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Investor sentiment networks: mapping connectedness in DJIA stocks

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Abstract

This study examines the connectedness of firm-level online investor sentiment using Dow Jones Industrial Average constituent stocks. Leveraging two proxies of online textual sentiment, namely news media and social media sentiment, we investigate sentiment connectedness at two levels: frequency interval and asymmetric level. Frequency connectedness dissects connectedness into short-, medium-, and long-term investing horizons, while asymmetric connectedness focuses on the transmission of positive and negative sentiment shocks on news and social media platforms. Our results reveal interesting patterns in which both news and social media sentiments demonstrate consistency in connectedness across the short-, medium-, and long-term. Regarding asymmetric connectedness, we observe that negative news sentiment has a higher connectedness than positive news sentiments.

Keywords: Behavioral finance, Sentiment contagion, Social media sentiment, News media sentiment

Introduction

"...investing in speculative assets is a social activity" (Shiller 1984, p. 457).

Investors spend a significant portion of their free time talking and reading about investments or snooping about others' investment triumphs and failures. Thus, it is conceivable that social movements would affect investor behavior (and, subsequently, the value of speculative assets). If investing is a social activity, as described above, ideologies and sentiments are likely to diffuse within a network of investors. In the contemporary world, where the Internet has enabled the interaction of large masses of investors (Ye and Li 2017), the potential for sentiment to diffuse across a network of investors has been amplified compared to the past, where, for example, the interaction was mostly face-to-face. If sentiment can diffuse among investors, sentiment directed toward specific stocks can diffuse to other stocks within a network (Zhou et al. 2023).

In this study, we examine sentiment contagion in Dow Jones Industrial Average (DJIA) stocks using the most commonly used proxies for online investor sentiment, social media, and online news media. Social and online news media platforms necessitate the transmission of information in real time as well as being accessible to millions of investors and thereby provide a good platform to investigate sentiment contagion. The importance of social media sentiment contagion is demonstrated by Sprenger et al. (2014), who show that individuals offering superior investment guidance receive more *retweets* and possess a larger follower base, thus enhancing their influence in discussions and, hence, the contagion of sentiment. This aligns with Shen et al. (2019), who posit that the frequency of *tweets* about a topic is important because it shows the attention of informed investors. Piñeiro-Chousa et al. (2018) suggest that the influence of textual sentiment on the stock market varies according to the characteristics of network users, suggesting that information diffusion on social media networks is likely to differ from that on news media networks.

Narrative economics investigates the contagious spread of popular narratives and their influence on economic behavior (Shiller 2019). These narratives, akin to infectious diseases, have the potential to alter economic decision-making on a large scale. The wider the narrative spreads, the more it permeates public discourse, both physically and through digital channels. Similar to an epidemic, a dominant narrative may eventually wane as public attention shifts, potentially paving the way for a new narrative. The proliferation of social and news media has further amplified the significance of narrative economics. These platforms function as vectors for the rapid dissemination of narratives, potentially affecting asset price formation through their influence on investor sentiment and, thereby, sentiment contagion.

This study aims to address two objectives. First, we investigate sentiment contagion in the time–frequency domain. The Heterogeneous Market Hypothesis posits that investors' reactions to information in financial markets are contingent upon their investment horizons and characteristic dealing frequency (Nyakurukwa and Seetharam 2023). Therefore, to cater to heterogeneous investors, it is ideal to disaggregate our analysis to capture the different investment horizons of individual investors. We address this objective by utilizing the time-varying parameter vector autoregression (TVP-VAR) frequency connectedness approach, which disaggregates connectedness among variables into different frequency intervals (Chatziantoniou et al. 2021). Second, we examine the asymmetric connectedness of online investor sentiment. Using a sample period encompassing the official COVID-19 period, Crocamo et al. (2021) report that negative emotional contagion is more pronounced than positive sentiment contagion and that this effect is amplified by significant events. Therefore, we disaggregate online investor sentiment into positive and negative components to understand the trajectories of negative and positive sentiment connectedness.

Ozsoylev et al. (2011) demonstrate that a large network's increased connection unambiguously boosts market efficiency. Therefore, understanding whether sentiment diffuses at the stock level is of paramount importance. In other words, does the sentiment directed toward one stock diffuse to other stocks within a network of companies? Which companies are the net receivers and transmitters of sentiment within a network? Is the sentiment correlation static or time-varying? These questions help in portfolio diversification, especially as the extant literature shows a causal relationship between investor sentiment and stock returns. For regulators, an understanding of sentiment contagion among a network of firms could also help predict asset bubbles and crashes if extreme sentiment contagion unrelated to fundamentals permeates the markets.

This paper proceeds as follows: Sect. "Literature review" reviews the related literature, Sect. "Data and methods" outlines the methodology used to examine sentiment contagion, Sect. "Results" presents the findings, Sect. "Discussion" discusses the results, and Sect. "Conclusion" concludes the paper.

Literature review

Most empirical studies on sentiment contagion concentrate on cross-asset contagion rather than on a single asset class. Pan (2018) investigates sentiment contagion across different asset classes by utilizing sentiment indices for large equities domiciled in the United States of America, large European equities, German equities, large Japanese equities, 10-year Eurobonds, 10-year US bonds, gold, crude oil, and USD-JPY and EUR-USD exchange rates. The authors test whether sentiment in one market significantly affects sentiment in other markets and/or asset classes using Toda and Yamamoto's (1995) Granger causality framework. Sentiment from the US bond market was reported as Granger-causing sentiment from equity markets.

Although the above studies show investor sentiment connectedness, the literature also shows that investors react differently to shocks in financial markets depending on their investment horizons. For example, investors who invest in the short-term are likely to react differently than those who invest in the medium or long term. Su and Li (2020) analyze the spillover of sentiment among three asset classes (bitcoin, crude oil, and gold) using methods that show the evolvement of the relationship in a time–frequency map like the Baruník and Křehlík (2018) frequency connectedness measure and wavelet coherence. The results reveal that the total sentiment spillover among markets is more pronounced in the short than in the long run. This finding implies that shocks that create linkages among the three asset classes mostly affect markets in the short-term. The study also reports that Bitcoin is a net transmitter of sentiment within the system connecting the three hedging assets. This leads to the following hypothesis:

H1 There are significant differences in firm-level online investor sentiment (news and social media) connectedness across the short-, medium-, and long-term.

A significant body of existing literature demonstrates that individuals respond to negative news more than they do to positive news. In Prospect Theory, Kahneman and Tversky (1979) reason that people care more about a loss in utility than about a gain of a comparable size. This is demonstrated by responses to macroeconomic news about the economy; when the economy shrinks, consumption typically declines more than it increases when the economy grows. According to Soroka (2015), because people are risk-averse, they do not instantly reduce spending after hearing that economic performance is predicted to decline, compelling them to reduce spending even more drastically when poor economic outcomes are achieved. Similarly, because people are not averse to gains, their early increase in consumption in the wake of good news indicates no significant increase in consumption once a positive outcome is achieved. Ideally, current income gains would have a modestly positive impact on current consumption, whereas current income decline would have a substantially negative impact. Soroka (2015) argues that while the literature has documented asymmetric responsiveness to mass media, another strand of the literature suggests that this asymmetry is due to the tendency of news to be more negative than positive. For example, news networks provide significantly more coverage for bad economic or firm-specific trends than for good ones (Harrington 1989).

According to Soroka (2015), journalists prioritize negative information in light of both their own (asymmetric) interests and the (asymmetric) interests of the people who read their news. According to this theory, the observed patterns in media content are the result of asymmetric responses to information at the individual level. The focus on bad news from media sources may reflect one of their primary institutional roles in democracy: keeping the present government (as well as businesses and individuals) accountable. Thus, individuals may respond asymmetrically to information that is already asymmetrically skewed if they receive information about the state of the world partially from the media. Therefore, it can be argued that asymmetric responsiveness may be amplified in situations where mass-mediated information is important. Owing to the aforementioned "negativity bias" in response to mass media news, we also expect the contagion of the associated negative news sentiment to be more pronounced than that of positive news sentiment.

While most studies have documented stronger investor reactions to negative news than they have to positive news, some have reported contradictory results. Ma et al. (2021) examine how investors in the Chinese stock market respond to both good and bad news. Based on news articles published in eight prominent Chinese business newspapers, the authors report that securities markets respond differently to positive and negative news. Their findings imply that, although negative news items lead to drift, positive news reports are followed by a reversal. In other words, the market overreacts to good news but underreacts to bad news. These results confirm earlier results reported by Frank and Sanati (2018), who investigate how the stock market absorbs shocks using a comprehensive set of news stories about S&P 500 firms from 1982 to 2013. Frank and Sanati (2018) find that the stock market overreacts to good news and underreacts to bad news. Zhou et al. (2023) report that optimistic investor sentiment is more connected than pessimistic investor sentiment is. Other studies have reported that both negative and positive news exert identical effects on financial markets, especially the cryptocurrency market (for example, Gherghina and Simionescu 2023), suggesting symmetric connectedness. This leads to the following hypothesis:

H2 There are differences in the connectedness of firm-level positive and firm-level negative textual (news and social media) sentiment.

While the connectedness of investor sentiment differs between positive and negative sentiment as well as between different time intervals (short-, medium-, and long-term), as explained above, other studies have also established that investor sentiment spillovers peak at the back of major crisis events, such as COVID-19 (Agyei et al., 2023; Tiwari et al. 2021).

Data and methods

Data

The study uses a population of firms constituting the DJIA between January 1, 2016 and April 30, 2023. The above-mentioned sample is selected for several reasons. First, these stocks are chosen because of the high quality of textual sentiment data extracted from Bloomberg Inc. for these specific stocks. Several studies focus on DJIA constituent stocks in terms of textual sentiment dynamics because of the quality of their sentiment scores (e.g. de Jong et al. 2017). Social media and news media sentiment scores are extracted from Bloomberg Inc. Bloomberg started incorporating social media sentiment data on January 1, 2015; however, the quality of sentiment scores only started to improve in 2016 as the percentage of missing values decreased. Therefore, we restrict the study period to the period after December 31, 2015. Firms listed or delisted in the middle of the sample period are not included in the study because Bloomberg Inc. only provides sentiment data for currently listed stocks. This leads to an ultimate dataset of 29 DJIA constituents (a full list of the sampled stocks is included in Table A1 in the Appendix).

Tables A2 and A3 show that most stocks have positive news and social media averages. This means that, on average, listed stocks are associated with positive sentiment on the two media platforms (News and Twitter[1]). Regarding stationarity, using the bootUR (Smeekes and Wilms 2022) test under the null hypothesis that each series has a unit root, the results across all variables for each sampled stock show statistically significant results at the 1% significance level. This means all series do not have unit roots and are, therefore, stationary. Using the Fat-tailed normality test, because of its robustness to financial variables (Jelito and Pitera 2021), we observe that for all stocks, the test statistic is statistically significant at the 1% level of significance. As expected, we conclude that our firm-level variables are not normally distributed at the 1% significance level.

Variables

Bloomberg computes daily news and social media sentiment scores using a unique approach that leverages the power of machine learning. In a two-step process, Bloomberg first trains machine learning models to understand how news and social media might affect investor confidence in a particular stock. Human experts analyze vast amounts of *tweets* and news articles, labeling them as positive, negative, or neutral based on a hypothetical investor's perspective. These labeled examples become the training ground for the machine learning model. Once trained, the model analyzes new *tweets* and news stories related to specific companies, assigning a sentiment score between −1 (very negative) and +1 (very positive) to each message. This score reflects the potential effect of information on investor confidence. Finally, Bloomberg calculates the daily average score for each company to provide investors with a real-time snapshot of market sentiment. This score considers all positive and negative *tweets* and news stories from the past 24 h. Updated every 10 min before the market opens, this daily sentiment score offers valuable insights into how the market perceives a particular company on that day.

[1] This is now called X, but was called Twitter for the period including the sample period used in this study.

Methods

TVP-VAR frequency connectedness

To establish the connectedness of online investor sentiment in a time–frequency space, we use the Chatziantoniou et al. (2021) connectedness approach. This method builds upon research by Baruník and Křehlík (2018) and Antonakakis et al. (2020). It decomposes time-series data into key components, revealing the fine-grained details of short-, medium-, and long-term relationships between assets. This approach incorporates time-varying coefficients and variance–covariance structures, offering valuable insights for investors. Chatziantoniou et al. (2021) highlight several improvements this method offers over traditional approaches. First, it avoids data discarding because it does not employ a rolling window. Second, it eliminates the need for arbitrary window size selection. Additionally, it mitigates the influence of outliers and prevents erratic or flattened parameter estimates. Finally, it provides confidence intervals for each connectedness measure, thereby enhancing the overall reliability of the analysis. The details of the TVP-VAR frequency connectedness approach can be found in Chatziantoniou et al. (2021). In line with existing literature (e.g. Baruník and Křehlík, 2018), we decompose our frequency bands into 1 to 5 days, 5 to 20 days, and 20 days to infinity, representing the short-, medium-, and long-term.

TVP-VAR asymmetric connectedness

To analyze the asymmetries in how online investor sentiment connects across different stocks, we identify three types of spillover effects: normal, positive, and negative. First, we separate the sentiment series into daily positive and negative sentiment scores as follows:

$$S_t = \begin{cases} 0, & if z_t < 0 \\ 1, & if z_t \geq 0 \end{cases}$$

$$z_t^{+} = S_t.z_t$$

$$z_t^{-} = (1 - S_{t)}.z_t$$

To examine how investor sentiment connects across different stocks and identify potential asymmetries in these connections, we adopt the asymmetric connectedness approach proposed by Adekoya et al. (2022). This approach builds on the work of Antonakakis et al. (2020) and utilizes a TVP-VAR model. The first step involves estimating a TVP-VAR (1) model using Bayesian Information Criterion (BIC) to determine the optimal lag length as follows:

$$z_t = \boldsymbol{B}_t z_{t-1} + u_t u_t \sim N(0, \Sigma_t) \tag{1}$$

$$vec(B_t) = vec(\boldsymbol{B}_{t-1}) + v_t v_t \sim N(0, \mathrm{R}_t) \tag{2}$$

where z_t, z_{t-1} and u_t are $k \times 1$ dimensional vectors in t, $t-1$ and the corresponding error term, respectively. $\boldsymbol{B}_t$ and Σ_t are the $k \times k$ dimensional matrices demonstrating the time-varying VAR coefficients and the time-varying variance-covariances, $vec(B_t)$ and v_t are the $k^2 \times 1$ dimensional vectors, and R_t is a $k^2 \times k^2$ dimensional matrix.

Results

Frequency connectedness

This section presents the results for the connectedness of firm-level sentiment across different investment horizons. For comparison, we present the results together with the total connectedness measures from the seminal Diebold and Yilmaz indices. Our frequency intervals are divided into short-term (1 to 5 days), medium-term (5 to 20 days), and long-term (20 days to infinity). We first report the results for static connectedness before moving on to the dynamic connectedness measures. Table 1 shows the net transmission of sentiment spillovers for the DJIA stocks. In Table 1, the positive (negative) net sentiment spillover values show that the respective stock is a net transmitter (receiver) of sentiment shocks because its contribution to other stocks is greater (lesser) than what it receives from other stocks.

Table 1 Net frequency sentiment spillovers

	News sentiment				**Twitter sentiment**			
	Total	**1–5 days**	**5–20 days**	**20-inf**	**Total**	**1–5 days**	**5–20 days**	**20-inf**
AAPL	0.04	0.69	−0.43	−0.23	3.83	2.96	0.75	0.11
AMGN	2.86	−1.27	2.24	1.89	−1.78	−2.21	0.32	0.11
AXP	−1.12	−1.28	−0.08	0.24	−3.92	−2.11	−1.17	−0.64
BA	0.12	0.52	−0.01	−0.39	0.47	0.21	0.09	0.17
CAT	−3.88	−2.21	−1.11	−0.56	−3.13	−3.65	0.17	0.35
CRM	−6.05	−3.17	−1.96	−0.92	−1.61	−0.12	−0.98	−0.51
CSCO	0.81	0.94	−0.14	0.01	−3.01	−1.69	−0.84	−0.48
CVX	−1.51	−0.16	−0.83	−0.52	−2.43	−0.23	−1.34	−0.86
DIS	2.09	1.47	0.56	0.06	0.91	−0.21	0.83	0.28
GS	−1.84	−0.98	−0.49	−0.38	0.28	−0.02	0.17	0.13
HD	−1.76	−1.13	−0.56	−0.08	−3.36	−1.08	−1.47	−0.8
HON	−3.85	−3.82	−0.14	0.11	0.06	−0.72	0.52	0.26
IBM	20.12	11.83	5.19	3.1	2.64	2.63	−0.04	0.05
INTC	8.46	3.33	3.21	1.92	−0.35	0.4	−0.61	−0.14
JNJ	−3.68	0.82	−2.52	−1.98	0.45	0.77	−0.23	−0.09
JPM	−1.92	−1.61	−0.06	−0.25	−2.88	−1	−1.23	−0.65
KO	6.36	2.73	2	1.63	4.81	3.4	0.89	0.52
MCD	−0.97	0.67	−0.92	−0.72	6.32	3.54	1.93	0.85
MMM	−1.51	−0.46	−0.47	−0.58	−0.6	−0.42	−0.14	−0.04
MRK	−4.78	−3.42	−0.89	−0.47	−0.53	−0.94	0.3	0.11
MSFT	7.59	4.41	2.22	0.96	5.58	4.63	0.67	0.28
NKE	−3.76	−2.2	−1.05	−0.52	2.97	0.87	1.3	0.81
PG	−1.07	−0.88	−0.09	−0.11	−1.38	−0.87	−0.3	−0.21
TRV	−3.82	−1.6	−1.53	−0.69	−2.76	−3.3	0.25	0.29
UNH	−1.8	−0.4	−0.99	−0.41	−0.61	−0.42	−0.1	−0.09
V	−6.09	−3.07	−1.75	−1.27	−0.45	−0.91	0.45	0.01
VZ	2.45	1.04	0.83	0.57	−0.94	0.21	−0.86	−0.3
WBA	−2.25	−1.17	−0.56	−0.52	−2.65	−1.7	−0.73	−0.22
WMT	0.77	0.36	0.33	0.09	4.09	1.98	1.41	0.7

Before interpreting the results in Table 1, we visualize the networks of the pairwise net sentiment spillovers. This is shown in Fig. 1 for news sentiment and Fig. 2 for Twitter sentiment.

Starting with news sentiment, Table 1 shows that IBM is the most influential stock across all three investment horizons as it has the highest positive net transmission of news sentiment shocks. The values for the net news sentiment transmissions for the IBM stock are 11.83, 5.19, and 3.1 in the short-, medium-, and long-term, respectively, and these constitute the maximum values across the hypothesized investment horizons. Interestingly, across all the sampled stocks, a pattern emerges where the net transmissions are higher in the short-term and lower in the medium- and long-term, respectively. Regarding net receivers of news sentiment shocks, the most vulnerable stock in the short-term is HON (-3.82), whereas in the medium- and long-term, JNJ receives the most net news sentiment shocks (-2.52 and -1.98, respectively). Figure 1 illustrates the pairwise net transmission among the stocks in terms of news sentiment. In the short-term, notable transmissions of news sentiment shocks can be observed between IBM and VZ, as well as between INTC and AXP. In the medium-term, IBM and VZ continue to have strong connections, while other notable news sentiment transmissions can be seen between KO and BA as well as IBM and MMM. In the long-term, the most notable pairwise connections have subsided, whereas KO and BA remain strongly connected.

Regarding Twitter sentiments, Table 1 shows notable differences compared with news sentiment. First, MSFT is the most influential stock in terms of the net transmission of Twitter sentiment shocks within the system in the short run. In the medium- and long-term, MCD is the most influential, with net transmissions of 1.93 and 0.85, respectively.

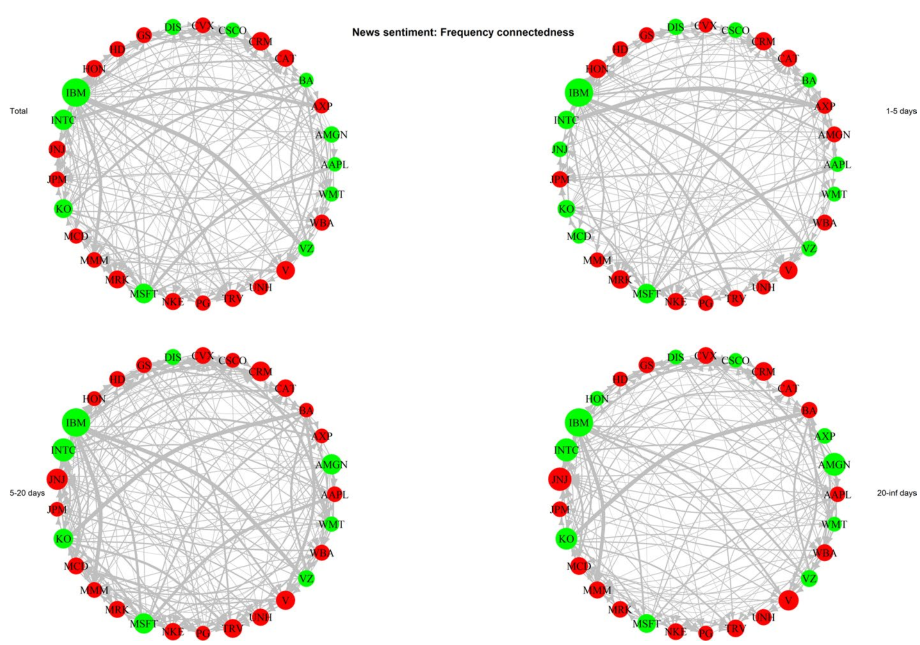

Fig. 1 Net frequency pairwise directional spillover network for news sentiment. Nodes coloured green (red) indicate the net sender (receiver) of shocks. Vertices are assigned weights based on the average net pairwise directional connectedness metrics. The node sizes reflect the weighted average net total directional connectedness

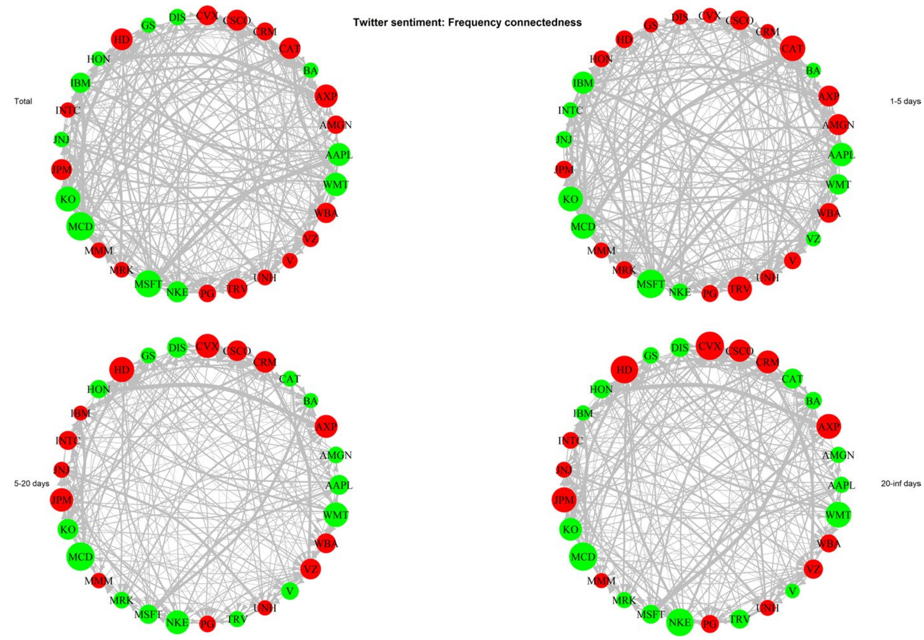

Fig. 2 Net frequency pairwise directional spillover network for Twitter sentiment. Nodes coloured green (red) indicate the net sender (receiver) of shocks. Vertices are assigned weights based on the average net pairwise directional connectedness metrics. The node sizes reflect the weighted average net total directional connectedness

However, the absolute values of the net transmissions for Twitter sentiment are low compared to the net transmissions observed for news sentiment. Regarding pairwise connectedness, Fig. 2 shows that the MCD-CAT, HON-AXP, and HON-AXP constitute the most connected pairs in terms of Twitter sentiment spillovers in the short-, medium-, and long-term, respectively. Interestingly, some stocks (e.g., HON) transition from net receivers of Twitter sentiment shocks in the short-term to net emitters in the medium- and long-term.

These results assume that the transmission of sentiment shocks within a system is static. However, in reality, time-specific events can alter the structure of sentiment spillovers within a system (e.g., national elections, pandemics). These can be accurately captured using time-varying connectedness frameworks. Therefore, we report the dynamic frequency sentiment spillovers in Fig. 3. In Fig. 3, the blue, green, red, and purple solid lines represent short-term, medium-term, long-term, and total connectedness, respectively. Using the dynamic model, some interesting points in the market can be noted, as shown in Fig. 3. For both online sentiment proxies, in most periods, there seems to be increased connectedness at lower frequencies compared to other frequency intervals. For both sentiment proxies, there are intermittent spikes in connectedness at various times, probably triggered by politically and economically significant events. For example, there is a spike in short-term connectedness at the beginning of 2017 and 2022 for Twitter sentiment, whereas the greatest spike in connectedness for news at all frequency intervals occurs in 2017 and 2019.

Significant events happened during these periods: at the beginning of 2017, the 45th president of the USA, Donald Trump, was officially inaugurated into office. Therefore, it

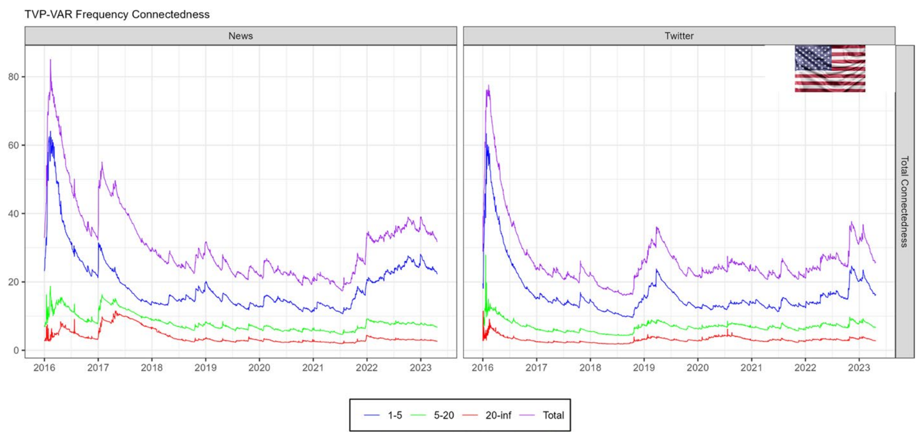

Fig. 3 Total frequency connectedness. Notes: The findings are derived from a TVP-VAR model employing a lag length determined by BIC and a 100-step-ahead generalized forecast error variance decomposition. The trajectories depicted by the red, green, blue, and purple lines illustrate the evolution of connectedness over short-term (1–5 days), medium-term (5–20 days), long-term (20 days and beyond), and aggregate levels (Total), respectively

can be inferred that increased connectedness is a response to this important event in the USA. In line with narrative economics, discourse on online platforms may have increased in response to election outcomes, thereby changing the connectedness structure of sentiment. Across the sample period and sentiment proxies, short-term connectedness is unambiguously higher than medium- and long-term connectedness. Medium- and long-term connectedness, though low, is stable and not as erratic as observed with short-term connectedness. Thus, sentiment shocks are transmitted mostly in the short-term. It can also be observed that the structure of news sentiment connectedness is almost similar to the structure of social media sentiment across the sample period.

Asymmetric connectedness

In this section, we report our findings on the asymmetric connectedness of online investor sentiment. As in the previous section, we report the static connectedness results before reporting the dynamic results that capture time-specific events. Table 2, Figs. 4 and 5 show the emitters and receivers of positive and negative online textual sentiment shocks in the market, together with the strength of the pairwise relationships.

As reported for frequency connectedness, IBM is the most influential emitter of both positive and negative news sentiment shocks in the market. Regarding pairwise news sentiment connections, the IBM-VZ and MSFT-AAPL pairs exchange the highest news sentiment shocks within the system. Twitter sentiment shows that a different picture emerges, in which MCD is the most influential transmitter of both positive and negative news sentiment shocks. Interestingly, some stocks (e.g., AAPL and WMT) are significant transmitters of negative Twitter sentiment shocks but become net receivers when considering positive Twitter sentiment shocks. Stronger pairwise connections are associated with negative sentiment than positive sentiment.

In Fig. 6, we introduce the time aspect of asymmetric sentiment connectedness by examining connectedness in time space. The red, green, and blue solid lines in the plots represent negative, positive, and total sentiment connectedness, respectively. For

Table 2 Net asymmetric sentiment spillovers

	News sentiment		Twitter sentiment	
	Negative	Positive	Negative	Positive
AAPL	−1.72	−1.32	0.66	−4.71
AMGN	3.28	−6.9	−2.08	0.27
AXP	−2.37	−5.76	−3.39	−6.49
BA	−0.73	14.49	0.34	1.53
CAT	−0.93	−1.42	−0.84	−2.97
CRM	−4.57	−11.83	−1.74	−9.11
CSCO	2.74	7.6	−3.23	−6.14
CVX	−1.89	2.21	−2.13	−1.77
DIS	−1.35	−2.96	−0.37	7.94
GS	−2.37	−0.68	0.14	2.95
HD	0.91	1.22	−0.93	1.26
HON	−2.89	−6.69	−0.66	−6
IBM	17.12	31.37	0.28	2.92
INTC	4.42	2.24	−1.76	−5.16
JNJ	−3.55	2.13	0.34	3.78
JPM	−2.78	14.08	−0.87	6.36
KO	7.76	5.34	4.48	5.78
MCD	−1.75	4.34	5.68	16.06
MMM	1.69	−7.37	0.61	3.54
MRK	−2.55	−2.93	−0.9	−0.33
MSFT	2.61	0.57	2.24	−1.39
NKE	−3.74	−5.11	3.22	1.54
PG	−0.17	−5.81	−1.02	−0.46
TRV	−1.26	−3.85	−0.28	−4.23
UNH	−2.87	−7.37	0.44	−2.91
V	−4.77	−6.37	−0.29	0.76
VZ	4.18	3.38	−1.58	3.52
WBA	1.44	−8.6	−1.87	−4.38
WMT	−3.89	−3.99	5.52	−2.17

comparison, we include total connectedness, which shows connectedness without disaggregating sentiment into positive and negative sentiment. First, regarding news, we observe that negative sentiment is unambiguously more connected than positive sentiment. Moreover, the time-varying total connectedness is consistently less than the negative sentiment connectedness, showing the significant asymmetric connectedness of news sentiment within the DJIA network of firms. We also notice simultaneous spikes in positive and negative news sentiment connectedness at the beginning of 2017 and 2022. Coincidentally, these periods coincide with the 2017 US elections and the 2022 Russian-Ukrainian war. The convergence of positive, negative, and total news sentiment connectedness can be observed in the second half of 2022. Regarding social media, there is a role-shifting behavior in connectedness, with negative sentiment dominating connectedness from 2016 to 2021. From 2021 to the second half of 2022, positive sentiment transmits more sentiment shock spillovers than negative sentiment does. In summary, there seem to be some similarities in the trajectories of the evolution of connectedness measures between the news and social media.

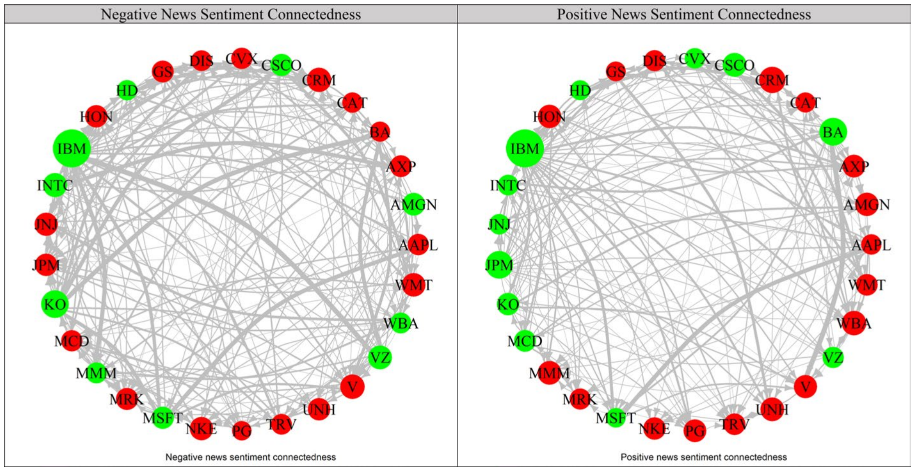

Fig. 4 Net asymmetric pairwise directional spillover network for news sentiment. Nodes colored green (red) indicate the net sender (receiver) of shocks. Vertices are assigned weights based on the average net pairwise directional connectedness metrics. The node sizes reflect the weighted average net total directional connectedness

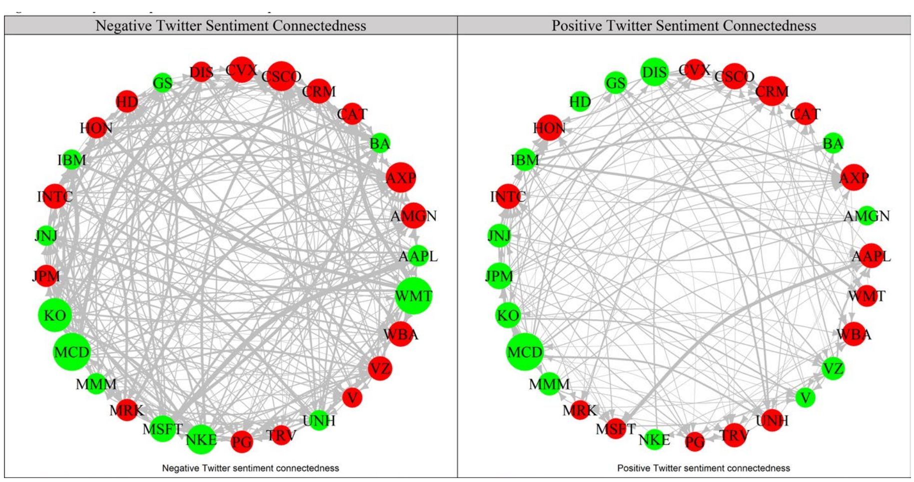

Fig. 5 Net asymmetric pairwise directional spillover network for Twitter sentiment. Nodes colored green (red) indicate the net sender (receiver) of shocks. Vertices are assigned weights based on the average net pairwise directional connectedness metrics. The node sizes reflect the weighted average net total directional connectedness

Discussion

The results presented in the previous sections show different patterns in the connectedness of firm-level sentiment across the two proxies for online sentiment. Starting with frequency connectedness, the results show that sentiment connectedness is dominant in the short-term frequency interval, indicating that sentiment shocks are mostly transmitted in the short-term. These results are in line with those of Su and Li (2020), who report that sentiment connectedness is more pronounced in the short run. This could signal improved market efficiency because reactions to sentiment shocks occur in the short-term. This means that the information received from the two online platforms is quickly cascaded across the network of stocks, and sentiment shocks are almost nonexistent

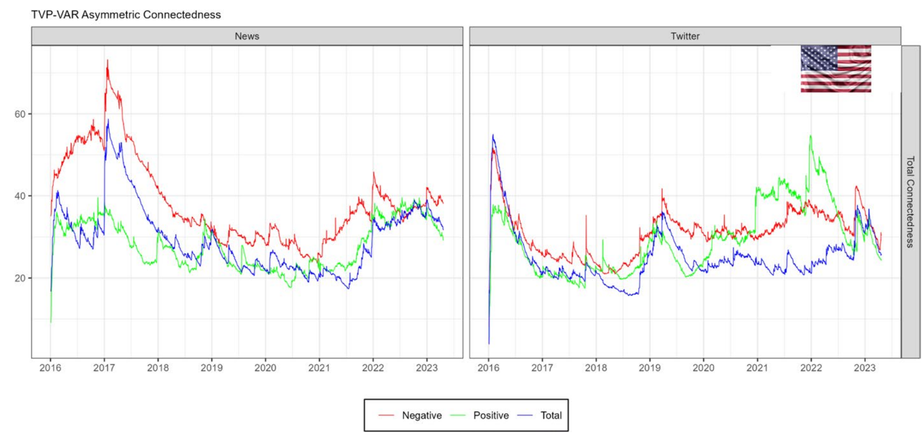

Fig. 6 TVP-VAR asymmetric total connectedness. The results are derived from a TVP-VAR model utilising a lag length determined by BIC and a generalized forecast error variance decomposition for a 100-step-ahead projection. The trajectories represented by the red, green, and blue lines denote the evolution of negative, positive and overall sentiment connectedness, respectively

in the long-term. The quick transmission of sentiment shocks across different stocks is consistent with the EMH, which postulates that information is instantaneously incorporated into asset prices. However, the fact that there is some level of connectedness that still exists in the medium- and long-term shows that markets are not "perfectly efficient" as the sentiment shocks transmitted across firms could still be used by long-term investors in their investing decisions. This is in line with the tenets of behavioral finance and narrative economics, in which sentiment directed at a single stock can spread across other stocks and potentially affect stock market outcomes.

For both news and social media, the TVP-VAR asymmetric connectedness results show that spikes in negative sentiment spillovers are simultaneously accompanied by corresponding spikes in positive and negative sentiment. The coexistence of the strong connectedness of positive and negative news sentiment can signal the prevalence of opposing narratives in the system. For example, Fig. 6 shows a simultaneous spike in both negative and positive news sentiment contagion in early January 2017. This is when Donald Trump assumed office as the 45th President of the USA. Since Donald Trump was elected in November 2016, we see a spike in both negative and positive news sentiment, with both sentiment states peaking seven days after Trump officially assumes office. Donald Trump has been cited as "one of the most viral celebrities of all time" (Shiller 2020, p. 797), while at the same time credited for presiding over arguably the most divided society in the history of the USA,[2] creating a conducive environment for the coexistence of opposing narratives online.

The "America First" narrative associated with the US president engendered strong positive sentiment from the supporters and strong negative sentiment from those against the narrative. Such a scenario potentially leads to investor disagreement in financial markets, as supporters of the narrative enter long positions and opposers enter short positions. We also observe that negative news sentiment is more connected than positive news sentiment. This is in line with the literature reporting that investors react more

[2] https://www.reuters.com/article/usa-trump-legacy-analysis-int-idUSKBN29P0EX

to negative news than they do to positive news, probably because of the negativity bias in news reporting (Sprenger et al. 2014). The findings provide additional proof that news platforms have a strong bias toward reporting more negative than positive occurrences, in line with the adage, “bad news is good news” (Soroka 2015). However, these results are contrary to those reported in a Chinese environment, where positive sentiment displays a more substantial contagion effect than negative sentiment, indicating that optimistic market sentiment has a greater impact on spreading and influencing other participants’ attitudes and behaviors within the financial ecosystem (Zhou et al. 2023).

Interesting results are also reported for static and pairwise sentiment connectedness. For example, IBM is reported as the most influential net transmitter of news sentiment shocks in the short run, medium-term, and long run. This finding indicates that IBM consistently plays a significant role in transmitting sentiment shocks to the broader market, beyond short-term fluctuations. The finding suggests that IBM’s news sentiment continues to have a strong effect on shaping investor sentiment and influencing news sentiment directed toward other stocks over an extended period. The results also show that sentiment connectedness peaks at the back of globally significant events such as COVID-19, in line with Agyei et al. (2023).

Conclusion

This study examines the connectedness of firm-level online investor sentiment within the DJIA stock network. We explore investor connectedness using two proxies for online textual sentiment at the aggregate, frequency interval, and asymmetric levels. Aggregate sentiment connectedness is consistent with the seminal work of Diebold and Yilmaz connectedness measures and measures total connectedness. Frequency connectedness seeks to disaggregate connectedness into three investment horizons, representing the short-, medium-, and long-term. In contrast, asymmetric connectedness disaggregates sentiment to understand how pessimistic and optimistic sentiment shocks are transmitted on news and social media platforms.

The results show that the connectedness using news sentiment and social media sentiment is almost consistent. Firm-level news and social media sentiment are strongly connected in the short-, medium-, and long-term in that order. Regarding asymmetric connectedness, negative news sentiment is more connected than positive news sentiment. The findings have several policy implications. Given the strong connectedness of online investor sentiment on both news and social media platforms, regulatory authorities in the USA can intensify their efforts to monitor and analyze sentiment data from these sources. This can facilitate the early detection of potential market disruptions and excessive volatility, thereby allowing timely risk management interventions. Policymakers and investors should pay particular attention to negative sentiment connectedness, as it appears to be stronger than positive sentiment connectedness. This can indicate increased market sensitivity to negative news, potentially leading to more pronounced market reactions during periods of uncertainty or negative events.

A limitation of this study is the bias toward large companies. This is necessitated by the lack of quality sentiment data for smaller stocks. Future studies can use larger and more heterogeneous samples, including smaller stocks, to gain a better understanding of sentiment connectedness. This can be made possible by utilizing primary data rather than depending on third-party data providers. Future studies can also link the findings of the investor connectedness measures obtained from the study with stock market outcomes such as returns and volatility, *inter-alia,* to establish whether these can be expanded for portfolio management purposes.

Appendix A

See Table 3.

Table 3 Sampled stocks

	Symbol	Company	Sector
1	AAPL	Apple Inc	Technology
2	AMGN	Amgen Inc	Healthcare
3	AXP	American Express Company	Financials
4	BA	Boeing Company	Industrials
5	CAT	Caterpillar Inc	Industrials
6	CRM	Salesforce Inc	Technology
7	CSCO	Cisco Systems Inc	Technology
8	CVX	Chevron Corporation	Energy
9	DIS	Walt Disney Company	Communication Services
10	GS	Goldman Sachs Group Inc	Financials
11	HD	Home Depot Inc	Consumer Discretionary
12	HON	Honeywell International Inc	Industrials
13	IBM	International Business Machines	Technology
14	INTC	Intel Corporation	Technology
15	JNJ	Johnson & Johnson	Healthcare
16	JPM	JPMorgan Chase & Co	Financials
17	KO	Coca-Cola Company	Consumer Staples
18	MCD	McDonald's Corporation	Consumer Discretionary
19	MMM	3 M Company	Industrials
20	MRK	Merck & Co. Inc	Healthcare
21	MSFT	Microsoft Corporation	Technology
22	NKE	NIKE Inc. Class B	Consumer Discretionary
23	PG	Procter & Gamble Company	Consumer Staples
24	TRV	Travelers Companies Inc	Financials
25	UNH	UnitedHealth Group Incorporated	Healthcare
26	V	Visa Inc. Class A	Financials
27	VZ	Verizon Communications Inc	Communication Services
28	WBA	Walgreens Boots Alliance Inc	Healthcare
29	WMT	Walmart Inc	Consumer Staples

Appendix B

See Tables 4, 5

Table 4 Summary and distributional characteristics (news sentiment)

Ticker	Mean	Median	SD	Min	Max	bootUR	FT. normality
AAPL	−0.0010	−0.0018	0.0862	−0.8542	0.7784	−3.3673***	86.8593***
AMGN	0.0608	0.0026	0.3772	−0.9991	0.9997	−2.0706***	20.1674***
AXP	−0.0111	0.0000	0.2000	−0.9869	0.9750	−3.4615***	63.8244***
BA	−0.0060	−0.0010	0.1483	−0.9815	0.8527	−3.0867***	82.6210***
CAT	0.0255	0.0000	0.3494	−0.9975	0.9933	−3.6323***	20.9695***
CRM	0.0590	0.0000	0.2042	−0.8527	0.9534	−4.9416***	37.9915***
CSCO	0.0162	0.0000	0.1743	−0.8997	0.9653	−3.9268***	73.5489***
CVX	−0.0022	0.0000	0.1604	−0.7995	0.8419	−3.9069***	59.4271***
DIS	−0.0003	−0.0002	0.0547	−0.5863	0.7938	−3.5180***	97.8415***
GS	−0.0258	−0.0023	0.1370	−0.9466	0.9566	−3.4599***	72.8500***
HD	0.0520	0.0037	0.2368	−0.9537	0.9860	−4.9925***	45.7016***
HON	0.0073	0.0000	0.1932	−0.9933	0.9117	−2.0637***	61.2458***
IBM	−0.0193	0.0000	0.2409	−0.9924	0.9893	−3.0957***	60.0605***
INTC	0.0027	0.0000	0.1063	−0.7041	0.8329	−3.9318***	85.6996***
JNJ	−0.0406	−0.0005	0.2247	−0.9976	0.9102	−2.9027***	45.9378***
JPM	−0.0155	−0.0026	0.0931	−0.8418	0.5378	−4.9483***	76.0772***
KO	0.0149	0.0000	0.1478	−0.9427	0.8802	−6.5666***	70.6448***
MCD	0.0007	0.0000	0.1550	−0.9359	0.9502	−3.5653***	74.1031***
MMM	−0.0337	0.0000	0.3643	−1.0000	1.0000	−2.8823***	19.9884***
MRK	0.0601	0.0000	0.2690	−0.9933	0.9933	−2.8266***	38.9688***
MSFT	0.0066	0.0000	0.0492	−0.2681	0.7345	−2.5118***	100.735***
NKE	0.0003	0.0000	0.1635	−0.9667	0.9449	−4.1083***	70.0664***
PG	0.0383	0.0000	0.2759	−0.9991	0.9913	−3.9426***	39.4504***
TRV	−0.0392	0.0000	0.3637	−0.9999	0.9997	−2.8061***	16.8877***
UNH	0.0563	0.0000	0.3268	−0.9975	0.9933	−3.6730***	27.8993***
V	0.0168	0.0000	0.1602	−0.9292	0.8760	−3.7121***	67.8804***
VZ	0.0044	0.0000	0.1283	−0.9560	0.9806	−3.9246***	85.8540***
WBA	−0.0046	0.0000	0.3420	−0.9975	0.9933	−3.1106***	28.3487***
WMT	0.0050	−0.0002	0.1301	−0.9534	0.9048	−4.0691***	88.3278***

The table shows the mean, median, standard deviation (SD), minimum value (Min), maximum value (Max), bootUR statistics (Smeekes and Wilms 2022) and Fat tail normality test (Jelito and Pitera 2021) statistics. ***, **, * represents statical significance at the 1%, 5% and 10% levels of significance

Table 5 Summary and distributional characteristics (news sentiment)

Ticker	Mean	Median	SD	Min	Max	bootUR	FT. normality
AAPL	−0.0057	−0.0021	0.0377	−0.3241	0.3218	−2.7123***	78.4273***
AMGN	0.0292	0.0165	0.1162	−0.9516	0.8902	−2.7139***	54.4354***
AXP	0.0182	0.0065	0.1239	−0.9795	0.9153	−2.7413***	65.0485***
BA	−0.0133	−0.0033	0.1032	−0.9119	0.8893	−3.4204***	72.8338***
CAT	0.0225	0.0123	0.1776	−0.9904	0.9510	−3.6737***	51.6769***
CRM	0.0124	0.0053	0.0688	−0.9725	0.5887	−2.5379***	87.4591***
CSCO	0.0202	0.0103	0.0927	−0.8672	0.7404	−4.2951***	66.1571***
CVX	0.0063	0.0079	0.1267	−0.9711	0.8630	−2.9634***	54.9377***
DIS	0.0003	−0.0004	0.0410	−0.9757	0.5366	−4.4327***	95.9119***
GS	−0.0185	−0.0021	0.1280	−0.9448	0.7441	−3.3964***	60.2197***
HD	0.0384	0.0155	0.1661	−0.9577	0.8680	−3.5293***	41.5436***
HON	0.0345	0.0090	0.1299	−0.9747	0.9108	−2.3582***	52.7578***
IBM	0.0033	0.0013	0.0400	−0.4410	0.6598	−7.5433***	100.7231***
INTC	0.0024	0.0030	0.0638	−0.8226	0.9712	−2.6161***	79.0261***
JNJ	−0.0060	0.0011	0.1443	−0.9925	0.9650	−4.1858***	62.9547***
JPM	0.0032	0.0047	0.1665	−0.9797	0.7775	−2.8586***	46.1880***
KO	0.0030	0.0000	0.1376	−0.9618	0.9762	−2.7781***	90.6095***
MCD	0.0028	0.0005	0.1065	−0.9789	0.8647	−3.7006***	80.0208***
MMM	0.0142	0.0094	0.1654	−0.9010	0.9658	−2.7063***	44.5803***
MRK	0.0207	0.0122	0.0922	−0.8487	0.7864	−3.0613***	64.9895***
MSFT	0.0014	0.0014	0.0458	−0.6997	0.5960	−2.6051***	100.9573***
NKE	0.0157	0.0048	0.1618	−0.9608	0.9897	−2.4254***	59.6669***
PG	0.0254	0.0057	0.1145	−0.9158	0.7772	−3.1611***	57.3445***
TRV	0.0421	0.0045	0.2278	−0.9600	0.9502	−8.7739***	34.8702***
UNH	0.0540	0.0172	0.1623	−0.8793	0.9204	−4.0062***	44.6801***
V	0.0159	0.0092	0.0972	−0.9882	0.7453	−3.4651***	74.5340***
VZ	−0.0006	0.0006	0.0689	−0.6866	0.6781	−4.0161***	88.4192***
WBA	0.0027	0.0000	0.1116	−0.9872	0.8177	−3.1318***	61.1199***
WMT	−0.0209	−0.0021	0.1310	−0.9682	0.7823	−3.0622***	79.2956***

The table shows the mean, median, standard deviation (SD), minimum value (Min), maximum value (Max), bootUR statistics (Smeekes and and Wilms 2022) and Fat tail normality test (Jelito and Pitera 2021) statistics. ***, **, * represents statical significance at the 1%, 5% and 10% levels of significance

Abbreviations

BIC	Bayesian information criterion
DJIA	Dow jones industrial average
EMH	Efficient markets hypothesis
HMH	Homogeneous markets hypothesis
TVP-VAR	Time-varying vector autoregression
USA	United States of America

Author contributions

Kingstone Nyakurukwa—conceptualisation, writing original draft, analysis; Yudhvir Seetharam—Supervision, revising, writing original draft.

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Declarations

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We declare no competing interests related to this work.

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