mathematics

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The Impact of Sentiment Indices on the Stock Exchange—The Connections between Quantitative Sentiment Indicators, Technical Analysis, and Stock Market

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Abstract: The stock market represents one of the most complex mechanisms in the financial world. It can be seen as a living being with complex ways to enact, interact, evolve, defend, and respond to various stimuli. Technical analysis is one of the most complex techniques based on financial data's graphical aspects. News sentiment indices are very complex and highlight another important part of behavioral finance. In this study, we propose an integrated approach in order to determine the correlation between news sentiment indices, the stock market, and technical analysis. The research methodology focuses on the stock market's practical and quantitative aspects. In this sense, we have used the graphical representation of technical analysis and econometric modeling techniques such as VAR and Bayesian VAR. The results of the empirical modeling techniques and analysis reveal some important connections between the stock market and news sentiment indices on the US stock market. The conclusions of this study highlight a strong connection between news sentiment indices, technical analysis, and the stock market which suggests that the behavioral finance aspect is a very important aspect in the analysis of the stock market.

Keywords: technical analysis; sentiment indices; stock market; quantitative approach; behavioral finance

MSC: 91B28; 91B84

Citation: Dumiter, F.C.; Turcaș, F.; Nicoară, Ș.A.; Bențe, C.; Boiță, M. The Impact of Sentiment Indices on the Stock Exchange—The Connections between Quantitative Sentiment Indicators, Technical Analysis, and Stock Market. *Mathematics* **2023**, *11*, 3128. https://doi.org/10.3390/math11143128

Academic Editors: Camelia Oprean-Stan and Radu Voichita Adriana

Received: 20 June 2023
Revised: 10 July 2023
Accepted: 12 July 2023
Published: 15 July 2023

1. Introduction

Behavioral economics gained attention due to the importance of psychological insights in explaining business, management, or financial decisions. Even more, behavioral economics and economic sentiment could offer some explanations for the evolution of business cycles and even the perception of national competitiveness (Necadova, 2019 [1]). Corr and Plagnol (2023) [2] debate the topic of behavioral economics to give some insights on the causes of the deviations from traditional economic model predictions.

Dumiter and Turcas (2022) [3] recognize that the forecasting methods of stock markets need to be developed to improve investment decisions, even if the technical analysis is known to significantly increase the performances of the investments (Dumiter and Turcas (2023) [4]).

The interpretation of financial news and financial sentiment influence over market performances is a topic of interest in the literature. Daxhammer et al. (2023) [5] argue the role of emotional finance in stock market behavior and speculative bubbles. Krishnamoorthy (2018) [6] argues the importance of financial text analysis of the word's sentiment on investments. Kräussl and Mirgorodskayad (2017) [7] found evidence of causality between news sentiment and market performance, and Gao and Martin (2021) [8] emphasize the importance of investor sentiment on volatility and financial bubbles. Galariotis et al. (2014) [9] highlight the role of investor sentiment in predicting UK stock profits. Zhang et al. (2018) [10] also sustain the importance of news sentiment in forecasting the price movements of stocks.

The research objectives focused on in this research are related to the connections established between sentiment indices, the stock market, and the macroeconomic environment. These elements are very closely related and between them, it manifests strong connections and correlations which are worth analyzing and testing in order to establish the mechanism of functioning the stock market, stricto sensu, and financial market, lato sensu.

The scope of the research is to evaluate and assess the impact of news sentiment indices on the stock market. The behavioral approach of the finance domain is analyzed in this research, highlighting the degree to which sentiment indices influence the stock market, what the influences are and how investors and traders can take into account these indices for trading purposes.

The methodology enriched in this article is both a quantitative and qualitative one. The qualitative part regards the quid pro quo arguments for linking the technical analysis to the sentiment indices and stock market. The quantitative approach tackles the graphical methods of technical analysis and econometric modeling techniques in order to establish the status of the connection between technical analysis, stock market, and news sentiment indices.

The novelty of the study brings forward complex research that deals with the actual and contemporary financial and behavioral aspects of the stock markets: the implications of technical analysis, the importance of news sentiment indices, and stock market evolution before and after the pandemic period.

The structure of the article is the following. In the first part of the article, the scope of the research is emphasized, the objectives and methodologies, and the rationale for tackling the research theme. The second part of the article analyzes the status quo of the theoretical and empirical literature on stock markets and technical analysis. The third part evaluates and assesses the impact of news sentiment figures on technical analysis. The fourth part deals with the quantitative approaches of the news sentiment on the stock market. The fifth part represents the discussion of the empirical findings in light of the other empirical research and gives several recommendations. The final part establishes the final remarks of the study and reveals the policy recommendations.

2. Literature Review

The role of sentiment has been noted since the Great Depression from 1920 to 1934 with Kabiri et al. (2023) [11] substantiating the influence on industrial production, S&P 500 Index, bank loans, and credit risk. Nakhli et al. (2022) [12] established a bidirectional Granger causality between investor sentiment and momentum strategy of stocks listed on the NYSE, NASDAQ, and AMEX. Analyzing 100 articles published in journals indexed in the Web of Science, Prasad et al. (2023) [13] observed that the topic of news sentiment is mostly debated in the case of developed economies with strong stock markets.

Han et al. (2022) [14] observed that equity performances can be explained by changes in market sentiment persistence. Financial performance was also explored by Yen et al. (2022) [15], who associated online public opinion about the Taiwanese listed companies and their future financial performance. Li et al. (2021) [16] used a two-step cross-sectional regression model and found a significant impact of investor sentiment on stock yield. Valle-Cruz et al. (2022) [17] provide evidence that social media publications had a significant influence on several worldwide financial indices during the COVID-19 pandemic.

Using the GARCH method, Figà-Talamanca and Patacca (2022) [18] established a positive effect of the news and Twitter feeds on the stock price of companies included in the S&P 500 Index, and Smith and O'Hare (2022) [19] using cross-correlations enhanced the major influence of financial news sentiment in stock price movements. The market sentiment was found to have also influenced precious metals prices (Maghyereh and Abdoh; 2022 [20]).

Wojarnik (2021) [21] reported similar results for stocks listed at the Warsaw Stock Exchange. Moreover, Xu et al. (2020) [22] using Principal Component Analysis upholds the rumors of a significant influence on the price of the Chinese A-shares market. The studies of McGurk et al. (2020) [23] and Chamberlain et al. (2023) [24] found a positive and significant effect of news sentiment on the return of shares included in the Russell 5000 Index and S&P500 Index using the OLS method and panel regression.

Chen et al. (2022) [25] explored the correlation between investor sentiment and stock excess return of Shanghai Stock Exchange 50 Index stocks and found an asymmetric effect of investor sentiment on excess returns. Mendoza-Urdiales et al. (2022) [26] observed the asymmetric effect of news and using the EGARCH model and established that negative news affects more significant stock prices. However, Sun et al. (2021) [27] proved that investor sentiment can be useful to predict changes in the Chinese CSI300 Index only for short time periods. Furthermore, Shi et al. (2020) [28] investigated the impact of investor sentiments on stock returns in emerging countries and using a panel fixed-effect regression model found that investor sentiments cannot predict expected stock returns in these markets.

Cevik et al. (2022) [29] studied the G20 stock markets using panel regression and found that investor sentiments have a significant influence on stock market returns and volatility. PH and Rishad (2020) [30] used the GARCH and Granger causality framework to prove the significant role of irrational investors' sentiments in determining stock market volatility. Li et al. (2022) [31] using machine learning algorithms established that the accuracy of volatility forecasting of stocks included in the S&P 500 Index is better expressed by economic policy uncertainty indicators, than by market sentiment indicators or financial stress indices. On the other hand, Khan et al. (2022) [32] found that social media and financial news increase the accuracy of S&P 500 Index predictions. Hsu et al. (2021) [33] applied Generalized Autoregressive Conditional Heteroskedasticity (GARCH) to bring evidence of the news sentiment on stock market volatility in Taiwan. Gao et al. (2022) [34] found trading sentiment to be the main factor that influences the volatility of stocks from the new energy, environmental protection, and carbon–neutral sectors of China.

Forecasting stock direction was also studied by Yang et al. (2022) [35] and Sharaf et al. (2022) [36] for several shares listed on NYSE and NASDAQ, proving that sentiment analysis and technical analysis improve significant prediction accuracy. At the same time, Wang et al. (2023) [37] argue the importance of integrating social sentiment with technical indicators in trending analysis. Additionally, Ji et al. (2023) [38] used Vector Regression (SVR) and recurrent neural networks (RNN) to proof of the better accuracy of models incorporating stock prices, and technical and sentiment indicators. Qiu et al. (2022) [39] bring evidence that supports the fact that the sentiment index effectively improves the predictability of stock trends of the Shanghai Stock Exchange 50 (SSE 50) Index. These results are also supported by the study of Das et al. (2022) [40] in the case of the Nifty-50 stock market index.

The following Table 1 summarizes the most recent studies related to news sentiment's influence on the US stock market trends, returns, and volatility.

Table 1. Studies regarding the influence of news sentiment on the US stock market.

Author	Research Purpose	Methodology	Sample	Conclusion
McGurk et al. (2020) [23]	The relationship between investor sentiment and stock returns.	Ordinary least squares (OLS), forecasting model.	NYSE—Russell 5000 Index.	Investor sentiment has a positive and significant effect on abnormal stock returns.
Yang et al. (2022) [35]	Forecasting stock direction using technical analysis and sentiment analysis.	Machine learning models—LASSO-LSTM model.	Shares of AAPL, MNST, and BAC on the NYSE and NASDAQ.	The sentiment analysis and technical analysis can improve prediction accuracy.
Li et al. (2022) [31]	The role of economic policy uncertainty indicators, market sentiment indicators, and financial stress indices in predicting volatility.	Machine learning models—MS-MIDAS-LASSO model.	S&P500 Index.	The forecasting accuracy is better expressed by economic policy uncertainty indicators, than mmarket sentiment indicators and financial stress indices.
Nakhli et al. (2022) [12]	Examining the Granger causality between investors' sentiment and momentum strategies.	Granger causality test, the rolling-window bootstrap. Approach, probit model.	Stocks listed on NYSE, NASDAQ, and AMEX.	Bidirectional Granger causality is manifesting between investor sentiment and momentum strategy.
Figà-Talamanca and Patacca (2022) [18]	The effect of investor sentiment on the mean returns and the variance of financial stocks.	GARCH family augmented.	S&P500 Index.	There is a positive impact of news and Twitter feeds on stock prices.
Valle-Cruz et al. (2022) [17]	The influence of Twitter posts on the behavior of financial indices during pandemics.	Machine learning models.	Stock market indices: IPC; S&P 500; NASDAQ 100; Dow Jones; FTSE 100; BOVESPA; CAC 40; DAX; Hang Seng; Nikkei 225; SSE Composite.	The markets react to the information shared on Twitter in 0 to 10 days during the COVID-19 pandemic.
Smith and O'Hare (2022) [19]	The influence of daily news sentiment and Twitter sentiment from CEOs on the market performance of companies.	Time-lagged cross-correlations.	23 companies included in S&P 500 Index.	Non-financial news sources have little influence on price movements, but financial news sentiment determines stock price movements.
Khan et al. (2022) [32]	The impact of social media and financial news on stock market prediction accuracy.	Machine learning algorithms.	S&P500 Index.	Using social media and financial news increases the accuracy of stock market predictions by 80.53% and 75.16%.
Maghyereh and Abdoh (2022) [20]	The role of market sentiment in predicting price bubbles.	SADF and GSADF approaches, probit approach.	US gold, silver, palladium, and platinum markets.	Including sentiment in the model improves the predictions of price bubbles of precious metals.
Han et al. (2022) [14]	Analysis of changes in US market sentiment.	Regression equations.	US.	Changes in sentiment persistence affect equity anomalies.
Sharaf et al. (2022) [36]	Analysis of stock news headlines in predicting the trend of stock during COVID-19.	Machine learning algorithms—Random Forest Classifier.	TSLA, AMZ, and GOOG stocks.	The accuracy for the prediction of TSLA, AMZ, and GOOG stocks increases by including the news sentiment.
Cevik et al. (2022) [29]	The relationship between investor sentiments and stock market returns and volatility.	Panel regression with fixed effects, panel quantile regressions, panel vector autoregression (PVAR) model.	G20 stock markets.	There is a significant relationship between investor sentiments and the stock market returns and volatility.
Wang et al. (2023) [37]	Investigating the stock trending prediction using technical indicators and social media sentiments.	Machine learning algorithms.	Shares GOOG, AMZN, AAPL, EBAY, C, and DJIA Index.	The stock market trending analysis is enhanced by integrating social opinions with technical indicators.
Chamberlain et al. (2023) [24]	Relationship between the stock market and news sentiment.	Fixed-effects panel regression.	S&P500 Index.	News sources are positively related to stock returns.
Kabiri et al. (2023) [11]	The role of sentiment in the US economy from 1920 to 1934.	Vector error correction model.	US.	The large role of sentiment was noted in the spread of industrial production, S&P 500, bank loans, and credit risk.

3. The Impact of News Sentiment Indices Figures in the Technical Analysis

The indicators are listed and behave like any asset listed on the stock exchange: it is traded regularly, indicators and oscillators can be applied to it, and specific conclusions can be drawn for technical analysis (Figures 1 and 2).

Figure 1. VanEck SENTIMENT ETF trends for the USA. Source: www.investing.com, accessed on 16 May 2023.

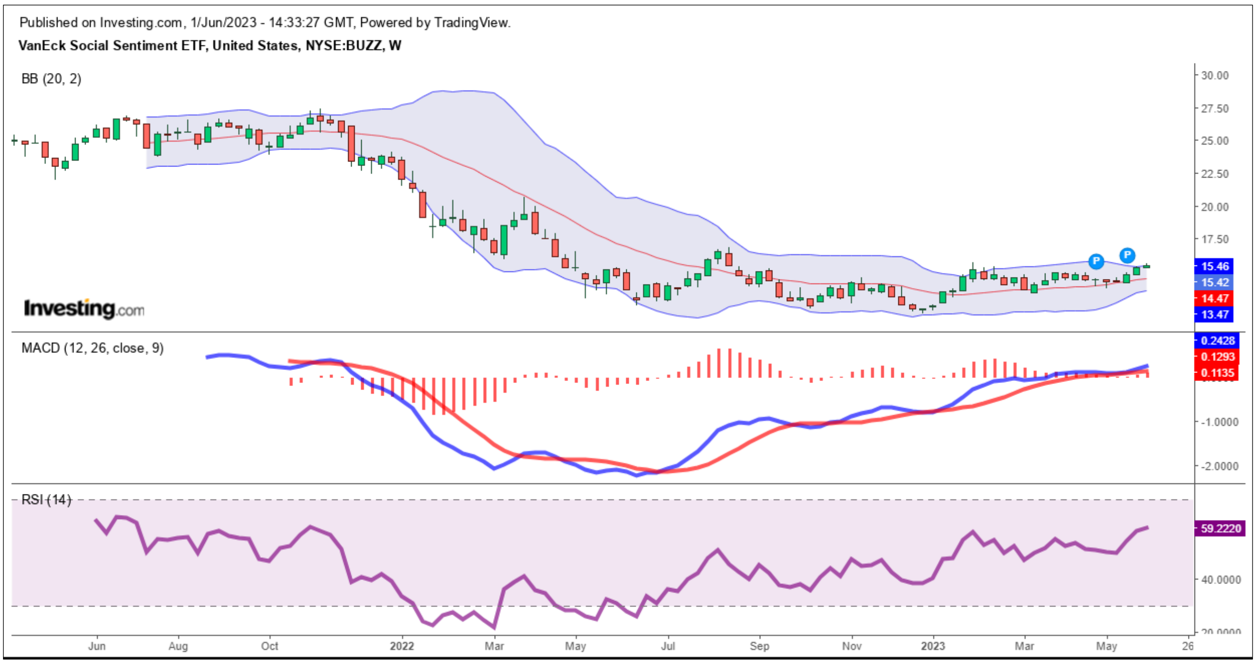

Figure 2. Technical analysis of VanEck sentiment ETF for the USA. Source: www.investing.com, accessed on 16 May 2023.

For example, BUZZ is an ETF calculated by VanEck and listed on the NYSE. According to www.thinkadvisor.com/2021/07/28/everything-you-need-to-know-about-the-buzz-etf/ "*BUZZTR uses artificial intelligence to gauge public sentiment about companies, specifically* *by reviewing online sources such as social media posts, blog posts, and online news media*" accessed on 16 May 2023. From the chart of quotation developments, we can draw the following conclusions:

1. The trend is downward, a fact confirmed by the decreasing volumes.
2. MACD intersection, nearby Bollinger bands, and RSI below 70% (only 60%).

It shows possibilities for growth, but without signaling this trend—more precisely, there are no signs of decline.

The construction of this indicator can be found here: www.vaneck.com/us/en/investments/social-sentiment-etf-buzz/buzz-reconstitution.pdf, accessed on 16 May 2023.

The graphs of the sentiment indicators are correlated with those of the main stock indices, which are also natural. It also confirms the behavior theory that growth starts on bad news and decreases on good news. On the BUZZ vs. S&P500 comparative chart, it is noticed that the beginning signal of the negative sentiment (the downward trend line) occurs before the actual market declines, and the encouraging one (the upward trend lines) begins after the market has recovered somewhat (Figure 3).

Figure 3. Comparative analysis BUZZ vs. US500 (S&P500). Source: www.investing.com, accessed on 16 May 2023.

Not only is this "meaningful", but it can be extremely useful for speculators.

Recall that BUZZ is a traded ETF, therefore speculators can take advantage of the correlation with the S&P500, especially since there is a temporary lag between the two. Instead of overlapping with the stock index, BUZZ shows a delay, probably due to the public's reaction time. This delay is extremely useful to speculators: they can observe the S&P500 and subsequently act on the BUZZ.

For example, after the BUZZ and S&P500 developments were perfectly synchronized, in Figure 4 the green arrow area we can see that the US500 confirmed the minor uptrend, while the ETF remains on a daily downtrend. This momentary divergence is very useful for speculators; although the individual BUZZ chart does not announce any trend change, the need to correlate with the S&P500 means that there is a strong bull signal on simultaneous charts, taking a long position on the ETF before initiating the uptrend can bring speculative profits.

Figure 4. Opportunity spotted on the S&P500 vs. BUZZ comparison chart. Source: www.investing.com, accessed on 16 May 2023.

More than the graphs themselves, the recommendations of various investment sites can determine the direction of movement of the market. For example, investing.com (accessed on 16 May 2023) recommended through technical analysis to buy the BUZZ sensing EFT, which can have the effect of increasing it and inducing a positive sense of optimism in the market (Table 2):

Table 2. Technical analysis recommendations for BUZZ.

Type	5 min	15 min	Hourly	Daily	Monthly
Moving Averages	Strong Buy	Strong Buy	Strong Buy	Strong Buy	Buy
Technical Indicators	Strong Buy	Buy	Strong Buy	Strong Buy	Sell
Summary	Strong Buy	Strong Buy	Strong Buy	Strong Buy	Neutral

Source: www.investing.com, accessed on 16 May 2023. Note: The green color is for buy, the red color is for sell, and the grey color is for neutral.

Obviously, the somewhat contradictory conclusion based on the monthly data is due to the far too short history of the asset (index introduced in August 2021).

Similar conclusions can also be drawn from European sentiment indicators. For example, for Germany, the CFD 0P0000P145 has not yet climbed, although the market has been on an upward subtrend since last autumn; in the rest of the listing periods, it had similar developments to the stock market (DAX). Here, we see that some non-recurring events have a greater effect on the stock market than on the general sentiment (Figure 5):

1. The economic lockdown generated by the pandemic was much more strongly felt by the DAX stock index (DE40) than by the sentiment indicator.
2. Similarly, the outbreak of the war in Ukraine caused a much more drastic drop in the DAX than the CFD.

Figure 5. CFD sentiment in Germany vs. DAX. Source: www.investing.com, accessed on 16 May 2023.

The way of constructing sentiment indicators can induce market manipulation. These are ultimately statistical products, the collection and interpretation of which can be altered, willfully or not. Investopedia.com believes that sentiment indicators follow the market: "*In broad terms, rising prices indicate bullish market sentiment while falling prices indicate bearish market sentiment*". If they were to sum up on that, the sentiment indicators would not have much value: they would not bring any added value to investors. On the contrary, we believe that a strong trend of sentiment measures has the power to strengthen market trends. Having recently been introduced to trading, it remains to be seen whether they can preface market movements, which would make them really valuable to investors/speculators.

It is worth mentioning that, from a financial point of view, it is radically different to express your simple opinion in an interview on the direction of movement of the market compared to investing or betting on shares, derivatives, or structured products.

Another measure of market sentiments is given by the volatility index, for example, the VIX. According to investopedia.com: "The Cboe Volatility Index (VIX) is a real-time index that represents the market's expectations for the relative strength of near-term price changes of the S&P 500 Index (SPX). Because it is derived from the prices of SPX index options with near-term expiration dates, it generates a 30-day forward projection of volatility. Volatility, or how fast prices change, is often seen as a way to gauge market sentiment, and in particular the degree of fear among market participants". With a much richer history and being much better known to investors, this index can be analyzed in more depth (Figure 6).

It is noted that the VIX reaction is mostly related to decreases; on the upward trend portions, the VIX reaction is mostly the opposite: volatility is reduced as long as the market is favorable to investors. The chart of the US stock index is logarithmic, thus resulting in strong volatility jumps even when the market does not have ample movements.

Another feature is the reaction time to market movements. In the case of rapid movements, the VIX reaction is immediate and correct. In contrast, in the case of large, lasting variations, the VIX reacts late, sometimes reaching high values very late.

Being a daily variation indicator, the VIX cannot be investigated from the perspective of technical analysis, but only statistically correlated with the underlying asset: the S&P500 market index.

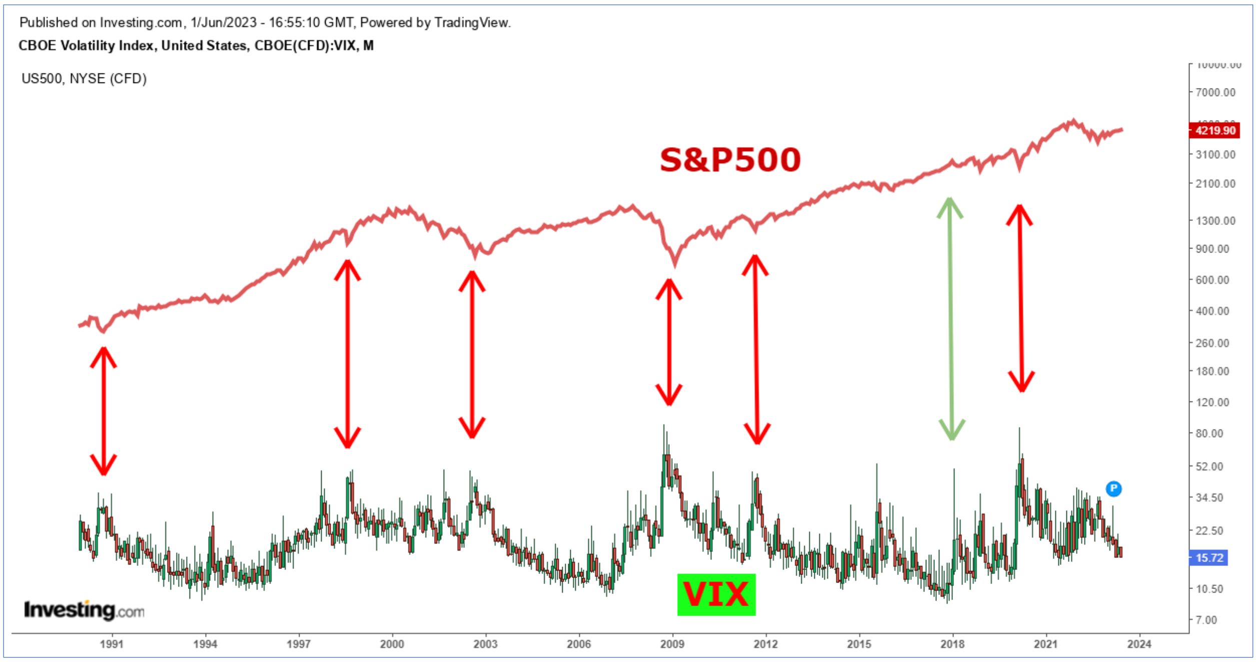

Figure 6. VIX vs. S&P500 (logarithmic graph). Source: www.investing.com, accessed on 16 May 2023.

4. Quantitative Approaches of Sentiment Indicators on the Stock Market

In this section, a quantitative approach is proposed regarding the impact of sentiment indicators on the stock market and their overall implication on the economy as a whole. In this sense, the study is focused on the US case study due to the fact that the American stock market is one of the most representative ones and its important implication for the worldwide economy.

4.1. Methodology and Data

The research hypothesis is focused on the main influence of news sentiment indices around the world nowadays. In the aftermath of the pandemic period, the American stock market index's reactions generated serious debates in the economic literature. Moreover, news sentiment is strongly correlated with the movements in the stock market indexes both on the American market and on the global financial market. The macroeconomic indicators, such as the key interest rates and inflation trends, are very important for the evaluation and assessment of the current international environment, and the evolution of the global economy in the post-pandemic period.

The research assumption is the following:

Hypothesis 1. *The evolution of the American stock market is influenced by the news sentiment indices which, ceteris paribus, have a direct impact on stock market indices, taking into account the technical analysis applications and having the background of a stable macroeconomic environment.*

The research hypothesis emphasis in the previous paragraph encompasses the strong connections and correlation between the stock market evolution and news sentiment indicators and between technical analysis application and stock market evolution the other hand. For the explanation of the complex connections between these variables, it is considered that there are several US stock market indices that have important implications. At first, Dow Jones Industrial Average, Google, Amazon, and Apple. Second, other important indexes such as the Concordance Index and Chicago Board Options Exchange CBOE Volatility Index. Third is the important evaluation and assessment of a comprehensive news sentiment index in order to evaluate the sentiment market scale and impact. Finally, the macroeconomic environment has two important barometers as the key interest rate and the inflation rate.

The models used in this study are the following: Vector Autoregressive Models (VAR) and Bayesian V. At first, VAR models are used for the analysis of the multivariate time series analysis where the news sentiment is the endogenous variable and each of the American stock market indices are the exogenous variables, and the Federal Funds Reserve Rate and inflation rate and the explanatory variables. Second, it is applied to the same distribution of variables as the Bayesian VAR modeling technique for a more comprehensive and complex sampling distribution. The econometric software used for modeling the time series was E-Views 12 Academic Edition.

The regression equations are the following:

$$\begin{aligned} NS_{it} = \alpha + \beta_1 \times NS(-1)_{it} + \beta_2 \times NS(-2)_{it} + \beta_3 \times DJI\_op_{it} + \beta_4 \times DJI\_hi_{it} + \beta_5 \times DJI\_low_{it} + \beta_6 \times DJI\_cl_{it} \\ + \beta_7 \times DJI\_vol_{it} + \beta_8 \times DJI\_r_{it} + \beta_9 \times FFR\_var_{it} + \beta_{10} \times INF_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

$$\begin{aligned} NS_{it} = \alpha + \beta_1 \times NS(-1)_{it} + \beta_2 \times NS(-2)_{it} + \beta_3 \times GOOGL\_op_{it} + \beta_4 \times GOOGL\_hi_{it} + \beta_5 \times GOOGL\_low_{it} \\ + \beta_6 \times GOOGL\_cl_{it} + \beta_7 \times GOOGL\_vol_{it} + \beta_8 \times GOOGL\_r_{it} \\ + \beta_9 \times FFR\_var_{it} + \beta_{10} \times INF_{it} + \varepsilon_{it} \end{aligned} \tag{2}$$

$$\begin{aligned} NS_{it} = \alpha + \beta_1 \times NS(-1)_{it} + \beta_2 \times NS(-2)_{it} + \beta_3 \times AMZN\_op_{it} + \beta_4 \times AMZN\_hi_{it} + \beta_5 \times AMZN\_low_{it} \\ + \beta_6 \times AMZN\_cl_{it} + \beta_7 \times AMZN\_vol_{it} + \beta_8 \times AMZN\_r_{it} + \beta_9 \times \mathrm{FFR\_var} + \beta_{10} \times INF_{it} + \varepsilon_{it} \end{aligned} \tag{3}$$

$$\begin{aligned} NS_{it} = \alpha + \beta_1 \times NS(-1)_{it} + \beta_2 \times NS(-2)_{it} + \beta_3 \times AAPL\_op_{it} + \beta_4 \times AAPL\_hi_{it} + \beta_5 \times AAPL\_low_{it} \\ + \beta_6 \times AAPL\_cl_{it} + \beta_7 \times AAPL\_vol_{it} + \beta_8 \times AAPL\_r_{it} + \beta_9 \times FFR\_var_{it} + \beta_{10} \times INF_{it} + \varepsilon_{it} \end{aligned} \tag{4}$$

$$\begin{aligned} NS_{it} = \alpha + \beta_1 \times NS(-1)_{it} + \beta_1 \times NS(-2)_{it} + \beta_3 \times C\_op_{it} + \beta_4 \times C\_hi_{it} + \beta_5 \times C\_low_{it} + \beta_6 \times C\_cl_{it} \\ + \beta_7 \times C\_vol_{it} + \beta_8 \times C\_r_{it} + \beta_9 \times FFR\_var_{it} + \beta_{10} \times INF_{it} + \varepsilon_{it} \end{aligned} \tag{5}$$

$$\begin{aligned} NS_{it} = \alpha + \beta_1 \times NS(-1)_{it} + \beta_1 \times NS(-2)_{it} + \beta_3 \times VIX\_op_{it} + \beta_4 \times VIX\_hi_{it} + \beta_5 \times VIX\_low_{it} \\ + \beta_6 \times VIX\_p_{it} + \beta_7 \times VIX\_ch_{it} + + \beta_8 \times FFR\_var_{it} + \beta_9 \times INF_{it} + \varepsilon_{it} \end{aligned} \tag{6}$$

where:

NS = News Sentiment.
α = free coefficient.
$\beta_{1,2,3,4,5,6,7,8,9,10}$ = predictor coefficients.
DJI = Dow Jones Industrial Average Index.
$GOOGL$ = Google Index.
$AMZN$ = Amazon Index.
$AAPL$ = Apple Index.
C = Concordance Index.
VIX = Chicago Board Options Exchange CBOE Volatility Index.
FFR_var = Federal Funds Reserve Rate Variation.
INF = Inflation.
ε = regression error.

Table 3 encompasses the data and variables of the main indicators used in this study. As can be seen, the time period was a daily series from 20 August 2004 to 31 December 2022, for all variables enriched in this study, for the American stock market case. The news sentiment index was downloaded from the Federal Reserve Bank of San Francisco, Daily News Sentiment Index. The Federal Funds Rate and the inflation rate were downloaded from the Federal Reserve Database. The stock market indices were downloaded from the www.stooq.com (accessed on 16 May 2023) database. The return of each index was processed by our own calculations.

Table 3. Data and variables.

Variables	Construction	Sources
	Dependent variables	
News Sentiment (NS)	The methodology of construction of this index is based on Shapiro et al. (2020) [41] and the database is based on Buckman et al. (2020) [42].	https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/, accessed on 16 May 2023
	Independent variables	
DJI Open Price (DJI_op) Google Open Price (GOOGL_op) Amazon Open Price (AMZN_op) Apple Open Price (AAPL_op) C Open Price (C_op) VIX Open Price (VIX_op)	The open price for all the stock market indices: DJI, GOOGL, AMZN, APPL, C, VIX.	www.stooq.com, accessed on 16 May 2023
DJI High Price (DJI_hi) Google High Price (GOOGL_hi) Amazon High Price (AMZN_hi) Apple High Price (AAPL_hi) C High Price (C_hi) VIX High Price (VIX_hi)	The high price for all the stock market indices: DJI, GOOGL, AMZN, APPL, C, VIX.	www.stooq.com, accessed on 16 May 2023
DJI Low Price (DJI_low) Google Low Price (GOOGL_low) Amazon Low Price (AMZN_low) Apple Low Price (AAPL_low) C Low Price (C_low) VIX Low Price (VIX_low)	The low price for all the stock market indices: DJI, GOOGL, AMZN, APPL, C, VIX.	www.stooq.com, accessed on 16 May 2023
DJI Close Price (DJI_cl) Google Close Price (GOOGL_cl) Amazon Close Price (AMZN_cl) Apple Close Price (AAPL_cl) C Close Price (C_cl) VIX Price (VIX_p)	The close price for all the stock market indices: DJI, GOOGL, AMZN, APPL, C, VIX.	www.stooq.com, accessed on 16 May 2023
DJI Volume Price (DJI_vol) Google Volume Price (GOOGL_vol) Amazon Volume Price (AMZN_vol) Apple Volume Price (AAPL_vol) C Volume Price (C_vol)	The volume price for all the stock market indices: DJI, GOOGL, AMZN, APPL, C, VIX.	www.stooq.com, accessed on 16 May 2023
DJI Return (DJI_r) Google Return (GOOGL_r) Amazon Return (AMZN_r) Apple Return (AAPL_r) C Return (C_r) VIX Change Price (VIX_ch)	Return = (close price − close price from the previous day)/open price Change price for VIX.	Own calculation.
	Explanatory variables	
Federal Funds Rate Variation (FFR_var)	Variation = (value n − value n_0)/value n_0 Percentage points.	Federal Reserve database.
Inflation (INF)	Consumer Price Index. Year-over-year percent change.	Federal Reserve database.

4.2. Empirical Results

The regression analysis of the seven models taken into account in this study is presented in Tables 4–10, and the VAR endogenous graph and residuals are in Figures 7–13. The test results show that all seven of the models are significant (R-squared and adjusted

R-squared = 0.99) both for VAR and Bayesian VAR techniques, being validated also by the F test.

Table 4. VAR and Bayesian VAR for Down Jones Industrial Average.

	VAR Estimates			Bayesian VAR Estimates	
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Coefficient**	**Std. Error**
NS (−1)	1.163652	0.01202	96.8304	1.152396	0.01161
NS (−2)	−0.168819	0.01198	−14.0914	−0.157583	0.01157
C	-5.30×10^{-5}	0.00039	−0.13460	-5.23×10^{-5}	0.00039
DJI_op	-3.47×10^{-6}	2.6×10^{-6}	−1.33814	-3.46×10^{-6}	2.6×10^{-6}
DJI_hi	-4.43×10^{-6}	2.2×10^{-6}	−1.97925	-4.51×10^{-6}	2.2×10^{-6}
DJI_low	1.46×10^{-5}	1.9×10^{-6}	7.49530	1.47×10^{-5}	1.9×10^{-6}
DJI_cl	-6.59×10^{-6}	2.4×10^{-6}	−2.80213	-6.64×10^{-6}	2.4×10^{-6}
DJI_vol	3.06×10^{-13}	1.2×10^{-12}	0.24469	2.95×10^{-13}	1.2×10^{-12}
DJI_r	0.049099	0.02728	1.80001	0.049626	0.02728
FFR_var	0.003169	0.00155	2.03804	0.003155	0.00155
INF	7.97×10^{-6}	8.4×10^{-6}	0.09524	7.46×10^{-6}	8.4×10^{-5}
R-Squared: 0.996462 Adjusted R-squared: 0.996457 Prob (F-statistic): 188,550.8 Akaike AIC: −6.006387 Schwarz SC: −5.995215				R-Squared: 0.996461 Adjusted R-squared: 0.996456 Prob (F-statistic): 188,550.8	

Table 5. VAR and Bayesian VAR for Google.

	VAR Estimates			Bayesian VAR Estimates	
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Coefficient**	**Std. Error**
NS (−1)	1.177690	0.01200	98.1611	1.165622	0.01159
NS (−2)	−0.180663	0.01199	−15.0631	−0.168584	0.01158
C	−0.000273	0.00032	−0.86115	−0.000271	0.00032
GOOGL_op	0.000353	0.00048	0.74041	0.000350	0.00048
GOOGL_hi	−0.000968	0.00051	−1.90429	−0.000973	0.00051
GOOGL_low	0.001340	0.00049	2.70961	0.001354	0.00049
GOOGL_cl	−0.000695	0.00048	−1.44860	−0.000701	0.00048
GOOGL_vol	1.12×10^{-12}	1.2×10^{-12}	0.93199	1.11×10^{-12}	1.2×10^{-12}
GOOGL_r	0.026976	0.00848	3.18019	0.027071	0.00848
FFR_var	0.003747	0.00156	2.39793	0.003738	0.00156
INF	-7.68×10^{-5}	9.6×10^{-5}	−0.79964	-7.84×10^{-5}	9.6×10^{-5}
R-Squared: 0.996416 Adjusted R-squared: 0.996411 Prob (F-statistic): 186,042.9 Akaike AIC: −5.993464 Schwarz SC: −5.982288				R-Squared: 0.996415 Adjusted R-squared: 0.996410 Prob (F-statistic): 186,014.6	

Table 6. VAR and Bayesian VAR for Amazon.

	VAR Estimates			Bayesian VAR Estimates	
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Coefficient**	**Std. Error**
NS (−1)	1.178937	0.01202	98.1205	1.166783	0.01161
NS (−2)	−0.181313	0.01201	−15.0930	−0.169147	0.01160
C	0.000257	0.00033	0.79134	0.000264	0.00033
AMZN_op	0.000708	0.00031	2.28082	0.000714	0.00031
AMZN_hi	−0.000593	0.00035	−1.71727	−0.000598	0.00035
AMZN_low	−0.000145	0.00029	−0.49574	−0.000144	0.00029
AMZN_cl	3.60×10^{-5}	0.00030	0.11915	3.33×10^{-5}	0.00030
AMZN_vol	-1.32×10^{-12}	1.7×10^{-12}	−0.78926	-1.36×10^{-12}	1.7×10^{-12}
AMZN_r	0.004738	0.00641	0.73879	0.004861	0.00641
FFR_var	0.003586	0.00156	2.29168	0.003576	0.00156
INF	-8.43×10^{-5}	8.4×10^{-5}	−1.00724	-8.61×10^{-5}	8.4×10^{-5}
R-Squared: 0.996406 Adjusted R-squared: 0.996400 Prob (F-statistic): 185,573.4 Akaike AIC: −5.990582 Schwarz SC: −5.979409				R-Squared: 0.996405 Adjusted R-squared: 0.996400 Prob (F-statistic): 185,544.9	

Table 7. VAR and Bayesian VAR for Apple.

	VAR Estimates			Bayesian VAR Estimates	
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Coefficient**	**Std. Error**
NS (−1)	1.175910	0.01200	97.9977	1.163969	0.01159
NS (−2)	−0.178680	0.01200	−14.8933	−0.166725	0.01159
C	0.000205	0.00032	0.63402	0.000208	0.00032
APPL_op	0.001176	0.00038	3.09220	0.001184	0.00038
APPL_hi	−0.001714	0.00042	−4.12533	−0.001727	0.00042
APPL_low	0.00232	0.00036	0.64637	0.000236	0.00036
APPL_cl	0.000328	0.00036	0.90507	0.000330	0.00036
APPL_vol	-4.13×10^{-13}	4.3×10^{-13}	−0.96770	-4.16×10^{-13}	4.3×10^{-13}
APPL_r	0.023721	0.00820	2.89151	0.024024	0.00820
FFR_var	0.003787	0.00156	2.42305	0.003780	0.00156
INF	-5.85×10^{-5}	0.00010	−0.57768	-6.11×10^{-5}	0.00010
R-Squared: 0.996421 Adjusted R-squared: 0.996415 Prob (F-statistic): 186,380.7 Akaike AIC: −5.994852 Schwarz SC: −5.983681				R-Squared: 0.996420 Adjusted R-squared: 0.996415 Prob (F-statistic): 186,352.9	

Table 8. VAR and Bayesian VAR for eBay.

	VAR Estimates			Bayesian VAR Estimates	
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Coefficient**	**Std. Error**
NS (−1)	1.179314	0.01201	98.2134	1.167135	0.01160
NS (−2)	−0.181969	0.01200	−15.1597	−0.169780	0.01159
C	−0.000379	0.00050	−0.76087	−0.000385	0.00050
EBAY_op	−0.000813	0.00072	−1.12230	−0.000809	0.00072
EBAY_hi	−0.000506	0.00076	−0.66517	−0.000516	0.00076
EBAY_low	0.001933	0.00082	2.36813	0.001941	0.00082
EBAY_cl	−0.000567	0.00079	−0.71527	−0.000568	0.00079
EBAY_vol	5.51×10^{-12}	8.7×10^{-12}	0.63066	5.62×10^{-12}	8.7×10^{-12}
EBAY_r	−0.002245	0.00909	−0.24686	−0.002243	0.00909
FFR_var	0.003529	0.00156	2.25650	0.003520	0.00156
INF	−0.000107	8.4×10^{-5}	−1.28489	−0.000110	8.4×10^{-5}
R-Squared: 0.996406 Adjusted R-squared: 0.996401 Prob (F-statistic): 185,609.4 Akaike AIC: −5.990758 Schwarz SC: −5.979585				R-Squared: 0.996406 Adjusted R-squared: 0.996401 Prob (F-statistic): 185,580.7	

Table 9. VAR and Bayesian VAR for C.

	VAR Estimates			Bayesian VAR Estimates	
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Coefficient**	**Std. Error**
NS (−1)	1.177807	0.01201	98.0878	1.165644	0.01160
NS (−2)	−0.182348	0.01200	−15.2018	−0.170175	0.01159
C	0.000581	0.00038	1.52706	0.000592	0.00038
C_op	0.000135	0.00012	1.16126	0.000134	0.00012
C_hi	−0.000237	0.00011	−2.13100	−0.000237	0.00011
C_low	0.000215	0.00012	1.78050	0.000217	0.00012
C_cl	−0.000108	0.00013	−0.83254	−0.000109	0.00013
C_vol	-1.43×10^{-11}	7.0×10^{-11}	−2.03519	-1.44×10^{-11}	7.0×10^{-12}
C_r	0.001564	0.00563	0.27797	0.001597	0.00563
FFR_var	0.003672	0.00156	2.34806	0.003662	0.00156
INF	−0.000129	7.8×10^{-5}	−1.65558	−0.000131	7.8×10^{-5}
R-Squared: 0.996416 Adjusted R-squared: 0.996411 Prob (F-statistic): 185,962.4 Akaike AIC: −5.992932 Schwarz SC: −5.981751				R-Squared: 0.996415 Adjusted R-squared: 0.996410 Prob (F-statistic): 185,933.7	

Table 10. VAR and Bayesian VAR for VIX.

	VAR Estimates			Bayesian VAR Estimates	
Variables	**Coefficient**	**Std. Error**	**t-Statistic**	**Coefficient**	**Std. Error**
NS (−1)	1.67224	0.01200	97.2460	1.155662	0.01160
NS (−2)	−0.174427	0.01196	−14.5820	−0.162878	0.01156
C	0.002945	0.00051	5.76590	0.002962	0.00051
VIX_p	0.000459	0.000222	2.11569	0.000455	0.00022
VIX_op	−0.000191	0.00019	−0.98205	−0.000189	0.00019
VIX_hi	−0.000673	0.00016	−4.18861	−0.000680	0.00016
VIX_low	0.000306	0.00021	1.43700	0.000314	0.00021
VIX_ch	−0.006745	0.00294	−2.29529	−0.006635	0.00294
FFR_var	0.002796	0.00156	1.79824	0.002782	0.002782
INF	-5.71×10^{-5}	7.5×10^{-5}	−0.76489	-5.85×10^{-5}	7.5×10^{-5}
R-Squared: 0.996460 Adjusted R-squared: 0.996455 Prob (F-statistic): 209,369.0 Akaike AIC: −6.005934 Schwarz SC: −5.995775				R-Squared: 0.996460 Adjusted R-squared: 0.996455 Prob (F-statistic): 209,339.8	

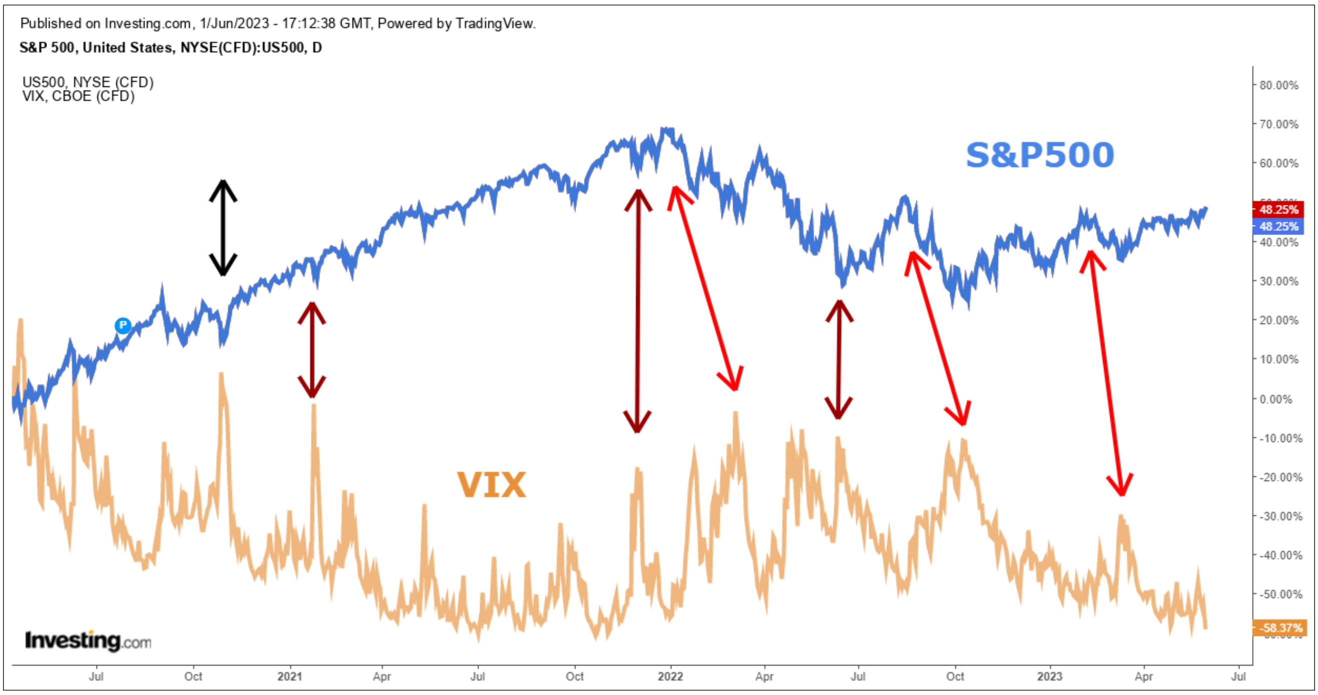

Figure 7. VIX vs. S&P500 (percentage chart). Source: www.investing.com, accessed on 16 May 2023.

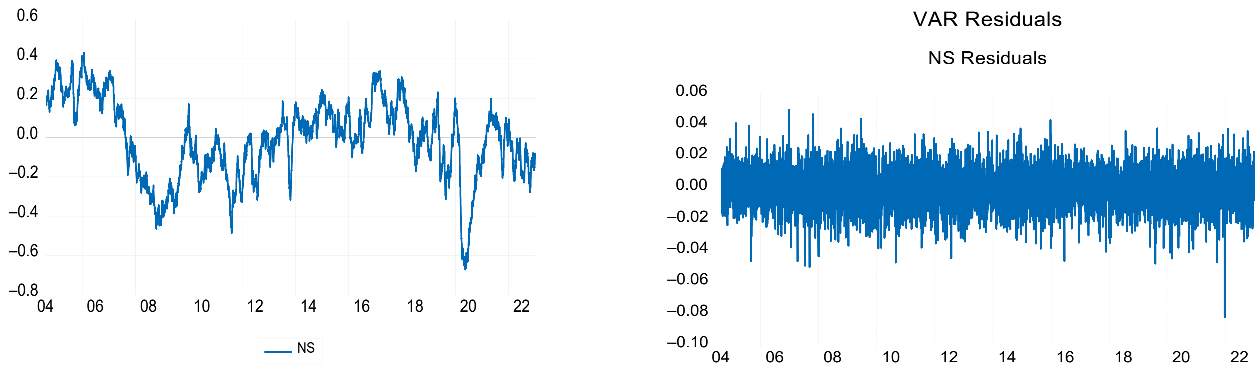

Figure 8. VAR endogenous graph and residuals for Dow Jones Industrial Average.

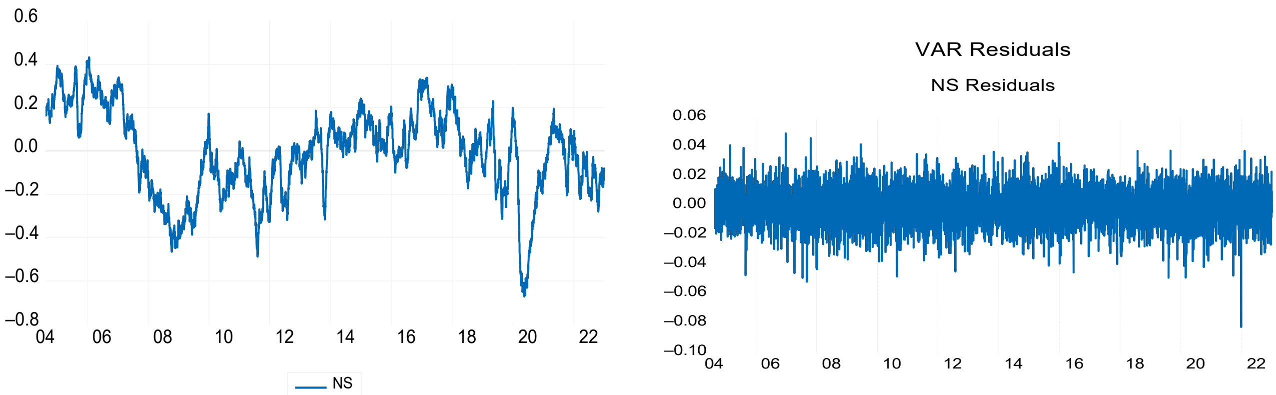

Figure 9. VAR endogenous graph and residuals for Google.

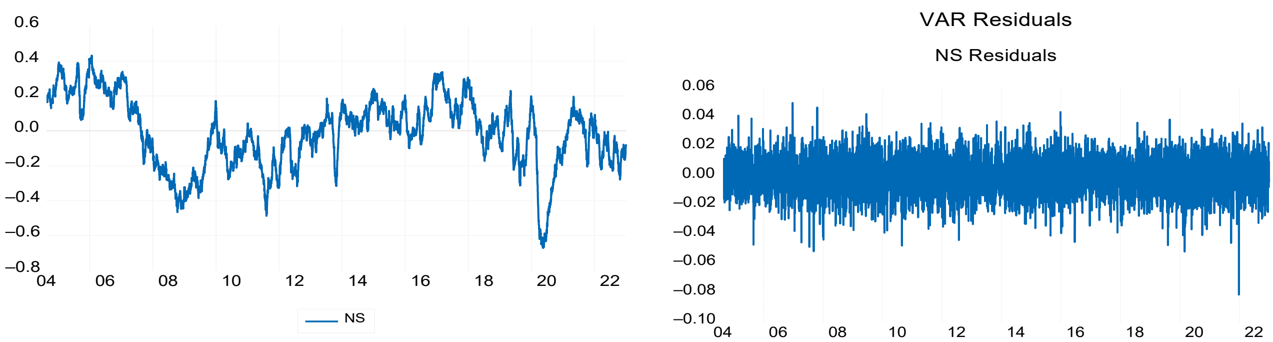

Figure 10. VAR endogenous graph and residuals for Amazon.

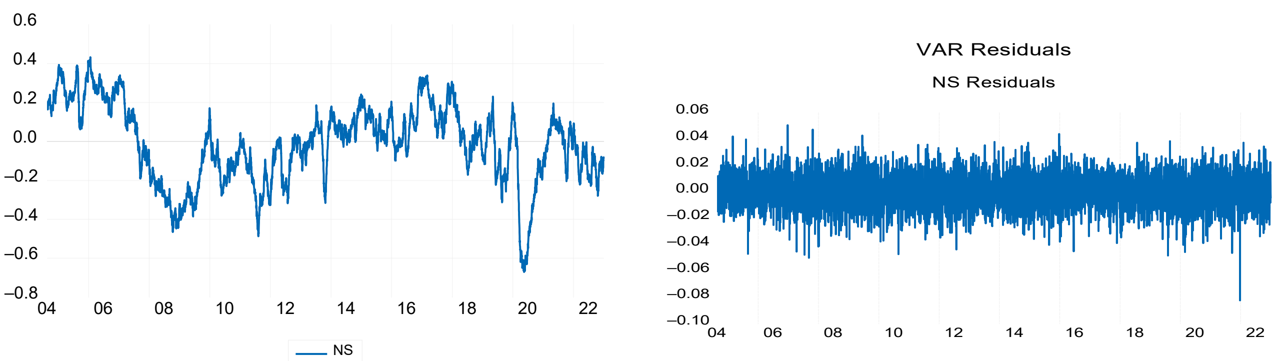

Figure 11. VAR endogenous graph and residuals for Apple.

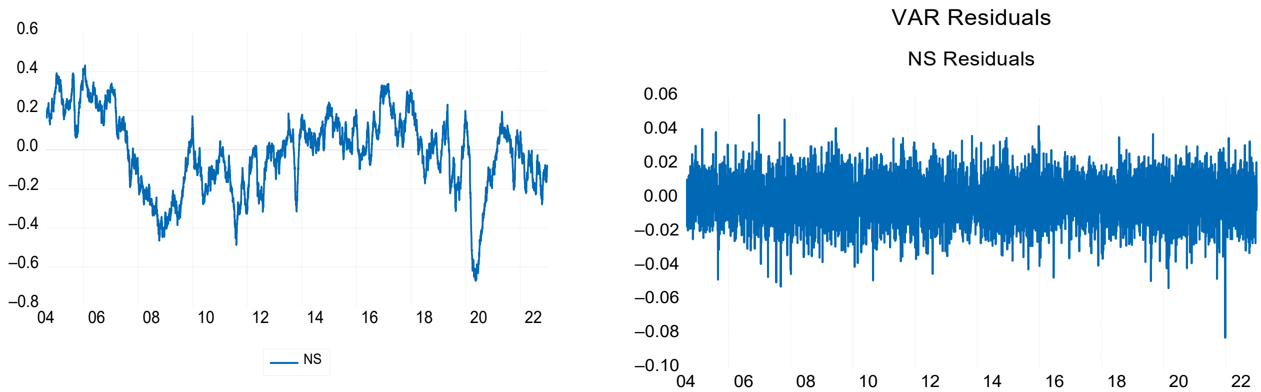

Figure 12. VAR endogenous graph and residuals for eBay.

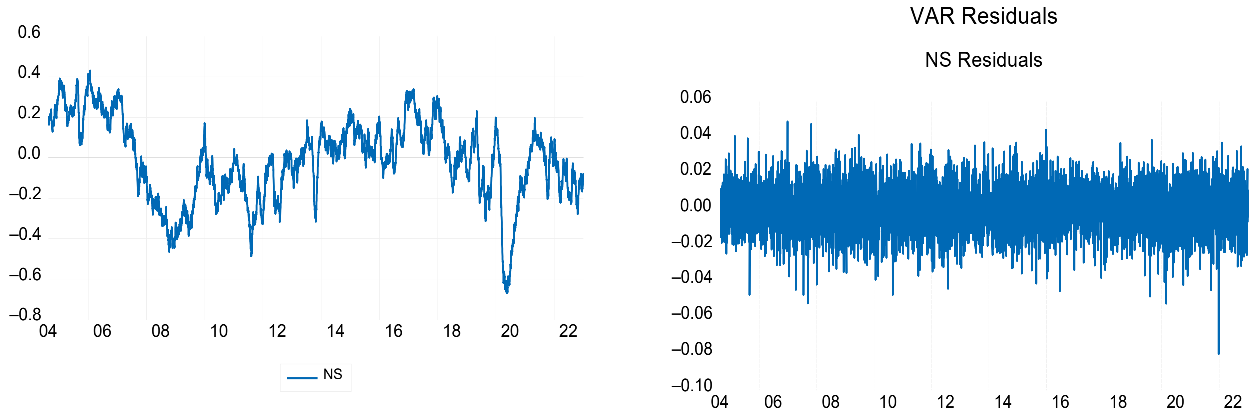

Figure 13. VAR endogenous graph and residuals for C.

Table 4 presents the empirical results of the VAR and Bayesian VAR methods. The empirical results for the Dow Jones Industrial Average show that there is a positive correlation between the news sentiment index and DJI low price, volume, DJI return, the variation of Federal Reserve Funds Rate and inflation rate, and a negative correlation with the other variables both for VAR and Bayesian VAR techniques.

Table 5 reveals the econometric results for the Google index with an interesting insight: the news sentiment index is negatively correlated with Google's high price, Google close price, and inflation rate, meanwhile, a positive correlation of the news sentiment index with the other variables can be observed.

In Table 6 the empirical results of the study regarding the Amazon index are presented with the following remarks: the news sentiment index is negatively correlated with Amazon's high price, low price, and volume price as well as with inflation; meanwhile, with the other variables, the news sentiment index has a positive correlation.

Table 7 encounters the empirical results for the Apple index with the following directions: the news sentiment index has a positive correlation with Apple's open price, low price, close price, return, and Federal Reserve Funds Rate variation and a negative one with Apple's high price, volume and inflation.

The empirical results presented in Table 8 for the eBay index reveal a positive correlation of the news sentiment index with eBay's low price, volume, and Federal Reserve Funds Rate variation, and a significant negative correlation with eBay's open price, high price, close price, return, and inflation.

The case study for the C index enriched in Table 9 reveals a significant positive correlation between the news sentiment index and C's open price, low price, return, and Federal Reserve Funds Rate, and a negative correlation with C's high price, close price, volume, and inflation.

Table 10 highlights the empirical results for the VIX index in the following register: the news sentiment index is positively correlated with VIX's price, low price, and Federal Reserve Funds Rate; meanwhile, it is negatively correlated with VIX's open price, high price, change, and inflation (Figure 14).

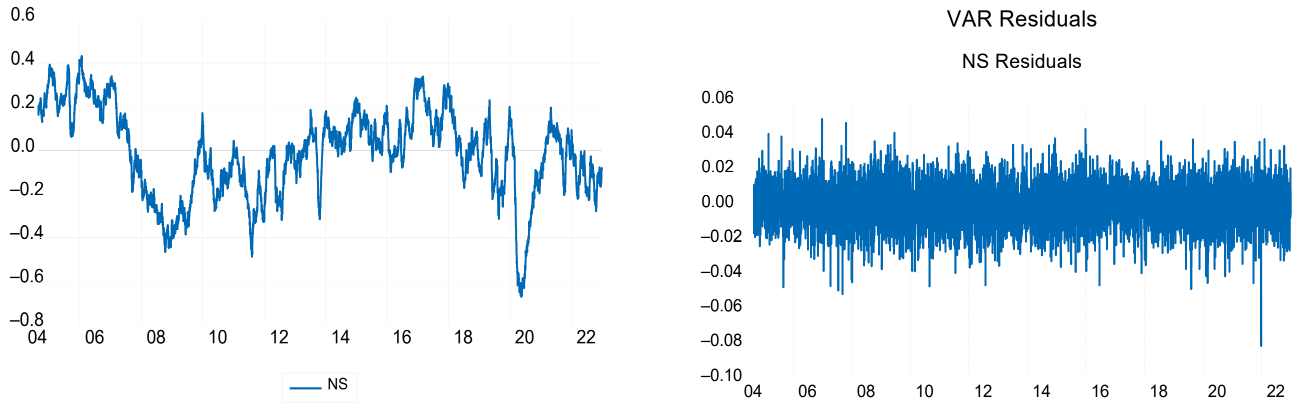

Figure 14. VAR endogenous graph and residuals for VIX.

4.3. Correlation Analysis for the Variables

In order to test the correlation between variables Figure 15 and Appendix A present the analysis outcomes regarding this correlation type between variables. In this study, we consider Evan's (1996) [43] scale for the absolute value of r: 0.00–0.19 "very weak", 0.20–0.39 "weak", 0.40–0.59 "moderate", 0.60–0.79 "strong", 0.80–1.0 "very strong". Moreover, the probability using the Pearson correlation coefficient was used with a scale of −1 for negative correlation, 0 for no correlation, and 1 for positive correlation.

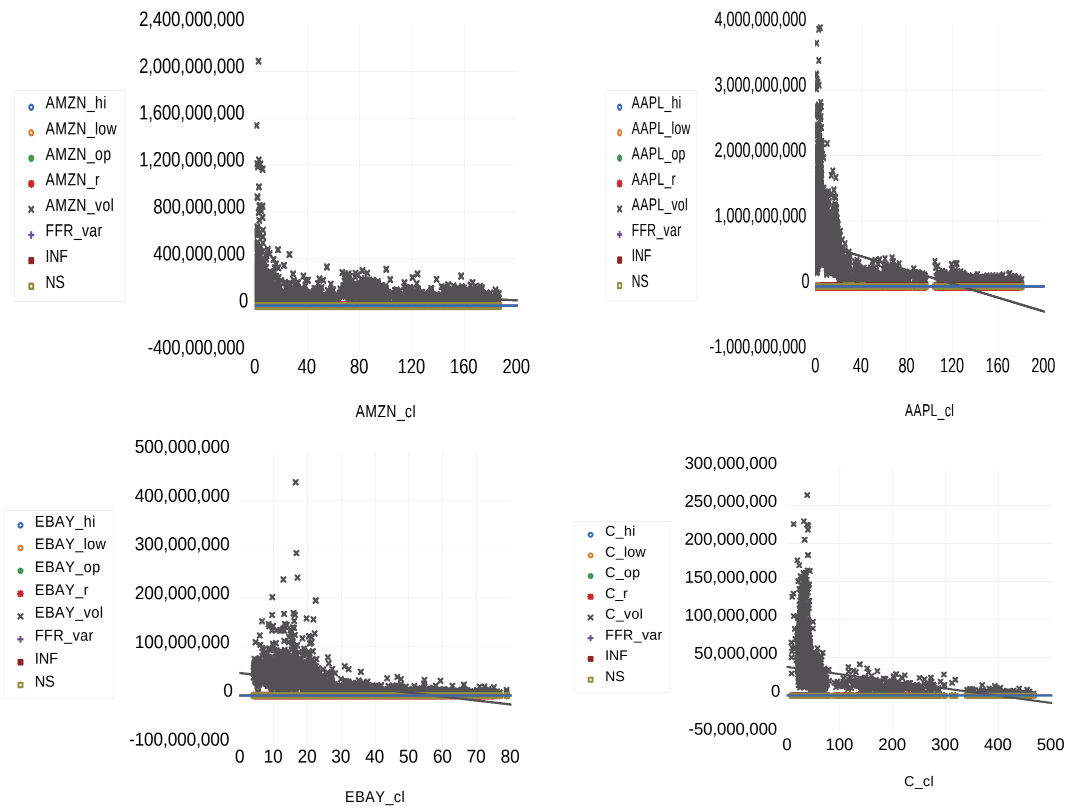

Figure 15. *Cont.*

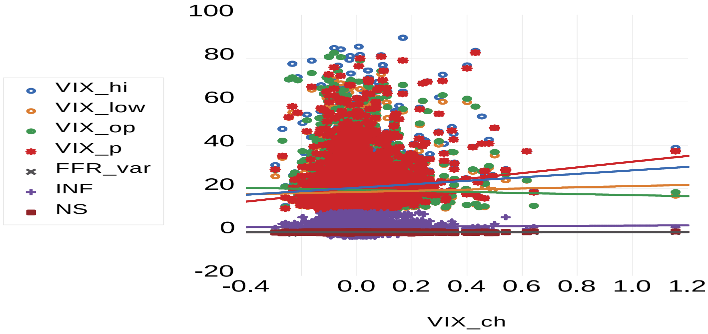

Figure 15. Scatter plots graphs regarding the correlation between variables.

In the first subfigure of Figure 15 and Appendix A.1 (DJI), the following results can be observed: regarding the r value one can observe a high correlation between HI, LOW, and OPEN prices; a moderate correlation for VOL and INF; and a lower correlation for return, FFR, and news sentiment. As for the probability, for all variables, there are minimum levels except for the return and FFR where a medium level of correlation can be identified.

In the second subfigure of Figure 15 and Appendix A.2 (GOOGL), for the r value a high correlation can be identified between HI, LOW, and OP prices; a moderate correlation between VOL and INF; and a low correlation between returns, FFR, and news sentiment index. The values of the probability highlight minimum levels for all variables except for returns and FFR.

From the third subfigure of Figure 15 and Appendix A.3 (AMZN), from the r values it can be seen that the variables with a high degree of correlation are HI, LOW, and OP, meanwhile with a lower degree of correlation are returns, VOL, FFR, INF, and news sentiment index. Regarding the probability, it can be observed that all the variables register no correlations between them, except in the case of returns.

The fourth subgraph of Figure 15 and Appendix A.4 (AAPL) reveals that the r values show a high degree of correlation for HI, LOW, and OP, a medium degree of correlation for VOL and INF, and a small degree of correlation for returns, FFR, and news sentiment index. The probability values show that all variables have no significant correlation, except for returns and FFR.

The fifth subgraph of Figure 15 and Appendix A.5 (eBay) shows that the r values suggest a high degree of correlation with HI, LOW, and OP; a medium level for VOL; and lower levels for returns, FFR, INF, and news sentiment index. Regarding the probability values, some high-degree correlations exist between variables such as HI, LOW, OP, VOL, and INF and medium correlation for news sentiment index and returns.

In the sixth subgraph of Figure 15 and Appendix A.6 (C), from the r values it can be observed that there is a high degree of correlation for HI, LOW, and OP; a medium correlation degree for VOL and news sentiment index; and a small correlation degree for returns, FFR and INF. The probability values show that all variables have no correlation except in the case for returns and FFR.

The last subgraph of Figure 15 and Appendix A.7 (VIX) highlights that the r values register a high correlation of LOW, OP, and P, meanwhile the other variables that can be identified low level of correlation. Regarding the probability values, they suggest a medium correlation level for FFR and INF, meanwhile, for the other variables small levels of correlation can be identified.

5. Discussion and Recommendations

According to the press (seekingalpha.com/article/4230982-algo-trading-dominates-80-percent-of-stock-market, accessed on 16 May 2023), 80% of transactions in the USA are made by computers: the so-called algorithmic *trading*. However, the human element is decisive: programs are written by people, decisions about the applicable algorithm are made by people, and starting or stopping the scriptures is made by people. Additionally, people are human, with knowledge but also with feelings, preconceptions, attitudes, and subjective decisions. We do not doubt that stock market trends are mostly behavioral.

Muhammad (2022) [44] using panel regression and the two-stage least squares methods researched the impact of investor behavior on returns, cash flows, and discount rates, and found a positive and significant impact of investor sentiment over the nonfinancial firms' performance in Pakistan.

Karavias et al. (2020) [45] investigated the investor sentiment on share price deviations of the FTSE 100 price index using a threshold panel data model and proved that investor sentiment influences share prices, dividend-to-price ratio, and earnings-to-price ratio. Bilel and Mondher (2022) [46] confirmed the negative correlation between investors' negative sentiment and their demand for dividends.

Amin and Harris (2022) [47] give some insights regarding investor sentiment in the case of donations to nonprofit organizations and found that high investor sentiment decreases stock-based donations and increases cash-based donations.

Wu et al. (2022) [48] agreed that multiple data and investor sentiment give a better prediction of stock prices. Additionally, Swathi et al. (2022) [49] showed that sentiment analysis of Twitter data improves the accuracy of price predictions. Khan et al. (2020) [50] found that the prediction of the trends of Google, Microsoft, and Apple stocks using machine learning algorithms is better if it considered the sentiment and political situation. Similar results were obtained by Kaplan et al. (2023) [51], who established that external knowledge and investor sentiment better predict the price movements in the crude oil market.

On the other hand, Qi et al. (2022) [52] confirmed that economic policy uncertainty has a negative influence on investor sentiment and financial stability in China, and Wang et al. (2022) [53] established that the Chinese stock market liquidity is influenced by air quality and pollution through investors emotions using multiple linear regression models.

However, we have great doubts about measuring the feelings of market participants. John Naisbitt determined the 10 megatrends in the American media, being sure that the information on which he relied was correct [54]. Why would we now think otherwise? Because it seems obvious to us that the information disseminated to the public is subjective and targeted.

1. Elon Musk is publicly accused of market manipulation through public intelligence sources: "According to Reuters, investors are claiming (opens in a new tab) that Musk used his influence on Twitter, TV appearances, and paid online influencers to trade profitably at the expense of other investors (mashable.com/article/elon-musk-dogecoin-lawsuit, accessed on 16 May 2023)".
2. The chaos created in social media on the subject of the pandemic.
3. All, but absolutely all of the press is partisan about the war in Ukraine—either on one side or the other, but we do not know any objective, equidistant source.
4. Banning Donald Trump on some social media during the election campaign.
5. Questionnaires (if used) are often ambiguous, and unclear, some even put in a certain direction.

Numerous instances substantiate the fact that the press is subject to censorship and significant influence from the proprietors of news broadcasting entities and social media networks.

With the advancement of OpenAI, an even more pronounced peril arises: the proliferation of a multitude of news articles, analyses, and reports that exhibit a deliberate inclination towards specific conclusions, despite their outward appearance of objectivity. This "information" can be swiftly disseminated, with its outcomes seamlessly integrated into councils, pools, and recommendations.

Apart from arbitrageurs, individuals engaged in the capital market are rarely indifferent, purely objective, or strictly rational in their market analyses. It is worth noting that we, as influencers ourselves, also fall into this category.

The potential for manipulation, particularly among the large cohort of investors, is feasible and can be orchestrated by a select few press conglomerates, influencers, and opinion leaders. Addressing this influential power and finding effective means of prevention poses a significant challenge.

Nonetheless, we can offer a recommendation to investors: regardless of their alignment with trends instigated by the majority of analysts, it is advisable not to oppose but rather to capitalize on the sentiments and behaviors exhibited by the herd. In other words, when conducting a top-down analysis that encompasses the examination of the macroeconomic landscape, it is worthwhile to incorporate sentiment indicators. While these indicators may not be flawless, they serve as a valuable gauge of *Homo Economicus Humanus* (https://economy-finance.ec.europa.eu/economic-forecast-and-surveys/business-and-consumer-surveys/latest-business-and-consumer-surveys_en, accessed on 16 May 2023).

6. Conclusions

Conducting a behavioral study pertaining to the stock market presents challenges, primarily due to the impracticality of simultaneously capturing the thoughts and perceptions of all participants or a representative sample at any given moment, thereby hindering the identification of behavioral patterns and subjective biases.

However, one potential approach involves comprehensive data collection: encompassing not only executed transactions but also all orders placed within the market, including those that were not performed or subsequently withdrawn. By employing statistical techniques on extensive databases through data mining, it becomes possible to discern and validate behavioral patterns exhibited during various market phases, such as trending, trading, overheating, and panic. This scientific methodology allows for a comparative analysis of investors' and speculators' behaviors during pivotal moments, as opposed to periods characterized by stability or momentum. Naturally, such research necessitates an immense volume of data and specialized pattern-searching methodologies. Nonetheless, in our perspective, it represents the sole concrete means by which stock market behaviors can be objectively studied.

The European Commission publishes a monthly confidence index, ESI3. As can be seen, it does not precede either falls or rebounds, so it is not very useful for investors.

In fact, the best indicator of sentiment remains the opinions of brokers, who from experience immediately notice whether the market and participants are agitated, panicky, super optimistic, or calm. Under GDPR conditions, it is difficult to initiate such research, but with postponed results (surveys conducted on time but verified and published after a reasonable time interval) such an approach can be conceived.

The econometrical results enriched in the quantitative part of this study reveal the fact that there is a strong significant correlation between news sentiment indices, technical analysis, and the stock market. The empirical part of this study highlights the linkages which manifest between the developments of the US stock market indices DJI, Google, Amazon, Apple, eBay, C, and VIX, the news sentiment index, and technical analysis.

The primary contribution of this paper lies in emphasizing the necessity of considering the dynamics of news sentiment indexes, the temporal patterns of the US stock market agenda, and the application of technical analysis tools within the domain of the stock market.

The limitations of this research encompass several aspects, including the restricted duration of the time interval examined, the exclusive focus on a single country for analysis, the utilization of a sole sentiment index from the multitude of available indexes in the stock market domain, and the imperative for further advancements in the realm of technical analysis for future research endeavors.

Future studies will persist in evaluating and assessing the most comprehensive news sentiment indexes accessible globally. It will be interesting, in future studies, to use the news sentiment index in order to determine future market returns. Moreover, there is a need to conduct analyses specifically targeted at the European stock market, while also expanding the exploration of the correlations between news sentiment indexes, technical analysis, and the evolution of the stock market, including the Asian stock market.

Author Contributions: F.C.D. is responsible for the project administration; F.C.D. has designed the research methodology and the econometric modeling technique construction and results interpretation; F.T. has developed the impact of sentiment indexes on the technical analysis section; F.T. and Ș.A.N. constructed the database; Ș.A.N. wrote the introduction section; F.C.D., F.T. and Ș.A.N. constructed the discussion and recommendation; Ș.A.N., C.B. and M.B. are responsible for the literature review section; F.C.D. and F.T. developed the conclusions section; C.B. was responsible for the English supervision of the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Acknowledgments: The authors thank the anonymous reviewers and editor for their valuable contribution.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Appendix A.1. DJI

Correlation Probability	DJI_CL	DJI_HI	DJI_LOW	DJI_OP	DJI_R	DJI_VOL	FFR_VAR	NS	INF
DJI_CL	1.0000								

DJI_HI	0.9998	1.0000							
	0.0000	-------							
DJI_LOW	0.9998	0.9997	1.0000						
	0.0000	0.0000	-------						
DJI_OP	0.9997	0.9998	0.9998	1.0000					
	0.0000	0.0000	0.0000	-------					
DJI_R	0.0204	0.0093	0.0116	0.0002	1.0000				
	0.0939	0.4445	0.3395	0.9844	------				
DJI_VOL	0.4140	0.4188	0.4102	0.4157	−0.0440	1.0000			
	0.0000	0.0000	0.0000	0.0000	0.0003	------			
FFR_VAR	0.0212	0.0213	0.0219	0.0217	−0.0396	−0.0112	1.0000		
	0.0824	0.0810	0.0722	0.0747	0.0012	0.3560	------		
NS	−0.0358	−0.0395	−0.0314	−0.0356	−0.1891	−0.1641	0.01636	1.0000	
	0.0033	0.0012	0.0100	0.0035	0.1199	0.0000	0.1802	------	
INF	0.4114	0.4129	0.4104	0.4118	−0.0284	0.2964	0.0255	0.0580	1.0000
	0.0000	0.0000	0.0000	0.000	0.0197	0.0000	0.0364	0.0000	------

Appendix A.2. GOOGL

Correlation Probability	GOOGL_CL	GOOGL_HI	GOOGL_LOW	GOOGL_OP	GOOGL_R	GOOGL_VOL	FFR_VAR	NS	INF
GOOGL_CL	1.000								

GOOGL_HI	0.9998	1.0000							
	0.0000	-------							
GOOGL_LOW	0.9998	0.9998	1.0000						
	0.0000	0.0000	-------						
GOOGL_R	−0.0123	−0.0185	−0.0176	1.0000					
	0.3124	0.1299	0.1478	-------					
GOOGL_OP	0.9997	0.9999	0.9998	−0.0231	1.0000				
	0.0000	0.0000	0.0000	0.0580	------				
GOOGL_VOL	−0.4504	−0.4489	−0.4516	0.0703	−0.4499	1.0000			
	0.0000	0.0000	0.0000	0.0000	0.0000	------			
INF	0.4936	0.4954	0.4925	−0.0385	0.4942	0.0976	1.0000		
	0.0000	0.0000	0.0000	0.0016	0.0000	0.0000	------		
NS	−0.1028	−0.1043	−0.1010	−0.0006	−0.1025	0.1958	0.0577	1.0000	
	0.0000	0.0000	0.0000	0.9571	0.0000	0.0000	0.0000	------	
FFR_VAR	0.0270	0.0269	0.0268	−0.0124	0.0266	−0.0140	0.0255	0.0163	1.0000
	0.0267	0.0275	0.0276	0.3072	0.0289	0.2502	0.0365	0.1807	------

Appendix A.3. AMZN

Correlation Probability	AMZN_CL	AMZN_HI	AMZN_LOW	AMZN_OP	AMZN_R	AMZN_VOL	FFR_VAR	INF	NS
AMZN_CL	1.000								

AMZN_HI	0.9998	1.0000							
	0.0000	-------							
AMZN_LOW	0.9998	0.9998	1.0000						
	0.0000	0.0000	-------						
AMZN_OP	0.9997	0.9999	0.9998	1.0000					
	0.0000	0.0000	0.0000	-------					
AMZN_R	−0.0146	−0.0195	−0.0188	−0.0233	1.0000				
	0.2315	0.1094	0.1219	0.0555	------				
AMZN_VOL	−0.2319	−0.2300	−0.2338	−0.2316	0.1257	1.0000			
	0.0000	0.0000	0.0000	0.0000	0.0000	------			
FFR_VAR	0.0162	0.0160	0.0164	0.0160	0.0090	−0.0155	1.0000		
	0.1832	0.1893	0.1779	0.1894	0.4609	0.2026	------		
INF	0.3616	0.3635	0.3603	0.3618	−0.0529	−0.0085	0.0255	1.0000	
	0.0000	0.0000	0.0000	0.0000	0.0000	0.4841	0.0364	------	
NS	−0.1788	−0.1799	−0.1772	−0.1785	−0.0209	−0.0520	0.0163	0.0579	1.0000
	0.0000	0.0000	0.0000	0.0000	0.0870	0.0000	0.1804	0.0000	------

Appendix A.4. AAPL

Correlation Probability	AAPL_CL	AAPL_HI	AAPL_LOW	AAPL_OP	AAPL_R	AAPL_VOL	FFR_VAR	INF	NS
AAPL_CL	1.000								

AAPL_HI	0.9998	1.0000							
	0.0000	-------							
AAP_LOW	0.9998	0.9998	1.0000						
	0.0000	0.0000	-------						
AAPL_OP	0.9997	0.9999	0.9998	1.0000					
	0.0000	0.0000	0.0000	-------					
AAPL_R	−0.0057	−0.0114	−0.0107	−0.0152	1.0000				
	0.6389	0.3487	0.3777	0.2103	------				
AAPL_VOL	−0.5173	−0.5161	−0.5185	−0.5171	0.0017	1.0000			
	0.0000	0.0000	0.0000	0.0000	0.8842	------			
FFR_VAR	0.0270	0.0269	0.0270	0.0268	−0.0401	−0.0182	1.0000		
	0.0265	0.0274	0.0267	0.0279	0.0010	0.1356	------		
INF	0.5353	0.5357	0.5350	0.5351	−0.0211	0.0273	0.0255	1.0000	
	0.0000	0.0000	0.0000	0.0000	0.0840	0.0249	0.0364	------	
NS	−0.1678	−0.1687	−0.1664	−0.1675	−0.0027	−0.0284	0.0163	0.0580	1.0000
	0.0000	0.0000	0.0000	0.0000	0.8189	0.0197	0.1802	0.0000	------

Appendix A.5. eBay

Correlation Probability	eBay_CL	eBay_HI	eBay_LOW	eBay_OP	eBay_R	eBay_VOL	FFR_VAR	INF	NS
eBay_CL	1.000								
	-------								
eBay_HI	0.9997	1.0000							
	0.0000	-------							
eBay_LOW	0.9997	0.9997	1.0000						
	0.0000	0.0000	-------						
eBay_OP	0.9994	0.9997	0.9997	1.0000					
	0.0000	0.0000	0.000	-------					
eBay_R	0.0035	−0.0006	−0.0006	−0.017	1.0000				
	0.7722	0.6044	0.5807	0.1621	------				
eBay_VOL	−0.5650	−0.5618	−0.5678	−0.5645	0.0211	1.0000			
	0.0000	0.0000	0.0000	0.0000	0.0833	------			
FFR_VAR	0.0225	0.0224	0.0225	0.0223	0.0014	−0.011	1.0000		
	0.0646	0.0665	0.0647	0.0672	0.9037	0.3487	------		
INF	0.3808	0.3836	0.3793	0.3817	−0.0411	−0.1011	0.0255	1.0000	
	0.0000	0.0000	0.0000	0.0000	0.0008	0.0000	0.0364	------	
NS	0.0071	0.0053	0.0098	0.0081	−0.0446	0.0536	0.0163	0.0579	1.0000
	0.5593	0.6601	0.4211	0.5071	0.0003	0.0000	0.1803	0.0000	------

Appendix A.6. C

Correlation Probability	C_CL	C_HI	C_LOW	C_OP	C_R	C_VOL	FFR_VAR	INF	NS
C_CL		1.000							

C_HI	0.9998	1.0000							
	0.0000	-------							
C_LOW	0.9999	0.9997	1.0000						
	0.0000	0.0000	-------						
C_OP	0.9998	0.9998	0.9998	1.0000					
	0.0000	0.0000	0.0000	-------					
C_R	−0.0012	−0.0067	−0.0056	−0.0104	1.0000				
	0.9165	0.5788	0.6443	0.3945	------				
C_VOL	−0.5100	−0.5089	−0.5109	−0.5095	−0.0039	1.0000			
	0.0000	0.0000	0.0000	0.0000	0.7493	------			
FFR_VAR	−0.0162	−0.0161	−0.0159	−0.0160	−0.0244	0.0038	1.0000		
	0.1848	0.1862	0.1925	0.1882	0.0456	0.7552	------		
INF	0.2129	0.2140	0.2120	0.2129	−0.0158	−0.2340	0.0257	1.0000	
	0.0000	0.0000	0.0000	0.0000	0.1950	0.0000	0.0350	------	
NS	0.4824	0.4784	0.4858	0.4816	0.0092	−0.3981	0.0164	0.0575	1.0000
	0.0000	0.0000	0.0000	0.0000	0.4479	0.0000	0.1782	0.0000	------

Appendix A.7. VIX

Correlation Probability	VIX_CH	VIX_HI	VIX_LOW	VIX_OP	VIX_P	FFR_VAR	INF	NS
VIX_CH	1.000							

VIX_HI	0.0635	1.0000						
	0.0000	-------						
VIX_LOW	0.0249	0.9876	1.0000					
	0.0411	0.0000	-------					
VIX_OP	−0.0207	0.9893	0.9932	1.0000				
	0.0899	0.0000	0.0000	-------				
VIX_P	0.1128	0.9926	0.9908	0.9843	1.0000			
	0.0000	0.0000	0.0000	0.0000	------			
FFR_VAR	0.0083	−0.0352	−0.0306	−0.0357	−0.0300	1.0000		
	0.4945	0.0038	0.0122	0.0034	0.0140	------		
INF	0.0186	0.0025	−0.0030	−0.0021	−0.0003	0.0256	1.0000	
	0.1275	0.8316	0.8045	0.8582	0.9784	0.0361	------	
NS	0.0300	−0.6806	−0.7045	−0.6963	−0.6892	0.0163	0.0579	1.0000
	0.0140	0.0000	0.0000	0.0000	0.0000	0.1796	0.0000	------

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