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

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ABSTRACT

This study examines the connectedness between sentiment and volatility across various asset classes. More specifically, we explore the spillover effects between social media sentiments and market-implied volatilities among stock, bond, foreign exchange, and commodity markets. We find that informational spillover comes mainly from volatility indices to sentiment indices, with the VIX being the most significant net transmitter. There is a stronger spillover from volatility to the sentiment of the same asset class, but a marginal effect for the opposite direction. Furthermore, the connectedness between sentiment and volatility increases in turbulent economic periods, such as the Global Financial Crisis (GFC), Brexit, the US-China trade war, and the COVID-19 pandemic. Finally, sentiment indices can switch from being a net receiver to a net transmitter of shocks during turbulent periods.

JEL Classification: C53; E44; F31; G15

Keywords: Social Media; Investor Sentiment; Market Volatility; Connectedness

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1. Introduction

It has been well documented that sentiment extracted from 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. The Reuters Institute digital news survey conducted by 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., Karagozoglu and Fabozzi, 2017; Rakowski et al., 2021; Al-Nasseri et al., 2021), bonds (Alomari et al., 2021), foreign exchange (Goddard et al., 2015; Sibande et al., 2021), and commodities (Han et al., 2017; Akyildirim et al., 2022).

Despite the extant studies on social media and financial markets, it remains underexplored whether sentiment from social media spillovers across different asset classes. The literature has shown that different asset classes are interconnected. For example, the safe haven literature finds a relationship between equity with gold markets (see, e.g., Baur and McDermott, 2016; Triki and Maatoug, 2021), while the investor fear and attention literature find a link between equity and foreign currency markets (Goddard et al., 2015; Smales and Kininmonth, 2016) or equity and commodity markets (Fernandez-Perez et al., 2020). We posit that the 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.

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 is often interpreted from the uncertainty transmission perspective (Andrada-Félix et al., 2018; Fernandez-Perez et al., 2020). Andrada-Felix et al. (2018), for instance, explain that volatility reflects the extent to which the market evaluates and assimilates new information. As such, volatility spillover captures how perceptions of uncertainty about economic fundamentals are manifested in prices across various asset classes. In the current work, we argue that linkages between assets can also be explained through a behavioral explanation. That is, during periods of heightened uncertainty about fundamentals, investors will turn to social media and rely on what most other people say about the topic. Umar et al. (2021), for instance, demonstrate the sentiment-driven pricing in the case of GameStop stock. We, therefore, examine whether sentiment may spillover from one asset to other asset classes.

Beyond the linkages between sentiments, we also assess the spillover effects between sentiment and volatility across asset classes. Existing studies mainly focus on examining sentiment and volatility spillover separately (Andrada-Félix et al., 2018; Audrino and Tetereva, 2019).[1] However, we can expect cross-linkages between sentiment and volatility. For instance, the crude oil literature documents that oil price volatility influences stock market sentiment. Oil price uncertainty leads to the postponement of investment decisions (Elder and Serletis, 2010) and increases the unemployment rate (Kocaasland, 2019). This may reduce investor sentiment in the equity markets (Chalmers et al., 2013; Bennani, 2020). Other studies, such as Da et al. (2015) and Goddard et al. (2015), also explore the sentiment and volatility linkage but within the same asset class.[2] To the best of our knowledge, this is the first paper that compares the effects of social media sentiment on asset volatility across various asset classes.

In this study, we assess the relations between sentiment and implied volatility across various asset classes. We employ Diebold and Yilmaz's (2012, 2014) measure of

[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.

connectedness, which measures the shares of forecast-error variation in an asset due to shocks arising elsewhere. Of particular interest in this study, we investigate the linkages across the equity, bond, precious metal, energy, and foreign exchange markets. The key novelty of our work compared to the previous studies is that we consider investor sentiment specific to each of the above asset classes. We take advantage of the Refinitiv MarketPsych Analytics (RMA) social media sentiment data. The RMA analyzes millions of real-time social media references from thousands of global media outlets daily and measures investor sentiment scores specific to each asset class. As a 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 Volatility Index, GVZ), and the crude oil market (the Crude Oil Volatility Index, OVX). We further assess the block connectedness between the sentiment and the 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 find that our market-specific sentiment and market-specific 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. 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. Finally, the sentiment indices can switch from being a net receiver to a net transmitter of shocks during turbulent periods.

Our contribution to the literature is twofold. First, this study sheds light on social media sentiment spillover across financial markets. The existing literature mainly focuses on the effect of general market sentiment on different asset classes. Zhang et al. (2022), for example, explore the spillover effects from Covid-19 media coverage to different asset classes such as crude oil, gold, and cryptocurrency. We examine sentiment specific to each asset class rather than general market sentiment. Hence, our findings provide a better understanding of the importance of social media irrespective of the asset classes. Second, we show that, in general, social media sentiment is a net receiver rather than a major trigger of market volatility. However, during periods of market turmoil, social media sentiment can turn into a net transmitter of shocks. This finding provides further evidence for social media being "echo chambers" (Jiao et al., 2020; Cookson et al., 2022), i.e., while social networks mainly repeat news, some investors interpret repeated signals as new information.

Our study has several implications. For market participants, our findings suggest that diversification benefits could be impaired at turbulent times when it is most needed. Thus, investors should consider the degree of volatility and investor sentiment when making asset allocation decisions, particularly in turbulent times. For regulators, connectedness among sentiment indices may also be considered a measure of market stability.

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

We first discuss the Diebold and Yilmaz (2012, 2014; hereafter, DY) approach as our primary measure of connectedness among different sentiment and volatility variables. We then discuss the 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 connectedness measure

To measure the connectedness of five market sentiments and their respective market volatilities, we follow the DY approach. 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: $x_t = \Theta(L)u_t$, $\Theta(L) = \Theta_0 + \Theta_1 L + \Theta_2 L^2 + \cdots, E(u_t, u_t') = I$. 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 the "variance decomposition table" of Diebold and Yilmaz (2014) 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 $D^H = [d_{ij}^H]$[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:

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

[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.

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:

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

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

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

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 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:

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

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. Following Diebold and Yilmaz (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 $D^{gH} = \left[d^{gH}_{ij}\right]$ is defined[5] as:

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

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

[5] 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 (by 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 $\widetilde{D}^g = [\tilde{d}_{ij}^g]$ with the necessary normalization $\tilde{d}_{ij}^g = \frac{d_{ij}^g}{\sum_{j=1}^N d_{ij}^g}$. By construction, $\sum_{j=1}^N \tilde{d}_{ij}^g = 1$ and $\sum_{i,j=1}^N \tilde{d}_{ij}^g = N$. Thus, the connectedness measures can be calculated by using $\widetilde{D}^g = [\tilde{d}_{ij}^g]$ matrix. The DY approach's forecast error variance decomposition is directly computed from the estimated parameters and covariance matrix of the VAR system.[6]

[Insert Table 1 Here]

2.2. Block connectedness measure

To investigate whether changes in market sentiment induce volatility variations and vice versa, we first combine the five market sentiment indices and five market volatility indices into two separate groups, which we refer to as the sentiment 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

[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.

connectedness measures into different desired levels (e.g., markets, countries) for comparisons. 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.

3. Data

In this section, we discuss the two sets of data 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.

3.1. Market volatility

To proxy for stock market volatility, we employ the CBOE Volatility Index (ticker: VIX). Using prices of options on the S&P 500 index, the VIX is designed to reflect investors' consensus for the upcoming 30-day expected volatility 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 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 Refinitiv Datastream at a daily frequency. Our sample period is from August 1, 2008, to May 15, 2020. This period covers a series of significant economic events, such as the GFC, Brexit, the US-China trade war, and the COVID-19 pandemic. The starting period is when the EVZ was first introduced, and the ending period is when TYVIX was discontinued.

Figure 1 plots the daily implied volatility indices (in logs).[7] 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 due to investors' fear surrounding 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.

[Insert Figure 1 Here]

3.2. Sentiment data

As our measure of asset-specific investor sentiment, we employ the Refinitiv MarketPsych Analytics (RMA) sentiment data (formerly Thomson Reuters MarketPsych Indices, TRMI). The RMA provides advanced and comprehensive finance-specific sentiment data for various financial assets for 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,

[7] The generalized variance decomposition requires normality. We, therefore, approximate it by taking natural logarithms in the volatility indices (see, e.g., Diebold and Yilmaz, 2015).

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 minimal information distortion and loss. As explained in Renault (2017), the accuracy of sentiment quantification is crucial as it directly influences the reliability and predictability of sentiment data. The RMA sentiment data has been used in recent studies, including Papakyriakou (2019), Michaelides et al. (2019), and Gan et al. (2020).

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 in our robustness tests. We collect the following five daily sentiment series from RMA: (1) the stock market sentiment, (2) the bond market sentiment, (3) the Euro/USD sentiment, (4) the gold sentiment, and (5) the oil sentiment. Appendix B lists the underlying markets along with the sentiment and volatility symbols used in our study. The sentiment score is calculated as the volume-weighted average difference between positive and negative mentions of the underlying asset over a 24-hour 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 score of 0 indicates neutral sentiment. The RMA updates the sentiment data every calendar day at 3:30 pm US Eastern time.

Figure 2 plots the various sentiment indices over the sample period. The plots show that the equity, oil, and foreign exchange 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 abundance of oil supply back in 2015. Many of the spikes in sentiment also coincide with the spike in volatility shown in Figure 1. 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 indices 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 correlation

We report the descriptive statistics for the volatility and social sentiment indices in Panel A of Table 2. On average, the stock and the foreign exchange markets 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 fact that our sample period coincides with several major crises, and gold is often considered a safe haven asset (see, e.g., Baur and Lucey, 2010). The crude oil market, on the other hand, has neutral sentiment (0.00) overall.

[Insert Table 2 Here]

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 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 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 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.

4. 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.

4.1. Static connectedness analysis

Table 3 reports the full-sample connectedness table for the sentiment and volatility indices.[8] The top row represents the transmitting variable, while the first column represents the affected variable. We first 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

[8] All results are based on VARs of order 2 and GVDs of 10-day ahead forecast errors. The results are qualitatively similar when we use alternative lag lengths in the VAR and forecasting horizons. These results are available from the authors.

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 from VIX to OVX (15.65%). These observations suggest that the connectedness between stock and oil markets is the strongest in both sentiment and volatility indices. The linkage between equity and oil markets can be explained by the financialization of commodity futures. Commodities, such as crude oil, has been widely held by institutional investors for diversification purpose. Therefore, shocks in one market are quickly transmitted to the other market (Büyükşahin and Robe, 2014; Christoffersen and Pan, 2018).

[Insert Table 3 Here]

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 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 VIX (2.17%). 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 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 sentiment and volatility indices 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), or 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 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, therefore, are weakly connected with one another. 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 indices are mildly connected.

[Insert Table 4 Here]

4.2. 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.[9]

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 a similar pattern between the sentiment and volatility blocks. In line with the results in Table 4, the connectedness for the volatility block is consistently higher than the connectedness for the sentiment block. The total connectedness fluctuates strongly in turbulent periods. We observe several periods where the total dynamic connectedness deviates from its average value 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 was in the middle of 2011, with a value of 45%, triggered by the US debt-ceiling crisis and the US credit rating downgrade. Total connectedness also spiked in June 2016 due to Brexit and in early 2020 during the COVID-19 global pandemic crisis, with an all-time high value 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, the 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; Zhang et al., 2022).

[9] The 200-day rolling window is standard in the literature (see, e.g., Andrada-Félix et al., 2018; Audrino and Tetereva, 2019). In Section 5, we conduct robustness analysis using rolling window of different widths (150- and 250-day).

[Insert Figure 3 Here]

4.3. Net directional connectedness

In this section, we examine the net directional connectedness of each sentiment and volatility index. In Figure 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, we observe that *StockSentiment* was a net spillover transmitter during the 2018 US-China trade war and the Covid-19 pandemic at the start of 2020 but a net receiver during other times. Similarly, *EuroSentiment,* generally a net receiver, was a net spillover transmitter during the Euro debt crisis in the middle of 2010. In Figure 4.b., we observe that volatility indices tend to be net spillover transmitters. However, its net connectedness varies over time. For instance, the VIX is a net transmitter the 95.70 % of the time, but this was a net spillover receiver in the second half of 2017 and early 2018 (due to the geopolitical events impacts on gold market and OPEC policy influence on oil market) Similarly, we observe that the EVZ, which is generally a net transmitter, was a net spillover receiver in 2010 during the European debt crisis and in 2020 during the Covid-19 pandemic.

[Insert Figure 4 Here]

We further investigate how the variables in our system are interconnected during some turbulent periods by examining the net and pairwise 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 2014); (d) Brexit

(June 2016 – November 2016); (e) US-China trade war (May 2018 – December 2018); (f) Covid-19 pandemic (December 2019 – May 2020).[10]

Figure 5 shows the bar plot of the net directional connectedness for each sentiment and volatility indices during the different turbulent periods.[11] As can be seen, many social media sentiments have negative net connectedness during the various turbulent periods, indicating that, in general, sentiment indices are net receivers of spillover from market volatility. However, some sentiment indices play a transmitter role during some turbulent periods. In particular, *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 has 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.[12] The US-China trade war harmed global growth prospects, with the EU being one of the biggest collateral victims of this event.

Other sentiment indices were net transmitters in turbulent periods. 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 crisis generated

[10] We report selected times and their associated landmark events in Appendix C.

[11] We also report the full connectedness tables for the six different turbulent periods in Appendix D.

[12] 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.

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 and elasticated rounds of retaliatory tariffs between US and China harm both US and China companies' confidence in the future business and China's countermeasure tariffs on the 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.

[Insert Figure 5 Here]

In terms of 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.

Overall, our findings show that most volatilities are net transmitters while most sentiments are net receivers. However, social media sentiment still matters as its role can switch from net receiver to net transmitter during turbulent periods. This provides further evidence for social media being "echo chambers," i.e., while social networks mainly repeat news, some investors interpret repeated signals as new information (see, e.g., Jiao et al., 2020; Cookson et al., 2022).

5. Robustness Tests

5.1. News and News&Social datasets

For our main specification, we use the sentiment indices from the RMA *Social* category. For our first robustness test, we use sentiment indices from the RMA *News* and *News&Social* categories. While the methodology remains the same, the *Social* category is based on social media outlets, while the *News* category is 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 for the *News* category, while Panel B reports the connectedness for the *News&Social* category. 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 panel. It is worth mentioning that the total connectedness for the *News* category is around 40%, while the total connectedness for the *Social* category is around 30% (see Table 3). This finding suggests that asset-specific sentiment indices from social media are less interconnected than that of news outlets. The finding also confirms that traditional news media remains the main source of information for financial markets. However, our results suggest that the importance of social media sentiment should not be dismissed as this can provide additional information in turbulent times.

[Insert Table 5 Here]

5.2. Different estimation horizons and rolling windows

We further examine the robustness of our findings using different parameters employed in our connectedness measure. First, we use 150 and 250-day windows (as opposed to the 200-day window in our main specification) as alternative rolling window lengths. Appendix E reports these results. As expected, the dynamic total connectedness is more persistent for longer windows. Three graphs show a similar pattern with an average correlation of 0.88, indicating that the total connectedness increases in turbulent periods across the three plots. Therefore, our findings are robust to the length of the rolling window.

Second, the forecast horizon length may also affect our results. The longer the forecast horizon, the more time the indices have to react to shocks from other indices. As such, 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 Appendix F. 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 predictive horizons.

6. Conclusions

We examine the connectedness between social media sentiment and market-implied volatility indices across various asset classes, such as stock, bond, foreign exchange, precious metals, and energy. Using data from August 2008 to May 2020, we find that social media sentiment and market volatility indices are weakly connected. There is a strong spillover from volatility to the sentiment index of the same market, but not the opposite. In particular, the VIX is the major net spillover transmitter. Second, the informational spillover comes mainly from the market volatility block to the market sentiment block, further confirming the importance of volatility indices. Third, the connectedness between market sentiment and volatility indices increases in turbulent economic periods, and sentiment indices can switch from being a net receiver to a net transmitter during such times.

Our study has several implications. For market participants, our findings suggest that diversification benefits could be impaired at turbulent times when it is most needed. Thus, investors should consider the degree of volatility and investor sentiment when making asset allocation decisions, particularly in turbulent times. For regulators, connectedness among sentiment indices may also be considered a measure of market stability.

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Appendix A. Block connectedness methodology

Greenwood-Nimmo et al.'s (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.

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):

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

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 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[13]:

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

and

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

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

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

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

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

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:

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

and the aggregated spillover effect within-block is:

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

[13] 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 B. Sentiment and volatility variables

This table lists the sentiment symbols, volatility indices, and the corresponding underlying market they represent in this study.

Asset class	Underlying market	RMA Code	Sentiment symbol	CBOE Volatility Index
Equity	Stock	ETFUS500	*StockSentiment*	VIX
Fixed income	Bond	US-bondSentiment	*BondSentiment*	TYVIX
Currency	Euro FX	EUR	*EuroSentiment*	EVZ
Precious metal	Gold	GOL	*GoldSentiment*	GVZ
Energy	Crude Oil	CRU	*OilSentiment*	OVX

Appendix C. 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	Greek sovereign debt crisis and requests a loan of €45 billion from the EU and IMF, and Standard & Poor's downgrades Greece's sovereign debt rating to "junk" grade (BB+).	February 28, 2011	The second Greek bailout & Portugal bailouts from EU-IMF this month.
US debt ceiling crisis	May 1, 2011	At the end of April 2011, US Congress delayed the approval 2011 budget, and the US hit the 14.29 trillion debt ceiling in May 2011.	August 31, 2011	Obama signed the debt ceiling bill to end the fears of default in August.
Russia-Ukraine conflicts	February 20, 2014	Russia began the annexation of Crimea.	May 1, 2014	Ukrainian parliament declared Crimea a territory temporarily occupied by Russia, and multiple major regional conflicts temporarily ended at the end of April.
UK Brexit	June 23, 2016	The referendum result was released, meaning that the UK voted to leave the EU by 52% to 48%.	November 25, 2016	Prime Minister Theresa May seeks negotiations for leaving the EU smoothly in public.
US-China trade war	May 29, 2018	The White House announced a 25% tariff on $50 billion of Chinese goods. China said it would respond & Trump declared an increased tariff on Twitter in the following days.	December 1, 2018	The US and China leaders call a truce for the trade war during the G20 summit in Argentina for negotiations.
Covid-19 pandemic	December 12, 2019	The National Bureau of Economic Research (NBER) lists the business cycle reference dates with the peak quarter in 2019 Q4.	May 15, 2020	NBER lists business cycle reference dates with trough quarter in 2020 Q2, and our dataset ended on May 15, 2020.

Appendix D. 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 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 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

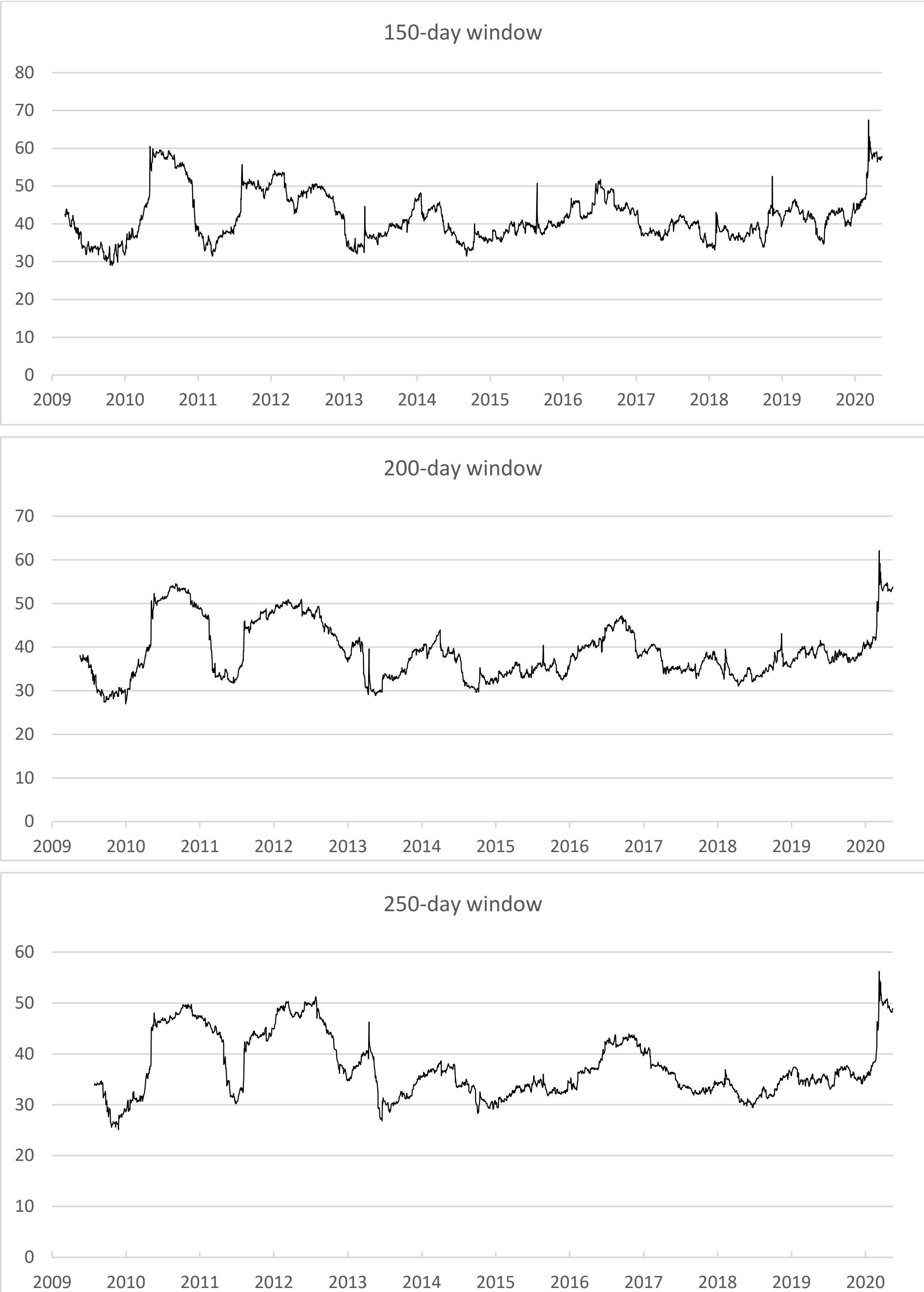
Panel C: Russia-Ukraine conflict											
StockSentiment	29.49	3.84	1.49	5.42	14.74	13.99	12.29	4.97	11.78	1.98	70.51
BondSentiment	4.37	64.45	2.47	4.79	3.65	3.83	1.39	3.29	5.46	6.31	35.55
EuroSentiment	7.71	6.49	39.66	0.75	9.12	5.14	4.27	9.29	12.01	5.56	60.34
GoldSentiment	2.40	2.06	1.88	45.30	9.40	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 E. Dynamic total connectedness using different windows

This figure plots the connectedness value over the sample period using different windows, including 150 days, 200 days, and 250 days.



Appendix F. 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 August 1, 2008, to May 15, 2020. Panel A and Panel B results are based on VARs of order two 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

Table 1. Connectedness table

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).

	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 logarithms. ADF is augmented Dickey-Fuller test. ***, ** and * represents 10%, 5% and 1% significance level.

	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***
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 and five 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 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 two 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 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. 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 block* represents the interconnection level of five indices in the block.

	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

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 August 1, 2008, to May 15, 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 two 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											
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

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 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.

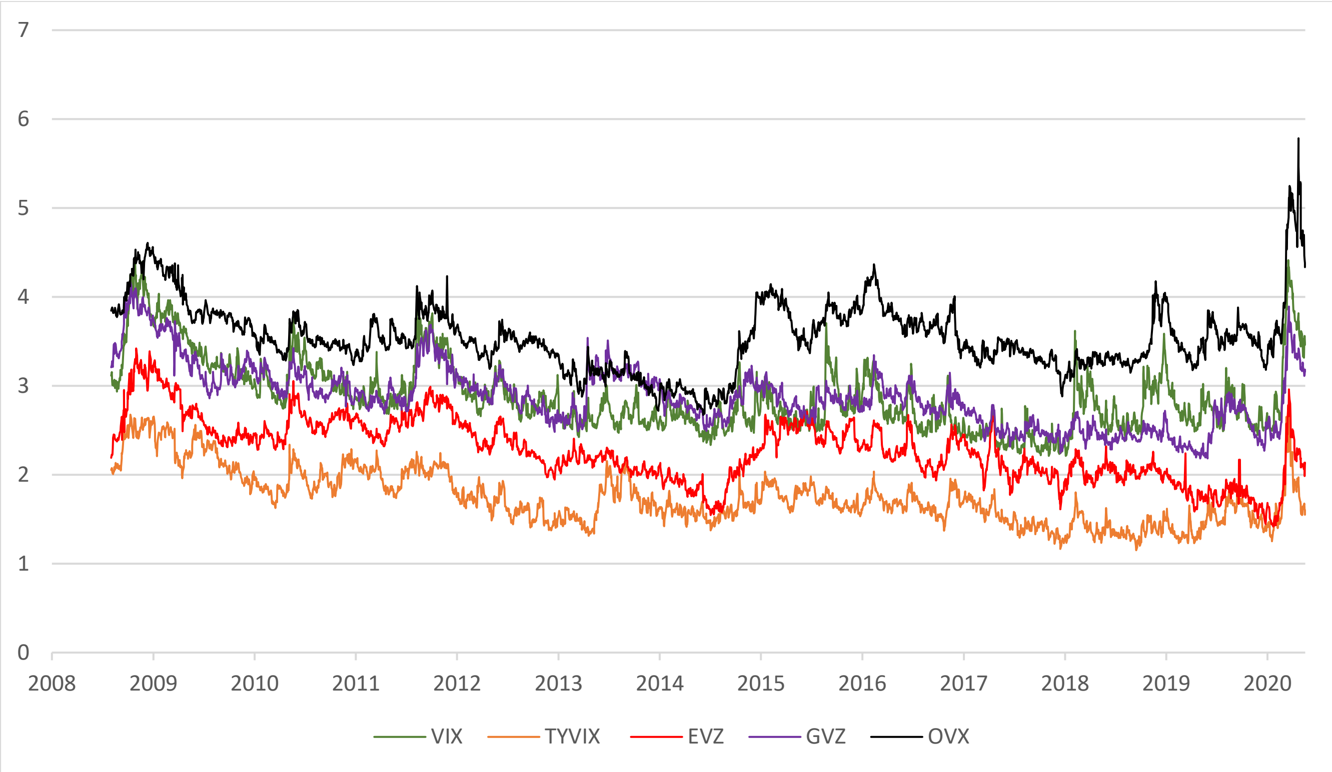


Figure 2. Sentiment score over time

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 August 1, 2008, to May 15, 2020.

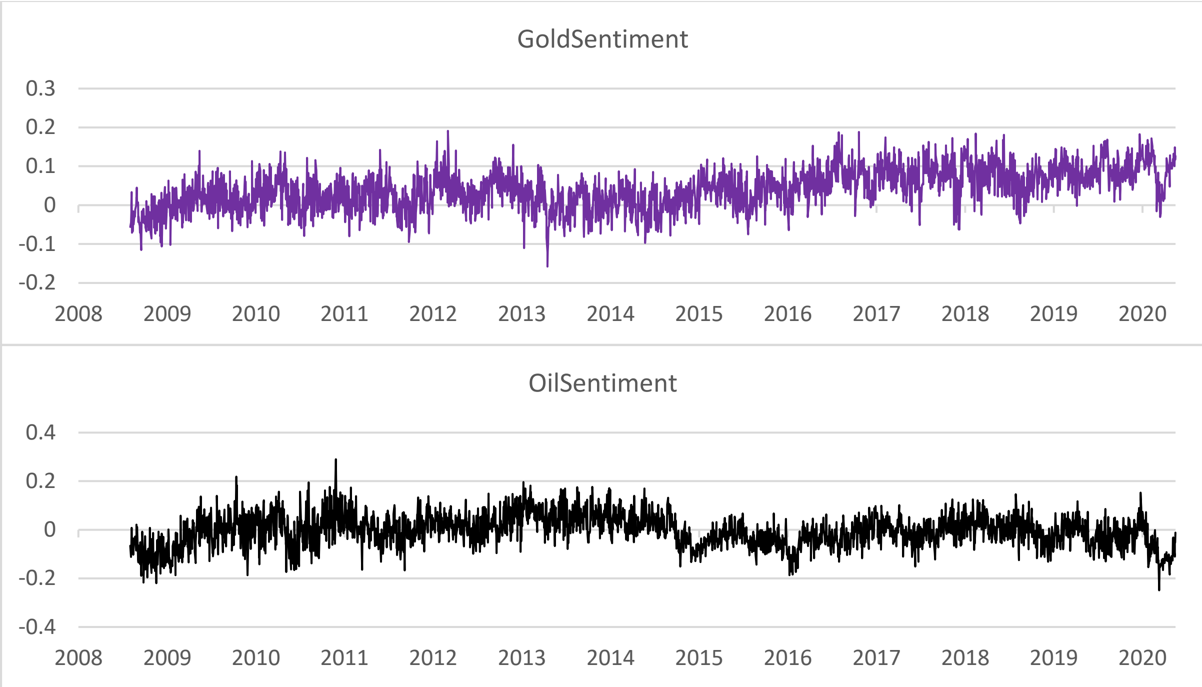

GoldSentiment
0.3
0.2
0.1
0
-0.1
-0.2
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
OilSentiment
0.4
0.2
0
-0.2
-0.4
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020

Figure 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.

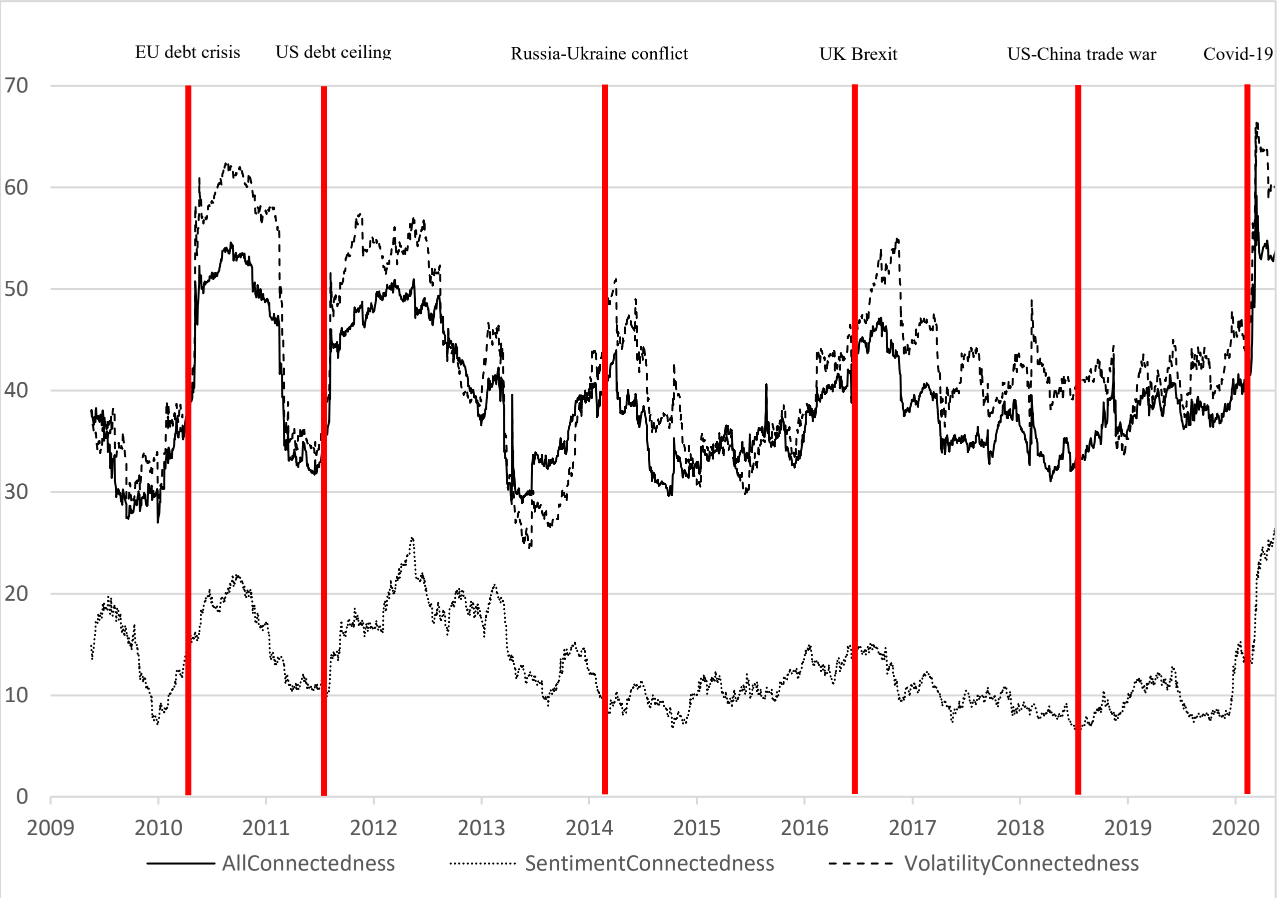


Figure 4. Sentiment and volatility net connectedness over time

This figure plots the net connectedness of each sentiment and volatility index from August 1, 2008, to May 15, 2020.

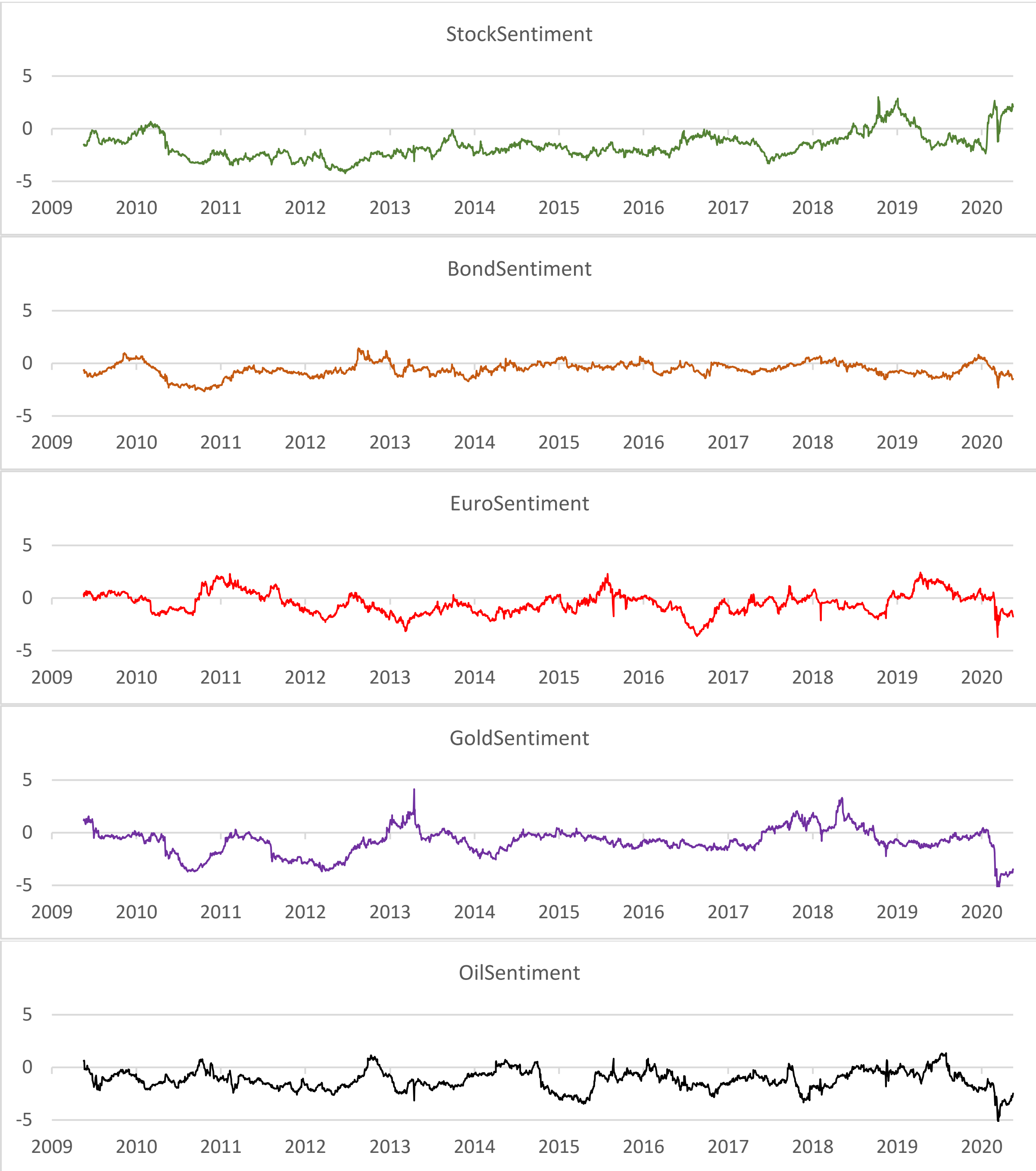


Figure 4.a. Sentiment Connectedness

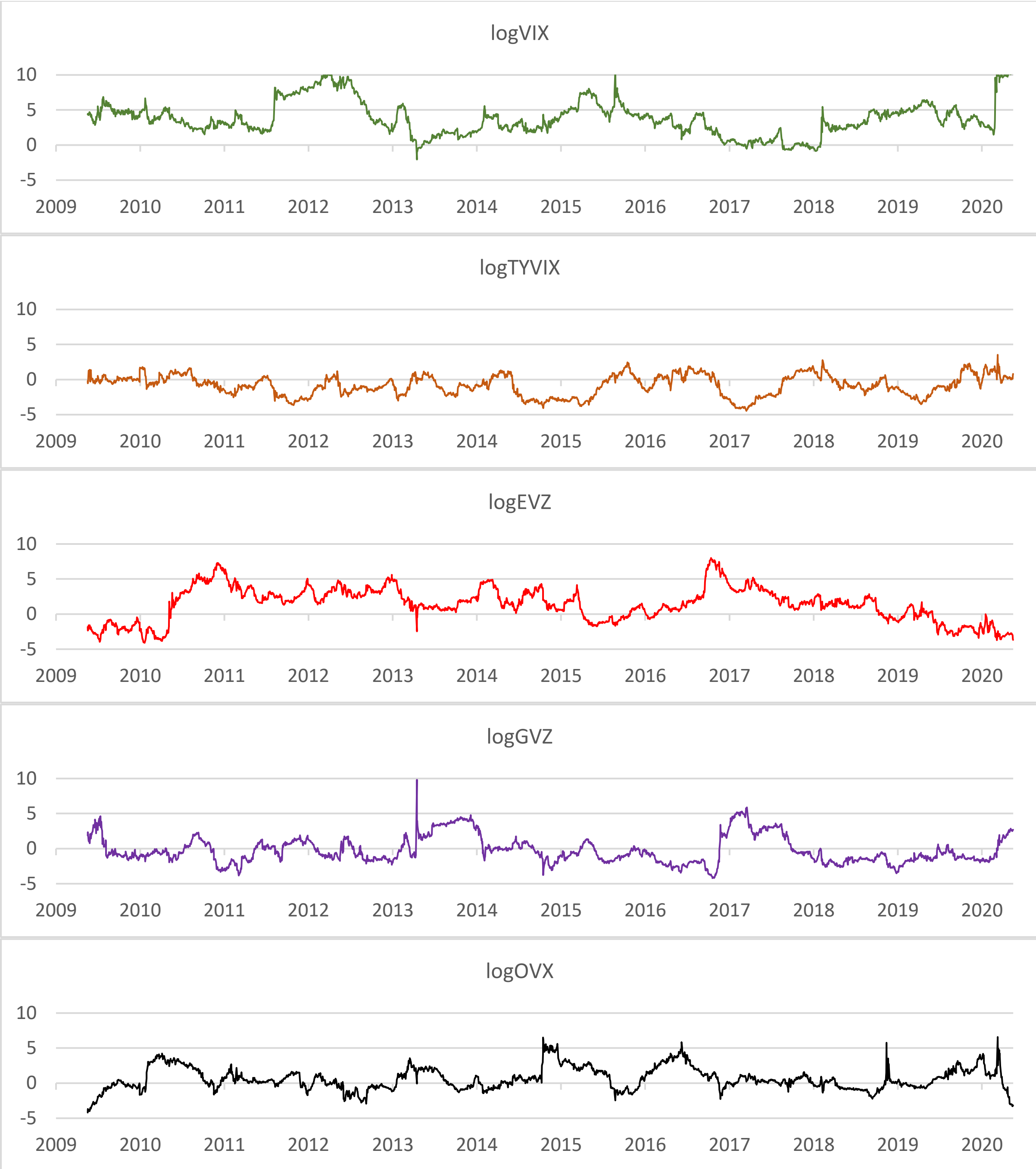


Figure 4.b. Volatility Connectedness

Figure 5. Net total directional connectedness during various crises

This figure plots the net total directional connectedness 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).