North American Journal of Economics and Finance 71 (2024) 102091

Contents lists available at ScienceDirect

North American Journal of Economics and Finance

journal homepage: www.elsevier.com/locate/najef

# Measuring market volatility connectedness to media sentiment

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ARTICLE INFO

*JEL Classification:*
G41
G14
E32

*Keywords:*
Financial market volatility
Time connectedness
Transmission mechanism
News sentiment
Twitter sentiment
Natural language processing

ABSTRACT

We examine directional connectedness patterns from news and social media to financial market volatility using textual analysis and high-frequency data. We find that media sentiment induces market volatility, but the magnitude of that connectedness is time-varying. In addition, news and social media sentiment pertinent to one market transmits volatility to other markets. Finally, we find that sentiment transmits sharp shocks to markets during major events. At other times, there are smaller spillover effects, indicating that the directional connectedness from sentiment to markets follows a spiky pattern over time. We conclude that news and social media play an important (but not constant) role in transmitting volatility across financial markets. This insight explains earlier divergent findings in the literature.

## 1. Introduction

A long line of research shows that, in addition to fundamentals and the interconnection of markets, news stories on topics such as political conflicts, the state of public opinion, economic events, or the general business climate can be sources of market volatility (e.g., Brenner et al. (2009), Lucca and Moench (2015), and de Oliveira et al. (2018)). Media can then spread investor sentiment and influence expectations about future market behavior (Brown and Cliff, 2004). In some instances, these mechanisms appear to have significant effects. For instance, there is a prevailing view that a surge in sentiment might have been a contributing factor to the challenges faced by the Silicon Valley Bank in 2023.

This evidence suggests that part of financial market volatility is connected to media sentiment. However, to date, limited attention has been devoted to examining how sentiment behaves across financial markets because quantifying sentiment from news stories and social media posts has been a challenge. In this paper, we use recent advances in natural language processing to extract and quantify market sentiment in higher volumes and with greater precision than has been possible previously. We then develop a new measure of news and social media sentiment, which we use to answer the following questions: (i) How much of the volatility seen in the market can be attributed to the sentiment embedded in news stories and social media? (ii) To what degree does this relation explain volatility transmitted to other markets? (iii) How do sentiment shocks behave across international markets?

To investigate the connectedness between sentiment and market volatility, we obtain daily values for six financial markets, including Brent crude oil and markets in five industrialized countries: the US (the Dow Jones Industrial Average (DJIA)), the UK (the Financial Times Stock Exchange (FTSE)), France (the CAC40), Germany (the DAX30), and Japan (the Nikkei). We gather news

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https://doi.org/10.1016/j.najef.2024.102091
Received 8 August 2023; Received in revised form 9 November 2023; Accepted 21 January 2024
Available online 29 January 2024
1062-9408/

headlines and tweets regarding each market from 4 August 2014, to 22 December 2020.

We extract sentiment from news headlines and Twitter tweets using advanced natural language processing, which enables us to convert textual data into numerical values. We employ the Bidirectional Encoder Representations from Transformers (BERT) model proposed by Devlin et al. (2018), and train it on financial language. We produce a total of 12 sentiment series for the news and tweets of each market with daily values between $+1$ (the most positive) and $-1$ (the most negative). Using the computed sentiment series, we measure the magnitude of volatility spillovers through the framework proposed by Diebold and Yilmaz (2012) (DY henceforth).[1] This framework is built upon predictive modeling under misspecification and can be used to measure causal connections. This approach enables us to uncover the mechanism behind volatility transmission.

Our main empirical finding is evidence of a degree of interdependence among the selected markets and media sentiment. How information affects markets on a general level is reasonably well understood in the classical finance literature. This study contributes by analyzing in more detail the information market participants use. We find that the effect of sentiment on markets varies over time and is more intense during extreme events.

Although the static results over our sample period do not capture the evolution of time-varying dependencies, they still document that sentiment has a long-lasting but relatively small effect on market volatility. Secondly, we document that the sentiment associated with a specific market induces volatility across other markets, indicating that volatility is transmitted between markets through news and social media. By including social media, a relatively new information medium, in our sample, we incorporate public perceptions into our analyses. We find that social media sentiment has a stronger long-lasting effect than news sentiment for some markets. Finally, using rolling-window analyses to examine the evolution of connectedness, we find that the connection between sentiment and volatility varies significantly over time. We further document how sentiment behaves within markets, showing that sentiment follows a spiky pattern, its effect appearing and disappearing over time.

From these findings, we conclude that news and the social media play a crucial role in transmitting volatility across financial markets. News stories—either fact-based, such as reporting posted on official news websites, or baseless like viral rumors on Twitter—contribute to the transmission of volatility across markets, though the salience of this transmission channel varies over time. Given the durability of massive contagions, we find that markets are highly capable of absorbing new information. In addition, the long-lasting effect we document implies that sentiment provides distinct information valuable for predicting volatility in the selected markets.

Our main contribution to the literature is showing that sentiment contributes to country-level volatility transmission in a time-varying and spiky pattern. Our study advances existing research on the relation between sentiment and financial markets (Behera and Rath, 2022; Costola et al., 2023; Mensi et al., 2023) by measuring dynamic directional connectedness from media sentiment to market volatility. This approach allows us to provide a granular analysis of the extent to which daily market volatility arises from media sentiment. We build exclusive sentiment indices for each market using both news headlines and Twitter feeds. This practice facilitates a broader analysis on both national and international scales, distinguishing our research from prior studies (Behera and Rath, 2022; Feng et al., 2022; Qiao et al., 2022; Basak et al., 2023; Zeitun et al., 2023). We document a tenuous connection between sentiment corresponding to one market and volatility across markets in other countries. Furthermore, our research distinguishes from prior studies by using exclusive sentiment indices for each market, which allows us to be the first to provide a comparative analysis of media sentiment related to different markets and their corresponding market volatility. We document that the long-lasting effect of news sentiment on market volatility is more pronounced than that of Twitter sentiment in all markets except for the UK and German markets. This discovery contributes new insights into the varying influences of different types of sentiment on financial market dynamics. Finally, we extend the literature on media sentiment and market dynamics as our sentiment measure is more sophisticated than those used in previous studies in two ways. Unlike prior studies that focus only on one aspect of news (see Rangel, 2011; Brandt and Gao, 2019; Dong et al., 2022; Feng et al., 2022; Gao et al., 2022; Koch et al., 2022; Basak et al., 2023), we cover the whole spectrum of news, ranging from business and economic to political and terrorism headlines. Furthermore, unlike previous studies that employ Google Trends, word-counting, or lexicon-based approaches to sentiment extraction, we capture semantic sentiment through a BERT model fine-tuned with a financial PhraseBank, which generates sentiment based on the meaning of the text. Our innovative use of BERT contributes to the literature by measuring the semantic sentiment of material posted on Twitter by the public in addition to news published by traditional media outlets, reducing the potential bias driven by news media. These contributions can help policymakers and investors who wish to hedge their risks across international markets understand behavioral drivers of volatility.

The paper proceeds as follows. Section 2 presents an overview of the literature together with hypothesis development. Section 3 describes the methodologies for sentiment extraction and econometric analysis. The data are described in Section 4. Section 5 reports the results, and Section 6 concludes the paper.

## 2. Related literature and hypothesis development

The literature has theorized the role of sentiment in the market dynamics. Grossman and Stiglitz (1980) suggest that market fluctuations can, in part, result from unexplained variations in public opinion, or *noise trading*. De Long et al. (1990) note that market dynamics can be influenced by nonfundamental factors, such as traders' erroneous stochastic beliefs, which deflect prices from

[1] The DY framework decomposes the total spillover into the spillover from one variable to another variable and overcomes the impact of ordering in the orthogonal decomposition results. Therefore, it fits to our study, whose aim is to capture the directional connectedness in a multivariate network.

fundamental values even when fundamental risk is absent. Klibanoff et al. (1998) propose that news is a source of financial information that affects investors' opinions, triggering some to react more quickly when news is particularly salient.

Building on this foundation, scholars have posited an analytical framework to quantify the sentiment from textual sources and assess its impact on financial data. Using word counts and a pre-existing sentiment dictionary, Tetlock (2007) finds that news pessimism puts downward pressure on prices. Subsequently, finance scholars began to pay more attention to textual analysis, leading Loughran and McDonald (2011) to build an exclusive sentiment dictionary for financial filings. These textual analytic techniques have advanced this line of research by providing a basic understanding of specific parts of textual data. More recently, Shiller (2020) suggests that more finely tuned quantitative methods should be developed to explore how various types of media influence financial markets. More specifically, Shiller points out the necessity of constructing a semantic sentiment proxy.[2]

Shifting to empirical studies, the relation between media and financial markets was first investigated by Niederhoffer (1971), who shows that investment-related news headlines impact price movement. Later, Ederington and Lee (1993) document that news announcements have a strong impact on volatility patterns across financial markets. Griffin et al. (2011) study the relation between volatility and public news arrival and find that in most developed markets the volatility is more on the news announcement day. Da et al. (2015) employ Google Trends metrics for specific economic keywords and document that their metrics predict temporary increases in market volatility. Manela and Moreira (2017) measure uncertainty from front-page articles in *The Wall Street Journal*, which they call news-based implied volatility (NVIX), and find that volatility peaks during extreme events like financial crises and world wars. Su et al. (2019) examine the spillover of three sentiment indices across nine markets and find that NVIX is the most powerful predictor of market volatility. Liu et al. (2019) use a geopolitical risk index to examine oil price volatility and conclude that serious geopolitical risk is important in determining oil price volatility. Also, a new line of research investigates the impact of sentiment embedded in social media on market volatility. Nishimura and Sun (2021) capture the impact of the US president tweets concerning the US-China economic conflict on market volatility and show the expanding impact of tweets on market volatility. Bouri et al. (2022) build a proxy for investor happiness through Twitter feeds and document that their proxy affects volatility more than returns. Aharon et al. (2022) employ a media coverage index tailored to COVID-19 and indicate the significant role of such a sentiment in volatility transmission across the G7 countries. Shen et al. (2022) use a dictionary-based approach to measure news tone and discover that sentiment has an asymmetric impact on future market volatility. Mensi et al. (2023) utilize established uncertainty indices, such as economic policy uncertainty, and find that these indices predominantly transmit volatility to the market during both bearish and tranquil market periods. Katsafados et al. (2023) use a lexicon-based approach to analyze tweets for positive and negative sentiments during a specific phase of the COVID-19 pandemic. Their findings indicate that positive sentiment is associated with lower volatility. Apergis et al. (2023) utilize Google Trends news to examine the influence of COVID-19-related sentiment on market volatility and find significant impacts from the pandemic.

Joseph et al. (2011) and Da et al. (2011) show that increased positive sentiment is related to increased prices and subsequently volatility. Fedyk (2018) finds that front-page financial news is incorporated in financial markets more rapidly than non-front-page news. Based on this literature, we expect that news sentiment can have a consistent and long-lasting effect on market dynamics, leading us to our first hypothesis:

**H1.** There is a long-lasting connectedness between sentiment expressed through news and social media and market volatility.

Ross (1989) finds that the volatility across a market directly corresponds to the intensity of information flow coming into that market. Williams (1999) links information efficiency to the speed of incorporating new information into prices. Nishimura and Sun (2018) propose that if a market is informationally efficient, information shocks in that market can cause volatility in other markets. Based on these findings, we expect that volatility will spread between different markets through news and social media. We formalize this reasoning in our second hypothesis:

**H2.** Volatility is transmitted between markets by news and social media.

Birz (2017) examines the effect of macroeconomic news on stock prices and documents that economic news stories influence prices during the announcement week, before reversing over the following week. Shiller (2020) argues that the contagious impact of news stories increases as the public talks about the stories, but the effects slow down when people eventually lose interest. Shiller proposes that the effect of news stories on the market can be analogous to the spread of an epidemic disease, where the rate of contagion is higher than the recovery in the early stages before it slows down. Hence, we anticipate that the behavior follows a spiky pattern. Based on this research, we expect that volatility spreads across markets in a spiky pattern, as stated in our third hypothesis:

**H3.** The transmitted volatility from media sentiment to the markets follows a spiky pattern.

## 3. Methodology

### *3.1. Textual analytics*

Bidirectional Encoder Representations from Transformers (BERT) is a pre-trained machine learning technique for textual analysis developed by Google. The model is trained on English Wikipedia and BookCorpus. BERT is a multilayer deep-learning model composed of an encoder in the first layer that takes the input text, such as news headlines or tweets, and a final layer that predicts the probabilities of the given text being positive, neutral, or negative. The final layer (output) of the neural network, called logits, returns the prediction probabilities, which here means how a given news headline/tweet is to be perceived. To calculate sentiment scores, a common practice is to

[2] "There should be more serious efforts at collecting further time series data on narratives, going beyond the passive collection of others' words, towards experiments that reveal meaning and psychological significance" (Shiller 2017, p. 48).

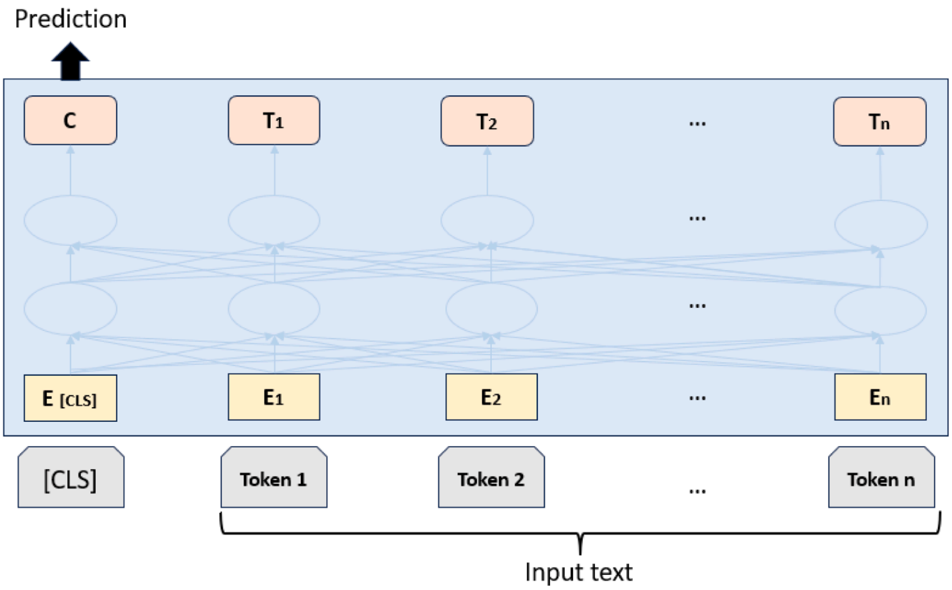



**Fig. 1.** BERT Simplified Structure (Adapted from Devlin et al. (2018)). This figure shows the structure of BERT for sentiment prediction. Starting with the input text which is divided into tokens of word sequentially. *[CLS]* is a special token added to the beginning of every input sequence, serving as an aggregation representation for classification tasks. Each token is embedded into vectors ($E_{[CLS]}$, $E_1$, $E_2$,…,$E_n$). These embeddings are then processed through several encoder layers (represented by ellipses), resulting in contextualized token representations ($T_1$, $T_2$,…,$T_n$). The prediction, in the context of sentiment analysis, is derived from the final encoder layer's output from the *[CLS]* token, denoted as *C*.

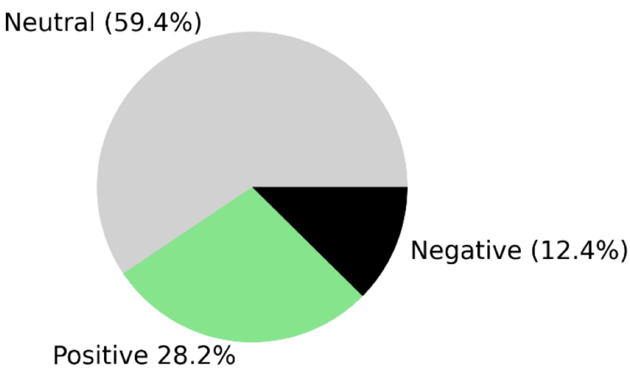



**Fig. 2.** Classification of Sentiment Labels in Financial PhraseBank. This figure shows the portion of sentiment labels in the Financial PhraseBank, a dataset of 4,845 news sentences annotated by 16 finance domain professionals.

simply calculate the difference between positive and negative logits (Lin and Luo, 2020), as shown in Equation (1). Therefore, the sentiment score always falls between −1 (the most negative) and 1 (the most positive). Fig. 1 depicts the simplified structure of BERT for sentiment analysis task.

$$SentimentScore = logit_{positive} - logit_{negative} \tag{1}$$

We use the BERT base version, which has 12 encoder layers, 12 multihead attention heads, a hidden size of 768, and 110 million parameters. Because our aim is to predict the sentiment label and score of news headlines and tweets in the context of finance, it is essential to fine-tune the model across this domain. Thus, we use the Financial PhraseBank (Malo et al., 2014), which comprises 4,845 selected sentences from financial news labeled as positive, negative, or neutral by 16 professionals within the finance domain. Labels indicate how the annotators perceive that the information embedded in a sentence might influence prices. Fig. 2 shows the proportion of positive, negative, and neutral sentences in the PhraseBank. Training the BERT with the Financial Phrasebank enhances the model's performance in processing text within the finance context as the model learns specialized terms used in the finance literature. We train the model using different split ratios and evaluate its performance using two standard metrics of accuracy and macro F1 average as shown in Equations (2) and (3) (Baeza-Yates and Ribeiro-Neto, 1999).

$$Accuracy = \frac{Numberofcorrectpredictions}{Totalnumberofsample} \tag{2}$$

$$F1scoreineachlable = 2 \times \frac{1}{\frac{1}{percision} + \frac{1}{recall}}$$

$$MacroF1average = \frac{\sum F1scoresineachlable}{Totalnumberoflables} \tag{3}$$

Finally, to obtain the sentiment score for each day, we compute the mean of all sentiment scores for that day. This produces daily proxies for both news and Twitter sentiment and leads to a set of novel and unique data that we incorporate into the econometric analysis.

### 3.2. The Diebold and Yilmaz (DY) framework

To investigate the connectedness between news headlines, tweets, and market volatility, we follow the framework proposed by Diebold and Yilmaz (2012, 2014).[3] We begin by modeling market volatility and our sentiment series as an $n$-variable vector autoregression (VAR) model in the first step. Then, we employ the generalized variance decomposition (GVD) introduced by Koop et al. (1996) and Pesaran and Shin (1998) to construct the $H$-step-ahead forecast and to decompose the forecast error variance for each variable corresponding to shocks coming from other variables at time $t$. Let $y_t = (y_{1t}, y_{2t}, \cdots, y_{nt})$ be a vector of market volatility and sentiment series:

$$y_t = \sum_{i=1}^{p} \theta_i y_{t-i} + \epsilon_t, \tag{4}$$

where $\theta_i$ (for $i = 1, 2, \ldots, p$) are $n \times n$ matrices, and $\epsilon_t$, as the error vector, has zero means and a variance–covariance matrix $\Sigma$. The moving-average representation of this $VAR_{(p)}$ process is:

$$y_t = \sum_{i=0}^{\infty} \varphi_i \epsilon_{t-1} t = 1, \cdots, T$$

$$\varphi_i = \theta_1 \varphi_{i-1} + \theta_2 \varphi_{i-2} + \cdots + \theta_m \varphi_{i-m}, \tag{5}$$

where $y_t$ denotes a $(K \times 1)$ vector for the involved series; $\varphi_0$ is $n \times n$ identity matrices and equals zero for $i < 0$; $\theta_i$ is $n \times n$ autoregression coefficient matrices; and $\epsilon_t$ denotes the vector of error terms ($i.i.d.$). Based on the generalized VAR, the $H$-step-ahead forecast error variance decomposition of the $i^{th}$ variable coming from the $j^{th}$ variable is:

$$\varphi_{ij}^{H} = \frac{\sigma_{ij}^{-1} \sum_{h=0}^{H-1} \left(e\hat{A}_i \varphi_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e\hat{A}_i \varphi_h \Sigma \varphi \hat{A}_h e_j\right)}, \tag{6}$$

where $\sigma_{ij}$ is the standard deviation for the error term in the $j^{th}$ equation, and $e_i$ denotes a selection vector. Finally, the directional connectedness, which is the shock transmitted from sentiment $j$ to market $i$, can be calculated as follows:

$$C_{i \leftarrow j} = \frac{\varphi_{ij}^{H}}{\sum_{ij=1}^{N} \varphi_{ij}^{H}}. \tag{7}$$

The DY framework allows us to estimate both static and dynamic connectedness. Static connectedness provides evidence of spillovers over the entire period, whereas dynamic connectedness provides evidence of the evolution of connectedness across time.

## 4. Data

We investigate market connectedness based on sentiment and historical data from the US (the DJIA index), the UK (the FTSE100 index), France (the CAC40 index), Germany (the DAX index), Japan (the Nikkei index), and Brent crude oil. Our selection of these markets is derived from multiple considerations. Firstly, these markets benefit from comprehensive coverage across both conventional news sources and social media platforms. Moreover, they stand as some of the most globally pivotal and interconnected financial centers. The dynamics of these markets have profound implications for worldwide financial stability, underscoring their significance in our analysis. Additionally, by opting for markets spread across diverse geographical regions, we try to encompass a wide spectrum of economic climates, policy environments,

[3] See Diebold and Yilmaz (2012, 2014) for further details about the applied framework. Note that we employ the DY framework only to measure the directional impact from sentiment to the market.

**Table 1**
**The Number of News and Tweets.** This table shows the number of relevant news headlines (panel A) and tweets (panel B) over the period from 04/08/2014 to 22/12/2020 for the US (the DJIA index), the UK (the FTSE100 index), France (the CAC40 index), Germany (the DAX index), Japan (the Nikkei index), and Brent crude oil markets.

| Market | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 | 2020 | Total |
|---|---|---|---|---|---|---|---|---|
| ***Panel A- News*** | | | | | | | | |
| DJIA | 348 | 1,047 | 1,443 | 1,795 | 1,550 | 1,286 | 1,898 | 9,367 |
| FTSE | 381 | 716 | 662 | 907 | 715 | 556 | 694 | 4,631 |
| CAC40 | 369 | 662 | 554 | 646 | 552 | 249 | 531 | 3,563 |
| DAX | 385 | 675 | 764 | 868 | 727 | 556 | 656 | 4,631 |
| Nikkei | 145 | 437 | 816 | 784 | 923 | 736 | 826 | 4,667 |
| Brent | 510 | 2,685 | 2,392 | 2,252 | 2,043 | 1,763 | 3,188 | 14,833 |
| **Total news** 41,692 | | | | | | | | |
| ***Panel B- Tweets*** | | | | | | | | |
| DJIA | 4,878 | 12,327 | 14,034 | 24,311 | 20,595 | 36,614 | 53,906 | 166,665 |
| FTSE | 15,729 | 42,276 | 43,069 | 22,462 | 21,841 | 23,510 | 24,069 | 192,956 |
| CAC40 | 1,483 | 4,052 | 3,177 | 2,208 | 2,719 | 3,126 | 5,275 | 22,040 |
| DAX | 7,173 | 15,506 | 16,172 | 10,425 | 7,017 | 10,837 | 15,707 | 82,837 |
| Nikkei | 711 | 7,897 | 6,762 | 4,274 | 3,779 | 2,597 | 2,759 | 28,779 |
| Brent | 2,329 | 14,127 | 20,376 | 17,778 | 20,257 | 13,702 | 27,894 | 116,463 |
| **Total tweets** 609,740 | | | | | | | | |

and prevailing sentiments. Lastly, recognizing the integral role oil plays in the global economy, the inclusion of Brent –a preeminent benchmark– offers a deeper understanding of the wider commodities market and its intricate relationship with media sentiment.

For the selected markets, we scrape Twitter tweets and news headlines from *investing.com*.[4] The news section of *investing.com* contains wide-ranging news from other sources like Reuters, Bloomberg, Business Insider, and Seeking Alpha, among others, as well as exclusive news stories written for the website. Drawing from esteemed outlets like Reuters and Bloomberg ensures the credibility and reliability of our news sample. Also, the market-centric approach of *investing.com* provides comprehensive coverage of relevant news specific to each market, offering real-time information. Moreover, with its global presence and publicly available news section, this website caters to a wide audience. These features justify our use of this website as our news source. Table 1 shows that our textual data between 4 August 2014, and 22 December 2020, contains a total of 41,692 news headlines and 609,740 tweets on specific hashtags germane to each market (see the list of hashtags in Appendix A1).[5]

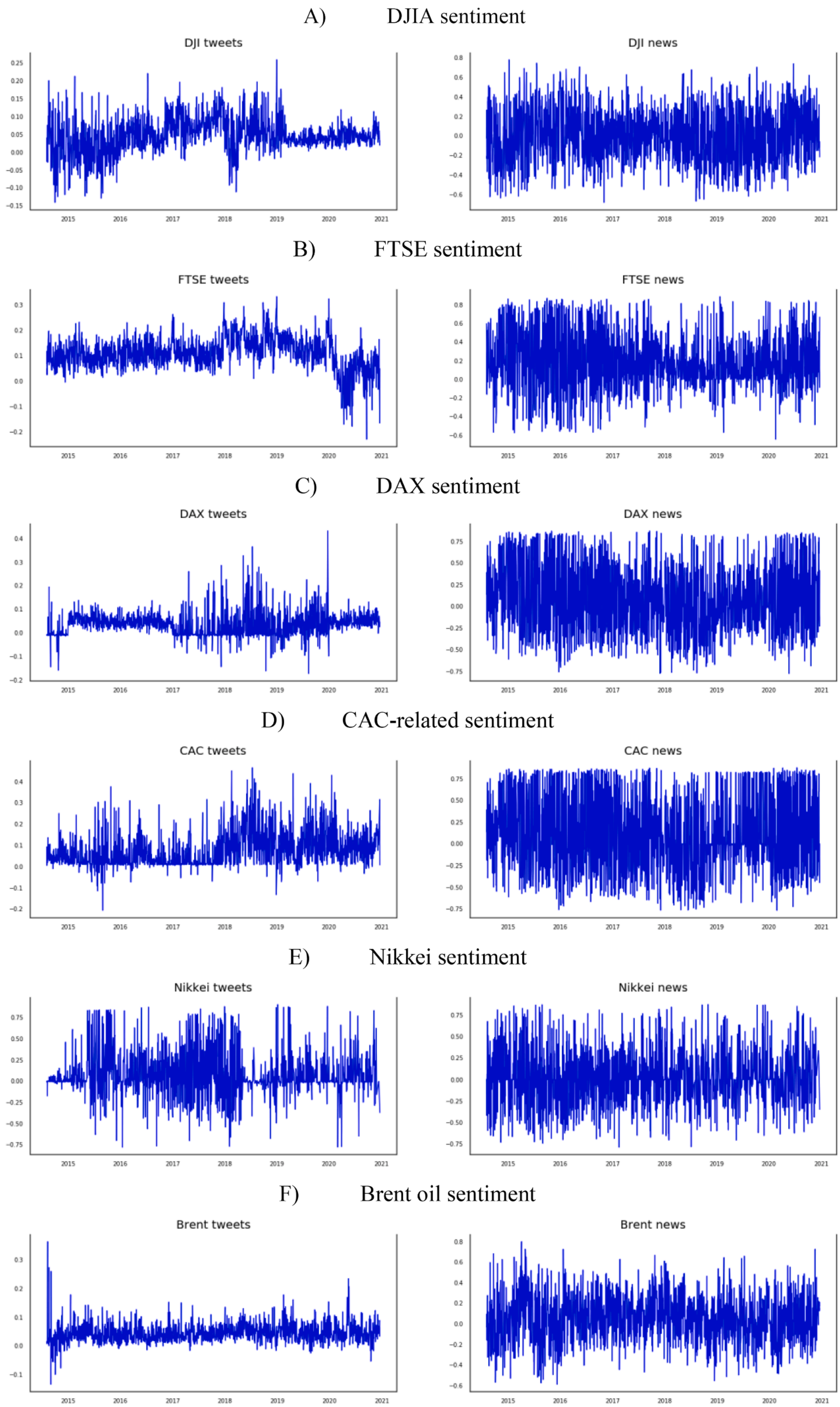
We select this timeframe based on several key considerations. Primarily, this interval coincides with when our data sources become robust and reliable, granting us access to a comprehensive compilation of news and tweets. Moreover, there are pivotal subperiods such as the Brexit implications for the UK, pivotal elections in the US, the Eurozone challenges faced by France and Germany, and Japan's evolving economic and foreign policies within this span. Additionally, this period bears witness to fluctuations in the Brent commodity market due to geopolitical tensions and global supply–demand dynamics. There are also instances of stability and growth, like the landmark Paris Climate Agreement or economic and political deals. Examining these nuanced phases facilitates a holistic understanding of how various news stories influence market volatilities. Furthermore, our dataset represents a continuous stream of public news along with tweets, ensuring a wide spectrum of information for an expansive investor demographic.

We train BERT using the Financial PhraseBank. For this purpose, we divide the PhraseBank into three subsets of training, validation, and test. The aim is to find the best generalization of the model. The training and validation data are used to fit the parameters to the model and tuning hyperparameters. The test data is then used to acquire an evaluation of the final model. In doing so, we apply different relative ratios of 70:30, 80:20, and 90:10 to find the best generalization of the model. Using Equation (2), the obtained accuracy metrics are 0.77, 0.83, and 0.81 for the 70:30, 80:20, and 90:10 split ratios, respectively. The macro F1 averages are obtained using Equation (3), which are 0.77, 0.82, 0.81 for the 70:30, 80:20, and 90:10 split ratios, respectively. These metrics are on a scale of 1 to 0, with 1 being the best value. We obtain the most quality outcomes using the relative ratio of 80:20. This means we use 80 % of the sentences for training and validation and 20 % for the test set. Therefore, we proceed with the BERT model trained on this ratio because it produces more accurate and quality data compared to the model trained on the other ratios. Fig. 3 shows the sentiment series obtained for each index for our sample period. Appendix A2 presents an example of the sentiment calculation process.

To explore the reliability of our sentiment series, we match them to similar established indicators. While we are unable to identify a widely recognized index directly analogous to our sentiment series, we utilize the most comparable benchmarks. For our news sentiment series, we reference the Geopolitical Risk Index introduced by Caldara and Iacoviello (2022), primarily focused on geopolitical, war, and terrorist events. For our Twitter sentiment series, we draw upon the Twitter Economic Uncertainty (Baker et al.,

[4] Investing.com is an online financial markets platform that provides real-time news updates on more than 250 international exchanges; see https://www.investing.com/about-us/.

[5] We use news headlines because those can be easily retrieved, and they convey the meaning of the full article (Li et al., 2019). Furthermore, using news headlines boosts the accuracy of the textual analysis as headlines generally include fewer repetitive or irrelevant words.




*(caption on next page)*

**Fig. 3.** Sentiment Series Extracted from News and Tweets for Each Market. News and Twitter sentiment series over the period from 04/08/2014 to 22/12/2020 for the US (the DJIA index), the UK (the FTSE100 index), France (the CAC40 index), Germany (the DAX index), Japan (the Nikkei index), and Brent crude oil. Panel A shows the DJIA sentiment series extracted from 166,665 tweets and 9,367 news headlines. Panel B illustrates the calculated FTSE sentiment series using 192,956 tweets and 4,631 news headlines. Panel C portrays the calculated sentiment series for the DAX using 82,837 tweets and 4631 news headlines. Panel D shows the CAC sentiment series extracted from 22,040 tweets and 3,553 news headlines. Panel E shows the calculated sentiment series for the Nikkei using 28,779 tweets and 4,667 news headlines. Panel F shows the calculated sentiment series for Brent oil using 116,463 tweets and 14,833 news headlines.

2021), which quantifies the usage of economic uncertainty-related words in tweets. It is important to note that our sentiment series encompass a comprehensive range of topics. Therefore, they should partly predict other sentiment indices, given the overlaps in content. Panel OLS regressions show that there is a negative and significant relation between our indices and the benchmarks.[6] These inverse relations stem from our sentiment series capturing both positive and negative aspects of news and tweets, while benchmark indices solely capture negative aspect. This means when our sentiment series shift towards a positive spectrum, the severity of the benchmark indices subsides. These results justify our use of the sentiment measures.

We obtain daily closing, minimum, and maximum prices for the selected markets from Refinitiv Eikon for 4 August 2014, to 22 December 2020. Because volatility is unobserved, we compute it using the following daily range-based measure proposed by Parkinson (1980) in Equation (8):

$$\sigma_t^2 = 0.361\left[ln(H_t) - ln(L_t)\right]^2 \tag{8}$$

where $H_t$ and $L_t$ are the maximum and minimum price, respectively, on day $t$. This measure uses a factor of 0.361 to make the estimation comparable to the more common square measures. Brandt and Diebold (2006) find that the efficiency of the high-low range-based measures is between realized measures using three-hour and six-hour estimations. Fig. 4 shows the time-series plot and volatility for all indices over the sample period. Table 2 presents descriptive statistics for the series.

For the FTSE– and Brent–Twitter sentiment, the standard deviation values are smaller than the average, while the opposite is true for all other series. Thus, Twitter sentiment regarding the FTSE and Brent is less spread out. Standard deviations confirm that Brent (0.002397) and the FTSE (0.000238) have the highest volatility level of the six markets studied, while the CAC–news sentiment (0.435580) and the Nikkei–Twitter sentiment (0.270947) fluctuate the most over time amongst the sentiment series of news and Twitter, respectively. All news series except for the Nikkei are fairly symmetrical, as the skewness is between −0.5 and 0.5. The sentiment series for the Nikkei–Twitter, Nikkei–news, and FTSE–Twitter are moderately skewed, with values between 0.5 and 1 (or −0.5 and −1). The remaining series are highly skewed.

We check the stationarity of the times series using the augmented Dickey-Fuller (ADF) test. The null hypothesis suggests the existence of a unit root in the series. The last column of Table 2 presents the results of the ADF test, confirming the stationarity of all series at the 5 % significance level. In other words, some features of the series like mean and variance do not vary over time.

## 5. Empirical results

### 5.1. Market volatility and sentiment

Hypothesis 1 posits a long-lasting connectedness between market volatility and sentiment expressed through news headlines and Twitter tweets. We estimate the existing static connectedness between the sentiment proxies and each market from August 2014 to December 2020 using Equations (5) and (7) with a forecasting time horizon of 15 days. Table 3 shows the magnitude of connectedness between each market and its associated sentiment. The results in Column 1 indicate a statistically significant connectedness between each market and its corresponding news sentiment. Among the markets studied, news sentiment holds the strongest connectedness with DJIA volatility, accounting for 5.23 % of the DJIA's volatility over the entire sample period. We interpret this finding as evidence that the volatility in the US market is influenced by shocks in news sentiment more than is the case in other markets. The German market (the DAX) is the least sensitive to the news, with 0.67 % of its volatility arising from news sentiment. This result suggests that DAX volatility is the least affected by shocks to its news sentiment.

Column 2 of Table 3 shows statistically significant volatility spillovers coming from Twitter sentiment to the relevant markets. The FTSE, with a magnitude of 4.4 %, holds the largest connectedness, while the French market is the least impacted, with a negligible connectedness of 0.46 % over the entire sample period. The DJIA, the CAC, the Nikkei, and Brent receive more shocks from news headlines than from Twitter, while the opposite is true for the FTSE and the DAX.

To further examine the validity of the findings, we assess overall connectedness using Fisher's test. Table 3 shows that the Fisher's test p-value equals zero. This test confirms a statistically significant association between market volatility and news sentiment. Consistent with Hypothesis 1, the static results for the entire sample indicate that sentiment shocks have a long-lasting effect on the volatility of the markets in question, though the estimation accounts for only a minuscule share of the total fluctuations. We conclude that part of the volatility for each market arises from the shocks coming from that market's sentiment series, indicating a long-lasting

[6] A one-unit change in our news sentiment series corresponds to a −0.71-unit change in the Geopolitical Risk Index, a significant relationship at the 5% level. Similarly, a one-unit change in our Twitter sentiment series corresponds to a −4.31-unit change in the Twitter Uncertainty Index, significant at the 10% threshold.

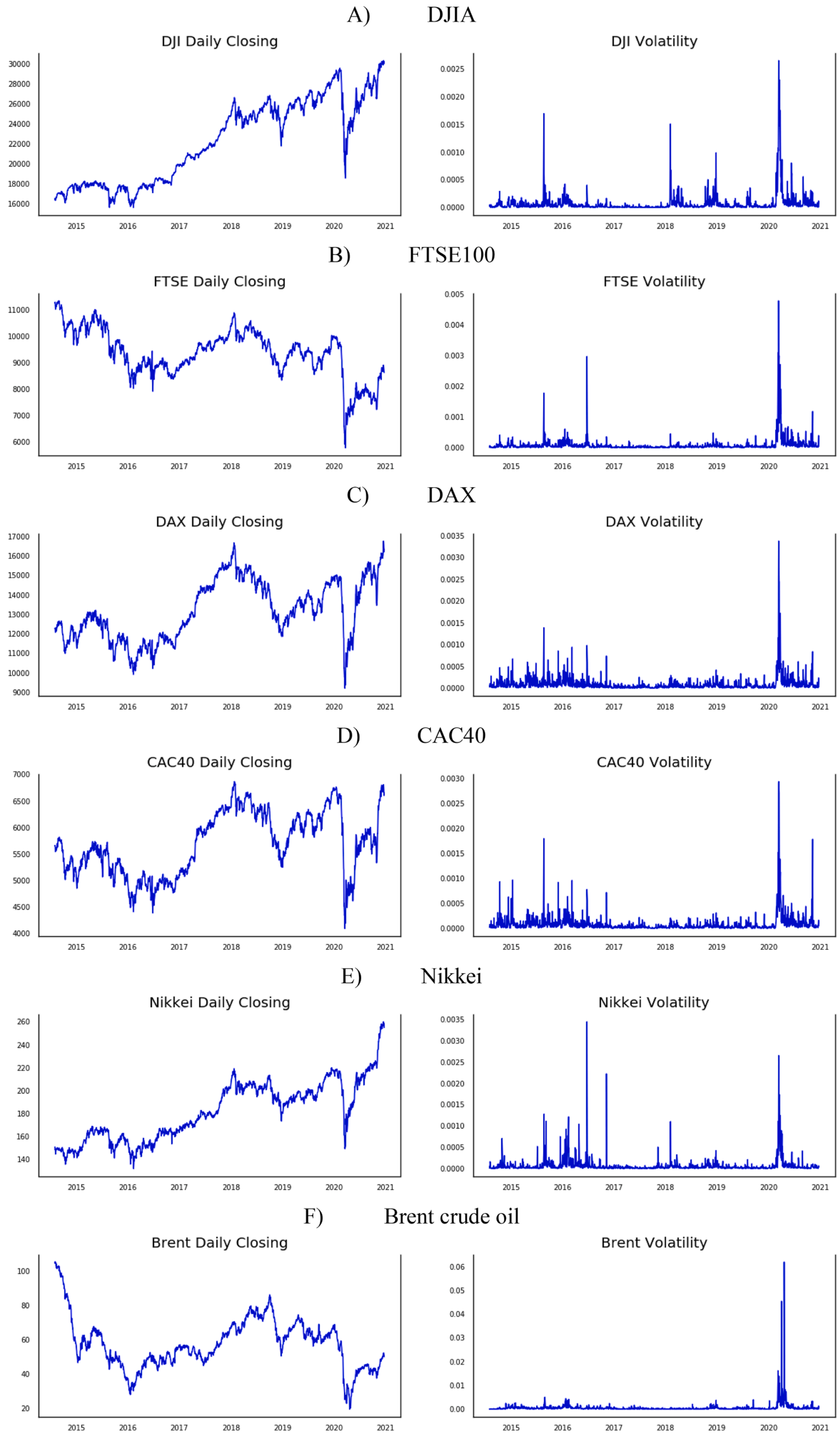



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**Fig. 4.** Historical Time Series and Volatility. Daily closing prices and range-based volatility over the period from 04/08/2014 to 22/12/2020 for the US (the DJIA index), the UK (the FTSE100 index), France (the CAC40 index), Germany the (DAX index), Japan (the Nikkei index), and Brent crude oil. Panel A-F shows the historical trends in closing price and volatility for the DJIA, FTSE100, DAX, CAC, Nikkei, and Brent crude oil, respectively.

**Table 2**
**Descriptive Statistics.** This table shows descriptive statistics for the US (the DJIA index), the UK (the FTSE100 index), France (the CAC40 index), Germany (the DAX index), Japan (the Nikkei index), and Brent crude oil markets, together with their corresponding news and Twitter sentiment series over the period from 04/08/2014 to 22/12/2020 through panel A-C. Values in the first column presents the daily mean for each series followed by the minimum and maximum values in the next two columns. SD stands for standard deviations. Numbers in parenthesis in the last column show the p-value at the 5% significance level.

| | Mean | Minimum | Maximum | SD | Skewness | ADF |
|---|---|---|---|---|---|---|
| ***Panel A- Volatility*** | | | | | | |
| **DJIA** | 0.000073 | 0.000001 | 0.002648 | 0.000190 | 7.721130 | −6.6726 (0) |
| **FTSE** | 0.000088 | 0.000002 | 0.004780 | 0.000238 | 10.946080 | −5.583 (0) |
| **CAC** | 0.0000905 | 0.0000007 | 0.002942 | 0.000187 | 8.7727 | −7.1212 (0) |
| **DAX** | 0.0000973 | 0.0000007 | 0.003377 | 0.000188 | 8.831979 | −6.5157 (0) |
| **Nikkei** | 0.000055 | 0 | 0.003441 | 0.000167 | 10.557571 | −7.6249 (0) |
| **Brent** | 0.000651 | 0.000019 | 0.061929 | 0.002397 | 17.873160 | −4.8465 (0.001) |
| ***Panel B- News*** | | | | | | |
| **DJIA News** | 0.006113 | −0.681537 | 0.780305 | 0.278095 | 0.043738 | −37.242 (0) |
| **FTSE News** | 0.188174 | −0.643356 | 0.889871 | 0.301199 | 0.210155 | −29.0329 (0) |
| **CAC News** | 0.116632 | −0.764512 | 0.875995 | 0.435580 | 0.1295 | −40.2754 (0) |
| **DAX News** | 0.094747 | −0.775066 | 0.872322 | 0.392180 | 0.144225 | −9.4413 (0) |
| **Nikkei News** | 0.017079 | −0.786002 | 0.873290 | 0.301482 | 0.586975 | −31.5618 (0) |
| **Brent News** | 0.060612 | −0.588032 | 0.799959 | 0.229696 | 0.017622 | −7.674 (0) |
| ***Panel C- Twitter tweets*** | | | | | | |
| **DJIA Twitter** | 0.046290 | −0.140883 | 0.259133 | 0.049346 | −0.057065 | −4.3457 (0.0004) |
| **FTSE Twitter** | 0.109994 | −0.228921 | 0.333787 | 0.063758 | −0.503394 | −2.7089 (0) |
| **CAC Twitter** | 0.078504 | −0.206283 | 0.465760 | 0.080821 | 1.2148 | −4.0091 (0.00014) |
| **DAX Twitter** | 0.036704 | −0.172351 | 0.432159 | 0.050949 | 1,209642 | −5.0889 (0) |
| **Nikkei Twitter** | 0.091734 | −0.778571 | 0.904280 | 0.270947 | 0.586975 | −25.2268 (0) |
| **Brent Twitter** | 0.044512 | −0.134497 | 0.364388 | 0.033485 | 1.349825 | −17.9132 (0) |

**Table 3**
**The DY Static Estimations for Each Market and its Corresponding Sentiments.** This table presents the estimation of static connectedness for the US (the DJIA index), the UK (the FTSE100 index), France (the CAC40 index), Germany (the DAX index), Japan (the Nikkei index), and Brent crude oil markets with their related news and Twitter sentiment series over the entire period from 04/08/2014 to 22/12/2020. The $ij^{th}$ entry represents the directional connectedness, namely the percentage of the forecast error variance of market *i* due to shocks from sentiment *j*. Numbers in parentheses are standard errors based on bootstrapping. ** and * denote significance at 5% and 10% levels, respectively. The last row presents the p-value of the Fisher's test against the null hypothesis of no connectedness.

| Index | News sentiment | Twitter sentiment |
|---|---|---|
| DJIA | 5.23 (0.407)** | 2.27 (0.05401)** |
| FTSE | 1.06 (0.0363)* | 4.4 (0.1014)** |
| CAC | 2.93 (0.0389)** | 0.46 (0.0396)** |
| DAX | 0.67 (0.0283)* | 0.92 (0.0243)** |
| Nikkei | 2.02 (0.0239)** | 1.04 (0.0224)* |
| Brent | 2.16 (0.035)** | 1.22 (0.0329)** |
| Fisher's p-value = 0 | | |

connectedness between media sentiment and market volatility.

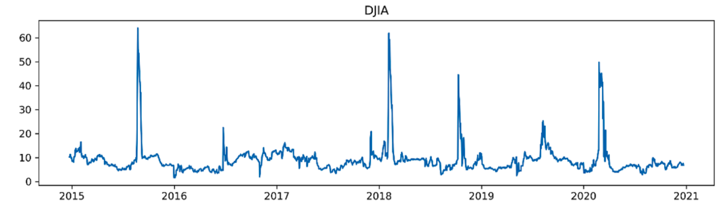
### *5.2. Market volatility and international sentiment*

Hypothesis 2 predicts that sentiment associated with one market can transmit volatility to other markets. That is, volatility can be transmitted between markets by news and social media. We again use the DY static framework, this time including all sentiment series in the analysis, to investigate the extent of connectedness between volatility in each market and sentiment of other markets. We note that in

**Table 4**
**The DY Static Estimation for all Markets and Sentiment series.** This table presents the estimation of static connectedness for the US (the DJIA index), the UK (the FTSE100 index), France (the CAC40 index), Germany (the DAX index), Japan (the Nikkei index), and Brent crude oil markets with own and other news and Twitter sentiment series over the entire period from 04/08/2014 to 22/12/2020. The $ij^{th}$ entry represents the directional connectedness, namely the percentage of the forecast error variance of market $i$ due to shocks from sentiment $j$. Numbers in parentheses are standard errors based on bootstrapping. ** and * denote significance at 5% and 10% levels, respectively. The last row presents the p-value of the Fisher's test against the null hypothesis of no connectedness.

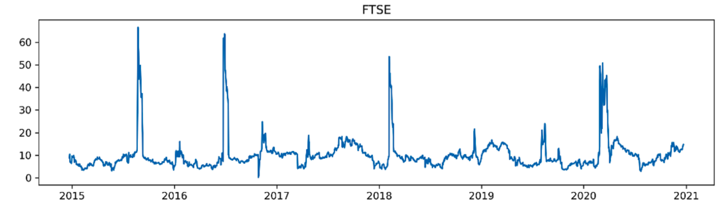
| | DJIA News | DJIA Twitter | FTSE News | FTSE Twitter | CAC News | CAC Twitter | DAX News | DAX Twitter | Nikkei News | Nikkei Twitter | Brent News | Brent Twitter |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DJIA | 3.37** (0.011) | 1.58** (0.007) | 2.55** (0.008) | 0.69** (0.013) | 0.48** (0.001) | 0.68** (0.006) | 1.04** (0.007) | 0.16**(0.005) | 1.51** (0.007) | 1.33**(0.009) | 2.37** (0.009) | 0.91** (0.005) |
| FTSE | 0.57** (0.006) | 0.58** (0.007) | 0.68** (0.007) | 2.04** (0.019) | 0.6**(0.097) | 0.75** (0.006) | 0.55** (0.006) | 0.44*(0.005) | 0.59** (0.006) | 0.8**(0.008) | 0.78** (0.007) | 0.6**(0.006) |
| CAC | 1.66** (0.198) | 1.84** (0.417) | 0.35** (0.008) | 2**(0.017) | 1.85** (0.008) | 0.29** (0.007) | 0.56** (0.006) | 0.26** (0.006) | 0.90** (0.007) | 0.86** (0.008) | 2.27** (0.07) | 1.34** (0.006) |
| DAX | 2.55** (0.005) | 1.10** (0.015) | 0.30** (0.008) | 1.72** (0.019) | 1.65** (0.006) | 0.3*(0.007) | 0.63** (0.006) | 0.51**(0.005) | 0.71** (0.006) | 1.25**(0.009) | 2.5**(0.007) | 0.31** (0.005) |
| Nikkei | 1**(0.005) | 0.47** (0.005) | 0.16*(0.006) | 1**(0.05) | 0.64** (0.006) | 0.56** (0.004) | 0.24*(0.005) | 0.6*(0.009) | 1.08** (0.006) | 0.76**(0.006) | 0.84**(0.05) | 1.03** (0.009) |
| Brent | 0.76** (0.007) | 0.15** (0.008) | 0.69**(0.01) | 2.05** (0.034) | 0.46** (0.007) | 0.24*(0.008) | 0.3**(0.007) | 0.22*(0.009) | 1.25** (0.009) | 0.49**(0.008) | 1.26** (0.008) | 1.08** (0.008) |
| Fisher's p-value = 0 | | | | | | | | | | | | |

A) Transmitted Volatility to DJIA



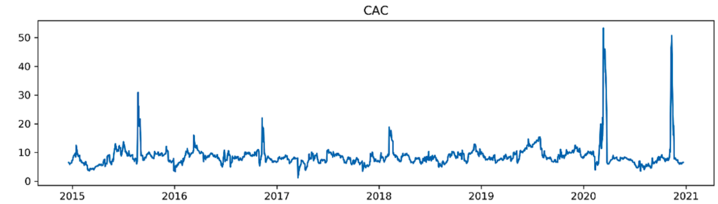

Maximum = 64.05 on24.08.2015, minimum = 1.63 on31.12.2015

B) Transmitted Volatility to FTSE



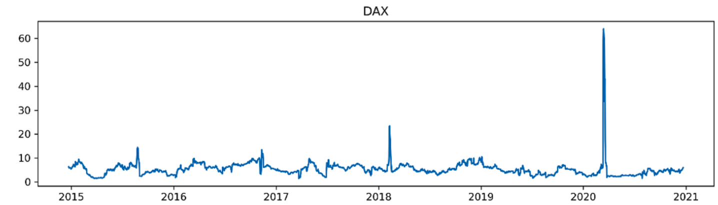

Maximum = 66.6 on 24.08.2016, minimum = 0.23 on 27.10.2016

C) Transmitted Volatility to CAC40



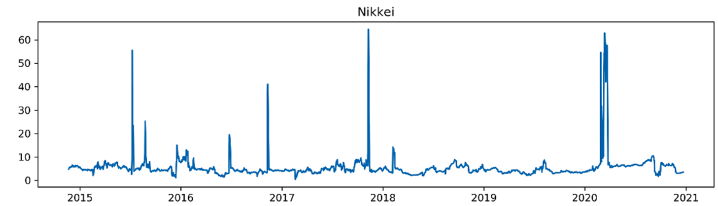

Maximum = 53.3 on 12-03.2020, minimum = 1.21 on 17.03.2017

D) Transmitted Volatility to DAX



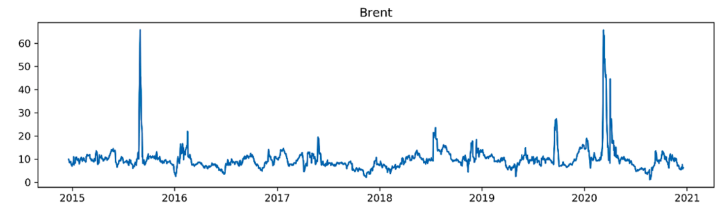

Maximum = 64 on 12.03.2020, minimum = 1.47 on 22.03.2017

E) Transmitted Volatility to Nikkei




Maximum = 64.45 on 09.11.2017, minimum = 0.49 on 18.02.2017

F) Transmitted Volatility to Brent




Maximum = 65.73 on 31.08.2015, minimum = 1.17 on 21.08.2020

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**Fig. 5.** Spillovers Transmitted from Sentiment to the Markets over a 100-day Rolling Window. This figure presents total connectedness from both news and Twitter sentiments to the US (the DJIA index), the UK (the FTSE100 index), France (the CAC40 index), Germany (the DAX index), Japan (the Nikkei index), and Brent crude oil markets through panels A-F over the period from 04/08/2014 to 22/12/2020 through 15-day ahead forecast horizon (H = 15) and 100-day rolling window estimations.

**Table 5**
**F-test for dynamic connectedness.** This table shows the result of the F-test on the changes in dynamic volatility spillovers when the connectedness is above or below 20% at the significance level of 5%.

| | |
|---|---|
| **F-statistics** | 11.2082 |
| **P-value** | 0 |

recent decades news stories are not limited by national boundaries. Reports show that 57 % of people around the world follow international news, and 48 % follow U.S. news specifically.[7] Hence, global or international news is likely to strongly influence national news. Because our sample of news headlines and tweets contains both national and international news relevant to our six focal markets, a part of the connectedness we capture may stem from global events such as the COVID-19 pandemic. Although our sample of textual data incorporates global events in the context of a particular country, national news is likely still linked to international news, particularly when we source the news from globally prestigious news outlets. To negate such an effect on our estimation, we also add a global financial index to the VAR estimation we use to calculate connectedness.

The DY framework first generates forecast errors through a VAR process and then applies generalized variance decomposition for the final estimation of connectedness. Using a financial global index allows us to cover the forecast errors stemming from global factors such that the new estimation is orthogonal to the global factors. This process may decrease the magnitude of connectedness, but the final estimation is more robust, allowing us to more effectively test our second hypothesis. For this purpose, we use the MSCI world index, which is a market index of 1,546 companies all over the world.

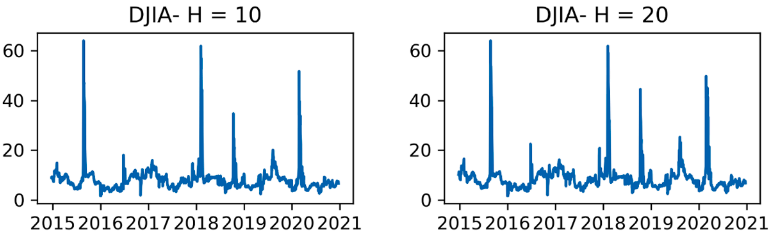
The results in Table 4 show a statistically significant connectedness between markets and various sentiment series. The connectedness between each market and its own sentiment series is a little smaller than the connectedness values presented in Table 3 due to the inclusion of the global factor and international sentiment series. Because our aim is to examine the connectedness across markets and sentiment, we only report the connection between each market and international sentiment series. The DJIA holds the largest connectedness with news about the FTSE and Brent, with magnitudes of 2.55 % and 2.37 %, respectively. We interpret this result as evidence that volatility in the US market is more connected with shocks in news sentiment associated with the FTSE and Brent than with other markets. The connection between CAC news sentiment and the DJIA is the weakest (0.48 %) of the relationships we test.

As for Twitter sentiment, the Nikkei and Brent send the biggest shocks to the DJIA; 1.33 % and 0.91 % of DJIA variability can be attributed to them, respectively. We also see that the US market is influenced by the Twitter sentiment of other markets. The second row of Table 4 shows a small connectedness between the FTSE and all sentiment series, with each international sentiment series accounting for less than 1 % of the FTSE volatility. The French market is most connected with news sentiment regarding Brent (2.27 %) and the least connected with Twitter sentiment regarding the DAX (0.26 %). For the German market, news sentiment regarding the DJIA and Brent transmit the largest shocks to the DAX, with magnitudes of 2.55 % and 2.5 %, respectively. However, CAC Twitter sentiment is the least connected with the DAX, with a magnitude of just 0.3 %. Twitter sentiment regarding the German market displays only negligible connectedness with the Nikkei (0.67 %). In addition, the Nikkei is most connected with the DJIA in terms of news sentiment (1 %). In regard to Twitter sentiment, however, Brent and the FTSE send the greatest shocks to the Nikkei, with values of 1.03 % and 1 %, respectively. Lastly, Brent has the strongest connectedness with FTSE Twitter sentiment (2.05 %) and the weakest connectedness with DJIA Twitter sentiment (0.15 %).

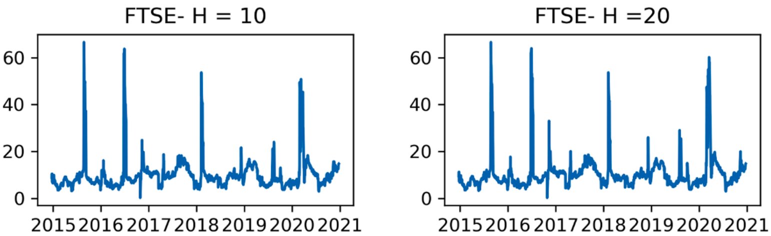
We examine the validity of these findings using Fisher's test, which checks the significance of connectedness between volatility and international sentiment. From the last row in Table 4, we see that the p-value is zero. Therefore, we reject the no-connectedness assumption at any conventional levels and confirm that there is a statistically significant association between market volatility and

[7] https://www.pewresearch.org/global/2018/01/11/publics-around-the-world-follow-national-and-local-news-more-closely-than-international/
.

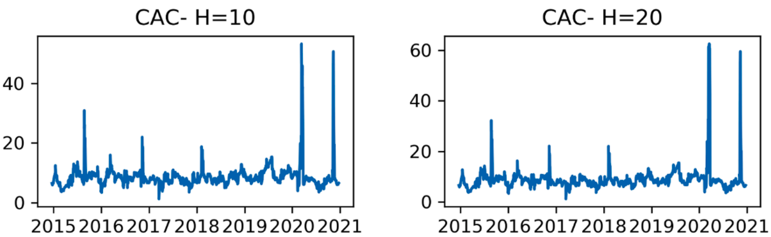
A) Transmitted volatility to DJIA



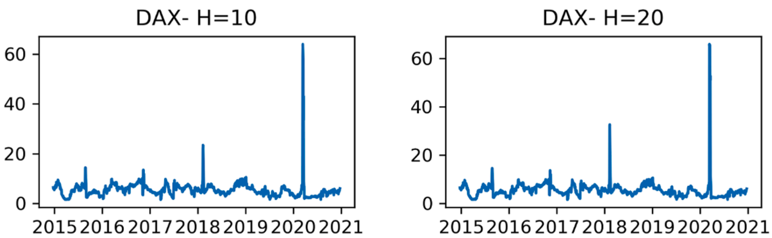

B) Transmitted volatility to FTSE100



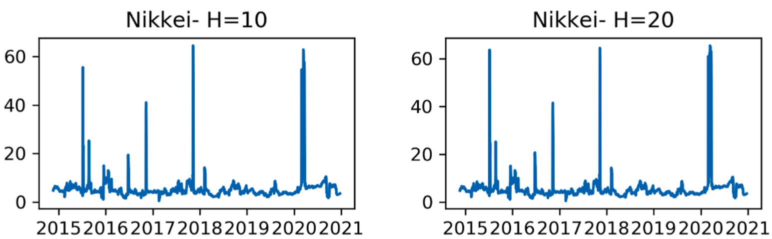

C) Transmitted volatility to CAC40




D) Transmitted volatility to DAX




E) Transmitted volatility to Nikkei




F) Transmitted volatility to Brent

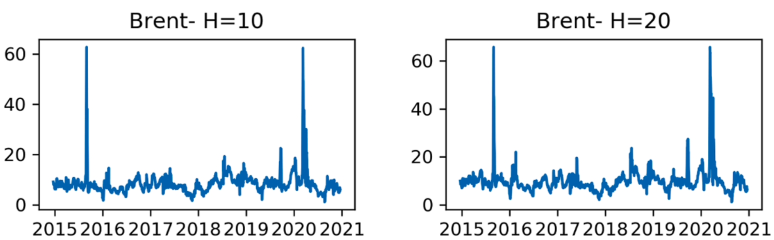



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**Fig. 6.** Sensitivity Analysis for Dynamic Connectedness. This figure presents the robustness check of the transmitted volatility from sentiment to the US (the DJIA index), the UK (the FTSE100 index), France (the CAC40 index), Germany (the DAX index), Japan (the Nikkei index), and Brent crude oil markets through panels A-F over the period from 04/08/2014 to 22/12/2020 through a 100-day rolling window with different forecast horizons.

international sentiment. These results are consistent with Hypothesis 2, indicating that volatility is transmitted between markets through news stories and social media.[8]

### 5.3. Dynamic connectedness

Hypothesis 3 predicts that the volatility arising from media sentiment and transmitted to the markets follows a spiky pattern. To test this hypothesis, we must examine volatility connectedness over a rolling window.[9] A pitfall of a VAR-based framework is that the same VAR parameters are unlikely to last over the entire sample (Lovcha and Perez-Laborda, 2020). Thus, the drawback of using the static model is that the coefficients cannot vary over time, and therefore it is unable to capture the evolution of time-varying dependencies. As one of the objectives of this study is to determine the trend of volatility transmission from sentiment to the markets over time and given the variability in real-time news and social media sentiment, we need to examine connectedness using a rolling window. Drawing from the literature, we choose 100-day subsamples (Wang et al., 2021) and re-estimate Equations (5) and (7) to find the dynamics.

Fig. 5 portrays the volatility connectedness between markets and relevant sentiment series across the rolling subsamples. Connectedness varies significantly over time, ranging from almost zero to more than 60 %. The variation between static and dynamic results is related to the fact that the VAR calculated over the entire sample smooths the results when the relation between variables is not constant (see Lovcha and Perez-Laborda, 2020). For instance, assume we divide a sample period into two subsamples of similar length. Shocks to the first variable negatively affect the second variable in one subsample, while the effect of the same shock is positive with a similar magnitude in the other. By estimating the VAR in each subsample, we can discern the magnitude and direction of these variables, and we obtain the degree of connectedness separately for each subsample based on their VAR estimations. Nevertheless, the VAR used for the entire sample tends to fit the two subsamples because we take the average of both positive and negative effects transmitting from the first to the second variable. This effect explains why the connectedness in the entire sample tends to be lower than the connectedness in the subsamples.

Fig. 5 shows that the volatility connectedness between each market and sentiment series varies across time. That is, the large degree of volatility in one series does not always spill over into other series. Seemingly, during some periods, sentiment or information circulation is of less importance. On average, spillovers from sentiment to the markets are around 10 % or lower in all markets. However, we identify some noteworthy contagions, highlighting the need for further investigation. Below, we discuss some of the major events.

On 9 July 2015, news and tweets regarding the Greek debt crisis and an unstable Chinese stock market sent shocks through the financial markets. The Japanese market was influenced the most, accounting for 63 % of the volatility in the Nikkei. Moreover, on 24 August 2015, news about uncertainty surrounding whether the Federal Reserve would increase interest rates attracted exceptional attention. This uncertainty coincided with the diffusion of "Black Monday" news in the Chinese market.[10] Later that day, *The New York Times* used the term "upheaval" to depict the condition of the markets. This eventually transmitted a dramatic shock to global stock markets, with the DJIA and FTSE receiving the biggest shocks, followed by the Nikkei the next day (25 % on 25 August 2015). Intensive connectedness arising from this setting lasted until 9 September 2015. The oil market also displayed increased connectedness from 27 August to 7 September 2015, when oil prices had their biggest three-day rally since January 2009. This rally stoked excitement among Twitter users. The move coincided with the release of the OPEC bulletin announcing that OPEC was willing to talk to other producers on a level playing field to protect their own interests. During this same period, Saudi (as the leader of OPEC) and Russian officials met about oil prices. These events eventually elevated the connectedness to 65 %.

From 24 June to 11 July 2016, the Brexit vote and Britain's decision to leave the European Union produced a strong connectedness between sentiment and markets. During this period, the media was rife with speculative articles, opinions, and predictions, leading to an atmosphere of heightened uncertainty. The magnitude of the connectedness peaked at 63 % for the FTSE index. Such a dramatic response in the connectedness underscores not only the weight of major geopolitical events on financial markets but also the rapid and forceful transmission of sentiments in shaping market behaviors and outcomes. On 9 November 2016, the announcement of Donald Trump's victory in the US presidential election sent a massive shock to the UK, French, and Japanese markets. The connectedness remained higher than usual for a few days thereafter, partly due to varying interpretations and uncertainty about the meaning of Trump's "America first" motto. In 2017, the implementation of oil production cuts and the announcement of a reduction in the global supply of nearly 1.5 million barrels per day pushed the connectedness magnitude to 20 % in the oil market.

In early February 2018, an announcement from the Federal Reserve about an inflation rate increase significantly impacted the DJIA on February 5–6. Concurrently, as the stock market faced a sharp decline, then-US President Donald Trump chose not to address the market's performance in his speech, despite his usual penchant for doing so. This deviation drew notable media attention, further intensifying market sentiments. The shock intensity, however, was tempered for other markets. Also in February 2018, the Bank of England noted that

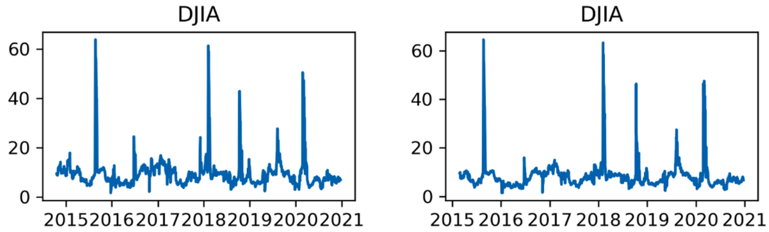
[8] We also check the connectedness by slicing the sample into low-, medium-, and high-volatility regimes. The results, presented in Appendix A3, do not change materially.

[9] The static connectedness between markets and their corresponding sentiment series assumes that spillover coefficients in the VAR analysis are time-invariant. This assumption fails to capture cyclical episodes or shifts in regimes across series. To overcome this shortcoming, we investigate the dynamic connectedness using a rolling window.

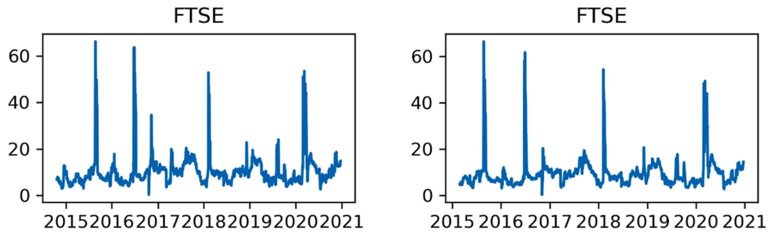
[10] The Chinese state media coined this term following an 8% drop in one day. This was the biggest drop in the Chinese market since 2007.

**50 days** **150 days**

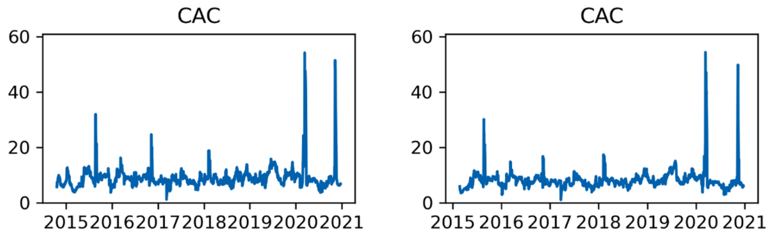
A) Transmitted volatility to DJIA



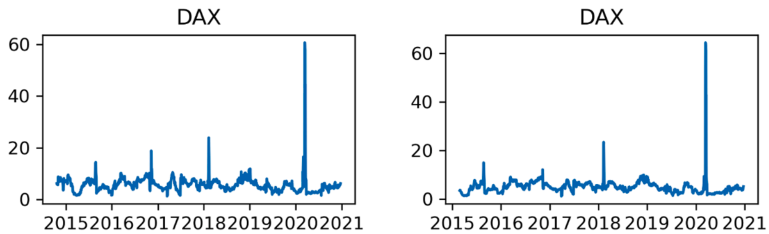

B) Transmitted volatility to FTSE100



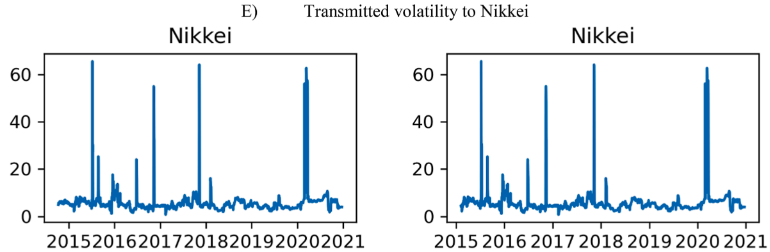

C) Transmitted volatility to CAC40



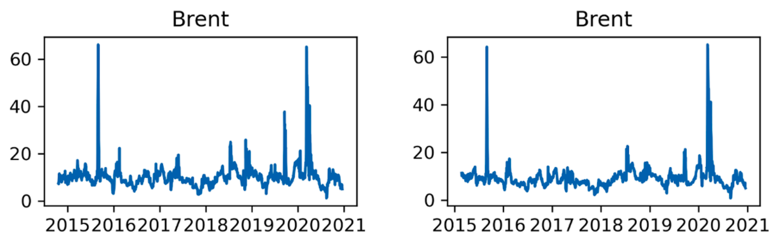

D) Transmitted volatility to DAX




E) Transmitted volatility to Nikkei




F) Transmitted volatility to Brent




*(caption on next page)*

**Fig. 7.** Sensitivity Analysis for Dynamic Connectedness. This figure presents the robustness check of the transmitted volatility from sentiment to the US (DJIA index), the UK (FTSE100 index), France (CAC40 index), Germany (DAX index), Japan (Nikkei index), and Brent crude oil markets through panels A-F over the period from 04/08/2014 to 22/12/2020 through rolling windows of 50 and 150 days with a 15-day forecast horizon.

UK interest rates were likely to increase earlier and faster than expected. During the first half of October, tariff clashes between the US and China, together with rising interest rates and concerns about possible overvalued US technology stocks, sent massive shocks to the DJIA. In December, the UK prime minister survived a no-confidence vote, lowering concerns in the media of turmoil in England's politics. During this time, the connectedness increased to around 25 %. In 2019, the US president announced in a series of tweets that a new tariff plan would be imposed on Chinese goods, causing a harsh reaction from China in August. Meanwhile, the conflict between Saudi and Russia over compliance with production cuts added more uncertainty to oil markets. The final dramatic shock during our sample period, the World Health Organization's (WHO) declaration characterizing COVID-19 as a pandemic, took place in March 2020. As media sentiment heightened, investors swiftly recalibrated their expectations. This sentiment-driven shift had a pronounced impact on all markets, inducing spikes in volatility largely attributed to intensified sentiment and the resulting investor apprehension. In Japan, media concerns about disrupted global trade were particularly salient. The Brent market, on the other hand, responded to sentiments of a precipitous decline in global oil demand in light of economic slowdowns. Our analyses indicate that at this point, over 50 % of the observed market volatilities were directly tied to changes in media sentiment.

News stories can also have a calming effect on the market. Such an impact is generally associated with high media coverage. For instance, the January 2020 statement by the WHO clarifying that the "coronavirus is not yet a global emergency" calmed market volatility. Another notable example arises from the oil market, which seems capable of smoothing the effect of anticipated events well beforehand. For instance, OPEC meetings are scheduled well in advance, and officials usually express their views in the press or on social media beforehand. Thus, the outcomes of the meetings can almost always be correctly predicted and gradually absorbed by the market.

As a formal test of our third hypothesis, we define a spiky pattern event as a period with connectedness above 20 %. We then use an F-test to compare volatility during such events to volatility during periods with no spikes. In Table 5, the F-statistic is 11.2082 and the p-value is zero. These results are consistent with Hypothesis 3, as sentiment extracted from news headlines and Twitter feeds has a noticeable impact on market volatility. Given the durability of the contagions, we conclude that the information flow seems speedy and spiky throughout major news events. During nonspiky times, spillover from sentiment to the markets still occurs but is weaker. We interpret these results as evidence that markets are able to process new information rapidly.

We also examine the robustness of the estimated results to check the validity of the findings using rolling-window subsamples. Similar to Diebold and Yilmaz (2009) and Lovcha and Perez-Laborda (2020), we examine the sensitivity of volatility spillovers to the forecast horizon and the length of rolling window. Fig. 6 depicts volatility transmitted to each market for 10- and 20-day forecast horizons. The sensitivity test shows no significant variation among the time-varying results. That is, the results for volatility connectedness are insensitive to different values for the $H$-step-ahead forecast horizon. Fig. 7 portrays volatility transmitted to each market over rolling windows of 50 and 150 days. We see no significant variation among the time-varying results. That is, the results for volatility connectedness are also insensitive to different values for rolling windows. In the robustness check, the 100-day rolling window serves as our benchmark. Moreover, we test our findings using different measures of volatility, as detailed in Appendix A4, and extend our robustness checks with the application of the time-varying parameter vector autoregressions (TVP-VAR) model, as presented in Appendix A5. Across these diverse measures and frameworks, our results consistently hold. Therefore, we conclude that our main results are robust to different forecast horizons, rolling windows, measures of volatility, and model configurations.

## 6. Conclusion

In this paper, we investigate the connectedness between media and market volatility across time. Although the finance literature suggests that media affects market volatility, empirical evidence of the time-varying evolution of such a relation is ambiguous. Additionally, much of the research has centered on economic news from official announcements and news outlets rather than covering the whole spectrum of news. Social media has, for instance, been an increasingly important arena for financial news and opinions in recent years. In addition, new textual analytics methods allow a level of precision in analyzing news that was simply not available only a few years ago.

We extract news sentiment by scraping the *investing.com* website, which covers a wide variety of news posted by various prestigious news outlets. The public may have distinct interpretations of the news. Those interpretations and ideas can be found on social media such as Twitter. We gather a total of 651,432 news stories and tweets for markets based in the US, UK, France, Germany, and Japan as well as Brent crude oil using a financially fine-tuned BERT model to extract daily sentiment for each market from August 2014 to December 2020. We then use the daily sentiment series together with historical data to examine the connectedness between news and market volatility through the DY framework. We find that news and social media sentiment have a long-lasting impact on international market dynamics. Our results also indicate that news germane to one market can transmit volatility to other markets. Lastly, we find that the connectedness between news sentiment and financial markets follows a spiky pattern.

These findings have several empirical implications. Investors, risk managers, hedgers, and other decision makers should consider the important role of news in their decision-making. Not only does media sentiment occasionally transmit massive shocks to markets, but we find evidence of a relatively constant spillover between sentiment and markets. These insights can be particularly interesting for regulatory authorities and market institutions, which may use sentiment analysis to monitor market volatility and distress.

The findings also offer theoretical insights. There is a substantial literature in classical finance on how information affects markets, but much less on how it is actually transmitted. Our work shows that whether it is fundamental information or noise, news and social media are important for transmitting information to financial markets, and the importance varies considerably over time.

Because news and social media sentiment play a role in market dynamics, future models of investment strategies, index tracking, or return/volatility forecasting should incorporate this variable, along with other sources of market volatility. Given the long-lasting effect of sentiment on market volatility we document, future research could investigate how media sentiment impacts market predictability. Future research could also examine the role of non-English news or weight news headlines based on the popularity/viewership of the media outlet and tweets based on their retweet number. Another avenue for future work would be identifying cross-sectional patterns of sentiment-driven volatility or studying the frequency connectedness.

## CRediT authorship contribution statement

**Hooman Abdollahi:** Conceptualization, Methodology, Software, Data Curation, Formal analysis, Writing - Original Draft, Writing - Review & Editing. **Sturla L. Fjesme:** Methodology, Supervision, Formal analysis, Writing - Original Draft, Writing - Review & Editing. **Espen Sirnes:** Methodology, Supervision, Formal analysis, Writing - Original Draft, Writing - Review & Editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

## Acknowledgement

We would like to thank Denis Becker, Derek John Clark, Karen DeVivo, Jens Kvaerner, Mikko Moilanen, Knut Nygaard, Oystein Strom, and Dan Zhang for helpful comments.

## Appendices

*A1*

**Table A1**
**Hashtags Searched for Tweet Curation.** This table presents different hashtags used to collect pertinent tweets for the US (the DJIA index), the UK (the FTSE100 index), France (the CAC40 index), Germany (the DAX index), Japan (the Nikkei index), and Brent crude oil markets with own and other news and Twitter sentiments over the entire period from 04/08/2014 to 22/12/2020.

| Index | Hashtags |
|---|---|
| Brent | #brentoil, #oilprice, #wtioilprice, #oilmarket |
| DJIA | #DowJonesIndustrial, #DowJonesIndustrialAverage, #DJI, #DJIA, #DowJonesIndustrialIndex, #DowJones, #DowJonesIndex |
| FTSE | #FTSE, #FTSE100index, #Footsie #FTSE100, #LondonStockExchange, #englishstockmarket |
| CAC40 | #EuronextParis, #francestockmarket, #frenchstockexchange, #BoursedeParis, #frenchstocks, #cac40, #parisstockexchange, #Frenchstockmarket, #frenchstockexchange |
| DAX | #DAX, #GermanyDAX30, #DeutscherAktienindex, #Germanstockindex, #GermanyStocks, #DeutscheBörse, #GermanStockExchange, #FrankfurtStockExchange, #FrankfurtStockMarket, #DAXPerformanceIndex |
| Nikkei | #nikkei225, #日経平均株価, #NikkeiStockAverage, #TokyoStockExchange, #TokyoStockMarket, #Nikkeiindex, #Japanstocks, #JapanStockExchange, #JapanStockMarket, #JapaneseStockMarket, #JapaneseStockExchange, #NikkeiIndexes |

*A2*

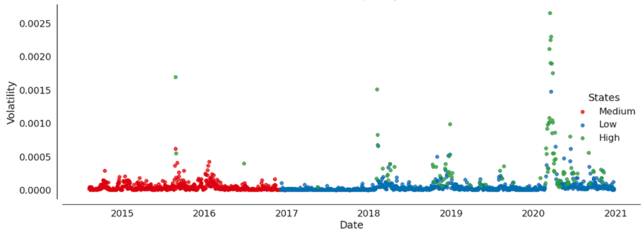
**Table A2**
**Textual Analysis Using Fine-Tuned BERT.** Table A2 provides an example of the textual analysis performed in this study. A given text is the input of algorithm, while the sentiment score is the final output. The Logit columns show the estimated probability as to classification for each sentence. The class (positive, negative, or neutral) with the greatest value determines the label of the given sentence. However, the sentiment score is calculated by subtracting negative from positive probability. The more difference in positive and negative logit values, the more positive or negative the sentence is.

| Input text | Logit | | | Label | Score |
|---|---|---|---|---|---|
| | Positive | Negative | Neutral | | |
| Oil pushes up on US inventory drop, supply restrictions. | 0.7833 | 0.1227 | 0.0939 | Positive | 0.6606 |
| Asian stock markets closed down on January 3rd and European ones opened lower. | 0.0837 | 0.8450 | 0.0711 | Negative | −0.7612 |
| No dodging the oil bullet as emerging economies risk demand hit. | 0.1614 | 0.1697 | 0.6687 | Neutral | −0.0082 |

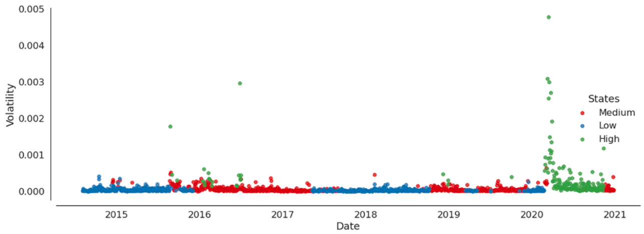
*A3*

We also examine the connectedness by splitting data samples. The aim is to check the connectedness within low/medium/high volatility states over time. To obtain a valid approximation as to dividing the time series into different volatility regimes, we use hidden Markov model which is an unsupervised machine-learning method for regime detection in stochastic time series. From a statistical vantage point, the hidden Markov model provides a more realistic depiction of the dynamics embedded in financial time series than linear models with constant variance. The core assumption of the model is the existence of hidden states that are not directly observable but have an impact on the observable values (observations). The model determines the existing hidden states from the observations. The known observations, in this case, are the returns that are indirectly affected by the hidden regimes of the market. Fitting the hidden Markov model to return data results in volatility regimes detection. From a quantitative finance perspective, the various regimes lead to adjustments of returns through changes in their means, variances or volatilities, covariances, and serial correlations. A first-order hidden Markov model has two assumptions: (i) The probability of a future state depends only on the current state (Markov assumption); (ii) The probability of an output observation depends only on the state that generated that observation and not on any other states or observations (output independence). We use a standard application of hidden Markov model here; further explanations as to model configuration can be seen in Bhar and Hamori (2004).

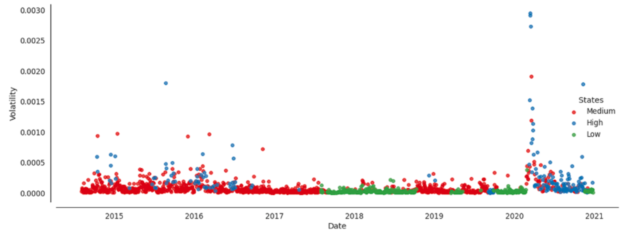
G) DJIA Volatility Regimes



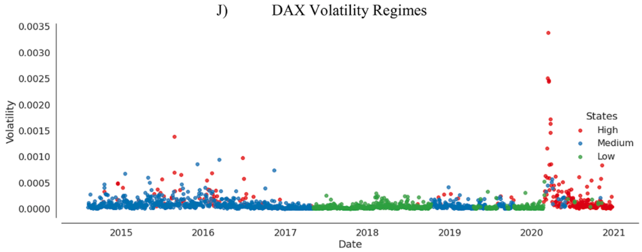

H) FTSE Volatility Regimes



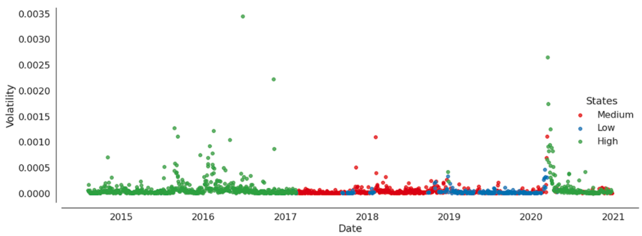

I) CAC40 Volatility Regimes



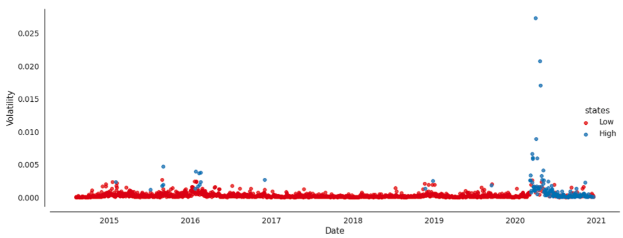

J) DAX Volatility Regimes




K) Nikkei Volatility Regimes




L) Brent Volatility Regimes




(caption on next page)

**Fig. A3.** Visualization of the Obtained Regimes Detected by a Hidden Markov Model. This figure presents low, medium, and high volatility regimes for the US (the DJIA index), the UK (the FTSE100 index), France (the CAC40 index), Germany (the DAX index), Japan (the Nikkei index), and Brent crude oil markets through panels A-F over the period from 04/08/2014 to 22/12/2020 using hidden Markov model for regime detection.

We re-estimate the DY connectedness to obtain the estimations during various volatility regimes for each market. Table A3 presents the duration, mean and variance, and volatility transmitted to each market by corresponding sentiments over the detected regimes for each index. The calculated means and variances are obtained using the return data for each regime. The lowest variance for returns indicates the low-volatile regime, the second-lowest variance shows medium volatility, and the highest variance for returns implies the high-volatile regime for each market. Columns 'news' and 'Twitter' present the contributions of sentiments to the market volatility within each regime. Results show that connectedness is higher over high-volatile regimes in all series which can be indicative of the contagion effect (sharp shocks) coming from news and Twitter to the market. Also, news sentiment sends more volatility to the markets in high-volatile regimes than Twitter sentiment. There is also a lasting connectedness over the periods with lower volatility which documents volatility spillovers from sentiment to the markets. Except for two low-volatile regimes in the CAC40 and Brent, twitter sentiment contributes to market volatility more than or almost equal with the news contributions. During medium sentiment the degree of connectedness varies between Twitter and news sentiment. For the DJIA and the FTSE, Twitter sends more volatility than news, while the opposite is true for the CAC40 and the Nikkei. Although there are periods in which the estimated connectedness is negligible, all the coefficients are statistically significant except for one occasion for the DAX Twitter sentiment (medium volatile regime), which signifies that sentiment cannot affect the market at some points.

**Table A3**

**The DY Static Estimations for Various Regimes.** This table presents the duration, mean and variance, detected volatility regime based on fitting the hidden Markov model to the corresponding return data, and directional volatility connectedness to each market by related news and Twitter sentiments within the detected regimes for each index. Numbers in parentheses are standard errors based on bootstrapping. ** and * denote significance at 5% and 10% levels, respectively. Panel A presents the estimations for the first two periods, while Panel B shows the same estimations for the last periods.

**Panel A.**

| Index | Period I | [Mean, Variance] | Volatility regime | News | Twitter | Period II | [Mean, Variance] | Volatility regime | News | Twitter |
|---|---|---|---|---|---|---|---|---|---|---|
| DJIA | 04.08.2014-02.12.2016 | [0.000353, 0.00007] | Medium | 0.47** (0.039) | 8.1** (0.146) | 05.12.2016-21.02.2020 | [0.00135, 0.000042] | Low | 7.22** (0.085) | 7.53** (0.182) |
| FTSE | 4.08.2014-4.11.2015 | [0.000196, 0.000061] | Low | 3.04** (0.132) | 3.73** (0.115) | 5.11.2015-11.05.2017 | [0.000174, 0.000101] | Medium | 0.47* (0.043) | 1.21** (0.078) |
| CAC | 4.08.2014-24.04.2017 | (-0.000023, 0.000114) | Medium | 2.75** (0.043) | 0.28** (0.05) | 25.04.2017-05.03.2020 | (0.00149, 0.00003) | Low | 5.8** (0.093) | 1.37** (0.065) |
| DAX | 04.08.2014-02.05.2017 | (0.000593, 0.000089) | Medium | 1.16** (0.027) | 0.05 (0.032) | 03.05.2017 –26.02.2020 | (0.000609, 0.000078) | Low | 0.57** (0.043) | 0.54** (0.038) |
| Nikkei | 04.08.2014-15.02.2017 | (0.000225, 0.000261) | High | 1.81** (0.033) | 0.47** (0.039) | 16.02.2017-18.12.2018 | (-0.000183, 0.000153) | Medium | 0.56* (0.025) | 0.38* (0.031) |
| Brent | 04.08.2014-05.03.2020 | (-0.00061, 0.000406) | Low | 1.86** (0.052) | 0.10** (0.013) | 06.03.2020-22.12.2020 | (0.006413, 0.008663) | High | 3.19** (0.106) | 2.19** (0.096) |

**Panel B.**

| Index | Period I | [Mean, Variance] | Volatility regime | News | Twitter | Period II | [Mean, Variance] | Volatility regime | News | Twitter |
|---|---|---|---|---|---|---|---|---|---|---|
| DJIA | 22.02.2020-22.12.2020 | [-0.00575, 0.001069] | High | 12.3** (0.157) | 1.68** (0.163) | — | — | — | — | — |
| FTSE | 12.05.2017-21.02.2020 | [0.000196, 0.000061] | Low | 0.93** (0.049) | 2.47** (0.113) | 24.02.2020-22.12.2020 | [-0.001942, 0.000698] | High | 3.69** (0.212) | 3.39** (0.174) |
| CAC | 06.03.2020-22.12.2020 | (-0.001298, 0.0007) | High | 4.09** (0.178) | 0.44* (0.138) | — | — | — | — | — |
| DAX | 27.02.2020–22.12.2020 | (-0.001649, 0.000728) | High | 1.28** (0.105) | 0.92* (0.076) | — | — | — | — | — |
| Nikkei | 19.12.2018-11.03.2020 | (0.001213, 0.000037) | Low | 0.4** (0.054) | 0.39** (0.048) | 12.03.2020-22.12.2020 | (0.000225, 0.000261) | High | 1.68** (0.054) | 1.21** (0.043) |
| Brent | — | — | — | — | — | — | — | — | — | — |

*A4*

We re-do the estimation using two different measures of volatility to further check the robustness of our results. For this purpose, we estimate the volatility using Garman and Klass (1980) and Rogers and Satchell (1991).

**A) Garman and Klass volatility measure**

Garman-Klass volatility estimator incorporates information about the open, close, high and low prices within a specific time interval.

$$\sigma_t^2 = 0.5\left(\ln(\frac{H_t}{L_t})\right)^2 - (2\ln(2) - 1)\ln(\frac{C_t}{O_t})^2$$

Where $H_t$, $L_t$, $O_t$, and $C_t$ are the maximum, minimum, opening, and closing price, respectively, on day $t$. We calculate the volatility using Equation A4.1 and re-do the analysis. Table A4.1 presents the results for the static connectedness. No significant variation is seen compared with the original results, and all the coefficients are statistically significant. We also estimate the static framework including all sentiment series in the analysis to scrutinize connectedness between volatility in each market and sentiment of other markets. The results are presented in Table A4.2 and are statistically significant. Finally, we examine the dynamic connectedness using a rolling window of 100 days. Fig. A4.1 portrays the volatility connectedness between markets and relevant sentiment series across the rolling subsamples. We observe no significant variations on the connectedness pattern from the original results.

**Table A4.1**

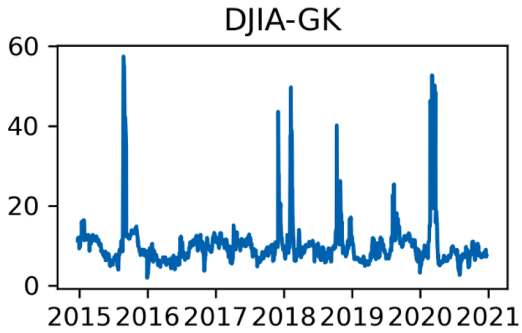
**The DY Static Estimations for Each Market and its Corresponding Sentiments.** This table presents the estimation of static connectedness for the US (the DJIA index), the UK (the FTSE100 index), France (the CAC40 index), Germany (the DAX index), Japan (the Nikkei index), and Brent crude oil markets with their related news and Twitter sentiment series over the entire period from 04/08/2014 to 22/12/2020. The $ij^{th}$ entry represents the directional connectedness, namely the percentage of the forecast error variance of market *i* due to shocks from sentiment *j*. Numbers in parentheses are standard errors based on bootstrapping. ** and * denote significance at 5% and 10% levels, respectively.

| Index | News sentiment | Twitter sentiment |
|---|---|---|
| DJIA | 5.50 (0.0161)** | 1.28 (0.0133)** |
| FTSE | 1.06 (0.0129)** | 3.74 (0.0419)** |
| CAC | 1.78 (0.0104)** | 1.00 (0.0107)** |
| DAX | 0.62 (0.0737)* | 0.98 (0.0736)** |
| Nikkei | 1.73 (0.0805)** | 1.09 (0.0876)** |
| Brent | 2.14 (0.0968)** | 0.97 (0.0101)** |

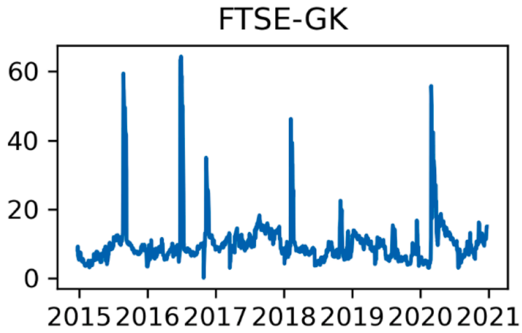
**Table A4.2**

**The DY Static Estimation for all Markets and Sentiment series.** This table presents the estimation of static connectedness for the US (the DJIA index), the UK (the FTSE100 index), France (the CAC40 index), Germany (the DAX index), Japan (the Nikkei index), and Brent crude oil markets with own and other news and Twitter sentiment series over the entire period from 04/08/2014 to 22/12/2020. The $ij^{th}$ entry represents the directional connectedness, namely the percentage of the forecast error variance of market *i* due to shocks from sentiment *j*. Numbers in parentheses are standard errors based on bootstrapping. ** and * denote significance at 5% and 10% levels, respectively.

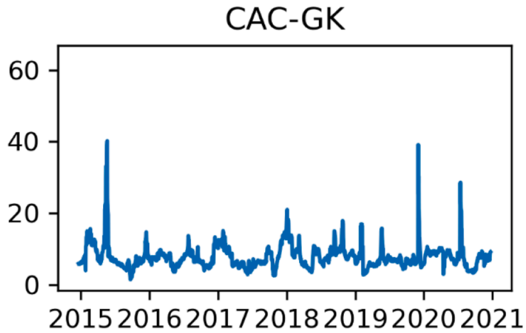
| | DJIA News | DJIA Twitter | FTSE News | FTSE Twitter | CAC News | CAC Twitter | DAX News | DAX Twitter | Nikkei News | Nikkei Twitter | Brent News | Brent Twitter |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DJIA | 3.28** | 1.51** | 2.68** | 0.61** | 0.59** | 0.69** | 1.16** | 0.16** | 1.58** | 1.47** | 2.16** | 0.78** |
| | (0.007) | (0.009) | (0.008) | (0.012) | (0.008) | (0.005) | (0.007) | (0. 005) | (0.007) | (0.009) | (0.009) | (0.006) |
| FTSE | 0.56** | 0.59** | 0.62** | 2.28** | 0.66** | 0.76** | 0.55** | 0.53** | 0.73** | 0.99** | 0.88** | 0.57** |
| | (0.007) | (0.007) | (0.007) | (0.024) | (0.007) | (0.006) | (0.006) | (0.006) | (0.007) | (0.009) | (0.008) | (0.006) |
| CAC | 1.46** | 1.69** | 0.43** | 2.02** | 1.98** | 0.41** | 0.67** | 0.18** | 0.95** | 0.83** | 2.16** | 1.21** |
| | (0.2) | (0.403) | (0.008) | (0.017) | (0.008) | (0.006) | (0.006) | (0.006) | (0.008) | (0.008) | (0.07) | (0.006) |
| DAX | 2.31** | 1.18** | 0.31** | 1.38** | 1.92** | 0.27* | 0.72** | 0.63** | 0.87** | 1.24** | 2.45** | 0.28** |
| | (0.004) | (0.012) | (0.006) | (0.02) | (0.005) | (0.006) | (0.005) | (0.005) | (0.006) | (0.009) | (0.007) | (0.004) |
| Nikkei | 1.04** | 0.77** | 0.22* | 0.96** | 0.86** | 0.64** | 0.33* | 0.77* | 0.98** | 0.69** | 1.03** | 1.09** |
| | (0.005) | (0.006) | (0.006) | (0.05) | (0.006) | (0.005) | (0.005) | (0.009) | (0.006) | (0.006) | (0.05) | (0.009) |
| Brent | 0.72** | 0.36** | 0.81** | 2.08** | 0.89** | 0.25* | 0.6** | 0.31* | 0.92** | 0.72** | 1.15** | 0.92** |
| | (0.008) | (0.008) | (0.009) | (0.028) | (0.008) | (0.01) | (0.008) | (0.009) | (0.008) | (0.007) | (0.008) | (0.009) |



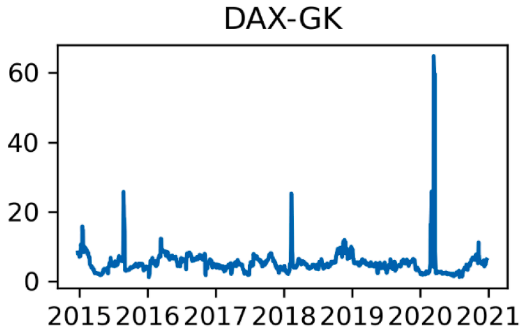

Transmitted volatility to DJIA



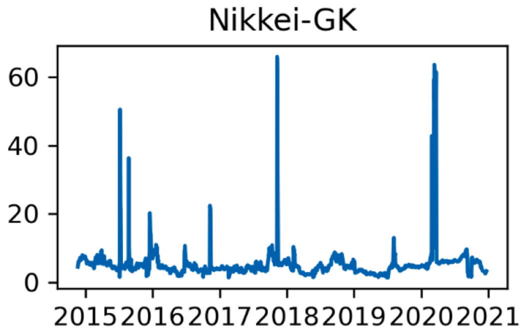

Transmitted volatility to FTSE100



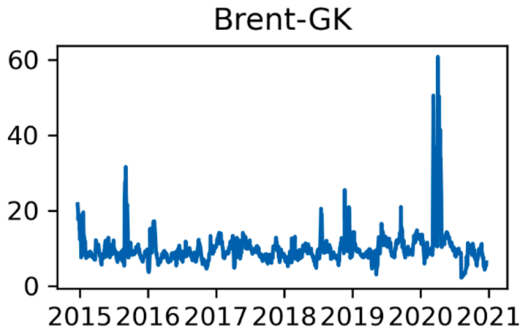

Transmitted volatility to CAC40




Transmitted volatility to DAX




Transmitted volatility to Nikkei




Transmitted volatility to Brent

**Fig. A4.1.** Dynamic Connectedness. This figure presents the robustness check of the transmitted volatility from sentiment to the US (DJIA index), the UK (FTSE100 index), France (CAC40 index), Germany (DAX index), Japan (Nikkei index), and Brent crude oil markets over the period from 04/08/2014 to 22/12/2020 using Garman-Klass measure of volatility.

**B) Rogers and Satchell volatility measure**

Rogers-Satchell volatility estimator also incorporates drift term (mean return not equal to zero).

$$\sigma_t^2 = \ln\left(\frac{H_t}{C_t}\right)\ln\left(\frac{H_t}{O_t}\right) + \ln\left(\frac{l_t}{C_t}\right)\ln\left(\frac{l_t}{O_t}\right) \tag{A42}$$

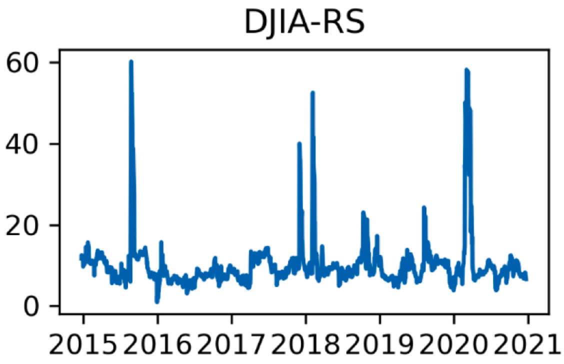
Where $H_t$, $L_t$, $O_t$, and $C_t$ are the maximum, minimum, opening, and closing price, respectively, on day $t$. We calculate the volatility using Equation A4.2 and re-do the analysis. Table A4.3 presents the results for the static connectedness. No significant variation is seen compared with the original results, and all the coefficients are statistically significant. We also estimate the static framework including all sentiment series in the analysis to scrutinize connectedness between volatility in each market and sentiment of other markets. The results are presented in Table A4.4 and are statistically significant. Finally, we examine the dynamic connectedness using a rolling window of 100 days. Fig. A4.2 portrays the volatility connectedness between markets and relevant sentiment series across the rolling subsamples. We observe no significant variations on the connectedness pattern from the original results.

**Table A4.3**
**The DY Static Estimations for Each Market and its Corresponding Sentiments.** This table presents the estimation of static connectedness for the US (the DJIA index), the UK (the FTSE100 index), France (the CAC40 index), Germany (the DAX index), Japan (the Nikkei index), and Brent crude oil markets with their related news and Twitter sentiment series over the entire period from 04/08/2014 to 22/12/2020. The $ij^{th}$ entry represents the directional connectedness, namely the percentage of the forecast error variance of market *i* due to shocks from sentiment *j*. Numbers in parentheses are standard errors based on bootstrapping. ** and * denote significance at 5% and 10% levels, respectively.

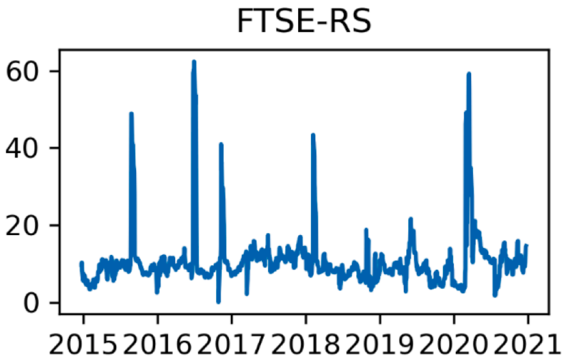
| Index | News sentiment | Twitter sentiment |
|---|---|---|
| DJIA | 4.82 (0.0124)** | 1.16 (0.0156)** |
| FTSE | 0.89 (0.0107)* | 3.44 (0.0343)** |
| CAC | 1.44 (0.01)** | 0.88 (0.0106)** |
| DAX | 0.65 (0.0074)** | 0.87 (0.0076)** |
| Nikkei | 1.4 (0.0853)** | 1.00 (0.0784)** |
| Brent | 2.05 (0.0912)** | 0.9 (0.0991)* |

**Table A4.4**
**The DY Static Estimation for all Markets and Sentiment series.** This table presents the estimation of static connectedness for the US (the DJIA index), the UK (the FTSE100 index), France (the CAC40 index), Germany (the DAX index), Japan (the Nikkei index), and Brent crude oil markets with own and other news and Twitter sentiment series over the entire period from 04/08/2014 to 22/12/2020. The $ij^{th}$ entry represents the directional connectedness, namely the percentage of the forecast error variance of market *i* due to shocks from sentiment *j*. Numbers in parentheses are standard errors based on bootstrapping. ** and * denote significance at 5% and 10% levels, respectively.

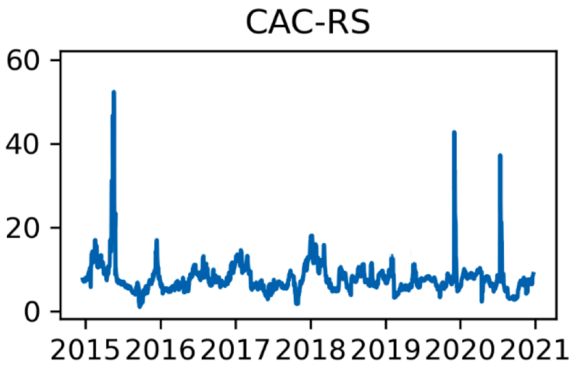
| | DJIA News | DJIA Twitter | FTSE News | FTSE Twitter | CAC News | CAC Twitter | DAX News | DAX Twitter | Nikkei News | Nikkei Twitter | Brent News | Brent Twitter |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DJIA | 2.92** | 1.43** | 2.68** | 0.58** | 0.68** | 0.71** | 1.12** | 0.27** | 1.55** | 1.44** | 2.01** | 0.77** |
| | (0.007) | (0.009) | (0.007) | (0.012) | (0.008) | (0.005) | (0.007) | (0. 005) | (0.007) | (0.01) | (0.008) | (0.005) |
| FTSE | 0.67** | 0.58** | 0.65** | 1.73** | 0.71** | 0.71** | 0.67** | 0.54* | 0.84** | 1.07** | 0.91** | 0.58** |
| | (0.007) | (0.007) | (0.007) | (0.024) | (0.097) | (0.008) | (0.007) | (0.007) | (0.01) | (0.008) | (0.008) | (0.007) |
| CAC | 1.71** | 1.81** | 0.38** | 1.93** | 1.72** | 0.28** | 0.61** | 0.31** | 0.88** | 0.55** | 2.08** | 1.2** |
| | (0.202) | (0.381) | (0.008) | (0.017) | (0.009) | (0.006) | (0.006) | (0.007) | (0.007) | (0.008) | (0.06) | (0.005) |
| DAX | 1.89** | 1.31** | 0.35** | 1.05** | 1.95** | 0.26* | 0.78** | 0.67** | 1.02** | 1.25** | 2.31** | 0.34** |
| | (0.005) | (0.012) | (0.007) | (0.018) | (0.005) | (0.006) | (0.005) | (0.005) | (0.006) | (0.01) | (0.007) | (0.004) |
| Nikkei | 1.03** | 0.93** | 0.25* | 1.05** | 0.66** | 0.65** | 0.37* | 0.75* | 1.07** | 0.68** | 0.87** | 1.23** |
| | (0.005) | (0.006) | (0.006) | (0.05) | (0.005) | (0.006) | (0.005) | (0.009) | (0.006) | (0.006) | (0.05) | (0.009) |
| Brent | 0.65** | 0.43** | 0.79** | 2.34** | 1.00** | 0.27* | 0.68** | 0.34* | 0.92** | 0.73** | 1.21** | 1.07** |
| | (0.007) | (0.008) | (0.008) | (0.028) | (0.007) | (0.009) | (0.008) | (0.009) | (0.008) | (0.008) | (0.008) | (0.009) |



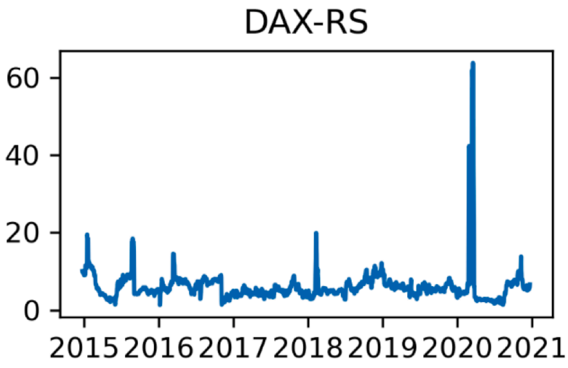

Transmitted volatility to DJIA



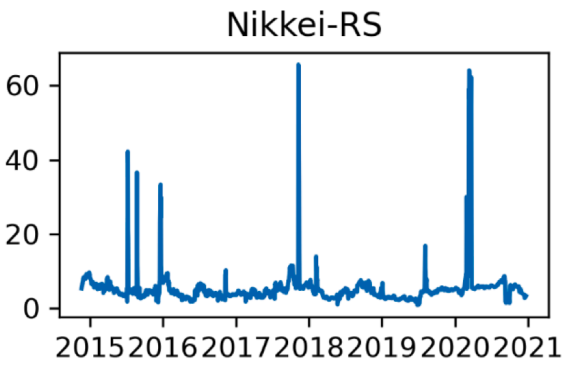

Transmitted volatility to FTSE100



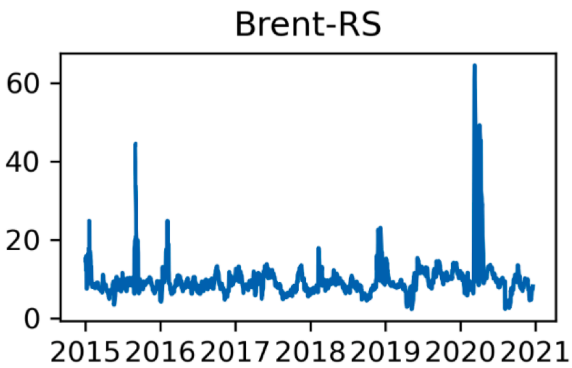

Transmitted volatility to CAC40




Transmitted volatility to DAX




Transmitted volatility to Nikkei




Transmitted volatility to Brent

**Fig. A4.2.** Dynamic Connectedness. This figure presents the robustness check of the transmitted volatility from sentiment to the US (DJIA index), the UK (FTSE100 index), France (CAC40 index), Germany (DAX index), Japan (Nikkei index), and Brent crude oil markets over the period from 04/08/2014 to 22/12/2020 using Rogers-Satchell measure of volatility.

*A5*

We re-do the analysis using the Time-Varying Parameter Vector Autoregression (TVP-VAR) connectedness framework proposed by Antonakakis et al. (2020). This model is designed as an enhancement to the DY framework. The TVP-VAR offers greater flexibility. Central to this framework is the adoption of forgetting factors derived from Koop and Korobilis (2014). These factors facilitate the inclusion of time-varying parameter, enabling the model to capture dynamic relationships with more resilience, especially in situations characterized by shifting connectedness at lower frequencies. A notable strength of the TVP-VAR framework lies in its robustness to limited time-series data and potential outliers. This reduces the potential for data attrition. While our dataset predominantly utilizes high-frequency data, the merits of the TVP-VAR model make it a tool to verify the robustness of our findings. If our findings regarding the spiky pattern in the dynamic connectedness remain consistent even with this distinct modeling approach, it would reaffirm the resilience of our results.

To validate this, we estimate the dynamic connectedness using the TVP-VAR model over a 15-day forecast horizon. Fig. A5 depicts the volatility connectedness among markets and the sentiment series. Although slight variations in connectedness magnitude are noted, the spiky pattern remains evident across all markets. On the whole, while the magnitude of connectedness showed a dampened trend, the distinctive spiky pattern remains consistent.

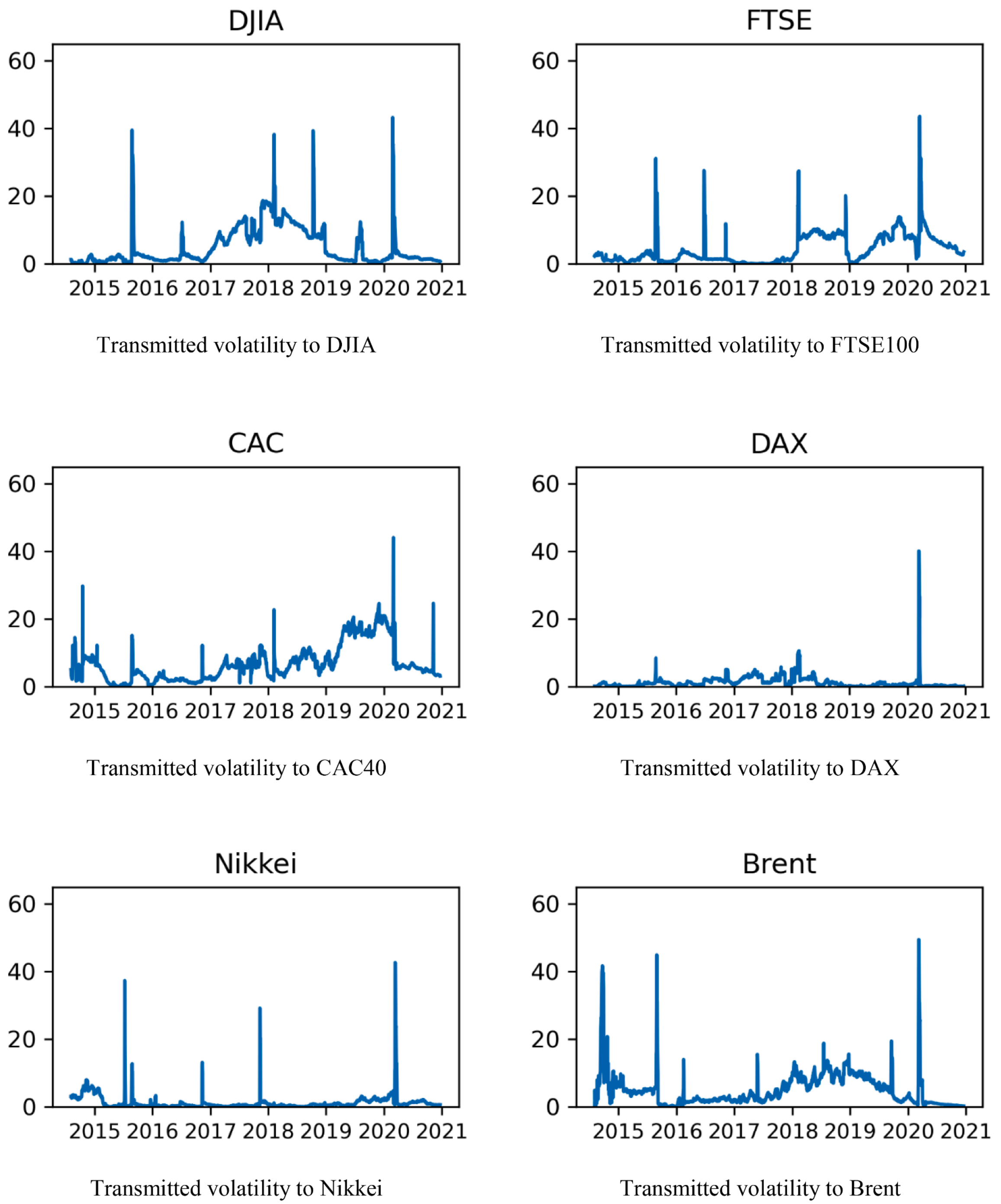



**Fig. A5.** Dynamic Connectedness. This figure presents the transmitted volatility from sentiment to the US (DJIA index), the UK (FTSE100 index), France (CAC40 index), Germany (DAX index), Japan (Nikkei index), and Brent crude oil markets over the period from 04/08/2014 to 22/12/2020 using TVP-VAR framework.

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