation of five major asset classes within developed economies.

Gong et al. (2024) conduct a similar analysis by examining the spillover effects between realized volatility, implied volatility, and risk aversion sentiment (extracted from the variance risk premium) in the Chinese ETF equity market options (Chinese SSE 50 ETF). They find that investor sentiment can trigger sudden shocks in realized volatility and expansive shocks in implied volatility. This result aligns with our findings, where we observe that social media sentiment acts as an echo chamber during turbulent times, generating uncertainty in options markets. However, this study differs from ours in that it focuses solely on the equity market within an emerging market, whereas we analyze multiple asset classes in developed markets.

All the above evidence points toward spillover effects from one asset class affecting the sentiment and volatility of another asset class. Several theories have been proposed to explain the interconnections between different asset classes. The literature on crude oil, for instance, highlights the impact of oil price uncertainty on stock returns. Such uncertainty can lead to the postponement of investment decisions (Elder & Serletis, 2010) and increases in the unemployment rate (Kocaaslan, 2019), which can slow economic activity and dampen investor sentiment in equity markets (Bennani, 2020; Chalmers et al., 2013).

The literature on safe-haven assets (Baur & Lucey, 2010; Baur & McDermott, 2010) suggests that gold often acts as a hedge against stocks under normal conditions and as a safe haven during extreme stock market turmoil. For example, Niu et al. (2022) document that speculative sentiment among stock market investors can influence volatility in the gold market.

The flight-to-quality literature (Baur & Lucey, 2009) posits that investors shift their money from riskier assets, like stocks, to more stable ones, such as bonds, during times of uncertainty. This behavior creates a linkage between stock market sentiment and bond market volatility. Bethke et al. (2017) show that when investor sentiment is low, corporate bond investors exhibit a stronger flight-to-quality behavior, resulting in higher bond correlation.

While it is not our goal to detail all possible interconnections between the five asset classes under consideration, the examples above illustrate how spillover effects can occur, with changes in one asset class influencing sentiment and volatility in another. Thus, our first hypothesis:

Hypothesis 1. Sentiment and volatility from one asset class spillover into the sentiment and volatility of another asset class.

Several studies have documented that investors tend to avoid trading during periods of low sentiment. For example, Yu and Yuan (2011) argue that sentiment traders, being more novice and less sophisticated, are less inclined to take short positions during low-sentiment periods, as measured by the composite sentiment index of Baker and Wurgler (2006). Antoniou et al. (2016) find that noise trading decreases during low sentiment (pessimistic) periods, while unsophisticated and overconfident traders become more active during high sentiment (optimistic) periods. This suggests that while sentiment may still influence individual asset classes, the cross-market spillovers of sentiment, where sentiment in one market affects others, are diminished in turbulent times. Therefore, our second hypothesis is as follows:

Hypothesis 2. The impact of sentiment spillovers is less pronounced during turbulent periods.

It is also possible that sentiment spillovers across asset classes are more pronounced during periods of economic turbulence. Garcia (2013) argues that sentiment is a significant market predictor during economic recessions, as investors face heightened uncertainty about fundamentals. Birru and Young (2022) further demonstrate that during turbulent periods, higher uncertainty regarding fundamentals prompts investors to place greater reliance on the sentiment of others. This reliance includes sentiment observed in different asset classes, especially as investors seek diverse information sources, including social media. This cross-asset sentiment spillover effect is expected to be stronger when

Table 1
Connectedness table.

	x_1	x_2	…	x_N	From others
x_1	d_{11}^H	d_{12}^H	…	d_{1N}^H	$\sum_{j=1}^N d_{1j}^H, j \neq 1$
x_2	d_{21}^H	d_{22}^H	…	d_{2N}^H	$\sum_{j=1}^N d_{2j}^H, j \neq 2$
⋮	⋮	⋮	⋱	⋮	⋮
x_N	d_{N1}^H	d_{N2}^H	…	d_{NN}^H	$\sum_{j=1}^N d_{Nj}^H$, $j \neq N$
To others	$\sum_{i=1}^N d_{i1}^H$, $i \neq 1$	$\sum_{i=1}^N d_{i2}^H$, $i \neq 2$	…	$\sum_{i=1}^N d_{iN}^H$, $i \neq N$	$\frac{1}{N}\sum_{ij=1}^N d_{ij}^H$, $i \neq j$

This table shows the schematic for the connectedness table for N assets. The rightmost column contains the row sums (total directional connectedness FROM others), the bottom row contains the column sums (total directional connectedness TO others), and the bottom-right cell contains the grand average (the overall connectedness).

traditional indicators are less reliable due to economic instability. Therefore, our third hypothesis is as follows:

Hypothesis 3. The impact of sentiment spillovers is more pronounced during turbulent periods.

In summary, existing spillover studies tend to focus on narrow aspects, such as implied volatility indices or sentiment indices in isolation, or they examine how sentiment impacts the volatility of a single asset class. There remains a gap in understanding the interaction between social media sentiment and implied volatility across multiple asset classes. For instance, there is no study that examines the ways in which sentiment in one asset influences another asset's volatility, and vice versa, or illustrates the evolving networks of connectedness among them over time. Our research provides a novel perspective on how the interplay between social media sentiment and volatility influences the broader financial markets. To accomplish this, we utilize asset-specific sentiment measures from RMA and the Diebold and Yılmaz (2012), Diebold & Yılmaz, 2014) connectedness methodology to disentangle their interconnected effects. We will explain this methodology next.

3. Methodology

We first discuss the DY approach as our primary measure of connectedness among different sentiment and volatility indices. We then discuss the generalized connectedness framework Greenwood-Nimmo et al. (2016, 2021) developed to capture the connectedness between sentiment and volatility blocks.

3.1. Diebold-Yilmaz connectedness measure

We follow the DY approach to measure the connectedness of five market sentiments and five market volatility indices. This approach is related to the economic notion of variance decomposition, in which the forecast-error variance of a variable is decomposed into parts attributed to the various variables in the system. Consider fitting a reduced-form, N-dimensional covariance-stationary vector autoregression (VAR) model: $x_t = \Theta(L)u_t$, $\Theta(L) = \Theta_0 + \Theta_1 L + \Theta_2 L^2 + \ldots, E(u_t, u_t') = I$. The contemporaneous aspects of connectedness are summarized in Θ_0, and dynamic aspects in $\{\Theta_1, \Theta_2, \ldots\}$.Transformations of $\{\Theta_1, \Theta_2, \ldots\}$ via variance decompositions can reveal connectedness.

We employ Diebold and Yılmaz (2014) "variance decomposition table" to understand the connectedness measures. Table 1 reports the variance decompositions where x_1 to x_N are the sentiment or volatility variables of each asset, H is the number of periods ahead forecast. The upper-left NxN block contains variance decompositions with denoted D^H where $D^H = \left[d_{ij}^H\right]$.[3] In particular, the pairwise directional connectedness from j to i as defined:

$$C_{i\leftarrow j}^H = d_{ij}^H. \tag{1}$$

The pairwise directional connectedness from i *to* j is $C_{j\leftarrow i}^H = d_{ji}^H$ where $C_{i\leftarrow j}^H \neq C_{j\leftarrow i}^H$, generally, and therefore, we define the net pairwise directional connectedness from i to j as follows:

$$C_{ij}^H = C_{j\leftarrow i}^H - C_{i\leftarrow j}^H. \tag{2}$$

For the rightmost column sum or bottom row sum (both $i \neq j$) means the share of forecast error variance of x_i coming from or going to shocks arising in all other variables. Thus, we label the rightmost column and the bottom row as "From others" and "To others" total directional connectedness measures. Hence, we define total directional connectedness from others to i (as)

$$C_{i\leftarrow\bullet}^H = \sum_{\substack{j=1\\ j\neq i}}^N d_{ij}^H, \tag{3}$$

while the total directional connectedness from i to others is defined as:

$$C_{\bullet\leftarrow i}^H = \sum_{\substack{j=1\\ i\neq j}}^N d_{ji}^H. \tag{4}$$

Accordingly, we define net total directional connectedness for i as:

$$C_i^H = C_{\bullet\leftarrow i}^H - C_{i\leftarrow\bullet}^H. \tag{5}$$

Lastly, the total of the off-diagonal entries in D^H on the bottom-right of Table 1 (equivalently, the sums of the rightmost column or the bottom row), measures total connectedness among all variables as:

$$C^H = \frac{1}{N}\sum_{\substack{i,j=1\\ j\neq i}}^N d_{ij}^H. \tag{6}$$

For the case of non-orthogonal shocks, the variance decompositions are not as easily calculated because the variance of a weighted sum is not an appropriate sum of variances. Following Diebold and Yılmaz (2014), we, therefore, use the generalized variance decomposition (GVD) proposed by Koop et al. (1996) and Pesaran and Shin (1998) to decompose the forecast error variance.[4] The H-step GVD matrix $D^{gH} = \left[d_{ij}^{gH}\right]$ is defined[5] as:

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i'\Theta_h \sum e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i'\Theta_h \sum \Theta_h' e_j\right)}, \tag{7}$$

where e_j is a vector with jth element unity and zeros elsewhere; Θ_h is the coefficient matrix (by multiplying the h-lagged shock vector) in the

[3] We denote d_{ij}^H by the ij-th H-step forecast error variance decomposition component, capturing the fraction of variable i's H-step forecast error variance due to shocks in variable j. The off-diagonal entries of D^H are the parts of the N forecast error variance decompositions of relevance from connectedness method.

[4] GVD is invariant to ordering of the variables in the VAR system.

[5] Note that under this circumstance, row sums of d_{ij}^{gH} are not necessarily unity because shocks do not have to meet the orthogonality setting.

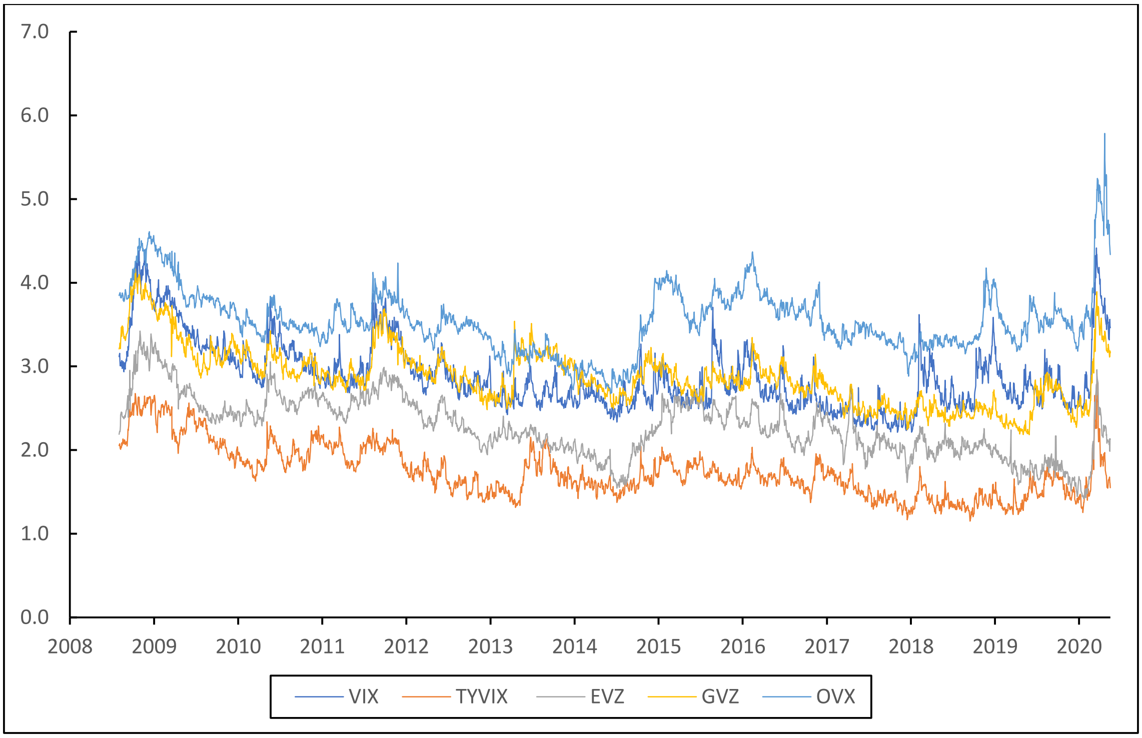

Fig. 1. Implied volatility over time.
This figure plots the daily implied volatility index across various asset classes, including the CBOE S&P500 volatility index (VIX), the 10-year Treasury Note volatility index (TYVIX), the Euro Currency implied volatility index (EVZ), the Gold ETF volatility index (GVZ) and the crude oil volatility index (OVX). The sample period is from August 1, 2008, to May 15, 2020. All series are in natural logarithms. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

infinite moving-average representation from the non-orthogonalized VAR; Σ is the covariance matrix of the shock vector in the non-orthogonalized VAR; σ_{jj} is the jth diagonal element of Σ. Particularly, the generalized connectedness index is $\widetilde{D}^g = \left[\widetilde{d}^g_{ij}\right]$ with the necessary normalization $\widetilde{d}^g_{ij} = \frac{d^g_{ij}}{\sum_{j=1}^{N} d^g_{ij}}$. By construction, $\sum_{j=1}^{N} \widetilde{d}^g_{ij} = 1$ and $\sum_{i,j=1}^{N} \widetilde{d}^g_{ij} = N$. Thus, the connectedness measures can be calculated by using $\widetilde{D}^g = \left[\widetilde{d}^g_{ij}\right]$ matrix. The DY approach's forecast error variance decomposition is directly computed from the estimated parameters and covariance matrix of the VAR system.[6]

3.2. Block connectedness measure

To investigate whether changes in sentiment induce volatility variations and vice versa, we first combine the five sentiment and five market volatility indices into two separate groups, which we refer to as the sentiment block and volatility block, respectively. We are interested in capturing the connectedness within and between sentiment and volatility blocks. Hence, instead of assessing the spillover effect for each variable individually, we measure block connectedness between sentiment and volatility. This analysis will enable us to determine whether sentiment or volatility as a block is the main source of spillover effects observed in our study.

We follow Greenwood-Nimmo et al.'s (2016) block connectedness methodology. This approach exploits aggregation of the estimated connectedness matrix to create generalized connectedness measures for comparisons at different desired levels (e.g., markets, countries). A similar methodology was also employed in recent studies such as Raddant and Kenett (2021) and Greenwood-Nimmo et al. (2021). In our case, we combine the ten variables in the system into two blocks based on their nature and then aggregate the estimated connectedness matrix according to the block structure. The technical details of this methodology can be found in Appendix A.

4. Data

This section discusses the two data sets employed in this study. First, we describe the implied volatility indices for the five asset classes we consider in our sample. Second, we explain the social media sentiment data as our measure of asset-specific investor sentiment. Our selection of these series offers the advantage of comparability across markets, given that they are calculated using the same methodologies.

4.1. Market volatility

To proxy for stock market volatility, we employ the CBOE Volatility Index (ticker: *VIX*). Using options prices on the S&P 500 index, the VIX is

[6] This calculation is subject to no additional restrictions beyond estimation and identification requirements, accounting for the contemporaneous effects and providing a measurement of connections embedded in the model.

designed to reflect investors' consensus for the upcoming 30-day expected volatility of the US equity market. For the bond market, we use the CBOE/CBOT 10-year US Treasury Note volatility index (*TYVIX*). TYVIX measures the expected volatility in its underlying 10-year Treasury Note futures over the next 30 days. For the foreign exchange market, we employ the CBOE Euro Currency Volatility Index (*EVZ*). EVZ estimates the expected 30-day volatility of the Euro/USD exchange rate by tracking the underlying options midquote prices on the Currency Shares Euro Trust. As an indicator of precious metals markets, we use the CBOE Gold ETF Volatility Index (*GVZ*). GVZ measures the expected 30-day volatility of underlying options midquote values on the SPDR Gold Shares ETF. For the energy market volatility, we use the CBOE Crude Oil ETF Volatility Index (*OVX*) as an estimate of the expected 30-day volatility of crude oil options as priced by the United States Oil Fund ETF. All volatility data is obtained from LSEG Datastream at a daily frequency.[7] Our sample period is from August 1, 2008, to May 15, 2020. The starting period is when the EVZ was first introduced, while the end date is when TYVIX was discontinued. This period covers significant economic events, such as the GFC, Brexit, the US-China trade war, and the early COVID-19 pandemic crisis.

Fig. 1 plots the daily implied volatility indices (in logs).[8] We observe some volatility spikes across markets that coincide with various economic events. For example, all indices surged in September 2008 due to the collapse of Lehman Brothers. Similarly, the spike around April 2010 was during the European sovereign debt crisis. From May to August 2011, the US debt-ceiling crisis and the US credit rating downgrade (from AAA to AA+) raised concerns about credit defaults. Countries holding large amounts of US dollars were concerned about their potential losses, aggravating investor uncertainty. In 2016, Brexit triggered economic distress among global investors. Finally, all implied volatilities soared to their historical highest during the COVID-19 pandemic at the beginning of 2020.

4.2. Sentiment data

There exist many types of investor sentiment measures. However, many measurements, such as volatility index (VIX), put-call ratio, short interest, and fund flows, are proxies of the equilibrium of the economic forces (Baker & Wurgler, 2007) rather than a direct measure of the prevailing investor sentiment. Other sentiment measures, such as market sentiment surveys (Brown & Cliff, 2004), have lagged issues due to the long survey and response process.

With those considerations, we employ a social media sentiment proxy, i.e., the LSEG MarketPsych Analytics (RMA) sentiment data, as our measure of asset-specific investor sentiment. Unlike the previous sentiment measures, social media sentiment is a direct and real-time reflection of prevailing investor sentiment in the market. Second, as a proxy of real-world investor sentiment, social media sentiment is associated with market-implied volatility for generating excessive stock price movements. For example, Dumas et al. (2009) document that sentiment can influence investors, leading to overreaction to market signals. It creates additional risks and causes excessive volatility to market prices, and such additional volatility is due to the fast-spreading investor sentiment factor.

The RMA sentiment data has been widely used in recent studies, such as Papakyriakou et al. (2019), Gan et al. (2020), and Eierle et al. (2022).[9] The data provides advanced and comprehensive asset-specific sentiment for various assets from all major countries at daily, hourly, and minute frequencies, dating back to 1998. The RMA analyzes millions of real-time mainstream news (e.g., Reuters markets coverage, the Wall Street Journal, the Financial Times, the New York Times) and social media messages (including the top 30 % of most followed blogs, microblogs, and forums worldwide, such as Reddit, Twitter, Yahoo! Finance, SeekingAlpha and StockTwits) and processes them with a high-speed AI-based machine learning algorithm for natural language processing (NLP). The extensive source coverage and advanced NLP of RMA ensure the precision of data quantification with the superiority of less information distortion, addressing heterogeneous issues (Zhang et al., 2022). This is crucial when it comes to the reliability and predictive power of sentiment data.

The RMA provides sentiment scores in three categories: *News*, *Social*, and *News&Social* (a combination of news and social). For this study, we concentrate on the sentiment indicators from the *Social* category and employ the other two for additional analyses. We collect the following five daily sentiment indices from RMA: (1) the stock market sentiment (RMA code: *ETFUS500*), (2) the bond market sentiment (*US-bondSentiment*), (3) the Euro/USD sentiment (*EUR*), (4) the gold sentiment (*GOL*), and (5) the oil sentiment (*CRU*). The sentiment score is calculated as the volume-weighted average difference between positive and negative mentions of the underlying asset over a 24-h window. It ranges from −1 to 1 and represents the degree of market optimism or pessimism for the underlying asset. A positive sentiment score suggests that investors are optimistic and have a bullish expectation for the underlying market. A negative score indicates that investors are pessimistic and have bearish expectations. A zero score indicates neutral sentiment. The RMA updates the sentiment data every calendar day at 3:30 pm U.S. Eastern time.

Fig. 2 plots the various sentiment indices over the sample period. The plots show that the equity, foreign exchange, and oil sentiment indices fluctuate around zero. In contrast, the bond market sentiment is almost persistently negative and highly volatile, while gold sentiment is relatively stable and positive over the sample period. We also observe that the sentiment indices vary over time. For instance, oil sentiment switched from bullish to bearish when the OPEC decided against cutting production despite the abundant oil supply in 2015. Many of the spikes in sentiment also coincide with the spike in volatility shown in Fig. 1. For example, during the GFC in 2008 and the COVID-19 pandemic in 2020, all sentiment indices turned into bearish territory, reflecting general pessimism across various markets. Investor sentiment gradually bounced back once uncertainty was reduced. The intuitive coincidence further motivates us to investigate the connection between sentiment and volatility across markets.

4.3. Descriptive statistics and correlation

We report the descriptive statistics for the volatility and social

[7] CBOE Volatility Indices have been widely used in financial market analysis. For example, to explore the long-term relationship between US sector stock returns and risk factors, López et al. (2023) use CBOE VIX, TYVIX, EVZ, and OVX indices to proxy the volatility of equity, fixed income, foreign exchange, and crude oil markets. Bhattacherjee et al. (2024) also apply CBOE VIX, EVZ, GVZ, and OVX indices to represent the stock, foreign exchange, gold, and crude oil markets to investigate the return connectedness across ESG markets. Additionally, recent studies by Li (2022) and Qiao et al. (2024) leverage the CBOE VIX and OVX indices to examine dynamic interrelations under different volatility-of-volatility risk regimes or to forecast market volatility.

[8] The generalized variance decomposition requires normality. We, therefore, approximate it by taking natural logarithms in the volatility indices.

[9] Papakyriakou et al. (2019) employ combined news and social media data from RMA to represent country-level investor sentiment, finding that it negatively impacts stock markets in G7 countries by causing greater economic losses after terrorist acts. Gan et al. (2020) use RMA's news and social media measurements as proxies for overall investor sentiment toward the largest 500 companies in the US, revealing a time-varying relationship between these sentiments and market returns and volatility. Notably, they discover that RMA's social media sentiment has become more influential than news sentiment in impacting markets since 2016. At the firm level, Eierle et al. (2022) find that adjusted RMA social media sentiment provides additional information beyond company financials and significantly impacts stock returns.

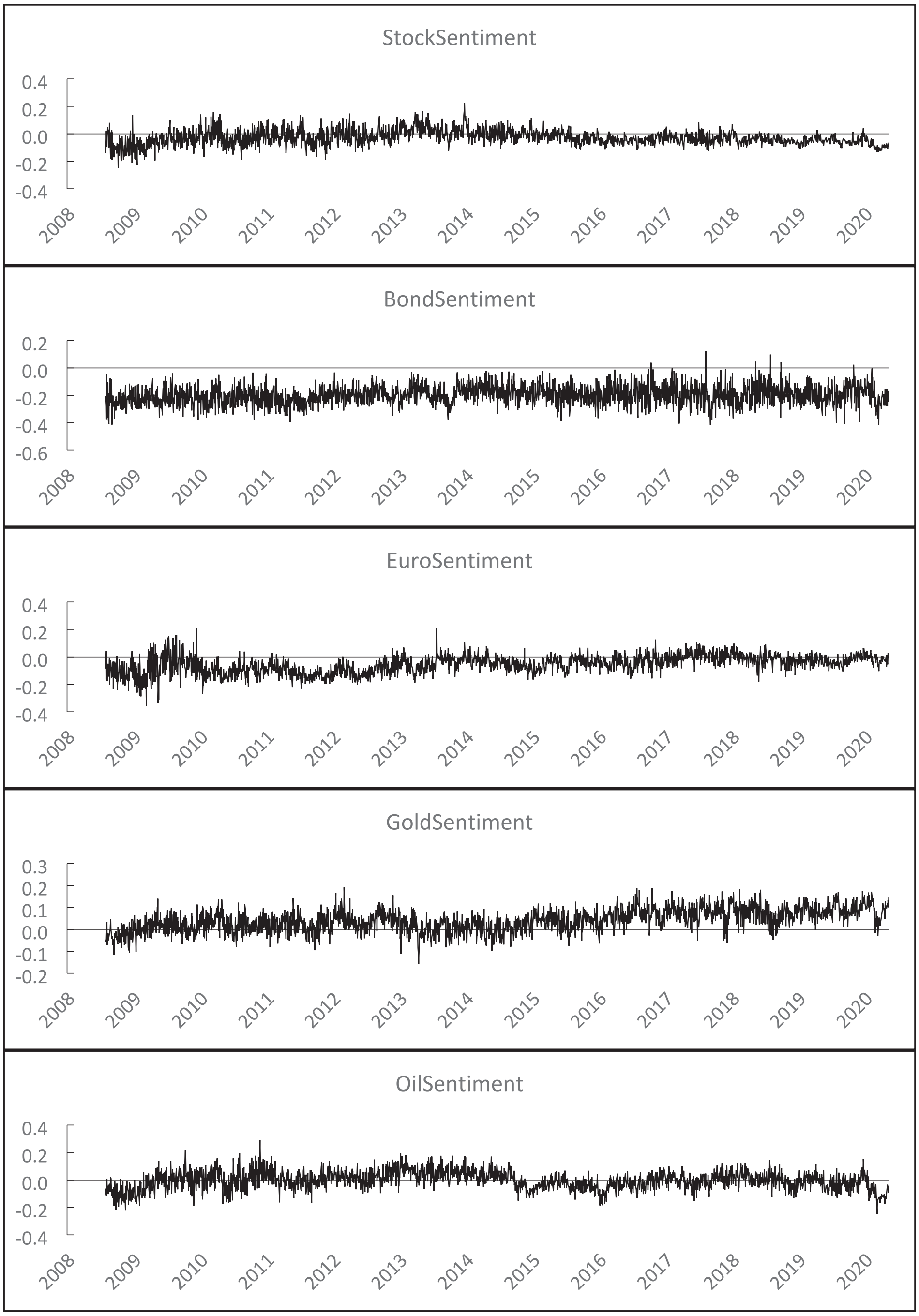

Fig. 2. Sentiment score over time.
This figure plots the daily LSEG MarketPsych Analytics (RMA) sentiment score across various asset classes, including stock, bond, currency, precious metal, and energy. The sample period is from August 1, 2008, to May 15, 2020.

sentiment indices in Panel A of Table 2. On average, *StockSentiment* and *EuroSentiment* have negative average scores (−0.03 and − 0.06, respectively). *BondSentiment* is particularly bearish over the sample period, with a score of −0.20. *GoldSentiment* has an overall positive sentiment (0.04), which could be because our sample period coincides with several major crises, and gold is often considered a safe haven asset (see, e.g., Baur & McDermott, 2016). *OilSentiment*, on the other hand, has a neutral sentiment (0.00) overall.

In terms of volatility, crude oil (OVX), equity (VIX), and gold markets (GVZ) have the highest uncertainty with (log) index values of 3.55, 2.89, and 2.88, respectively. The foreign exchange (EVZ) and the bond market (TYVIX) report the lowest average volatility (2.28 and 1.75, respectively). The augmented Dickey-Fuller (ADF) test in the last row of Panel A shows that both the sentiment and volatility indices are stationary.

Panel B reports the correlation coefficients among the implied volatility and sentiment indices. Turning first to the sentiment correlations in the upper left section, we observe that sentiment indices across different markets are positive but only weakly correlated. The strongest sentiment correlation is between equity and oil markets, with a correlation coefficient of 0.41. This is consistent with Gao and Süss (2015), who also document a close connection between equity and commodity markets, particularly energy. Second, the implied volatilities at the bottom right section are positively correlated with average values higher

Table 2
Descriptive statistics and correlation matrix.

	StockSentiment	*BondSentiment*	*EuroSentiment*	*GoldSentiment*	*OilSentiment*	*VIX*	*TYVIX*	*EVZ*	*GVZ*	*OVX*
Panel A: Descriptive Statistics										
Obs.	2968	2968	2968	2968	2968	2968	2968	2968	2968	2968
mean	−0.03	−0.20	−0.06	0.04	0.00	2.89	1.75	2.28	2.88	3.55
median	−0.03	−0.20	−0.05	0.04	−0.01	2.79	1.69	2.27	2.86	3.51
SD	0.05	0.07	0.07	0.05	0.07	0.40	0.31	0.36	0.35	0.39
5th percentile	−0.11	−0.31	−0.17	−0.04	−0.12	2.39	1.32	1.71	2.38	2.95
95th percentile	0.07	−0.08	0.04	0.12	0.10	3.74	2.39	2.89	3.56	4.25
skew	0.34	0.14	−0.19	−0.04	−0.01	1.12	0.74	0.23	0.68	0.90
kurtosis	3.84	3.26	3.35	2.72	3.12	4.11	3.16	2.87	3.59	5.34
ADF	−20.79***	−29.33***	−21.98***	−21.96***	−18.70***	−5.41***	−6.31***	−5.23***	−5.32***	−3.43***
Ljung- Box	1522***	278***	1996***	2169***	1812***	5621***	5698***	5762***	5723***	5749***
Panel B: Correlation Matrix										
StockSentiment	1									
BondSentiment	0.13***	1								
EuroSentiment	0.08***	0.11***	1							
GoldSentiment	−0.02	0.11***	0.29***	1						
OilSentiment	0.41***	0.13***	0.10***	0.03	1					
VIX	−0.41***	−0.22***	−0.43***	−0.32***	−0.37***	1				
TYVIX	−0.20***	−0.24***	−0.42***	−0.42***	−0.24***	0.77***	1			
EVZ	−0.17***	−0.20***	−0.51***	−0.37***	−0.21***	0.70***	0.80***	1		
GVZ	−0.17***	−0.18***	−0.45***	−0.49***	−0.24***	0.77***	0.83***	0.75***	1	
OVX	−0.44***	−0.16***	−0.22***	−0.02	−0.57***	0.72***	0.57***	0.58***	0.56***	1

This table summarizes the data used in this study. The sample period is from August 2008 to May 2020. Panel A reports the descriptive statistics, and Panel B reports the correlation matrix. All volatility series (VIX, TYVIX, EVZ, GVZ, OVX) are in natural logarithms. ADF is the augmented Dickey-Fuller test. Ljung-Box test is also reported. ***, ** and * represents 10 %, 5 % and 1 % significance level.

Table 3
Full sample connectedness.

	StockSentiment	*BondSentiment*	*EuroSentiment*	*GoldSentiment*	*OilSentiment*	*VIX*	*TYVIX*	*EVZ*	*GVZ*	*OVX*	from others
StockSentiment	71.26	0.34	0.40	0.44	3.92	14.22	1.39	1.09	1.24	5.71	28.74
BondSentiment	0.49	93.85	0.04	0.21	0.55	1.44	2.36	0.45	0.37	0.25	6.15
EuroSentiment	0.37	0.07	85.47	0.23	0.91	3.80	0.81	5.73	2.28	0.34	14.53
GoldSentiment	0.24	0.17	0.74	81.82	0.85	4.22	1.71	2.39	7.10	0.75	18.18
OilSentiment	3.39	0.35	0.65	1.27	72.67	6.13	1.25	0.61	1.84	11.83	27.33
VIX	2.17	0.30	1.28	0.21	2.06	55.79	10.13	7.48	10.73	9.85	44.21
TYVIX	1.15	0.70	0.36	0.05	1.70	14.39	58.12	9.35	8.83	5.35	41.88
EVZ	0.31	0.54	1.36	0.29	0.55	10.63	10.20	59.64	10.93	5.54	40.36
GVZ	0.43	0.08	1.92	1.53	0.78	14.52	8.21	9.23	56.63	6.67	43.37
OVX	1.28	0.04	0.16	0.07	4.06	15.65	7.11	4.34	6.58	60.71	39.29
to others	9.82	2.59	6.91	4.30	15.38	85.01	43.17	40.68	49.90	46.29	Total
Net (To-From)	-18.92	-3.56	-7.62	-13.88	-11.95	40.80	1.29	0.32	6.53	6.99	30.40

This table reports the full-sample GVD connectedness for sentiment and volatility indices using RMA Social Media sentiment and CBOE volatility indices from August 1, 2008, to May 15, 2020. The diagonal elements measure the connectedness of the ten indices themselves. The off-diagonal elements are the measurements of the connectedness between the sentiment indices (upper-left grey shade), the implied volatility indices (bottom-right grey shade), or the sentiment indices and implied volatility indices. All results are based on VARs of order two and GVDs of 10-day ahead forecast errors. The *ij*th entry of the upper left 10 × 10 submatrix is the estimated *ij*th pairwise directional connectedness contribution to the forecast-error variance of market *i*'s sentiment (or implied volatility) rising from sentiment (or implied volatility) shocks to market *j*. The off-diagonal row sums (last column) and column sums (second last row) are the total directional connectedness from all others (different markets' sentiment or implied volatility) to *i* and to all others (different markets' sentiment or implied volatility) from *i*.

than 0.56, indicating a stronger co-movement among market volatilities than sentiments. Notably, the correlations between the bond and the gold market volatilities (0.83) and between the bond and the foreign exchange volatilities (0.80) are high, which is in line with the literature (Andrada-Félix et al., 2018). The bottom left section shows that correlations between sentiment and volatility are mostly negative (e.g., −0.57 between *OilSentiment* and OVX and − 0.51 between *EuroSentiment* and EVZ). This indicates that market volatility is negatively associated with market sentiment.

5. Empirical results

This section reports our empirical results. We first report the results for the static connectedness across all the variables. We then proceed to the connectedness between the sentiment and volatility blocks. Finally, we show the dynamic connectedness over our sample period and during some turbulent periods.

5.1. Static connectedness analysis

Our first objective is to test our first hypothesis, which posits that there is a spillover effect between sentiment and volatility across various asset classes. As discussed in Section 2, multiple theories suggest a linkage between different asset classes. Additionally, the correlations in Panel B of Table 2 indicate a significant association between the sentiment and volatility series. These findings suggest a dynamic interplay between social media sentiment and volatility within financial markets.

Table 3 reports the full-sample connectedness table for the sentiment and volatility indices. The top row represents the transmitting variables, while the first column represents the affected variables. Focusing on the diagonal elements, which measure each variable's own connectedness, we observe the highest values, ranging from 55.79 % for the *VIX* to 93.85 % for *BondSentiment*. A higher diagonal value indicates that an index is less connected to others. For example, *StockSentiment* shows a forecast error variance attributed to its own shock at 71.26 %, suggesting that the combined contribution from all other indices to the forecast error variance is 28.74 %. Second, the off-diagonal elements represent the connectedness between the studied variables. Among the sentiment indices, the highest pairwise connectedness is from *OilSentiment* to *StockSentiment* (3.92 %), while the next highest is from *StockSentiment* to *OilSentiment* (3.39 %). Among the volatility indices, the highest pairwise connectedness is observed from *VIX* to *OVX* (15.65 %). These observations suggest a strong interconnection between stock and oil markets in sentiment and volatility indices. The financialization of commodity futures can explain the linkage between equity and oil markets. Institutional investors have widely held commodities, such as crude oil, for diversification purposes. Therefore, sentiment shocks in one market are quickly transmitted to the other market (Büyükşahin & Robe, 2014; Christoffersen & Pan, 2018).

Across sentiment and volatility indices, the pairwise connectedness is stronger from volatility to sentiment indices than the opposite, as shown by the top right block. For instance, the highest volatility to sentiment spillover is from the *VIX* to *StockSentiment* (14.22 %), followed by the spillover from the *OVX* to *OilSentiment* (11.83 %). In contrast, the highest sentiment to volatility spillover is from *OilSentiment* to the *OVX* (4.06 %), followed by the spillover from *StockSentiment* to the *VIX* (2.17 %).[10] As further evidence, we refer to the net directional connectedness at the bottom row of Table 3. All implied volatilities are net transmitters, while all sentiment indices are net receivers of informational shock. Most notably, the VIX is the largest net spillover transmitter (40.80 %), suggesting that stock market volatility is the dominant shock generator to all the sentiment and volatility indices. This aligns with existing literature, which finds that stock market volatility provides useful signals for investors in other asset classes, including bonds and commodities (see, e.g., Laborda & Olmo, 2014; Gao & Süss, 2015). Conversely, the *StockSentiment*, *GoldSentiment,* and *OilSentiment* are the main receivers with negatively high net connectedness −18.92 %, −13.88 %, and − 11.95 %, respectively. These findings support our Hypothesis 1, which is that social media sentiment and volatility spillover from one asset class to another.

The total connectedness of all the sentiment and volatility indices is 30.4 %, indicating that almost 70 % of variation comes from the index's own idiosyncratic innovations. The magnitude of our total connectedness is close to the total connectedness of 31.3 % among four major foreign exchange rates (Antonakakis, 2012), 33.5 % among media coverage, oil, gold, and bitcoin volatilities (Zhang et al., 2022), or 38.8 % among five implied volatility indices (Andrada-Félix et al., 2018).

Table 4
Full sample block connectedness.

	Sentiment Block	Volatility Block
Sentiment Block	84.14	15.86
Average own connectedness	81.01	–
Total connectedness within the sentiment block	3.13	–
Volatility Block	4.67	95.33
Average own connectedness	–	58.18
Total connectedness within the volatility block	–	37.15
Net (To–From)	−11.19	11.19
Total connectedness across Blocks	–	10.27

This table reports the full sample static block connectedness. Five sentiments and five volatilities are aggregated as one sentiment block and one volatility block, respectively. We gauge spillovers between and within the two blocks. The sample period is from August 1, 2008, to May 15, 2020. *Average own connectedness* represents the mean of five indices idiosyncratic innovations. *Total connectedness within the block* represents the interconnection level of five indices in the block.

Overall, the sentiment and volatility indices are mildly connected (supporting our Hypothesis 1). The largest net contributor is the stock market volatility, and the largest net receiver is the stock market sentiment.[11]

Due to the nature of the data, CBOE implied volatility indices focus on future price changes, while the social media sentiment indices reflect the past. To address the concerns of whether it is volatility that leads to investor sentiment, or it is the usefulness of the VIX in predicting future variations, we employ a backward-looking volatility measure. Specifically, we use Parkinson (1980)'s daily volatility as follows:

$$Volatility_{i,t} = \frac{1}{4ln2}\left(lnH_{i,t} - lnL_{i,t}\right)^2 \tag{8}$$

where $H_{i,t}$ and $L_{i,t}$ are the highest and lowest prices for asset i on day t, respectively. To construct this volatility, we use prices for the SPDR S&P 500 ETF (ticker: SPY) for the equity market, 10-year US Treasury Bond Futures (TYc1) for bond market, Invesco CurrencyShares Euro Trust (FXE) for foreign exchange market, SPDR Gold Shares ETF (GLD) for gold market, and United States Oil Fund (USO) for movements of crude oil market. We then follow the methodology in Section 3 to obtain the connectedness table by employing our five social media sentiment indices and the newly constructed five (backward-looking) volatility indices.

We investigate the static connectedness with the new volatility method and report the results in Appendix C. The findings indicate that our primary conclusions remain consistent with the new backward-looking volatility indices. The overall connectedness value (33.43 %) closely aligns with the main result in Table 3 (30.40 %), confirming that the spillovers primarily flow from volatility to sentiment indices. Notably, all sentiment indices are net receivers, while volatility acts as the net generator, with the exception of bond volatility, which emerges as a net receiver with negative spillovers. These results reinforce the idea that volatility tends to drive sentiment, regardless of whether the

[10] The correlation matrix (Table 2) captures the negative linear association between volatility and sentiment variables, indicating that increases in one variable are associated with decreases in the other. However, the DY connectedness approach (Table 3), derived from the forecast error variance decomposition of a vector autoregressive model, shows how the variance of one variable is explained by shocks from other variables in the system, and it suggests that shocks originating from the implied volatility indices tend to spill over into the sentiment indices.

[11] Our results are based on VARs of order 2 and GVDs of 10-day ahead forecast errors. We used alternative VARs from one to four lags and obtain qualitatively similar results. We also employed 5 days and 15 days as alternative forecast horizons, since the longer the forecast horizon, the more time the indices have to react to shocks from other indices. As expected, the longer forecast horizon is, the higher total connectedness with 27 %, 30 %, and 33 % for 5, 10, and 15 days, respectively. Therefore, our results are robust to the choice of forecast horizons.

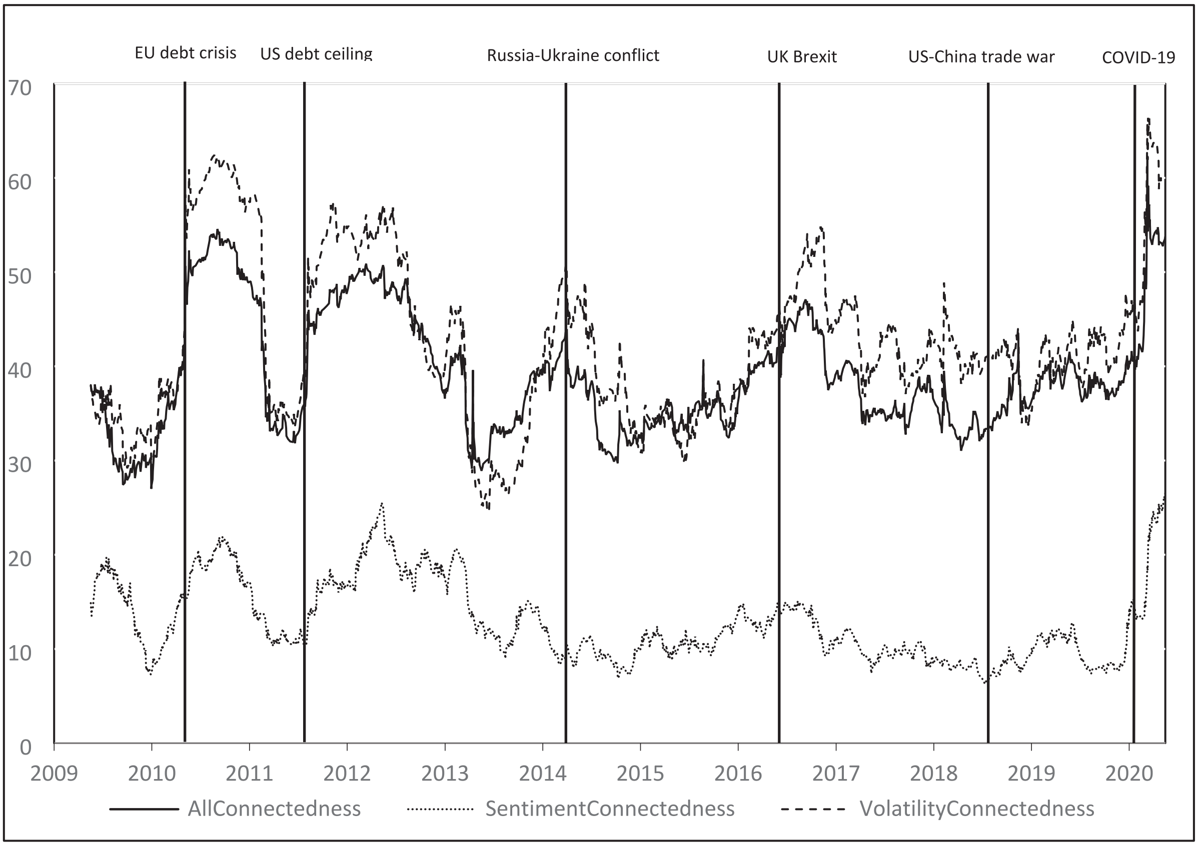

Fig. 3. Dynamic total connectedness.
This figure plots the connectedness value over the sample period from August 1, 2008, to May 15, 2020. The solid line represents the total connectedness among all sentiment and volatility measures. The dashed line represents the connectedness among the sentiment measures. The dotted line represents the connectedness among the volatility measures.

volatilities are forward- or backward-looking.[12]

In addition to the connectedness among the individual series, we measure the connectedness between sentiment and volatility blocks following Greenwood-Nimmo et al. (2016, 2021). We report the full sample static block connectedness results in Table 4. We observe that the sentiment and volatility blocks have high average own connectedness values at 81.01 % and 58.18 %, respectively. This indicates that the two blocks have high idiosyncratic innovations and are weakly connected. The total connectedness within the sentiment block is 3.13 %, suggesting that the sentiment indices are segmented. In contrast, the volatility block shows that the volatility indices are interconnected with a total block connectedness of 37.15 %. The main finding of the block connectedness analysis is that volatility indices are the main source of shocks to sentiment indices, with a net contribution of 11.19 %. The entire system has a total connectedness of only 10.27 %, suggesting that sentiment and volatility have a weak block-connection.

5.2. Dynamic connectedness analysis

The previous section shows the static connectedness of the ten variables based on the full period sample. Next, we examine how the connectedness among the sentiment and volatility indices evolves over time. This analysis is informative as it highlights the importance of economic events on the linkage between sentiment and volatility indices. We follow the DY approach and conduct a connectedness analysis using a 200-day rolling window.

In Fig. 3, we plot the dynamic total connectedness (solid black line), connectedness for the sentiment block (dashed black line), and connectedness for the volatility block (dotted grey line). In line with the results in Table 4, the connectedness for the volatility block is consistently higher than the sentiment block's. The total connectedness fluctuates strongly in turbulent periods. We observe several periods where the total dynamic connectedness deviates from its full sample average of 39 %. The total connectedness reached a value of 50 % in 2010, coinciding with the European sovereign debt crisis. The next spike in total connectedness started in mid-2011, with values ranging from approximately 45 % to 50 % during this phase and the subsequent months, triggered by the US debt-ceiling crisis and the US credit rating downgrade. Total connectedness also spiked in June 2016 due to Brexit and early 2020 during the COVID-19 global pandemic crisis, with an all-time high of around 62 %. In addition, we also observed two short-duration spikes over the average level in early 2014 during the Russia-Ukraine conflict and in the second half of 2018 during the US-China trade war. In sum, total connectedness increases in turbulent economic periods as uncertainty about the financial markets is associated with fears and pessimism across various asset classes (see, e.g., Antonakakis & Kizys, 2015; Zhang et al., 2022).

The 200-day rolling window is standard in the literature (see, e.g., Andrada-Félix et al., 2018; Audrino & Tetereva, 2019). Nevertheless, to ensure our results are robust to this selection, we employ alternative

[12] We also compare the main connectedness results (Table 3) with the lead-lag Granger causality test which is on five sentiment and five implied volatility indices for the same period using a VAR of order two and we report results in Appendix D. The volatility indices show more significant results than the sentiment indices. The right-most GC Others column indicates that our volatility indices are more likely to Granger cause other variables compared to the sentiment indices. This finding aligns with our static connectedness results, where we observed that volatility indices tend to Granger cause sentiment indices.

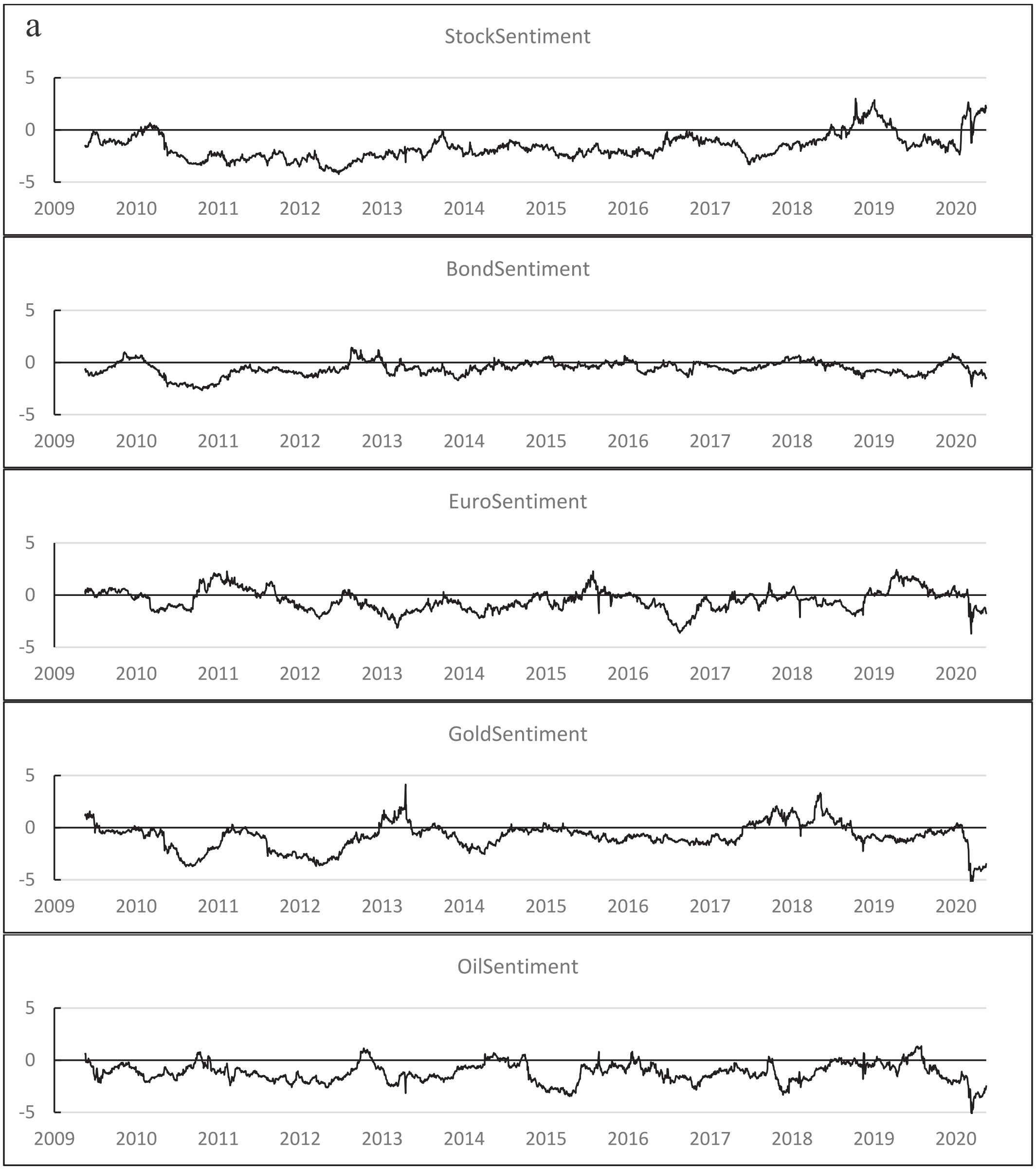

Fig. 4. Sentiment and volatility net connectedness over time.
This figure plots the net connectedness of each sentiment and volatility index from August 1, 2008, to May 15, 2020.
a. Sentiment Connectedness.
b. Volatility Connectedness.

rolling window lengths, i.e., 150 and 250-day windows. Appendix E reports these results. As expected, the dynamic total connectedness is more persistent for longer windows. The three graphs show a similar pattern with an average correlation of 0.88, indicating that the total connectedness increases in turbulent periods regardless of the rolling window lengths.

5.3. Sentiment and volatility net connectedness over time

With the time-varying characteristics that the connectedness exhibits, we wonder whether each index has variant features across time and contributes differently during different events. Next, we examine the net directional connectedness of each sentiment and volatility index. In Fig. 4.a., we show that the net directional connectedness varies over time, where each index plays a different role (net transmitter or net receiver) at different periods. For example, *StockSentiment* was a net spillover transmitter during the 2018 US-China trade war and the COVID-19 pandemic at the start of 2020, but it was also a net receiver at other times. Similarly, *EuroSentiment,* generally a net receiver, was a net spillover transmitter during the Euro debt crisis in the middle of 2010. In Fig. 4.b., we observe that volatility indices demonstrate different roles over time. For instance, the VIX tends to be a constant net transmitter for 96 % of the time. However, the net directional connectedness of the other indices varies over time with the switching role between a net spillover transmitter and receiver. For example, the EVZ, generally a net transmitter, was a net spillover receiver in 2010 during the European debt crisis and in 2020 during the COVID-19 pandemic.

We further investigate how the variables in our system are interconnected during some turbulent periods by examining the net directional connectedness. We study six turbulent periods: (a) Euro Debt crisis (April 2010 – February 2011); (b) US debt-ceiling crisis (May 2011–August 2011); (c) Russia-Ukraine conflict (February 2014–May

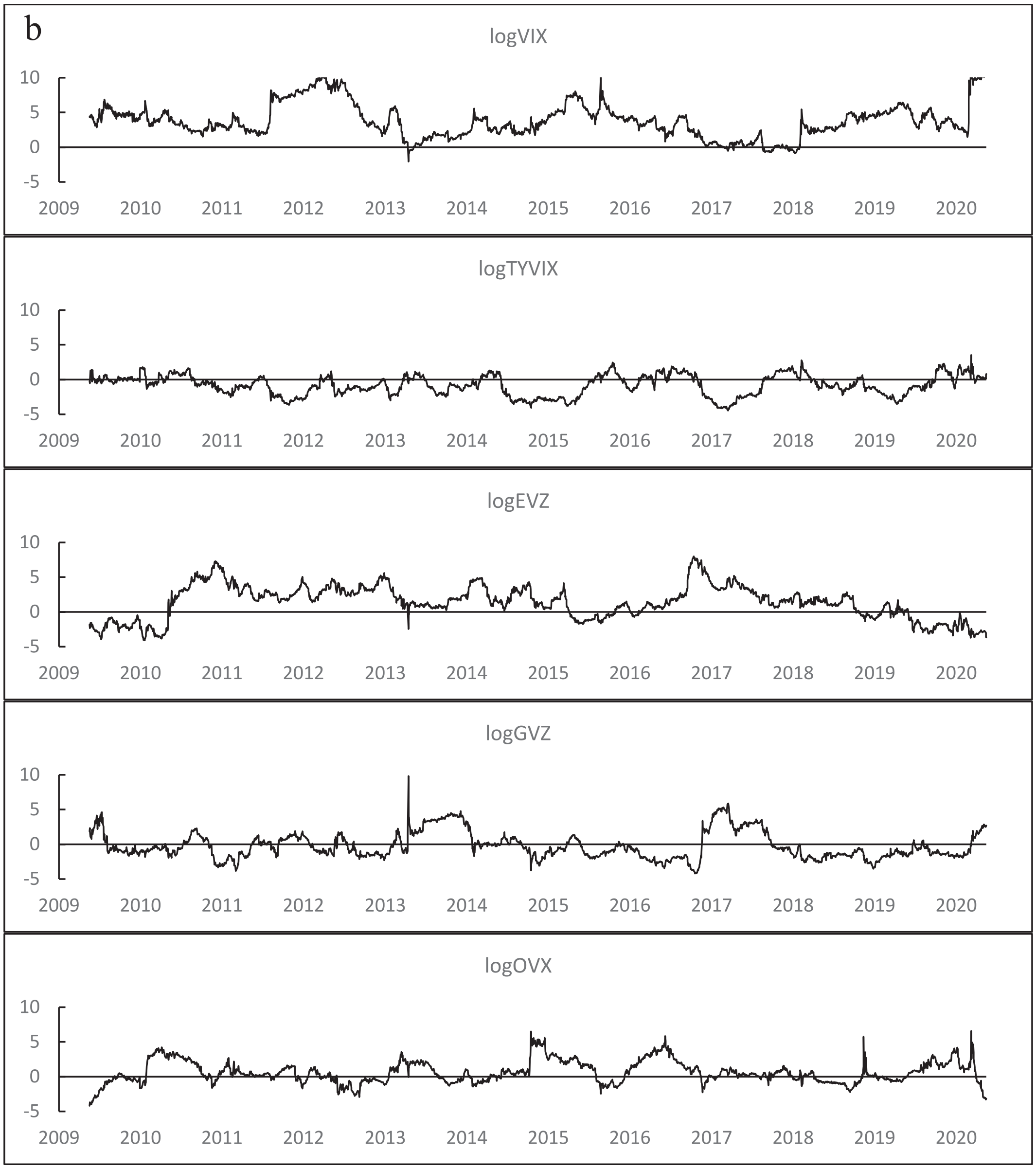

Fig. 4. (*continued*).

2014); (d) Brexit (June 2016 – November 2016); (e) US-China trade war (May 2018 – December 2018); (f) the early period of the COVID-19 pandemic crisis (December 2019 – May 2020).[13] Our benchmark for comparison is the result in the last row of Table 3, where all volatility indices show positive net connectedness and the sentiment indices show negative net connectedness. This suggests that social media sentiments (volatilities) are generally net receivers (triggers) of shocks over the sample period.

Fig. 5 presents a bar plot illustrating the net directional connectedness of sentiment and volatility indices during various turbulent periods. As shown, during times of market turbulence, sentiment indices transition from being net receivers to becoming net transmitters of spillovers. However, the impact varies depending on the specific crisis. For instance, *EuroSentiment* is a net spillover transmitter during the Euro debt crisis, the UK Brexit, and the US-China trade war. The European debt crisis undermined investor confidence in the Euro/dollar foreign exchange market, transmitting Euro sentiment and uncertainty to other markets' sentiment and volatility indices. Similarly, Brexit destabilized the EU economy and increased the uncertainty about the stability of the Euro. *EuroSentiment* was also a net transmitter during the US-China trade war. This can be explained by international trade between these two countries, with the US being the main export partner and China being the main import partner for the EU.[14] The US-China trade war affected the global growth prospects, with the EU being one of the main casualties of this event.

We also observe other sentiment indices were net transmitters in turbulent periods. For example, during the 2011 US debt-ceiling crisis, *BondSentiment* was a net transmitter to the other markets. The potential of a US default crisis originated from the US sovereign bond market impacted bond market sentiment, which generated uncertainty in other asset classes. *OilSentiment* was the net transmitter during the 2014 Russia-Ukraine conflict. This can be explained by Russia being one of the world's leading oil and gas producers and exporters. The geopolitical

[13] We provide more details for these events in Appendix B.

[14] The EU is the third major economic region in the world after US and China. US-China economy constitutes about 40 % of the global GDP.

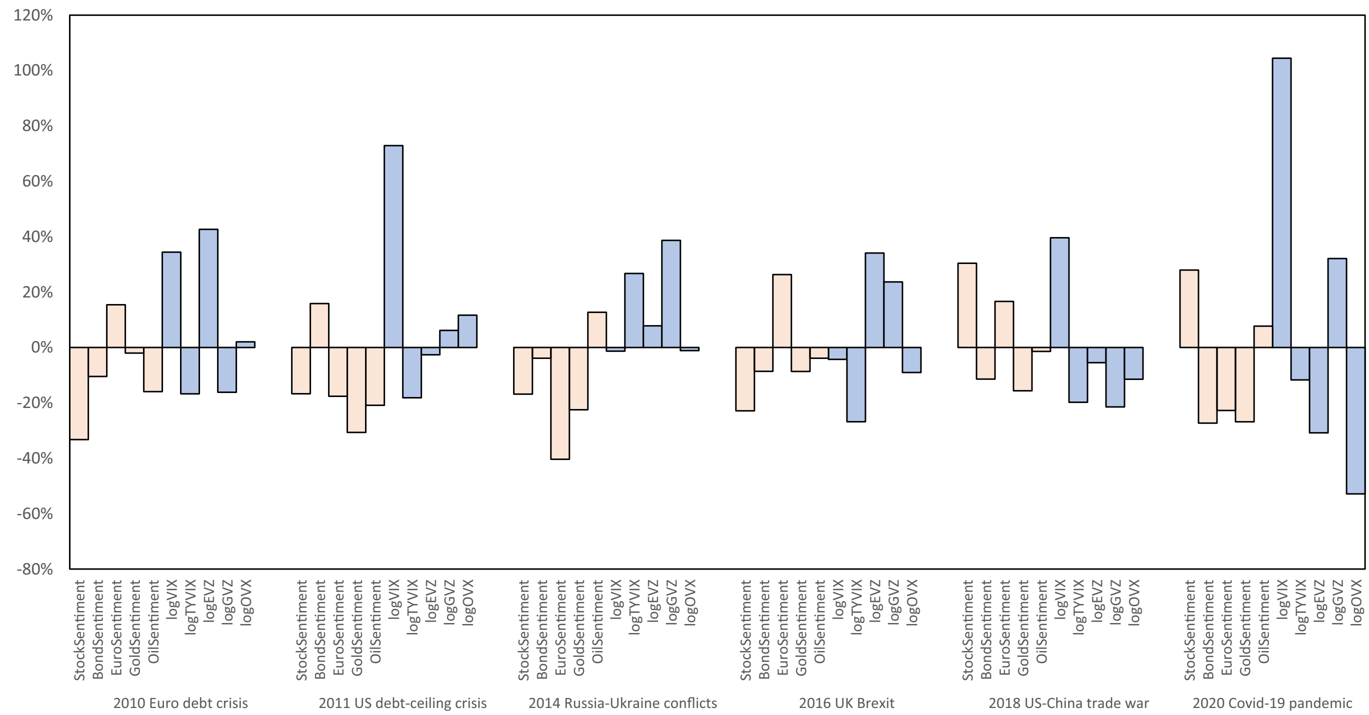

Fig. 5. Net total directional connectedness during various crises.
This figure plots the net total directional connectedness during various crises: (a) the Euro Debt Crisis (Apr 2010 – Feb 2011); (b) the US debt-ceiling crisis (May 2011- Aug 2011); (c) the Russia-Ukraine conflicts (Feb 2014 - May 2014); (d) the UK Brexit (Jun 2016 – Nov 2016); (e) the US-China trade war (May 2018 – Dec 2018); (f) the COVID-19 pandemic (Dec 2019 – May 2020).

crisis generated by the conflict increased uncertainty among investors due to the potential effect of the energy crisis on the global economy (Gao et al., 2022).

Finally, *Stocksentiment* was the largest sentiment net transmitter during the 2018 US-China trade war. The continuous rounds of retaliatory tariffs between the US and China led to high uncertainty in the financial markets. China's countermeasure tariffs on US products led to a decline in US exports to China and caused slumps in many US sectors. *StockSentiment* and *OilSentiment* were also net spillover transmitters during the COVID-19 pandemic. Lockdowns and border closures during the pandemic strongly affected the stock and oil markets and lowered overall business confidence.[15] In conclusion, the spillovers from sentiment are more substantial during turbulent periods, which aligns with our third hypothesis.[16]

Regarding volatility, the VIX was the most dominant transmitter in many turbulent periods, including the US debt-ceiling crisis, the US-China trade war, and the COVID-19 pandemic. This is consistent with Greenwood-Nimmo et al. (2021), who document that, during high connectedness periods, world trade flows and GDP growth are influenced by the spillover originating from the equity market. The EVZ is another important net spillover transmitter, particularly during the Euro debt crisis, The Russia-Ukraine conflict, and the UK Brexit.

However, there is a possibility that both social media sentiment and implied volatility are driven by the state of the business cycles and market conditions, which may affect our outcomes. To ensure that our results are not driven by market fundamentals, we follow Baker and Wurgler (2006) and orthogonalize all ten indices using a set of business cycle proxies. More specifically, we control for the term spread (calculated as the difference between the 10-year and 2-year Treasure Bonds), the 3-month Treasury Bill, the credit spread (calculated as the difference between Moody's Baa corporate bond yield and the 10-year Treasure Bond rate), and the TED spread which is a proxy of funding liquidity. All these business cycle variables are downloaded from the Federal Reserve Bank of St. Louis. We also control for Pástor and Stambaugh's (2003) liquidity factor as a proxy of market liquidity.[17] First, we regress each sentiment and implied volatility series against the above five business cycle proxies and take the residual series. We then use the orthogonalized series to compute the static and dynamic connectedness tables during various crises. For brevity, we report only the results for the net directional connectedness during turbulent periods.

The results reported in Appendix H suggest that our main result holds after controlling for the state of the business cycle and market conditions, i.e., sentiment indices are net triggers of shocks during turbulent times. All the patterns are consistent with those reported in Fig. 5, except for the 2014 Ukraine-Russia conflict and the UK Brexit, where the effect of the sentiments turned weaker.

5.4. Social media as an echo chamber

Our findings so far show that most volatilities are net transmitters while most sentiments are net receivers of shocks. However, social media sentiment still matters as its role can switch from net receiver to net transmitter during turbulent periods. We further explore why that is the case. We test for the social media echo chamber channel (Jiao et al., 2020). The echo chamber effect suggests that while social media often repeat existing news, some investors interpret repeated signals as genuinely new information. Hence, the spillover effect from sentiment to volatility observed in turbulent periods may be driven by traditional news media rather than social media content.

[15] We report the analysis of the connectedness tables during periods of market turbulent in Appendix F.

[16] We also visualised a net pairwise directional connectedness network figures for detailed spillovers across various indices during various crises in Appendix G.

[17] Source: https://finance.wharton.upenn.edu/~stambaug/.

Table 5
Full sample connectedness for the *News* category.

	StockSentiment	*BondSentiment*	*EuroSentiment*	*GoldSentiment*	*OilSentiment*	*VIX*	*TYVIX*	*EVZ*	*GVZ*	*OVX*	from others
Panel A: News											
StockSentiment	42.05	0.42	4.00	4.47	12.00	22.18	2.49	3.07	3.82	5.48	57.95
BondSentiment	2.07	84.45	0.21	0.66	1.76	5.75	2.17	0.23	1.24	1.46	15.55
EuroSentiment	5.43	0.23	72.75	1.91	5.65	5.32	0.28	4.37	2.56	1.50	27.25
GoldSentiment	7.25	0.58	1.90	60.85	9.88	8.23	1.34	1.78	6.27	1.91	39.15
OilSentiment	11.62	0.61	4.71	6.81	50.14	11.65	1.32	1.10	3.00	9.04	49.86
VIX	4.31	0.31	1.20	1.35	4.05	52.45	9.63	7.06	10.10	9.53	47.55
TYVIX	1.67	0.51	0.35	0.22	1.52	14.03	58.88	9.04	8.45	5.33	41.12
EVZ	1.43	0.22	1.27	0.55	0.96	10.28	9.94	59.12	10.83	5.41	40.88
GVZ	2.11	0.35	1.08	2.03	2.11	14.32	7.94	9.00	54.58	6.48	45.42
OVX	2.49	0.19	0.97	0.76	5.34	14.85	6.84	4.05	6.01	58.50	41.50
to others	38.37	3.43	15.68	18.76	43.27	106.61	41.93	39.71	52.29	46.15	Total
Net (To-From)	-19.57	-12.11	-11.58	-20.39	-6.58	59.07	0.81	-1.16	6.87	4.65	40.62
Panel B: News&Social											
StockSentiment	43.70	0.45	4.60	4.39	12.49	21.23	1.80	2.60	3.21	5.52	56.30
BondSentiment	2.22	83.52	0.21	0.57	1.91	6.07	2.42	0.26	1.39	1.44	16.48
EuroSentiment	5.86	0.17	71.97	1.93	5.57	5.34	0.29	4.84	2.67	1.35	28.03
GoldSentiment	6.89	0.49	2.08	60.19	9.38	8.50	1.57	2.16	7.08	1.65	39.81
OilSentiment	11.85	0.65	4.67	6.50	49.49	11.76	1.45	1.12	2.87	9.63	50.51
VIX	4.17	0.39	1.36	1.20	4.36	52.21	9.67	7.05	10.09	9.50	47.79
TYVIX	1.55	0.62	0.38	0.17	1.75	14.18	58.49	9.07	8.48	5.33	41.51
EVZ	1.11	0.30	1.43	0.55	1.07	10.24	9.95	59.13	10.84	5.38	40.87
GVZ	1.70	0.42	1.24	2.18	2.14	14.25	7.95	9.02	54.63	6.48	45.37
OVX	2.39	0.21	0.91	0.55	5.71	14.84	6.85	4.04	6.03	58.48	41.52
to others	37.73	3.70	16.88	18.05	44.37	106.41	41.96	40.15	52.65	46.29	Total
Net (To-From)	-18.57	-12.79	-11.15	-21.76	-6.14	58.62	0.45	-0.72	7.28	4.77	40.82

This table reports the full-sample GVD connectedness for sentiment and volatility indices using RMA *News* sentiment (Panel A), *News&Social* sentiment (Panel B), and CBOE volatility indices from August 1, 2008, to May 15, 2020. The diagonal elements measure the connectedness of the ten indices themselves. The off-diagonal elements are the measurements of the connectedness between the sentiment indices (upper-left grey shade), the implied volatility indices (bottom-right grey shade), or the sentiment indices and implied volatility indices. All results are based on VARs of order two and GVDs of 10-day ahead forecast errors. The *ij*th entry of the upper left 10×10 submatrix is the estimated *ij*th pairwise directional connectedness contribution to the forecast-error variance of market *i*'s sentiment (or implied volatility) rising from sentiment (or implied volatility) shocks to market *j*. The off-diagonal row sums (last column) and column sums (second last row) are the total directional connectedness from all others (different markets' sentiment or implied volatility) to *i* and to all others (different markets' sentiment or implied volatility) from *i*.

To test this, we use sentiment indices from the RMA *News* and the *News&Social* categories. While the *Social* category we employed in our main specification is based on social media outlets, the *News* category is based on news media outlets. *News&Social* combines both groups. We present the results for the two additional groups in Table 5.

Panel A reports the static connectedness for the *News* category. Consistent with our Hypothesis 1, market-specific sentiments and volatilities are interconnected. The stock market volatility remains the most significant net transmitter. It is worth mentioning that the static total connectedness for the *News* category is around 40 %, while the static total connectedness for the *Social* category is 30.40 % (see Table 3). This indicates that while traditional news media (online in digital form) remains one of the main sources of information for financial markets, social media sentiment also provides substantial new information. However, when we consider both *News&Social* (Panel B), we observe that total connectedness only increased from 40.62 % to 40.82 % with the addition of social media signals. This points toward social media adding little information to the market. Compared to traditional news sentiment, the marginal increase in informative value provided by social media sentiment indicates the echo chamber effect within social media.

To further examine the echo chamber effect, we aim to capture the true social media sentiment beyond the confounding effect of traditional news sentiment. To do so, we orthogonalize each social media sentiment against the sentiment from the *News* category. More specifically, we regress each social media sentiment series on its respective asset-specific news sentiment. The residual from this regression is the orthogonalized social media sentiment series[18], which we then use to recalculate the connectedness results during the various turbulent periods.

The plots in Fig. 6 show that many social media sentiments are no longer the net transmitter of shocks after controlling for news sentiment. While *OilSentiment* remains an important net transmitter of shocks during the Russia-Ukraine conflicts and the COVID-19 pandemic, the importance of *EuroSentiment* during the Euro debt crisis and the UK Brexit disappears. Similarly, the importance of *StockSentiment* during the US-China trade war and the COVID-19 pandemic also recedes. These results suggest that high social media coverage periods are associated with higher volatility, primarily because social media posts repeat (e.g., reshare) existing news, which is in line with Jiao et al. (2020)'s theory that social media acts as an echo chamber of news. Therefore, we attribute the echo chamber effect to the main mechanism of why social media sentiment may turn into a net trigger of connectedness during turbulent times.

6. Discussion and conclusion

Our study reveals several important findings about the interplay between social media sentiment and volatility in financial markets. First, we demonstrate that volatility indices generally act as net transmitters of shocks, while sentiment indices are net receivers. This distinction highlights the dominant role that market volatility plays in influencing

[18] For example, we regress bond market social media sentiment index on bond market news sentiment index, and the resulting residual series is the true social media sentiment.

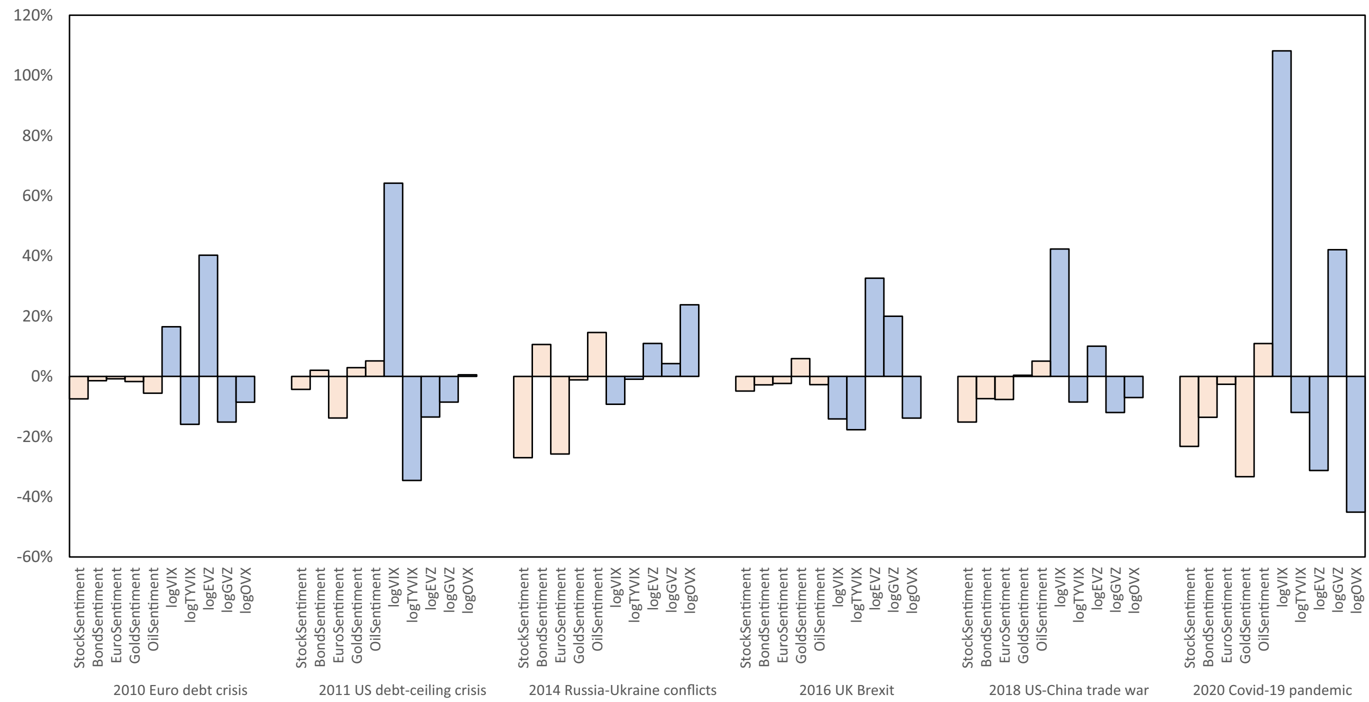

Fig. 6. Net total directional connectedness during various crises (controlling for news sentiment).
This figure plots the net total directional connectedness during various crises after orthogonalizing the social media sentiment with the news sentiment: (a) the Euro Debt Crisis (Apr 2010 – Feb 2011); (b) the US debt-ceiling crisis (May 2011- Aug 2011); (c) the Russia-Ukraine conflicts (Feb 2014 - May 2014); (d) the UK Brexit (Jun 2016 – Nov 2016); (e) the US-China trade war (May 2018 – Dec 2018); (f) the COVID-19 pandemic (Dec 2019 – May 2020).

sentiment across various asset classes. For instance, the VIX, representing stock market volatility, emerged as a particularly strong transmitter of shocks, significantly affecting other indices, including sentiment indices.

Second, we also document the dynamic nature of these relationships during turbulent economic periods. We show that the interconnectedness between market sentiment and volatility significantly increases during crises such as the Global Financial Crisis, Brexit, the US-China trade war, and the COVID-19 pandemic. In such times, social media sentiment can transition from being a net receiver to a net transmitter of shocks, suggesting that social media platforms amplify existing market sentiments during heightened uncertainty.

The implication of this is that social media often mirrors traditional news media. During turbulent periods, repeated signals on social media can be misinterpreted as new information, potentially amplifying market reactions. This phenomenon, often called echo chambers, indicates that while social media typically reflects existing market sentiments, it can also exacerbate volatility when investors perceive repeated information as novel. Our findings suggest that investors and regulators should pay close attention to the signals emanating from these platforms, as they can profoundly impact market behavior and stability. Investors, in particular, should exercise caution and prioritize reputable and official news sources over social media, especially during turbulent periods.

Finally, we recognize that utilizing self-generated investor sentiment could provide a valuable advantage in identifying the specific emotions that drive market sentiment. Analyzing how various core emotions, such as fear, anger, and joy, correlate with market volatility would offer a more nuanced understanding of the influence of social media-driven emotions on financial markets. This area presents opportunities for future research.

Declaration of competing interest

None.

Data availability

The authors do not have permission to share data.

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Appendix A. Block connectedness methodology

Greenwood-Nimmo et al. (2016, 2021) developed the block aggregation approach and improved the flexibility of the DY approach. The generalized aggregation approach supports any desired block structure with re-ordered variables, as the GVD method is not order-sensitive.

We have five different variables for each group or block i $\{v_{it}, w_{it}, x_{it}, y_{it}, z_{it}\}$ in the order $Y_t = (v_{1t}, w_{1t}, x_{1t}, y_{1t}, z_{1t}, \cdots, v_{Nt}, w_{Nt}, x_{Nt}, y_{Nt}, z_{Nt})'$. We can assess the spillover of the two blocks in the model as a whole by considering all five variables in each block. The connectedness matrix D^H can be reformulated in block form as follows, with $g = N$ blocks and each containing m variables ($m = 5$ in this illustration):

$$\mathrm{D^H} = \begin{bmatrix} B_{11}^H & \cdots & B_{1N}^H \\ \vdots & \ddots & \vdots \\ B_{N1}^H & \cdots & B_{N1}^H \end{bmatrix}, \tag{A.1}$$

where $B_{ij}^H = \begin{bmatrix} d_{v_iv_i}^H & d_{v_iw_i}^H & d_{v_ix_i}^H & d_{v_iy_i}^H & d_{v_iz_i}^H \\ d_{w_iv_i}^H & d_{w_iw_i}^H & d_{w_ix_i}^H & d_{w_iy_i}^H & d_{w_iz_i}^H \\ d_{x_iv_i}^H & d_{x_iw_i}^H & d_{x_ix_i}^H & d_{x_iy_i}^H & d_{x_iz_i}^H \\ d_{y_iv_i}^H & d_{y_iw_i}^H & d_{y_ix_i}^H & d_{y_iy_i}^H & d_{y_iz_i}^H \\ d_{z_iv_i}^H & d_{z_iw_i}^H & d_{z_ix_i}^H & d_{z_iy_i}^H & d_{z_iz_i}^H \end{bmatrix}$ for $i,j = 1, 2, \cdots, N$, hence, the block B_{ii}^H captures the within-block connectedness for block i while B_{ij}^H captures all spillover effects from block j to block i. Therefore, we can define the total within-block forecast error variance contribution for block i (as)

$$W_{ii}^H = \frac{1}{m} e_m' B_{ii}^H e_m, \tag{A.2}$$

where m is the number of variables in each block and e_m is an $m \times 1$ vector of ones. Likewise, we define the total pairwise directional spillover from market block j to block i ($i \neq j$) at horizon H (as)

$$P_{ij}^H = \frac{1}{m} e_m' B_{ij}^H e_m. \tag{A.3}$$

Finally, the aggregated connectedness matrix by using the Greenwood-Nimmo et al. (2021) approach is re-formed as:

$$\mathrm{D^H} = \begin{bmatrix} W_{11}^H & P_{12}^H & \cdots & P_{1N}^H \\ P_{21}^H & W_{22}^H & \cdots & P_{2N}^H \\ \vdots & \vdots & \ddots & \vdots \\ P_{N1}^H & P_{N2}^H & \cdots & W_{NN}^H \end{bmatrix} \tag{A.4}$$

Based on the above illustration, W_{ii}^H, the total within-block contribution can be decomposed into common-variable forecast error variance contribution within-block i (K_{ii}^H), and cross-variable effects (C_{ii}^H), we define K_{ii}^H and C_{ii}^H as[19]:

$$K_{ii}^H = \frac{1}{m} trace\left(W_{ii}^H\right), \tag{A.5}$$

and

$$C_{ii}^H = W_{ii}^H - K_{ii}^H. \tag{A.6}$$

Now, the aggregated connectedness to block i is as follows:

$$P_{i\leftarrow \bullet}^H = \sum\nolimits_{j=1, j\neq i}^N P_{ij}^H, \tag{A.7}$$

while the aggregated connectedness from block i can be written as:

$$P_{\bullet \leftarrow i}^H = \sum\nolimits_{j=1, j\neq i}^N P_{ji}^H, \tag{A.8}$$

thus, the net directional spillover from block i to all other blocks is:

$$P^H = P_{\bullet \leftarrow i}^H - P_{i\leftarrow \bullet}^H. \tag{A.9}$$

Finally, the aggregated spillover effect between-block can be expressed as:

[19] K_{ii}^H is the proportion of forecast error variance of Y_{it} that is not attributable to spillovers among innovations within block i nor to the spillovers from block j with $(i \neq j)$. $C_{ii}^H$is the proportion of forecast error variance of Y_{it} attributable to spillovers among innovations within block i.

$$B\_B^{H} = \frac{1}{N}\sum\nolimits_{i=1}^{N} P^{H}_{i\leftarrow\bullet} \tag{A.10}$$

and the aggregated spillover effect within-block is:

$$W\_B^{H} = 100 - B_{B}{}^{H}. \tag{A.11}$$

Appendix B. The choices of the time frame for each period

This table lists the six turbulent periods considered in the study and their associated landmark events.

	Phase starts	Associated event(s)	Phase ends	Associated event(s)
Euro debt crisis	April 12, 2010	Greece requested a loan of €45 billion from the EU and the IMF. Standard & Poor's downgraded Greece's sovereign debt rating from BB+ to "junk".	February 28, 2011	The second of the Greek bailout. Portugal reached a bailout deal with the EU and the IMF.
US debt ceiling crisis	May 1, 2011	At the end of April 2011, US Congress delayed the approval of the 2011 budget. The US hit the 14.29 trillion debt ceiling in May 2011.	August 31, 2011	Obama signed the debt ceiling bill to avert a financial default.
Russia-Ukraine conflicts	February 20, 2014	Russia began the annexation of Crimea.	May 1, 2014	The Ukrainian parliament declared Crimea a territory temporarily occupied by Russia. Multiple regional conflicts temporarily ended at the end of April.
UK Brexit	June 23, 2016	The referendum result was released. 52 % of the UK voters chose to leave the EU.	November 25, 2016	Prime Minister Theresa May sought to negotiate to leave the EU smoothly.
US-China trade war	May 29, 2018	The White House announced a 25 % tariff on $50 billion of Chinese goods. Former US president Donald Trump declared the increased tariff on Twitter the following day.	December 1, 2018	The US and China leaders agreed on a truce for the trade war during the G20 summit in Argentina.
COVID-19 pandemic	December 12, 2019	The National Bureau of Economic Research (NBER) lists the business cycle reference dates, with the peak being in Q4 2019.	May 15, 2020	The NBER lists business cycle reference dates with the trough in Q2 2020.

Appendix C. Full sample connectedness with alternative volatility indices

This table reports the full-sample GVD connectedness for sentiment and volatility indices using RMA Social Media sentiment and the Parkinson's (1980) volatility from August 1, 2008, to May 15, 2020. The diagonal elements measure the connectedness of the ten indices themselves. The off-diagonal elements are the measurements of the connectedness between the sentiment indices (upper-left grey shade), the implied volatility indices (bottom-right grey shade), or the sentiment indices and implied volatility indices. All results are based on VARs of order two and GVDs of 10-day ahead forecast errors. The *ij*th entry of the upper left 10×10 submatrix is the estimated *ij*th pairwise directional connectedness contribution to the forecast-error variance of market *i*'s sentiment (or implied volatility) rising from sentiment (or implied volatility) shocks to market *j*. The off-diagonal row sums (last column) and column sums (second last row) are the total directional connectedness from all others (different markets' sentiment or implied volatility) to *i* and to all others (different markets' sentiment or implied volatility) from *i*.

	StockSentiment	*BondSentiment*	*EuroSentiment*	*GoldSentiment*	*OilSentiment*	*SPY_ volatility*	*10yBond_ volatility*	*FXE_ volatility*	*GLD_ volatility*	*USO_ volatility*	from others
StockSentiment	73.49	0.60	0.47	0.80	8.49	7.58	0.95	0.80	1.25	5.59	26.51
BondSentiment	0.91	90.34	0.35	0.46	0.63	2.30	1.92	1.49	1.02	0.60	9.66
EuroSentiment	0.35	0.40	78.52	2.35	0.51	6.17	3.15	4.11	3.53	0.91	21.48
GoldSentiment	0.38	0.37	3.64	75.39	0.59	5.43	3.51	3.51	7.00	0.17	24.61
OilSentiment	6.87	0.38	0.37	0.54	71.35	3.99	1.21	0.54	1.02	13.73	28.65
SPY_ volatility	5.45	0.99	3.34	2.59	3.43	53.87	7.67	6.62	8.74	7.29	46.13
10yBond_ volatility	0.90	1.25	2.70	2.37	1.14	12.97	54.54	9.09	10.47	4.57	45.46
FXE_ volatility	0.62	0.98	4.45	2.16	1.33	9.85	7.35	54.03	11.40	7.83	45.97
GLD_ volatility	0.53	0.56	3.63	4.20	1.00	11.20	7.98	10.51	55.33	5.06	44.67
USO_ volatility	5.02	0.47	0.77	0.06	10.99	10.64	3.26	4.85	5.09	58.85	41.15
to others	21.02	6.00	19.72	15.52	28.10	70.12	37.01	41.53	49.52	45.76	Total
Net (To-From)	-5.49	-3.66	-1.76	-9.09	-0.55	23.99	-8.46	45.97	4.86	4.61	33.43

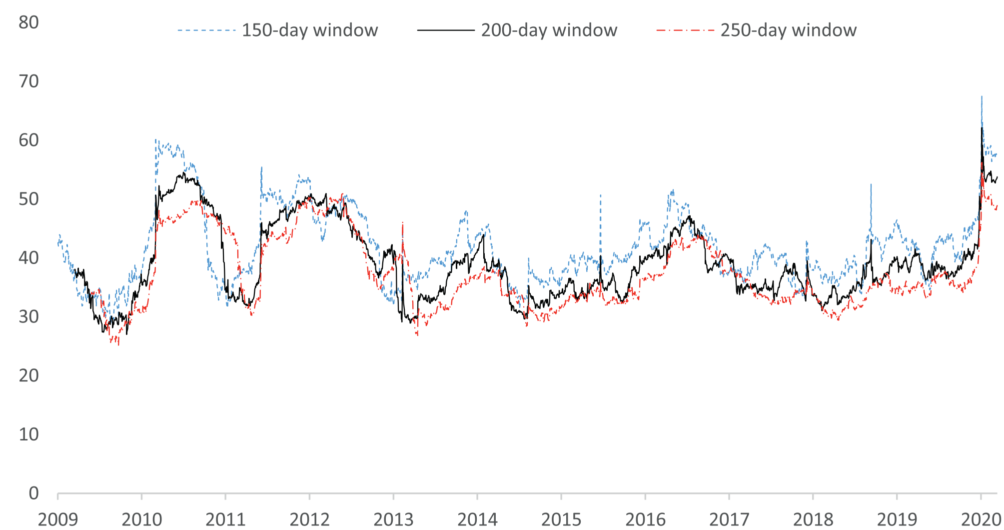
Appendix D. Granger causality test

This table presents the Granger causality test results for five sentiment indices and five volatility indices, based on a VAR(2) specification to ensure comparability with our main static connectedness results. The Wald test statistics are shown with the null hypothesis that the row variable does not Granger cause the column variable. The analysis covers the sample period from August 1, 2008, to May 15, 2020. *, ** and *** denote statistical significance at the 10 %, 5 % and 1 % level, respectively. The final column, labeled "GC Others," indicates the number of variables that are Granger caused by the row variable.

	StockSentiment	*BondSentiment*	*EuroSentiment*	*GoldSentiment*	*OilSentiment*	*VIX*	*TYVIX*	*EVZ*	*GVZ*	*OVX*	GC others
StockSentiment		8.35***	0.39	2.51	29.88***	0.50	1.69	0.02	0.46	3.40**	3 / 9
BondSentiment	2.43		3.22**	0.82	1.42	2.19	0.16	2.51	1.17	1.65	1 / 9
EuroSentiment	1.80	6.32***		18.09***	0.11	4.25**	2.88	0.95	6.96***	0.76	4 / 9
GoldSentiment	6.42***	4.44**	12.05***		0.37	1.04	1.88	2.37	1.81	0.23	3 / 9
OilSentiment	46.63***	6.02***	1.85	3.14**		2.83	3.77**	2.75	0.71	10.23***	5 / 9
VIX	96.43***	30.21***	25.52***	33.62***	56.75***		5.75***	16.29***	14.65***	30.61***	9 / 9
TYVIX	14.77***	39.01***	34.54***	36.25***	11.91***	5.60***		12.26***	15.35***	16.58***	9 / 9
EVZ	14.68***	24.41***	68.68***	27.00***	11.74***	2.82	9.05***		1.37	6.00***	7 / 9
GVZ	15.08***	22.88***	37.58***	45.68***	18.38***	5.61***	13.21***	15.00***		12.34***	9 / 9
OVX	45.32***	11.29***	3.39**	1.45	77.63***	0.61	1.76	4.77***	0.69		5 / 9

Appendix E. Dynamic total connectedness using different windows

This figure plots the dynamic total connectedness value over the sample period using different windows, i.e., 150 days, 200 days, and 250 days.



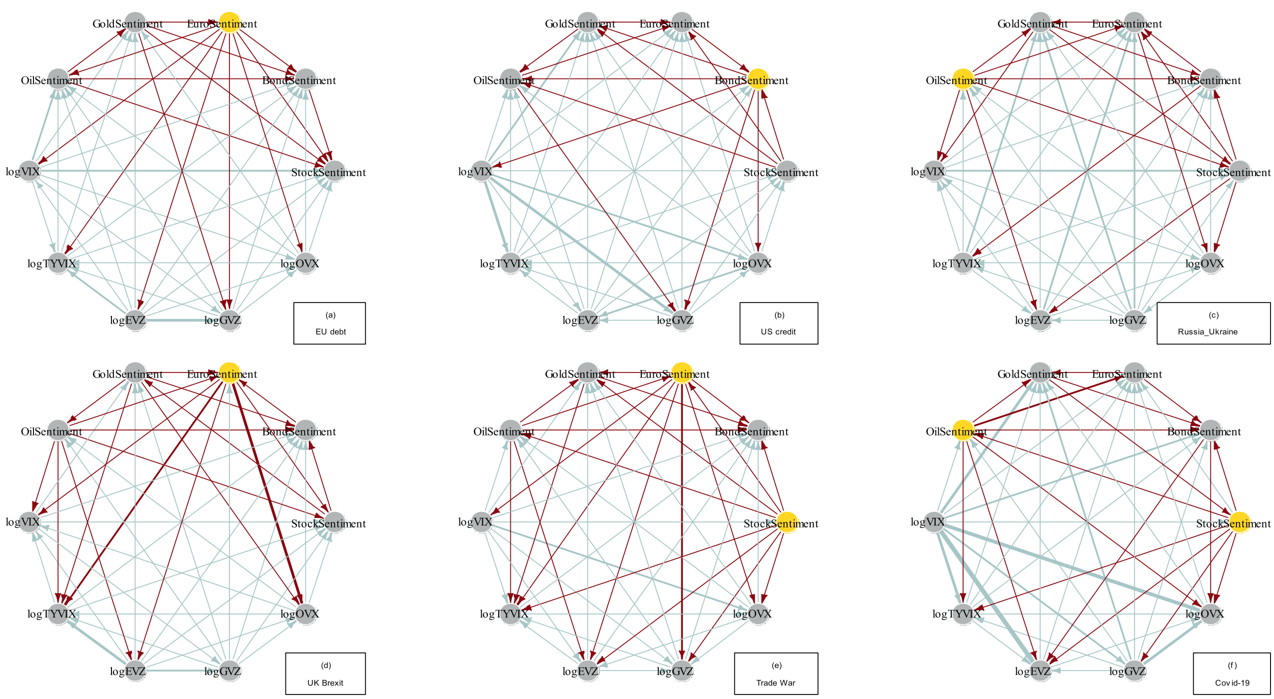
Appendix F. Connectedness during various turbulent periods

This table reports the connectedness for five sentiment and five volatility indices during six different periods: The Euro Debt crisis (Apr 2010 – Feb 2011), US debt-ceiling crisis (May 2011- Aug 2011), Russia-Ukraine conflicts (Feb 2014 - May 2014), UK Brexit (Jun 2016 – Nov 2016), US-China trade war (May 2018 – Dec 2018), and Covid-19 pandemic (Dec 2019 – May 2020). For each panel in this table, the diagonal elements measure the ten indices' own connectedness. The off-diagonal elements are the measurements of the connectedness between the sentiment indices (upper-left grey shade), the implied volatility indices (bottom-right grey shade), or the sentiment indices and implied volatility indices. All results are based on VARs of order two and GVDs of 10-day ahead forecast errors.

	StockSentiment	*BondSentiment*	*EuroSentiment*	*GoldSentiment*	*OilSentiment*	*VIX*	*TYVIX*	*EVZ*	*GVZ*	*OVX*	from others
Panel A: Euro debt crisis											
StockSentiment	56.09	2.90	4.36	4.13	2.97	12.49	1.48	9.71	1.61	4.26	43.91
BondSentiment	2.25	81.01	2.56	1.25	2.76	1.91	2.13	2.29	2.48	1.36	18.99
EuroSentiment	2.57	1.49	62.17	3.87	6.08	7.69	3.54	7.69	2.78	2.13	37.83
GoldSentiment	1.55	0.31	1.01	84.94	1.39	3.31	0.89	4.76	1.24	0.59	15.06
OilSentiment	0.81	1.39	6.32	0.58	56.67	13.67	2.70	3.15	3.11	11.59	43.33
VIX	0.75	0.45	10.67	0.39	4.36	35.48	6.88	15.65	8.32	17.06	64.52
TYVIX	0.08	0.77	6.48	0.24	1.98	8.80	50.64	15.36	8.80	6.85	49.36
EVZ	1.28	0.06	10.45	1.05	2.62	13.60	6.06	44.94	12.12	7.82	55.06
GVZ	0.95	0.28	8.03	1.52	2.38	13.56	3.09	28.52	33.51	8.17	66.49
OVX	0.41	0.88	3.38	0.04	2.87	23.91	5.85	10.59	9.86	42.21	57.79
to others	10.64	8.53	53.24	13.07	27.42	98.96	32.62	97.72	50.32	59.83	Total
Net (To-From)	-33.26	-10.46	15.41	-2.00	-15.92	34.43	-16.74	42.66	-16.17	2.04	45.23
Panel B: US debt-ceiling crisis											
StockSentiment	53.03	5.78	0.48	2.95	3.03	11.14	4.35	7.66	6.59	4.99	46.97
BondSentiment	8.44	58.21	3.56	1.32	0.97	6.71	3.78	5.91	6.52	4.58	41.79
EuroSentiment	0.79	2.17	55.41	2.41	5.42	2.30	1.44	13.96	5.89	10.22	44.59
GoldSentiment	4.33	9.80	2.04	50.12	2.78	10.81	3.82	5.41	4.45	6.45	49.88
OilSentiment	3.33	3.72	5.26	4.22	52.63	5.88	8.08	6.22	2.46	8.18	47.37
VIX	3.39	6.90	1.24	0.92	3.25	47.76	6.47	4.17	13.84	12.07	52.24
TYVIX	1.79	2.43	0.31	2.90	2.90	23.91	39.85	11.83	9.87	4.22	60.15
EVZ	4.47	5.62	9.23	2.23	2.75	12.33	4.96	31.33	11.05	16.02	68.67
GVZ	1.20	10.49	1.32	0.08	2.89	29.99	6.72	4.16	29.02	14.14	70.98
OVX	2.52	10.74	3.55	2.20	2.51	22.08	2.39	6.72	16.48	30.81	69.19
to others	30.28	57.65	26.99	19.22	26.49	125.15	42.00	66.05	77.15	80.86	Total
Net (To-From)	-16.70	15.86	-17.60	-30.66	-20.87	72.90	-18.15	-2.63	6.17	11.67	55.18
Panel C: Russia-Ukraine conflict											
StockSentiment	29.49	3.84	1.49	5.42	14.74	13.99	12.29	4.97	11.78	1.98	70.51
BondSentiment	4.37	64.45	2.47	4.79	3.65	3.83	1.39	3.29	5.46	6.31	35.55
EuroSentiment	7.71	6.49	39.66	0.75	9.12	5.14	4.27	9.29	12.01	5.56	60.34
GoldSentiment	2.40	2.06	1.88	45.30	9.40	6.95	11.53	7.01	11.86	1.61	54.70
OilSentiment	10.30	2.31	3.41	5.05	47.31	4.60	11.79	2.18	5.65	7.41	52.69
VIX	2.17	3.06	1.49	10.27	11.48	25.13	18.54	6.66	16.52	4.69	74.87
TYVIX	4.75	5.34	2.66	1.23	4.78	12.13	37.23	8.16	11.63	12.10	62.77
EVZ	9.20	0.64	0.28	1.01	4.73	6.44	10.82	37.97	24.30	4.60	62.03
GVZ	7.78	3.16	0.62	2.44	1.98	12.87	7.26	20.91	35.74	7.24	64.26
OVX	4.99	4.79	5.71	1.29	5.53	7.61	11.63	7.37	3.72	47.37	52.63
to others	53.67	31.67	20.00	32.24	65.42	73.55	89.51	69.85	102.94	51.51	Total
Net (To-From)	-16.83	-3.88	-40.34	-22.46	12.73	-1.32	26.73	7.82	38.68	-1.12	59.04
Panel D: UK Brexit											
StockSentiment	51.50	0.99	4.07	2.40	5.92	9.06	4.20	6.62	8.89	6.34	48.50
BondSentiment	1.73	78.22	1.13	4.36	1.09	0.99	6.55	0.81	3.33	1.78	21.78
EuroSentiment	2.90	3.01	75.29	2.20	2.80	1.04	0.49	5.84	2.81	3.61	24.71
GoldSentiment	6.23	4.23	1.28	68.36	2.04	2.73	1.05	2.89	8.27	2.92	31.64
OilSentiment	3.73	0.61	1.65	3.56	59.84	8.15	0.81	2.05	9.07	10.52	40.16
VIX	1.99	0.74	1.80	1.45	9.06	44.43	10.44	13.01	9.85	7.23	55.57
TYVIX	1.45	2.35	12.54	1.43	2.97	6.15	31.91	19.48	16.43	5.29	68.09
EVZ	3.69	0.13	8.05	0.87	6.80	7.20	3.87	53.57	11.30	4.53	46.43
GVZ	2.86	0.24	2.70	3.18	1.90	10.86	9.60	22.12	43.75	2.79	56.25
OVX	1.04	0.88	17.80	3.54	3.73	5.09	4.26	7.72	9.97	45.95	54.05
to others	25.62	13.18	51.02	22.99	36.30	51.28	41.28	80.54	79.93	45.02	Total
Net (To-From)	-22.87	-8.60	26.32	-8.65	-3.85	-4.29	-26.81	34.11	23.68	-9.03	44.72
Panel E: US-China trade war											
StockSentiment	62.35	0.28	5.99	0.78	3.40	15.62	3.68	2.33	3.55	2.00	37.65
BondSentiment	1.24	76.31	3.22	4.75	3.61	0.87	2.61	3.36	1.41	2.61	23.69
EuroSentiment	10.98	2.61	53.73	1.08	4.46	10.01	1.38	6.92	4.91	3.91	46.27
GoldSentiment	7.80	3.19	2.31	70.32	2.47	6.13	2.10	2.74	1.50	1.44	29.68
OilSentiment	7.15	1.16	3.37	1.88	64.22	7.51	2.41	2.47	2.57	7.27	35.78
VIX	10.07	0.43	10.31	0.83	4.22	43.01	10.57	6.47	10.80	3.30	56.99
TYVIX	6.60	1.24	3.83	3.01	4.05	14.69	43.46	10.66	10.55	1.91	56.54
EVZ	6.62	0.86	11.37	0.36	9.01	7.96	5.69	50.80	2.48	4.85	49.20
GVZ	11.73	1.24	14.63	0.63	1.70	17.32	6.21	4.24	39.01	3.28	60.99
OVX	5.88	1.27	7.85	0.71	1.43	16.52	2.11	4.53	1.75	57.96	42.04
to others	68.06	12.28	62.89	14.03	34.36	96.62	36.76	43.72	39.53	30.57	Total
Net (To-From)	30.41	-11.41	16.62	-15.65	-1.42	39.62	-19.78	-5.48	-21.46	-11.46	43.88
Panel F: Covid-19 pandemic											
StockSentiment	43.77	0.78	4.70	6.99	14.28	12.35	4.84	2.03	6.73	3.54	56.23
BondSentiment	5.12	60.65	1.53	5.78	3.56	11.86	4.66	0.88	5.75	0.21	39.35
EuroSentiment	6.62	1.45	56.81	1.99	12.74	4.58	5.24	6.89	2.10	1.59	43.19
GoldSentiment	6.41	1.56	3.52	32.40	4.11	20.67	9.94	4.88	13.79	2.72	67.60
OilSentiment	20.69	1.25	2.92	3.79	35.52	10.70	7.88	1.77	8.78	6.70	64.48
VIX	11.73	1.27	1.26	6.76	7.51	35.77	9.18	6.20	19.26	1.06	64.23
TYVIX	10.16	1.63	4.00	4.50	7.93	24.30	21.89	8.79	14.17	2.63	78.11
EVZ	7.78	1.73	1.46	4.54	5.63	31.71	10.53	19.04	16.50	1.10	80.96
GVZ	7.66	1.18	0.71	4.32	5.22	32.08	7.43	11.77	28.01	1.62	71.99
OVX	8.04	1.18	0.37	2.10	11.23	20.44	6.71	6.94	17.03	25.97	74.03
to others	84.21	12.03	20.46	40.76	72.21	168.69	66.40	50.14	104.10	21.16	Total
Net (To-From)	27.98	-27.32	-22.73	-26.84	7.73	104.46	-11.71	-30.82	32.12	-52.87	64.02

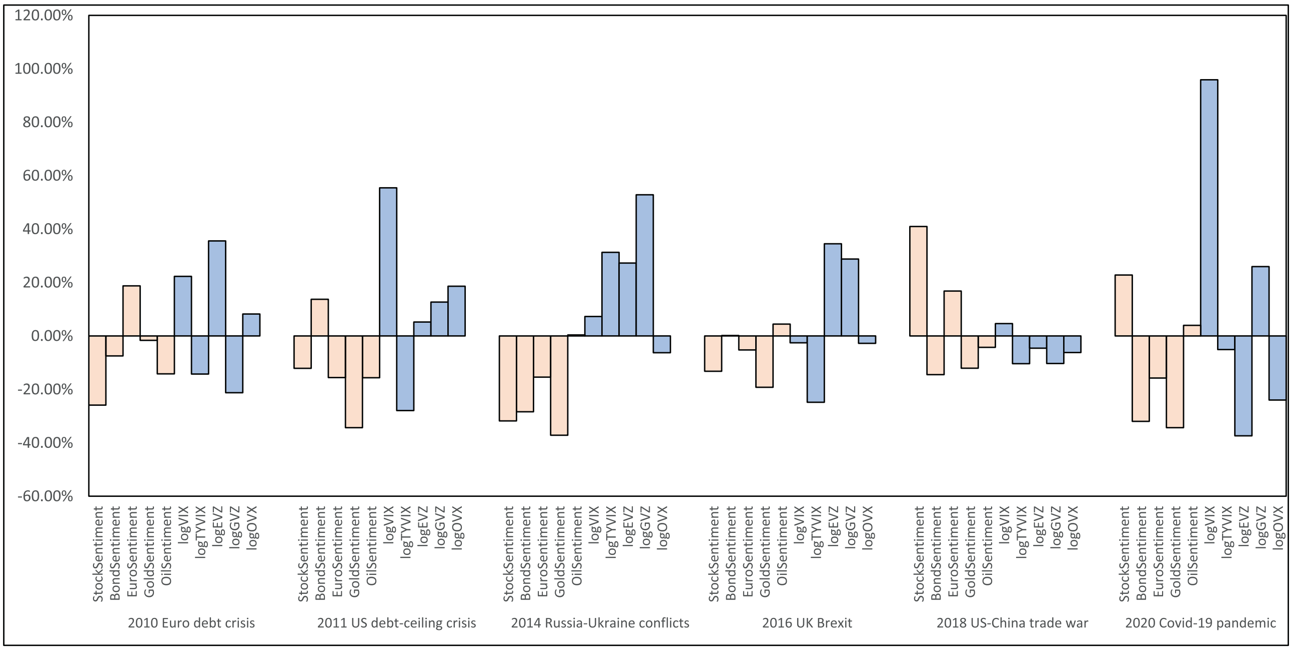
Appendix G. Net pairwise directional connectedness during various crises

This figure plots the net pairwise directional connectedness during six crises: (a) Euro Debt crisis (Apr 2010 – Feb 2011); (b) US debt-ceiling crisis (May 2011- Aug 2011); (c) Russia-Ukraine conflicts (Feb 2014 - May 2014); (d) UK Brexit (Jun 2016 – Nov 2016); (e) US-China trade war (May 2018 – Dec 2018); (f) COVID-19 pandemic (Dec 2019 – May 2020). The arrow width reflects the value in net connectedness. The unidirectional red arrows and turquoise arrows represent the sentiment spillovers and volatility spillovers during various crises, respectively. Gold nodes are the greatest net transmitter sentiments at different turbulent periods.



Appendix H. Net total directional connectedness after controlling for market conditions during various crises

This figure plots the net total directional connectedness for the orthogonalized sentiment and volatility indices during various crises: (a) Euro Debt crisis (Apr 2010 – Feb 2011); (b) US debt-ceiling crisis (May 2011- Aug 2011); (c) Russia-Ukraine conflicts (Feb 2014 - May 2014); (d) UK Brexit (Jun 2016 – Nov 2016); (e) US-China trade war (May 2018 – Dec 2018); (f) COVID-19 pandemic (Dec 2019 – May 2020). We control for the term spread, the 3-month Treasury Bill rate, the credit spread, the TED spread, and Pástor and Stambaugh's (2003) liquidity factor.



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