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Stock Market Investors' Reactions to the Tone of Press Articles

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Abstract

Theoretical background: The investigation into investor reactions to non-financial information was motivated by two key considerations. First, within financial theory, an unresolved debate persists regarding how stock market investors discount information. This article references two paradigms central to this issue: the neoclassical and the behavioural. The second motivation stems from the emergence of a new type of data in the literature, known as Big Text, which refers to large, unstructured collections of textual data. This phenomenon is associated with the development of non-financial reporting and the increasing quantity and diversity of information providers in financial markets.

Purpose of the article: The aim of the study was to assess investors' reactions to the content of press articles based on their emotional tone. To achieve this goal, two hypotheses were tested. First, it was hypothesized that the appearance of a press article would be reflected in the stock returns of the companies under study. Second, it was hypothesized that this reaction would be asymmetrical, depending on whether the article's tone was positive or negative.

Research methods: The study focused on companies included in the WIG20 index of the Warsaw Stock Exchange from 2013 to 2022. For these companies, a database of English-language press publications with a high degree of positive or negative emotional tone was constructed. The research was conducted using the event study methodology, with the event defined as the day the article appeared.

Main findings: The results supported the hypotheses. Additionally, differences in the way information was discounted depending on emotional tone were observed. Negative publications triggered strong, abrupt, and short-lived reactions, while reactions to positive publications were weaker and more prolonged over time.

Introduction

This article explores how investors react to the emotional tone of press articles. It is motivated by two factors: the ongoing debate in finance over how stock market investors process information and the rise of "Big Text" – large, unstructured datasets. The analysis is based on two paradigms: neoclassical finance, which assumes rational investor behavior, and behavioral finance, which highlights the influence of cognitive biases and framing effects on decision-making.

The research aims to assess how press articles with positive or negative emotional tones affect stock returns, testing two hypotheses: that stock returns are influenced by the appearance of a press article and that reactions are stronger to negative news. Focusing on companies from the WIG20 index of the Warsaw Stock Exchange (2013–2022), the study analyzes a dataset of English-language press articles using both the Loughran–McDonald Master Dictionary (LM) and the Harvard General Inquirer (HGI) to measure emotional tone, applying the event study methodology with the release of the article as the event. The results indicate that investor reactions depend on emotional tone: negative articles lead to sharp, short-lived stock price changes, while positive articles cause weaker, longer-lasting responses. With the HGI, similar effects are observed for negative articles, but results for positive articles are inconsistent, suggesting its limited suitability for financial market research.

The study enhances understanding of investor behaviour by exploring how media-generated information affects stock prices, contributing to the growing body of research on the influence of both traditional and social media on stock market performance. Investors may benefit from sentiment analysis when interpreting news and adjusting strategies, being mindful of potential short-term overreactions to negative information.

The article is divided into several sections. The first presents a literature review. The second outlines the research methodology and presents the results of the study. Finally, a discussion is offered along with suggestions for future research directions.

Literature review

In finance theory, a key debate centers on how stock market investors process and discount information. Fama's Efficient Market Hypothesis (EMH) emphasizes the speed and manner in which information is processed, impacting asset pricing decisions. Fama (1970) defines an efficient market as one where "prices always fully reflect available information" (p. 384). However, the interpretation of "fully reflected" information remains unclear, and a precise definition of "information" is still lacking. Generally, information is categorized into three types: (1) price information, (2) public information, and (3) private information.

This article focuses on public information within the framework of the EMH, specifically examining semi-strong form efficiency, where market prices reflect all publicly available information (Fama, 1970). Such information includes reports, disclosures, and statements from issuers (Fama, 1970, p. 383). However, investors now have access to a broader range of information. Research by the Polish Individual Investors Association (2023) shows that over 85% of respondents use websites as their primary source of information. Therefore, this article analyzes press articles about companies listed in the WIG20 index of the Polish stock exchange.

A key characteristic of this content is that it is processed to varying degrees by its authors, often referred to as EBF journalists (Economy, Business, and Finance) (Merrill, 2019). Research shows that financial media not only serve as a major source of information but also help shape market participants' expectations and event predictions (Thompson, 2009). While academic interest has largely focused on investor reactions to information directly from issuers (Gurgul, 2019), there is a research gap concerning how investors process information from newspaper articles in the local market context.

Journalism researchers have identified a specific mechanism in media communication known as framing, through which information providers influence how events are interpreted, evaluated, and understood. Frames manifest in the inclusion or omission of certain words or phrases, the selection of sources, and other rhetorical techniques. Their purpose is to shape the message, incorporating both facts and subjective judgments (Entman, 1993). If investors were fully rational, the emotional tone of a newspaper article would not influence how they process information. Any such effect suggests otherwise.

Two paradigms address this issue. Neoclassical finance assumes that investors act rationally, interpret information accurately, and make optimal decisions based on utility (Szyszka, 2013, p. 9). Within this framework, a rational investor should be indifferent to how information is framed, provided that outcome probabilities remain unchanged (Gajdka, 2013, pp. 22–24). Consequently, new information should be swiftly incorporated into asset prices (Fama, 1965). Conversely, behavioral finance challenges this assumption, arguing that human cognition does not always adhere to the axiom of invariance. Prospect theory, introduced by Kahneman and Tversky (1979), highlights that decision frames – the way a problem is presented – can influence investor choices, as individuals often struggle to separate content from its framing (Shefrin, 2002, p. 23).

A key difference between these paradigms is how they value outcomes. Neoclassical theory links value to absolute wealth, while prospect theory sees gains and losses as relative to a reference point. Investors tend to be loss-averse, meaning losses feel more significant than gains (Tversky & Kahneman, 1984, p. 346). As a result, they may overreact to negative news and underweight positive news, leading to suboptimal investment decisions.

On the other hand, recent observations emphasize the growing importance of unstructured data, now comprising 80–90% of global data (IDC, 2023; Zikopoulos et al., 2012). Textual data, or "Big Text" (Das, 2014), has gained prominence due to the internet revolution and the rise of non-financial reports, such as Corporate Social Responsibility disclosures, alongside traditional financial reporting.

The recognition of these processes has led to numerous efforts to incorporate text data into financial research. These studies are generally categorized according to the source of the text data: (1) corporate documents, (2) press articles, and (3) social media. Growing interest in this area has prompted researchers to explore the use of sentiment analysis within reports to assess market conditions. In the context of this type of research, "sentiment" can be defined as the degree of positivity or negativity in the text (Kearney & Liu, 2014). The effectiveness of these models has been demonstrated in both long-term (Feuerriegel & Gordon, 2018) and short-term analyses (Yekini et al., 2016). It is important to note that corporate documents use formal language without metaphors, jokes, or sarcasm, whereas social media often includes these elements. Despite this, studies have also demonstrated a correlation between internet posts and financial market dynamics. Major social networking sites, including Twitter (e.g. Herrera et al., 2022), Yahoo! Finance (e.g. Das & Chen, 2007), and Facebook (e.g. Siganos et al., 2014), have been analyzed from this perspective.

However, one of the most widely used sources of text data for analyzing the impact of textual sentiment on security prices is press articles. The development of this trend could be noticed in the United States in 2007 by Tetlock. He investigated the effect of negative media sentiment on stock market performance and discovered that increased pessimism in the media correlates with a decline in the Dow Jones Industrial Average's returns on the following day. Tetlock also found that heightened pessimism could predict increased trading volume and anticipate price declines, which were subsequently followed by a return to fundamental prices (Tetlock, 2007). Shorter time frames have also been examined. For instance, Schumaker and Chen (2009) analyzed companies in the S&P500 index, focusing on estimating stock prices twenty minutes after the publication of an article. Their AZFinText model, which integrates data from articles and stock prices, demonstrated superior performance in terms of accuracy, directional prediction, and trade simulation. The NASDAQ index has also been analyzed in this context. Khedr and colleagues (2017) also analyzed the NASDAQ index and developed a model for predicting market trends, achieving over 70% forecasting accuracy using sentiment data alone.

Similar studies have been conducted across most Western European countries. In 2021, Alomari and colleagues examined the impact of press and social media sentiment on the performance of London Stock Exchange stocks and bonds from 1998 to 2017. They found that press sentiment had a greater impact on stock performance compared to social media sentiment (Alomari et al., 2021). A similar study in Norway by Larsen and Thorsrud (2017) revealed that certain entities are highly sensitive to press publications, with negative returns in the absence of news but statistically significant abnormal returns following relevant press articles. On the local market, Rostek and Młodzianowski conducted a similar analysis on the main indices of the Warsaw Stock Exchange, using text data from online business press services over 280 trading sessions. Although they did not develop a satisfactory forecasting model, their classification model achieved results exceeding 60% (Rostek & Młodzianowski, 2017).

Some researchers are investigating whether the influence of press sentiment on investor behavior is symmetrical, specifically whether positive and negative emotions are discounted in a similar manner. Two research teams have examined this issue on the Dutch market but reached different conclusions. Kleinnijenhuis and colleagues (2013) found that the media play a significant role in conveying negative market sentiment, contributing to the exacerbation of the 2007 financial crisis. In contrast, Strauß and colleagues not only failed to observe an impact of textual sentiment on security prices but also argued that the media merely reflect existing market sentiment. According to their findings, the media do not add significant value in a research context (Strauß et al., 2016). Despite these findings, research conducted a few years later on the American market confirmed the presence of asymmetry. Zubair and Cios (2015) analyzed texts from the Reuters archive and found a correlation between negative sentiment and changes in the S&P 500 index in five of the seven years studied. No such correlation was observed for positive sentiment.

The preceding discussion leads to several key conclusions. First, press articles about companies can be viewed as a form of public information. Second, one method of utilizing this type of data is through sentiment analysis. Third, a definitive answer has not yet been reached regarding how investors discount press content based on its emotional tone. This ambiguity is evident both in the theoretical framework described earlier and in empirical research. Fourth, while incorporating text data into financial market research is gaining traction in developed markets, there remains a research gap in this area within the local market. The studies presented in this article aim to fill this gap and are described in the following sections.

Research methods

The aim of this study was to evaluate the response of stock market investors to the content of press articles based on their emotional tone. To achieve this objective, two hypotheses were tested:

H1: The occurrence of an event, such as the publication of a press article, will be reflected in investor reactions, as measured by abnormal stock returns.

H2: Investors' reactions to the occurrence of an event will be asymmetric, depending on whether the tone of the article is positive or negative.

The entities included in the study sample had to meet three criteria: (1) during the study period, they were part of the WIG20 index of the Warsaw Stock Exchange;[1] (2) they had been included in the index for at least one year; (3) it was possible to gather a minimum of one hundred English-language press articles about them, published during the study period. Thus, 33 out of 39 companies were selected for the sample. The research period spanned ten years, from January 1, 2013, to December 31, 2022, allowing for the capture of both boom-and-bust periods in the local capital market.

The study utilized two types of data. The first type comprised the daily closing prices of the shares of the companies under study. These data were essential for calculating daily rates of return, which were used to perform the event analysis. The source of these data was the stooq.pl portal. The second type consisted of textual data in the form of English-language press articles, which were sourced from the Emerging Markets Information Service. The articles included in the study had to meet two criteria: (1) their titles contained the names of the companies in the research sample;[2] (2) they were published in English.

The choice of language was based on three considerations. First, there has been a notable increase in the proportion of foreign investors trading shares of companies listed on the Polish stock exchange, including the Main Market. By the final year of the research period, this proportion had exceeded 60% (GPW, 2016, 2023). Moreover, foreign investors' interest in our stock exchange was growing throughout the analyzed decade, as illustrated in Figure 1.

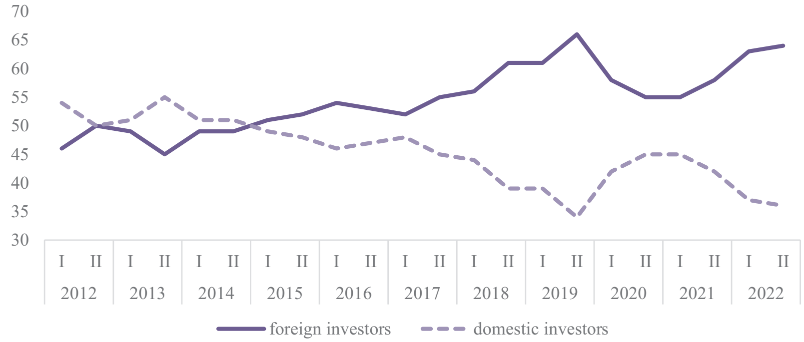

Figure 1. Percentage share of foreign investors in stock trading on the Main Market of the Warsaw Stock Exchange

Source: Author's own study.

Second, English is widely regarded as the standard language for business communication (Crawford Camiciottoli, 2020). Third, given the research gap in this area

[1] This index comprises companies with the highest trading volumes on the Polish stock market.

[2] Articles mentioning companies only in relation to other entities or the broader market were excluded to focus solely on those directly related to the companies under study.

within the local market, it was prudent to utilize established research tools for text analysis and sentiment extraction. For this study, the Loughran–McDonald Master Dictionary (LM) was employed. This dictionary is specifically designed for use in finance and economics and is well-established in relevant literature (e.g. Fedorova et al., 2022; Fraiberger et al., 2021; Li et al., 2020). Additionally, the Harvard General Inquirer (HGI) dictionary was applied to verify the robustness of the results. This dictionary is widely used in social sciences and humanities research; however, it was not originally designed for economic analyses. Nevertheless, a review of the literature indicates that it has been applied to studies in this field (see Guo et al., 2016). Consequently, a total of 56,953 press articles that met the specified criteria were collected.

Sentiment extraction was conducted by assigning each word in the articles a value corresponding to its emotional connotation as defined by the dictionary. Words with a positive connotation were coded as "1", while those with a negative connotation were coded as "-1". Words with neutral connotations were assigned a value of "0". Subsequently, each article was assigned a sentiment score ranging from -1 to 1, based on the following formula (Li et al., 2014):

$$sentiment = \frac{N_{pos} - N_{neg}}{N_{pos} + N_{neg}}$$

N_{pos} – number of positive words
N_{neg} – number of negative words

The sentiment scores of press articles classified as positive fell within the range (0, 1], while those classified as negative ranged from [-1, 0). It is important to note that these ranges indicate varying degrees of definitiveness. For example, an article with a score of -0.2 was classified as negative, just as an article with a score of -0.9 was. To avoid defining events based on publications with ambiguous emotional connotations in subsequent stages of the research, a "gray zone" was established, encompassing the range (-0.9, 0.9). Publications with sentiment scores within the gray zone were deemed insufficiently definitive in terms of their emotional tone (Ardia et al., 2022). Only articles with scores ranging from [0.9, 1] for positive sentiment and [-1, -0.9] for negative sentiment were qualified for the subsequent stage of the study. A total of 5,861 publications met these criteria and were included in the event analysis, comprising 3,185 with a positive tone and 2,676 with a negative tone.

The presented study employs the event analysis method, which enables the verification of abnormal reactions among stock market investors within a specific time window. The first step of this method is to define the event itself, which in this case was the publication date of the press article.[3] The events were categorized into

[3] Some articles in the study were published on non-trading days and were assigned to the nearest trading session date on the Warsaw Stock Exchange.

two groups – positive and negative – based on the sentiment assigned during the sentiment extraction stage. Each group was analyzed separately, resulting in the event analysis being conducted twice.

Subsequently, the event window was defined as the period during which investors' reactions to the publication of the article were examined. The decision on the length of this window was guided by two considerations. First, the analysis was based on daily rates of return, with the assumption that any changes in response to the event would be observable over similarly short intervals. Gurgul (2019, pp. 38–39) highlights this issue, noting that if the event window is set too long, significant market reactions to the event may become diluted, resulting in cumulative abnormal returns that are statistically insignificant. Secondly, the selection of text sources in the form of press publications, to some extent, necessitated the choice of a short event window. The goal was to minimize the probability that closely spaced events, which might influence each other, would distort stock prices and affect the study results (Bouteska, 2019). In this study, the event window was defined as starting one day before the publication of the article and ending five days after, following the approach used by Allen et al. (2019).

The next step was to define the estimation window, which is used to estimate the expected rates of return within the event window (Gurgul, 2019, p. 40). Determining the event window presents challenges that also apply to the estimation window. For example, when studying periodic reports, the frequency of events can be determined and the estimation windows adjusted accordingly. However, when examining press articles or social media, events occur more frequently, and there is no regulation on publication frequency, increasing the risk of disruptive events. In this study, the estimation window was set at 30 days to balance accurate return estimation with minimizing disruptive events. To verify the results, alternative windows of 60 and 90 days were also tested.

To estimate the expected rates of return, the market model was employed, using the following formula (Gurgul, 2019, p. 42):

$$\hat{R}_{i,t} = \alpha_i + \beta_i R_{m,t}$$

α_i – intercept term
β_i – risk coefficient of the i-th stock
$R_{m,t}$ – market index return in period t

One of the variables in the model is the rate of return on the market index. Since all entities under study were part of the WIG20 index, which showed a high correlation with the WIG index (0.98), the latter was not used. Instead, the Stooq Poland All Stocks Price Index was employed. This alternative index encompasses both the Main Market and NewConnect and assigns equal weight to each security, reducing the risk of the largest entities disproportionately influencing the benchmark.

To estimate investors' reactions to the occurrence of events, daily rates of return were first calculated using the following formula:

$$R_{i,t} = \frac{P_{i,t_2}}{P_{i,t_1}} - 1$$

P_{i,t_1} – closing price on the day t_1
P_{i,t_2} – closing price on the day t_2

Next, the actual rates of return were compared with the expected rates, allowing for the calculation of daily abnormal returns (Gurgul, 2019, p. 51):

$$AR_{i,t} = R_{i,t} - E(R_{it}|\Omega_{EW})$$

$R_{i,t}$ – real rate of return of i-th stock in period *t*
$E(R_{i,t})$ – expected rate of return of the i-th stock in period *t*

Limiting the analysis to calculating abnormal returns would address the question of how investors in each of the analyzed companies reacted to each event. However, from a research perspective, it is more insightful to aggregate and average the results. This approach facilitates statistical inference and provides a general assessment of the phenomenon. Therefore, the abnormal returns were averaged for both event groups – positive and negative – using the following formula (Gurgul, 2019, pp. 50–51):

$$AAR_t = \frac{\sum_{i=1}^{N} AR_{i,t}}{N}$$

N – number of companies
$AR_{i,t}$ – abnormal rate of return of the i-th stock in period *t*

To capture a more comprehensive picture of investor reactions throughout the event window, average abnormal returns were aggregated into cumulative average abnormal returns (Agrawal et al., 2009, p. 1609):

$$CAAR_{t_1}^{t_2} = \sum_{t=t_1}^{t_2} AAR_t$$

t_1 – beginning of the observation window
t_2 – end of the observation window
AAR_t – average abnormal rates of return in period *t*

All financial data used in the study considered only the price aspect, excluding dividends paid. The evaluation of the obtained results involved several steps applied to both groups. First, it was assessed whether the abnormal returns differed significantly from zero. In this context, the following hypothesis was tested:

H0: AAR = 0 and CAAR = 0

If the results equaled zero, it would indicate no impact on stock returns and no investor reaction, leading to the rejection of H1. Conversely, deviations from zero would support H1. Secondly, the direction of stock price changes was key. Negative returns were expected for negative news, while positive returns indicated a reaction to positive news. Thirdly, the statistical significance of the results was tested using the Student's *t*-test to assess whether they reflected market dynamics or resulted from random chance. Fourth, the continuity and duration of the reaction were analyzed to assess the symmetry of investor responses. If both groups showed statistically significant AARs and CAARs within the same event window, H2 would be rejected; otherwise, it would be accepted.

Results

The results will be presented in two groups. The first group includes the AARs and CAARs in response to the publication of articles with positive sentiment, based on an analysis of 3,185 events. The second group comprises results related to the publication of articles with negative sentiment, with 2,676 events analyzed. The presentation of results will cover three tested estimation windows: 30 days, 60 days, and 90 days.

In general terms, it can be observed that the appearance of press publications with positive sentiment has had a minimal impact on the stock returns of companies listed on the WIG20 index between 2013 and 2022. Firstly, the observed AARs in none of the analyzed scenarios exceeded 0.11%. For CAARs, the highest value recorded was 0.14%. Thus, the changes in stock prices can be considered objectively minor.

Table 1. Event study results for the group of articles with positive sentiment

Estimation window:		30 days		60 days		90 days	
Rate of return:		AAR	CAAR	AAR	CAAR	AAR	CAAR
Event window	-1	0.0004	0.0004	0.0005	0.0005	0.0005	0.0005
	0	-0.0003	0.0001	-0.0002	0.0003	-0.0003	0.0002
	1	0.0006*	0.0007	0.0008**	0.0011*	0.0007*	0.0009
	2	0	0.0007	0.0001	0.0012	0.0001	0.001
	3	0	0.0007	0.0001	0.0014	0.0001	0.0011
	4	-0.0003	0.0004	-0.0002	0.0012	-0.0001	0.001
	5	-0.0011***	-0.0007	-0.001***	0.0002	-0.001***	0

***/**/* – statistical significance of results at the $\alpha = 0.01/0.05/0.1$ level

Source: Author's own study.

Secondly, most results did not exhibit statistical significance. This generally means that the null hypothesis, which posits that the result does not significantly differ from zero, cannot be rejected. However, exceptions can be observed on certain days within the event window, particularly concerning AAR values. Regardless of the scenario analyzed, statistical significance was found at the α = 0.01 or α = 0.05 level on the day following the publication of the article. Moreover, the direction of the returns is positive, indicating a favorable reaction to press releases with extremely positive sentiment.

An interesting result is observed on the final day of the event window. Notably, on four of the analyzed days, the AARs were either zero or slightly above zero. The situation differed on the event day and the last two days of the window. While the results for days 0 and 4 did not show statistical significance, the returns on the fifth day after the publication of the article were statistically significant at the α = 0.01 level. This may indicate that the positive reaction to the information was fully discounted, leading to a reversal in the direction of the returns.

Nevertheless, for CAARs, the statistically significant effect is virtually nonexistent. The only exception is the 90-day estimation window, where the result for the first day after the event was significant at the α = 0.1 level. However, these results are insufficient for drawing general conclusions about investor reactions as reflected in cumulative average abnormal returns.

The characteristics of the results differ notably for articles with extremely negative sentiment. As presented in Table 2, for AAR results, above-average returns are evident from the day preceding the event to the second day after the event across all examined scenarios. It is important to note that the AAR values slightly exceed those observed in the analysis of responses to positively-sentimented articles, with the lowest value being -0.36%. However, the key difference lies in the statistical significance of the results. Overall, the AAR results showed significance at the α = 0.01, α = 0.05, and α = 0.1 levels, depending on the day, within the window from the day preceding the event to two days after the event. For CAAR results, a high level of significance is observed across nearly the entire examined window.

Table 2. Event study results for the group of articles with negative sentiment

Estimation window:		30 days		60 days		90 days	
Rate of return:		AAR	CAAR	AAR	CAAR	AAR	CAAR
Event window	-1	-0.0012***	-0.0012***	-0.001**	-0.001**	-0.0011***	-0.0011**
	0	-0.0036***	-0.0048***	-0.0035***	-0.0045***	-0.0035***	-0.0046***
	1	-0.0008*	-0.0057***	-0.0007*	-0.0052***	-0.0007*	-0.0053***
	2	0.0008*	-0.0049***	0.0009**	-0.0042***	0.0007*	-0.0046***
	3	0.0004	-0.0045***	0.0005	-0.0038***	0.0003	-0.0043***
	4	0.0002	-0.0043***	0.0004	-0.0034***	0.0002	-0.0041***
	5	0	-0.0043***	0.0001	-0.0032***	-0.0001	-0.0042***

***/**/* – statistical significance of results at the α = 0.01/0.05/0.1 level

Source: Author's own study.

The reaction to the publication of the article is already evident on the day preceding the event. Although the returns were again relatively low, their direction is consistent with expectations. A similar pattern occurred with positive articles; however, in that case, the results were not statistically significant at any of the accepted levels. It is important to note, that press articles are secondary sources. Their publication is typically preceded by some primary event, such as a report release, a change in management, or a strike. Drawing conclusions about market participants' anticipation of negative events in this context would be an overreach.

The strongest reaction is observed on the event day, i.e. the day of publication of the article with an extremely negative sentiment. For the AARs, the values hovered around -0.35%. The CAARs, due to the calculation methodology, ranged from -0.45% to -0.48%. Furthermore, all results demonstrated statistical significance at the $\alpha = 0.01$ level. Considering that this effect is evident both for the single day and for the cumulative values, it provides a strong basis for rejecting the null hypothesis.

The reaction to the publication of the article is also observable on the first and second days following the event. However, it is important to pay attention to the direction of the returns. For CAAR, although the values remain negative, they are consistently higher on the second day after the event compared to the first day. This is attributable to the values observed in the AAR, which are above zero on the second day following the event. This phenomenon is evident regardless of the estimation window and is statistically significant at the $\alpha = 0.01$ level. Therefore, it can be inferred that the reaction, manifested as a decline in stock prices, is observable within the event window [-1, 1]. Following this period, there is a reversal, and the abnormal rate of return becomes positive.

Results of the CAARs are also noticeable on days 3, 4, and 5 following the event. In all scenarios, these values are negative, significantly different from zero, and statistically significant at the $\alpha = 0.01$ level. However, it should be noted that the results observed in the CAAR columns for the window [3:5] primarily reflect the effect of accumulation. The AAR columns indicate that within this window, not only statistically significant results were not achieved, but the returns are only marginally different from zero. In other words, the reaction of investors to the publication of the article is no longer apparent.

To determine the robustness of the obtained results, the study was repeated using the HGI dictionary. The input data and applied models remained unchanged. The results are presented in the tables below. The results of the event study conducted based on articles classified using this dictionary generally support the previous findings regarding negative sentiment, particularly in the case of the 30-day estimation window. It can be observed that throughout the entire event window, CAAR values remained negative and statistically significant. In the remaining estimation window variants, CAAR values aligned with expectations, although they did not exhibit statistical significance in windows broader than [-1;2]. An interesting observation is the reversal of the direction of returns across all estimation windows. A similar pattern was observed when using the LM dictionary.

Table 3. Event study results for the group of articles with negative sentiment (HGI dictionary)

Estimation window:		30 days		60 days		90 days	
Rate of return:		AAR	CAAR	AAR	CAAR	AAR	CAAR
Event window	-1	-0.0012**	-0.0012**	-0.001**	-0.001**	-0.001**	-0.001**
	0	-0.0007	-0.0019***	-0.0005	-0.0015**	-0.0007	-0.0017**
	1	-0.0005	-0.0024***	-0.0003	-0.0018**	-0.0004	-0.002**
	2	-0.0001	-0.0025**	0.0003	-0.0015	0.0002	-0.0018*
	3	0.0	-0.0025**	0.0003	-0.0012	0.0002	-0.0016
	4	-0.0002	-0.0026**	0.0001	-0.0011	0.0001	-0.0015
	5	0.0002	-0.0024*	0.0005	-0.0006	0.0003	-0.0011

***/**/* – statistical significance of results at the α = 0.01/0.05/0.1 level

Source: Author's own study.

Regarding the category of positive articles, no clear consistency can be observed. The returns are predominantly negative, and statistical significance appears rather sporadically, with the exception of the 30-day estimation window. However, given the direction of the returns, the robustness of these results warrants further scrutiny. Several factors may explain this phenomenon. First, in the case of the LM dictionary, the results for positive sentiment were also less conclusive than for negative sentiment. This may indicate a broader issue related to investors' ambiguous reactions to positive press articles. Second, as previously noted, the HGI dictionary was not originally designed for financial research. Scholars who have applied this dictionary have reported similar challenges. An example is the study by Zubair and Cios (2015) on the S&P500 index. Their findings indicated a correlation between negative sentiment and index dynamics in five out of the seven years analyzed. However, they did not observe a similar relationship in the case of positive sentiment.

Table 4. Event study results for the group of articles with positive sentiment (HGI dictionary)

Estimation window:		30 days		60 days		90 days	
Rate of return:		AAR	CAAR	AAR	CAAR	AAR	CAAR
Event window	-1	-0.0	-0.0	0.0001	0.0001	0.0	0.0
	0	-0.0	-0.0001	0.0001	0.0002	0.0001	0.0001
	1	-0.0	-0.0001	0.0001	0.0003	0.0001	0.0002
	2	-0.0004***	-0.0005	-0.0003**	0.0001	-0.0003**	-0.0
	3	-0.0003**	-0.0008**	-0.0002	-0.0002	-0.0002	-0.0002
	4	-0.0003**	-0.0011***	-0.0002	-0.0003	-0.0002	-0.0004
	5	-0.0002	0.0013***	-0.0	-0.0004	-0.0001	-0.0005

***/**/* – statistical significance of results at the α = 0.01/0.05/0.1 level

Source: Author's own study.

In summary, the conducted study allowed for the verification of two research hypotheses. The first hypothesis (H1) posited that the occurrence of an event, such as the publication of a press article, would be reflected in the reaction of stock market investors, as measured by abnormal returns. For both groups examined – albeit with varying degrees of strength – and across all analyzed variants, confirmation of this hypothesis was found in the analysis conducted using the LM dictionary. In the case of the HGI dictionary, the reaction pertains to negative sentiment and is observable in CAAR returns.

The second hypothesis (H2), which suggested that investors' reactions to the occurrence of an event would be asymmetrical depending on whether the event had a positive or negative tone, was also positively validated. It is important to note that the appearance of press publications with extremely positive sentiment generally did not correlate with a strong reaction from stock market investors. The value of abnormal returns did not exceed 0.11%. The CAAR results were statistically insignificant, with few exceptions. However, the AAR results highlighted the significance of the events on specific days, namely on the first and fifth days after the event. While in the first case, the returns were positive, in the second case, their direction reversed. This pattern was observed across all scenarios and was statistically significant at the $\alpha = 0.01$ level. A similar process can be observed in the reaction to articles with negative sentiment. However, in this context, it was more pronounced. The trend reversal occurred as early as the second day after the event. Nonetheless, the cumulative abnormal returns remained negative until the last day of the event window, with these results being statistically significant at the $\alpha = 0.01$ level, regardless of the scenario analyzed. Ananalogous phenomenon was found in the robustness test. In each of the estimation window variants, the CAAR values remained negative until the last day of the event window. However, based on the AAR values, a reversal in direction is noticeable between the second and third days after the event. As for the robustness tests, a noticeable difference in response depending on the sentiment was observed, although the results for reactions to the positive tone of the articles leave some doubts.

Discussions

The obtained results align with the existing body of research related to both the behavioral paradigm and studies involving text analysis for financial market dynamics. The findings particularly emphasize the need to pay close attention to investor reactions to news with negative emotional connotations.

Several studies on Western markets confirm investor reactions to press sentiment (Allen et al., 2019), highlighting asymmetry in responses, particularly to negative news, in both American (e.g. Ardia et al., 2022) and European markets (e.g. Damstra & De Swert, 2020). This pattern has also been observed in derivatives (Smales, 2014). The results of this study align with Tetlock's (2007) findings, which noted that negative returns after negative sentiment often reverse in a few days, though this study highlights this mechanism for both negative and positive sentiment.

One explanation for this phenomenon is rooted in behavioral finance, where investors are driven by loss aversion, prioritizing the potential for loss (Chen et al., 2018). The paradigm also considers other factors, like heuristics and cognitive biases, including herd behavior, where investors mimic others. This behavior has been observed in both individual and institutional investors (Menkhoff et al., 2006), leading to overreaction to new information and continued following of short-term stock price trends (Borowski, 2014, p. 46).

A stronger investor reaction to negative news may stem from an imbalance in the number of extremely positive versus negative articles (over half of the sample was classified as positive). Journalism experts note this imbalance is due to journalists' concerns about maintaining access to information sources, as negative narratives might hinder future interviews and affect journalistic effectiveness (Borden, 2007). Additionally, the rise of professional corporate communication and extensive public relations departments aimed at building a positive company image can limit access to accurate information (Picard et al., 2014).

The existence of these processes may not only contribute to the reluctance to publish extremely negative content but also reinforce mechanisms related to information asymmetry. An investor who relies on price information and public news for decision-making is aware that they do not possess complete knowledge. In the current era, gathering all published news is practically impossible. Moreover, as Akerlof (1984) argues, the demand side can never be certain about the true value of the purchase. Therefore, to avoid taking on any risk, the buyer tends to underestimate the value.

Conclusions

The findings of this study carry significant implications. They underscore the importance for investors to stay mindful of sentiment-driven fluctuations and to take the broader market context into account when making investment decisions. Additionally, understanding how sentiment influences stock prices can help in developing more informed strategies, particularly when managing risk during periods of heightened media attention. Furthermore, financial journalists should be aware of the impact that media framing can have on market stability.

The results align with existing research and the behavioral paradigm, suggesting that investors' reactions are driven by loss aversion. Nevertheless, the presented research has several limitations. First, a lexical approach was used for sentiment extraction, while machine learning methods like Bayesian algorithms and neural networks could offer more nuanced analysis (Guo et al., 2016). Second, the event study used a market model to calculate expected returns, but alternative models like CAPM might provide different perspectives. Third, the research relied on a simple positive-negative sentiment dichotomy, whereas some argue for a more nuanced emotional spectrum (e.g. Lazzini et al., 2022). Additionally, the study focused on English-language texts. While many articles were published in both English and Polish, the results may reflect stronger reactions from foreign investors. It is also worth noting that the analyzed textual data set was quite large. Although most articles came from the Polish Press Agency and *Parkiet* magazine, they were not categorized by theme or source before the study. Categorizing them could provide more conclusive insights. Furthermore, given the long research period, the study must account for the possibility of disruptive events occurring.

Acknowledging the limitations, further research in this area seems valuable. Firstly, conducting a follow-up study with an alternative Polish-language dictionary would be beneficial, as no such study has been done to date. Secondly, examining how investor responses to press sentiment vary under different macroeconomic conditions would provide useful insights. Thirdly, verifying the results using alternative models for estimating expected returns would enhance the robustness of the findings. Fourthly, exploring a broader range of emotions beyond the typical positive-negative sentiment dichotomy could offer deeper understanding. The same applies to classifying the press articles into smaller groups for more nuanced analysis. Investigating these aspects could lead to a more comprehensive understanding of how media sentiment affects investor behavior and financial market dynamics.

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