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News sentiment and international equity markets during BREXIT period: A textual and connectedness analysis

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Abstract

This study used textual analysis of 34,209 news articles to quantify news sentiment into three main clusters—positive, negative and neutral—before analysing how they co-move with international equity indices, using the time-varying connectedness of Diebold and Yilmaz (2009, 2012). Better understanding of the spillover of news sentiment to stock markets could aid the decision-making of institutional investors when strong uncertainty is present across major economies. We found that limited spillover from news sentiment to equity markets existed for both the European and international indices examined in the analysis, with spillover being stronger among smaller subsets of news articles more relevant for financial market participants. Additionally, the results indicated that, in the full sample, directional spillover was especially strong in times of larger uncertainty concerning BREXIT developments, whereas the smaller subsets, although also displaying stronger spillover during BREXIT uncertainty, revealed additional spillover peaks at times less related to major BREXIT developments. Differentiation between news about UK-based and EU-based companies also showed less spillover from news sentiment regarding EU-based companies, possibly implying that investors saw BREXIT developments as less relevant for the latter.

KEYWORDS

BREXIT, connectedness, international equity, news sentiment, textual analysis

1 | INTRODUCTION

Brexit, which is an abbreviation for "British exit" that refers to the withdrawal of the United Kingdom from the European Union, presents an unprecedented challenge for financial markets participants, especially in the stock market. Large parts of the process have been dominated by strong uncertainty, from the outcome of the 2016 referendum to the complex deal-making process and the rejection of potential deals by the British parliament. As the final negotiation outcome could result in anything between almost no changes and the loss of access to the European Single Market for UK-based companies (Escribano & Íñiguez, 2021; Gottschalk, 2021; Ionescu et al., 2021) and vice versa, the valuation of companies operating in and out of the United Kingdom and the European Union has become inherently more difficult. People tend to choose e-digital over other forms of communication, which enables them to rapidly acquire information. Such behaviour might influence financial markets with sensitivity to news in specific time intervals (for example, 1 min; Gorodnichenko et al., 2021). Concomitantly, the Brexit event is unprecedented, and has therefore received considerable attention in the media.

Since the turn of the century, much effort has been expended to understand the relationship between news sentiment and stock prices. Researchers, such as Mittermayer (2004), have improved the accuracy of predictions of stock price movements based on sentiment analysis of financial news articles. This study takes a slightly different approach, pairing sentiment analysis with the spillover measure developed by Diebold and Yilmaz (2009, 2012) to analyse the influence of news articles about Brexit in a financial newspaper on European and international equity indices. Greater understanding of the spillover of news sentiment to stock markets could potentially help institutional investors make better decisions when uncertainty exists, not only for a single company or industry, but for many multinational corporations and the economies of large nations.

We summarize our research design as consisting of three main steps. First, we obtained newspaper text data from the Financial Times (FT) by which to generate sentiment scores based on textual analysis. The process was supported by data standardization (dictionaries, negation and construction). Second, we separated the FT articles into sub-groups to consider differences in sentiment. Finally, we estimated the financial connectedness between news sentiment and financial indices using the spillover measures developed by Diebold and Yilmaz (2009, 2012). We also evaluated the difference in spillover effects among the aforementioned article sub-groups to obtain further insights. This study was motivated by Diebold and Yilmaz (2009, 2012), because their method permits analysis of high frequency data (such as at 5-min intervals) without losing information (Katsiampa et al., 2019; Zhang & Ma, 2021). Further, this methodology is suitable for financial research studies due to its improvement over metrics such as time-varying estimators, dynamic correlation and so forth. In addition, news released on the financial markets every minute conveys valuable information; therefore, estimating spillover effects could capture market movements as well as market structure in terms of returns (Bouri et al., 2021) and volatility (Ameur et al., 2021).

The key findings can be summarized as follows: Negative articles (67% of articles) greatly outnumbered positive articles (2.9% articles) during the Brexit period. In addition, news spiked around the time of the Brexit referendum, the day after the vote, and other crucial days. Regarding spillover estimations, the total estimated contribution of the spillovers (financial markets and news sentiment) was significant, at 39.16% (5-min data) and 26.0% (60-min data). More noticeably, there existed time-varying connectedness between news sentiment and financial markets (both European and international scope). Finally, there were disproportionate effects of BREXIT news sub-categories on different financial markets. Our study contributes to the extant literature in three central ways. First, to the best of our knowledge, this is the first study to employ financial news from a newspaper to quantify news sentiment about Brexit events. Second, we found a time-varying relationship between news sentiment and international equity markets, using cutting-edge quantitative methods to determine connectedness. We found that spillover from news sentiment to equity markets, although small, existed for both European and international indices and was stronger in times of uncertainty. Additionally, news potentially more relevant for financial market participants exhibited more substantial spillover effects than did a more general dataset. Differing results for information about UK-based and EU-based companies were also found. Our unique high-frequency dataset represents the third contribution of this research. Analysing such data (from 5- to 60-min frequency) could increase understanding of the structure of financial markets and the immediate impact of financial news in times of political and economic uncertainty.

2 | LITERATURE REVIEW

Today, there is a sizeable and growing collection of financial literature on the topic of news sentiment analysis, with researchers trying to understand whether and how financial news articles or company press releases can be used to predict stock price movements. Tetlock (2007) was among the first to provide empirical evidence that news media content could predict stock market performance. Using the General Inquirer, a program for textual analysis, and the Harvard psychosocial dictionary, he created a measure of media pessimism based on articles in the Wall Street Journal "Abreast of the Market" column. Tetlock (2007) then used basic vector autoregression to estimate the connection between this measure and the American stock market. He found that "high levels of media pessimism robustly predict downward pressure on market prices" (p. 1140) and that "unusually high or low values of media pessimism forecast high market trading volume" (p. 1140). Loughran and McDonald (2011) later developed a list of positive and negative words more suited for textual analysis in a financial context. Both are examples in which a dictionary-based approach was chosen to determine the sentiment of a document.

Another common approach among researchers trying to use sentiment analysis to predict stock market developments is the use of machine learning techniques, such as naïve Bayes algorithms (see, for example, Khedr et al., 2017) or support vector machines (SVM). Mittermayer (2004) used SVM as the basis of his NewsCATS (News Categorization and Trading System), which can automatically categorize company press releases and "derive trading rules for the corresponding stock" (p. 3). In a market simulation, NewsCATS can "significantly outperform a trader randomly buying and shorting stocks immediately after the publication of press releases" (p. 9). However, machine learning approaches are not suitable for analysing the influence of news sentiment in Brexit articles on stock markets, as they are used to predict stock market developments and not to further understand a possible relationship between news sentiment and stock market behaviour; this is why we used the aforementioned dictionary-based approach for sentiment analysis.

It is also worth noting that the Brexit literature is well-established. There are numerous studies of the economic consequences of this event; for example, UK services exports (Douch & Edwards, 2021), currency values (Dao et al., 2019), market co-crashes (Ben Ameur & Louhichi, 2021), and so forth. Brexit can be considered the event uncertainty (Husted et al., 2020) that substantially created both market shocks and market information flow (Nishimura & Sun, 2018). Beyond the news within Britain, Brexit was an international event, which exerts effects of considerable magnitude on different financial markets, such as the international FX market (Dao et al., 2019), global equity indices (Nishimura & Sun, 2018), sovereign CDS, and 10-year interest rates among 19 predominantly European countries (Belke et al., 2018), among others. Undoubtedly, the Brexit event could be seen as a political disaster for the European countries, and it likely will have long-term consequences for the financial markets. With the development of the Internet, there are increasingly many studies of the real-time impacts of news on financial markets. A body of literature has highlighted market reactions within 30 min of macroeconomics news (Kurov et al., 2019). Similarly, trading volume and volatility significantly change after public news announcement (Bollerslev et al., 2018; Brogaard et al., 2018). Both studies illuminate the relationship between market changes and belief disagreements after critical events. Before explaining how our study differs from the existing literature, we summarize the relevant studies of Brexit news and financial markets.

According to agent-based simulations, financial stability is one of the biggest concerns for both the UK and European countries (Samitas et al., 2018). Moreover, market seemed to experience high volatility during the Brexit referendum (Belke et al., 2018; Stoupos & Kiohos, 2021). Further, Arshad et al. (2020) offered insights into the specific industries that might suffer from the Brexit event (i.e., banking, real estate investment trusts and technology). Most noticeably, financial services between Europe and the United Kingdom become more challenging, implying the need for a timely bilateral agreement (Armour, 2017). By drawing on 17 selected Brexit events, Hudson et al. (2020) explored their effects on both risk and returns, implying support for rational asset pricing models, even given an unprecedented event (i.e., Brexit). However, to the best of our knowledge, no study has considered the impacts of news, especially the tone of journalists, on the financial markets during the Brexit period. Specifically, sought to understand how and when spillover occurred from news sentiment in articles about Brexit changes between 2015 and 2019 to European and international financial markets, and to determine possible underlying reasons. It is conceivable that in times of significant, complex developments, investors turn to financial journalists, who combine information and knowledge from different sources, to understand how these developments will potentially affect companies, sectors, or the economy in general. Although recent literature has explored the connectedness of financial markets (Aristeidis & Elias, 2018; Ben Ameur & Louhichi, 2021), our study illuminates the relationship between sentiment news and financial markets during specifically the Brexit period.

Additionally, it is plausible that spillover is more substantial for European than international indices, as the European companies and economies are likely more affected by Brexit. Clearly, the Brexit event was associated with high disagreement among the British population according to the Brexit referendum vote (Gorodnichenko et al., 2021). In turn, this study considers most of the financial newspaper news to capture journalists' tone regarding the event. Then, the impacts on European and international markets are explored.

In summary, after reviewing the existing literature, we distinguish our study based on three unique aspects. First, this is the first work to examine the tone of newspaper articles regarding Brexit during the period from 2015 to 2019 by clustering words using sentiment scores. While Brexit did not reach high agreement among citizens, the phenomenon might be more pronounced in the newspapers. Second, instead of using daily data, we used high-frequency data with different time intervals to test the connection between the tone of news articles and international equity markets. Finally, although Diebold and Yilmaz's (2009, 2012) studies focused on daily data, we developed a model to utilize our high-frequency data. Therefore, this paper newly illuminates the relationship between news sentiment and the stock market over the Brexit period.

3 | DATA AND METHODOLOGY

3.1 | News data collection

The data for the analysis was taken solely from the website of the FT.[1] In this case, the international version of the website was used; however, this did not affect the search results or the number of articles available. The FT was chosen due to its position as an internationally renowned newspaper with an emphasis on financial and business news. With more than three-quarters of FT readers accessing the newspaper digitally (Eriksson, 2019), the website is likely a source of news for investors interested in Brexit developments worldwide.

In the first step of gathering the data, all articles with some reference to Brexit were selected (this was carried out by simply searching for the term "Brexit" on the website). For the 5 years to be considered (1 January 2015–31 December 2019) this yielded a total of 34,209 results. To increase the relevance of the articles, a topic filter was employed to only show articles covering the topic of "Brexit", which left a total of 14,404 search results for analysis. With some of these search results being videos, live tickers, or other unreadable formats, 13,132 articles were available for analysis.

3.2 | Sentiment scoring

The goal of analysing the news data was to determine the sentiment score of each article. To provide a better overview of the data, the news articles were classified into three categories: "positive sentiment", "negative sentiment" or "neutral sentiment". First, all text, headlines and body received standard text pre-processing to enable the textual analysis. Subsequently, they were evaluated using the Loughran-McDonald financial dictionary and assigned a sentiment score given the relative use of positive and negative words. The sentiment score was later used in the calculation of spillover from news to indices. Numerous studies have used textual analysis to explore the relationship between content and financial markets, such as newspaper columns (Tetlock, 2007), internet message board postings (Antweiler & Frank, 2004), firms' annual reports (Buehlmaier & Whited, 2018). The body of text and headlines sometimes do not fully reflect the sentiment of writers. Loughran and McDonald (2016) noted that textual analysis depends on the document narratives. Therefore, having both news and headlines could provide much valuable information (Buehlmaier & Whited, 2018; Seki & Shibamoto, 2017). Furthermore, Loughran and McDonald (2016) indicated that misspecification could occur when misidentifying headings and the length and content of the subsequent news. Investors sometimes read headlines to obtain information quickly; however, they often read the whole body of text to process the information (Glasserman & Mamaysky, 2019). In summary, our method analysed the effects of both headlines and body text as different aspects of information on international financial markets.

Compared to other works in the field of sentiment analysis regarding news, only a limited amount of text pre-processing was employed in this work. Here, we relied solely on tokenisation and data standardization.

1. Tokenisation: The full text is split into tokens, which each represent a single word.
2. Data standardization: All words in headlines and article bodies are transformed into lower case, for consistency.

Unlike many other papers that analysed the effects of news sentiment on stock markets or specific stocks, processing techniques such as stop-word removal or stemming, as used by Khedr et al. (2017) and Mittermayer (2004), were not employed in this analysis. Stop-word removal is the removal of words such as articles or prepositions, which cannot be used to determine sentiment and are therefore not relevant for sentiment analysis. Stemming techniques are applied to remove prefixes and suffixes (e.g., de-, pre-, -ed, -ing) to reduce the number of total features in a document and to improve the performance of a model. Both methods are common in natural language processing; however, in this analysis they would be counterproductive, as the removal of stop words would remove words such as "no" or "not" and other negation words, which were essential to the text evaluation. Since stemming techniques are primarily applied to increase the speed at which a computer can analyse a document, they were not required in this analysis as the program was not intended to work with dynamic data; thus, the dictionary employed could consider text that was not reduced to word stems. Three steps of text evaluation followed:

1. Dictionaries: To be able to define the sentiment of a text, each word was compared to a dictionary of positive and negative words. The two most commonly used dictionaries for sentiment analysis are the General Inquirer's Harvard IV-4 psychosocial dictionary, as used by Tetlock (2007), and the list of positive and negative financial words developed by Loughran and

McDonald (2011). While Tetlock used the dictionary to analyse the "Abreast the Market" column in the Wall Street Journal, Loughran and McDonald developed their dictionary to analyse the sentiment in company 10-K reports. While Tetlock's work seemed more relevant in the context of this study, Heston and Sinha found that using the Loughran-McDonald dictionary on a set of Reuters news articles led to better predictions of stock returns than when using the more general Harvard dictionary. Thus, for this analysis, the financial word list developed by Loughran and McDonald was used.

2. Negation: A list of negation words (see Appendix A) was used to check for negation in sentences. If a negation word was found up to three words before a positive or negative word, the evaluation of that word was inverted.
3. Sentiment score: The approach to determine the article score was similar to Feldman et al. (2011). The number of positive and negative sentiment words in the text were summed. The sentiment score was determined the following:

$$S = \frac{P-N}{P+N} \tag{1}$$

where P and N indicate the number of positive and negative instances, respectively, and S describes the sentiment polarity of the article, which can be between −1 and 1. The calculated sentiment score was used to classify each observation into one of three categories. Sentiment polarity greater than 0.33 indicated "positive sentiment", whereas sentiment polarity below −0.33 indicated "negative sentiment". If the sentiment score was between 0.33 and −0.33, inclusive the article was classified as "neutral". This classification of articles was solely used to obtain an overview over the dataset and was not relevant for the measurement of spillover.

The body and title of articles were first analysed separately, which led to markedly different results. The titles had an average sentiment score of −0.205, with 859 positive, 8709 neutral, and 3564 negative articles. The article bodies had an average sentiment score of −0.415, with 388 positive, 3967 neutral, and 8777 negative articles. This significant difference in results can be explained by the lack of sentiment words in the titles. The average length of titles was only 8.8 words (compared to 707.5 words for the article body), and 8528 titles lacked a single sentiment word (compared to 56 article bodies). The combined analysis of headlines and body revealed an average article length of 716.3 and an average sentiment score of −0.419, with 390 positive, 3893 neutral, and 8849 negative articles. The similarity of the sentiment of article bodies compared to the combined analysis highlights the low informative power of the titles. Figure 1 visualizes the distribution of positive, neutral and negative news articles over the 5 years on a daily basis.

Several interesting observations can be made about the news data. Initially, the negative articles (67% of articles) greatly outnumbered the positive articles (2.9%), consistent with the negative average sentiment score. On average, there were approximately 2.44 times as many negative words in articles as there were positive words. If one assumed total objectivity within the articles and the

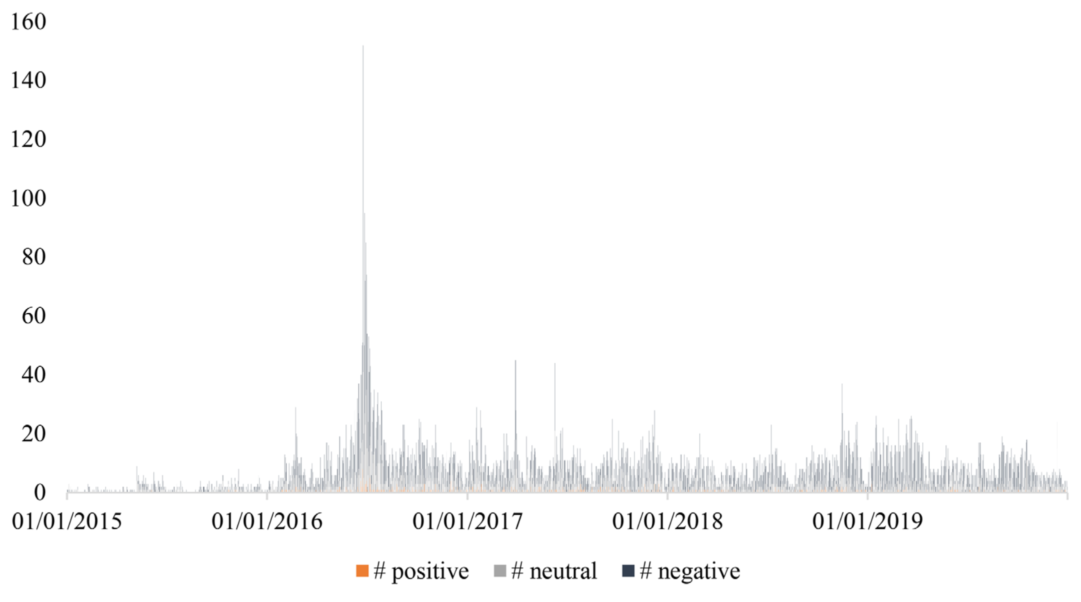


FIGURE 1 Number of positive, neutral and negative news articles on a daily basis. [Colour figure can be viewed at wileyonlinelibrary.com]

sentiment analysis process, this dominance of negative articles and the negative average sentiment could lead to the conclusion that Brexit was objectively negative. However, two factors could potentially reduce the objectivity of the articles. First, the authors of the articles could have a personal positive or negative view of Brexit. In either case, this subjective opinion could reduce the objectivity of the articles. Thus, the average negative sentiment of Brexit articles could be partly due to the authors' subjective opinions. Additionally, the large share of negative articles could be explained by what is commonly referred to as "bad news sells". Trussler and Soroka (2014) showed that participants "exhibit a preference for negative news content" (p. 360). However, as the average sentiment score of the article titles was higher than that of the article bodies, and the FT is renowned as a credible news source, this is most likely not a feasible explanation of average negative sentiment score of the articles. Thus, when assuming journalistic objectivity by FT authors and dismissing the possibility of sensationalism, the sentiment score can be seen as a generally objective measurement of the sentiment surrounding Brexit. Additionally, there were several "spikes" in the data, most notably around the time of the Brexit referendum. In the week of and the week after the referendum, a total of 809 articles concerning Brexit were published, with a peak of 152 articles on 24 June 2016, the day after the vote. Three more peaks appeared on 29 March 2017, the day Article 50 of the Treaty on the European Union was triggered, 9 June 2017, the day after a snap election was held in the United Kingdom, and 15 November 2018, the day after Prime Minister Theresa May had finalized her Brexit deal. A final peak occurred on 13 December 2019, the day after the UK general election.

Within the news dataset, several subsets were defined to study whether differences in spillover existed for different topics. The grouping of articles and naming the different topics was according to the FT. The topics selected for subsets were "UK Business & Economy", "Markets" and "Companies", which in turn had two subsets, namely "UK Companies" and "EU Companies". All articles in the subsets were part of the original dataset of 13,132 "Brexit" articles; however, it was possible for one article to be classified into multiple topics at once. For example, 822 articles belonged to both the topic "UK business & economy" and "Companies", while 236 articles belonged to both the topic "EU Companies" and "UK Companies". These overlaps were unsurprising since the activities of large companies undoubtedly affect the UK economy, and many companies exist that are active both in the UK and the rest of the EU.

Again, several interesting observations can be made about the subsets of the data. When accounting for the overlap of articles for different topics, the subsets former only a little over half of the total articles on the topic "Brexit". This indicates that only approximately half of the articles about Brexit covered topics that were likely relevant to investors. The average length of articles varied among subsets. While the average length of articles in full dataset was 716.3 words, the "UK Business & Economy" articles were almost 50 words longer on average, at 762.1 words, and articles in the "Markets" and "Companies" datasets were over 50 words shorter, at 646.5 words and 655.8 words, respectively. Although they differed in length, datasets had c. 3.05% sentiment words per article on average. The only outlier was the "Markets" dataset, with a comparatively high share of 3.37% sentiment words per article on average. Probably the most interesting observation is the difference in average sentiment score among subsets. While the "UK Business & Economy" dataset had an average sentiment score of −0.421 and was therefore quite similar to the "*Brexit*" dataset, with an average sentiment score of −0.419, the "Markets" and "Companies" datasets diverged quite sharply, with an average sentiment score of −0.449 and −0.403, respectively. These sentiment scores indicate that, on average, there were c. 2.63 and 2.35 times as many negative words in an article than there were positive words, respectively. Within the "Companies" dataset, there was also a notable difference between the "UK Companies" and "EU Companies" subsets, with a −0.399 average sentiment score for the former articles and a −0.438 average sentiment score for the latter articles. This difference in average sentiment score may imply that the Brexit and its consequences were perceived as more negative for EU-based companies than for UK-based companies. Our information can be illustrated in Table 1. However, this implication appears counterintuitive, given that most articles were written when the nature of a Brexit deal was unclear. Thus, UK-based companies faced considerable uncertainty and could have, in the worst case, lost access to the European Single Market and the EU customs union. In contrast, EU-based companies could have, in the worst case, only lost access to the British market.

3.3 | Financial data

The financial data for the GFEVD was gathered using tickstory.[2] tickstory enables the downloading of historical tick data using Dukascopy of Dukascopy Bank SA as a free data source. This approach was chosen because due to the low predictability of stock and thereby index movements, the shortest possible intervals between data points were required to measure significant spillover. Accessing index data at a 1-min intervals from elsewhere would

TABLE 1 The summary of the most relevant facts about the different datasets.

Topic/dataset	No. of articles	Average length (% sent. words)	Average sentiment	Positive articles	Neutral articles	Negative articles
Brexit	13,132	716.3 words (3.11%)	−0.419	390 (3.0%)	3893 (29.6%)	8849 (67.4%)
UK business & economy	3545	762.1 words (3.07%)	−0.421	70 (2.0%)	1082 (30.5%)	2393 (67.5%)
Markets	1647	646.5 words (3.37%)	−0.449	42 (2.6%)	454 (27.6%)	1151 (69.9%)
Companies	2661	655.8 words (2.99%)	−0.403	127 (4.8%)	799 (30.0%)	1735 (65.2%)
UK companies	854	682.1 words (3.03%)	−0.399	38 (4.4%)	265 (31.0%)	551 (64.5%)
EU companies	880	677.4 words (3.05%)	−0.438	30 (3.4%)	249 (28.3%)	601 (68.3%)

Note: All articles in the subsets are part of the original dataset of 13,132 "Brexit" articles.

have been beyond the scope of the resources available for this study. One disadvantage of using Dukascopy as a data source is that it only has historical prices for contract for differences (CFD) on the relevant indices. However, a correlation analysis of 2016 closing prices of the FTSE 100 using Thomson Reuters Eikon as a data source and the Dukascopy contracts for the difference (CFD), 2016 daily closing prices showed a correlation of 99.8%. Thus, although it is not an exact representation of the actual index prices, all further discussion assumes that the Dukascopy CFD data is representative of the actual index prices.

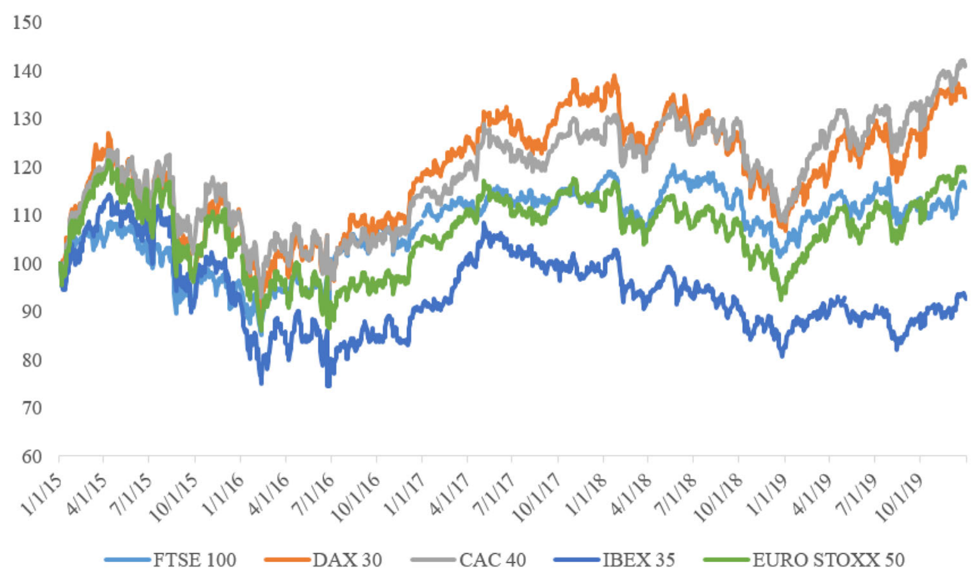
Besides the main British index, the FTSE 100 (termed FTSE hereafter), four more European indices were selected for the GFEVD analysis. These were the indices of three of the four largest economies in the European Union as measured by GDP (International Monetary Fund, 2019), namely Germany (DAX 30, termed DAX), France (CAC 40, termed CAC), and Spain (IBEX 35, termed IBEX), and the pan-European index EURO STOXX 50 (termed STOXX). The Italian FTSE MIB 40 had to be excluded from the spillover analysis due to a lack of data in the crucial period from early 2015 to mid-2016 (until after the Brexit referendum). All three countries are among the 10 largest trading partners of the United Kingdom and in 2017 together they accounted for over 40% of the total trade between the United Kingdom and the European Union and c. 20% of the total trade volume of the United Kingdom (McCrae, 2019). Due to this level of economic interaction and the corresponding interest of financial markets, the indices were considered a reasonable proxy for the influence that Brexit complications could have on each of the country's largest companies and their economy. Thus, these countries were interesting subjects for the observation of potential spillover. The STOXX acts as an indicator of general development in the Eurozone (thereby excluding the United Kingdom); however, it is predominately formed of companies based in one of the three previously mentioned Eurozone economies.

The European equity indices began the year with a short slump, with the Spanish and pan-European indices down c. 5% compared to the start of the year in the first week. Then, most equities gained sharply until mid-April, with the DAX up 25% since the beginning of the year. The FTSE was left relatively undisturbed by these losses and gains. In August 2015, slowing economic growth in China and devaluation of the yuan led to a flash crash across most of the indices covered in this analysis. Although there was some recovery throughout October and November, selloffs in December left all indices below the pre-August levels at the end of the year. Extremely low oil prices and a negative interest rate in Japan led to tumultuous financial markets again in mid-February 2016, when substantial losses were quickly followed by equally strong gains. The result of the Thursday Brexit vote in June led to large selloffs across all European indices on Friday and a smaller bounce back the following Monday. However, the shock of the vote was relatively short-lived, with most indices recovering to pre-vote values within the next 2 months. Most notably, the FTSE recouped all losses by the following Friday. The U.S. presidential election in November 2016 had a short shock effect on European equities, but they finished the year with a strong rally in December. This rally turned into a steady rise for the first 6 months of 2017 with a sizeable spike around the time of the French presidential election. Although there was some reversal until September, all indices except the IBEX experienced some gains in the final months of the year. Gains in January 2018 were fuelled by the U.S. Tax Reform Bill signed at the end of 2017, but the first week of February was marked by heavy losses. Although there were some more robust gains in May, the China – United States trade war and uncertainty about Brexit overshadowed the rest of the year, which was characterized by continuous losses and left the FTSE and the DAX down more than 12% and 18%, respectively. These heavy losses were largely reversed in 2019, which was characterized by continuous gains with some smaller corrections in May and August. The FTSE finished the year particularly strongly after the Conservative Party of Mr. Boris Johnson won the United Kingdom general election mid-December. The CAC and the DAX gained over 25% in 2019, while the FTSE finished the year up 12%.

Although there was some variation in the extent to which the different European indices reacted to specific events, the general movements of the selected indices were very similar, especially when reacting to larger shocks. This is consistent with Wang et al. (2018), who argued that world stock markets are more closely correlated during crises. The close connection of the German DAX and the French CAC, as described by Wang et al. (2018), can also be seen. Figure 2 visualizes the development of the selected European indices over the time-period from 2015 to 2019.

To enable an international comparison, three international indices were also selected for the GFEVD analysis. The first was the S&P 500 (denoted S&P), given that the United States is the largest single trading partner of the United Kingdom (McCrae, 2019). A disruption of trading relations between the UK and the European Union could therefore see trading volume with the United States growing. Thus, developments in the Brexit process could have led to more significant spillovers to the S&P than usual. Since the spillover measure employed also considered spillover between indices (although this is not the focus of this paper), the leading role the US market has for European markets was adjusted for through inclusion of the S&P. With China being another major trading partner of the United Kingdom, the Hong Kong Hang Seng Index (termed Hang Seng) was selected due to both its closeness to the Chinese capital markets, as described by Wang et al. (2018), and Hong Kong's past relationship with the United Kingdom. Australia, as a country with close economic and political ties with the United Kingdom and a member of the Commonwealth of Nations, could also benefit from a distancing between the UK and the EU post-Brexit; thus, the S&P/ASX 200 (termed ASX) was also selected. Although the availability of data limited the selection of international indices, the selected indices were considered suitable for analysis of the influence of the Brexit headlines worldwide.

Due to the interconnectedness of global stock markets, many of the events that greatly influenced the European indices between 2015 and 2019 also affected the international indices. For example, both the August 2015 flash crash and the selloffs in mid-February 2016 affected all of the international indices with similar strength. They were equally impacted by the 2016 Brexit vote but recovered considerably faster than did the European indices. The S&P and the ASX were down shortly before the U.S. presidential election but recovered quickly, while the Hang Seng remained on a downward trend until the end of the year. The year 2017 was very strong for both the Hang Seng and the S&P, which were up over 35% and



Notes: The figure represents the changes of European indices over the period from 2015 to 2019 during the BREXIT time.

FIGURE 2 Development of the selected European indices from 2015 to 2019 indexed to 100. The figure represents the changes of European indices over the period from 2015 to 2019 during the BREXIT time. [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE 3 Development of the selected international indices from 2015 to 2019 indexed to 100. (EURO STOXX 50 added as a visual comparison). [Colour figure can be viewed at wileyonlinelibrary.com]

over 19% by the end of the year, respectively, whereas the Australian index spent most of the year in sideways movement with a small rally at the end of the year. The S&P and the Hang Seng extended their 2017 gains until the end of January 2018, before being hit by sharp selloffs in February. Weighed down by the ongoing trade war, the Hang Seng lost consistently throughout the rest of the year, while the American index recovered to an all-time high in September 2018, before heavy losses in the final 3 months of the year wiped out most of the excess gains compared to the Hang Seng. Similar to the European indices, the first 4 months of 2019 were marked by continuous gains for the international indices before corrections in May and August, with the China – United States trade war escalating. Due to the aforementioned closeness of Chinese and Hong Kong financial markets, these corrections were reflected markedly in the Hong Kong index, while the ASX was relatively undisturbed. Thus, the Hang Seng finished the year up only c. 9%, the S&P climbed to record highs and was up over 28% at the end of the year and the Australian index gained over 18% by the end of the year.

Although the differences among the international indices were considerably larger than those among the five European indices, in times of larger shocks, some co-movement of two or all three of the international indices was observed. Again, this is consistent with Wang et al. (2018). Figure 3 visualizes the development of the selected international indices from 2015 to 2019, with the STOXX added to enable a visual comparison between the development of international and European indices.

After collecting the financial and news data, we followed the literature (Barndorff-Nielsen et al., 2009; Dimpfl & Peter, 2014; Hollstein et al., 2020; Khademalomoom & Narayan, 2019) to process our data. In doing so, we chose the overlapping data from the markets and removed all non-trading days and recording errors. Therefore, we particularly focused on the overlapping trading period, which offered simultaneously processed information (Dimpfl & Peter, 2014). In this process, we did not consider the confounding effects of overnight news on leading or lagged markets (Chan, 1992; Lockwood & Linn, 1990). Similar to Groß-Klußmann and Hautsch (2011), we accessed the news releases with GMT time stamps of up to a millisecond precision. We chose different window horizons to capture the sensitivity of news releases, which is discussed in detailed in the following sections.

3.4 | Definition and measurement of spillovers

To assess the influence or, more precisely, the spillover, that the news articles have on the various indices, a forecast error vector decomposition in a generalized VAR framework, hereafter denoted as GFEVD, as described by Diebold and Yilmaz (2012), is employed. The so-called Spillover Index, as developed in Diebold and Yilmaz (2009), focuses on variance decompositions in an N-variable VAR, which allow "to split the forecast error variances of each variable into parts attributable to the various system shocks" (p. 159). It can be used to determine to what extent shocks to a variable i or j explain the error variance in forecasting i or j, respectively. As Diebold and Yilmaz (2012) described, using a simple VAR framework could lead to order-dependent results due to Cholesky factor orthogonalization. Since a generalized VAR framework "eliminates the possible dependence of the results on ordering" (p. 58) and "allows correlated shocks but accounts for them appropriately using the historically observed distribution of the errors" (p. 58), it is the basis of the GFEVD. As described in Diebold and Yilmaz (2012), the following spillover calculations of the return (x) in the time-period (t) are based on:

A covariance stationary N-variable VAR(p), $x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$ where ε (residual) $\sim (0,\Sigma)$ is a vector of independently and identically distributed disturbances (i.d.d). Saying differently, Σ denotes the variance–covariance matrices or residuals. The moving average representation is $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where the $(N \times N)$ coefficient matrices A_i follow the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$, with A_0 being an $(N \times N)$ identity matrix and with $A_i = 0$ for $i < 0$ and the Φ represents the set of estimated coefficients.

Diebold and Yilmaz (2012) defined that own variance shares as the fractions of the H-step-ahead error variances in forecasting xi that are due to shocks to x_i, for $i = 1, 2, \ldots, N$, and cross variance shares, or spillovers, as the fractions of the H-step-ahead error variances in forecasting xi that are caused by shocks to x_j, for i,j = 1, 2, ..., N, where i ≠ j.

Following Koop et al. (1996) and Pesaran and Shin (1998), Diebold and Yilmaz (2012) denote the H-step-ahead forecast error variance decompositions by $\theta_{ij}^{g}(H)$, for $H = 1,2, \ldots$, as:

$$\theta_{ij}^{g}(H) == \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h' \Sigma e_i\right)} \tag{2}$$

In which, Σ is the variance matrix for the error vector ε, σ_{jj} is the *SD* of the error term for the j^{th} equation, and e_i denotes the selection vector with 0 and 1. In which, 1 for the value at ith element and the remaining positions have zeros. To contain the current information in the variance decomposition matrix in the calculation of the spillover index, this approach normalizes each entry of the variance decomposition matrix by the row sum as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{3}$$

where H-step-ahead forecast error variance decompositions $\theta_{ij}^{g}(H)$ were defined before. Then the Equation 3 indicates the normalized values. Following Diebold and Yilmaz (2012), the total spillover index is defined as:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \bullet 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \bullet 100 \tag{4}$$

with $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$. Within the scope of this work, the total spillover index measures how both spillovers of news sentiment and return shocks in the indices contribute to the total forecast error variance.

Because the total spillover index does not allow for a distinction between the contribution of spillovers caused by news sentiment and spillovers caused by return shocks due to other, unrelated events, a measure of directional spillovers can be used as a more appropriate tool to study the effects of the sentiment of newspaper articles. Following Diebold and Yilmaz (2012), the directional spillovers from variable *i* (i.e., the sentiment of the news articles) to all other variables j (i.e., the return of the different indices) is defined as (in which H-step-ahead forecast error variance decompositions $\theta_{ij}^{g}(H)$ were defined before):

$$S_{\cdot i}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \times 100 \tag{5}$$

The directional spillover from the news sentiment to the indices returns can be understood as positive/negative return shocks following the release of news articles with positive/negative sentiment. The directional spillovers from all other variables j (i.e., the return of the different indices) to variable *i* (i.e., the sentiment of the news articles) is defined as (in which H-step-ahead forecast error variance decompositions $\theta_{ij}^{g}(H)$ were defined before):

$$S_{i\cdot}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \times 100, \tag{6}$$

which would be understood as positive/negative sentiment in news articles following positive/negative return shocks. However, this interpretation of the directional spillover is impossible due to the integration of news sentiment and index returns in the calculation. The reason for this is discussed in the next section. This also means that further spillover measures developed by Diebold and Yilmaz cannot be employed in the paper. To sum up, our estimations have two steps. First, we estimated the VAR model with news sentiment and international equities. Next, we compute the spillovers by using the GFEVD with directional and total connectedness.

3.5 | Implementation

To integrate the financial data with the sentiment scores (calculated as described in Section 3.2), the returns of each index were calculated for 5-, 10-, 20-, 30-, 45- and 60-min intervals after the release of the news article. As the publication time of news articles were collected with an accuracy of 1 min, and the index developments were collected at 1-min intervals, there should not have been any inaccuracy across observations. All historical financial data were captured in the British time zone (UTC), ensuring that there were no mismatched observations. Because we are used contract for differences to measure index developments (a more in-depth reason for this is given in Section 3.3), which can be traded 24 h per day, 7 days per week, there was no reason to remove newspaper articles published at times during which relatively little trading is usually conducted. Nevertheless, the historical prices revealed some gaps in the data, usually between 11 PM and 8 AM UTC. Newspaper articles published when no financial data were available were excluded from the spillover measurement. Because only the returns of indices after the publication of news articles were collected, and the development of indices before news articles were published was not recorded, an interpretation of the directional spillover from indices to news sentiment was not feasible. The total spillover measured from the different financial indices included this inaccessible directional spillover, but since the spillover between indices was not the focus of the paper, this small error in the measurement was accepted. All calculations were executed using R software with the R package frequencyConnectedness created by Tomas Krehlik. Before analysing the connectedness, Table 2 summarizes the descriptive statistics of all main variables. As may be seen, most equity indices exhibited negative returns, except MIB. Concomitantly, all indices displayed the heavy-tail phenomenon, representing high kurtosis values.

TABLE 2 Summary of descriptive statistics.

Variable	Mean	*SD*	Skewness	Kurtosis
Sentiment	−0.419	0.332	0.813	4.448
Sentiment (negative)	−0.387	0.332	0.735	4.295
FTSE100	−0.0001	0.003	−22.591	599.759
DAX30	−0.0001	0.003	−30.887	1084.465
CAC49	−0.0001	0.003	−30.465	1054.690
MIB	0.0002	0.003	0.799	26.71554
IBEX35	−0.0001	0.007	−21.672	531.1559
AEX	0.0002	0.002	8.947	596.8996
STOXX59	−0.0007	0.003	−29.429	989.0833
SP500	−0.0001	0.001	−20.647	634.7298
HIS	−0.0001	0.003	−0.766	26.04920
ASX200	0.0001	0.001	1.990	111.1390

Note: The table summarizes the descriptive statistics of 5-min data frequency.

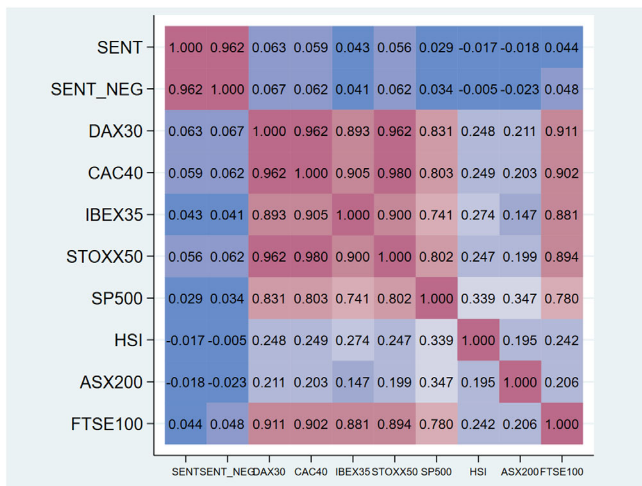


FIGURE 4 Correlation matrix among variables. [Colour figure can be viewed at wileyonlinelibrary.com]

Figure 4 depicts a correlation heatmap among the variables. On initial inspection, we observed a weak linear correlation between sentiment scores and equity indices. Therefore, connectedness with time-varying parameters was likely a suitable solution to capture spillover effects.

4 | RESULTS

4.1 | Static spillover effects

Following Diebold and Yilmaz (2009, 2012), Tables 3–14 are termed spillover tables, in which each cell ij is the

TABLE 3 Spillover table, European indices, 5 min.

	News sentiment	FTSE	DAX	CAC	IBEX	STOXX	FROM
News Sentiment	96.99	0.10	0.66	1.08	0.43	0.75	0.50
FTSE	0.02	58.07	2.82	0.97	30.95	7.17	6.99
DAX	0.07	16.27	43.59	5.95	27.09	7.02	9.40
CAC	0.06	15.91	2.81	48.23	26.44	6.54	8.63
IBEX	0.01	18.36	2.83	0.67	70.45	7.68	4.92
STOXX	0.07	16.18	3.13	5.22	27.67	47.73	8.71
TO	0.04	11.14	2.04	2.31	18.76	4.86	39.16

TABLE 4 Spillover table, European indices, 10 min.

	News sentiment	FTSE	DAX	CAC	IBEX	STOXX	FROM
News sentiment	98.39	0.08	0.16	0.90	0.31	0.16	0.27
FTSE	0.01	58.77	0.87	3.12	28.01	9.22	6.87
DAX	0.01	0.54	96.88	1.50	0.39	0.68	0.52
CAC	0.05	14.33	4.13	48.71	23.09	9.68	8.55
IBEX	0.02	15.78	0.79	2.52	71.63	9.26	4.73
STOXX	0.06	14.09	4.18	6.73	23.80	51.14	8.14
TO	0.03	7.47	1.69	2.46	12.60	4.84	29.08

TABLE 5 Spillover table, European indices, 20 min.

	News sentiment	FTSE	DAX	CAC	IBEX	STOXX	FROM
News sentiment	99.03	0.06	0.05	0.34	0.29	0.24	0.16
FTSE	0.01	69.91	4.38	2.44	21.72	1.54	5.01
DAX	0.02	0.56	95.50	1.67	0.26	1.99	0.75
CAC	0.11	24.87	4.30	39.90	27.45	3.36	10.02
IBEX	0.03	17.74	3.81	1.82	75.11	1.50	4.15
STOXX	0.12	23.92	4.07	3.90	27.99	40.00	10.00
TO	0.05	11.19	2.77	1.69	12.95	1.44	30.09

TABLE 6 Spillover table, European indices, 30 min.

	News sentiment	FTSE	DAX	CAC	IBEX	STOXX	FROM
News sentiment	99.20	0.02	0.01	0.14	0.35	0.29	0.13
FTSE	0.00	68.28	5.25	1.21	22.88	2.37	5.29
DAX	0.06	0.74	93.94	2.48	0.85	1.93	1.01
CAC	0.10	19.39	6.81	41.19	30.20	2.31	9.80
IBEX	0.03	12.38	4.14	1.30	80.20	1.96	3.30
STOXX	0.11	18.92	6.38	3.30	31.08	40.20	9.97
TO	0.05	8.58	3.76	1.41	14.22	1.47	29.50

estimated contribution from changes in variable j to the forecast error variance of variable i.[3] However, unlike in Diebold and Yilmaz, the TO row and FROM column are not the respective off-diagonal sums. Instead, the TO row and FROM column are the off-diagonal row and column sums compared to the total sum of the matrix expressed

TABLE 7 Spillover table, European indices, 45 min.

	News sentiment	FTSE	DAX	CAC	IBEX	STOXX	FROM
News sentiment	99.04	0.07	0.05	0.45	0.29	0.10	0.16
FTSE	0.02	74.05	5.13	1.56	15.79	3.45	4.32
DAX	0.07	0.80	90.17	5.01	0.72	3.23	1.64
CAC	0.12	20.04	5.60	45.55	24.00	4.69	9.08
IBEX	0.03	11.16	2.97	0.51	83.32	2.02	2.78
STOXX	0.10	18.77	5.24	2.23	23.79	49.87	8.36
TO	0.06	8.47	3.16	1.63	10.76	2.25	26.33

TABLE 8 Spillover table, European indices, 60 min.

	News sentiment	FTSE	DAX	CAC	IBEX	STOXX	FROM
News sentiment	98.56	0.12	0.12	0.45	0.22	0.52	0.24
FTSE	0.01	72.66	10.15	4.04	11.61	1.53	4.56
DAX	0.05	0.63	90.27	5.91	0.84	2.32	1.62
CAC	0.06	15.32	11.01	50.47	21.04	2.10	8.26
IBEX	0.02	7.36	6.00	2.13	83.61	0.88	2.73
STOXX	0.06	14.65	10.29	4.56	22.03	48.40	8.60
TO	0.03	6.35	6.26	2.85	9.29	1.22	26.00

TABLE 9 Spillover table, international indices, 5 min.

	News sentiment	S&P	Hang Seng	ASX	FROM
News sentiment	99.76	0.08	0.05	0.11	0.06
S&P	0.14	94.72	2.21	2.93	1.32
Hang Seng	0.06	0.12	99.28	0.55	0.18
ASX	0.03	0.03	0.61	99.33	0.17
TO	0.06	0.06	0.72	0.90	1.73

TABLE 10 Spillover table, international indices, 10 min.

	News sentiment	S&P	Hang Seng	ASX	FROM
News sentiment	99.77	0.08	0.03	0.12	0.06
S&P	0.17	95.22	0.94	3.66	1.19
Hang Seng	0.08	0.05	99.29	0.58	0.18
ASX	0.04	0.05	0.55	99.36	0.16
TO	0.07	0.05	0.38	1.09	1.59

TABLE 11 Spillover table, international indices, 20 min.

	News sentiment	S&P	Hang Seng	ASX	FROM
News sentiment	99.50	0.29	0.03	0.19	0.13
S&P	0.13	94.68	0.90	4.30	1.33
Hang Seng	0.07	0.06	99.41	0.45	0.15
ASX	0.05	0.39	1.04	98.52	0.37
TO	0.06	0.18	0.49	1.23	1.97

TABLE 12 Spillover table, international indices, 30 min.

	News sentiment	S&P	Hang Seng	ASX	FROM
News sentiment	99.61	0.24	0.06	0.09	0.10
S&P	0.13	94.62	0.52	4.74	1.35
Hang Seng	0.04	0.11	99.62	0.24	0.10
ASX	0.05	0.08	1.34	98.53	0.37
TO	0.05	0.11	0.48	1.27	1.91

TABLE 13 Spillover table, international indices, 45 min.

	News sentiment	S&P	Hang Seng	ASX	FROM
News sentiment	99.41	0.32	0.04	0.22	0.15
S&P	0.13	95.52	0.85	3.50	1.12
Hang Seng	0.02	0.08	99.81	0.09	0.05
ASX	0.06	1.99	1.00	96.95	0.76
TO	0.05	0.60	0.47	0.95	2.08

TABLE 14 Spillover table, international indices, 60 min.

	News sentiment	S&P	Hang Seng	ASX	FROM
News sentiment	99.67	0.20	0.01	0.11	0.08
S&P	0.09	96.18	1.39	2.33	0.95
Hang Seng	0.03	0.20	99.69	0.08	0.08
ASX	0.04	1.74	0.98	97.23	0.69
TO	0.04	0.54	0.60	0.63	1.80

as a percentage. Although differing from previous literature, using this spillover "share" allowed direct comparison of the impact of the news sentiment across the different time frames, between European and international indices, and over the full sample and its subsets. The bottom right corner is the sum of all off-diagonal cells, excluding the TO row and FROM column, and thereby describes the estimated total contribution of the spillovers to the total forecast error variance. For all time frames selected for the analysis, the total estimated spillover share from news sentiment to European and international indices ranged from 0.03% to 0.06% and 0.04% to 0.07%, respectively. These values were relatively similar and very low. Considering the European indices, the spillover from news sentiment to the CAC and the STOXX indices was relatively strong compared to the spillover to the FTSE and the IBEX for all time frames, while the spillover to the DAX varied. For the international indices, the spillover from news sentiment was always strongest for the S&P. Additionally, spillover was stronger to the Hang Seng than to the ASX for the 5- to 20-min windows, but this reversed for the 30- to 60-min windows. The spillover of news sentiment onto the different indices was expected to be very small, if it existed at all, due to the large number of factors that influence the price development of single stocks and the proportionately higher number of factors that influence indices. Regarding the spillover from the European indices, another pattern can be observed. The IBEX and the FTSE displayed relatively large spillover share to all others, while the STOXX and the CAC exhibited a comparably low share of spillover. Again, the spillover share from the DAX varied. Finally, the total estimated contribution of the spillovers was significant, at 39.16% for the 5-min data and 26.0% for the 60-min data. However, the total spillover share needs to be considered carefully, as it was almost wholly the result of the spillover to the financial indices. The results were very different for the international indices, with spillover shares from a single index ranging between 0.05% and 1.27% and the total spillover share between 1.59% and 2.08%; both of these ranges were drastically lower compared to the European indices. Thus, while the spillover share of Brexit news was similar for both the European and the international indices, this may imply that there was significantly less connection between the international financial indices compared to the European indices. Considering the results of Wang et al. (2018), this is a very plausible implication. For all these results, it must be recognized that all calculations were based upon financial data following the release of

Brexit news. Thus, while providing an accurate result for the spillover of news sentiment, the spillovers between the financial indices may not fully represent the actual spillovers between the markets. Additionally, the limitations described in Section 3.5 hold, rendering any interpretation of the FROM column for news sentiment impossible. A closer look at the contribution from others to the individual indices is omitted, as it was not the focus of the paper.

4.2 | Rolling sample analysis

Over the five-year period considered, there were many defining moments in the Brexit process, such as the 2016 referendum, the triggering of Article 50, two elections in 2017 and 2019, and several developments in the deal-making process. As Diebold and Yilmaz (2012) stated, the previously shown spillover tables are only "a summary of the "average" [...] spillover behavior" (p. 61); thus, rolling samples are required to identify changes in spillover over time. Following Diebold and Yilmaz (2012), Figures 4 and 5 show so-called spillover plots. Figure 5 shows the total spillover plots of the "*Brexit*" dataset for all time frames, both for the European and the international indices. That is, the figure displays not only the spillover from the news to the individual indices but also the spillover among the different financial markets. As such, it is the equivalent of rolling window estimation of the total contribution of the spillovers to the total forecast error variance.

Considering the total spillover plots for the European indices, substantial similarity exists among all six different time frames, except for the 5-min data, which did not exhibit the same drop in spillover in late 2016 that all other plots showed, and the 20-min data, which exhibited an additional peak in early 2016. Additionally, the total spillover was slightly reduced over longer timeframes, with cycle peaks reaching or exceeding 60% in the 5-min data but only reaching c. 55% in the 60-min data. Due to the similarities, results can be described in a general sense; that is, not describing each graph individually and only describing individual events where appropriate. Total spillover was relatively stable at between 40% and 45% at the end of 2015, before presenting a sharp increase in early 2016, especially in the 20-min data, when the Brexit debate intensified in the United Kingdom. A peak in spring 2016 was followed by some reduction in spillover before a shock-like spillover of over 80% was reached at the time of the Brexit referendum. Afterward, all plots except the 5-min plot show a reduction in spillover to c. 30% in late summer 2016 before a rise to c. 50%–60% at the end of the year. At this time, most European indices had gained strongly, and the UK parliament voted to trigger Article 50 in early 2017, which would officially start the withdrawal of the UK from the European Union. The spillover decreased to c. 40% by mid-2017, around the time of the UK general election, before again rising to c. 50%–60% in autumn. This was followed by a short cycle in the final months of the year, from a low of 40% to c. 50%, with a reversal of approximately 5% through to early 2018. After an increase to between 50% and 60% at a time of strong selloffs, the spillover remained relatively stable in the first half of the year, before a drop to 40% until the spillover again increased around November 2018 (especially in the shorter time frames), when the Brexit withdrawal agreement was published, and indices experienced a downward trend in general. The total spillover then decreased again and remained relatively low in early 2019 (again, particularly in the shorter time frames) before fluctuating between 40–50% for the rest of the year, which was characterized by political instability in the United Kingdom but nevertheless saw a generally positive trend for most European indices. Examining the total spillover plots for the international indices, there were more significant difference among the six time frames than for the European indices, although they also shared many similarities. However, these similarities were predominately in the relative spillover trend (i.e., whether it was increasing or decreasing at a certain point in time), with the absolute spillover peaks generally decreasing over the longer time frames. Similar to the European data, the plots show an increase in spillover in early 2016 and around the time of the Brexit vote. However, after a short reduction in spillover, it again increased in autumn 2016 before falling to c. 10% at the turn of the year. Total spillover rose again in early 2017 and fluctuated between 10% and 30% (depending on the time frame) with a slight downward trend for the rest of the year. Spillover spiked again in early 2018, when short-lived but sharp selloffs hit markets worldwide, then fluctuated between 10% and 30% (again, depending on the time frame) for most of the year, before another high in the final months of 2018 as the S&P in particular experienced substantial losses. Depending on the time frame, the spillover estimate exhibited 3–5 cycles in 2019, a year in which the S&P and the Hang Seng developed quite differently during the ongoing trade war. When considering all spillover plots in Figure 4 and the underlying developments in the Brexit process and other events worldwide, a relationship between these events and the spillover between the news sentiment and financial markets becomes apparent. However, analysing only the total estimated spillover does not allow differentiation between spillover from Brexit news sentiment to the indices and spillover among the different indices due to other, unrelated events.

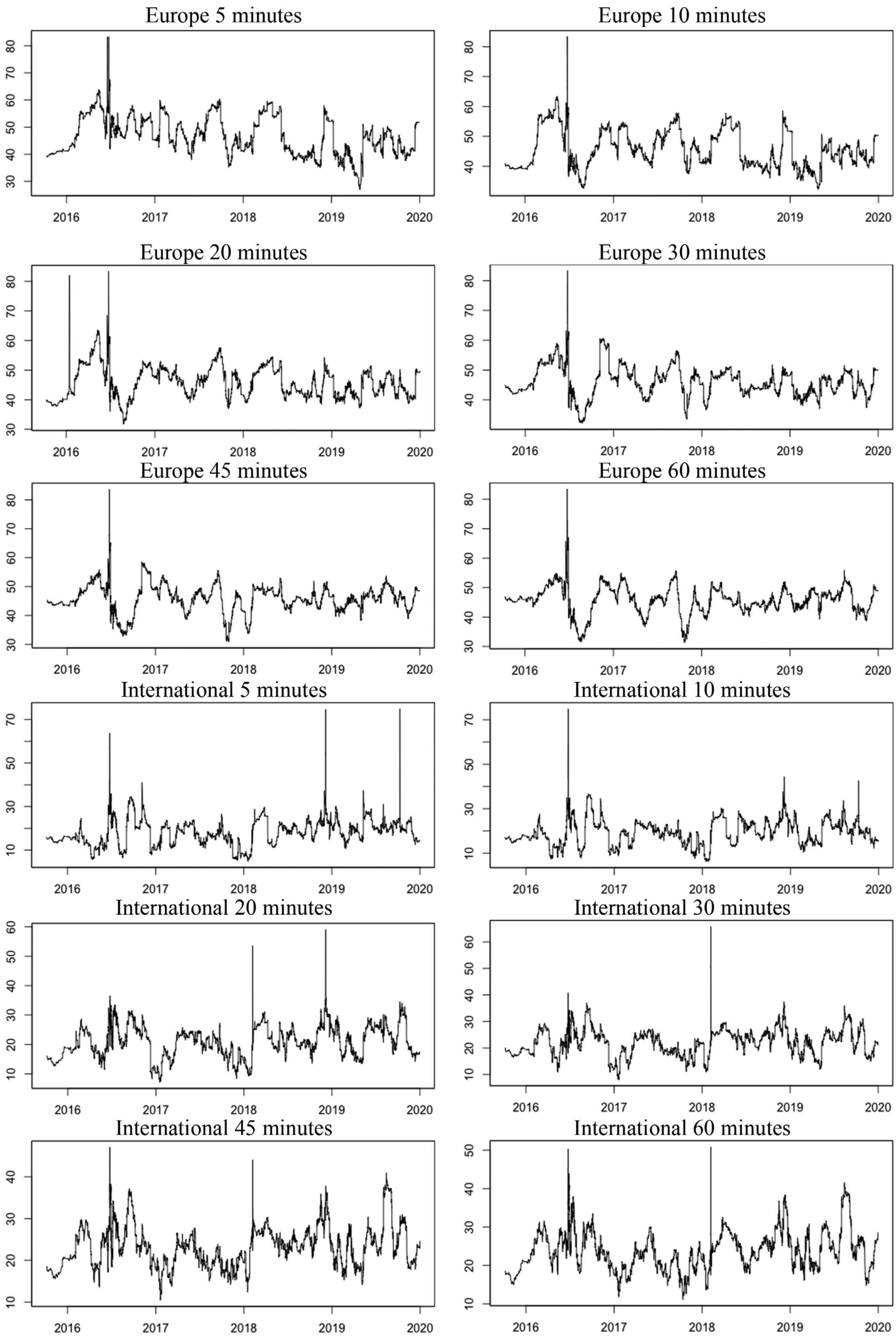


FIGURE 5 Total spillover plots for European and international indices for all time frames.

To examine the impact of Brexit news in a differentiated way, directional spillover plots, as named by Diebold and Yilmaz (2012), were used. Specifically, Figure 5 shows directional spillover plots from news sentiment to the indices, with the rolling window equivalent of the TO row for the news sentiment column. A first observation of the directional spillover plots is that spillover from Brexit news was small compared to the total spillover, with peak spillovers reaching c. 8% and directional spillover usually fluctuating between 1% and 3%. Again, this is consistent with what one would expect and consistent with the spillover tables shown previously (TO row of news sentiment compared to financial indices). Additionally, both the spillover plots for the European and international indices (Figure 6) exhibit much less similarity over the different time frames. Thus, the following analysis focused primarily on the peak spillovers that were consistent across time frames. A first peak was the spillover of news sentiment to European indices around the time of the Brexit, which was also clearly visible in the estimated total spillover. The second peak, consistent over most time frames, was in the first half of 2017, around the time that Article 50 was triggered, which began the formal exit process. Another peak can be observed in the middle of 2017, around the time of the UK general election. Spillover was relatively low at 1%–2% for the rest of the year and most of 2018, before stronger fluctuations during early 2019, while the Brexit withdrawal agreement was debated in the UK parliament and two extensions of the Article 50 period were granted. Although at a reduced level, fluctuations continued throughout the year as Boris Johnson became Prime Minister after Theresa May's resignation. In all cases, peaks occurred at times of uncertainty, first and foremost around the time of the Brexit referendum, when it was unclear how the British people would decide and what the “Leave” outcome of the vote meant for the country and the rest of the EU. Although the triggering of Article 50 brought certainty that Brexit would indeed happen, at this point, there was no imminent deal between the UK and the EU, and the outcome of negotiations was still highly uncertain. The 2017 general election led to uncertainty, as its outcome could have led to anything between a no-deal Brexit and a reversal of the whole process. The rejection of the withdrawal agreement by the UK parliament in early 2019 increased the likelihood of a no-deal Brexit, and thereby uncertainty. The directional spillover plots for the international indices show similarity to those of the European indices both in the trend (occurrence of cycles) and extent (contribution of spillovers in percent), only with more extreme peak spillovers and additional spillover peaks in late 2017 and the first months of 2018. Nevertheless, the spillover peaks at the time of the referendum, when Article 50 was triggered, and the sharp fluctuations in 2019 are consistent with the directional spillover plots for European indices. That a no-deal Brexit could have favoured the development of trade relations with the United Kingdom's international partners may explain the more substantial spillover effect in early 2019. Thus, the observation that spillovers from news sentiment are more significant in times of greater uncertainty was true for the international indices.

4.3 | UK business and economy subset

4.3.1 | Static spillover effects

Spillover Tables 15 and 16 show that the spillover share from news sentiment to both the European and the international indices was considerably larger for the “UK Business & Economy” subset than for the overall “Brexit” dataset. Although as low as 0.12% for the 5-min international indices, the spillover effect of news sentiment was always at least twice as strong for the data from the subset. As explained previously, this direct comparison between datasets was possible due to the values in the TO row being a percentage of the total contribution to the forecast error variance of all variables. Similar to the “Brexit” dataset, the spillover was strongest to the DAX, CAC, and STOXX for the European indices; however, this varied across timeframes, with the spillover being especially large to the Spanish index and relatively stronger to the FTSE in the shorter time frames. The spillover from news sentiment to the international indices was relatively balanced across most time frames. While the total spillover in the subset was similar to that of the Brexit dataset for the international indices, spillover was significantly lower for the European indices, at only 4.47%. The highest total spillover was reached in the 45 min time frame, but was also only 5.26% of total spillover.

A possible interpretation of this is that news about the UK businesses and economy, although having its own spillover, did not lead to significant spillover between financial markets. The higher spillover of news sentiment for the subset in general may imply that investors paid more attention to news about the effects Brexit developments had or were likely to have on businesses and the economy; this was thereby more relevant news to financial investors than was generalized Brexit news.

4.3.2 | Rolling sample analysis

The rolling-sample total spillover plots for the European and international indices in Figure 7 show three

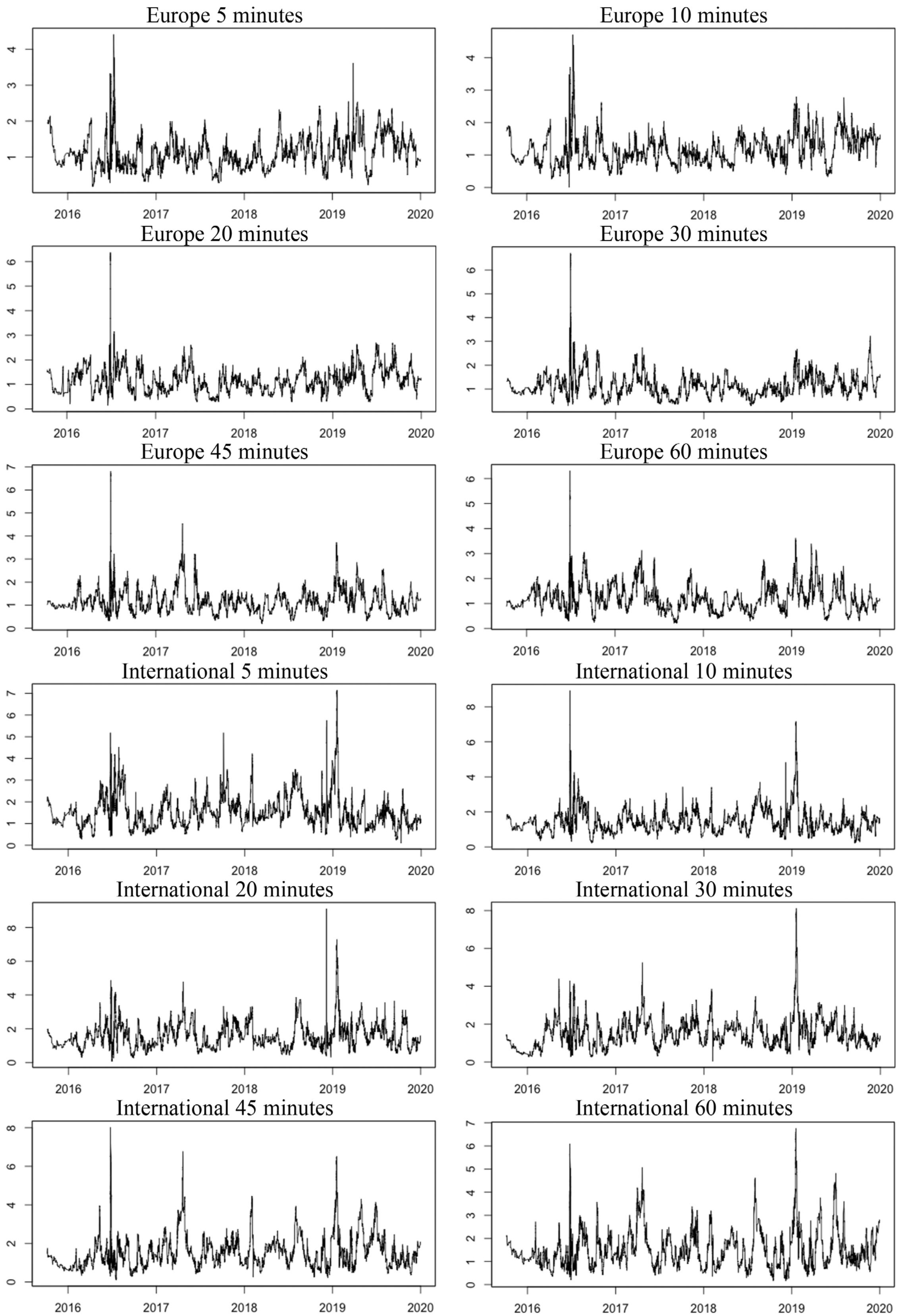


FIGURE 6 Directional spillover plots for European and international indices for all time frames.

TABLE 15 Spillover table, "UK business & economy" subset, European indices, 30 min.

	News sentiment	FTSE	DAX	CAC	IBEX	STOXX	FROM
News sentiment	95.79	0.16	0.51	0.69	0.38	2.47	0.70
FTSE	0.07	98.40	0.16	0.26	0.58	0.52	0.27
DAX	0.48	0.47	96.09	1.63	0.55	0.78	0.65
CAC	0.38	0.99	1.80	94.27	0.71	1.86	0.96
IBEX	0.12	0.46	3.54	0.15	94.09	1.64	0.99
STOXX	0.40	0.94	1.92	1.47	0.71	94.56	0.91
TO	0.24	0.50	1.32	0.70	0.49	1.21	4.47

TABLE 16 Spillover table, "UK business & economy" subset, international indices, 30 min.

	News sentiment	S&P	Hang Seng	ASX	FROM
News sentiment	99.26	0.32	0.15	0.26	0.18
S&P	0.40	98.20	1.29	0.12	0.45
Hang Seng	0.31	0.53	99.09	0.07	0.23
ASX	0.37	0.32	0.80	98.51	0.37
TO	0.27	0.29	0.56	0.11	1.23

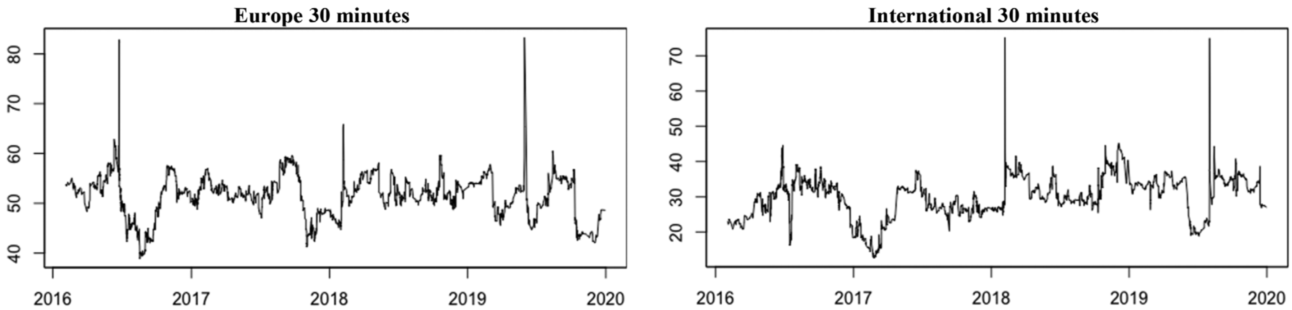


FIGURE 7 Total spillover plots for "UK business & economy" subset. 30-min time frame for European and international indices.

distinctive spillover peaks, which were consistent across time frames. First, slightly before the Brexit referendum, then at the time of global market turbulence in early 2018, and finally, in mid-2019, when Theresa May resigned at the end of May for the European indices, and when Boris Johnson became the Prime Minister at the end of July for the international indices. Across the different time frames, there were also peaks in the final months of 2016, 2017 and 2018, and in early 2017, around the time that Article 50 was triggered. In general, total spillover was more significant among the European indices, for which it primarily fluctuated between 40% and 60%, as compared with between 20% and 40% for the international indices.

The directional spillover plots in Figure 8 show greater variation over time compared to the "Brexit" dataset, with the directional spillover of the former reaching higher peaks in most cycles. Consistent for both European and international indices, noticeable peaks occurred in mid- and late 2016, early and mid-2017, early and late 2018, and early and mid-2019. The European indices also showed significant spillover from news sentiment in late 2017 and mid-2018, while the international indices exhibited a sharp increase in directional spillover in the final months of 2019. While stronger, the peaks in spillover were generally consistent with major events or developments, which can also be noticed in the "Brexit" dataset, again showing that the spillover effect was more substantial in times of uncertainty concerning Brexit. Outliers, such as the peak in early 2018, may be explained by a greater relevance of the ongoing developments to the data subset. In this case, the peak occurred during intense discussions about a possible customs union, something that is arguably relevant to UK businesses and economy; however, since no definitive decisions were made, this may not have impacted the spillover in the "*Brexit*" dataset rolling sample. The generally increased strength of directional spillover for the

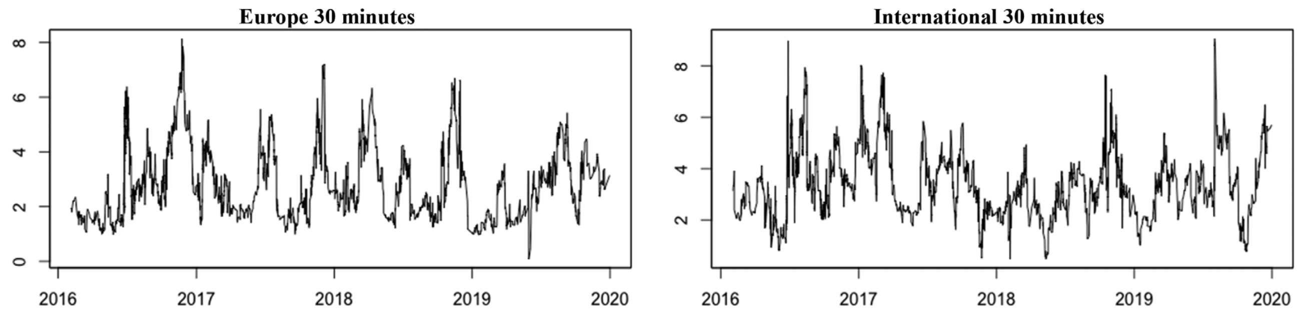


FIGURE 8 Directional spillover plots for "UK business & economy" subset. 30-min time frame for European and international indices.

TABLE 17 Spillover table, "markets" subset, European indices, 30 min.

	News sentiment	FTSE	DAX	CAC	IBEX	STOXX	FROM
News sentiment	87.59	1.21	0.26	6.12	0.34	4.48	2.07
FTSE	0.61	76.91	1.79	1.51	13.30	5.89	3.85
DAX	0.83	3.35	78.92	6.27	4.98	5.65	3.51
CAC	0.44	25.51	2.45	35.02	26.75	9.83	10.83
IBEX	0.14	8.39	0.61	3.19	78.04	9.63	3.66
STOXX	0.44	24.78	2.38	5.86	28.36	38.18	10.30
TO	0.41	10.54	1.25	3.82	12.29	5.91	34.22

TABLE 18 Spillover table, "markets" subset, international indices, 30 min.

	News sentiment	S&P	Hang Seng	ASX	FROM
News sentiment	99.27	0.29	0.06	0.37	0.18
S&P	0.17	93.53	3.20	3.09	1.62
Hang Seng	0.04	0.78	97.75	1.43	0.56
ASX	0.26	1.79	0.42	97.52	0.62
TO	0.12	0.72	0.92	1.22	2.98

subset may again indicate greater influence of more relevant news.

4.4 | Markets subset

4.4.1 | Static spillover effects

Similar to the "UK Business and Economy" subset, spillover Tables 17 and 18 show greater spillover share from news sentiment to the indices than in the "Brexit" dataset. However, in the European indices, the spillover from news sentiment was particularly high, ranging from 0.33% to 0.36% for all other time frames. For the international indices, spillover from news sentiment also reached 0.31% for the 10-min time frame. This stronger spillover share compared to the "Brexit" dataset can again be explained by the greater relevance of the news articles for investors. The spillover of the European indices was remarkably higher compared to both the international indices in the same subset and to the European indices in the "UK Business and Economy" subset, which has two possible interpretations: First, since the FT is based in England, although it covers international financial markets developments, it may be more focused on the European markets, and more articles are published during the trading times of the European indices, leading to more substantial spillover both from news and the indices for the observations analysed. Second, the result is similar to the "Brexit" dataset and thereby consistent with the interpretation that the European financial markets may be more connected than the international indices, and are thus experienced greater spillover.

4.4.2 | Rolling sample analysis

The total spillover plots in Figure 9 show only one significant peak in spillover for the European indices, namely

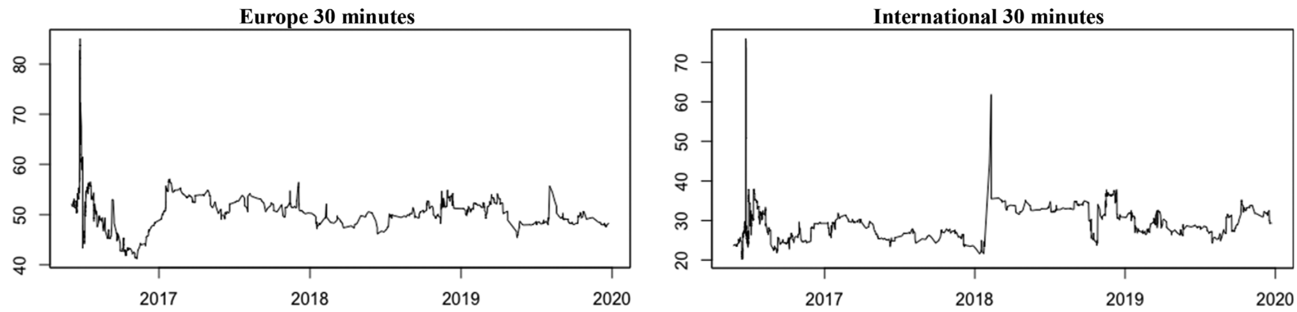


FIGURE 9 Total spillover plots for “markets” subset. 30-min time frame for European and international indices

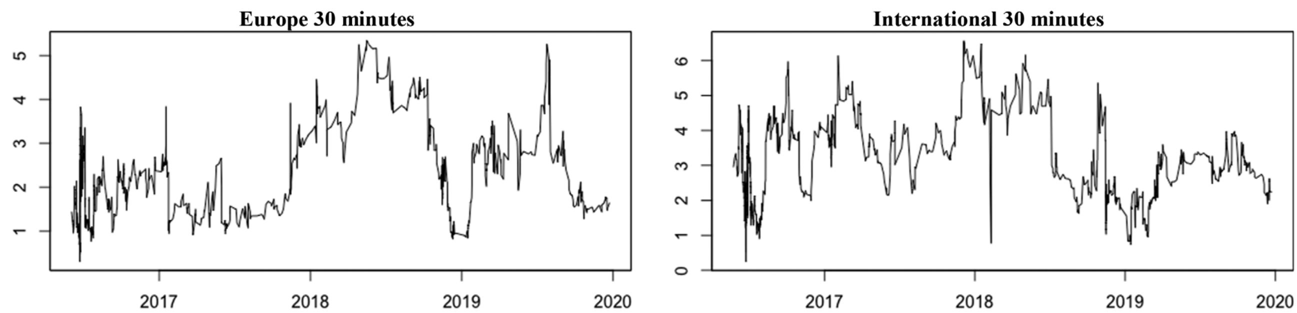


FIGURE 10 Directional spillover plots for “markets” subset. 30-min time frame for European and international indices.

during the Brexit referendum, and only one additional peak for the international indices in early 2018, the time of brief global turmoil in financial markets. There was also an increase in total spillover of 10%–15% for the European indices at the turn of the year 2016/2017, but otherwise, turnover primarily fluctuated around 50% for the remaining dataset. The spillover for the international indices fluctuated around 25% for most of the time before the early 2018 peak and then moved between 25% and 35% for the rest of the period analysed. Although there was more variation among the shorter time frames, the data were generally consistent over the time frames. Again, note that total spillover was more significant for the European indices, fluctuating between 40% and 60%, than for the international indices, which fluctuated between 20% and 40%.

The directional spillover plots in Figure 10 also show less variation over time compared to both the “UK Business & Economy” subset and the “Brexit” dataset. Additionally, there was a greater difference between the European and international indices. For the European indices, directional spillover was consistently low throughout 2017 but generally higher throughout most of 2018, a generally bad year for most stock markets worldwide. The international indices exhibited a general upward trend in spillover from 2016 to mid-2018, with spillover generally lower afterward, excluding peaks. Additionally, the European data showed spillover peaks from news in mid-2016; early, mid-, and late 2017; early and mid-2018; and mid-2019, whereas the international indices showed spillover peaks in late 2016, early and late 2017, and late 2018 and 2019. Thus, there were peaks at times of Brexit uncertainty, such as the turn of the year 2016/2017, the triggering of Article 50 in early 2017, and the change of Prime Minister in 2019, as well as some peaks at times unrelated to Brexit. The divergence in general development and peaks between the European and international data may be due to news articles in the “Markets” subset being more focused on covering regional developments, which may have been less related to Brexit in general. The lack of more visible peaks or cycles, especially in the total spillover plots, may be due to professional traders using faster news sources about financial markets developments. This would also explain the greater variation in shorter time frames, with financial markets information being only useful for investment decisions for a very limited time.

4.5 | Companies subset

4.5.1 | Static spillover effects

Spillover Tables 19 and 20 of the “Companies” subset revealed a slightly different picture compared to the two previous subsets. The spillover share from news sentiment to

TABLE 19 Spillover table, "markets" subset, European indices, 30 min.

	News sentiment	FTSE	DAX	CAC	IBEX	STOXX	FROM
News sentiment	87.59	1.21	0.26	6.12	0.34	4.48	2.07
FTSE	0.61	76.91	1.79	1.51	13.30	5.89	3.85
DAX	0.83	3.35	78.92	6.27	4.98	5.65	3.51
CAC	0.44	25.51	2.45	35.02	26.75	9.83	10.83
IBEX	0.14	8.39	0.61	3.19	78.04	9.63	3.66
STOXX	0.44	24.78	2.38	5.86	28.36	38.18	10.30
TO	0.41	10.54	1.25	3.82	12.29	5.91	34.22

TABLE 20 Spillover table, "markets" subset, international indices, 30 min.

	News sentiment	S&P	Hang Seng	ASX	FROM
News sentiment	99.27	0.29	0.06	0.37	0.18
S&P	0.17	93.53	3.20	3.09	1.62
Hang Seng	0.04	0.78	97.75	1.43	0.56
ASX	0.26	1.79	0.42	97.52	0.62
TO	0.12	0.72	0.92	1.22	2.98

the European indices was comparably low, at only 0.08% for the 30-min time frame, but the value lay between 0.10% and 0.18% for the other time frames, spillover was higher than in the "Brexit" dataset for every time frame. The spillover share from news was comparatively high for the international indices, varying between 0.20% and 0.25% across all time frames. Many news articles cover companies that contribute to one of the indices, thus again having higher relevance for investors, which explains the stronger spillover effect. As was previously the case, total spillover was greater for the European indices than for the international indices, whereas the total spillover for the European indices was relatively low compared to that of the "Brexit" dataset, but still larger than that of the "UK Business & Economy" subset.

4.5.2 | Rolling-sample analysis

With only one peak in mid-2016 for the European indices and one in early 2018 for the international indices, the total spillover plots in Figure 10 show some similarity to those in Figure 8 for the "Markets" subset. However, shorter time frames also exhibited cycles in early and late 2017, at the beginning and the end of 2018 and mid-2019 for the European indices, and peaks in late 2016, early and late 2017, mid- and late 2018, and in autumn 2019. Although peaks in total spillover across both groups of indices were partly consistent with major Brexit developments, the detached development of spillover peaks indicates that significant events less related to Brexit also led to more substantial total spillovers. Note that if the events were completely unrelated, they would not have appeared in the dataset.

This reduced influence of developments closely related to the Brexit process can also be seen in the directional spillover plots in Figure 11, which show that the Brexit referendum, which was a clear peak of directional spillover from news to markets in almost all previous plots, led to comparably low directional spillover. This observation was relatively consistent for both groups of indices across all time frames. A potential reason for this becomes apparent when examining the directional spillover plots for the "UK Companies" and "EU companies" subsets, which revealed stronger directional spillover among UK companies and relatively low spillover among EU companies. Possible interpretations for this are given in the relevant section. However, the spillover cycles in early 2017 for both groups of indices do also indicate the relevance of major Brexit developments for the "Companies" subset (Figure 12).

4.6 | UK companies subset

4.6.1 | Static spillover effects

Spillover Tables 21 and 22 show that the largest spillover share from news sentiment to both the European and the international indices was 0.57% and 0.31% for the 30-min time frame, respectively, and varied from 0.40% to 0.81% and 0.33% to 0.64%, respectively, for the other time

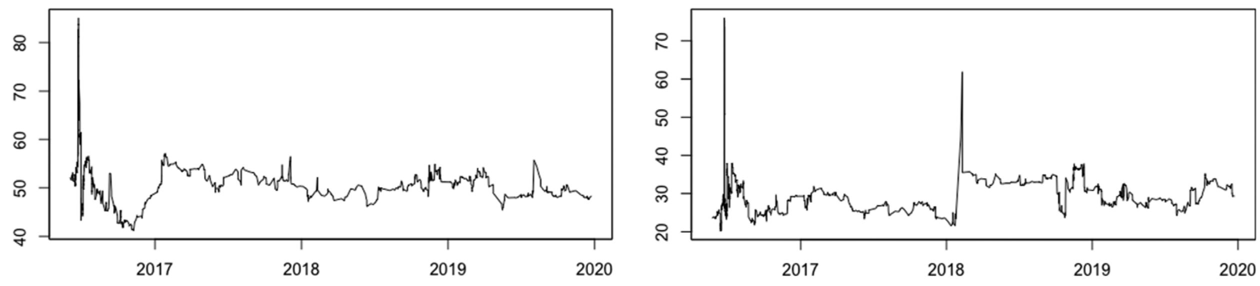


FIGURE 11 Total spillover plots for "markets" subset. 30-min time frame for European and international indices.

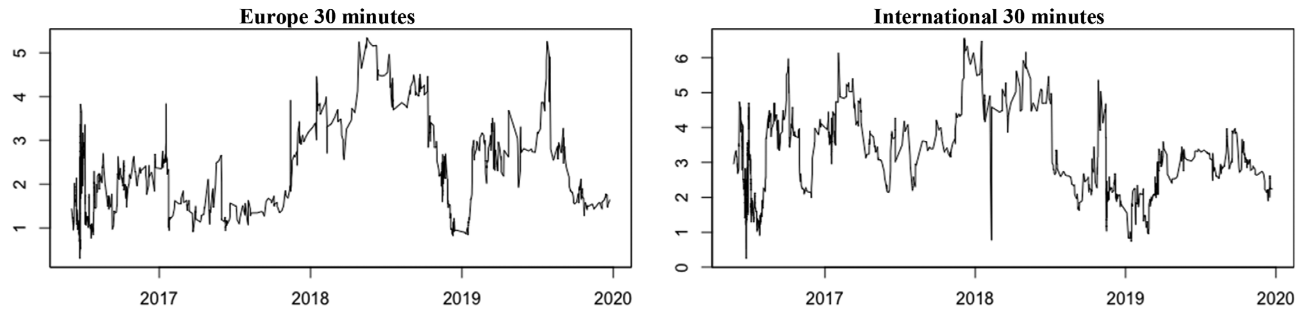


FIGURE 12 Directional spillover plots for "markets" subset. 30-min time frame for European and international indices.

TABLE 21 Spillover table, "UK companies" subset, European indices, 30 min.

	News sentiment	FTSE	DAX	CAC	IBEX	STOXX	FROM
News sentiment	93.72	0.57	0.98	0.78	0.38	3.57	1.05
FTSE	0.70	88.88	2.23	4.14	2.44	1.61	1.85
DAX	0.30	1.50	82.33	8.87	1.86	5.14	2.94
CAC	0.66	0.83	5.69	80.14	1.72	10.96	3.31
IBEX	1.20	0.37	4.78	15.02	69.55	9.09	5.08
STOXX	0.55	0.82	5.72	23.05	1.53	68.33	5.28
TO	0.57	0.68	3.23	8.64	1.32	5.06	19.51

TABLE 22 Spillover table, "UK companies", subset, international indices, 30 min.

	News sentiment	S&P	Hang Seng	ASX	FROM
News sentiment	98.85	0.63	0.05	0.47	0.29
S&P	0.30	96.24	1.29	2.17	0.94
Hang Seng	0.57	0.85	97.98	0.60	0.50
ASX	0.37	1.24	1.30	97.09	0.73
TO	0.31	0.68	0.66	0.81	2.46

frames. This comparably strong spillover could have been due to both the higher relevance of the news for stock traders, as described for the previous subsets, and the more substantial effect of Brexit developments on UK-based companies, as outlined in Section 4.2. The total spillover was also higher for both groups of indices compared to the "Companies" subset.

4.6.2 | Rolling sample analysis

The total spillover plots in Figure 13 show two peaks for the European indices in mid-2016 and early 2018, and spillover fluctuating between 50% and 55% from the beginning of 2017 to the end of 2019. In comparison, the international indices peaked in late 2016, mid-2017, and

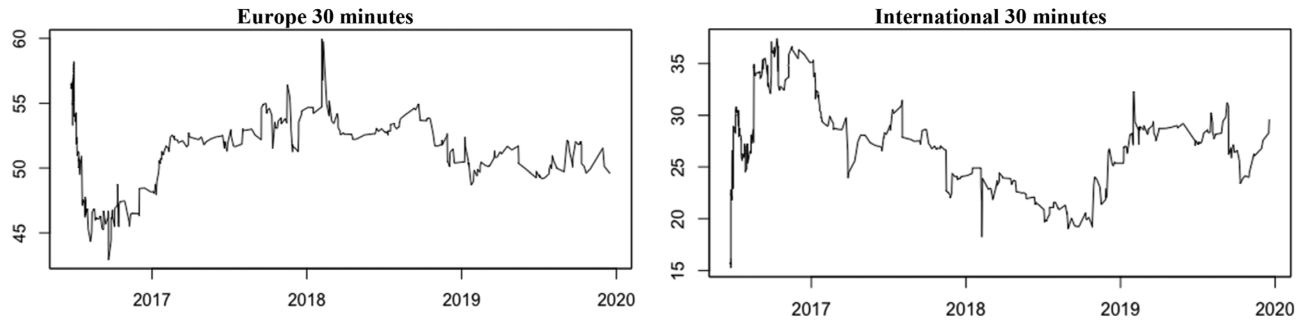


FIGURE 13 Total spillover plots for "UK companies" subset. 30-min time frame for European and international indices.

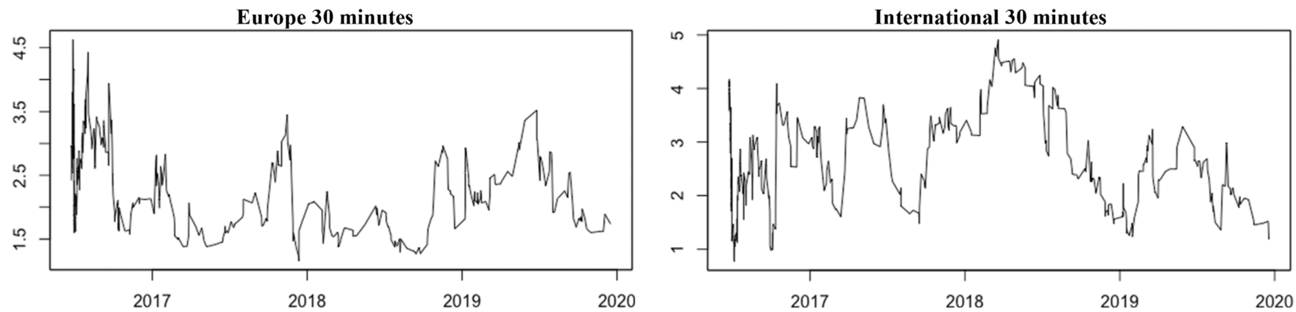


FIGURE 14 Directional spillover plots for "UK companies" subset. 30-min time frame for European and international indices.

TABLE 23 Spillover table, "EU companies" subset, European indices, 30 min.

	News sentiment	FTSE	DAX	CAC	IBEX	STOXX	FROM
News sentiment	75.98	0.34	0.60	11.08	0.55	11.45	4.00
FTSE	0.80	80.14	3.91	11.33	0.62	3.21	3.31
DAX	0.13	1.87	79.09	14.19	2.44	2.28	3.48
CAC	0.08	3.97	6.51	83.16	1.50	4.78	2.81
IBEX	0.55	0.97	12.22	20.45	58.82	6.98	6.86
STOXX	0.07	3.90	7.22	13.93	1.16	73.73	4.38
TO	0.27	1.84	5.08	11.83	1.04	4.78	24.84

early and late 2019, but exhibited a general decline in spillover from late 2016 to 2019, when spillover increased again. Besides a total spillover peak in mid-2019 for the 5-min European indices and a peak in early 2018 for the 60-min international indices, the results were relatively consistent across time frames for each group of indices. The interpretation of these plots follows the interpretation of the total spillover plots for the "Companies" subset.

The directional spillover plots in Figure 14 show peak spillover in mid- and late 2016, late 2017 and mid-2019, and smaller spillover cycles in early 2017 and late 2018 for the European indices, while showing spillover peaks in mid- and late 2016, mid-2017, and early 2018, with three smaller peaks throughout 2019 for the international indices. In addition to the spillover tables, the directional spillover peaks at the times of significant Brexit developments, especially for the European indices (e.g., mid-2016, early 2017, late 2018, and mid-2019) could imply that Brexit developments were of greater relevance to UK-based companies; thus, the indices experienced stronger directional spillover from the news. The interpretation of peaks at times less related to major Brexit developments follows the interpretation in the "Companies" subsection.

4.7 | EU companies subset

4.7.1 | Static spillover effects

Spillover Tables 23 and 24 show the spillover share at 0.27% for the 30-min time frame and varying between 0.16% and 0.32% across the remaining time frames for the

TABLE 24 Spillover table, "EU companies" subset, European indices, 30 min.

	News sentiment	S&P	Hang Seng	ASX	FROM
News sentiment	97.98	0.84	0.50	0.68	0.50
S&P	0.04	95.03	3.26	1.66	1.24
Hang Seng	0.73	1.47	95.14	2.66	1.22
ASX	0.05	3.91	3.05	92.99	1.75
TO	0.20	1.56	1.70	1.25	4.71

TABLE 25 The spillover table of news sentiment and stock volatility.

	Sentiment	Negativity	DAX30	CAC40	IBEX35	STOXX50	SP500	HSI	ASX200	FTSE100	FROM others
Sentiment	51.66	47.79	0.04	0.04	0.26	0.04	0.04	0.05	0.05	0.04	48.34
Negativity	47.32	51.13	0.16	0.16	0.39	0.16	0.17	0.18	0.16	0.16	48.87
DAX30	0.20	0.24	14.61	14.54	3.73	14.56	14.26	11.97	11.31	14.58	85.39
CAC40	0.20	0.25	14.59	14.61	3.74	14.51	14.22	12.04	11.27	14.57	85.39
IBEX35	0.21	0.25	14.21	14.15	5.47	14.22	13.99	12.01	11.28	14.21	94.53
STOXX50	0.20	0.25	14.51	14.4	3.89	14.56	14.34	11.83	11.49	14.52	85.44
SP500	0.20	0.22	14.43	14.34	3.94	14.52	14.54	11.72	11.66	14.44	85.46
HSI	0.20	0.21	14.18	14.21	3.91	14.08	13.66	14.47	10.85	14.23	85.53
ASX200	0.20	0.25	14.42	14.34	3.91	14.43	14.21	11.87	11.95	14.42	88.05
FTSE100	0.19	0.21	14.58	14.52	3.74	14.56	14.26	12.03	11.31	14.6	85.4
TO others	48.92	49.67	101.13	100.7	27.5	101.08	99.15	83.69	79.38	101.16	792.39
Inc. own	100.58	100.8	115.73	115.32	32.97	115.64	113.7	98.16	91.33	115.77	TCI
NET	0.58	0.80	15.73	15.32	−67.03	15.64	13.7	−1.84	−8.67	15.77	79.24

European indices, 0.2% for the 30-min time frame, and ranging from 0.17% up to 0.41% across the other time frames for the international indices. In both cases, the spillover share was relatively high compared to the "Companies" subset and the overall "Brexit" dataset, although not quite as high as for the "UK companies" subset. The general strength of spillover could again be explained by the higher relevance of the news articles for stock traders. The lower spillover compared to the "UK companies" subset may be due to the smaller effect Brexit developments potentially had on EU-based companies, which, while potentially losing access to a large market, would lose less than UK-based companies that lost access to the European Single Market. Total spillover of 24.84% and 4.71% for the European and international indices, respectively, was again higher than that of the "Companies" subset for both groups of indices (Table 25).

4.7.2 | Rolling sample analysis

Although only one clear spillover peak is visible in each of the total spillover plots of the 30-min time frame in Figure 15, the total spillover plots across the other time frames consistently show two clear peaks in mid-2016 and early 2018, for both the European and international indices. Besides these peaks, the spillover plots fluctuate relatively little otherwise in all time frames, the total spillover primarily moving between 45%–55% and 20%–40% for the European and international indices, respectively.

Besides the 60-min European indices plot and the 5- and 10-min international indices plot, the directional spillover plots in Figure 16 for both groups of indices generally do not exhibit recognizable peaks for mid-2016, and spillover peaks from news sentiment to indices in early 2018 are also not entirely consistent across time frames and groups of indices. Instead, there were directional spillover peaks in late 2017 and 2018 for the European indices, the late 2017 peak also appearing for the international indices. With the early 2018 peak most likely due to the general financial market turmoil, the low spillover effect of news sentiment around the time of the Brexit referendum, which triggered significant directional spillover in most other datasets across all time frames and for both groups of indices, may indicate that investors believed that Brexit developments would not

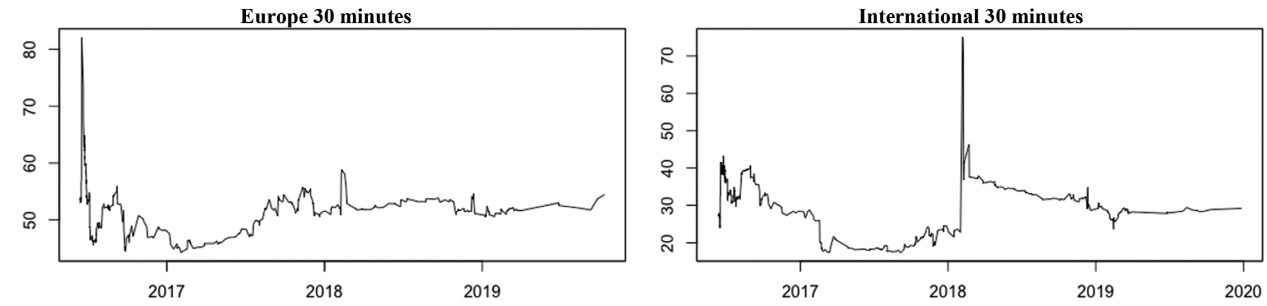


FIGURE 15 Total spillover plots for "EU companies" subset. 30-min time frame for European and international indices.

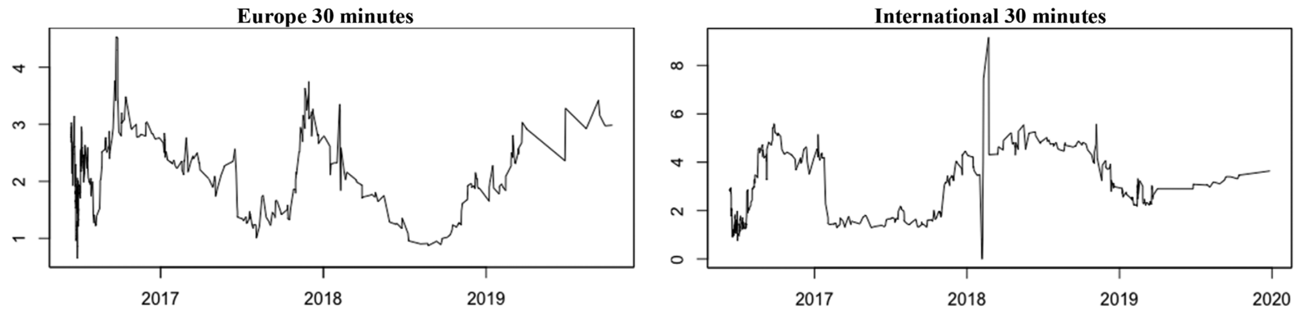


FIGURE 16 Directional spillover plots for "EU companies" subset. 30-min time frame for European and international indices.

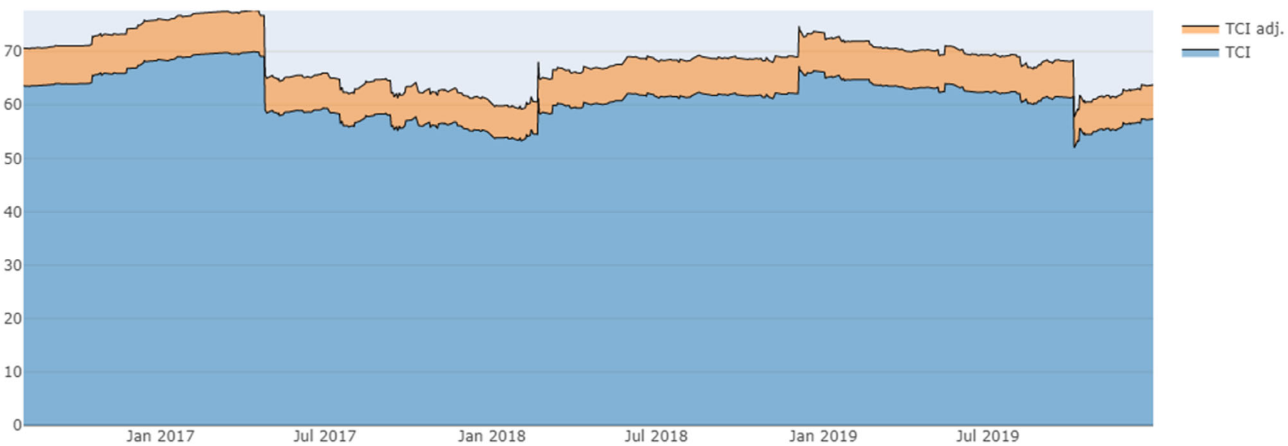


FIGURE 17 The total connectedness between new sentiment and stock market volatility. [Colour figure can be viewed at wileyonlinelibrary.com]

affect the EU-based companies that form the financial indices as adversely as the UK-based companies. Nevertheless, smaller directional spillover cycles in early and mid-2017 show that Brexit developments also had some spillover effect on the European indices.

4.8 | Volatility spillover effects

Since our study only focuses on the return connectedness, we calculated the daily volatility by estimating the *SD* from 5-min observations. We also employed the Time-varying VAR (TVP-VAR)[4] spillover estimations to see the transmitted network (Chatziantoniou & Gabauer, 2021). Figure 17 summarizes the total connectedness between the news sentiment and the stock market volatility when considering all variables.

As seen, the total of connectedness varies from 60% to 70% during the period. More noticeably, the beginning months of 2017 also have the relatively high connectedness, reflecting the news spreading and its impacts on the financial markets. Our further estimations on volatility also validated the influence of news sentiment on the international equities during the BREXIT time.

4.9 | Summary of results

The results of the spillover analysis show that spillover from news sentiment to equity indices was relatively small, with most of the total spillover contributed by the equity indices themselves. The rolling-sample analysis of the total "Brexit" dataset revealed an apparent connection between significant Brexit developments and spillover, with directional spillover from news sentiment to financial indices especially strong at times of considerable uncertainty concerning said Brexit developments. Further analysis of different subsets of the news dataset showed that the spillover from news sentiment increased compared to that of the complete sample when considering only news on topics that were more relevant to investors rather than generalized news about Brexit. Similar to the full-sample analysis, the "UK Business & Economy" subset demonstrated spillover peaks at times of greater Brexit uncertainty, while the directional spillover plots of the "Markets" and "Companies" subsets were less comparable to the "Brexit" dataset and showed additional spillover peaks at times less related to significant Brexit developments. This may imply that the subsets included a larger share of news articles of more generalized financial market information that were less relevant to Brexit developments. These results have two implications for investors: First, although its effect is generally very small, news sentiment can be a better indicator of financial market development in times of higher uncertainty and, second, and a possibly more obvious implication, sentiment in news articles of greater relevance to financial markets is a better indicator than is more general news.

The further differentiation of the "Companies" subset into the "UK companies" and "EU companies" subsets also revealed substantially stronger spillover from news sentiment for articles about UK-based companies compared to EU-based companies, with directional spillover plots showing little spillover at the times of major Brexit developments. This indicates that investors potentially saw and possibly still see Brexit as a smaller threat for EU-based companies than for UK-based companies and, by extension, as less of a threat for EU economies compared to the British economy.

Another observation that is consistent across all datasets is that spillover between the European indices was stronger than that between the international indices. Although not relating to the actual research question, this confirms the findings of Wang et al. (2018). In terms of the volatility of shock transmission, we found that the early 2017 and 2019 had stronger connections to equity volatility. However, the financial markets' volatilities were more likely to be connected by themselves rather than relying on news sentiment. Finally, our study further explains the mechanisms of sending and receiving uncertainties in the financial markets, particularly news sentiment with negative tone (Foglia & Dai, 2021). Further, our study also considers the mechanisms of shock transmission by creating the subset groups, which could aid understanding of different reactions from different industries, companies, and specific sectors.

5 | CONCLUSION

We studied the effect of news sentiment in FT articles about Brexit on European and international equity indices using the spillover measurement developed by Diebold and Yilmaz (2009, 2012) over the 5 years from 2015 to 2019. The results showed that limited spillover from news sentiment to equity markets existed for both the European and international indices used in the analysis, with spillover stronger among smaller subsets of news articles that were more relevant to financial market participants. Additionally, we found that in the full sample, directional spillover was especially strong in times of larger uncertainty concerning Brexit developments, whereas the smaller subsets, although also showing stronger spillover during Brexit uncertainty, demonstrated additional spillover peaks at time less related to major Brexit developments. These latter peaks may have been due to smaller events, which, although covered in the scope of Brexit news, were more relevant for the smaller subsets, therefore causing spillover only within the analysis of the subsets and not the whole dataset. A further explanation of this phenomenon can be drawn from the divergence of different sectors during times of uncertainty, which was explored in previous studies (Audrino & Tetereva, 2019; Huynh et al., 2021). Accordingly, the uncertainties could be more dominant in the smaller subsets, whereby firms, businesses, or specific industries tend to react to changes in the financial markets.

Our study has some relevant policy implications. First, investors could obtain appropriate portfolio diversification strategies to avoid the negative shocks caused by news amplifying the uncertainties raised from political decisions. More noticeably, this diversified approach does not stem from an international equity perspective, but rather from consideration of different industries and news categories. Second, the speed of news, the tone of writers, and the delivery (online or paper) of news could be considered by investors to quantify their impacts on trading platforms. Third, policymakers could also learn how to communicate with the media about policy uncertainties. The experience of the Brexit event could be generalized to other "big events" of diverse types, such as economic and trade conflicts (Burggraf et al., 2020), pandemics (Ambros et al., 2021), and so forth.

The study has several limitations, which could be explored in future work. First, in measuring the spillover of sentiment in general, no differentiation was made between positive and negative sentiment in news articles. Additionally, we focused on index returns and only considered volatility in the equity markets to a limited degree. Exploring these aspects could provide investors with a more holistic sense of the influence of news sentiment on equity markets. The scope of the analysis could also be broadened to a larger selection of equity indices or include additional financial products, such as government or corporate bonds. To be better able to use news sentiment for financial decision-making, especially in prediction models, it is also important to study the influence of financial market developments on news sentiment, so differentiation can be made between positive or negative news sentiment due to good or bad market developments and positive or negative news sentiment due to news with good or bad implications for financial markets. Once discovered, combining and incorporating this knowledge into decision-making could give investors a small but significant advantage in financial markets.

CONFLICT OF INTEREST

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ENDNOTES

[1] Please see www.ft.com

[2] Please see more at tickstory.com

[3] Results in all spillover tables ('Brexit' dataset and subsets) are based on vector Auto-regression of order 4 and generalized variance decompositions of 100-observation-ahead forecast errors. The rolling-sample analysis are done using a 200-observation rolling window for the 'Brexit' dataset and, due to fewer observations, a 100-observation rolling window for all subsets.

[4] TVP-VAR has two main advantages. First, the model is not sensitive to the selection of window rolling. Second, the model has the quick responses to shocks and event for parameters.

REFERENCES

Ambros, M., Frenkel, M., Huynh, T. L. D., & Kilinc, M. (2021). COVID-19 pandemic news and stock market reaction during the onset of the crisis: Evidence from high-frequency data. *Applied Economics Letters*, *28*(19), 1686–1689.

Ameur, H. B., Ftiti, Z., & Louhichi, W. (2021). Intraday spillover between commodity markets. *Resources Policy*, *74*, 102278.

Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of internet stock message boards. *The Journal of Jinance*, *59*(3), 1259–1294.

Aristeidis, S., & Elias, K. (2018). Empirical analysis of market reactions to the UK's referendum results—How strong will Brexit be? *Journal of International Financial Markets Institutions and Money*, *53*, 263–286.

Armour, J. (2017). Brexit and financial services. *Oxford Review of Economic Policy*, *33*(1), S54–S69.

Arshad, S., Rizvi, S. A. R., & Haroon, O. (2020). Impact of Brexit vote on the London stock exchange: A sectorial analysis of its volatility and efficiency. *Finance Research Letters*, *34*, 101240.

Audrino, F., & Tetereva, A. (2019). Sentiment spillover effects for US and European companies. *Journal of Banking & Finance*, *106*, 542–567.

Barndorff-Nielsen, O. E., Hansen, P. R., Lunde, A., & Shephard, N. (2009). Realized kernels in practice: Trades and quotes. *The Econometrics Journal*, *12*(3), C1–C32.

Belke, A., Dubova, I., & Osowski, T. (2018). Policy uncertainty and international financial markets: The case of Brexit. *Applied Economics*, *50*(34–35), 3752–3770.

Ben Ameur, H., & Louhichi, W. (2021). The Brexit impact on European market co-movements. *Annals of Operations Research*. https://doi.org/10.1007/s10479-020-03899-9

Bollerslev, T., Li, J., & Xue, Y. (2018). Volume, volatility, and public news announcements. *The Review of Economic Studies*, *85*(4), 2005–2041.

Bouri, E., Cepni, O., Gabauer, D., & Gupta, R. (2021). Return connectedness across asset classes around the COVID-19 outbreak. *International Review of Financial Analysis*, *73*, 101646.

Brogaard, J., Carrion, A., Moyaert, T., Riordan, R., Shkilko, A., & Sokolov, K. (2018). High frequency trading and extreme price movements. *Journal of Financial Economics*, *128*(2), 253–265.

Buehlmaier, M. M., & Whited, T. M. (2018). Are financial constraints priced? Evidence from textual analysis. *The Review of Financial Studies*, *31*(7), 2693–2728.

Burggraf, T., Fendel, R., & Huynh, T. L. D. (2020). Political news and stock prices: Evidence from Trump's trade war. *Applied Economics Letters*, *27*(18), 1485–1488.

Chan, K. (1992). A further analysis of the lead–lag relationship between the cash market and stock index futures market. *The Review of Financial Studies*, *5*(1), 123–152.

Chatziantoniou, I., & Gabauer, D. (2021). EMU risk-synchronisation and financial fragility through the prism of dynamic connectedness. *The Quarterly Review of Economics and Finance*, *79*, 1–14.

Dao, T. M., McGroarty, F., & Urquhart, A. (2019). The Brexit vote and currency markets. *Journal of International Financial Markets Institutions and Money*, *59*, 153–164.

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal*, *119*, 158–171.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Forecast-based measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57–66.

Dimpfl, T., & Peter, F. J. (2014). The impact of the financial crisis on transatlantic information flows: An intraday analysis. *Journal of International Financial Markets Institutions and Money*, *31*, 1–13.

Douch, M., & Edwards, T. H. (2021). The Brexit policy shock: Were UK services exports affected, and when? *Journal of Economic Behavior & Organization*, *182*, 248–263.

Dukascopy contracts for the difference (CFD) 2016. Dukascopy Bank SA, https://www.dukascopy.com/swiss/english/home/.

Eriksson, K. (2019). FT tops one million paying readers. Financial Times. https://aboutus.ft.com/en-gb/announcements/ft-tops-one-million-paying-readers/

Escribano, A., & Íñiguez, C. (2021). The contagion phenomena of the Brexit process on main stock markets. *International Journal of Finance and Economics*, *26*(3), 4462–4481.

Feldman, R., Rosenfeld, B., Bar-Haim, R., & Fresko, M. (2011). The stock sonar - sentiment analysis of stocks based on a hybrid approach. Innovative applications of artificial intelligence. https://www.aaai.org/ocs/index.php/IAAI/IAAI-11/paper/view/3506/4024

Foglia, M., & Dai, P.-F. (2022). "Ubiquitous uncertainties": Spillovers across economic policy uncertainty and cryptocurrency uncertainty indices. *Journal of Asian Business and Economic Studies*, *29*(1), 35–49. https://doi.org/10.1108/JABES-05-2021-0051

Glasserman, P., & Mamaysky, H. (2019). Does unusual news forecast market stress? *Journal of Financial and Quantitative Analysis*, *54*(5), 1937–1974.

Gorodnichenko, Y., Pham, T., & Talavera, O. (2021). Social media, sentiment and public opinions: Evidence from# Brexit and# USElection. *European Economic Review*, *136*, 103772.

Gottschalk, S. (2021). From black Wednesday to Brexit: Macroeconomic shocks and correlations of equity returns in France, Germany, Italy, Spain, and the United Kingdom. *International Journal of Finance and Economics*. https://doi.org/10.1002/ijfe.2567

Groß-Klußmann, A., & Hautsch, N. (2011). When machines read the news: Using automated text analytics to quantify high frequency news-implied market reactions. *Journal of Empirical Finance*, *18*(2), 321–340.

Hollstein, F., Prokopczuk, M., & Wese Simen, C. (2020). The conditional capital asset pricing model revisited: Evidence from high-frequency betas. *Management Science*, *66*(6), 2474–2494.

Hudson, R., Urquhart, A., & Zhang, H. (2020). Political uncertainty and sentiment: Evidence from the impact of Brexit on financial markets. *European Economic Review*, *129*, 103523.

Husted, L., Rogers, J., & Sun, B. (2020). Monetary policy uncertainty. *Journal of Monetary Economics*, *115*, 20–36.

Huynh, T. L. D., Foglia, M., Nasir, M. A., & Angelini, E. (2021). Feverish sentiment and global equity markets during the COVID-19 pandemic. *Journal of Economic Behavior and Organization*, *188*(8), 1088–1108.

International Monetary Fund. (2019). World economic outlook: Global manufacturing downturn, Rising Trade Barriers. https://www.imf.org/en/Publications/WEO/Issues/2019/10/01/world-economic-outlook-october-2019

Ionescu, R. V., Zlati, M. L., & Antohi, V. M. (2021). Brexit impact on European Union's destructuration and its contribution to a new economic crisis: A new modelling approach. *International Journal of Finance and Economics*, *26*(1), 1586–1610.

Katsiampa, P., Corbet, S., & Lucey, B. (2019). High frequency volatility co-movements in cryptocurrency markets. *Journal of International Financial Markets Institutions and Money*, *62*, 35–52.

Khademalomoom, S., & Narayan, P. K. (2019). Intraday effects of the currency market. *Journal of International Financial Markets Institutions and Money*, *58*, 65–77.

Khedr, A. E., Salama, S. E., & Yaseen, N. (2017). Predicting stock market behavior using data mining technique and news sentiment analysis. *International Journal of Intelligent Systems and Applications*, *9*(7), 22–30.

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in non-linear multivariate models. *Journal of Econometrics*, *74*, 119–147.

Kurov, A., Sancetta, A., Strasser, G., & Wolfe, M. H. (2019). Price drift before US macroeconomic news: Private information about public announcements? *Journal of Financial and Quantitative Analysis*, *54*(1), 449–479.

Lockwood, L. J., & Linn, S. C. (1990). An examination of stock market return volatility during overnight and intraday periods, 1964–1989. *The Journal of Finance*, *45*(2), 591–601.

Loughran, T., & McDonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *Journal of Finance*, *66*, 35–65.

Loughran, T., & McDonald, B. (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research*, *54*(4), 1187–1230.

McCrae, R. (2019). 09 geographical breakdown of the current account, The Pink Book. Office for National Statistics. https://www.ons.gov.uk/economy/nationalaccounts/balanceofpayments/datasets/9geographicalbreakdownofthecurrentaccountthepinkbook2016

Mittermayer, M. (2004). Forecasting intraday stock price trends with text mining techniques. 37th Annual Hawaii International Conference on System Sciences, Big Island, HI.

Nishimura, Y., & Sun, B. (2018). The intraday volatility spillover index approach and an application in the Brexit vote. *Journal of International Financial Markets Institutions and Money*, *55*, 241–253.

Pesaran, M. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. *Economics Letters*, *58*, 17–29.

Samitas, A., Polyzos, S., & Siriopoulos, C. (2018). Brexit and financial stability: An agent-based simulation. *Economic Modelling*, *69*, 181–192.

Seki, K., & Shibamoto, M. (2017). Constructing financial sentiment lexicons by integrating textual and time-series data. 2017 IEEE International Conference on Information Reuse and Integration (IRI), IEEE (pp. 121–126).

Stoupos, N., & Kiohos, A. (2021). BREXIT referendum's impact on the financial markets in the UK. *Review of World Economics*, *157*(1), 1–19.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance*, *62*, 1139–1168.

Trussler, M., & Soroka, S. (2014). Consumer demand for cynical and negative news frames. *The International Journal of Press/Politics*, *19*(3), 360–379.

Wang, G., Xie, C., & Stanley, H. E. (2018). Correlation structure and evolution of world stock markets: Evidence from Pearson and Partial correlation-based networks. *Computational Economics*, *51*, 607–635.

Zhang, Y. J., & Ma, S. J. (2021). Exploring the dynamic price discovery, risk transfer and spillover among INE, WTI and Brent crude oil futures markets: Evidence from the high-frequency data. *International Journal of Finance and Economics*, *26*(2), 2414–2435.

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APPENDIX A

Negation words (apostrophies are removed for consistency): aint, arent, cannot, cant, couldnt, darent, didnt, doesnt, ain't, aren't, can't, couldn't, daren't, didn't, doesn't, dont, hadnt, hasnt, havent, isnt, mightnt, mustnt, neither, don't, hadn't, hasn't, haven't, isn't, mightn't, mustn't, neednt, needn't, never, none, nope, nor, not, nothing, nowhere, oughtnt, shant, shouldnt, wasnt, werent, oughtn't, shan't, shouldn't, wasn't, weren't, without, wont, wouldnt, won't, wouldn't, rarely, seldom, despite, no, nobody.