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Leveraging sentiment connectedness for portfolio optimisation: a minimum connectedness approach

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Abstract

Purpose – This study proposes a novel portfolio optimisation approach that leverages minimum online sentiment connectedness. We investigate the effectiveness of this portfolio optimisation technique.

Design/methodology/approach – The minimum online sentiment connectedness portfolio utilises sentiment analysis to construct portfolios that minimise sentiment spillovers, measured by the pairwise directional connectedness index. We compare the minimum negative news sentiment connectedness portfolios to traditional methods like the minimum variance portfolio (MVP) and the equally weighted portfolio (EWP).

Findings – Our findings demonstrate that minimum sentiment connectedness portfolios outperform conventional approaches in terms of cumulative returns, while the MVP outperforms in risk-adjusted returns (Sharpe ratio). Furthermore, we employ the concept of hedging effectiveness to show that minimum negative news connectedness portfolios significantly reduce the risk of the overall portfolio.

Originality/value – This research contributes to the growing body of knowledge on sentiment analysis in portfolio management, suggesting its potential to improve investment decision-making.

Keywords Portfolio optimization, Investor sentiment, Behavioural finance, Sentiment analysis

Paper type Research article

1. Introduction

The quest for optimal portfolio construction has been a cornerstone of modern finance. Traditional methods, such as Markowitz (1952)'s seminal work on mean-variance optimisation, have laid the groundwork for efficient portfolio construction by focusing on historical returns and volatility. However, the ever-evolving landscape of financial markets necessitates a continuous exploration of new frontiers in portfolio optimisation. Recent research suggests that incorporating investor sentiment, an important driver of asset prices, can significantly enhance portfolio performance (Liu *et al*., 2023). Banholzer *et al*. (2019) found that investor sentiment often carries valuable investment information that can be used to optimise portfolios. This study proposes a novel approach to portfolio optimisation that minimises spillovers of news and social media sentiment shocks within a network of stocks.

A growing body of research emphasises the interconnectedness of financial markets, with a particular focus on return and volatility connectedness. Pioneered by the seminal work of Diebold and Yilmaz (2009, 2012, 2014), the concept of financial market connectedness shows that return and volatility spillovers can spread among a network of related and sometimes unrelated assets. Over the years, some variants of this line of research have emerged, and these include frequency connectedness (Baruník and Křehlík, 2018), TVP-VAR connectedness (Antonakakis *et al*., 2020a, b) and asymmetric connectedness (Adekoya *et al*., 2022), among others. This research trajectory provides contributions to portfolio construction, highlighting the importance of diversification to mitigate risks associated with contagion. Several studies

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have since used return and volatility connectedness for portfolio optimisation (e.g. Niţoi and Pochea, 2022; Nyakurukwa and Seetharam, 2024b). However, with the increasing importance of sentiment in financial decision-making, understanding whether minimising exposure to textual sentiment outperforms traditional optimisation methods is important.

Although recent studies have examined investor sentiment connectedness, their contributions remain largely unused in portfolio optimisation. Tiwari *et al*. (2021) find nonlinear, time-varying sentiment spillovers across global regions using kernel-based causality tests. Specifically, Eurozone sentiment influences the US, Asia, and Japan, while Japan and Latin America also transmit sentiment regionally. Bi-directional spillovers intensify during crisis periods, demonstrating dynamic global sentiment linkages. Using DJIA stocks, Nyakurukwa and Seetharam (2025) show that both news and social media sentiment exhibit stable connectedness across short-, medium-, and long-term horizons, with negative news sentiment displaying stronger spillover effects than positive sentiment. Seetharam and Nyakurukwa (2025) investigate connectedness of firm-level social media, news media and ESG news sentiment and find that social media is the main transmitter of sentiment shocks, particularly toward negative ESG sentiment, while ESG signals are generally isolated but shift roles during global events. These patterns provide information on sentiment flows and sectoral influence, yet they have not been translated into practical portfolio construction or risk management strategies.

While existing literature outlined above primarily focuses only on the dynamics of sentiment connectedness, this study builds upon this foundation by introducing minimum news and social media sentiment connectedness portfolios. By focusing on minimising online sentiment spillovers measured through the asymmetric TVP-VAR approach, we aim to construct portfolios that are least susceptible to online sentiment spillovers. We posit that by identifying and overweighting assets whose online sentiment is minimally connected with other assets in a system, investors can construct a portfolio that is minimally affected by online sentiment spillovers.

We compare the performance of our minimum online sentiment connectedness portfolios with traditional techniques like minimum variance and equally weighted portfolios. Our findings show that sentiment-based portfolios outperform equally weighted portfolios in generating risk-adjusted returns. In terms of cumulative returns, sentiment-based portfolios outperform both conventional methods. Our framework contributes to knowledge in several ways. First, by incorporating sentiment analysis, we capture an important driver of asset prices that traditional portfolio optimisation methods often neglect. Second, the focus on minimum online sentiment connectedness provides a unique perspective for portfolio construction, aiming to mitigate risk contagion and enhance portfolio resilience.

The study proceeds as follows: Section 2 outlines the data and methods used, Section 3 presents the results, and Section 4 concludes.

2. Data and methods

2.1 Data

Our main variables are firm-level daily news sentiment, social media sentiment and closing prices of Dow Jones Industrial Average (DJIA) constituent stocks. We chose the DJIA because of the size of the stocks, which guarantees them being mentioned frequently on online media platforms and hence produces good-quality sentiment scores. We get these variables from Bloomberg Inc. Our sample period starts from 1 January 2015 to 24 April 2024 because Bloomberg only started incorporating social media sentiment data in 2015. Our study population are all the stocks that are constituents of the DJIA. On a day that a stock is not mentioned on news platforms, Bloomberg returns a missing value for that particular stock on that specific date. We exclude such stocks with missing sentiment scores because methodologically, the analytical framework we use does not permit missing values in the variables. Ultimately, we remain with 23 DJIA-constituent stocks [1] with non-missing sentiment scores. Previous optimisation methods using various connectedness measures have used a comparable number of assets for model convergence (e.g. Adekoya *et al*., 2022; Broadstock *et al*., 2022).

Online sentiment is the extent to which news articles and social media postings are positive or negative about the prospects of a company. Bloomberg collects thousands of these news articles and social media postings from more than 50,000 premium news sources and two social media platforms (*X and StockTwits*). Bloomberg Inc. uses machine learning models to infer the extent to which these postings are bullish or bearish about the prospects of that company. The average daily sentiment is integrated into the Bloomberg terminal every day before the market opens. Daily average sentiment ranges from a minimum of -1 to a maximum of $+1$. This means that an average daily sentiment of 0 denotes that the news articles or social media posts are, on average, neutral about the prospects of the mentioned company. We use log returns as a proxy for daily stock price performance.

2.2 Methods

2.2.1 Asymmetric connectedness. To capture online news sentiment connectedness, we utilise the asymmetric TVP-VAR connectedness approach of Adekoya *et al.* (2022), which disaggregates total connectedness into its positive and negative constituents. We use daily online sentiment scores for all the stocks as inputs into the asymmetric online sentiment connectedness approach. Initially, we split the sentiment series into positive and negative daily sentiment using Eq. (1):

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

where z_t^+ and z_t^- represent positive and negative online investor sentiment.

Asymmetric connectedness uses the Antonakakis *et al.* (2020a, b) framework and starts with an estimation of a TVP-VAR (1) based on the Bayesian Information Criterion (BIC) as follows:

$$z_t = \boldsymbol{B}_t z_{t-1} + u_t \qquad u_t \sim N(0, \Sigma_t) \tag{2}$$

$$vec(B_t) = vec(\boldsymbol{B}_{t-1}) + v_t \qquad v_t \sim N(0, \mathrm{R}_t) \tag{3}$$

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, while $vec(B_t)$ and v_t are the $k^2\times 1$ dimensional vectors and R_t is a $k^2\times k^2$ dimensional matrix. We transform the estimated TVP-VAR into its TVP-VMA process by the following equality: $z_t = \sum_{i=1}^{p} \boldsymbol{B}_{it} \boldsymbol{z}_{t-i} + \boldsymbol{u_t} = \sum_{j=0}^{\infty} \boldsymbol{A}_{jt} \boldsymbol{u}_{t-j}$. The (scaled) generalised forecast error variance decomposition (GFEVD) (Koop *et al.*, 1996; Pesaran and Shin, 1998) normalises the unscaled GFEVD, $\psi_{ij,t}^{g}(H)$, such that each row sums to 1. By implication, $\widetilde{\psi}_{ij,t}^{g}(H)$, shows the variable *j*'s influence on the variable *i* as its forecast error variance, defined as pairwise directional connectedness in the same direction. This is estimated as:

$$\psi_{ij,t}^{g}(H) = \frac{\sum_{ii,t}^{-1} \sum_{t=1}^{H-1} \left(\boldsymbol{\iota}' \boldsymbol{A}_t \sum_t \boldsymbol{\iota}_j\right)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} \left(\boldsymbol{\iota}_i \boldsymbol{A}_t \sum_t \boldsymbol{A}_t' \boldsymbol{\iota}_i\right)} \; \widetilde{\psi}_{ij,t}^{g}(H) = \frac{\psi_{ij,t}^{g}(H)}{\sum_{j=1}^{k} \phi_{ij,t}^{g}(H)} \tag{4}$$

where $\sum_{j=1}^{k} \widetilde{\psi}_{ij,t}^{g}(H) = 1, \sum_{i,j=1}^{k} \widetilde{\psi}_{ij,t}^{g}(H) = k,$ H represents the forecast horizon and $\boldsymbol{\iota}_i$ represents a selection vector with unity on the *i*th position and zero otherwise. We examine a scenario where *i* emits shocks to all other variables *j*, and this is defined as total directional connectedness TO others and is represented by:

$$C^g_{i\rightarrow j,t}(H) = \sum_{j=1, i\neq j}^{k} \widetilde{\psi}^g_{ij,t}(H) \tag{5}$$

Conversely, the shock that i receives from all other variables (j) is called total directional connectedness FROM others and is represented by:

$$C^g_{i\leftarrow j,t}(H) = \sum_{j=1, i\neq j}^{k} \widetilde{\psi}^g_{ij,t}(H) \tag{6}$$

The difference between connectedness TO and FROM gives us the NET total directional connectedness, defined as the impact that variable i has on the analysed network. This is represented as follows:

$$C^g_{i}(H) = C^g_{i\rightarrow j,t}(H) - C^g_{i\leftarrow j,t}(H) \tag{7}$$

The market interconnectedness (Total Connectedness Index – TCI) is then calculated using the formula:

$$C^g_{t}(H) = \frac{\sum_{i,j=1, i\neq j}^{k} \widetilde{\psi}^g_{ij,t}(H)}{\sum_{i,j=1}^{k} \widetilde{\psi}^g_{ij,t}(H)} = \frac{\sum_{j=1, i\neq j}^{k} \widetilde{\psi}^g_{ij,t}(H)}{k} \tag{8}$$

Finally, the TCI is decomposed into the pairwise connectedness index (PCI), which measures the interconnectedness between two variables i and j:

$$C^g_{ijt}(H) = 2\left(\frac{\widetilde{\psi}^g_{ij,t}(H) + \widetilde{\psi}^g_{ji,t}(H)}{\widetilde{\psi}^g_{ii,t}(H) + \widetilde{\psi}^g_{ij,t}(H) + \widetilde{\psi}^g_{ji,t}(H) + \widetilde{\psi}^g_{jj,t}(H)}\right) \tag{9}$$

The analyses are based on a TVP-VAR model with a lag order of one, selected using the BIC, and a 20-step-ahead generalised forecast error variance decomposition following Adekoya *et al*. (2022). The PCI ranges from 0 to 1 and captures the extent of bilateral interconnectedness between variables i and j, which is otherwise obscured by the aggregate TCI.

2.2.2 Portfolio construction. 2.2.2.1 Traditional portfolio construction methods. Our hypothetical portfolio constructions are premised on the assumption of exclusive interest in DJIA stocks. Our first portfolio, the minimum variance portfolio (MVP) (Markowitz, 1952) strategy, which seeks to create a portfolio with the lowest volatility based on a variety of assets, is one of the most popular methods used in portfolio construction. The following formula is used to determine the portfolio's weights:

$$\omega_{Ht} = \frac{H_t^{-1} I}{I H_t^{-1} I} \tag{10}$$

where ω_{Ht} is an $m \times 1$ dimensional portfolio weight vector, I is an $m-$ dimensional vector of ones, and H_t is the $m \times m$ dimensional conditional variance-covariance matrix in period t.

Our second portfolio, known as the equally weighted portfolio (EWP), distributes weights evenly across all stocks held in the portfolio. The allocation of weights for each security in an EWP is determined by the following equation:

$$w_i = \frac{1}{n} \tag{11}$$

where w_i represents the weight of security i, and n represents the total number of securities in the portfolio.

2.2.2.2 Minimum online sentiment connectedness portfolio. Our key portfolios are created using firm-level daily online sentiment. We create minimum connectedness (MCoP) portfolios following Broadstock *et al.* (2022). We use all pairwise connectedness indices to generate a minimum connectedness portfolio. A portfolio that is less significantly impacted by network shocks is possible by minimising the interconnectedness between stocks and, consequently, their spillovers. As a result, the portfolio will assign a higher weight to stocks that least influence or are least influenced by others in terms of sentiment spillovers. This is created as follows:

$$\omega_{pci} = \frac{PCI_t^{-1} I}{IPCI_t^{-1} I} \tag{12}$$

where PCI_t is the pairwise connectedness index matrix, and I is the identity matrix.

We specifically create six minimum sentiment connectedness portfolios. The first two are based on minimising connectedness of negative news sentiment (MCoP_negN) and negative social media sentiment (MCoP_negT). The next two portfolios are based on minimising the connectedness of positive news (MCoP_posN) sentiment and positive social media (MCoP_posT) sentiment. Finally, we create two portfolios that do not disaggregate sentiment into its positive and negative constituents but minimise the connectedness of aggregate sentiment for news (MCoP_allN) and social media (MCoP_allT).

2.2.3 Portfolio performance. We use various metrics to measure the performance of the different portfolios created in Section 2.2.2. First, we use dynamic daily cumulative returns to gauge the performance of our different portfolios over the sampled period. Second, we utilise the Sharpe ratio (Sharpe, 1966) to evaluate the risk-adjusted returns of each of the portfolios constructed. The ratio calculates the excess return of a portfolio over the risk-free rate per unit of volatility or total risk, as shown in Eq. (13):

$$SR = \frac{\overline{r}_p}{\sqrt{Var(r_p)}} \tag{13}$$

where r_p denotes the returns on the portfolio [2]. A higher Sharpe Ratio indicates a better risk-adjusted return, meaning that the portfolio provides more return per unit of risk taken. Following Ederington (1979), we also estimate the hedge effectiveness (HE) score, which measures the percentage reduction in risk from a single stock by different portfolio allocation methods. The HE is computed as follows:

$$HE = 1 - \frac{Var(y_p)}{Var(y_{unhedged})} \tag{14}$$

where $Var(y_p)$ represents the variance of the portfolio returns and $Var(y_{unhedged})$ the variance of the unhedged stock. The significance of the HE ratios is assessed through the Fligner-Killeen Test, following Antonakakis, Chatziantoniou and Gabauer (2020a, b), who demonstrate through Monte Carlo simulations that the reduction in volatility adheres to an F-distribution, thereby allowing for the application of an F-test to determine the significance of volatility reduction resulting from portfolio creation.

3. Results

In this section, we discuss the performance of the different portfolios we constructed. We start by discussing the time-varying portfolio weights associated with each of the portfolios in Figure 1. MVP-based portfolios have higher weights for some stocks through the sample

Figure 1. Dynamic portfolio weights. Source: Authors' own work

period (e.g. JNJ) while sentiment-based portfolios have higher weights for some stocks throughout the period (e.g. UNH and MSFT).

Figure 2 shows the daily cumulative returns of all the portfolios created. Using cumulative returns to gauge the performance of the portfolios, the two portfolios created to minimise negative sentiment spillovers (MCoP_negN and MCoP_negT) outperform the other portfolios. This echoes Ho *et al.* (2023), who used DJIA-constituent stocks and the nearest neighbours (kNN) algorithm for portfolio optimisation and found that news sentiment contributes to portfolio return. The minimum variance portfolio and the MCoP_posT perform worse compared to the other competing portfolios. It is interesting to note the trajectories of the cumulative returns around the COVID-19 period. Though we witness a sharp fall in cumulative returns across the portfolios around this time, the worst-affected portfolio is the

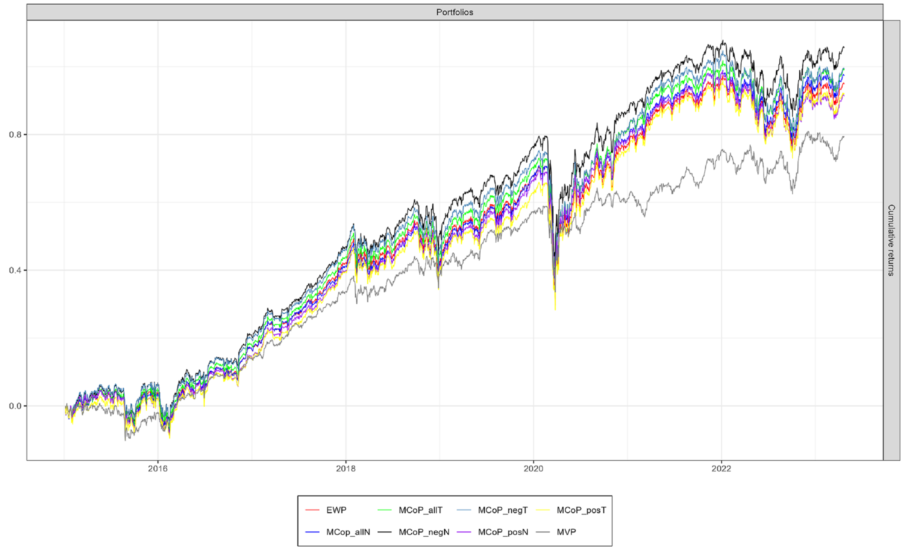

Figure 2. Cumulative portfolio returns. Source: Authors' own work

MCoP_posT portfolio. The underperformance of the MCoP_posT portfolio can be attributed to the heightened influence of retail investors during the COVID-19 lockdowns. As economic activity slowed, retail participation in financial markets surged, accompanied by a wave of optimistic market-related content on social media. This positive sentiment became a key driver of returns, disadvantaging portfolios with lower exposure.

In Table 1, we show the performance of the portfolios in terms of reward-to-volatility ratios. In terms of the average returns, the MCoP_negN portfolio has the highest daily average returns (0.0487%). Regarding portfolio risk, as expected, MVP has the lowest volatility as measured by standard deviation, and MCoP_negT has the highest standard deviation. Regarding risk-adjusted returns, MVP has the best performance with the highest return per unit of risk, followed by MCoP_negN.

We further show the hedging qualities of our portfolios using hedge effectiveness ratios in Table 2.

Hedge effectiveness varies across different stocks. Some stocks, like BA and CRM, show very high HE values (above 0.8 and 0.7, respectively) for all portfolios, indicating that portfolios containing these stocks could be particularly effective hedges. On the other hand, stocks like MCD and PG have lower HE values for all portfolios, suggesting they might not be as effective for hedging purposes. Generally, in terms of portfolio hedging, MVP fares better than sentiment-based portfolios, while sentiment-based portfolios fare better than EWP. In summary, the MCoP_negN fares reasonably well, showing that online sentiment can be used to optimise portfolios.

Table 1. Risk-adjusted performance

	EWP	MVP	MCoP_ negN	MCOP_ negT	MCOP_ posT	MCOP_ posN	MCoP_ allN	MCoP_ allT
Mean	0.0438%	0.0367%	0.0487%	0.0459%	0.0424%	0.0422%	0.0449%	0.0457%
SD	0.0111	0.0080	0.0112	0.0113	0.0110	0.0110	0.0111	0.0111
Sharpe	0.0393	0.0457	0.0434	0.0405	0.0385	0.0384	0.0406	0.0413

Source(s): Authors' own work

Table 2. Hedge effectiveness ratios

Ticker	EWP	MVP	MCoP_negN	MCoP_negT	MCoP_posN	MCoP_posT	MCoP_allN	MCoP_allT
AAPL	0.6336	0.8098	0.6276	0.6216	0.6444	0.6413	0.6378	0.6384
AMGN	0.4768	0.7283	0.4681	0.4597	0.4922	0.4878	0.4828	0.4836
AXP	0.6819	0.8349	0.6767	0.6716	0.6913	0.6887	0.6856	0.6861
BA	0.8162	0.9046	0.8132	0.8103	0.8217	0.8201	0.8184	0.8186
CAT	0.6488	0.8177	0.6430	0.6373	0.6592	0.6562	0.6529	0.6534
CRM	0.7392	0.8646	0.7349	0.7307	0.7469	0.7448	0.7423	0.7427
CVX	0.6689	0.8281	0.6635	0.6581	0.6787	0.6759	0.6728	0.6733
GS	0.6308	0.8083	0.6248	0.6188	0.6417	0.6387	0.6351	0.6357
HD	0.4961	0.7384	0.4878	0.4797	0.5110	0.5068	0.5020	0.5027
HON	0.4458	0.7123	0.4367	0.4277	0.4621	0.4575	0.4522	0.4530
IBM	0.4629	0.7211	0.4540	0.4454	0.4787	0.4742	0.4691	0.4699
JNJ	0.0598	0.5118	0.0443	0.0292	0.0875	0.0797	0.0707	0.0721
JPM	0.5997	0.7922	0.5931	0.5867	0.6115	0.6082	0.6043	0.6050
MCD	0.2752	0.6237	0.2633	0.2516	0.2966	0.2906	0.2836	0.2847
MMM	0.4229	0.7003	0.4133	0.4040	0.4399	0.4351	0.4295	0.4304
MRK	0.3276	0.6509	0.3165	0.3057	0.3474	0.3418	0.3354	0.3364
MSFT	0.5910	0.7877	0.5843	0.5777	0.6031	0.5997	0.5958	0.5964
NKE	0.6249	0.8053	0.6188	0.6127	0.6360	0.6329	0.6293	0.6298
PG	0.1102	0.5380	0.0955	0.0812	0.1364	0.1290	0.1205	0.1218
TRV	0.4788	0.7294	0.4702	0.4618	0.4942	0.4899	0.4849	0.4857
UNH	0.5383	0.7603	0.5307	0.5233	0.5519	0.5481	0.5437	0.5444
V	0.5115	0.7464	0.5035	0.4956	0.5259	0.5218	0.5172	0.5179
WMT	0.3215	0.6477	0.3103	0.2993	0.3415	0.3358	0.3293	0.3303
Mean	0.5027	0.7418	0.4945	0.4865	0.5174	0.5132	0.5085	0.5092

Source(s): Authors' own work

4. Conclusion

This study investigates the potential of incorporating online sentiment connectedness into portfolio optimisation. By looking beyond traditional methods that solely rely on historical returns and volatility, we explore the potential role of investor sentiment in creating portfolios resilient to online sentiment shocks. The analysis demonstrates that negative news sentiment spillovers can have a significant impact on portfolio performance. This can be observed from our findings, which show that using our sample, minimising negative sentiment connectedness into portfolio construction (McoP_negN) outperforms traditional methods like EWP in terms of risk-adjusted returns. From our sample, these findings suggest that incorporating sentiment-driven strategies, especially negative sentiment minimisation, can improve cumulative returns while acknowledging potential trade-offs in volatility. Practical implications include tailoring portfolio strategies to balance return, risk, and hedging efficiency, with MVP emerging as a strong candidate for risk-averse investors and sentiment-based portfolios offering opportunities for higher returns in dynamic market conditions. Future research could explore the effectiveness of this sentiment-driven approach across different markets and asset classes. Additionally, incorporating real-time sentiment analysis, along with a broader timeframe and larger dataset, could drive future research. While our analysis focuses on assets with complete sentiment data to ensure the reliability of the connectedness measures, we acknowledge that this sample restriction may introduce survivorship bias and limit the broader applicability of the findings. Future research could address this limitation by employing alternative sentiment sources or expanded datasets with more comprehensive coverage.

Appendix

Table A1. List of 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	CVX	Chevron Corporation	Energy
8	GS	Goldman Sachs Group Inc	Financials
9	HD	Home Depot Inc.	Consumer Discretionary
10	HON	Honeywell International Inc.	Industrials
11	IBM	International Business Machines	Technology
12	JNJ	Johnson & Johnson	Healthcare
13	JPM	JPMorgan Chase & Co	Financials
14	MCD	McDonald's Corporation	Consumer Discretionary
15	MMM	3 M Company	Industrials
16	MRK	Merck & Co. Inc.	Healthcare
17	MSFT	Microsoft Corporation	Technology
18	NKE	NIKE Inc. Class B	Consumer Discretionary
19	PG	Procter & Gamble Company	Consumer Staples
20	TRV	Travelers Companies Inc	Financials
21	UNH	UnitedHealth Group Incorporated	Healthcare
22	V	Visa Inc. Class A	Financials
23	WMT	Walmart Inc.	Consumer Staples

Source(s): Authors' own work

Notes

1. A full list of the stocks is found in the Appendix.
2. Following Broadstock *et al*. (2022) we assume the risk-free rate is equal to zero for simplicity.

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