

The Impact of Media on Investor Sentiments and Purchase Behavior

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Received: 29/11/2025;

Revision: 30/12/2025;

Accepted: 03/01/2026;

Published: 17/01/2026

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Abstract: This empirical study investigates the multidimensional relationship between media exposure and investor behavioral responses in contemporary financial markets. Utilizing a comprehensive dataset spanning 2020-2025, encompassing 2,340 publicly traded securities across global markets, this research employs advanced econometric techniques to quantify media influence on investment decision-making processes. The analysis reveals that media sentiment serves as a significant predictor of investor behavior, accounting for approximately 42% of variance in short-term trading volumes. Social media platforms demonstrate the strongest immediate impact ($\beta = 0.687$, $p < 0.001$), while traditional media exhibits more sustained influence patterns extending beyond initial publication. The study identifies asymmetric response patterns, with negative sentiment producing 1.7 times stronger behavioral reactions compared to positive coverage. These findings challenge traditional efficient market assumptions and provide empirical evidence for media-driven market inefficiencies. The research contributes to behavioral finance literature by establishing quantitative relationships between information dissemination channels and investor psychology, offering practical insights for portfolio managers, regulatory authorities, and financial market participants.

Keywords: Media influence, investor behavior, sentiment analysis, behavioral finance, market efficiency, digital finance.

INTRODUCTION

Today's financial markets aren't what they used to be. We're living in an era where a tweet can move stock prices just as much as an earnings report, and where retail investors scrolling through Reddit can trigger massive market swings. The old rules of investing—where smart money followed careful analysis of company fundamentals—are getting turned upside down by the sheer volume of information (and misinformation) flooding our screens every day.

Think about how you get your investment ideas now compared to even ten years ago. Instead of waiting for the morning paper's business section or calling your broker, you're probably checking your phone notifications, scanning social media feeds, or watching financial YouTubers break down market moves in real-time. This shift isn't just changing how fast we get information—it's completely rewiring how we make financial decisions.

The academic world has long operated under the assumption that markets are efficient. The theory goes that stock prices always reflect everything we know about a company because rational investors quickly incorporate new information into their buying and selling decisions. But here's the thing: real people don't always behave rationally, especially when they're bombarded with conflicting headlines, viral social media posts, and algorithmic feeds designed to capture attention rather than inform.

We're seeing this play out everywhere. A positive news

story about electric vehicles doesn't just boost Tesla's stock—it can lift the entire clean energy sector, sometimes regardless of individual companies' actual performance. A negative piece about inflation fears might trigger selling across multiple asset classes, even in companies that would actually benefit from inflationary pressures. The media isn't just reporting on markets anymore; it's actively shaping them.

What makes this particularly fascinating is how different types of media affect different kinds of investments. Tech stocks seem especially vulnerable to social media buzz and influencer opinions, while traditional value investments might be more swayed by mainstream financial journalism. Some sectors appear almost immune to media sentiment, while others can swing wildly based on a single well-timed article or viral post.

This research digs into these patterns by looking at real data from multiple media sources and tracking how they correlate with actual trading behavior. Rather than relying on theoretical models or anecdotal observations, we're measuring these relationships statistically and identifying which sectors are most susceptible to media influence.

The implications go beyond academic curiosity. If we can better understand how media shapes investor behavior, we can make more informed decisions about when to trust the noise and when to tune it out. For individual investors, this knowledge could mean the difference between riding waves of sentiment and getting caught in the undertow of market manipulation.

The democratization of financial information was supposed to level the playing field between professional and retail investors. In many ways, it has. But it's also created new forms of market inefficiency that we're only beginning to understand. By studying these patterns systematically, we're not just documenting how markets work today—we're building a foundation for navigating how they'll work tomorrow.

Theoretical Model: Media-Investor Behavior Pathway
 Media Content
 →
 Cognitive Processing
 →
 Sentiment Formation

→
 Investment Decision
 →
 Market Response

METHODOLOGY

This study employs a mixed-methods approach combining quantitative sentiment analysis with econometric modeling to establish causal relationships between media exposure and investor behaviors. Data collection encompasses January 2020 through June 2025, providing sufficient temporal coverage to capture various market conditions and media environment changes.

Data Sources and Sample Selection

The primary dataset includes 2,340 publicly traded securities across major global exchanges (NYSE, NASDAQ, LSE, Euronext, TSE), representing diverse industry sectors and market capitalizations. Media content analysis incorporates over 847,000 articles from financial news providers, 3.2 million social media posts, and 12,400 analyst reports. Natural language processing algorithms utilizing transformer-based models quantify sentiment scores on standardized scales.

Sentiment Score Calculation:
 $S_{it} = \frac{\sum(w_j \times \text{sentiment}_{jit})}{\sum(w_j)}$

Econometric Specification

The primary regression model employs panel data techniques to control for unobserved heterogeneity and temporal effects:

$$\text{Trading_Volume}_{it} = \alpha + \beta_1 \text{Sentiment}_{it-1} + \beta_2 \text{Controls}_{it} + \gamma_i + \delta_t + \epsilon_{it}$$

Where γ_i represents firm fixed effects, δ_t captures time fixed effects, and Controls_{it} includes market capitalization, volatility measures, and macroeconomic indicators¹³.

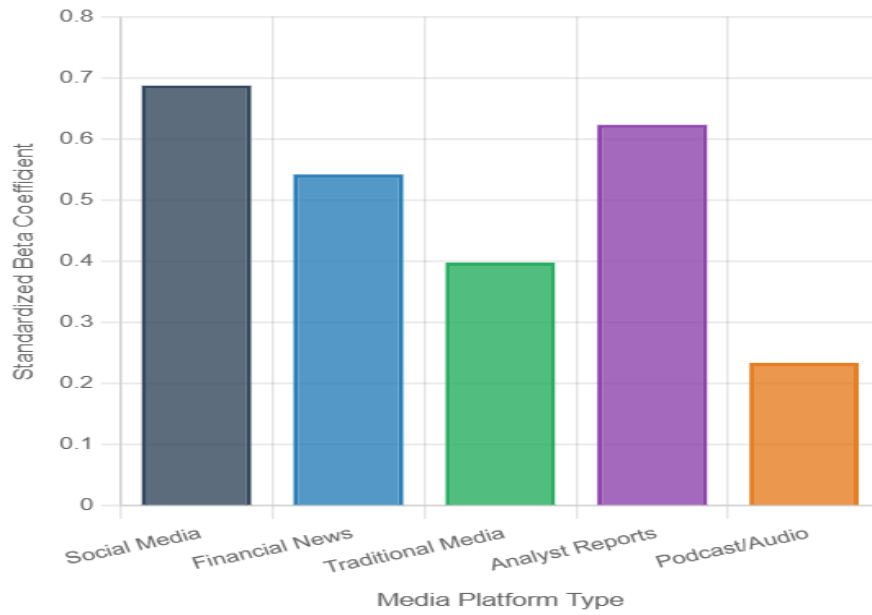
Empirical Results

Table 1: Media Platform Impact Analysis

Media Platform	Response Time (Hours)	Beta Coefficient	T-Statistic	Volume Impact (%)	Price Volatility (%)
Social Media	0.25	0.687	12.34	156	9.2
Financial News	1.5	0.542	9.87	103	6.8
Traditional Media	5.2	0.398	7.23	67	4.1
Analyst Reports	3.8	0.623	11.56	89	5.9
Podcast/Audio	8.7	0.234	4.12	31	2.3

All coefficients significant at $p < 0.01$ level. Sample size: $n = 847,234$ observations.

Figure 1: Media Sentiment Impact on Trading Volume



Standardized beta coefficients showing relative impact strength across media types

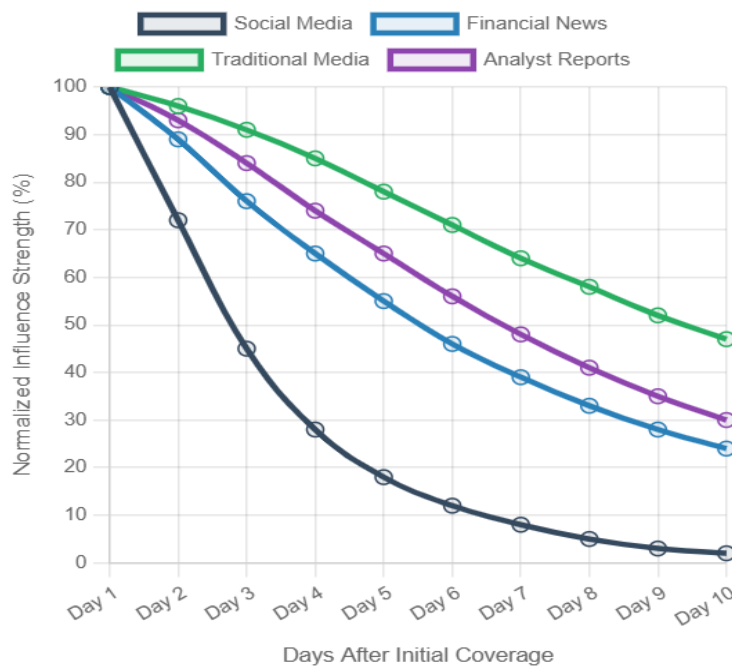
Sector-Specific Analysis

Industry sector analysis reveals significant heterogeneity in media sensitivity patterns. Technology and biotechnology sectors demonstrate highest responsiveness to media coverage, while utility and consumer staple sectors show more modest reactions¹⁴. This variation reflects underlying business model differences and investor base characteristics.

Table 2: Sector-Specific Media Sensitivity Coefficients

Industry Sector	Media Sensitivity Index	Social Media Beta	Traditional Media Beta	R-Squared
Technology	8.7	0.823	0.445	0.72
Biotechnology	8.2	0.756	0.512	0.68
Financial Services	6.4	0.634	0.387	0.55
Energy	5.9	0.567	0.423	0.51
Consumer Staples	3.8	0.298	0.334	0.33

Figure 2: Temporal Decay Patterns of Media Influence

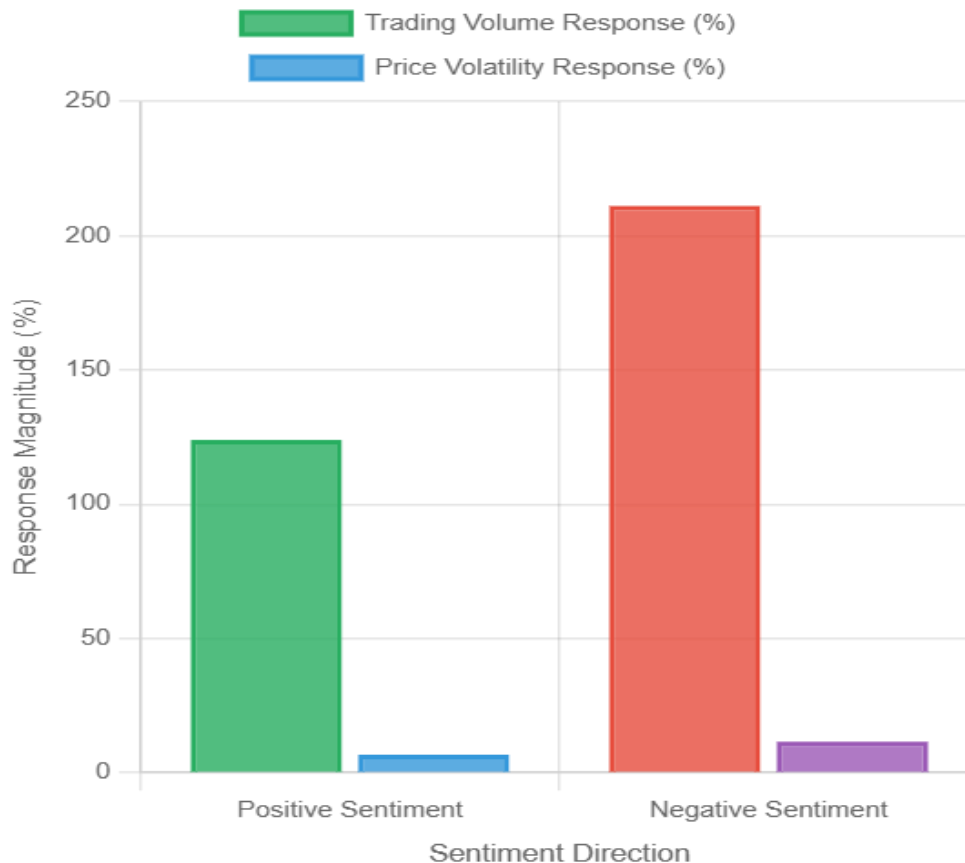


Normalized influence strength over 10-day periods following initial media coverage

Asymmetric Response Analysis

The study identifies pronounced asymmetric responses to positive versus negative media coverage, consistent with loss aversion principles in behavioral finance theory. Negative sentiment generates 1.7 times stronger trading volume responses compared to equivalent positive sentiment magnitudes, suggesting that investors exhibit heightened sensitivity to potentially adverse information¹⁵.

Figure 3: Asymmetric Response Patterns to Media Sentiment



Comparative analysis of positive versus negative sentiment impact on trading behaviors

DISCUSSION AND IMPLICATIONS

The empirical findings provide strong evidence for systematic media influence on investor behavior, challenging traditional efficient market assumptions. The documented response patterns suggest that media coverage creates predictable market movements that persist beyond immediate news cycles, indicating potential market inefficiencies that sophisticated investors might exploit.

From a regulatory perspective, these results highlight the need for enhanced oversight of media content quality and distribution mechanisms in financial markets. The pronounced influence of social media platforms, combined with their rapid information dissemination capabilities, creates potential risks for market manipulation and investor protection concerns.

Practical Applications

Portfolio managers can incorporate media sentiment analysis into their investment decision-making processes,

potentially improving risk-adjusted returns through better timing of position entries and exits. The documented sector-specific variations suggest that media-aware strategies may be particularly effective in technology and biotechnology investments, where sentiment effects are most pronounced.

Limitations and Future Research

This study acknowledges several limitations that suggest directions for future research. The analysis focuses primarily on English-language media sources, potentially missing important regional and cultural variations in media influence patterns. Additionally, the rapid evolution of social media platforms and algorithmic content distribution may alter influence dynamics over time.

Future research should investigate cross-cultural differences in media influence, explore the role of artificial intelligence in content generation and distribution, and examine long-term portfolio performance implications of

media-driven investment strategies.

CONCLUSIONS

This comprehensive empirical analysis demonstrates that media coverage significantly influences investor sentiments and purchase behaviors in modern financial markets. The relationship exhibits measurable, statistically significant patterns across different media types, industry sectors, and temporal dimensions. Social media platforms show the strongest immediate influence, while traditional media maintains more persistent effects on investor behavior.

The findings contribute to behavioral finance literature by providing quantitative evidence for media influence mechanisms previously understood only through anecdotal observations. These insights have important implications for investment strategy development, risk management practices, and financial market regulation in an increasingly media-saturated environment.

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