International Journal of Information Management Data Insights 5 (2025) 100337

Contents lists available at ScienceDirect

International Journal of Information Management Data Insights

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

Financial textual sentiment connectedness: Evidence from alternative data

Yudhvir Seetharam, Kingstone Nyakurukwa *

University of the Witwatersrand, School of Economics and Finance, 1 Jan Smuts Avenue, Braamfontein, Johannesburg, South Africa

A R T I C L E I N F O

JEL classifications:
G11
G40
G41

Keywords:
Investor sentiment
Esg sentiment
Behavioural finance, sustainable finance

A B S T R A C T

This study investigates the connectedness of various firm-level investor sentiment proxies—news, social media, ESG positive (ESGpos), and ESG negative (ESGneg) sentiment using aggregate connectedness measures and a sample of DJIA stocks between 2015 and 2024. Our findings reveal that each sentiment proxy maintains strong internal consistency, predominantly shaped by its own sources. Specifically, news and social media exhibit high self-connection scores, indicating that these proxies are primarily influenced by their respective content. ESG sentiment proxies show minimal cross-influence from news and social media, indicating their distinct and independent nature. Network analysis further highlights that news and social media transmit sentiment shocks, while ESG-based proxies are predominantly receivers. The most significant flow of sentiment shocks is from social media to ESG negative sentiment. This reflects the central role of social media in shaping sentiment within the system, in contrast to the more isolated influence of news. During significant global event periods, ESGpos and ESGneg shift roles, with ESGpos becoming a transmitter and ESGneg a receiver of sentiment shocks. Sector-specific analysis shows that the Financials (Technology) sector is a net transmitter (receiver) of sentiment shocks. The practical implications of the findings are discussed. The paper contributes to the literature, which has treated different sentiment proxies as distinct phenomena despite their interconnectedness. Additionally, we find that the aggregate connectedness measures used in this study exhibit stronger connectedness compared to the traditional Diebold-Yilmaz framework.

1. Introduction

Understanding the spillover effects within financial markets has long been a central focus of economic research, with much of the traditional analysis concentrating on the connectedness of direct financial measures such as returns (Bouri, Cepni et al., 2021), volatility (Bouri, Gabauer et al., 2021), trading volumes (Yousaf & Yarovaya, 2022) and so on. These metrics provide insights into how shocks propagate across markets and influence the broader financial landscape. However, recent research has increasingly highlighted the significant role of investor sentiment in shaping market behaviours. Unlike traditional financial indicators, investor sentiment encompasses more abstract elements of market psychology, which are inherently more challenging to quantify and analyse. This is especially true in contemporary financial markets where sentiment from text has become fundamental at the back of increasing computing power.

Investor sentiment, particularly when captured through textual proxies, offers a fresh dimension for exploring financial market connectedness, especially in the contemporary highly connected world. Proxies of textual sentiment have been used in empirical finance research and include sentiment extracted from online news (Alamsyah et al., 2019), social media (Shao et al., 2023), as well as sentiment reflected from news about companies' Environmental, Social and Governance (ESG) (Nyakurukwa & Seetharam, 2023; Yu et al., 2023). Despite their utility, these proxies are not direct sentiment measures but approximations derived from various textual data sources. Consequently, understanding how these sentiment proxies are connected and the associated spillover shocks can contribute to a broader comprehension of which ones are most important for market timing purposes.

The interplay between social media sentiment, news media sentiment, and ESG-related news sentiment has become a critical study area in understanding financial market dynamics. Social media platforms amplify real-time reactions, often characterised by high volatility and rapid shifts, while traditional news media provides more structured and validated narratives. ESG sentiment, on the other hand, reflects growing investor focus on sustainability and ethical considerations, which adds a long-term dimension to market behaviour. Despite their distinct characteristics, the interactions among these sentiment sources remain

* Corresponding author.
E-mail addresses: Yudhvir.Seetharam@wits.ac.za (Y. Seetharam), knyakurukwa@gmail.com (K. Nyakurukwa).

https://doi.org/10.1016/j.jjimei.2025.100337

Available online 8 April 2025

underexplored, particularly regarding how they propagate shocks. This gap necessitates a more robust and adaptive framework to uncover the complex relationships between these sentiment measures and their collective impact on financial market connectedness.

The Signalling Theory provides an important framework for understanding how various sentiment proxies (such as news, social media, and ESG sentiment) act as signals to market participants, conveying underlying information about market conditions, company performance, and broader economic outlooks. As Spence (1973) proposed, signalling occurs when one party conveys information to another when information asymmetries exist. In financial markets, where investors may have incomplete or uncertain information, sentiment indicators such as positive or negative news, social media posts, and ESG reports can serve as signals that influence investor behaviour and market dynamics. These signals help reduce information asymmetry by providing additional context guiding investors' buying, selling, or holding securities decisions.

Additionally, the Signalling Theory supports that market participants react to direct financial indicators and signals derived from non-financial data, such as sentiment analysis. Chan et al. (2017) observed that sentiment proxies—such as those derived from textual sources—do not always correlate strongly, implying that different proxies might provide distinct signals regarding market conditions. This aligns with Bu (2023), who argued that sentiment proxies measure different facets of market psychology, each carrying its own set of implications for financial markets. By applying this theory, our study explores how different sentiment proxies act as distinct signals that transmit shocks to market connectedness. We intend to establish the information-sharing dynamics among the various sentiment proxies. This helps determine the system's most important shock receivers and/or transmitters.

Several studies have reported that though various proxies of investor sentiment proxies exist, they primarily do not measure the same latent phenomena. Chan et al. (2017) argue that if sentiment proxies measure the same phenomenon, they should at least correlate with each other. However, the empirical results of the test for equivalence of various textual and survey-based investor sentiment proxies, Chan et al. (2017) conclude that these proxies do not measure the same latent phenomena as they are weakly correlated. This intuitively implies that at least one of the sampled proxies used is an invalid proxy of investor sentiment. This aligns with Bu (2023), who found weak correlations amongst a host of investor sentiment proxies, supporting the potential for these proxies to measure different phenomena. Additionally, Lee and Ryu (2024) suggested that a variable might not be suitable as a proxy for investor sentiment, even if it shows some degree of correlation with sentiment. Thus, it is crucial to understand which one among the proxies transmits the most shocks.

Though researchers have no universal agreement on the equivalence and/or validity of different investor sentiment proxies, literature shows that most of these proxies transmit shocks in the financial markets. For example, Bouri et al. (2022) show that investor sentiment derived from Twitter (now called X[1]) data substantially impacts return and volatility spillovers. Wang and Huang (2024) report that investor sentiment connectedness, developed using the TVP-VAR model, effectively predicts increased banking systemic risk. Liu et al. (2023), analysing investor sentiment spillovers across 10 countries from 2003 to 2020, find that these spillovers are significant and time-varying, intensifying during extreme events, with developed countries and those closely tied to such events exhibiting more substantial effects. Tiwari et al. (2021) reveal that sentiment causality among the U.S., Latin America, Eurozone, Japan, and Asia (excluding Japan) is nonlinear, with Eurozone sentiment influencing the US, Asia, and Japan, and bidirectional spillovers evident during the recent global financial crisis. These studies all show that investor sentiment, using different proxies, can transmit shocks that can alter the connectedness of financial markets. It is, therefore, essential to understand the propagation of these sentiment shocks among different sentiment proxies.

In this study, we fill the gaps in the literature by making several key contributions to understanding sentiment-driven spillovers in financial markets. First, we address a significant gap in the existing literature by examining the connectedness of multiple investor sentiment proxies rather than focusing on a single sentiment measure. Existing studies often rely on one proxy, such as news or social media sentiment, to analyse market dynamics. However, as previous research has demonstrated, different sentiment proxies capture distinct facets of market psychology and are often weakly correlated (Chan et al., 2017; Bu, 2023). By investigating how various proxies — including news, social media, positive ESG, and negative ESG sentiment — interact and transmit spillovers, we provide a more detailed understanding of which sentiment proxies are most influential. This allows us to identify the key sentiment drivers in financial markets, offering actionable insights for market timing and investment decision-making. This contribution is particularly relevant for market participants seeking to leverage sentiment data for trading strategies or risk management, as they can focus on the most impactful proxies.

Second, our use of firm-level sentiment data represents a methodological departure from previous studies that typically employ macro and market-level sentiment proxies. Firm-level sentiment data captures a more granular view of how individual companies' sentiment influences broader market dynamics. Prior research has established that firm-level sentiment provides better aggregate market sentiment measures than macro-level indicators (Nyakurukwa & Seetharam, 2024). By incorporating micro-level sentiment, we can detect more precise spillovers and provide a clearer picture of how sentiment at the firm level affects connectedness across different sentiment proxies. This approach helps bridge the gap between microeconomic behaviour and macroeconomic market trends, enhancing our understanding of sentiment's role in financial market connectedness.

Third, we include ESG sentiment in the analysis. While ESG-based investment decisions have gained considerable traction in recent years, there has been limited research on how ESG sentiment interacts with other sentiment proxies in transmitting spillover shocks. To our knowledge, this study is one of the first to incorporate firm-level ESG sentiment —positive and negative — into a connectedness framework that includes the traditionally used proxies (news and social media). Given the increasing emphasis on sustainable investing and corporate responsibility, understanding how ESG sentiment interacts with traditional online sentiment sources (like news and social media) provides fresh insights into the behaviour of financial markets.

We focus our study on eight DJIA constituent stocks, four from the Financial Services sector and four from the Technology sector, due to their prominence and frequent mention across textual platforms. By employing a Time-Varying Parameter Vector Autoregression (TVP-VAR) model, we use aggregate connectedness measures (Gabauer & Gupta, 2018) to determine how sentiment, as proxied by news sentiment, social media sentiment, and positive and negative ESG sentiments, influences shock transmission within these sectors. The TVP-VAR approach extends the traditional connectedness measures (Diebold & Yilmaz, 2009, 2012) and offers several key improvements over the existing method. It enables more precise detection of potential changes in parameter values, reduces the influence of outliers on results, removes the need to specify an arbitrary rolling window size, and preserves all observations while calculating dynamic measures. The enhancements were substantiated in a study (Antonakakis et al., 2020) by evidence from Monte Carlo simulations. Robustness tests conducted by Antonakakis et al. (2020) further confirm that TVP-VAR estimations are superior to rolling-window approaches, particularly in handling outliers and adapting to changes in parameter values. Additionally, the TVP-VAR model captures nonlinearity by allowing time-varying coefficients,

[1] We use Twitter and X interchangeably and represent the same thing whenever used in the study.

which enable it to adapt to changing dynamics and account for evolving, potentially nonlinear relationships between variables over time (Lubik & Matthes, 2015). Our static results show that news and social media sentiment are primary emitters of sentiment spillovers, while ESG-based sentiment proxies are primary receivers. We also report that the Technology sector primarily emits sentiment shocks to the Financials sector. The findings also show that the aggregate connectedness measures report stronger connectedness than the traditional Diebold-Yilmaz.

The results of the study suggest several actionable strategies for investors. First, understanding the spillover effects between sentiment proxies can enhance market timing decisions. Since news and social media sentiment are identified as the primary transmitters of sentiment shocks, investors can focus on monitoring real-time sentiment in these areas to capture early signals of market movements. Positive shifts in news or social media sentiment may indicate potential bullish trends, while negative sentiment may signal bearish market behaviour, allowing investors to adjust their portfolios accordingly. In terms of sectoral shocks, the results indicate that the Technology sector primarily emits sentiment shocks to the Financials sector. Investors may benefit from proactive risk management strategies. This could include hedging strategies, sector rotation, or focusing on technology-driven financial services companies, where spillover effects might be less pronounced. Moreover, ESG sentiment, which is primarily a receiver of sentiment shocks, presents an opportunity for long-term investors who prioritise sustainability. The finding that ESG sentiment has a weaker connectedness suggests that firms focusing on positive ESG behaviour are more insulated from short-term market noise. Thus, integrating ESG considerations into investment decisions could act as a risk mitigation strategy, especially for investors looking for more stable, long-term growth prospects. The sectoral difference in the propagation of shocks reflects the fact that the technology sector often reacts rapidly to technological innovations and shifts, whereas the financial sector exhibits a more measured, slower response. The study's results highlight how the technology sector is more sensitive to its own internal shocks, such as innovations, compared to the financial sector, where external factors like market regulations or economic policy can moderate the effects. Understanding this sectoral difference in shock propagation is crucial for investors seeking to anticipate market movements and for policymakers aiming to mitigate the impact of technological disruptions across different sectors.

Our study proceeds as follows: Section 2 describes the data and methods, Section 3 presents the results, and Section 4 concludes.

2. Data and methods

This section looks at the data and empirical methods used to address the aim of the study. The data section outlines the variables used, their definitions and how they were estimated. The sample used in the study is also described in the data section. The methods section describes the methods used to understand the connectedness of the different textual sentiment proxies.

2.1. Data

This section outlines the data used in the study. Section 2.1.1 explains the investor sentiment proxies analysed, including news, social media, and ESG sentiment, and how Bloomberg's algorithms quantify them. Section 2.1.2 details the sample selection, focusing on eight DJIA companies, the sample period, and challenges related to missing data.

2.1.1. Variables[2]

We use the Bloomberg terminal[3] to get the data related to the four investor sentiment proxies used in this study. Bloomberg uses a variety of sources and proprietary algorithms to gauge sentiment. These algorithms analyse news articles, financial reports, and other texts to assess the overall sentiment associated with a company, industry, or financial instrument. Sentiment is often quantified on a scale (−1 to 1), reflecting the sentiment's positivity or negativity. News sentiment (henceforth news) is estimated by analysing the tone of news articles related to a specific entity. Natural Language Processing techniques determine whether the news is positive, negative, or neutral. Social media sentiment is estimated using sentiment analysis tools that process posts, *tweets*, comments, and other social media content. To estimate social media sentiment scores, Bloomberg primarily relies on two sources: X[4] and StockTwits.

Bloomberg evaluates ESG news sentiment by categorising it into positive ESG sentiment (henceforth ESGpos) and negative ESG sentiment (henceforth ESGneg). To accomplish this, Bloomberg reviews over 80,000 news articles on ESG issues, including content from Bloomberg Media Group, press releases, and reports from various sources such as governments, industries, and stock markets. Positive ESG sentiment is quantified as a *z-score* indicating changes in positive ESG behaviour over the past 30 days. Conversely, negative ESG sentiment is represented by a *z-score* reflecting changes in negative ESG behaviour during the same period. These sentiment scores are generated using a machine learning model developed by Bloomberg analysts, which assesses firm behaviour as positive, negative, or neutral from an investor's viewpoint. Higher positive sentiment values indicate a firm's engagement in positive ESG activities, while higher negative sentiment values suggest involvement in adverse ESG actions.

2.1.2. Sample

We use eight companies which are constituents of the Dow Jones Industrial Average. Our methods depend on the availability of complete data cases with no missing values. The estimation of daily sentiment scores from social media and news media on the Bloomberg platform depends on how much a stock is mentioned. Thus, when a stock is not mentioned on the news and social media platforms, Bloomberg returns N/A (missing value) for sentiment on that particular day. This presents challenges, especially for sentiment scores encompassing ESG-related news, as only large stocks will likely be mentioned daily online. As a result, the data is biased towards the most prominent companies frequently mentioned on online news and/or social media platforms. Among the DJIA constituent stocks, we restrict our sample to companies with non-missing data for all four variables. This led to the exclusion of most stocks, leaving eight stocks from two sectors, Financials and Technology. This procedure reduces the sample size and may not reflect the general market. However, other studies that looked at the connectedness of sentiment predominantly used comparable sample sizes; for example, Yousaf et al. (2022) and El Oubani (2024) used six assets, respectively. The limited sample size, therefore, limits the generalisability of results but provides a preliminary exploration of potential linkages. The sample period starts from 1 January 2015 to 30 April 2024 because Bloomberg only started incorporating some of the proxies for investor sentiment (e.g. social media sentiment) after 31 December 2014, making this the natural starting point of our sample. The complete list of the sampled stocks used in the study is in Table 1:

[2] A detailed explanation of how the firm-level sentiment scores are estimated is included in the appendix.

[3] The Bloomberg Terminal offers real-time financial data, analytics, and tools across global markets. It includes textual sentiment metrics, economic indicators and other important variables essential for finance professionals.

[4] Twitter and X are used interchangeably in this study.

Table 1
Sampled stocks.

Ticker symbol	Full name	Sector
AXP	American Express Company	Financials
GS	Goldman Sachs Group Inc	Financials
JPM	JPMorgan Chase & Co	Financials
V	Visa Inc.	Financials
AAPL	Apple Inc.	Technology
CSCO	Cisco Systems Inc.	Technology
IBM	International Business Machines	Technology
MSFT	Microsoft Corporation	Technology

2.2. Methods

This section describes the methods used to analyse sentiment proxy connectedness. It starts with the Time-Varying Parameter Vector Autoregression (TVP-VAR) model, followed by the generalized forecast error variance decomposition (GFEVD) to measure spillovers between variables. The section concludes with an aggregated connectedness approach to assess spillovers within sentiment proxies and across sectors.

2.2.1. TVP autoregressions

Our analysis starts with the estimation of a Time-Varying Parameter Vector Autoregression (TVP-VAR) model[5] as detailed below:

$$\begin{aligned} z_t &= B_t z_{t-1} + u_t \; u_t \sim N(0, S_t) \\ vec(B_t) &= vec(B_{t-1}) + v_t \; v_t \sim N(0, R_t) \end{aligned} \tag{1}$$

Where:

z_t, z_{t-1} and u_t are $k \times 1$ dimensional vectors, representing all IRS series in t, $t-1$, and the error term, respectively. B_t and S_t are $k \times k$ dimensional time-varying parameter and variance-covariance matrices and $vec(B_t)$, v_t are $k^2 \times 1$ dimensional vectors and R_t is a $k^2 \times k^2$ dimensional parameter variance-covariance matrix.

2.2.2. Connectedness approach

We use the concept of generalised forecast error variance decomposition (GFEVD) with a forecast horizon of H as defined by Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998):

$$\Theta_{ij}^{g}(H) = \frac{\sum\left((\tau)_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i'\Omega_h(\tau)\sum(\tau)e_j\right)^2\right.}{\sum_{h=0}^{H-1}\left(e_i'\Omega_h(\tau)\sum(\tau)\Omega_h(\tau)'e_j\right)} \tag{2}$$

The notation e_i represents a zero vector with a one at the i^{th} position. In the decomposition matrix, the normalisation of the elements is denoted as follows:

$$\widetilde{\Theta}_{ij}^{g}(H) = \frac{\Theta_{ij}^{g}(H)}{\sum_{j=1}^{k}\Theta_{ij}^{g}(H)} \; with \; \sum_{j=1}^{k}\widetilde{\Theta}_{ij}^{g}.1 \; and \; \sum_{ij=1}^{k}\Theta_{ij}^{g}(H) = 1, \tag{3}$$

The GFEVD-based spillover measures are defined according to the framework established by Diebold and Yilmaz (2012).

$$TO_{j,t} = \sum_{i=1,\; i\neq j}^{k}\widetilde{\Theta}_{ij,t}^{g}(H) \tag{4}$$

$$FROM_{j,t} = \sum_{i=1,\; i\neq j}^{k}\widetilde{\Theta}_{ji,t}^{g}(H) \tag{5}$$

$$NET_{j,t} = TO_{j,t} - FROM_{j,t} \tag{6}$$

$$TCI_t = \frac{\sum_{i,j=1,\; i\neq j}^{k}\widetilde{\Theta}_{ji,t}^{g}(H)}{k-1} \tag{7}$$

The symbol TO_j represents the influence of variable j on variable i, while FROM denotes the effect of i on j. A negative (positive) value of NET signifies that the variable is a net recipient (transmitter) of spillovers. TCI indicates the overall level of connectivity. Eqs. (2) to 7 show how different variables influence each other using generalised forecast error variance decomposition (GFEVD). This approach helps measure the degree to which one variable impacts another over a set period. It also normalises these influences to make them easier to compare. By breaking down the relationships, we can identify whether a variable primarily affects others, is mostly influenced by them, or has a balanced interaction. A positive net value shows that a variable transmits more effects than it receives, while a negative value indicates it is mainly affected by others. The overall connectedness across all variables is summarised in a single measure, clearly showing how interconnected the system is.

2.2.3. Aggregated connectedness approach

We adopt the decomposition method outlined by Gabauer and Gupta (2018). We gain insight into the overall propagation mechanism by examining the aggregated spillovers between four sentiment proxies or two sectors. Specifically, we analyse the extent to which spillovers occur within sentiment proxies irrespective of their sector and the spillovers between sectors without considering sentiment proxies. This approach allows us to assess the impact of sentiment proxies and sectors separately. Initially, we aggregate the GFEVD for d groups—either four for sentiment proxies or two for sectors: $C_{mm,t}^{a} = \sum_{i\in k_m}\sum_{j\in k_m}\widetilde{\varnothing}_{ij,t}^{g}(H)$ is a specific instance of the earlier metric, reflecting the initial spillovers within group m (i.e., all spillovers within the same sentiment proxy or sector). The GFEVD is entirely unaffected by the ordering of variables, unlike the orthogonalised forecast error variance decomposition (Stenfors et al., 2022). We then proceed to estimate the spillovers specific to each group as follows:

$$C_{m\rightarrow.,t}^{a} = \sum_{n=1, m\neq n}^{d} C_{nm,t}^{a} \tag{8}$$

$$C_{m\leftarrow.,t}^{a} = \sum_{n=1, m\neq n}^{d} C_{nm,t}^{a} \tag{9}$$

$$C_{m,t}^{a} = \sum_{n=1, m\neq n}^{d} C_{m\rightarrow.,t}^{a} - C_{m\leftarrow.,t}^{a} \tag{10}$$

$$C_t^{a} = \frac{d}{d-1}\sum_{m=1}^{d} C_{m\rightarrow.,t}^{a} \equiv \frac{d}{d-1}\sum_{m=1}^{d} C_{m\leftarrow.,t}^{a} \tag{11}$$

Where $C_{m\rightarrow.,t}^{a}$ reflects total group-specific connectedness to others, $C_{m\leftarrow.,t}^{a}$ reflects group-specific connectedness from others, $C_{m,t}^{a}$ is the net total group-specific connectedness and C_t^{a} is the total group-specific connectedness index.

3. Results

This section presents the results from the empirical models used to address the study's aim. Before reporting the results from the empirical models, we first report the descriptive and distributional characteristics of the variables used in the study. This allows us to know whether the variables satisfy model assumptions. We then report the findings from the empirical models, starting with the static results and moving on to the dynamic results.

[5] The length of the TVP-VAR is 1 in line with Bayesian Information Criterion (BIC).

3.1. Descriptive

We start by reporting the summary statistics (Table A1 in the Appendix) of the variables used in the study. In the news category, the sentiment scores show that most stocks have slightly negative average sentiment, with only a few, such as Visa (V) and Cisco (CSCO), exhibiting mildly positive sentiment. This suggests that news coverage generally generates a more negative outlook for these stocks. The variance in sentiment scores is generally low, indicating relatively stable perceptions, with some exceptions like IBM, where sentiment fluctuates more significantly. The skewness is predominantly negative, indicating a tendency for sentiment to be skewed towards negative values. For instance, stocks like Goldman Sachs (GS) and JPMorgan (JPM) show pronounced negative skewness, suggesting that news negatively impacts sentiment with fewer positive outliers. Microsoft (MSFT), on the other hand, displays positive skewness, indicating occasional spikes in positive sentiment. High excess kurtosis across most stocks suggests that while the average sentiment may be mild, extreme sentiment shifts are frequent, both positive and negative.

In the social media category, sentiment scores are generally more positive for most stocks, with American Express (AXP), Visa (V), and Cisco (CSCO) standing out with notably positive average scores. This indicates generally favourable sentiment on social media platforms compared to news sources. The variance in sentiment is relatively low, suggesting less volatility in social media sentiment. Skewness values show mixed tendencies, with some stocks like AXP exhibiting positive skewness, meaning there is a tendency for occasional strong positive sentiment, while others show negative skewness. High kurtosis values point to significant occurrences of extreme sentiment events, indicating that although average sentiment might be positive, there are notable swings towards both positive and negative sentiments.

For the ESGpos category, sentiment scores vary widely. Stocks like Apple (AAPL) and JPMorgan (JPM) have positive average sentiment scores, while others like American Express (AXP) and Visa (V) have negative average scores. In the ESGneg category, mean sentiment scores are predominantly negative for most stocks. However, stocks like Apple (AAPL) and Visa (V) show positive mean sentiment; the high kurtosis values reveal that while average sentiment might be negative, there are significant swings towards extreme sentiments, indicating that negative ESG news can provoke sharp reactions, both negative and occasionally positive.

We also examine the correlations of the firm-level sentiment proxies in Fig. 1. Fig. 1 shows the correlations among the stocks by proxy. Statistically significant correlations are shown by asterisks. It can be observed in Fig. 1 that most of the proxy-specific correlations at the firm level are positive. This provides elementary evidence that sentiment shocks will likely permeate the other stocks in the sample. This means positive (negative) sentiment in one stock is likely to be associated with positive (negative sentiment) in the other stocks. However, regarding statistical significance, it is clear that news sentiment has more statistically significant correlations than the other sentiment proxies.

3.2. Empirical results

This section presents the empirical results of the study, highlighting the key findings related to the connectedness of investor sentiment proxies. It details the outcomes of the Time-Varying Parameter Vector Autoregression (TVP-VAR) model, the generalised forecast error variance decomposition (GFEVD), and the aggregated connectedness analysis.

3.2.1. Proxy-specific connectedness

The results in Table 2 show the connectedness of firm-level investor sentiment proxies, highlighting their interactions and influence on one another. Each sentiment proxy—news, social media, ESG positive (ESGpos), and ESG negative (ESGneg)—demonstrates a high degree of self-consistency, meaning that its own sources predominantly influence each. For example, news sentiment shows strong internal coherence with a self-connection score of 72.26, while social media sentiment maintains significant internal consistency, reflected in a self-connection score of 73.1. These scores suggest that news and social media sentiments are primarily shaped by their content and exhibit substantial internal stability. This is the same with ESGpos and ESGneg.

The interaction between news and social media shows a moderate level of influence. News impacts social media sentiment at 17.17, and social media affects news sentiment at 17.43. This moderate cross-influence indicates a noticeable but not overwhelming relationship between news-driven and social media sentiment, where news can affect social media discussions and vice versa. In contrast, the influence of news and social media on the ESG sentiment proxies is minimal. News has a limited impact on ESG positive sentiment (5.73) and ESG negative sentiment (4.83), while social media's influence on these ESG proxies is also weak, with scores of 5.07 and 4.8, respectively. This minimal cross-influence suggests that ESG sentiment operates largely independently of news and social media sentiment, reflecting the distinct nature of ESG-related information.

The aggregate connectedness measure stands at 22.78, indicating the overall connectedness among the sentiment proxies. This value suggests a relatively modest level of connectedness, meaning that while the proxies are connected, the interactions among them are not overwhelmingly strong. The Total Connectedness Index derived from the aggregated measures is 22.78, compared to the 7.57 connectedness value reported by the traditional Diebold-Yilmaz[6] framework for the entire system. This indicates that the traditional DY approach underestimates connectedness within the system. The net influence (NET) values indicate whether a proxy acts as a transmitter or receiver of sentiment shocks. Positive NET values suggest that a proxy functions as a transmitter, spreading sentiment shocks to other proxies, while negative NET values indicate that a proxy acts as a receiver, absorbing sentiment shocks from others. The relatively small NET values for the proxies suggest that while each proxy is consistent within itself, their direct influence on one another is limited.

Fig. 2 shows the network connectedness graph, which visualises the static results. The green (red) nodes represent proxies that primarily transmit (receive) sentiment shocks. The nodes, sized according to their net pairwise directional connectedness measures, reflect the weighted sum of their directional connections. The thickness of the grey lines connecting the nodes indicates the strength of these connections, while the direction of the arrows on the lines shows the direction of the connectedness. Unlike earlier analyses examining the interaction between each market and the overall system, network analysis emphasises the directional connections between each pair of sentiment proxies. Fig. 2 shows that news and social media sentiment are the primary transmitters of shocks in the system, whereas ESG-based sentiment proxies are the primary receivers of sentiment shocks. The strongest flow of shocks originates from social media sentiment and is directed towards negative ESG sentiment. Interestingly, social media sentiment is central to the system as it is connected with all the remaining sentiment proxies, while news sentiment is only connected to social media sentiment.

When considering dynamic connectedness, we observe that total connectedness is not static (Fig. 3). Total connectedness peaks in 2018 and 2020, for example - periods associated with elections in the USA and the global COVID-19 pandemic, respectively. This supports existing studies showing that financial market connectedness peaks during globally significant events.

Regarding net directional connectedness at the sentiment proxy level, we observe constant shifts in the system's transmitters and receivers of sentiment shocks (Fig. 4). Though the static results in Table 2 have shown that ESGpos and ESGneg are receivers of sentiment shocks

[6] Results are not reported here for brevity but are available upon request.

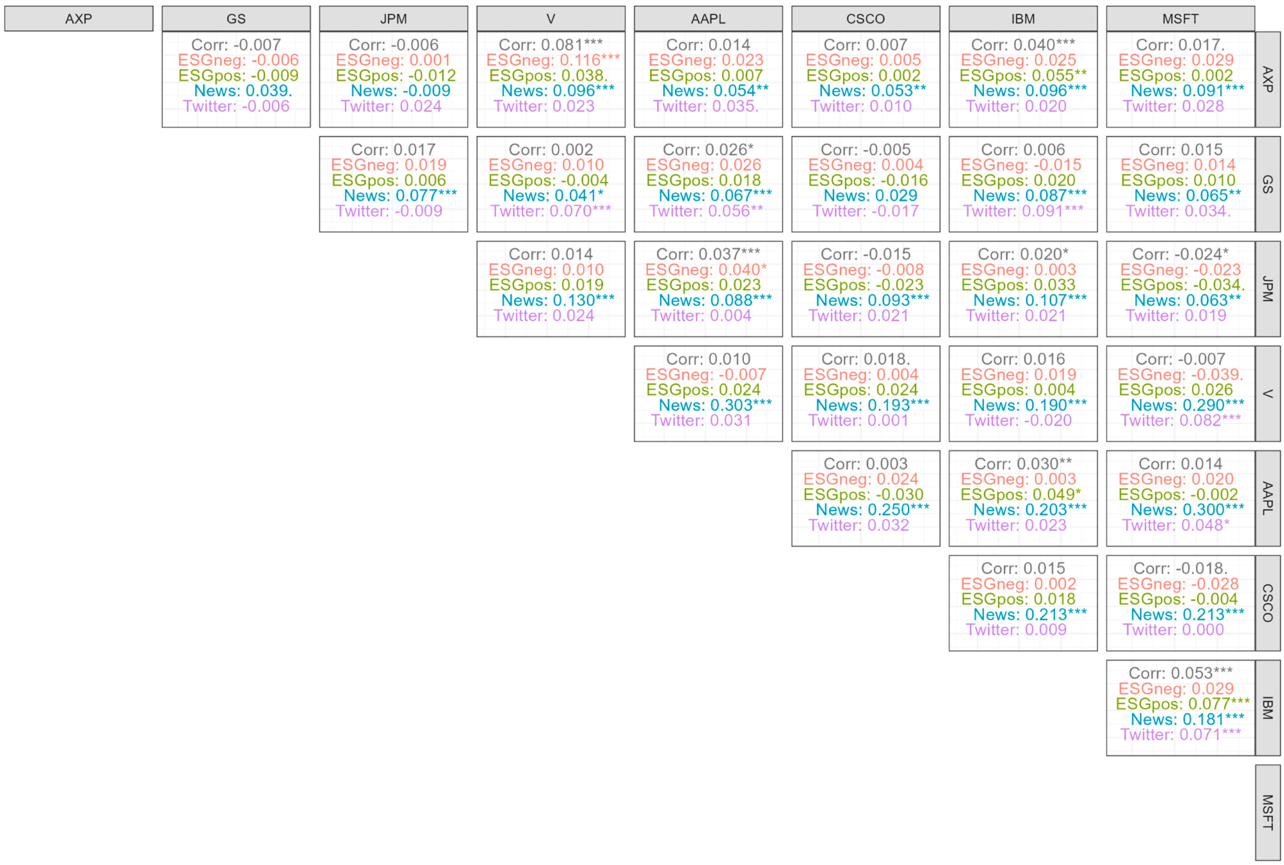

Fig. 1. Correlation matrix.
Notes: *, **, *** show correlation coefficients statistically different from zero at the 10 %, 5 % and 1 % significance levels.

Table 2
Proxy-specific connectedness.

	News	Social media	ESGpos	ESGneg	FROM
News	72.26	17.17	5.73	4.83	27.74
Social media	17.43	73.1	5.22	4.25	26.9
ESGpos	5.71	5.07	81.11	8.11	18.89
ESGneg	4.92	4.8	7.86	82.42	17.58
TO	28.05	27.05	18.82	17.19	91.11
Inc.Own	100.32	100.15	99.93	99.61	cTCI/TCI
NET	0.32	0.15	−0.07	−0.39	30.37/22.78

Notes: Inc.own refers to the spillover connectedness for the jth column to all variables, including itself. The conditional total connectedness index (cTCI) measures connectedness after controlling for other factors or variables.

on average, dynamically, we observe that both sentiment proxies enter episodes of being transmitters and receivers of sentiment shocks over the period. Notably, we observe that roughly, between 2018 and 2020, ESGpos and ESGneg are both net transmitters of sentiment shocks. This differs from the period from mid-2020 to the end of 2020, where we observe the opposing effects of ESG sentiment proxies. In this period, ESGpos was a net transmitter, whereas ESGneg was a net receiver of sentiment shocks.

The pandemic introduced unprecedented market volatility and a heightened focus on how companies addressed health and social issues. As a result, positive ESG sentiment (ESGpos) transitioned to being a net transmitter of sentiment shocks. This shift indicates that positive news about corporate responsibility and effective crisis management became more influential in spreading sentiment across the market, reflecting its increased significance during the pandemic. In contrast, negative ESG sentiment (ESGneg) became a net receiver of sentiment shocks during this period. The pandemic magnified scrutiny of companies' failures to respond adequately or support stakeholders, making negative ESG news more impactful. This suggests that the negative sentiment surrounding ESG issues was more reactive to external shocks, with its influence shaped by the growing concerns and criticisms arising during the crisis and the accompanying political uncertainties from the U.S. elections. Thus, the dynamic roles of sentiment proxies during these periods highlight how external events can significantly alter the flow and impact of sentiment within financial markets.

3.2.2. Sector-specific aggregate connectedness

Regarding sector-specific aggregate connectedness (Table 3), both sectors show impressive self-connectedness scores, with the Financials sector at 85.79 and the Technology sector at 89.8. This high internal connectedness indicates that sentiment within each sector is strongly influenced by its own sentiment proxies. For the Financials sector, sentiment derived from news, social media, and ESG factors related to financial topics remains consistently stable and self-reinforcing. Similarly, the Technology sector's higher score suggests that its sentiment, based on these same proxies, is even more stable and internally consistent.

The net sentiment impact scores reveal that the financial sector, with a net sentiment impact of −3.03, is a receiver of sentiment shocks from the technology sector. This implies that sentiment changes in the Technology sector—whether driven by news, social media, or ESG factors—tend to impact the sentiment within the Financials sector.

This relationship could be attributed to the interplay between economic conditions and technological advancements, where positive financial sentiment often boosts confidence in technology and vice versa. Using aggregate connectedness involving multiple sentiment proxies provides a comprehensive view of how sentiment dynamics unfold. The analysis captures a broad spectrum of sentiment influences

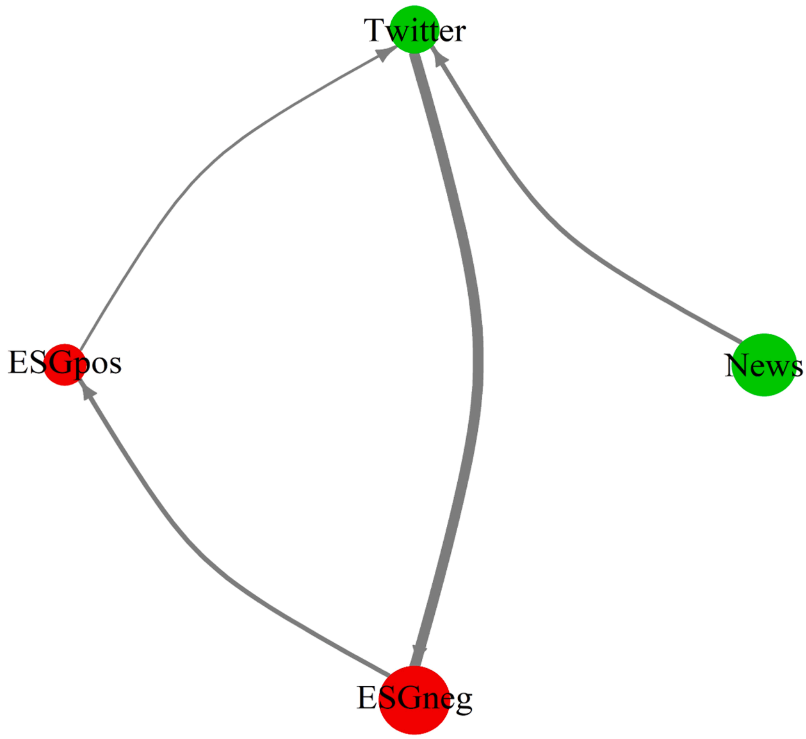

Fig. 2. Connectedness network.
Notes: The green (red) nodes represent proxies that primarily transmit (receive) sentiment shocks. The nodes, sized according to their net pairwise directional connectedness measures, reflect the weighted sum of their directional connections.

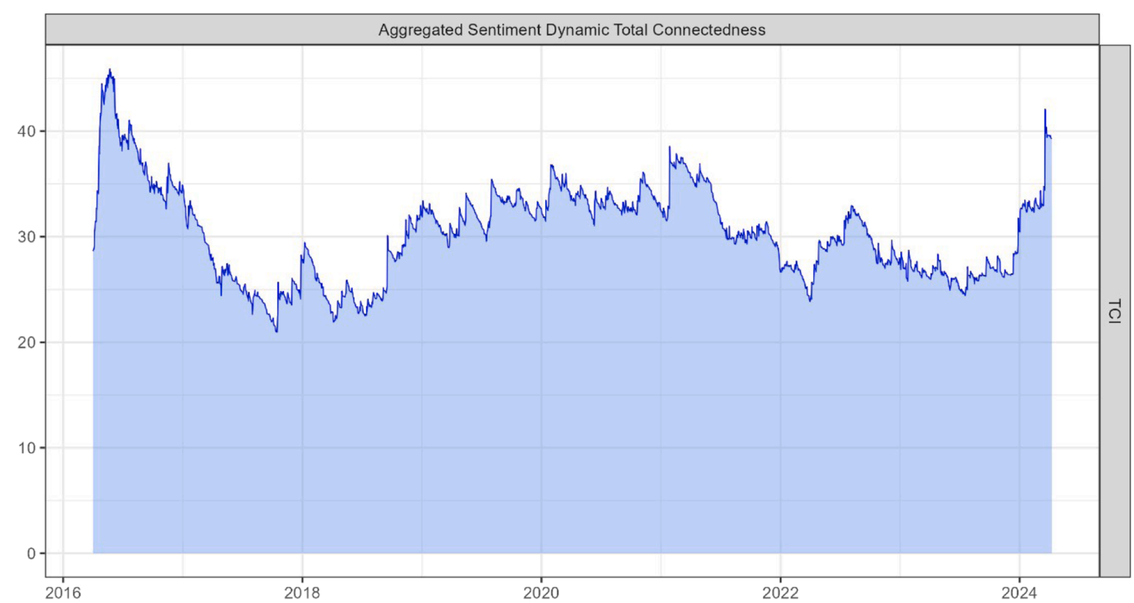

Fig. 3. Aggregated sentiment dynamic total connectedness.

by incorporating news, social media sentiment, and both positive and negative ESG factors.

Fig. 5 shows that sector-specific total connectedness is not static when considering the dynamic relationships. Periods of calm are interspersed with spikes in total connectedness (e.g. early 2018). This shows that sentiment connectedness is not static but responds to external events, such as significant global events like elections, pandemics, *etc*.

Fig. 6 shows the net total directional connectedness between the sampled sectors. For the full sample period, the Financial sector is a net receiver of aggregate sentiment, while the Technology sector is a net transmitter of textual sentiment shocks. The results depicted in Fig. 6 highlight distinct roles for the Financial and Technology sectors regarding sentiment connectedness. As a net receiver of aggregate sentiment, the financial sector absorbs more sentiment shocks from the market than it transmits. This reflects its high sensitivity to overall economic conditions, market volatility, and investor sentiment. As financial institutions are closely tied to broader market movements and economic indicators, they react more significantly to shifts in aggregate

Fig. 4. Aggregated sentiment net total directional connectedness.
Notes: Periods where a sentiment proxy was a net receiver (transmitter) of shocks are shown in red (green).

Table 3
Sector-specific connectedness.

	Financials	IT	FROM
Financials	85.79	12.01	12.01
IT	8.99	89.8	8.99
TO	8.99	12.01	21
Inc.Own	94.78	101.82	cTCI/TCI
NET	−3.03	3.03	21.00/10.50

Notes: Inc.own refers to the spillover connectedness for the jth column to all variables, including itself. The conditional total connectedness index (cTCI) measures connectedness after controlling for other factors or variables.

sentiment, indicating their role as a barometer for market mood.

In contrast, the technology sector is a net transmitter of textual sentiment. This means that sentiment derived from textual sources—such as news articles, social media discussions, and analyst reports—has a more substantial impact on spreading through this sector. The technology sector's high visibility, rapid pace of innovation, and frequent media coverage mean that news and public discourse about tech companies significantly influence and propagate sentiment within the sector. Thus, while the financial sector is more reactive to overall market sentiment, the technology sector plays a pivotal role in disseminating sentiment based on textual content, highlighting its influence on market dynamics through media and public attention.

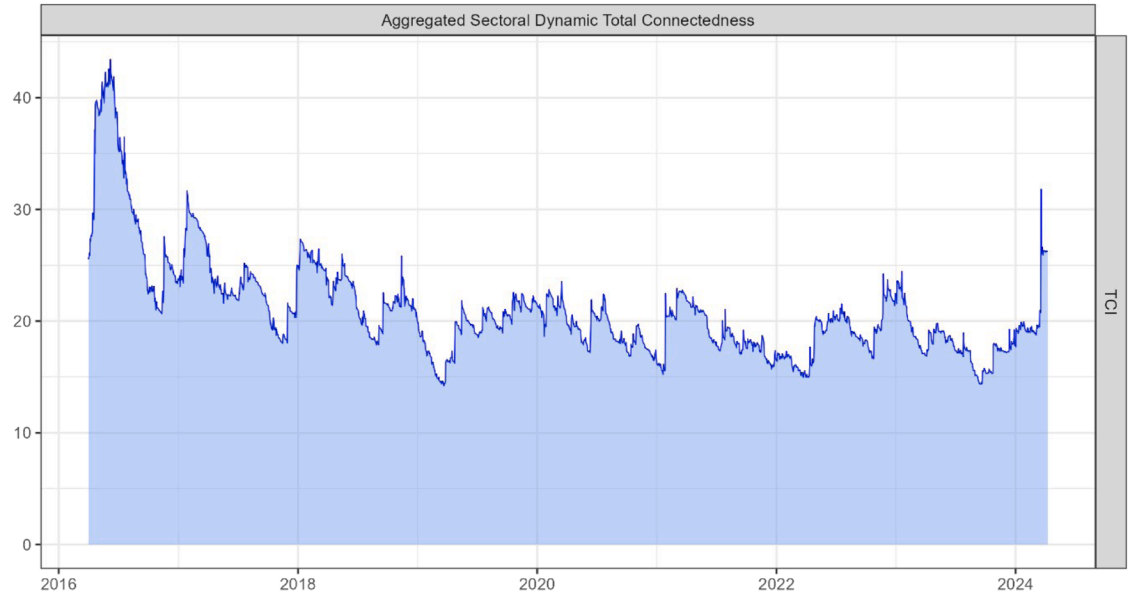

Fig. 5. Aggregated sectoral total connectedness.

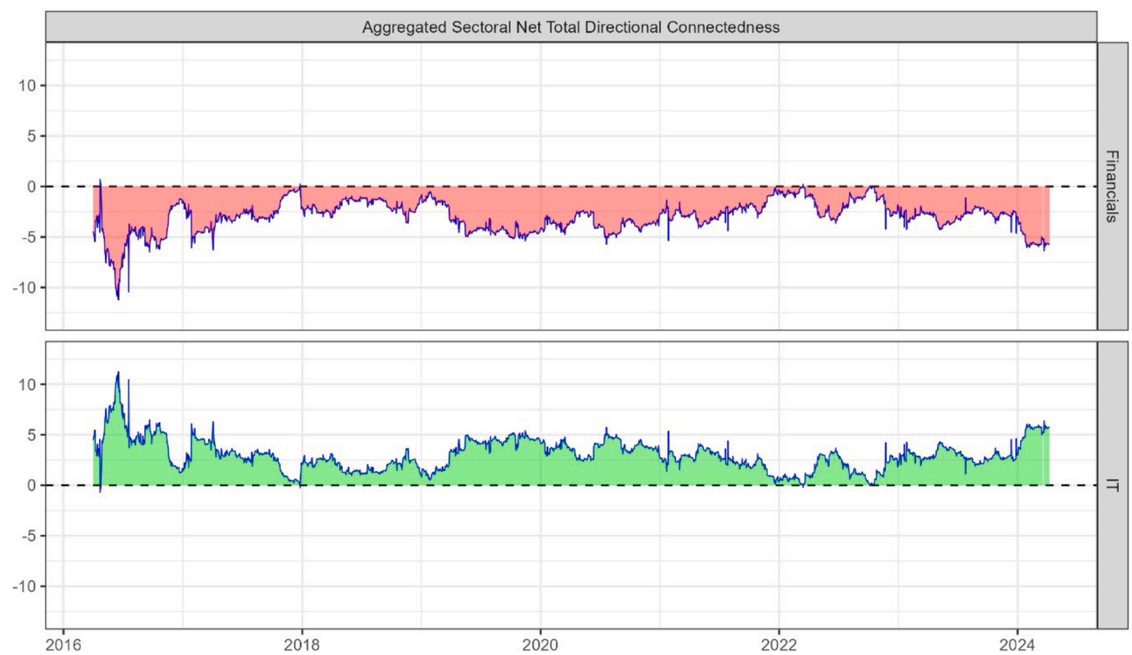

Fig. 6. Aggregated sectoral net total connectedness.
Notes: Periods where a sector was a net receiver (transmitter) of shocks are shown in red (green).

4. Robustness

We conduct several robustness tests to ensure the reliability of our findings. First, we estimate the TVP-VAR model under various assumptions regarding the selection of prior hyperparameters. The primary TVP-VAR analysis employed a Bayesian VAR procedure with a hyperparameter estimation size of 200 days. Given that this choice might influence the results of the TVP-VAR model, we examined whether the outcomes from our main empirical tests were sensitive to different prior sizes. Consequently, we recalculated the dynamic TCIs using Bayesian prior sizes of 100, 150, 250, and 300 days. Second, we investigated the potential sensitivity of our main results to different lag orders. To do this, we re-estimated the TVP-VAR connectedness specification for lag orders ranging from 1 to 4. Finally, we assessed the robustness of our results against varying forecast horizon selections by replicating the TVP-VAR-based connectedness analysis with horizon values of 50, 75, 125, and 150 days. The outcomes from these robustness tests (not reported here for brevity but available upon request) indicate no qualitative changes in our findings. Regardless of the variations in prior hyperparameter sizes, lag orders, and forecast horizons, the core results remained consistent, reinforcing the reliability of our primary empirical conclusions.

To address concerns about the small sample size in our dataset, we employed both bootstrap and Monte Carlo simulations to validate the robustness of our Total Connectedness Index (TCI) results. The bootstrap method involved resampling the original dataset with replacement, calculating the TCI for each resample, and constructing a distribution of TCI values. This allowed us to compare the observed TCI against the empirical distribution and assess its stability. Similarly, Monte Carlo simulations generated synthetic datasets based on the mean and covariance of the original data, allowing us to compare the TCI calculated from synthetic data with the observed TCI. Both methods were repeated 10,000 times to ensure robustness. A *t-test* was conducted to compare the TCI values from the original dataset with those derived from the synthetic data. The results from both the bootstrap and Monte Carlo simulations showed that the TCI values from the synthetic datasets were not significantly different from the observed TCI (*p-value* > 0.05). This indicates that the TCI results are stable and not influenced by the small sample size, suggesting that our findings are robust and would likely hold with a larger, more representative sample.

5. Conclusion

The study examines sentiment connectedness across various firm-level proxies, revealing insights into their interactions and the broader implications for financial markets. Our findings highlight that sentiment proxies such as news, social media, and ESG sentiment operate with notable internal consistency but exhibit varied levels of cross-influence. Specifically, news and social media transmit sentiment shocks, while ESG sentiment proxies function primarily as receivers. The dynamic nature of sentiment connectedness, particularly during global events like the 2018 U.S. elections and the COVID-19 pandemic, underscores how external shocks can shift the roles of sentiment proxies, influencing their capacity to transmit or receive sentiment. Regarding sector-specific dynamics, our analysis shows that the Financial sector is a net receiver of sentiment shocks while the Technology sector is a net transmitter.

Several studies have already demonstrated that investor sentiment can predict asset returns, as sentiment often captures market mood and investor expectations before they are reflected in prices. For example, sentiment derived from news, social media, or even ESG factors can signal changes in market behaviour, providing a forward-looking indicator for returns. However, while sentiment is broadly recognised as a predictor, there is considerable variation in the effectiveness of different sentiment proxies in capturing this predictive power. This study contributes to the literature by identifying which sentiment proxies are the primary transmitters of sentiment shocks across the financial market system. Understanding these transmission patterns is key because not all sentiment proxies are equally influential. Knowing which proxy—news sentiment, social media sentiment, or ESG sentiment—transmits the most significant shocks helps investors determine the most reliable source of sentiment to monitor. The findings of this study are not definitive because of the small available sample size. Future studies could explore this study using a much broader sample, depending on the availability of usable data. This will assist in the generalisability of the results. Future studies could also validate the results using other methods that capture nonlinearities in the evolution of sentiment. Finally, future studies could also validate these results using alternative data sources which are not proprietary.

CRediT authorship contribution statement

Yudhvir Seetharam: Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization. **Kingstone Nyakurukwa:** Writing – original draft, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare no potential conflict of interest in the process of writing this manuscript.

Appendix A

Table A1
Summary statistics.

News								
	AXP	GS	JPM	V	AAPL	CSCO	IBM	MSFT
Mean	−0.008*	−0.023	−0.015	0.015	−0.005	0.014	−0.015	0.006
Variance	0.037	0.018	0.008	0.024	0.008	0.029	0.057	0.002
Skewness	−0.593***	−1.814***	−3.561***	0.432***	−0.762***	0.670***	−0.439***	6.501***
Ex.Kurtosis	9.491***	16.612***	31.278***	10.744***	28.079***	11.371***	5.477***	69.047***
JB	7974.235***	25,201.221***	89,695.382***	10,126.982***	68,926.849***	11,427.240***	2681.681***	430,297.203***
ERS	−14.943	−16.123	−11.035	−14.534	−12.731	−16.306	−16.709	−16.01
Q(20)	464.195***	154.552***	199.894***	427.457***	1553.595***	402.108***	103.524***	299.214***
Q2(20)	1469.752***	83.472***	115.790***	275.181***	373.601***	271.929***	2093.821***	50.458***
Social media								
	AXP	GS	JPM	V	AAPL	CSCO	IBM	MSFT
Mean	0.019***	−0.015***	−0.002	0.015***	−0.007***	0.017***	0.003***	0.001
Variance	0.013	0.015	0.026	0.009	0.002	0.009	0.001	0.002
Skewness	0.793***	−2.268***	−1.070***	−1.047***	−3.427***	0.036	5.573***	−3.365***
Ex.Kurtosis	17.481***	16.133***	8.169***	34.274***	54.040***	20.791***	110.379***	105.149***
JB	26,855.571***	24,479.375***	6216.475***	102,776.645***	258,648.111***	37,678.115***	1072,835.238***	967,685.130***
ERS	−17.372	−16.09	−11.392	−15.295	−15.656	−1.173	−13.482	−17.928
Q(20)	72.466***	247.663***	1860.420***	86.351***	446.544***	287.319***	248.455***	163.173***
Q2(20)	40.290***	93.997***	2051.918***	31.605***	70.836***	155.469***	36.906***	29.658***
POSITIVE ESG								
	AXP	GS	JPM	V	AAPL	CSCO	IBM	MSFT
Mean	−0.018	0.053**	0.095***	−0.025	0.138***	−0.009	−0.006	0.092***
Variance	0.654	1.075	1.291	0.522	1.285	0.696	0.669	1.265
Skewness	5.739***	3.943***	3.263***	6.630***	2.588***	5.534***	5.483***	3.131***
Ex.Kurtosis	33.123***	15.376***	10.159***	44.487***	6.918***	30.439***	30.354***	9.609***
JB	107,115.813***	26,031.010***	12,708.484***	187,839.915***	6507.072***	91,440.999***	90,791.846***	11,466.243***
ERS	−19.153	−15.449	−12.485	−18.875	−13.741	−20.258	−17.966	−14.08
Q(20)	37.511***	57.643***	91.754***	33.274***	101.314***	23.988***	35.018***	51.218***

(*continued on next page*)

Table A1 (*continued*)

News								
	AXP	GS	JPM	V	AAPL	CSCO	IBM	MSFT
Q2(20)	15.071	24.816***	37.600***	11.192	36.652***	13.355	12.977	23.043***
NEGATIVE ESG								
	AXP	GS	JPM	V	AAPL	CSCO	IBM	MSFT
Mean	−0.049***	0.032	0.108***	−0.003	0.105***	−0.021*	−0.004	0.050**
Variance	0.374	0.975	1.246	0.543	1.38	0.288	0.908	1.04
Skewness	8.008***	4.288***	3.280***	6.506***	3.152***	9.118***	4.629***	3.890***
Ex.Kurtosis	65.558***	17.906***	10.639***	42.540***	9.419***	86.223***	21.108***	15.070***
JB	396,988.543***	34,359.230***	13,617.310***	172,503.360***	11,195.720***	677,015.899***	46,310.736***	25,072.719***
ERS	−19.333	−15.377	−19.673	−20.445	−15.743	−19.498	−16.601	−18.813
Q(20)	16.780*	37.173***	48.022***	37.531***	113.001***	45.761***	74.462***	103.131***
Q2(20)	9.252	20.222**	20.239**	14.573	54.484***	12.084	25.351***	57.015***

Notes: ***, **, * represents statistical significance at the 1 %, 5 % and 10 % levels respectively.

Appendix B: Computation of sentiment scores

Bloomberg utilises sophisticated machine learning techniques to generate sentiment scores for news articles and social media content. Training models develop these scores to mimic the evaluations of human experts specialising in processing textual information. These experts, often native speakers with domain-specific knowledge in finance, manually assess and assign sentiment scores to content, categorising it as positive, neutral, or negative. Their evaluation is guided by the question: “If an investor holding a long position in the mentioned security reads this news or tweet, would they feel bullish, bearish, or neutral about their holdings?”

The manually labelled data is then used to train machine learning models, such as support vector machines, enabling the models to automatically classify new content by estimating the probability of it being positive, neutral, or negative. Bloomberg’s sentiment analysis operates at two levels. First, at the story level, each piece of content is assigned a categorical sentiment score of 1 (positive), −1 (negative), or 0 (neutral), along with a confidence level ranging from 0 to 100 that reflects the model’s certainty about the classification. Second, at the company level, sentiment scores are aggregated into a single numerical value ranging from −1 (most negative) to +1 (most positive), with 0 indicating neutrality.

The company-level sentiment is further refined using rolling windows. The intraday sentiment is updated every two minutes for news stories using an 8-hour rolling window and every minute for social media content using a 30-minute rolling window. Daily sentiment scores are calculated by averaging the story-level sentiment scores from the past 24 h, weighted by confidence, and are published each morning 10 min before the market opens. By offering granular story-level insights and aggregated company-level sentiment, Bloomberg provides a robust and widely used financial market analysis and decision-making tool.

- The company-level sentiment scores are computed as follows:

$$Sent_{i,t} = \frac{\sum k \in P(i,T) S_i^k C_i^k}{N_{i,T}},\ T \in [t-24h, t] \tag{A1}$$

Where:
$Sent_{i,t}$ is the news/Twitter sentiment score for firm i at time t;
S_i^k is the sentiment polarity score for *tweet*/news k that references firm i;
C_i^k is the confidence of *tweet*/news k that references firm i;
$P(i, T)$ is the set of all non-neutral *tweet*/news feeds that reference firm i in the 24 h-period, *T;*
$N_{i,T}$ is firm i';s total number of positive or negative *tweets*/news during period *T*.

The news stories used for calculating news sentiment by Bloomberg Inc. come from all sources except Twitter and StockTwits, while the *tweets* used to calculate the Twitter sentiment scores are gathered from Twitter and StockTwits

References

Alamsyah, A., Ayu, S. P., & Rikumahu, B. (2019). Exploring relationship between headline news sentiment and stock return. In *2019 7th International Conference on Information and Communication Technology (ICoICT)* (pp. 1–6). https://doi.org/10.1109/ICoICT.2019.8835298

Antonakakis, N., Chatziantoniou, I., & Gabauer, D. (2020). Refined measures of dynamic connectedness based on time-varying parameter vector autoregressions. *Journal of Risk and Financial Management, 13*(4). https://doi.org/10.3390/jrfm13040084. Article 4.

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*, Article 101646. https://doi.org/10.1016/j.irfa.2020.101646

Bouri, E., Demirer, R., Gabauer, D., & Gupta, R. (2022). Financial market connectedness: The role of investors’ happiness. *Finance Research Letters, 44*, Article 102075. https://doi.org/10.1016/j.frl.2021.102075

Bu, Q. (2023). Are all the sentiment measures the same? *Journal of Behavioral Finance, 24* (2), 161–170. https://doi.org/10.1080/15427560.2021.1949718

Chan, F., Durand, R. B., Khuu, J., & Smales, L. A. (2017). The validity of investor sentiment proxies: Sentiment proxies. *International Review of Finance, 17*(3), 473–477. https://doi.org/10.1111/irfi.12102

Diebold, F. X., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global Equity markets. *The Economic Journal, 119* (534), 158–171. https://doi.org/10.1111/j.1468-0297.2008.02208.x

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting, 28*(1), 57–66. https://doi.org/10.1016/j.ijforecast.2011.02.006

El Oubani, A. (2024). Investor sentiment and sustainable investment: Evidence from North African stock markets. *Future Business Journal, 10*(1). https://doi.org/10.1186/s43093-024-00349-x. Article 1.

Gabauer, D., & Gupta, R. (2018). On the transmission mechanism of country-specific and international economic uncertainty spillovers: Evidence from a TVP-VAR connectedness decomposition approach. *Economics Letters, 171*, 63–71. https://doi.org/10.1016/j.econlet.2018.07.007

Koop, G., Pesaran, M. H., & Potter, S. M. (1996). Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics, 74*(1), 119–147. https://doi.org/10.1016/0304-4076(95)01753-4

Lee, G., & Ryu, D. (2024). Investor sentiment or information content? A simple test for investor sentiment proxies. *The North American Journal of Economics and Finance, 74*, Article 102222. https://doi.org/10.1016/j.najef.2024.102222

Liu, Y., Zhang, J., Guo, N., & Liu, J. (2023). Investor sentiment contagion and network connectedness: Evidence from China and other international stock markets. *The Manchester School, 91*(6), 587–613. https://doi.org/10.1111/manc.12457

Lubik, T. and Matthes, C. (2015). Time-varying parameter vector autoregressions: Specification, estimation, and an application, Available at SSRN: Https://ssrn.com/abstract=2864239 or https://doi.org/10.21144/eq1010403.

Nyakurukwa, K., & Seetharam, Y. (2023). Investor reaction to ESG news sentiment: Evidence from South Africa. *Economia (Pontificia Universidad Catolica del Peru. Departamento de Economia), ahead-of-print(ahead-of-print)*. https://doi.org/10.1108/ECON-09-2022-0126

Shao, J., Hong, J., Wang, X., & Yan, X. (2023). The relationship between social media sentiment and house prices in China: Evidence from text mining and wavelet analysis. *Finance Research Letters, 57*, Article 104212. https://doi.org/10.1016/j.frl.2023.104212

Spence, M. (1973). Job market signaling. *The Quarterly Journal of Economics, 87*(3), 355–374. https://doi.org/10.2307/1882010

Stenfors, A., Chatziantoniou, I., & Gabauer, D. (2022). Independent policy, dependent outcomes: A game of cross-country dominoes across European yield curves. *Journal of International Financial Markets, Institutions and Money, 81*, Article 101658. https://doi.org/10.1016/j.intfin.2022.101658

Tiwari, A. K., Bathia, D., Bouri, E., & Gupta, R. (2021). Investor sentiment connectedness: Evidence from linear and nonlinear causality approaches. *Annals of Financial Economics, 16*(04), Article 2150016. https://doi.org/10.1142/S2010495221500160

Wang, L., & Huang, W.-Q. (2024). Can investor sentiment connectedness predict banking systemic risk: Evidence from China. *Applied Economics Letters, 0*(0), 1–8. https://doi.org/10.1080/13504851.2024.2339371

Yousaf, I., & Yarovaya, L. (2022). The relationship between trading volume, volatility and returns of non-fungible tokens: Evidence from a quantile approach. *Finance Research Letters, 50*, Article 103175. https://doi.org/10.1016/j.frl.2022.103175

Yousaf, I., Youssef, M., & Goodell, J. W. (2022). Quantile connectedness between sentiment and financial markets: Evidence from the S&P 500 twitter sentiment index. *International Review of Financial Analysis, 83*, Article 102322. https://doi.org/10.1016/j.irfa.2022.102322

Yu, H., Liang, C., Liu, Z., & Wang, H. (2023). News-based ESG sentiment and stock price crash risk. *International Review of Financial Analysis, 88*, Article 102646. https://doi.org/10.1016/j.irfa.2023.102646