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ŁUKASZ KOŁODZIEJCZYK[a]

MACHINE LEARNING AND SENTIMENT ANALYSIS IN BEHAVIOURAL INVESTING: EVIDENCE FROM POLAND

UCZENIE MASZYNOWE I ANALIZA SENTYMENTU W INWESTOWANIU BEHAWIORALNYM – PRZYKŁAD POLSKI

The recent popularity of behavioural finance, combined with machine learning, offers an opportunity to challenge the duopoly of fundamental and technical analysis in stock selection. Behavioural analysis – an indirect method of stock evaluation based on the direct analysis of investor behaviour – offers a novel approach to investing. Its most popular instrument, sentiment analysis, has been shown to be useful in investing, although the relation between investor sentiment and stock prices is not yet clear, and behavioural investing is not well described in the literature. Moreover, there are only a few papers concerning investor sentiment in the Polish equity market, which creates a research gap, compared to other developed markets. The goal of this paper is to examine this relation and to test the efficacy of sentiment-based methods in behavioural investing. The relationship between investor sentiment and stock price movements was examined using Matthews and Pearson correlation coefficients, and the efficacy of sentiment-based investment strategies was compared with the buy-and-hold approach. By leveraging threads from the Bankier.pl forum, this paper confirms a positive but modest correlation between investor sentiment and returns of WIG20 stocks, consistent with prior findings. While previous papers found low correlations and modest investment gains, this paper recognizes a statistically significant and stronger relationship between cumulative sentiment and cumulative returns (29.7%) compared to daily sentiment and fluctuations (5.4%, 2.7%, 3.0%). Moreover, this study tests behavioural methods in investment strategies, where sentiment-based trading outperformed the buy-and-hold approach in two-thirds of cases. The theoretical profitability is eliminated by including transaction costs, underscoring limited practical utility, and suggesting future research.

Keywords: behavioural investing; sentiment analysis; machine learning; natural language processing; PolBERT
JEL: G40

Obserwowalne na gruncie finansów behawioralnych zależności, w połączeniu z uczeniem maszynowym, mogą zachwiać duopol analizy fundamentalnej i technicznej w doborze akcji. Analiza behawioralna, czyli pośrednia metoda analizy akcji poprzez bezpośrednią analizę zachowań inwestorów – jest nowym podejściem w inwestycjach finansowych. Jej najpopularniejsze narzędzie: analiza sentymentu, już teraz jest przydatne w inwestowaniu, chociaż związek między nastro-

[a] SGH Warsaw School of Economics, Poland / Szkoła Główna Handlowa w Warszawie, Polska
lk114395@sgh.waw.pl, https://orcid.org/0000-0001-7330-5858

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jami inwestorów a cenami akcji nie jest jeszcze do końca jasny, a same przykłady inwestowania behawioralnego nie są dobrze opisane w literaturze. Co więcej, istnieje tylko kilka artykułów podejmujących temat wykorzystania nastrojów inwestorów na polskim rynku akcji, co tworzy lukę badawczą. Celem artykułu jest określenie charakteru tych relacji, a także przetestowanie skuteczności strategii opartych na sentymencie w inwestowaniu behawioralnym. Podczas gdy relacja nastrojów inwestorów i ruchów cen akcji została zbadana za pomocą współczynników korelacji Matthewsa i Pearsona, skuteczność strategii inwestycyjnych opartych na sentymencie została porównana z podejściem *kup i trzymaj*. Wykorzystując wpisy z forum Bankier.pl, niniejszy artykuł potwierdza pozytywną, ale niewielką korelację między nastrojami inwestorów a zwrotami z akcji z indeksu WIG20, co jest zgodne z wynikami wcześniejszych badań. Podczas gdy poprzednie badania wskazywały na niskie współczynniki korelacji i niewielkie zwroty, artykuł dostrzega silniejszy związek między skumulowanym sentymentem a skumulowanymi zwrotami (29,7%) w porównaniu z dziennym sentymentem i wahaniami (5,4%, 2,7%, 3,0%). Ponadto niniejsze badanie testuje behawioralne metody w strategiach inwestycyjnych, w których handel oparty na sentymencie pozwolił na zrealizowanie wyższych zwrotów niż strategie *kup i trzymaj* w 2/3 przypadków. Uwzględnienie kosztów transakcyjnych eliminuje teoretyczną zyskowność, co wskazuje na ograniczoną przydatność praktyczną i sugeruje dalsze badania.

Słowa kluczowe: inwestowanie behawioralne; analiza sentymentu; uczenie maszynowe; przetwarzanie języka maszynowego; PolBERT
JEL: G40

I. INTRODUCTION

Behavioural finance, combined with advances in machine learning, is increasingly challenging the dominance of fundamental and technical analysis in investment practice. Sentiment analysis, which quantifies investor attitudes from textual sources, is gaining recognition for its potential role in explaining and forecasting stock price movements. Despite this, little research has examined its effectiveness in the Polish equity market, where a notable gap persists both in understanding sentiment-return relationships and in developing long-term, sentiment-based investment strategies.

While most studies recognize the positive impact of investor sentiment on share price fluctuations, this conclusion remains ambiguous, as some evidence suggests that sentiment may negatively predict stock returns, especially in the long term. Moreover, many papers question the efficacy of sentiment analysis. This leads to the hypothesis tested in this paper: whether there is a relationship between investor sentiment and stock returns. If so, what is the direction and magnitude of this relationship? Three sentiment measures are used to assess the relationship between investor views and stock returns – daily sentiment, signal-based sentiment and cumulative sentiment. With only one broad-market study concerning the relation of investor sentiment and stock price movements in the Polish equity market, this study helps address this research gap. Moreover, no behavioural strategy has been tested for the Polish equity market and the efficacy of sentiment-based behavioural investing might be questioned due to insufficient samples or data limitations. All these points lead to the second hypothesis tested in this paper: is it possible to create a sentiment-based behavioural investment strategy that could work in a time frame longer than 10 years?

To fill these gaps, this work analyses 14 years of investor forum data using a fine-tuned Polish BERT model to classify sentiment, evaluating the correlation between sentiment and stock returns and the efficacy of trading strategies compared with the buy-and-hold (B&H) approach. The paper is structured to present context and hypotheses, detail data and methodology, highlight results, and discuss the implications for research and practice in behavioural investing.

II. BEHAVIOURAL INVESTING: LITERATURE REVIEW

1. Behavioural analysis as a new paradigm in investing

Fundamental and technical analyses are widely regarded as the main methods of stock analysis and prediction by most researchers, as Nti et al. (2020) highlighted. However, the efficacy of these methods has recently been questioned. Academics are sceptical of technical analysis (Malkiel, 1981, p. 139; Menkhoff & Taylor, 2007), with some recent studies showing that individual investors who use it experience higher turnover and lower returns (Hoffmann & Shefrin, 2014). Early studies dismissed technical analysis, whereas later ones often supported it; however, Park and Irwin (2007) identified biases and flawed testing that undermined these findings. Moreover, there is increasing evidence questioning value investing, which is based on fundamental analysis (Asness et al., 2015), as an outdated paradigm associated with the traditional economy. Lev and Srivastava (2022) showed that value investing has been very unprofitable for the last 30 years, attributing it to accounting deficiencies, ignoring the growing importance of intangible assets in strengthening a firm's competitive position, and mean-reversion of glamour companies, driven by economic changes. Lev and Gu (2016, pp. 61–65) discovered that the usefulness of financial reports has sharply decreased since 1976, stressing that financial statements contain information that is no longer crucial to outperforming the market. Cornell and Damodaran (2021) listed other possible explanations, suggesting that the underperformance of traditional metrics of fundamental value is a consequence of various factors: the increasing importance of intangible assets and inadequate accounting rules, a different macroeconomic environment with persistently lower interest rates, commoditized access to information, and changes in the global economy. On the other hand, many financial paradigms have changed since the former glory of value investing, a predominantly neoclassical phenomenon. Behavioural finance has emerged as a new paradigm that updates earlier assumptions and guides financial research, as De Bondt et al. (2007) noted.

Behavioural finance emerged as a field that updated the neoclassical paradigm (Statman, 2017, p. 3). There is evidence that behavioural finance can reshape investment paradigms (Statman, 2019), yet its practical applications remain limited. Mitroi and Oproiu (2014) argued that fundamental and technical analysis are outdated and proposed behavioural finance as an alternative, leveraging investor biases to improve outcomes and complement stock analysis. Today, the two most popular measures of investor interest in stocks are investor sentiment and investor attention. A review of the literature suggests that investor sentiment is more promising as an indicator used in equity investing, given that the most popular measure of investor attention, Google Search Volume Index, yields inconsistent results across countries and studies (Akarsu & Süer, 2022) and primarily affects volatility and trading volume (Ayala et al., 2024).

It is worth noting that some authors see behavioural analysis as a part of technical analysis (Ding et al., 2023; Zielonka, 2004). The practice suggests that the reality is more complex, and given how mature and well-developed behavioural methods are today, they should be treated as a standalone group, especially since they have a unique foundation in investor psychology and their own characteristics (Kahneman & Riepe, 1998). There is no commonly accepted definition of sentiment (Aggarwal, 2022), but in this paper sentiment is defined as the investor attitude towards the discussed stocks, describing how eager investors are to invest in companies (Baker & Wurgler, 2006), which serves as an indirect measure of investor demand. This definition guided sentiment classification in the test and train samples.

2. Sentiment analysis

For a very long time, measuring sentiment was difficult and inefficient. Baker and Wurgler (2006) were the first to successfully develop a model of investor sentiment in investing – the authors introduced a simplified sentiment measure consisting of six sentiment proxies. They confirmed that sentiment impacts the cross-section of stock returns and recognized that hard-to-value stocks are more prone to investor sentiment. Later, the authors replenished the findings with a conceptual framework, suggesting that the behavioural model considering sentiment and arbitrage constraints better explains stock fluctuations than neoclassical models assuming investor rationality. According to Baker and Wurgler (2007), sentiment persistently drives market mispricing through recurring patterns of overreaction and underreaction. Smart money investors might be able to exploit such market anomalies and leverage sentiment in investment strategies (Woo et al., 2020). The model proved less effective for individual stocks, since it lacked personalization and flexibility. Stock-specific sentiment gained traction with the rise of forums and social media enabling real-time tracking.

Recent systematic literature review papers recognize sentiment as a significant and complex driver of stock prices. Kearney and Liu (2014) concluded that most studies indicate that sentiment has a strong but rather short-term impact on stock price, returns, trading volumes, and abnormal returns. The authors emphasized that negative sentiment generally exerts a stronger influence than positive sentiment, although exceptions exist. By contrast, the positive relation between sentiment and stock returns shows far fewer deviations. Similar tendencies were identified by McGurk et al. (2020) in their literature review. Nardo et al. (2016) also noted that most studies highlight that web activity, which is often measured through sentiment or attention measures, impacts stock returns and trade volumes, although they questioned the gain, which rarely yields more than additional 5%. As Nardo et al. stressed, the popularity of sentiment analysis as a subject of academic research accelerated when online sources of data became more popular, attracting investors at scale sufficient to look for dependencies. Das and Chen (2007) and Antweiler and Frank (2004), both using Yahoo! Finance message board, were the first to examine this phenomenon – the former discovered that stock forum activity predicts lower next-day returns, is driven by disagreement, helps to forecast volatility, and quickly reflects public information, while the latter showed that aggregated investor sentiment based on stock forum posts tracks market returns, reduces individual stock noise, and influences market activity. The first applications of sentiment analysis were not very encouraging, with Kim and Kim (2014) confirming, with a large set of data, that investor sentiment is influenced by stock price fluctuations and that it is ineffective for predicting future returns, volatility or trading volumes. Nguyen et al. (2015) highlighted that many sentiment studies rely on insufficient samples or unrepresentative sources. This limitation spurred greater academic interest once social media and online forums provided broader investor perspectives.

There are numerous studies confirming that Twitter sentiment was a useful predictor for future returns of single stocks and indices (Bollen et al., 2011; Pagolu et al., 2016; Oliveira et al., 2017; Teti et al., 2019; Sul et al., 2017), which also applies to StockTwits (Batra & Daudpota, 2018). While most studies focus on US equities, Duz Tan and Tas (2021) analysed S&P 350 Europe and S&P EM Core in 2015–2017, finding that Twitter sentiment positively and significantly predicted returns, especially in less efficient market segments. In a comprehensive literature review, Nardo et al. (2016) noted that there is a significant and positive but low correlation between investor sentiment and market returns. Such dependency was recognized by Alanyali et al. (2013), Ranco et al. (2015), and Anusakumar et al. (2017). An even stronger significant positive correlation (up to 88% for Dow Jones Industrial Average [DJIA]) was noted by Rao and Srivastava (2012), although the results varied across companies and indices, the authors discovered examples of high and significant both negative and positive correlations, although the positive variables were prevailing. Zhang et al. (2011), by contrast, found a low, negative and partially significant correlation between emotional tweets and the DJIA, NASDAQ, and S&P 500 indices. A similar low and negative correlation was observed for the bullishness variable and returns by Antweiler and Frank (2004). Mixed results were shown by Kim and Kim (2014). Hence, despite the positive correlations dominate in the results, there still is no consensus on the relation between investor sentiment and stock returns.

Nardo et al. (2016) note that simple correlations are insufficient. Some studies additionally model sentiment-return dynamics. Few works, however, examine sentiment-based investment strategies, leaving a research gap. Tetlock (2007) was the first to popularize sentiment-base trading strategies – the author achieved a significant daily return of a zero-cost strategy of 4.4 basis points, slightly ahead of the average daily excess return of DJIA. Tetlock's pessimism-based strategy yielded 7.3% of annual return. Zhang and Skiena (2010) combined Twitter and blog data to achieve an astonishing annual return of 80% between 2005 and 2009, making it one of the most profitable and transparent sentiment-based strategies found in the literature. Kazemian et al. (2016) leveraged a similar approach in momentum strategies and achieved a 3-day return of between 1% and 2.8% for a few strategies with an accuracy of between 62% and 81%. The 30-day return fell between 0.4% and 3.8%. Sul et al. (2017) found that information provided in the tweets of less popular authors yields 11–15% annual return, ahead of the market's historical returns. Yang and Mo (2016) leveraged sentiment analysis in trading strategies for the S&P 500 index between 2012 and 2014 and achieved annual profit of 15.6% for sentiment-based strategy and 21.7% for sentiment-based strategy with technical indicators, which exceeds the 8.8% achieved by a simple B&H approach. Olawale et al. (2023) also used the sentiment in automated strategies and achieved returns of between 19.25% and 38.79% between October 2022 and January 2023 for 11 selected US stocks. In the absence of a benchmark, it is difficult to assess the results. Hence, there are some sentiment-based investment strategies, which bodes well for the efficacy of behavioural investing, although the results are mostly either based on very small sample of data or tested during an extremely short time frame.

There are only a few studies concerning the impact of investor sentiment on stock prices in Poland, which constitutes a research gap, given that such studies exist for numerous markets, as shown by Duz Tan and Tas (2021). Probierz et al. (2021) examined how stock market-related tweets correlated with actual stock market fluctuations for WIG20 stocks during 6 months in 2021. Through multiple regression analyses the authors found no universal relation and overall, the compound R^2 for returns across the sentiment was just 14.25%. The authors concluded that the relation was stronger across non-state-owned companies. There are also a few studies concerning the impact of investor sentiment on price fluctuations in specific market sectors. Polak (2021) used sentiment derived from news headlines and found no significant impact on the one-day direction of stock price changes for WIG-Banking stocks. Wojarnik (2022) used comments from the Stockwatch.pl forum to forecast price movements for WIG-Energy stocks and found no useful relation between these variables, although the author concluded that investor sentiment might be a supplementary factor in performance forecasting. There are no investment strategies concerning investor sentiment for the Polish equity market, which constitutes a research gap. As there is a research gap on both the relation of investor sentiment and stock price movements as well as the efficacy of behavioural investing in Poland, the Polish equity market is the subject of this study.

While most studies indicate the positive impact of investor sentiment on share price fluctuations, the conclusion remains ambiguous, as some authors argue that sentiment may negatively predict stock returns, particularly in the long term. Moreover, the efficacy of sentiment analysis remains contested, indicating another gap in the literature.

III. DATASET AND METHOD

1. Dataset

The data used in this research were obtained from the forum of Bankier.pl,[1] one of the most popular websites dedicated to finance and the economy. The Bankier forum is the biggest discussion board in Poland (Wojarnik, 2022), where retail investors share their opinions and create threads about every firm listed on the Warsaw Stock Exchange and on NewConnect market. The titles of threads from the forum were used in sentiment analysis. While much information can be gathered from the forum, thread titles are much more emotional than the full texts, the following comments, and the remaining metadata. In the titles, investors provide a short description of the thread – the informative value is compressed and even enhanced to draw users' attention, encouraging them to click on a thread, read it and reply to reach a broader audience. Data was scraped through a technique called web scraping, implemented with the Scrapy library for Python.

To test the hypotheses, data related to 20 companies included in WIG20 since the first thread on the forum of Bankier.pl to 15 March 2021 was scraped and used to build a sentiment index and a cumulative sentiment index. The list of companies was established as of quarterly adjustment on 18 December 2020. However, a new company was included in this adjustment, Allegro, which had its first listing on 12 October 2020. Given that the investigated time frame for Allegro was shorter than 12 months, which may not have been sufficient to draw far-reaching conclusions, Allegro was replaced with MBank, which has a longer history in WIG20 and a much longer history of being discussed on the forum, which should strengthen the paper's relevance. The stock companies analysed in the study, sorted by the names used by WSE, are: ALIOR, ASSECOPOL, CCC, CDPROJEKT, CYFRPLSAT, DINOPL, JSW, KGHM, LOTOS, LPP, MBANK, ORANGEPL, PEKAO, PGE, PGNIG, PKNORLEN, PKO, PZU, SANPL, and TAURONPE.

The data scraped for this study consists of thread titles and the dates of their last edit. The data consists of every single thread title that was posted and was not deleted nor removed by the administrator in the history of the forum for all examined companies. The scrape date for all companies was 16 March 2021, therefore the last threads included in this study were published on 15 March 2021. Some of the earliest threads included in this analysis were published on 19 January 2007, which sets the study's time frame at more than 14 years. Given that the data quality in the forum is low – users often

[1] https://www.bankier.pl/forum/forum_gielda,6,1.html

misspell words and use incorrect grammar – the paper requires the use of the most advanced natural language processing (NLP) methods. Thus, there is a side hypothesis tested in this study: is it possible to leverage a fine-tuned language model to annotate investor sentiment in Polish, which yields an accuracy, measured through F1-score, of more than 70%?

Daily data on stock returns, trading volume, number of transactions, and the value of transactions were downloaded from the Warsaw Stock Exchange price archive. Stock returns are measured logarithmically. The analysis was conducted separately for all 20 companies.

2. Method

The most popular sentiment analyses examining the impact of investor sentiment on stock price movements use a bag-of-words approach, lexicons, or fixed word and sentence encoders, which are not very accurate but yield satisfactory results when the data quality is high (Mishev et al., 2020). As Mishev et al. (2020) observed, the most advanced sentiment methods – NLP transformers with fine-tuning – deliver superior accuracy by tailoring models to specific datasets. Since this study relies on relatively low-quality data and examines the Polish equity market, such an approach is required. However, despite rapid LLM progress since ChatGPT, most innovations target English, leaving Polish resources limited. Therefore, a fine-tuned Polish BERT model was employed, as this class of models is well-documented and has proven effective in financial NLP applications.

There are only a few studies leveraging BERT-class models or other large LLMs in stock-related sentiment analysis. Liu et al. (2023) used a FinBERT model to predict stock price fluctuations based on Stocktwits sentiment. The authors achieved a prediction accuracy of 65%. Lee et al. (2020) used a BERT model to predict sentiment and achieved a prediction accuracy of over 87%. Olawale et al. (2023) evaluated the ability of sentiment analysis derived from Twitter data, when used in conjunction with past stock price information, to forecast stock price fluctuations with 93% accuracy. Koptyra et al. (2024) used BERT-class models to classify emotions (anger, anticipation, joy, sadness, and trust) in press articles of WIG20 companies. The authors compared different models and achieved an accuracy of 82% in document classification using HerBERT and 91% in sentence classification for RoBERTa. While all these papers show very high accuracy, they all concern high-quality data input. There are no studies on BERT-class models in sentiment analysis leveraging low-quality data in Polish.

IV. THE MODEL

1. Fine-tuning

As there is no finance-adjusted BERT-class model in Polish, unlike FinBERT in English (Araci, 2019), Polish BERT models should be fine-tuned to adapt their capabilities to the dataset. In this process, the training and test sample consisted of 5,000 thread titles divided in an 80% (train) to 20% (test) proportion. Thread titles used in the fine-tuning process were scraped from the forum for multiple firms (mainly JSW, DATAWALK, KERNEL, CDPROJECT) to provide a sufficient differentiation of threads and minimize the risk that a LM is bias.

The sentiment was annotated in a 3-form classification: negative (−1), positive (1) and neutral (0). While annotating titles of threads, the author's attitude to the company is considered as a determinant of annotated sentiment, according to sentiment's definition used in this paper.

The comments were selected to provide the same number of positive, negative, and neutral comments. The number of threads with negative sentiment is 1,432, while the number of threads annotated as positive is 1,790. The number of neutral opinions amounts to 1,778 threads. The lower number of negative threads reflects their lower representation in the population.

F1-score was used to evaluate the accuracy of the fine-tuned model on the test set. Three BERT-class models were tested for sentiment classification in this study: HerBERT (Mroczkowski et al., 2021), PolBERT (Kłeczek, 2020), and RoBERTa (Dadas et al., 2020). Among all these models, PolBERT yielded the best results, achieving an accuracy of 73%, compared with 71% for HerBERT and 70% for RoBERTa. PolBERT's classification report is shown in Appendix, Table A1.[2]

The logistic regression classifier was applied as it yielded higher accuracy than the naive Bayes classifier, the random forest classifier, and the linear support vector classifier. Vectorisation was based on SK learn's CountVectorizer class with a word tokenizer based on lowercase letters and an *n*-gram range consisting only of unigrams; TF-IDF weighting was not applied. A custom prediction function was created and applied to the model based on a text-cleaning function.

The F1-score accuracy of 73% achieved by the PolBERT model confirms the secondary hypothesis that it is possible to leverage a fine-tuned language model to annotate investor sentiment in Polish with an accuracy higher than 70%, despite the low-quality dataset.

2. Machine learning in sentiment classification

A fine-tuned LM classified sentiment in all threads, which were then matched with price changes. Only threads posted between the end of the previous session (after 5 p.m.) and the start of the next session (before 9 a.m.) were used, ensuring they were not influenced by intra-session price movements, as suggested by the literature. Sentiments from these threads were summed daily to create a variable representing investor sentiment for each company.

[2] Appendix, containing detailed results of the study and characteristics of the model, is available at https://osf.io/wc7pa

To evaluate the relationship between daily sentiment and stock returns, the Matthews correlation coefficient (MCC) and the Pearson correlation coefficient (PCC) were calculated and assessed. MCC and PCC values were tested for statistical significance.

To simplify the MCC analysis, sentiment and stock returns were converted into signals instead of assessing each individual data point – the goal was to develop a simple 3 × 3 confusion matrix. A negative sentiment triggered a sell signal, a positive sentiment – a buy signal, and all else was neutral. To reduce noise and overtrading, signals were limited to no more than 5% of trading days, selecting only the most extreme sentiment values for each company. If that was not feasible, the neutral range (zero-interval) was adjusted to capture more signals. Price returns were also converted into signals – here, signals represented an excess price change. To reduce noise, returns within the range of −1% to 1% (inclusive) were considered neutral, as noise, while larger returns were classified as either positive (above 1%) or negative (below −1%). This ensured that only meaningful price movements were treated as signals. The relationship between sentiment signals and price movement signals was then assessed using MCC. Statistical significance was tested using a z-test under the assumption of a normal distribution.

While only sentiment signal and excess price change were considered in confusion matrices and in the calculation of the MCC, for the PCC the correlation and statistical significance were calculated for all the available variables, to capture a broader relationship. The assessed variables were daily return (CHANGE), daily volume of transactions (VOLUME), daily number of transactions (TRANSACT.), daily value of transactions (VALUE), a signal of change (CHANGE (SIG.)), and cumulative value of change (CHANGE CUM.). The PCC for the assessed variables was calculated for both daily values of investor sentiment and cumulative values of investor sentiment since the first day on record. The results were tested for statistical significance with t-statistic. Two-tail distribution was assumed.

In Table 1 and Table A2 (Appendix), statistical significance was classified for p-value as: ** for $p \leq 0.01$ and * for $0.01 < p \leq 0.05$.

3. Investment strategies

Based on the relationship between sentiment and stock prices, six investment strategies were tested to evaluate the effectiveness of behavioural analysis based on investor sentiment in real market conditions:

1. Daily trading strategy based on daily sentiment – when investor sentiment between the end of the previous session and the beginning of the next session was positive (negative), a long (short) position was taken at the opening price and closed at the closing price. The difference between the closing and opening price was a gain or loss.

2. Daily inverse trading strategy based on daily sentiment – given that the literature reports both the negative and positive impact of sentiment on stock prices, the second strategy mirrored the first but in reverse: a short

position was taken on positive sentiment and a long position on negative sentiment.

3. Signal-based investment strategy – the third strategy represents a practical application of investment rather than daily trading. This strategy was based on sentiment signals isolated for confusion matrices and MCC. A positive signal indicated taking a long position – a long position was held until a negative signal had occurred, after which the position was closed. After a negative sentiment occurred again, a short position was opened – and it was held until a positive signal was noted. A neutral position remains until a sentiment signal appears – positive or negative. To change the current position, an inverse signal must occur, and it takes one more signal to take a position again. Neutral sentiment or signals consistent with the current position did not change anything. Given that this strategy naturally considers a longer holding period than the daily trading strategy, profitability was assessed by the cumulation of daily stock returns (opposite values in the case of a short position).

4. Inverse signal-based investment strategy – the fourth strategy mirrored the third but in reverse.

5. Investment strategy based on cumulative sentiment – an investment strategy based on cumulative values of daily sentiment. If a cumulative sentiment based on daily values was negative (positive), a short (long) position was opened, and the returns were calculated as negative (positive) daily returns. Returns are calculated based on cumulated daily returns.

6. Inverse investment strategy based on cumulative sentiment – the sixth strategy mirrored the fifth but in reverse.

Performance was measured as the cumulative sum of daily gains and losses. Since trading days with sentiment signals varied by company, the results were compared with a benchmark strategy, defined as a long position held from the first to the last trading day. A strategy was considered successful if its cumulative returns exceeded those of the parallel strategy for most companies, thereby supporting the hypothesis.

The method assumes perfect market liquidity. Transaction costs, taxes and fees were not considered in any of the strategies. There were no additional costs of taking a short position, such as the costs of borrowing shares. It was assumed that taking a short position was possible at any time. Dividends and other equity rights were not considered.

V. RESULTS

1. The relationship between investor sentiment and stock prices

The average MCC value for 20 assessed companies was 5.4%, while the median was 5.8% – Table 1 includes the respective values. The study showed a low but positive correlation between investor sentiment, measured through signals to reduce noise, and price movements, indicating a modest positive relation. Interestingly, only one company, CYFRPLSAT exhibited a negative correlation, indicating a strong positive tendency across WIG20. However, only 50% of the results were statistically significant, with only 20% significant at the maximum 1% level. In general, companies for which the number of days in the model was higher, and sentiment showed a clear direction (either highly positive or highly negative) through more days, which implied a higher zero-interval, exhibited higher statistical significance.

Table 1

Matthews correlation coefficient for sentiment signals and stock returns (signals)

Company	MCC (%)	Zero-interval	Days in model	Signals as % of days
ALIOR	7.3*	< −1 ; 1 >	890	17%
ASSECOPOL	6.7	< 0 ; 0 >	690	46%
CCC	7.3*	< −1 ; 1 >	1,058	21%
CDPROJECT	6.1**	<−3 ; 3 >	2,572	20%
CYFRPLSAT	−0.2	< 0 ; 0 >	380	44%
DINOPL	4.2	< −1 ; 1 >	585	17%
JSW	7.3**	<−3 ; 3 >	1,992	15%
KGHM	5.9**	< −2 ; 2 >	2,779	14%
LOTOS	4.1	< −1 ; 1 >	1,397	12%
LPP	6.0	< −1 ; 1 >	324	5%
MBANK	7.5	< −1 ; 1 >	552	6%
ORANGEPL	5.7*	< −1 ; 1 >	1,349	10%
PEKAO	3.2	< −1 ; 1 >	1,220	20%
PGE	5.4*	< −2 ; 2 >	1,938	6%
PGNIG	5.5*	< −1 ; 1 >	1,760	12%
PKNORLEN	4.1	< −1 ; 1 >	1,380	19%
PKO	4.8*	< −1 ; 1 >	1,965	19%
PZU	4.5	< −1 ; 1 >	1,777	21%
SANPL	7.6	< 0 ; 0 >	356	44%
TAURONPE	7.2**	< −2 ; 2 >	1,795	27%
average	5.4		1,338	20%
median	5.8		1,365	19%

* $0.01 < p \leq 0.05$. ** $0.01 < p \leq 0.01$.

Source: the author's own elaboration.

The detailed PCC shown in Table A2 (in Appendix) mostly confirmed the results of the MCC with a visible positive correlation between daily sentiment and evaluated trading variables. Daily sentiment correlates positively with all the evaluated trading data, although the correlation between daily sentiment and daily price change is even lower than in the MCC, at 2.7%, with most results being statistically insignificant even at the 5% level. The correlation of daily sentiment with cumulative stock returns and stock returns based on signals is slightly higher – 3.1% and 3.0% respectively, but most results are not statistically significant either. The correlation between daily sentiment and the number of transactions is the highest among all trading variables, 4.9%. Interestingly, the PCC for daily sentiment and trading volume, as well as the value of transactions, is lower, suggesting that daily sentiment reflects retail investor trading, which usually contributes to the number of transactions but not to the volume or transactions' value. However, also here most results are not statistically significant at 5% level.

Cumulative sentiment showed an even more interesting relation with the trading data. While the correlation of cumulative sentiment with daily stock returns as well as stock returns based on signals is close to 0 and most results are not statistically significant even at the 5% level, there is a moderately strong correlation between cumulative sentiment and cumulative stock returns, which is about 30% on average and even higher, 36%, on median; 17 out of 20 records are statistically significant at 1% level and 18 out of 20 are statistically significant at 5% level. This relation shows, to some extent, that cumulative sentiment might be a measure of investor interest in stocks, although the causality and direction of this relationship are still unclear and should be the subject of further research. Similarly, for daily sentiment the PCC is relatively high for cumulative sentiment and the number of transactions – 16.6% on average and 23.8% on median 17 out of 20 records are statistically significant at 1% level. Again, the correlation for trading volume and value of transactions with cumulative sentiment is lower but in this case it is even negative: −5.8% on average (−11.7% on median) for volumes, and −4.0% on average for transaction value; 19 out of 20 records for transaction value and cumulative sentiment and 15 out of 20 records for trading volume and cumulative sentiment are statistically significant at 1% level. It suggests that higher cumulative sentiment might indicate higher participation of retail investors in trading, as retail investors usually have a lower contribution to the value of transactions and the volume of transactions, but they contribute to more trades (Boehmer et al., 2021). A summary of the PCC results is shown in Table 2.

The results of the MCC and PCC confirm the first hypothesis: there is a positive but low correlation between investor sentiment and stock returns. The daily sentiment positively correlates with daily stock returns and cumulative sentiment positively correlates with cumulative stock returns: while the first relation is low, the second is moderately high.

Table 2

A summary of Pearson correlation coefficients (%)

Evaluated variable	Daily sentiment		Cumulative sentiment	
	Average	Median	Average	Median
CHANGE	2.7	1.8	−0.4	0.0
VOLUME	1.6	1.4	−5.8	−11.7
TRANSACT.	4.9	4.5	16.6	23.8
VALUE	2.6	1.8	−4.0	−3.3
CHANGE (SIGNAL)	3.0	2.9	−1.2	−1.2
CHANGE (CUMUL)	3.1	4.5	29.8	36.2

Source: the author's own elaboration.

2. Efficacy of behavioural investing

The efficacy of behavioural investment strategies based on investor sentiment is presented in Table 3. Of the six strategies, only the most basic one – a daily trading strategy – can be considered successful and useful. The first investment strategy turned out to be more profitable than taking a long position in the assessed stocks over the same period – 13 out of 20 stocks in WIG20 recorded a higher rate of return under the applied investment strategy, which is almost two-thirds of the records. The second strategy, being the inverse version of the first strategy, was more profitable than the parallel strategy only for 40% of the listed companies. A greater number of failures than successes makes an inverse sentiment-based trading strategy ineffective. This not only confirms a positive correlation between daily sentiment and stock returns (PCC), as well as the correlation between signal-based sentiment and signal-based stock returns (MCC), but also suggests that this relation can be exploited by behavioural investors.

Despite a relatively high correlation between cumulative sentiment and cumulative stock returns, both the fifth and sixth strategies failed to be useful in investing, as they underperformed the parallel strategy in most cases. While the first two strategies tested the potential of behavioural analysis in trading, the third and fourth aimed to evaluate behavioural investing as an alternative to financial analysis. However, both signal-based strategies underperformed – the third in 60% and the fourth in 80% of the cases. This suggests that, for now, behavioural investing cannot replace neoclassical methods, though future developments may change this. The results reaffirm that for rallying stocks (e.g. CDPROJECT), B&H remains superior, as the opportunity cost of missing gains is too high. However, for non-rallying companies, behavioural strategies may hold potential. Finally, the study assumes no transaction costs, taxes, short-selling fees, or liquidity constraints. Adjusting for these factors would render even the first strategy unprofitable.

Table 3

Efficacy of investment strategies based on investor sentiment – summary (%)

Company name	Strategy 1	Strategy 2	Strategy 3	Strategy 4	Strategy 5	Strategy 6	Return in all the periods
	Daily based on sentiment	Daily inverse	Based on signals	Inverse based on signals	Based on cum. signals	Inverse based on cum. signals	
ALIOR	1.3	−1.3	20.1	−51.8	−25.9	−40.3	−21.0
ASSECOPOL	59.3	−37.2	165.2	−68.4	98.7	−60.7	55.8
CCC	147.7	−59.6	88.8	−81.2	−95.0	429.0	44.9
CDPROJECT	−79.6	390.4	431.0	−97.5	2,594.3	−99.7	9,432.1
CYFRPLSAT	−9.3	10.3	−29.4	24.8	−58.7	102.1	136.4
DINOPL	43.7	−30.4	−44.0	32.0	110.9	−69.1	177.1
JSW	−60.9	155.5	82.4	−91.6	−13.8	−91.6	−10.5
KGHM	−65.3	188.2	2,135.7	−98.9	1,605.1	−99.2	452.5
LOTOS	215.4	−68.3	13.4	−52.9	−91.7	342.8	169.3
LPP	90.0	−47.4	−19.4	−1.0	−58.8	89.2	66.4
MBANK	18.5	−15.6	105.8	−68.6	−62.8	41.7	−28.8
ORANGEPL	3.1	−3.00	−49.1	17.3	−25.1	−31.4	−39.2
PEKAO	376.3	−79.0	−21.0	−33.7	−38.7	−27.8	−16.9
PGE	−40.5	68.1	−31.6	−37.1	−45.4	−42.3	−56.4
PGNIG	73.2	−42.3	140.6	−77.2	215.4	−84.9	262.2
PKNORLEN	11.9	−10.6	73.4	−68.8	−75.6	80.4	−46.9
PKO	−32.7	48.5	−55.7	15.4	−76.8	61.8	−35.7
PZU	200.1	−66.7	55.1	−53.5	12.2	−47.7	68.1
SANPL	−43.6	77.1	−2.1	−17.4	106.7	−64.2	35.6
TAURONPE	233.9	−70.1	−88.9	307.0	−57.6	−21.6	−31.6
Share of results better than return in all the periods	65%	40%	40%	20%	25%	45%	

Source: the author's own elaboration.

VI. CONCLUSIONS

The results confirmed that there is a positive relation between investor sentiment and stock returns (5.4%, 2.7%, 3.0% or 29.7% on average, depending on the measure), which is significant for half of the analysed companies. Observations are consistent with Baker and Wurgler's (2006) initial study and further evidence (Kearney & Liu, 2014). This study confirms the observations of Nardo et al. (2016), who highlighted that the correlation between investor sentiment and returns is rather modest, but it also brings a fresh perspective by discovering that the relation is more pronounced in cumulative returns and cumulative sentiment than between daily sentiment and daily returns. While the causality and interdependence between assessed variables were not examined, cumulative sentiment appears to serve as an indicator of investor interest, potentially signalling herd behaviour, especially given that it is not useful in investment strategies and does not offer a straightforward mechanism for systematic investment gains. The study also reinforces the idea that sentiment-driven trading is predominantly a retail phenomenon, with a strong and highly significant correlation between daily sentiment and cumulative sentiment with the number of transactions but not with trading volume and the value of transactions. The findings do not support the view that investor sentiment is a negative predictor of long-term returns. Most correlations instead point to a positive relationship.

From an investment strategy perspective, the findings cast doubt on the standalone efficacy of behavioural investing. While sentiment-based trading was shown to be useful in the daily strategy in two thirds of the single stock records, particularly for non-rallying stocks, other forms of non-trading behavioural strategies failed to provide any value, which suggests that it is still premature to rely on behavioural investing, at least in Poland. Nonetheless, the results are constrained by transaction costs and market frictions. This implies a critical limitation: the theoretical profitability of these strategies is negated by adjusting for these market realities, which severely restricts the practical utility of sentiment-based investment strategies. This presents a compelling avenue for future research aimed at developing cost-effective execution strategies.

The results are unique and yield material implications given the large sample of data used in the study, the long time frame in which the study was conducted (over 14 years), as well as a diverse set of companies for which the sentiment was evaluated and tested in investment strategies. Moreover, the exclusion of threads written during the session to mitigate evaluation of threads impacted by emotions driven by stock returns, and reduction of noise through the focus on unusual sentiment signals while calculating the MCC reinforce the study's relevance. Given that this paper addresses most of the prior research's limitations – as highlighted by Nguyen et al. (2015) – it is one of the first such comprehensive and valid analyses of the relation between investor sentiment and stock prices as well as behavioural investing, which creates a standalone value of this study.

Moreover, the study proves that a fine-tuned LM used in sentiment classification, with 73% accuracy, can be useful in investing and yield significant results in correlation metrics despite the low quality of the Internet data, which often limits drawing conclusions.

While behavioural investing is still in its early stages, it already offers profitable strategies which outperform the B&H approach in two thirds of the cases. Due to advancements in NLP and machine learning, behavioural finance's most basic method, sentiment analysis, can be effectively leveraged in trading strategies but not yet in investing strategies, which is confirmed by this study. The paper confirms a positive but low correlation between daily and signal-measured investor sentiment and stock returns as well as a positive and modestly high correlation between cumulative sentiment and cumulative stock returns. Furthermore, it recognizes that investor sentiment – both daily and cumulative – is correlated with the number of transactions but not so much with the trading volume and value of transactions, which confirms that the investor sentiment scraped from the online forum is a proxy for retail investors' activity and attitude to stocks. It should be noted, however, that the results are not statistically significant in all cases. Finally, the paper shows that investor sentiment scraped from an online forum and classified with LM can be useful in investing due to advancements in NLP and successful fine-tuning of BERT-class LM despite the low quality of input data.

Further recommendations include a more in-depth study of the relation between investor sentiment and price fluctuations – especially the causality and interrelation or dependency of these two variables. Furthermore, as this study failed to apply behavioural analysis in any other form than trading, there still is room to create a behavioural investment strategy, potentially through a joint application of fundamental and behavioural methods. At the end, given how rapidly LLMs have evolved over the last few years, the application of more advanced large language models could considerably improve sentiment classification and contribute to higher efficacy of strategy and potentially more significant correlations – a 73% accuracy achieved after the model's fine-tuning in this study can be considerably improved, as the literature suggests. This may include, but is not limited to, data cleaning.

Author contributions / Indywidualny wkład autora (CRediT): **Łukasz Kołodziejczyk** – 100% (Conceptualization / Konceptualizacja; Data curation / Zarządzanie danymi; Formal analysis / Formalna analiza; Investigation / Przeprowadzenie badań; Methodology / Metodologia; Software / Oprogramowanie; Validation / Walidacja; Writing – original draft / Pisanie – pierwszy szkic; Writing – review & editing / Pisanie – recenzja i edycja).

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The use of AI tools / Wykorzystanie narzędzi AI: Machine learning-based language models were employed for sentiment classification. Three models were evaluated: PolBERT, HerBERT, and RoBERTa. The final sentiment classification was conducted using a fine-tuned PolBERT model. Details are available in section III and IV. / Wykorzystano model

językowy poprzez uczenie maszynowe w klasyfikacji sentymentu. Testowane były trzy modele językowe: PolBERT, HerBERT i RoBERTa. W ostatecznym badaniu klasyfikacji sentymentu dokonał douczony (fine-tuning) model PolBERT. Szczegółowe informacje znajdują się w części III i IV artykułu.

Data availability / Dostępność danych: The data is available on request. / Dane dostępne na życzenie.

Supplementary materials / Materiały dodatkowe: Appendix available online at: / Aneks dostępny online: https://osf.io/wc7pa

References / Bibliography

Aggarwal, D. (2022). Defining and measuring market sentiments: A review of the literature. *Qualitative Research in Financial Markets*, *14*(2), 270–288. https://doi.org/10.1108/QRFM-03-2018-0033

Akarsu, S., & Süer, Ö. (2022). How investor attention affects stock returns? Some international evidence. *Borsa Istanbul Review*, *22*(3), 616–626. https://doi.org/10.1016/j.bir.2021.09.001

Alanyali, M., Moat, H. S., & Preis, T. (2013). Quantifying the relationship between financial news and the stock market. *Scientific Reports*, *3*(1), 1–6. https://doi.org/10.1038/srep03578

Antweiler, W., & Frank, M. Z. (2004). Is all that talk just noise? The information content of internet stock message boards. *The Journal of Finance*, *59*(3), 1259–1294. https://doi.org/10.1111/j.1540-6261.2004.00662.x

Anusakumar, S. V., Ali, R., & Wooi, H. C. (2017). The effect of investor sentiment on stock returns: Insight from emerging Asian markets. *Asian Academy of Management Journal of Accounting and Finance*, *13*(1), 159–178. https://doi.org/10.21315/aamjaf2017.13.1.7

Araci, D. T. (2019). FinBERT: Financial sentiment analysis with pre-trained language models. *arXiv preprint arXiv:1908.10063*, 1–10. https://doi.org/10.48550/arXiv.1908.10063

Asness, C. S., Frazzini, A., Israel, R., & Moskowitz, T. J. (2015). Fact, fiction, and value investing. *Journal of Portfolio Management*, *42*(1), 1–31. http://dx.doi.org/10.2139/ssrn.2595747

Ayala, M. J., Gonzálvez-Gallego, N., & Arteaga-Sánchez, R. (2024). Google search volume index and investor attention in stock market: A systematic review. *Financial Innovation*, *10*(1), 70–99. https://doi.org/10.1186/s40854-023-00606-y

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, *61*(4), 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Baker, M., & Wurgler, J. (2007). *Investor sentiment in the stock market. Journal of economic perspectives, 21*(2), 129–151. https://doi.org/10.1257/jep.21.2.129

Batra, R., & Daudpota, S. M. (2018). Integrating StockTwits with sentiment analysis for better prediction of stock price movement. In *2018 international conference on computing, mathematics and engineering technologies (ICoMET)* (pp. 1–15). IEEE. https://doi.org/10.1109/ICOMET.2018.8346382

Boehmer, E., Jones, C. M., Zhang, X., & Zhang, X. (2021). Tracking retail investor activity. *The Journal of Finance*, *76*(5), 2249–2305. https://doi.org/10.1111/jofi.13033

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. *Journal of Computational Science*, *2*(1), 1–8. https://doi.org/10.1016/j.jocs.2010.12.007

Cornell, B., & Damodaran, A. (2021). Value investing: Requiem, rebirth or reincarnation? *SSRN*. https://doi.org/10.2139/ssrn.3779481

Dadas, S., Perełkiewicz, M., & Poświata, R. (2020). Pre-training Polish transformer-based language models at scale. *Artificial Intelligence and Soft Computing: 19th International Conference, ICAISC 2020* (pp. 301–314). Springer International Publishing. https://doi.org/10.1007/978-3-030-61534-5_27

Das, S. R., & Chen, M. Y. (2007). Yahoo! for Amazon: Sentiment extraction from small talk on the web. *Management Science*, *53*(9), 1375–1388. https://doi.org/10.1287/mnsc.1070.0704

De Bondt, W. F., Muradoglu, Y. G., Shefrin, H., & Staikouras, S. K. (2007). Behavioral finance: Quo vadis? *Journal of Applied Finance*, *18*(2), 1–15.

Ding, W., Mazouz, K., Gwilym, O., & Wang, Q. (2023). Technical analysis as a sentiment barometer and the cross-section of stock returns. *Quantitative Finance*, *23*(11), 1617–1636. https://doi.org/10.1080/14697688.2023.2244991

Duz Tan, S., & Tas, O. (2021). Social media sentiment in international stock returns and trading activity. *Journal of Behavioral Finance*, *22*(2), 221–234. https://doi.org/10.1080/15427560.2020.1772261

Hoffmann, A. O., & Shefrin, H. (2014). Technical analysis and individual investors. *Journal of Economic Behavior & Organization*, *107*(1), 487–511. https://doi.org/10.1016/j.jebo.2014.04.002

Kłeczek, D. (2020). Polbert: Attacking Polish NLP tasks with transformers. In *Proceedings of the PolEval 2020 workshop* (pp. 79–88). Institute of Computer Science, Polish Academy of Sciences.

Kahneman, D., & Riepe, M. W. (1998). Aspects of investor psychology. *Journal of Portfolio Management*, *24*(4), 52–65. https://doi.org/10.3905/jpm.1998.409643.

Kazemian, S., Zhao, S., & Penn, G. (2016). Evaluating sentiment analysis in the context of securities trading. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics* (pp. 2094–2103). Association for Computational Linguistics. https://doi.org/10.18653/v1/P16-1197

Kearney, C., & Liu, S. (2014). Textual sentiment in finance: A survey of methods and models. *International Review of Financial Analysis*, *33*(1), pp. 171–185. https://doi.org/10.1016/j.irfa.2014.02.006

Kim, S.-H., & Kim, D. (2014). Investor sentiment from internet message postings and the predictability of stock returns. *Journal of Economic Behavior & Organization*, *107*(1), pp. 708–729. https://doi.org/10.1016/j.jebo.2014.04.015

Koptyra, B., Oleksy, M., Dzięcioł, E., & Kocoń, J. (2024). Small language models for emotion recognition in Polish stock market investor opinions. In *2024 IEEE International Conference on Data Mining Workshops (ICDMW)* (pp. 463–470). IEEE. https://doi.org/10.1109/ICDMW65004.2024.00065

Lee, C.-C., Gao, Z., & Tsai, C.-L. (2020). BERT-based stock market sentiment analysis. In *2020 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-Taiwan)* (pp. 1–2). ICCE. https://doi.gov/10.1109/ICCE-Taiwan49838.2020.9258102

Lev, B., & Gu, F. (2016). *The end of accounting and the path forward for investors and managers.* John Wiley & Sons.

Lev, B., & Srivastava, A. (2022). Explaining the recent failure of value investing. *Critical Finance Review,* 11(2), 330–360. https://doi.org/10.1561/104.00000115

Liu, J.-X., Leu, J.-S., & Holst, S. (2023). Stock price movement prediction based on Stocktwits investor sentiment using FinBERT and ensemble SVM. *PeerJ Computer Science*, *9*(1), 1–25. https://doi.org/10.7717/peerj-cs.1403

Malkiel, B. (1981). *A random walk down Wall Street.* Norton.

McGurk, Z., Nowak, A., & Hall, J. C. (2020). Stock returns and investor sentiment: Textual analysis and social media. *Journal of Economics and Finance*, *44*(1), 458–485. https://doi.org/10.1007/s12197-019-09494-4

Menkhoff, L., & Taylor, M. P. (2007). The obstinate passion of foreign exchange professionals: Technical analysis. *Journal of Economic Literature*, *45*(4), 936–972. https://doi.org/10.1257/jel.45.4.936

Mishev, K., Gjorgjevikj, A., Vodenska, I., Chitkushev, L. T., & Trajanov, D. (2020). Evaluation of sentiment analysis in finance: From lexicons to transformers. *IEEE Access*, *8*(1), 131662–131682. https://doi.org/10.1109/ACCESS.2020.3009626

Mitroi, A., & Oproiu, A. (2014). Behavioral finance: New research trends, socionomics and investor emotions. *Theoretical and Applied Economics*, *21*(4), 153–166.

Mroczkowski, R., Rybak, P., Wróblewska, A., & Gawlik, I. (2021). HerBERT: Efficiently pretrained transformer-based language model for Polish. *Proceedings of the 8th Workshop on Balto-Slavic Natural Language Processing* (pp. 1–10). Association for Computational Linguistics.

Nardo, M., Petracco-Giudici, M., & Naltsidis, M. (2016). Walking down Wall Street with a tablet: A survey of stock market predictions using the web. *Journal of Economic Surveys*, *30*(2), 356–369. https://doi.org/10.1111/joes.12102

Nguyen, T. H., Shirai, K., & Velcin, J. (2015). Sentiment analysis on social media for stock movement prediction. *Expert Systems with Applications*, *42*(24), 9603–9611. https://doi.org/10.1016/j.eswa.2015.07.052

Nti, I. K., Adekoya, A. F., & Weyori, B. A. (2020). A systematic review of fundamental and technical analysis of stock market predictions. *Artificial Intelligence Review*, *53*(4), 3007–3057. https://doi.org/10.1007/s10462-019-09754-z

Olawale, I. O., Iworiso, J., & Amaunam, I. (2023). Predicting stock investments based on sentiment and historical price data. *International Journal of Data Envelopment Analysis and Operations Research*, *4*(1), 1–32.

Oliveira, N., Cortez, P., & Areal, N. (2017). The impact of microblogging data for stock market prediction: Using Twitter to predict returns, volatility, trading volume and survey sentiment indices. *Expert Systems with applications*, *73*(1), 125–144. https://doi.org/10.1016/j.eswa.2016.12.036

Pagolu, V. S., Reddy, K. N., Panda, G., & Majhi, B. (2016). Sentiment analysis of Twitter data for predicting stock market movements. In *2016 International Conference on Signal Processing, Communication, Power, and Embedded Systems (SCOPES)* (pp. 1345–1350). IEEE. https://doi.org/10.1109/SCOPES.2016.7955659

Park, C.-H., & Irwin, S. H. (2007). What do we know about the profitability of technical analysis? *Journal of Economic Surveys*, *21*(4), 786–826. https://doi.org/10.1111/j.1467-6419.2007.00519.x

Polak, K. (2021). The impact of investor sentiment on direction of stock price changes: Evidence from the Polish stock market. *Journal of Banking and Financial Economics*, *16*(2), 72–90.

Probierz, E., Gałuszka, A., Klimczak, K., Jędrasiak, K., Wiśniewski, T., & Dziada, T. (2021). Financial sentiment on Twitter's community and it's connection to Polish stock market movements in context of behavior modelling. *European Research Studies Journal*, *24*(4B), 56–65.

Ranco, G., Aleksovski, D., Caldarelli, G., Grčar, M., & Mozetič, I. (2015). The effects of Twitter sentiment on stock price returns. *PloS one*, *10*(9), 1–21. https://doi.org/10.1371/journal.pone.0138441

Rao, T., & Srivastava, S. (2012). Analyzing stock market movements using Twitter sentiment analysis. In *2012 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining* (pp. 119–123). IEEE. https://dl.acm.org/doi/10.5555/2456719.2456923

Renault, T. (2017). Intraday online investor sentiment and return patterns in the U.S. stock market. *Journal of Banking & Finance*, *84*(1), 25–40. https://doi.org/10.1016/j.jbankfin.2017.07.002

Statman, M. (2017). *Finance for normal people: How investors and markets behave.* Oxford University Press.

Statman, M. (2019). A second generation behavioral finance. In *Behavioral Finance: The Coming of Age* (pp. 3–21). World Scientific. https://doi.org/10.1142/9789813279469_0001

Sul, H. K., Dennis, A. R., & Yuan, L. (2017). Trading on Twitter: Using social media sentiment to predict stock returns. *Decision Sciences*, *48*(3), 454–488. https://doi.org/10.1111/deci.12229

Teti, E., Dallocchio, M., & Aniasi, A. (2019). The relationship between Twitter and stock prices. Evidence from the US technology industry. *Technological Forecasting and Social Change*, *149*(1), 1–9.

Tetlock, P. C. (2007). Giving content to investor sentiment: The role of media in the stock market. *The Journal of Finance*, *62*(3), 1139–1168. https://doi.org/10.1016/j.techfore.2019.119747

Wojarnik, G. (2022). Sentiment analysis towards listed companies in the energy sector on the example of the WIG-Energia index on the WSE. *Procedia Computer Science*, *207*(1), 2059–2067. https://doi.org/10.1016/j.procs.2022.09.265

Woo, K.-Y., Mai, C., McAleer, M., & Wong, W.-K. (2020). Review on efficiency and anomalies in stock markets. *Economies*, *8*(1), 1–51. https://doi.org/10.3390/economies8010020

Yang, S. Y., & Mo, S. Y. (2016). Social media and news sentiment analysis for advanced investment strategies. In W. Pedrycz & S.-M. Chen, *Sentiment analysis and ontology engineering: An environment of computational intelligence* (pp. 237–272). Springer. https://doi.org/10.1007/978-3-319-30319-2_11

Zhang, W., & Skiena, S. (2010). Trading strategies to exploit blog and news sentiment. In *Proceedings of the International AAAI Conference on Web and Social Media* (pp. 375–378). AAAI. https://doi.org/10.1609/icwsm.v4i1.14075

Zhang, X., Fuehres, H., & Gloor, P. A. (2011). Predicting stock market indicators through Twitter "I hope it is not as bad as I fear." *Procedia-Social and Behavioral Sciences*, *26*(1), 55–62. https://doi.org/10.1016/j.sbspro.2011.10.562

Zielonka, P. (2004). Technical analysis as the representation of typical cognitive biases. *International Review of Financial Analysis*, *13*(2), 217–225. https://doi.org/10.1016/j.irfa.2004.02.007