

RESEARCH ARTICLE OPEN ACCESS

Social Media, Traditional News and Stock Returns: A Causal Mediation Analysis

Kingstone Nyakurukwa  | Yudhvir Seetharam

University of the Witwatersrand, Johannesburg, South Africa

Correspondence: Kingstone Nyakurukwa (knyakurukwa@gmail.com)

Received: 29 April 2024 | **Revised:** 19 June 2025 | **Accepted:** 7 July 2025

Keywords: behavioural finance | causal mediation | investor sentiment | textual sentiment

ABSTRACT

Increasing computing power and access to the internet have amplified the role of social media and online news media on financial market outcomes. However, these two sources of information are intertwined in such a way that information flows between them. As a result, sentiment expressed in one source can affect stock market outcomes through the other source. This study examines this interplay between news media sentiment, social media sentiment and stock returns within the Dow Jones constituent companies from 2016 to 2023. Leveraging an extensive dataset, we adopt an approach that combines causal mediation models with robust statistical techniques to establish the mediation effects of one sentiment proxy on the relationship between the other proxy and stock returns. We also use a range of other methods like path analysis, panel vector autoregression and causal forests for robustness. The study finds that news sentiment is more influential in directly affecting stock returns than *Twitter* sentiment while the latter is more influential indirectly when mediated by news sentiment.

JEL Classification: G14, G40

1 | Introduction

Under classical finance, capital markets are informationally efficient. This implies that the possibility of attaining returns exceeding those adjusted for risk is limited. De Long et al. (1990) support this by arguing that rational arbitrageurs consistently restore asset prices to their intrinsic values by counterbalancing the effect of irrational investors. However, contrary to the Efficient Market Hypothesis (EMH), the Limited Arbitrage Hypothesis contends that complete arbitrage is not feasible in the real world due to challenges faced by arbitrageurs such as those arising from the inherent risk and capital requirements associated with arbitrage activities (Shleifer and Vishny 1997). Thus, the activity of irrational traders can lead to frequent deviations from market efficiency.

A more recent body of literature attributes a subset of stock market anomalies observed in financial markets to the distortions introduced by trades influenced by investor sentiment

(Baker and Wurgler 2006; Black 1986). However, investor sentiment is a latent variable and over the years various proxies of investor sentiment have been used including market variables (Song et al. 2023), surveys (Hasan and Al-Najjar 2025) and other variables. With the increasing computing power and language processing technology, recent literature has shifted its focus to investor sentiment extracted from text. Two of the most used sources of textual sentiment are online news media and social media. Online news media are more formal sources of information that normally disseminate information after verifying facts. Social media, on the other hand, is more informal and seeks to give information in real-time by posting as events occur.

Several studies show that sentiment extracted from news and social media can predict stock returns. However, most of these studies have independently looked at whether each proxy can predict stock returns. This is against the increasing information flow between these two sources of information as these

This is an open access article under the terms of the [Creative Commons Attribution-NonCommercial-NoDerivs](https://creativecommons.org/licenses/by-nc-nd/4.0/) License, which permits use and distribution in any medium, provided the original work is properly cited, the use is non-commercial and no modifications or adaptations are made.

© 2025 The Author(s). Intelligent Systems in Accounting, Finance and Management published by John Wiley & Sons Ltd.

two platforms are quickly converging. Some journalists and companies have active social media handles and usually share snippets of official news on social media platforms. Seetharam and Nyakurukwa (2024) state that news media and social media exhibit information flows between them and there is a need to simultaneously model these information flows to establish how they affect stock market outcomes. As a result, there is a potential for one of the proxies mediating the other in affecting stock returns. In this study, we therefore examine whether social media (news media) sentiment can potentially mediate the relationship between news media (social media) and stock returns.

Empirically, studies have shown different ways in which news and social media sentiment affect stock returns. Gianstefani et al. (2022) suggest that the processing of social media signals is subject to *echo chambers*. This means that social media simply repeats existing news media signals, and some naïve traders may interpret this as new information. News media, on the other hand, contains new and fundamental information which often leads to less disagreement about asset prices and thereby drives prices to their intrinsic values (Jiao et al. 2020). Thus, social media and news media are likely to have opposite effects on stock returns in such scenarios. Ren et al. (2021) postulate that it is very unlikely that social media can act as a sentiment generator for financial news. Rather, they propose a hypothesis that stipulates that the sentiment role of social media is mostly of being a sentiment filter. This means that news media react to the discussions of previous posts on social media and in the process set the sentiment of later news articles on the same topic. Thus, future news media articles on the same topic may reflect the new curated sentiment.

Ren et al. (2021) state that contrary to popular belief of objective reporting by news media, competition for advertising revenue and viewership may lead to news media companies reporting the same information set with different sentiments catering to different audience groups. News media companies may therefore align their sentiments with the sentiments of their readers (from observing their sentiments on social media) to increase viewership. As a result, there is therefore a complex interplay between news sentiment and social media sentiment which may result in one source being a mediator in the other's role in affecting stock market outcomes like returns and volatility. We, therefore, test the following hypotheses that succinctly show the interplay between these two sources of information in affecting stock returns:

Hypothesis 1. *Social media sentiment (M) mediates the relationship between news media sentiment (X) and stock returns (Y).*

Hypothesis 2. *News media sentiment (M) mediates the relationship between social media sentiment (X) and stock returns (Y).*

We assume that X is the main independent variable, M is the mediating variable and Y is the dependent variable. Because we do not want to pre-empt the relationship between these variables, we test two hypotheses with each sentiment proxy respectively assuming an independent and mediator role.

We leverage our understanding of the complex relationship between these three variables using causal mediation models (CMM). Causal mediation models are increasingly becoming popular in the business domain (Asiedu and Mensah 2023; Carpena and Zia 2020; Celli 2022), having mostly been used in other fields in the social and health sciences. Over the years, these models have been increasing in complexity to deal with assumptions inherent in linear models like normality, stationarity and fat tails. We use one such method (robust mediation model) to robustly test the mediation model consisting of social media sentiment, news media sentiment as well as stock returns. This method is appropriate for this study as it is robust even when a distribution deviates from normality. It also intrinsically down-weights outliers and is robust with distributions that have fatter tails. In sum, it allows us to understand the relationship between the two sources of information in a framework that acknowledges that one can affect stock returns through another source.

This study contributes to the literature by employing a causal mediation framework to quantify the mediating role of sentiment in the relationship between news sentiment, social media sentiment, and stock returns. Unlike prior research that examines sentiment as a direct driver of stock prices, this study explicitly tests for mediation effects, identifying whether social media sentiment mediates the effect of news sentiment on stock returns or whether news sentiment mediates the effect of social media sentiment on stock returns. The findings of the study show that news sentiment and *Twitter* sentiment both act as mediators in the relationship between one proxy of investor sentiment and returns. However, when we compare these *indirect effects*, we find that the mediating role of news sentiment in influencing the relationship between *Twitter* sentiment and stock returns is stronger than the mediating role of *Twitter* sentiment in influencing the relationship between news sentiment and stock returns. When it comes to direct effects, we report that news sentiment is more influential in affecting stock returns compared to *Twitter* sentiment. These results hold across a multitude of methods including path analysis, panel vector autocorrelation and causal forests.

We proceed as follows: Section 2 looks at data and methods, Section 3 presents the results, Section 4 discusses the results and Section 5 concludes.

2 | Data and Methods

2.1 | Data

We get our social media and news media daily sentiment scores from Bloomberg. Our sample includes 30 constituents of the Dow Jones Industrial Average (DJIA). The DJIA has some of the largest and most liquid stocks in the world and, as a result, are more likely to be frequently mentioned on the two online platforms we use in this study. Thus, we get better sentiment scores from bigger companies which attract considerable attention on online platforms. Several studies investigating how online textual sentiment is related to stock returns have also used DJIA constituent stocks (e.g., Seetharam and Nyakurukwa 2025). A full list of the stocks, as

well as the procedure used to compute the sentiment scores by Bloomberg, is included in Appendices S1 (Table S1) and S2, respectively. Daily firm-level news sentiment and social media sentiment score range from a minimum of -1 (the most pessimistic score) to $+1$ (the most optimistic score). Stock returns are estimated as the daily log returns of each sampled stock. Our sample period starts from 1 January 2016 to 30 April 2023, motivated by the availability of data.

2.2 | Methods

2.2.1 | Preliminary Examination of the Relationships Among the Variable

Before looking at the main model which looks at the causal mediation relationships among the variables, we start with examining the relationships among the variables without considering mediation. To accomplish this, we employ path analysis and Panel Vector Autoregression (PVAR). Path analysis is used to model the direct relationships between these variables. This method allows us to assess how changes in news sentiment and *Twitter* sentiment impact stock returns while considering potential feedback loops between these variables. By specifying direct paths between news, *Twitter* sentiment, and returns, path analysis provides insight into the magnitude and direction of these relationships, ensuring a clear understanding of the immediate connections before considering more complex causal mediation.

We utilise the PVAR model in the generalised method of moments (GMM) framework, as outlined by Abrigo and Love (2016). This method is designed to handle panel data with potentially endogenous variables and unobserved heterogeneity. In this framework, the PVAR model is estimated using GMM to address endogeneity by exploiting the orthogonality conditions between the lagged values of the endogenous variables and the error terms. This approach helps to correct the bias that may arise from simultaneity or omitted variable bias in the standard estimation of dynamic panel models. The GMM estimator in the PVAR context provides consistent and efficient estimates of the parameters, even when the variables in the system are correlated with individual effects or exhibit time-varying relationships, making it a powerful tool for analysing complex dynamic relationships in panel data settings. By combining path analysis and PVAR, we gain a preliminary understanding of the total and dynamic relationships among the key variables before proceeding to the causal mediation analysis.

2.2.2 | Causal Mediation

In our main empirical analysis, we use a mediation model in which stock returns are the dependent variable, either social media (or news media) is one of the main independent variables and either news media (or social media¹) is the mediating variable. In effect, we run two high-level models, one in which news media is the main independent variable and the other in which social media sentiment is the main independent variable. Assuming that the main independent variable

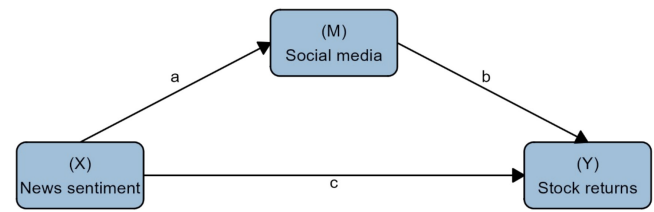


FIGURE 1 | Visualisation of the mediation model.

is news sentiment, and the mediating variable is social media sentiment, we can visualise our mediation model as shown in Figure 1.

The model in Figure 1 can be represented using the following equations:

$$M = i_1 + aX + e_1 \quad (1)$$

$$Y = i_2 + bM + cX + e_2 \quad (2)$$

$$Y = i_3 + c'X + e_3 \quad (3)$$

where stock return (Y) is the dependent variable, news sentiment (X) is the independent variable and social media sentiment (M) is the hypothesised mediator. The regression coefficients to be estimated are represented by i_1 , i_2 , i_3 , a , b , c and c' while e_1 , e_2 and e_3 represent random error terms. The coefficients of c and c' are, respectively, called the direct effect and total effect of X on Y . The product of the coefficients a and b is called the indirect effect of X on Y , which in this study will be our main parameter of interest in the mediation model. The indirect effect represented by ab can be interpreted as follows: A change of one unit in the independent variable explains a change of a units in the mediator, which in turn explains a change of ab units in Y .

Estimation of the coefficients for the mediation model visualised in Figure 1 is normally done by utilising normal-theory maximum likelihood procedures, the most common being ordinary least squares (OLS). However, financial variables often have stylised characteristics like non-normality, fat tails and excess kurtosis, characteristics which deviate from the assumptions of models based on OLS. For this study, we therefore utilise the robust test for mediation (ROBMED) of Alfons et al. (2022) that builds on bootstrapping the indirect effect via linear regression. Alfons et al. (2022) employ a robust method that builds upon the bootstrap technique for examining mediation (see Bollen and Stine 1992). However, their approach substitutes conventional OLS regressions with the robust MM-estimator of regression (Yohai 1987) and swaps out the standard bootstrap methodology with the rapid and robust bootstrap procedure (Salibián-Barrera and Zamar 2002). The MM-estimator can be interpreted as a variant of the weighted least-squares estimator, where the weights are data-driven. These weights reflect the extent to which each observation deviates from the norm; an observation showing substantial residual (high deviation) is assigned a weight approaching 0, whereas an observation with minimal residual (low deviation) is assigned a weight close to 1. Thus, the MM estimator robustly accounts for outliers in the models by down-weighting them.

2.2.3 | Robustness

To ensure the robustness of the causal mediation analysis, we also employ causal forest, a non-parametric machine learning technique. Causal forest allow us to estimate heterogeneous treatment effects by capturing complex, non-linear relationships between the treatment (news/*Twitter* sentiment) and the outcome (returns) while controlling for covariates. This method provides a more flexible alternative to traditional regression-based approaches, allowing for better handling of high-dimensional data and uncovering treatment effects that may vary across different subgroups within the sample, thus complementing the findings from the causal mediation analysis. We use a causal forest framework to analyse the impact of news (*Twitter*) sentiment on stock returns, with daily *Twitter* (news) sentiment included as a covariate. Here, stock returns (Y) are the outcome variable, the treatment variable is news (*Twitter*) sentiment (T) and the covariate is daily *Twitter* (news) sentiment (X). The causal relationship is modelled as

$$Y = f(T, X) + \epsilon, Y = f(T, X) + \epsilon, \quad (4)$$

where $f(T, X)$ represents the relationship between returns, news sentiment and *Twitter* sentiment and ϵ is the error term. The analysis focuses on estimating the average partial effect (APE) of the treatment T on the outcome Y , which represents the average marginal effect of news sentiment on stock returns across the entire sample. The APE is expressed as

$$APE = \frac{1}{N} \sum_{i=1}^N \frac{\partial E[Y | T, X]}{\partial T_i} \quad (5)$$

This formulation captures the overall sensitivity of stock returns to changes in daily news sentiment, accounting for variations in *Twitter* sentiment. To control for potential confounding by X , the causal forest algorithm incorporates an orthogonalisation step. This step involves residualising both the outcome (Y) and the treatment (T) with respect to X :

$$Y_{residual} = Y - g(X) \quad (6)$$

$$T_{residual} = T - h(X) \quad (7)$$

where $g(X)$ and $h(X)$ are estimated using regression forests to capture the dependence of returns and news sentiment on *Twitter* sentiment. The $Y_{residual}$ and $T_{residual}$ are then used to isolate the treatment effect, ensuring that the marginal effect of T on Y is not confounded by X . The causal forest algorithm constructs an ensemble of decision trees, each designed to optimise the estimation of treatment effects. Splitting criteria focus on maximising the heterogeneity of the partial effect of T on Y . The APE is calculated as the average treatment effect across all observations, leveraging the flexibility of causal forests to account for non-linear relationships and interactions among variables. The interpretation of results centres on the magnitude and sign of the APE. A positive APE indicates that, on average, an increase in favourable news sentiment leads to an increase in stock returns, while a negative APE suggests the opposite. The robustness of the APE is validated through out-of-bag sampling, ensuring that the results are not overfitted to the training data.

3 | Results

3.1 | Distributional Characteristics and Summary Statistics

Before we report on the results from the empirical mediation models, we first outline some firm-level distributional characteristics of the variables shown in Tables S2–S4. We test for stationarity using the bootUR (Smeekes and Wilms 2022) test for stationarity which circumvents the shortcomings of asymptotic inference by utilising bootstrap unit root tests. Using the bootUR test under the null hypothesis that each series has a unit root, the results across all the stocks and all the variables show statistically significant results at the 1% level of significance. This means that all the series do not have a unit root and are therefore stationary. We also test for normality using the fat-tailed normality test (Jelito and Pitera 2021), which is robust with financial variables. Using the novel fat-tailed normality (F.Normality) test to test for normality, the null hypothesis is that the test statistic (N) equals zero. We perform a one-sided statistical test for each series and reject normality if the computed value is greater than the empirical critical values generated from a Monte Carlo simulation. The last columns of each of Tables S2–S4 show the N statistics. We observe that for all stocks and all variables, the N statistic is statistically significant at the 1% level of significance. As expected, we conclude that our firm-level variables are all not normally distributed at the 1% level of significance. However, beyond testing for normality, the absolute value of the N statistic helps us to quantify the fatness/slimness of the variable distributions. A negative value symbolises slimmer tails while a positive value symbolises fatter tails. The further the N statistic is from zero, the slimmer (for negative N statistic) or the fatter (for positive N statistic) the distributions. For all the variables, the N statistics are positive and further from zero, showing that all series exhibit fat tails, in line with the well-known stylised facts of financial variables.

3.2 | Results From Preliminary Variable Relationships

We first report results from the preliminary analyses that do not take into account mediation channels among the variables. Table 1 shows the results from the PVAR model.

In Table 1, we report the results from the PVAR model using 5-day lags as suggested by the Bayesian Information Criterion. The results from the PVAR model suggest a dynamic interplay between stock returns, *Twitter* sentiment and news sentiment. Stock returns exhibit significant negative autocorrelation over time, indicating some degree of mean reversion. *Twitter* sentiment shows strong persistence, with its own lagged values significantly driving current sentiment, while also influencing returns. News sentiment exhibits a similarly strong self-reinforcing effect and significantly impacts both returns and *Twitter* sentiment, with the effects persisting across multiple lags. We also observe that lagged values of news (*Twitter*) sentiment significantly affect *Twitter* (news), all suggesting that there is a potential mediating effect of social media (news media) sentiment on the relationship between news (social media) sentiment and stock returns. This warrants a robust

TABLE 1 | Results from the PVAR model.

	Returns		Twitter		News	
ReturnsL.1	−0.0843*** (0.0144)	−0.0815*** (0.0142)	0.0001 (0.0003)	0.0002 (0.0004)	−0.0020*** (0.0005)	−0.0018*** (0.0005)
ReturnsL.2		0.0469*** (0.0119)		0.0004 (0.0003)		0.0003 (0.0005)
ReturnsL.3		−0.01197*** (0.0044)		0.0002 (0.0002)		0.0002 (0.0004)
ReturnsL.4		−0.0256*** (0.0056)		0.0007*** (0.0002)		−0.001** (0.0006)
ReturnsL.5		0.0067 (0.0067)		0.0004 (0.0003)		−0.0018*** (0.0006)
TwitterL.1	0.7820*** (0.0983)	0.8389*** (0.1011)	0.2572*** (0.0181)	0.2402*** (0.0147)	0.1252*** (0.0210)	0.1204*** (0.0210)
TwitterL.2		−0.1683*** (0.0543)		0.0297*** (0.0104)		−0.0095 (0.0116)
TwitterL.3		0.0047 (0.0413)		0.0535*** (0.0075)		0.0107 (0.0096)
TwitterL.4		−0.0851** (0.0392)		0.0227** (0.0110)		−0.0217*** (0.0068)
TwitterL.5		−0.0903* (0.0489)		0.0362*** (0.0089)		0.0209** (0.0101)
NewsL.1	0.3321*** (0.0715)	0.3555*** (0.0765)	0.0246*** (0.0048)	0.0214*** (0.0041)	0.2418*** (0.0154)	0.2236*** (0.0146)
NewsL.2		−0.0908*** (0.0345)		0.0042 (0.0032)		0.0500*** (0.0113)
NewsL.3		−0.0921** (0.0365)		−0.004 (0.0029)		0.0140* (0.0082)
NewsL.4		0.0632** (0.0312)		−0.0091 (0.0042)		0.0409*** (0.0113)
NewsL.5		−0.0172* (0.0337)		−0.0012 (0.0029)		0.0396*** (0.0070)

Note: L.1–L.5 show the respective lag orders. Standard errors clustered at the stock level are shown in parentheses.

***, ** and * represent statistical significance at the 1%, 5% and 10% respectively.

analysis using a method that separates the direct and indirect effects of independent variables on dependent variables. This is further supported by the results from Granger causality (Table 2) which shows a complex relationship among the variables. Specifically, Table 2 shows that News (*Twitter*) sentiment Granger causes *Twitter* (News) sentiment while both proxies Granger cause stock returns. It is therefore essential to quantify the direct and indirect effects of each proxy on stock returns to understand the channels through which each affects returns.

TABLE 2 | Results from Granger causality.

	Returns	Twitter	News
Returns		2.5289	9.3423***
Twitter	219.79***		262.02***
News	161.7***	132.35***	

Note: The table reports the Chi-square of the Granger causality tests.

***shows statistical significance at the 1% level.

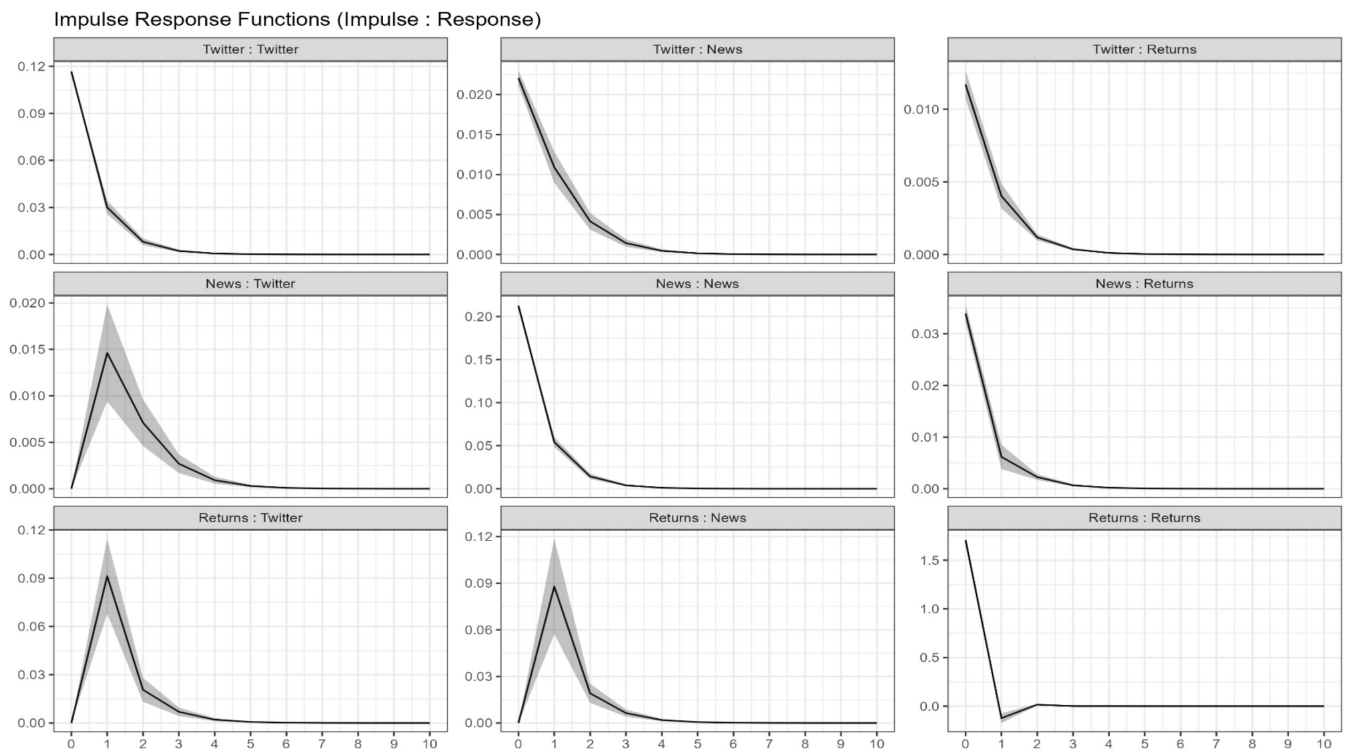


FIGURE 2 | Impulse response functions. The grey shaded area represents the 95% confidence interval. For each panel, the first variable is the impulse and the second variable is the response variable.

Figure 2 shows the impulse response functions (IRFs) from the PVAR model providing insights into the dynamic relationships between *Twitter* sentiment, news sentiment, and stock returns.

The results indicate a significant and immediate positive response of news (*Twitter*) sentiment to a shock in *Twitter* (news) sentiment, suggesting that news (*Twitter*) sentiment influences the broader (*Twitter*) news narrative. This finding establishes a directional pathway where news (*Twitter*) sentiment could indirectly affect stock returns through its impact on *Twitter* (news) sentiment. Further, stock returns exhibit a sharp and immediate response to shocks in both *Twitter* and news sentiment, with the effects gradually dissipating over time. Specifically, a shock in *Twitter* sentiment increases returns by approximately 0.01 at lag 1, while a news sentiment shock results in a return increase of about 0.03 over the same horizon. These effects then decay rapidly, with responses approaching zero by lag 4, confirming the transitory nature of sentiment shocks on return dynamics. The similarity in these patterns reflects the importance of both sentiment sources in explaining stock return fluctuations. Notably, the significant news (*Twitter*)-to-*Twitter* (News) and News (*Twitter*)-to-returns relationships suggest that news (*Twitter*) sentiment may act as a mediator in the relationship between *Twitter* (news) sentiment and stock returns. Figure 3 shows the results from path analysis.

Figure 3 shows the standardised regression coefficients (in black square brackets) and the residual error (in red square brackets), mapping the relationships among three variables: News, *Twitter*, and returns. The path from news to returns has a standardised coefficient of [0.148***], indicating a moderate and statistically significant positive influence of news sentiment on returns.

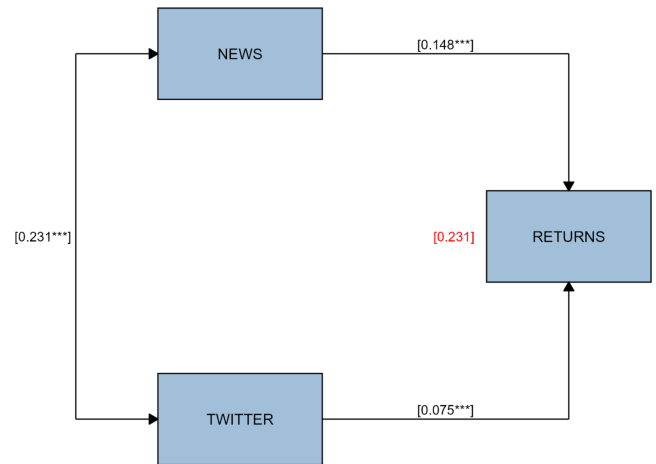


FIGURE 3 | Path analysis. The figure shows results from path analysis. Standardised regression coefficients are shown in black square brackets and the residual error is in red square brackets. *** shows statistical significance at the 1% level.

Similarly, *Twitter* also has a direct positive effect on returns, albeit weaker, with a coefficient of [0.075***]. Both coefficients suggest that news has a stronger influence on returns compared to *Twitter* sentiment. Additionally, there is a direct positive relationship between *Twitter* and news, with a coefficient of [0.231***], highlighting that *Twitter* activity substantially contributes to news sentiment. Overall, the model highlights the significant paths and the relative strength of connections, with news exerting a more pronounced impact on returns than *Twitter*, and a meaningful interplay between *Twitter* and news contributing to the overall dynamics.

3.3 | Causal Mediation

In Tables S6 and S7, we report the results of the mediation model featuring news (*Twitter*) sentiment as the main independent variable and *Twitter* (news) as the mediator respectively. In Tables S6 and S7, a represents the effect of X on M , b the effect of M on Y , c the direct effect of X on Y , c' the total effect of X on Y and ab the indirect effect of X on Y . The estimated coefficient is represented by est , standard error by $S.E$, the z -statistic by z value, lower bound of the 95% confidence interval by $L.CI$ and the upper bound of the 95% confidence interval by $U.CI$. Since we used stock level regressions in Tables S6 and S7, we summarise the results in Table 3.

The results highlight key differences in how news sentiment and *Twitter* sentiment mediate stock returns. When news sentiment serves as the independent variable and *Twitter* sentiment is the mediator (see Table S6), 86.87% of firms exhibit a significant relationship between news and *Twitter*, suggesting that news strongly influences discussions on social media. However, only 36.37% of firms show a significant effect of *Twitter* sentiment on stock returns, implying that while news drives social media sentiment, the transmission to returns is weaker. The direct effect of news on returns remains strong, with 83.33% of firms showing significance, while the indirect effect through *Twitter* is significant in 70.00% of firms, indicating that some influence flows through social media.

In contrast, when *Twitter* sentiment is the independent variable and news sentiment the mediator (see Table S7), 70.00% of firms show a significant relationship between *Twitter* and news, suggesting that social media sentiment can shape media narratives but to a lesser extent than the reverse. However, the impact of news on stock returns is stronger in this case, with 66.67% of firms exhibiting significance. The direct effect of *Twitter* sentiment on returns is weaker, significant in only 40.00% of firms, while the indirect effect through news sentiment is significant in 86.87% of firms, highlighting that news serves as a more effective transmission channel to stock returns than social media sentiment alone. Overall, the findings suggest that news sentiment plays a dominant role in influencing returns both directly and indirectly, whereas *Twitter* sentiment primarily affects returns through its impact on news coverage.

TABLE 3 | Proportion of firms with statistically significant mediation effects.

Effect	X: News; M: <i>Twitter</i>	X: <i>Twitter</i> ; M: News
X on M	86.87%	70.00%
M on Y	36.37%	66.67%
Direct effect	83.33%	40.00%
Indirect effect	70.00%	86.87%
Total effect	86.67%	86.87%

Note: The table presents the percentage of firms for which each path in the causal mediation analysis is statistically significant. 'X on M' represents the effect of the independent variable on the mediator, 'M on Y' captures the effect of the mediator on stock returns and 'Direct Effect' refers to the direct impact of X on Y . 'Indirect Effect' measures the mediated effect through M , while 'Total Effect' is the sum of the direct and indirect effect.

Our findings also reveal some interesting patterns among specific stocks. For instance, stocks like DIS and WMT exhibit both non-significant direct news sentiment effects on stock returns and insignificant indirect coefficients. This suggests that these companies' stock prices may not be significantly influenced by either direct news sentiment or the mediated sentiment through social media. Conversely, stocks like AAPL and BA, which display high coefficients for the effect of news sentiment on the mediator (social media), paradoxically feature statistically insignificant parameters for the indirect effect of news sentiment on stock returns. This implies that although news sentiment may strongly impact social media sentiment directed at these companies, this curated sentiment does not have a significant subsequent impact on their stock returns.

3.4 | Findings From Robustness Checks

The results from the causal forest model (Table S5) show that news sentiment has a stronger and more consistent relationship with stock returns compared to *Twitter* sentiment. Across firms, the estimates for news treatment are often positive and significant, suggesting that favourable news coverage tends to drive higher stock returns. This highlights the substantial role that traditional media plays in shaping investor perceptions and influencing market performance. In contrast, *Twitter* sentiment exhibits a more mixed and less robust relationship with stock returns. While some stocks display positive effects of *Twitter* sentiment, these effects are generally weaker and less consistent across firms. Specifically, only 5 stocks show statistically significant positive effects of *Twitter* sentiment at the 5% level. In contrast, 22 stocks exhibit significant positive effects from news sentiment. Additionally, *Twitter* effects show greater variability in direction and statistical strength. For instance, firms like AAPL and NKE show negative or insignificant *Twitter* effects despite strong and significant news sentiment effects.

4 | Discussion

The strong indirect effect of *Twitter* sentiment on stock returns, mediated by news sentiment (86.87% of firms), can be effectively explained through the lens of demand-driven media bias. According to Gentzkow et al. (2015), demand-driven media bias occurs when media outlets cater to the preferences or interests of their audience, leading them to select or emphasise content that aligns with the audience's beliefs or expectations. In the context of financial news, this theory suggests that news outlets tailor their coverage based on what is likely to attract more views or engagement from their audience. In this case, social media platforms like *Twitter* generate a vast amount of real-time sentiment, which often reflects the collective mood of the public or specific interest groups. News organizations, seeking to maximise their audience and engagement, often report on or amplify sentiments trending on social media platforms because they know that such content resonates with their audience. This process introduces a bias in how news is reported; stories related to *Twitter* trends are often framed in ways that highlight their potential relevance to stock market movements, thereby reinforcing the sentiment conveyed on social media. The indirect effect we observe; where *Twitter* sentiment affects stock returns primarily through its

mediation by news sentiment; can thus be seen as a result of news media's response to the demand for content that aligns with public interest and sentiment. When *Twitter* sentiment reflects popular opinions or trends, news outlets are more likely to amplify this content, further shaping investor perceptions and ultimately influencing stock prices.

The absence of a significant effect of lagged returns on Twitter sentiment, as shown in Tables 1 and 2, is consistent with recent evidence from Nyakurukwa and Seetharam (2024), who find that in the South African market, stock returns Granger-cause social media sentiment, while the reverse does not hold. Their results suggest that Twitter activity tends to be reactive, with users predominantly engaging in retrospective discussions of market movements rather than expressing forward-looking sentiment. Furthermore, they propose a directional flow in which traditional news sentiment shapes stock returns, and these returns subsequently influence social media sentiment. In this context, the non-significant predictive effect of returns on Twitter sentiment in the present study may reflect the temporal sequencing of information processing; where market outcomes serve as a trigger for post-event commentary rather than as a determinant of sentiment formation *ex ante*.

5 | Conclusion

The manuscript aimed to investigate the interplay between news media sentiment, social media sentiment, and stock returns by understanding the potential mediating roles played by either of the proxies of investor sentiment on stock returns. The findings show that sentiment extracted from both news media and social media can predict stock returns. Two main hypotheses are tested through a robust mediation model, one assuming social media sentiment acts as a mediator and another with news media sentiment as the mediator. Either proxy mediates the relationship between one proxy and stock returns. However, the direct influence of social media sentiment on stock returns is limited. Conversely, news sentiment displays a strong direct connection with stock returns. The indirect effect of news sentiment through social media is weaker than the indirect effect of social media on returns through news. Investors should be encouraged to develop a more critical approach to interpreting news and social media trends, recognising how media can amplify sentiment and potentially lead to market distortions.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Endnotes

¹ We use Twitter sentiment and social media sentiment interchangeably throughout the article.

References

- Abrigo, M. R. M., and I. Love. 2016. "Estimation of Panel Vector Autoregression in Stata." *Stata Journal: Promoting Communications on Statistics and Stata* 16, no. 3: 778–804. <https://doi.org/10.1177/1536867X1601600314>.
- Alfons, A., N. Y. Ateş, and P. J. F. Groenen. 2022. "Robust Mediation Analysis: The R Package robmed." *Journal of Statistical Software* 103, no. 13: 1–45. <https://doi.org/10.18637/jss.v103.i13>.
- Asiedu, M. A., and E. Mensah. 2023. "Re-Examining the Corporate Governance—Firm Performance Nexus: Fresh Evidence From a Causal Mediation Analysis." *Cogent Economics & Finance* 11, no. 1: 2223414. <https://doi.org/10.1080/23322039.2023.2223414>.
- Baker, M., and J. Wurgler. 2006. "Investor Sentiment and the Cross-Section of Stock Returns." *Journal of Finance* 61, no. 4: 1645–1680. <https://doi.org/10.1111/j.1540-6261.2006.00885.x>.
- Black, F. 1986. "Noise." *Journal of Finance* 41, no. 3: 528–543. <https://doi.org/10.1111/j.1540-6261.1986.tb04513.x>.
- Bollen, K. A., and R. A. Stine. 1992. "Bootstrapping Goodness-of-Fit Measures in Structural Equation Models." *Sociological Methods & Research* 21, no. 2: 205–229. <https://doi.org/10.1177/0049124192021002004>.
- Carpena, F., and B. Zia. 2020. "Causal Mechanism of Financial Education: Evidence From Mediation Analysis." *Journal of Economic Behavior & Organization* 177: 143–184. <https://doi.org/10.1016/j.jebo.2020.05.001>.
- Celli, V. 2022. "Causal Mediation Analysis in Economics: Objectives, Assumptions, Models." *Journal of Economic Surveys* 36, no. 1: 214–234. <https://doi.org/10.1111/joes.12452>.
- De Long, J. B., A. Shleifer, L. Summers, and R. Waldmann. 1990. "Noise Trader Risk in Financial Markets." *Journal of Political Economy* 98, no. 4: 703–738.
- Gentzkow, M., J. M. Shapiro, and D. F. Stone. 2015. "Chapter 14—Media Bias in the Marketplace: Theory." In *Handbook of Media Economics*, edited by S. P. Anderson, J. Waldfogel, and D. Strömberg, vol. 1, 623–645. North-Holland. <https://doi.org/10.1016/B978-0-444-63685-0.00014-0>.
- Gianstefani, I., L. Longo, and M. Riccaboni. 2022. "The Echo Chamber Effect Resounds on Financial Markets: A Social Media Alert System for Meme Stocks." Papers, Article 2203.13790. <https://ideas.repec.org/p/arx/papers/2203.13790.html>.
- Hasan, F., and B. Al-Najjar. 2025. "Consumer Confidence as a Mediator Between Dividend Announcements and Stock Returns." *Review of Quantitative Finance and Accounting*. <https://doi.org/10.1007/s11156-025-01388-3>.
- Jelito, D., and M. Pitera. 2021. "New Fat-Tail Normality Test Based on Conditional Second Moments With Applications to Finance." *Statistical Papers* 62, no. 5: 2083–2108. <https://doi.org/10.1007/s00362-020-01176-2>.
- Jiao, P., A. Veiga, and A. Walther. 2020. "Social Media, News Media and the Stock Market." *Journal of Economic Behavior & Organization* 176: 63–90. <https://doi.org/10.1016/j.jebo.2020.03.002>.
- Nyakurukwa, K., and Y. Seetharam. 2024. "Sentimental Showdown: News Media vs. Social Media in Stock Markets." *Heliyon* 10, no. 9: e30211. <https://doi.org/10.1016/j.heliyon.2024.e30211>.
- Ren, J., H. Dong, B. Padmanabhan, and J. V. Nickerson. 2021. "How Does Social Media Sentiment Impact Mass Media Sentiment? A Study of News in the Financial Markets." *Journal of the Association for Information Science and Technology* 72, no. 9: 1183–1197. <https://doi.org/10.1002/asi.24477>.
- Salibian-Barrera, M., and R. H. Zamar. 2002. "Bootstrapping Robust Estimates of Regression." *Annals of Statistics* 30, no. 2: 556–582.

- Seetharam, Y., and K. Nyakurukwa. 2024. "Headlines or Hashtags? The Battle in Social Media for Investor Sentiment in the Stock Market." *International Journal of Information Management Data Insights* 4, no. 2: 100273. <https://doi.org/10.1016/j.jjime.2024.100273>.
- Seetharam, Y., and K. Nyakurukwa. 2025. "Financial Textual Sentiment Connectedness: Evidence From Alternative Data." *International Journal of Information Management Data Insights* 5, no. 1: 100337. <https://doi.org/10.1016/j.jjime.2025.100337>.
- Shleifer, A., and R. W. Vishny. 1997. "The Limits of Arbitrage." *Journal of Finance* 52, no. 1: 35–55. <https://doi.org/10.1111/j.1540-6261.1997.tb03807.x>.
- Smeeke, S., and I. Wilms. 2022. "bootUR: An R Package for Bootstrap Unit Root Tests." (No. arXiv:2007.12249). arXiv. <https://doi.org/10.48550/arXiv.2007.12249>.
- Song, Z., X. Gong, C. Zhang, and C. Yu. 2023. "Investor Sentiment Based on Scaled PCA Method: A Powerful Predictor of Realized Volatility in the Chinese Stock Market." *International Review of Economics and Finance* 83: 528–545. <https://doi.org/10.1016/j.iref.2022.10.007>.
- Yohai, V. J. 1987. "High Breakdown-Point and High Efficiency Robust Estimates for Regression." *Annals of Statistics* 15, no. 2: 642–656.

Supporting Information

Additional supporting information can be found online in the Supporting Information section.