Spillover between Investor Sentiment and Volatility: The Role of Social Media

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ABSTRACT

This study examines the attributes of informational spillover across different asset volatilities and social media sentiments. Specifically, we uncover the spillover effect between investor sentiment and market implied volatility among stock, bond, foreign exchange and commodity markets. We find that sentiments and volatilities are weakly connected. There is a stronger spillover from the market-specific volatility to the sentiment of the same market, but a marginal effect the other way round. Second, the informational spillover is mainly from market volatilities to market sentiments, and the most significant net transmitter is the VIX. Third, the connectedness of market sentiment and volatility increases in turbulent economic periods. Lastly, the role of sentiments can switch from net receiver to net transmitter at turmoil times.

JEL Classification: C53; E44; F31; G15

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1. Introduction

It is well documented that investor sentiment extracted from the traditional news media influences financial markets (see, e.g., Fang and Peress, 2009; Engelberg and Parsons, 2011; Dougal et al., 2012). Over the last decade, however, social media has become investors' leading source of information. In the 2021 Reuters Institute Digital News Report, Newman et al. (2021) document that 56% of the respondents worldwide use social media to access news and information. Unsurprisingly, social media sentiment has been shown to affect financial markets.

Among the equity market literature, social media sentiment has been associated with stock returns, trading volume, and volatility (see, e.g., Da et al., 2015; Karagozoglu and Fabozzi, 2017; Rakowski et al., 2021). For example, Da et al. (2015) find that Twitter sentiment is associated with stock return reversals and transitory spikes in volatility. Karagozoglu and Fabozzi (2017) show that a signal constructed from social media sentiment can be used to predict VIX-related product volatility. Rakowski et al. (2021) document that Twitter posts can impact investors' stock trading volume and generate abnormal returns. Social media sentiment has also been shown to influence other asset classes, including bonds (Piñeiro-Chousa et al., 2021), foreign exchange (Goddard et al., 2015; Sibande et al., 2021), and commodities (Smales, 2014; Han et al., 2017; Fernandez-Perez et al., 2020). For instance, Piñeiro-Chousa et al. (2021) argue that social network sentiment can positively influence green bond returns as it reflects crowds' opinions. Sibande et al. (2021) shows that concurrent social media sentiment signals the potential speculative actions in foreign exchange markets.

Despite the extant literature on social media and financial markets, there are several issues the literature has not addressed. First, most studies focus on how sentiment from one asset class affects the returns of other asset classes (Gao and Süss, 2015; Islam, 2021; Chen, 2021). For example, Gao and Süss (2015) document that eight different commodity futures returns are sensitive to changes in S&P 500 sentiment, particularly for futures with high volatility. Chen (2021) shows that equity market sentiment is negatively associated with contemporaneous bond returns but positively relates to subsequent bond returns. Since financial assets are linked to one another, it can be expected that asset-specific news sentiments are interconnected.[1] However, it remains a question how sentiment from one asset class affects investor sentiments of other asset classes.

Second, existing studies link sentiment and volatility of the same asset (Da et al., 2015; Goddard et al., 2015; Audrino et al., 2020).[2] However, study on how sentiments and volatilities across different asset classes influence each other is still lacking, even though such linkage is to be expected. As an example, the crude oil literature documents that oil price volatility influence stock returns. Oil price uncertainty leads to postponement of investment decisions (Elder and Serletis, 2010) and increases unemployment rate (Kocaasland, 2019). A slowing down in economic activity may reduce investor sentiment in the equity markets.

To address the above gap in the literature, we examine the connectedness between sentiment and volatility among the equity, bond, precious metal, energy, and foreign exchange markets. As sentiment proxy, we employ the Refinitiv MarketPsych Analytics (RMA) social media sentiment data for each of these markets. RMA analyzes millions of real-time social media references from thousands of global media outlets to account for the sentiment scores of relevant market investors' expectations. As volatility measure, we use the Chicago Board Options Exchange (CBOE) implied volatility indices for the US equity market (the CBOE Volatility Index, VIX), the US bond market (the 10-year T-Note Volatility Index, TYVIX), for the foreign exchange market (Eurocurrency Volatility Index, EVZ), the gold market (the Gold

[1] The literature of safe haven assets often link equity with gold markets (see, e.g., Baur and McDermott, 2016; Triki and Maatoug, 2021) while literature on investor fear and attention often link equity with foreign currency markets (Goddard et al., 2015; Smales and Kininmonth, 2016).

[2] Goddard et al. (2015), for instance, show that investor attention in the foreign exchange markets, comoves with contemporaneous foreign exchange market volatility and predicts subsequent volatility. Audrino et al. (2020) document that stock market sentiment proxied using Google searches and firm-specific messages on StockTwits influence stock market volatility.

Volatility Index, GVZ), and the crude oil market (the Crude Oil Volatility Index, OVX). We assess connectedness among the above variables using the static and dynamic Diebold and Yilmaz's (2014) connectedness measure. We further assess among-group connectedness 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 find that all market-specific sentiments and market-specific volatilities are interconnected with a total connectedness of 30.4%. There is a stronger spillover from volatility to sentiment of the same market, but a marginal effect the other way round. Second, informational spillover comes mainly from market volatilities to market sentiments, with the VIX being the most significant net transmitter. Third, the connectedness of market sentiment and volatility increases in turbulent economic periods, such as the GFC, Brexit and the COVID-19 pandemic crisis periods. Finally, the sentiments can switch from being net receiver to net transmitter at turmoil times, consistent with the previous literature on the spillover effect (Antonakakis and Kizys, 2015; Andrada-Félix et al., 2018; Zhang et al., 2022).

Our contribution to the literature is twofold. First, this study sheds light on social media sentiment spillover across financial markets. The existing literature usually focuses on the effect of equity market sentiment on different asset classes. Our findings provide a better understanding on the importance on social media irrespective of the asset classes. Second, we show that social media sentiment is not a major trigger of market volatility. Instead, we find that social media sentiment is a net absorber of the shocks from market volatility. This provides more evidence to the literature on the "echo chambers" of social media (Jiao et al., 2020). Different from comparing the news and social media buzz (number of words and phrases referring to an asset) for stocks at monthly level, we show that social media sentiment could be less informative than the implied volatility at daily level for asset classes.

Our study has several implications. For market participants, our findings suggest that investors should consider both volatility and sentiment for portfolio management and decision making, particularly in turbulent times. In other words, diversification benefits could be impaired at turbulent times when it is most needed. For regulators, they may design a new gauge of market stability using sentiment connectedness.

The remainder of the paper proceeds as follows. Section 2 presents the methodology. Section 3 introduces the volatility and sentiment datasets and provides descriptive statistics. In Section 4, we report the empirical results. We perform robustness tests in Section 5. Section 6 concludes.

2. Methodology

The primary methodology we use for measuring the connectedness among different variables is based on the decomposition of a forecast error variance following Diebold and Yilmaz (2012, 2014), hereafter DY approach. Second, we present a generalized connectedness framework developed by Greenwood-Nimmo et al. (2016, 2021) to capture the connectedness within and between sentiment and volatility blocks.

2.1. Diebold-Yilmaz approach

To measure the connectedness of five market sentiments and the corresponding five market volatilities, we follow the DY approach and use forecast error variance decomposition to assess the fraction of H-step-ahead error variance in predicting the x_i (sentiment or volatility of an asset) with respect to shocks from the same or other components at time t. Specifically, the variance decomposition method starts with fitting a reduced-form vector autoregression (VAR) model to build an H-step-ahead forecast. Then, it decomposes the forecast error variance with respect to shocks from the same and other components. 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 connectedness measures are based on the "non-own", or "cross", variance decompositions, d_{ij}^{H}, i, j = 1, 2…, N, $i \neq j$.

Consider an N-dimensional covariance-stationary data generating process with orthogonal shocks: $x_t = \Theta(L)u_t$, $\Theta(L) = \Theta_0 + \Theta_1 L + \Theta_2 L^2 + \cdots, E(u_t, u_t') = I$. Note that Θ_0 need not be diagonal. All aspects of connectedness are contained in this very general representation. The contemporaneous aspects of connectedness are summarized in Θ_0, and dynamic aspects in $\{\Theta_1, \Theta_2, \ldots\}$. Transformation of $\{\Theta_1, \Theta_2, \ldots\}$ via variance decompositions can reveal and compactly summarize connectedness.

We employ the "variance decomposition table" of Diebold and Yilmaz (2014) to understand the various connectedness measures and their relationships. For illustrative purposes, Table 1 reports the variance decomposition table 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 $D^H = \left[d_{ij}^H\right]$. The off-diagonal entries of D^H are the parts of the N forecast error variance decompositions of relevance from connectedness method. 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 follow:

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

For the off-diagonal row sums, i.e., the rightmost column of Table 1 means the share of the H-step forecast error variance of x_i coming from shocks arising in all other variables. While the off-diagonal column sums, i.e., the bottom row of Table 1, means the share of the

H-step forecast error variance of x_i 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:

$$C^H_{i\leftarrow\bullet} = \sum_{\substack{j=1\\ j\neq i}}^{N} d^H_{ij}, \tag{3}$$

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

$$C^H_{\bullet\leftarrow j} = \sum_{\substack{j=1\\ i\neq j}}^{N} d^H_{ij}. \tag{4}$$

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

$$C^H_i = C^H_{\bullet\leftarrow i} - C^H_{i\leftarrow\bullet}. \tag{5}$$

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

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

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. Therefore, and following Diebold and Yilmaz (2014), we use the generalized variance decomposition (GVD[3]) proposed by Koop et al. (1996) and Pesaran and Shin (1998) to decompose the forecast error variance. The H-step GVD matrix $D^{gH} = \left[d^{gH}_{ij}\right]$ is defined[4] as:

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

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

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

where e_j is a vector with jth element unity and zeros elsewhere; Θ_h is the coefficient matrix (with multiplying the h-lagged shock vector) in the 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 $\widetilde{D}^g = \left[\tilde{d}_{ij}^g\right]$ with the necessary normalization $\tilde{d}_{ij}^g = \frac{d_{ij}^g}{\sum_{j=1}^N d_{ij}^g}$ where by construction $\sum_{j=1}^N \tilde{d}_{ij}^g = 1$ and $\sum_{i,j=1}^N \tilde{d}_{ij}^g = N$. Thus, the generalized connectedness measures can be calculated by using $\widetilde{D}^g = \left[\tilde{d}_{ij}^g\right]$ matrix.

[Insert Table 1 Here]

In summary, the above described DY approach is a preferred method for directly measuring the direction and strength of the spillover effect among our sentiment and volatility variables. The forecast error variance decomposition is directly computed from the estimated parameters and covariance matrix of the VAR system[5].

2.2. A generalization of the Diebold-Yilmaz's approach

To investigate whether market sentiment changes induce volatility variations or the other way around, we aggregate the five market sentiments as a whole (i.e., sentiment block) and the five market volatilities as a whole (i.e., volatility block) to capture the connectedness within and between sentiment and volatility blocks. We follow Greenwood-Nimmo et al.'s (2016, 2021) block aggregation approach that exploits block aggregation of the connectedness matrix. See the detailed technical annex in Appendix B.

[5] 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.

Namely, instead of assessing the spillover effect individually for each variable, we gauge connectedness for a sentiment block (five sentiments aggregated) and a volatility block (five volatilities aggregated). Specifically, we gauge spillovers between and within the two blocks. More importantly, this approach enables us to reach general conclusions regarding whether sentiment or volatility is the main source of the spillover effects.

3. Data

We employ two sets of data in this study. First, we collect the implied volatility indexes for the five asset classes we consider in our sample. Second, we use social media sentiment data for all five respective markets as our measure of investor sentiment.

3.1. Market volatility

To proxy for stock market volatility, we employ the CBOE Volatility Index (ticker: VIX). Using the real-time prices of options on the S&P 500 index, the VIX is designed to reflect investors' consensus for the upcoming 30-day expected stock market volatility. Hence, the VIX is often seen as a "fear gauge" of the US equity market. For the bond market, we take CBOE/CBOT 10-year US Treasury Note volatility index (TYVIX). TYVIX measures the expected volatility in its underlying 10-year Treasury Note futures over next 30 days. For the FX market, we employ the CBOE Euro Currency Volatility Index (EVZ). The 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. Lastly, for the energy commodity 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 Refinitiv Datastream at a daily frequency. Our sample period is from 1 August 2008 to 15 May 2020, covering a series of significant events on financial markets, such as the Global Financial Crisis (GFC) and the COVID-19 pandemic.[6]

Figure 1 plots the daily implied volatility series (in logs). From Figure 1, one can notice 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 due to investors' fear surrounding the European sovereign debt crisis. In August 2011, the US debt-ceiling crisis and US credit rating (AAA to AA+) downgrade raised universal concerns about credit defaults. Countries holding large amounts of US dollars were concerned about their potential losses, aggravating investor uncertainty. In 2016, the Brexit process (the UK voted to exit the European Union) triggered economic concerns and enlarged the distress among global investors. Finally, all implied volatilities soared to maximum historical values from the beginning of 2020 because of the COVID-19 pandemic crisis.

[Insert Figure 1 Here]

3.2. Sentiment Data

As a measure of investor sentiment, we employ the Refinitiv MarketPsych Analytics (RMA) sentiment data. Previously called Thomson Reuters MarketPsych Indices (TRMI), the RMA provides advanced and comprehensive finance-specific sentiment data on various financial

[6] The CBOE EVZ volatility index became available from 01 August 2008 while the TYVIX was delisted after 15 May 2020.

assets for all major countries at daily, hourly and minute frequency dating back from 1998. 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 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 less information distortion and loss. As explained in Renault (2017), the accuracy of sentiment quantification can directly influence the reliability and predictability of sentiment data. The RMA sentiment data has been used in many studies, including Papakyriakou (2019), Michaelides et al. (2019), and Gan et al. (2020).

The RMA provides sentiment scores in three content categories: News, Social, and News&Social (a combination of news and social). We concentrate on the overall sentiment indicators of Social sentiment data for this study and use the other two for robustness tests. We collect the following five daily sentiment series from RMA: (1) the stock market sentiment (*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*). Appendix A lists the underlying markets along with the sentiment and volatility symbols used in our study. The sentiment score is calculated as the positive references less negative references over a 24-hour window. The score represents the degree to which market optimism or pessimism for an underlying asset and ranges from -1 to 1. A sentiment score of -1 indicates extremely negative sentiment, while a score of 1 indicates extremely positive sentiment. A score of 0 indicates neutral sentiment. The daily level data we employed in this study is updated every calendar day at 3:30 pm US Eastern time by RMA.

Figure 2 plots the various sentiment series over the sample period. 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. The sentiment plots show that bond market sentiment is almost persistently negative and highly volatile, while gold sentiment is relatively stable and positive over the sample period. The equity, oil and FX sentiments fluctuate around zero. However, FX sentiment was generally negative following the 2010 European sovereign debt crisis while the oil sentiment switched from a persistent bullish to bearish with OPEC shifting its policies back in 2015. Many of the spikes in sentiment coincide with the spike in the volatility shown in the previous figure. For example, during the GFC in 2008 and the COVID-19 pandemic in 2020, uncertainty among investors led to a surge in implied volatility indices. All sentiment series turned into a bearish territory during the same periods, reflecting general pessimism across various markets. Investor sentiment gradually bounced back once uncertainty was reduced.

[Insert Figure 2 Here]

3.3. Descriptive Statistics and Contemporaneous Correlation

We report the descriptive statistics for the volatility and social sentiment series in Panel A of Table 2. On average, the stock market and the FX market have negative average sentiment scores (-0.03 and -0.06, respectively). The bond market is particularly bearish over the sample period with a score of -0.20. The gold market has an overall positive sentiment (0.04), which could be due to the safe haven feature of gold (see, e.g., Baur and Lucey, 2010) and the fact that our sample period coincides with several major crises. The crude oil market, on the other hand, has an overall neutral sentiment (0.00).

[Insert Table 2 Here]

In terms of volatility, crude oil, equity, and gold markets have the highest uncertainty with (log) index values of 3.55, 2.89, and 2.85, respectively. The FX and the bond market report the lowest average volatility (2.28 and 1.75, respectively). The augmented Dickey Fuller (ADF) test shows that both the sentiment and volatility series are stationary.

Panel B reports the correlation coefficient among the implied volatility and sentiment series. Turning first to the sentiment correlations in the upper left section, we observe that sentiments 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, including the energy market. Second, the implied volatilities at the bottom right section are positively correlated with average values higher than 0.56, indicating a stronger co-movement among market volatilities compared to sentiments. Notably, the correlations between the bond and the gold market volatilities (0.83) and between the bond and the FX 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 negative (e.g., -0.57 between OilSentiment and OVX and -0.51 between EuroSentiment and EVZ). This indicates that when markets are more volatile, the market sentiments are more pessimistic.

4. Empirical results

This section reports the empirical results for the sentiments and volatilities connectedness across different markets. We first report the results for the static full-sample unconditional connectedness across all the variables before proceeding to the connectedness between the sentiment and volatility groups. We then show the dynamic total and net directional connectedness over our sample period.

4.1. Static (full-sample, unconditional) analysis

Table 3 reports the full-sample connectedness table for the sentiment and volatility series.[7] First, we focus on the diagonal elements, which measure each variable's own connectedness. These elements show the greatest values, ranging from 55.79% for the VIX to 93.85% for BondSentiment, indicating that the series are relatively independent of each other. 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 between the VIX and OVX (15.65%). These observations suggest that connectedness between stock and oil markets is the strongest in both sentiment and volatility indices. This finding aligns with Andrada-Félix et al. (2018), who document that the strongest pairwise connectedness among our same implied volatility indices is from the VIX to OVX. Our evidence for sentiment and volatility connectedness across equity and oil markets can be explained by the financialization of commodity futures[8], suggesting that shocks coming from any of these two markets spill over to each other.

[Insert Table 3 Here]

[7] All results are based on VARs of order 2 and GVDs of 10-day ahead forecast errors.

[8] Commodities, such as crude oil, has been widely held by institutional investors for diversification purpose (Büyükşahin and Robe, 2014). Therefore, the stock market and commodity market have integrated closely since early 2000s.

Across sentiment and volatility indices, the pairwise connectedness is stronger from volatility to sentiment indices than the other way round. For instance, the highest volatility to sentiment spillover is from the VIX to StockSentiment, (14.22%), followed by the spillover from OVX to OilSentiment (11.83%). In contrast, the highest sentiment to volatility spillover is from OilSentiment to OVX (4.06%), followed by the spillover from StockSentiment to the VIX (2.17%). As further evidence, we refer to the net directional connectedness at the bottom row. 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 volatility in the stock market is the dominant shock generator to all the sentiment and volatility indices. This is in line 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 and Olmo, 2014; Gao and Süss, 2015). On the opposite extreme, the StockSentiment, GoldSentiment and OilSentiment have the lowest net connectedness with -18.92%, -13.88%, and -11.95%, respectively.

The total connectedness of all the sentiments and volatilities is 30.4%, indicating that almost 70% of variation comes from the index's 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), 38.8% among five implied volatility indices (Andrada-Félix et al., 2018). Overall, we find that the sentiment and volatility indices are mildly connected. The largest net contributor is the stock market volatility, and the largest net receiver is the stock market sentiment.

In addition to the connectedness among the individual series, we measure the connectedness between sentiment and volatility groups. We measure block connectedness following Greenwood-Nimmo et al.'s (2016, 2021).[9] We report the full sample static block connectedness results in Table 4. The main finding is that volatility indices are the main source of shocks to sentiment indices with a net contribution of 11.19%. We also observe that the sentiment (84.14%) and volatility blocks (95.33%) have high own connectedness values, indicating that the two blocks 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 inter-connected with a total block connectedness of 37.15%.

[Insert Table 4 Here]

4.2. Dynamic total connectedness analysis

The previous section shows the static connectedness 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, particularly during important economic events. We follow Diebold and Yilmaz (2012) and conduct a connectedness analysis using a 200-day rolling window.

In Figure 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). The three plots fluctuate over time, with similar pattern between the sentiment and volatility groups. In line with the results in Table 4, the total connectedness for sentiment group is always lower than the connectedness for the volatility group. The total connectedness fluctuates strongly in turbulent periods. We observe numerous periods where the total connectedness deviates from its average value of 39%. During the European sovereign debt

[9] Appendix B elaborates the steps taken to measure block connectedness.

crisis in the middle of 2010, total connectedness reached to around 50%, indicating worsened investors' confidence. The next spike in the total connectedness was in early August 2011 (around 45%), triggered by the US debt-ceiling crisis and the downgrade of US credit rating, increasing uncertainty in the market and decreasing market confidence. Total connectedness increased again in June 2016 due to the Brexit and in early 2020 during the COVID-19 global pandemic crisis with a value of around 62%. Thus, we Total connectedness increases in turbulent economic periods as uncertainty about the financial markets are associated with fears and pessimism across various asset classes (see, e.g., Antonakakis and Kizys, 2015; Andrada-Félix et al., 2018; Zhang et al., 2022).[10]

[Insert Figure 3 Here]

Figure 4 plots the dynamic net total connectedness of sentiment block, i.e., the connectedness among sentiment series minus the connectedness among the volatility series. The sentiment block is persistently a net absorber of volatility. Notably, the effect of information spillover from volatility to the sentiment block is more significant during turbulent times, indicating that investors are in a bearish mood due to market volatility, instead of the opposite. Overall, we show that social media sentiment is not a major trigger of market volatility. Instead, we find that social media sentiment is a net absorber of the shocks from market volatility. This provides more evidence for recent literature on the "echo chambers" role of social media sentiment (see e.g., Jiao et al., 2020).

[Insert Figure 4 Here]

[10] Appendix C reports the net directional connectedness of each sentiment and volatility series. The results suggest that the net total directional connectedness vary over time, displaying different roles (net transmitter or receiver) in different periods.

4.3. Net pairwise directional connectedness

We further investigate how the variables in our system are interconnected during some turmoil periods by examining the net pairwise directional connectedness. We study four turbulent periods: (i) the European sovereign debt crisis (from April 12, 2010 to February 28, 2011), (ii) the US debt-ceiling and credit downgrade crisis (from August 4, 2011 to December 17, 2012), (iii) the UK Brexit (from February 11, 2016 to November 25, 2016) and (iv) the COVID-19 global pandemic crisis (from December 12, 2019 to the end of sample period).

According to Equation (2), the net pairwise directional connectedness from variable $j\ to\ i$ is, $C_{ij}^{H} = C_{j\leftarrow i}^{H} - C_{i\leftarrow j}^{H}$, thus, there are $\frac{N^2-N}{2}$ net pairwise directional connectedness measures, where N is the number of variables. Hence, there are 45 net pairwise directional spillovers with the variables. To visualize how our variables are connected, we plot a network diagram in Figure 5 where we highlight the most critical net pairwise directional spillover transmitters and receivers during the four turbulent periods. The gold nodes represent the sentiment series, the grey nodes represent the volatility variables, and the orange node reflects the most significant net transmitter during each period. The links with a unidirectional arrow show the spillover direction from one node or variable to another. Additionally, the width of the link stands for the value of each net pairwise directional spillover, and the wider width means a greater spillover value. The top ten (out of 45) net pairwise directional spillovers are dark red, the rest eleventh to forty-five spillovers are in sky-blue.

[Insert Figure 5 Here]

As can be seen, the role of different variables played in spillover switches during different times. For example, during the European sovereign debt crisis (Fig. 5.a.), the EVZ was the most significant net volatility spillover transmitter. During the same period, EuroSentiment was a net sentiment spillover transmitter. This highlights the importance of the debt crisis event where the crisis has severely undermined investor confidence in the Euro/dollar foreign exchange market, transmitting Euro sentiment to other markets' investor sentiment and volatility. During the UK Brexit (Fig. 5.c.), all sentiments were net receivers, especially the StockSentiment.

The VIX is the most dominant transmitter during the US debt-ceiling and credit downgrade crisis (Fig. 5.b.) and the COVID-19 global pandemic crisis (Fig. 5.d.). This is in line 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. All sentiments were net spillover receivers during the US credit crisis and the COVID-19 pandemic, with the StockSentiment being the largest net receiver during the former, and the GoldSentiment during the latter.

Our findings show that most volatilities are net transmitters while most sentiments are net receivers during turbulent market conditions. However, this role can switch depending on the underlying cause of the crisis. Also, we find that the importance of each index varies over time. For instance, the stock market volatility is a persistent net transmitter of volatility, but its impact is weaker during the EU debt crisis and UK Brexit than during the US credit crisis and COVID-19 pandemic crises.[11]

5. Robustness tests

5.1. Robustness test with News dataset and News & Social dataset

For our main specification, we use the sentiment indices from the RMA *Social* category. In the first robustness test, we use sentiment indices from the RMA *News* and *News&Social*

[11] We also report the static connectedness tables for the four different periods in Appendix D.

categories. While the methodology remains the same, the *Social* category are based on social media outlets while the *News* category are based on news media outlets. *News&Social* combines both groups. We present the connectedness table for both additional groups in Table 5.

[Insert Table 5 Here]

Panel A reports the static connectedness based on news media outlets while Panel B reports the connectedness using the news & social media outlets. The results are qualitatively similar to our main finding. All market-specific sentiments and volatilities are interconnected, with the stock market volatility being the most significant net transmitter in either Panels. Interestingly, total connectedness in both panels is around 40%, which is 10% higher than the total connectedness using social media sentiment in Table 3. This implies that the inter-connection of market volatility with sentiment coming from news media is stronger than with sentiment coming from social media. This relates to the results of Jiao et al.'s (2020) distinguishing news media and social media types by using the same RMA dataset (former Thomson Reuters MarketPsych Indices). They find that more discussion about a stock on social media predicts high subsequent return volatility and social media discussion can be a stale echo chamber of news media. However, instead of using social media buzz, we directly measure the inter-relationship between social media sentiment and market implied volatilities.

[Insert Table 5 Here]

5.2. Robustness test with different estimation horizons and rolling windows

Following Diebold and Yilmaz (2014), we further examine the impact of the choice of the DY approach parameters on the findings. For example, the connectedness is less wiggly when the window width is longer. Also, a shorter window length and forecast horizon can narrow the difference between the total connectedness measures due to the choice of GVDs and Cholesky-factor orthogonalization.

We first test the robustness of our dynamic results to alternative rolling window widths. We use 150 and 250-day windows (as opposed to the 200-day window in our main specification). Appendix E reports these results. The results for longer window are smoother and our findings are robust to the width of the rolling window.

We also change the predictive horizon for the DY approach. In addition to the 10-day ahead predictive horizon, we use alternative values of forecast horizons (5 days and 15 days). We report the static connectedness results in Table 6. The total connectedness varies slightly (27%, 30% and 33%) due to different predictive horizons. Nevertheless, our findings are consistent to those reported in Table 3, that is the connectedness values are robust to the choice of predictive horizons.

[Insert Table 6 Here]

6. Concluding remarks

We examine the connectedness between the social media sentiment and market implied volatility indices across asset classes, such as stock, bond, foreign exchange, precious metal and energy markets. Based on August 2008 to May 2020 sample, we find that social media sentiment and market volatility indices are weakly connected. There is a stronger spillover from the market-specific volatility to the sentiment of the same market, with the VIX being the most significant net transmitter. The inverse direction spillover is marginal. Second, as a group, informational spillover comes mainly from market volatility to market sentiment. Third, connectedness between market sentiment and volatility increases in turbulent economic periods, but sentiments can switch from being net receiver to net transmitter during such times.

Our study has several implications. For market participants, our findings suggest that investors should consider both volatility and sentiment for portfolio management and decision making, particularly in turbulent times. In other words, diversification benefits could be impaired at turbulent times when it is most needed. For regulators, they may design a new gauge of market stability using sentiment connectedness.

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Appendix A. Sentiment and volatility variables

Asset class	Underlying market	RMA Code	Sentiment symbol	CBOE Volatility Index
Equity	Stock	ETFUS500	StockSenti	VIX
Fixed income	Bond	US-bondSentiment	BondSenti	TYVIX
Currency	Euro FX	EUR	EuroSenti	EVZ
Precious metal	Gold	GOL	GoldSenti	GVZ
Energy	Crude Oil	CRU	OilSenti	OVX

Appendix B. Block connectedness methodology

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

If we have five different variables for each group or block i $\{v_{it}, w_{it}, x_{it}, y_{it}, z_{it}\}$ in the order $Y_t = (v_{1t}, w_{1t}, x_{1t}, y_{1t}, z_{1t}, \cdots, v_{Nt}, w_{Nt}, x_{Nt}, y_{Nt}, z_{Nt})'$ and we aim to 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):

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

$$\text{where } B_{ij}^H = \begin{bmatrix} d_{v_i v_i}^H & d_{v_i w_i}^H & d_{v_i x_i}^H & d_{v_i y_i}^H & d_{v_i z_i}^H \\ d_{w_i v_i}^H & d_{w_i w_i}^H & d_{w_i x_i}^H & d_{w_i y_i}^H & d_{w_i z_i}^H \\ d_{x_i v_i}^H & d_{x_i w_i}^H & d_{x_i x_i}^H & d_{x_i y_i}^H & d_{x_i z_i}^H \\ d_{y_i v_i}^H & d_{y_i w_i}^H & d_{y_i x_i}^H & d_{y_i y_i}^H & d_{y_i z_i}^H \\ d_{z_i v_i}^H & d_{z_i w_i}^H & d_{z_i x_i}^H & d_{z_i y_i}^H & d_{z_i z_i}^H \end{bmatrix} \text{ for } i, j = 1,2, \cdots, N,$$

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:

$$W_{ii}^H = \frac{1}{m} e'_m B_{ii}^H e_m \tag{B.2}$$

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:

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

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

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

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[12]:

$$K_{ii}^{H} = \frac{1}{m} trace(W_{ii}^{H}) \tag{B.5}$$

and

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

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

$$P_{i\leftarrow\cdot}^{H} = \sum_{j=1, j\neq i}^{N} P_{ij}^{H}, \tag{B.7}$$

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

$$P_{\cdot\leftarrow i}^{H} = \sum_{j=1, j\neq i}^{N} P_{ji}^{H}. \tag{B.8}$$

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

$$P^{H} = P_{\cdot\leftarrow i}^{H} - P_{i\leftarrow\cdot}^{H} \tag{B.9}$$

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

$$B\_B^{H} = \frac{1}{N} \sum_{i=1}^{N} P_{i\leftarrow\cdot}^{H} \tag{B.10}$$

and the aggregated spillover effect within-block is:

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

[12] 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.

Appendix C. Sentiment and volatility net connectedness over time

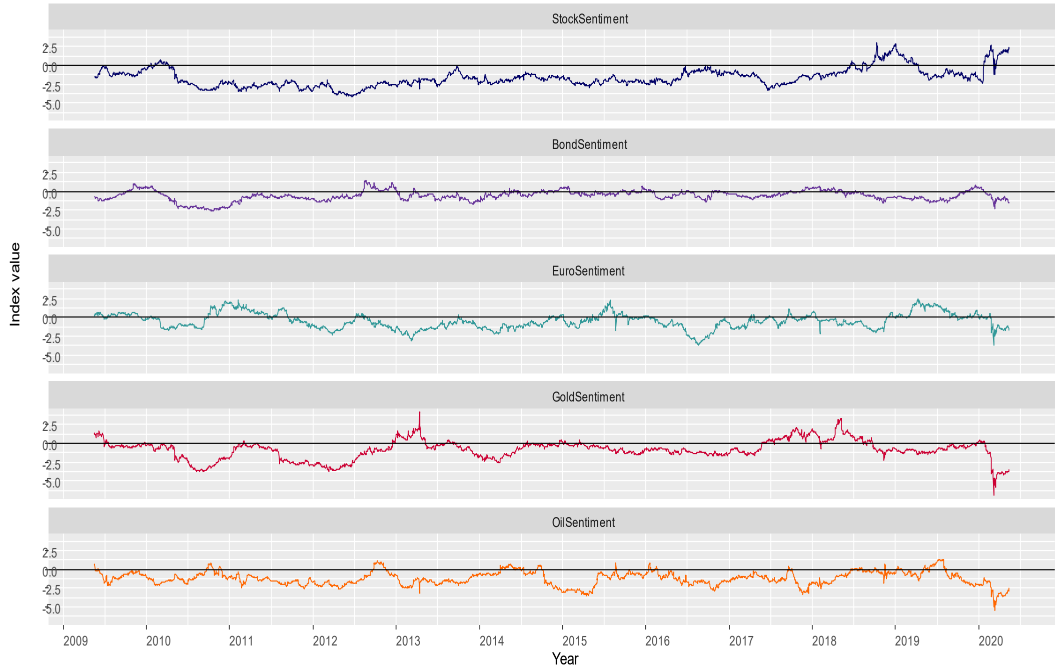

Figure C.1. Sentiment Connectedness

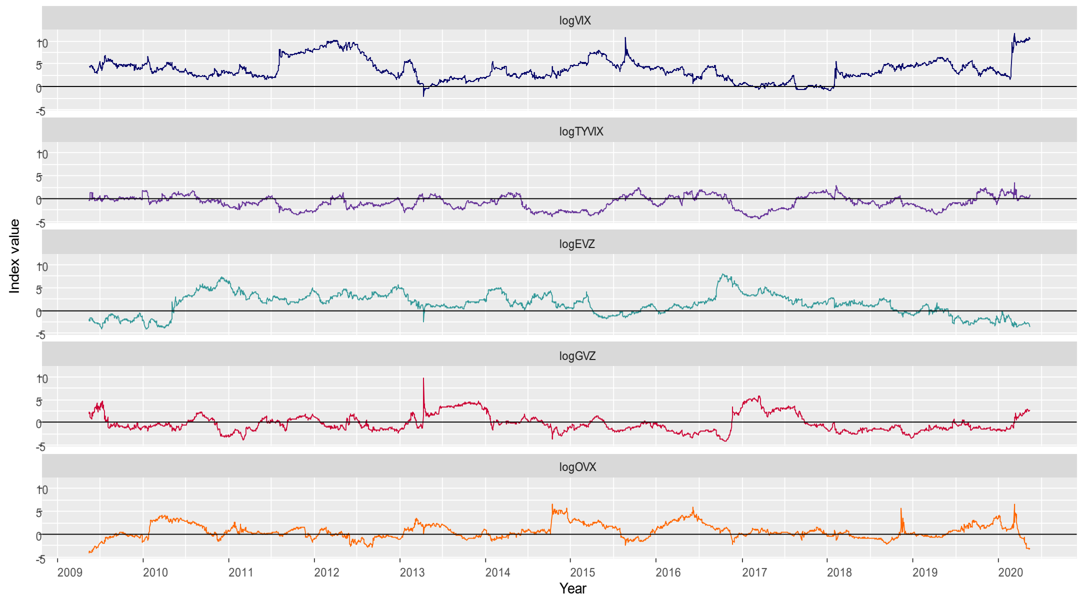

Figure C.2. Volatility Connectedness

Appendix D. Connectedness during various crises

	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	52.00	0.75	6.69	2.03	1.47	16.60	0.63	6.83	3.28	9.73	48.00
BondSentiment	0.58	80.86	0.17	3.03	0.94	3.30	2.87	2.44	4.68	1.13	19.14
EuroSentiment	6.37	0.16	62.71	3.43	1.14	9.38	0.40	11.12	3.23	2.04	37.29
GoldSentiment	3.53	0.38	4.43	57.74	1.70	13.41	1.39	5.47	6.01	5.93	42.26
OilSentiment	2.41	1.43	1.16	3.35	76.91	3.56	0.94	1.73	3.39	5.11	23.09
VIX	1.51	1.25	2.17	2.04	0.21	46.62	3.75	19.91	9.37	13.17	53.38
TYVIX	0.43	1.64	0.39	1.30	0.23	11.14	65.92	12.54	4.32	2.09	34.08
EVZ	1.46	1.91	1.70	1.30	0.40	20.96	5.85	48.64	14.36	3.40	51.36
GVZ	0.68	2.36	1.72	3.17	1.00	21.91	6.43	24.57	31.40	6.76	68.60
OVX	2.27	1.62	0.86	4.03	0.34	26.01	2.06	11.48	6.11	45.23	54.77
to others	19.24	11.51	19.29	23.68	7.43	126.28	24.32	96.09	54.74	49.38	Total
Net (To-From)	-28.75	-7.63	-17.99	-18.57	-15.66	72.90	-9.77	44.73	-13.86	-5.40	43.20

Panel C: UK Brexit											
StockSentiment	62.91	0.85	1.79	0.69	3.73	10.55	4.63	2.24	10.11	2.49	37.09
BondSentiment	1.17	88.57	0.23	1.77	0.85	0.69	4.00	0.53	2.04	0.15	11.43
EuroSentiment	4.08	1.43	75.20	0.78	2.65	3.12	1.16	6.93	4.02	0.65	24.80
GoldSentiment	0.85	4.68	0.62	74.27	2.39	4.87	2.28	5.51	2.84	1.70	25.73
OilSentiment	3.58	0.83	2.25	1.18	61.31	9.32	3.29	1.62	9.64	6.98	38.69
VIX	5.02	0.16	0.81	2.15	4.43	39.05	7.02	19.95	13.94	7.46	60.95
TYVIX	0.74	2.46	4.85	0.95	1.46	8.47	42.51	23.05	11.25	4.28	57.49
EVZ	0.21	0.65	1.83	1.12	1.81	9.92	4.42	66.71	9.54	3.80	33.29
GVZ	5.09	0.13	1.66	1.38	1.20	14.44	4.86	23.18	43.40	4.66	56.60
OVX	3.12	0.07	5.55	1.09	1.13	8.15	4.77	7.62	14.32	54.18	45.82
to others	23.85	11.26	19.57	11.11	19.64	69.53	36.44	90.64	77.69	32.16	Total
Net (To-From)	-13.24	-0.18	-5.23	-14.62	-19.04	8.58	-21.05	57.35	21.09	-13.66	39.19

Panel D: 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 E. Dynamic total connectedness using different windows

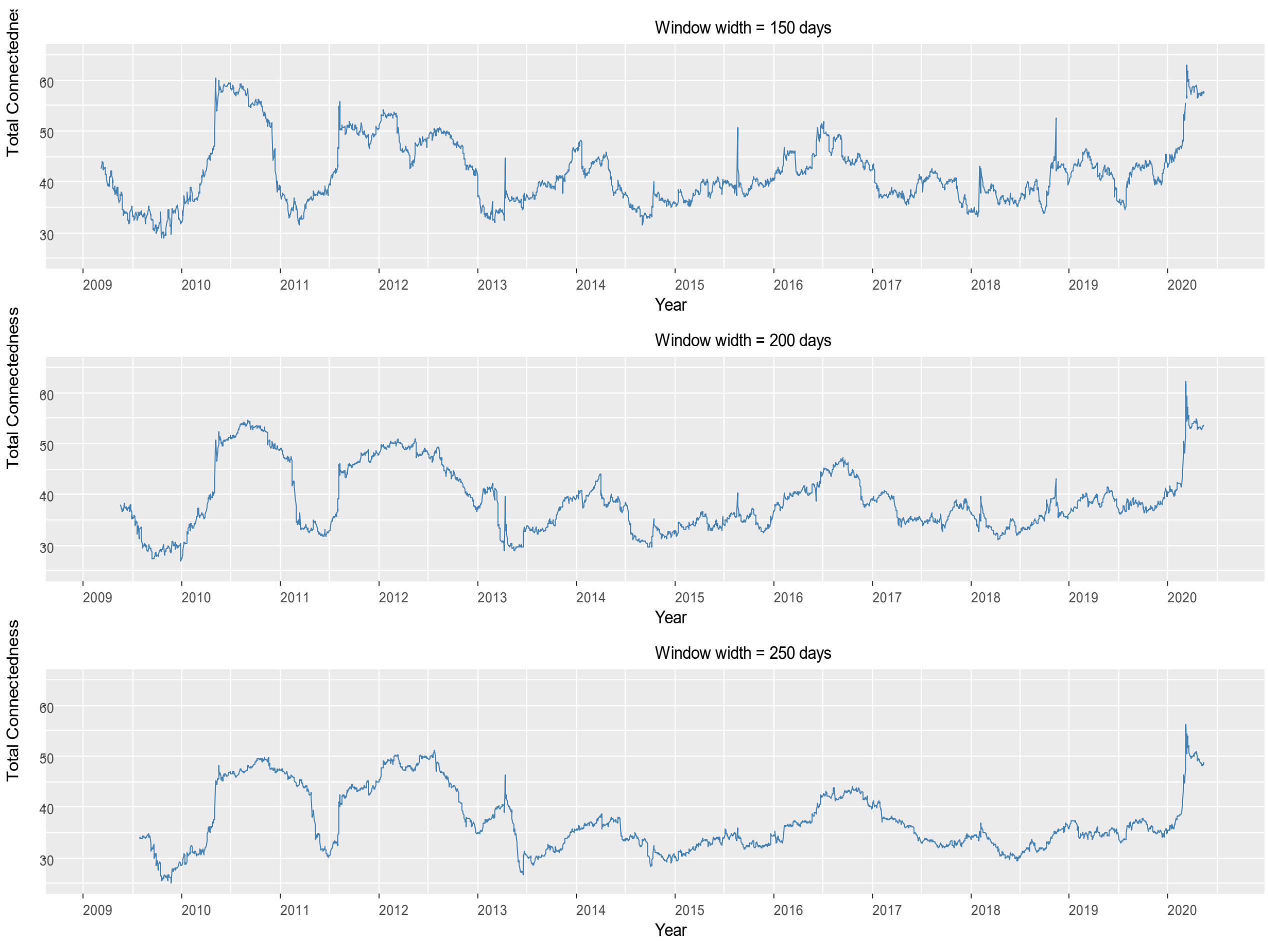

Table 1. Connectedness table

This table shows the schematic for the connectedness results among assets is presented. 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).

	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	$\sum_{j=1}^{N} d_{2j}^H, j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
x_N	d_{N1}^H	d_{N2}^H	...	d_{NN}^H	$\sum_{j=1}^{N} d_{Nj}^H, j \neq N$
To others	$\sum_{i=1}^{N} d_{i1}^H, i \neq 1$	$\sum_{i=1}^{N} d_{i2}^H, i \neq 2$	...	$\sum_{i=1}^{N} d_{iN}^H, i \neq N$	$\frac{1}{N}\sum_{ij=1}^{N} d_{ij}^H, i \neq j$

Table 2. Descriptive statistics and correlation matrix

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 logarithm.

	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
min	-0.25	-0.42	-0.36	-0.16	-0.25	2.21	1.15	1.42	2.18	2.67
max	0.22	0.12	0.21	0.19	0.29	4.42	2.80	3.42	4.17	5.78
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***
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

Table 3 Full sample connectedness

This table reports the full-sample GVD connectedness for five sentiment series and five volatility series using RMA Social Media sentiment and CBOE volatility indices from 1 August 2008 to 15 May 2020. The diagonal elements measure the connectedness of the ten indices themselves. The off-diagonal elements are the measurements of the connectedness either between the sentiment indices (upper-left grey shade), between the implied volatility indices (bottom-right grey shade) or between the sentiment indices and implied volatility indices. All results are based on VARs of order 2 and GVDs of 10-day ahead forecast errors. The ijth entry of the upper left 10×10 submatrix is the estimated ijth 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	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

Table 4 Full sample block connectedness

This table reports the full sample static block-by-block connectedness. Five sentiments and five volatilities are aggerated as one sentiment block and one volatility block, respectively. We gauge spillovers between and within the two blocks.

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

Table 5 Full sample connectedness for the *News* and *News&Social* categories

This table reports the full-sample GVD connectedness for five sentiment series and five volatility series using RMA News sentiment (Panel A) and News&Social sentiment (Panel B) and CBOE volatility indices from 1 August 2008 to 15 May 2020. In each panel, the diagonal elements measure the connectedness of the ten indices themselves. The off-diagonal elements are the measurements of the connectedness either between the sentiment indices (upper-left grey shade), between the implied volatility indices (bottom-right grey shade) or between the sentiment indices and implied volatility indices. All results are based on VARs of order 2 and GVDs of 10-day ahead forecast errors. The ijth entry of the upper left 10×10 submatrix is the estimated ijth 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	VIX	TYVIX	EVZ	GVZ	OVX	from others
Panel A: News sentiment											
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 sentiment											
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

Table 6 Full sample connectedness based on 5-day and 15-day horizons forecast

This table reports the full-sample GVD connectedness for five sentiment series and five volatility series using RMA Social Media sentiment and CBOE volatility indices from 1 August 2008 to 15 May 2020. Panel A and Panel B results are based on VARs of order 2 and GVDs of 5-day and 15-days ahead forecast errors, respectively. In each panel, the diagonal elements measure the connectedness of the ten indices themselves. The off-diagonal elements are the measurements of the connectedness either between the sentiment indices (upper-left grey shade), between the implied volatility indices (bottom-right grey shade) or between the sentiment indices and implied volatility indices. The ijth entry of the upper left 10×10 submatrix is the estimated ijth 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	VIX	TYVIX	EVZ	GVZ	OVX	from others
Panel A: 5-day horizon											
StockSentiment	74.41	0.33	0.40	0.37	3.59	13.05	1.12	1.13	1.28	4.30	25.59
BondSentiment	0.44	95.08	0.04	0.21	0.51	1.03	1.85	0.32	0.35	0.17	4.92
EuroSentiment	0.38	0.05	89.49	0.23	0.97	2.76	0.56	3.77	1.43	0.36	10.51
GoldSentiment	0.25	0.16	0.55	85.98	0.90	3.78	1.07	1.64	5.08	0.59	14.02
OilSentiment	3.30	0.37	0.69	1.30	76.23	5.83	1.03	0.64	1.74	8.88	23.77
VIX	2.23	0.25	1.07	0.34	1.89	57.29	9.63	7.25	10.36	9.70	42.71
TYVIX	0.86	0.65	0.27	0.06	1.33	13.18	62.69	8.28	7.30	5.37	37.31
EVZ	0.34	0.45	1.23	0.40	0.53	10.18	9.33	61.72	10.46	5.36	38.28
GVZ	0.46	0.07	1.36	1.57	0.69	13.45	6.81	9.06	59.87	6.66	40.13
OVX	1.15	0.03	0.19	0.13	3.59	14.21	6.67	4.14	6.49	63.39	36.61
to others	9.42	2.37	5.81	4.61	13.99	77.47	38.08	36.22	44.51	41.39	Total
Net (To-From)	-16.16	-2.55	-4.70	-9.41	-9.78	34.76	0.77	-2.07	4.37	4.77	27.39
Panel B: 15-day horizon											
StockSentiment	69.31	0.33	0.39	0.44	3.98	14.91	1.55	1.06	1.21	6.82	30.69
BondSentiment	0.51	92.95	0.04	0.21	0.57	1.73	2.71	0.57	0.39	0.31	7.05
EuroSentiment	0.36	0.09	81.93	0.24	0.88	4.70	1.09	7.31	3.07	0.33	18.07
GoldSentiment	0.23	0.18	0.87	78.59	0.82	4.46	2.29	3.00	8.57	0.99	21.41
OilSentiment	3.34	0.34	0.63	1.22	70.29	6.31	1.40	0.59	1.89	13.99	29.71
VIX	2.13	0.31	1.37	0.17	2.12	54.51	10.58	7.67	11.11	10.03	45.49
TYVIX	1.23	0.71	0.45	0.06	1.79	15.17	54.84	10.29	10.22	5.25	45.16
EVZ	0.32	0.57	1.42	0.25	0.57	11.00	10.87	58.01	11.36	5.63	41.99
GVZ	0.44	0.09	2.14	1.45	0.84	15.41	9.51	9.42	54.11	6.58	45.89
OVX	1.36	0.05	0.16	0.05	4.21	16.82	7.40	4.49	6.66	58.79	41.21
to others	9.91	2.68	7.47	4.08	15.79	90.51	47.41	44.41	54.48	49.92	Total
Net (To-From)	-20.78	-4.37	-10.60	-17.33	-13.92	45.02	2.25	2.42	8.59	8.72	32.67

Figure 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 volatilty index (GVZ) and the crude oil volatility index (OVX). The sample period is from 1 August 2008 to 15 May 2020. All series are in natural logarithms.

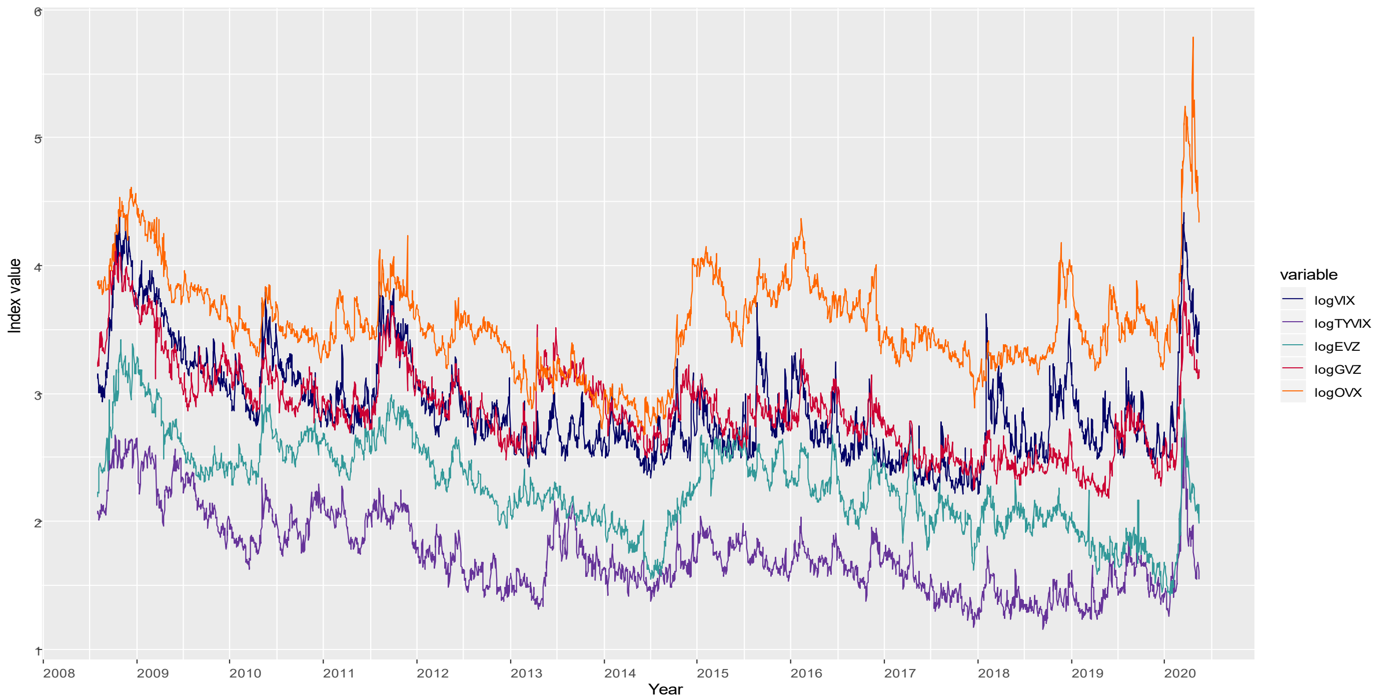

Figure 2. Sentiment score over time

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

Figure 3. Dynamic total connectedness

This figure plots the connectedness value over the sample period from 1 August 2008 to 15 May 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.

Figure 4. Net connectedness from sentiment to volatility block

This figure plots the net connectedness from the sentiment to the volatility block over the sample period from 1 August 2008 to 15 May 2020.

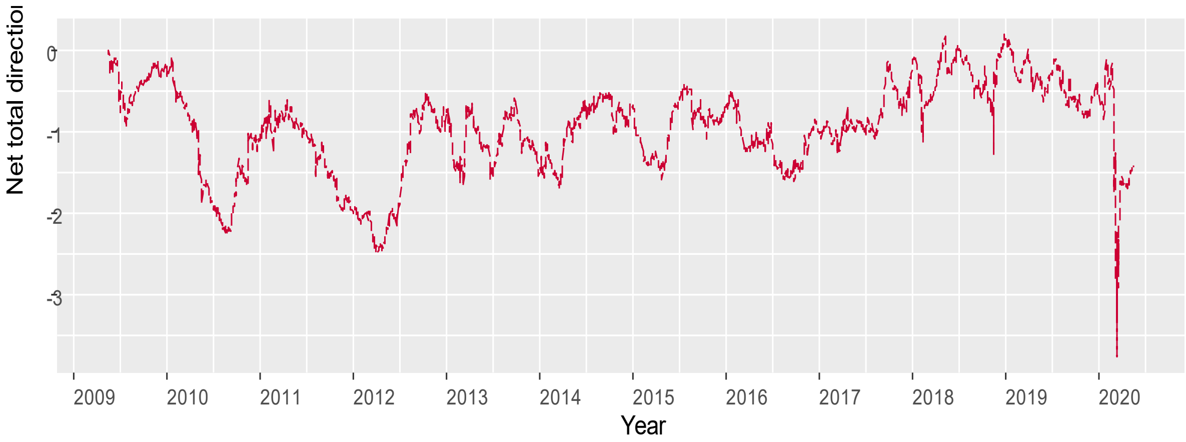

Figure 5. Net pairwise directional connectedness during various crises

This figure plots the net pairwise directional connectedness during various crises: (a) the Euro Debt crisis (April 2010 – February 2011); (b) The US debt-ceiling crisis (August 2011 to December 2012); (c) the UK Brexit (February 2016 – November 2016); (d) Covid-19 pandemic (December 2019 – May 2020). Given that we have 10 variables, there are 45 net pairwise directional spillovers. Arrow width reflects the value in net connectedness. Arrow colour reflects the ranking of connectedness: top 10 connectedness (dark red), rest rank 11-45 (sky-blue).