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Affect Indicators for Stock Market Forecasting

Abstract

In behavioural economics, Big Social Data plays a crucial role in predicting stock market trends. This study aims to compare the effectiveness of the VAR model and the LSTM neural network in forecasting the relationship between social media and stock markets. Two hypotheses guide this work: first, verifying a statistically significant link between Twitter (X) activity and stock market metrics, and second, assessing the relative accuracy of the methods. Sentiment analysis, using both lexicon-based (VADER, NRC) and supervised learning (Naïve Bayes), was applied to construct affective indicators from textual data. Findings suggest that Twitter activity holds predictive value for trading volume and closing prices, though effects vary across timeframes and methods. Both VAR and LSTM yield stable insights over shorter periods. This analysis, focused on Apple and Amazon during 2016–2017, contributes to methodological advancements in exploring social media's impact on financial markets.

Keywords

behavioural economics | VAR | LSTM | sentiment analysis | NLP

JEL Codes

C32, C45,G17

1. Introduction

The Efficient Market Hypothesis (EMH) posits that financial markets are efficient, with asset prices reflecting all available information (Fama, 1970). Yet, the exponential growth of social media has transformed how information is produced, disseminated, and absorbed (Michalak & Kruszewski, 2021). In ultra-high-frequency information environments, investors often face challenges in gathering and processing sufficient information within short time frames to make fully rational decisions consistent with EMH. Platforms such as Twitter generate real-time streams of market-relevant signals but also amplify noise and emotional content (Michalak, 2024b). This raises a critical question: can markets remain efficient when investors face unprecedented volumes of unstructured, emotionally charged information?

Behavioural and psychological research shows that cognitive overload and emotional cause strongly shape decision-making. Leading investors to rely on heuristics rather than rational evaluation (Ekman & Davidson, 2002; Thaler, 2015). Emotions such as fear, anger, or optimism can spread rapidly through digital networks, influencing collective sentiment and triggering market reactions. Social media thus functions not only as a channel of information but as a driver of sentiment shocks that challenge rational market dynamics (Ekman, 1972; Ekman & Davidson, 2002; Thaler, 2015; Michalak & Kruszewski, 2021).

A growing body of research has linked online sentiment to stock market movements (Bollen et al., 2011; Fischer & Krauss, 2018). However, several limitations persist. Most studies employ either traditional econometric models or machine learning approaches in isolation, leaving their comparative strengths unclear (Mao et al, 2012; Aldridge, 2017; Nagle & Gibbons, 2018; Petrescu & Gherghina, 2020; Ranjan et al., 2021; Dissanayake et al., 2021; Katsafados et al., 2022). In addition, few analyses tweets for multiple sentiment dimensions or test how different modelling frameworks capture nonlinear dynamics between online activity and market behaviour. Addressing these gaps is essential to advance both theory and practice in financial forecasting.

This study makes three key contributions. First, it systematically compares the predictive power of Vector Autoregression (VAR), a widely used econometric approach, and Long Short-Term Memory (LSTM) neural networks, a state-of-the-art deep learning method. Second, it integrates multiple sentiment indicators derived from Twitter, capturing not only polarity but also specific emotions. Third, it tests their ability to forecast two core market variables – trading volume and closing price – for major technology firms (Apple and Amazon).

Based on this framework, we formulate two hypotheses: (H1) Twitter activity is significantly associated with market changes, and (H2) LSTM models outperform VAR models in capturing these dynamics. The first hypothesis aims to establish a reliable connection between processes, addressing the literature's lack of clear interdependencies, including not only positive and negative sentiment but also specific emotion indicators (for example, anger and fear). The second hypothesis addresses the study's objective of evaluating the predictive capabilities of VAR and LSTM models (Laney, 2001; Antweiler & Frank, 2004; Manovich, 2011; Siganos et al., 2014; Ishikawa, 2015; Bello-Orgaz et al., 2016; Reinsel et al., 2017; Michalak & Kruszewski, 2021).

By bridging econometrics, machine learning, and behavioural finance, this research advances understanding of how digital sentiment influences financial markets. Beyond theoretical implications, our findings highlight the potential of social media monitoring as a practical tool for investors, risk managers, and policymakers operating in increasingly information-driven markets.

2. Literature Review

The relationship between social media communication and stock market dynamics can be examined through multiple interdisciplinary approaches, including behavioural finance, sociology, and economic psychology. What brings together these perspectives is the fact that financial decisions are not purely cognitive but are profoundly shaped by affective processes that guide attention, judgment, and collective behaviour. Even apparent deviations from the Efficient Market Hypothesis (EMH) can be understood as the outcome of emotional interference with rational information processing.

To provide a stronger theoretical foundation, this study draws on the theory of constructed emotion (Barrett, 2017). From a theoretical perspective, emotions are not universal, hardwired responses but contextually constructed experiences that arise from the interaction of interoceptive predictions, cultural concepts, and situational context. Investor reactions to Twitter activity, therefore, should not be interpreted as direct indicators of sentiment but as affective interpretations shaped by shared financial narratives, prior experiences, and social norms. These constructed emotions activate specific neural and behavioural pathways, potentially driving observable market behaviours such as rapid asset withdrawal, herding, or sudden shifts in trading patterns (Michalak, 2024a).

This process unfolds as follows: social media signals (e.g., tweets, news, trending topics) are perceived and filtered through the investor's internal state, prior experiences, and socially constructed financial concepts. These signals generate discrete emotions—such as fear, optimism, or anger—which are not automatic reactions but rather constructed interpretations. The brain integrates these affective states with predictions about future market outcomes, which then guide attention allocation, risk assessment, and decision-making (Barrett, 2017; Michalak, 2024).

Consequently, emotions can trigger specific trading behaviours: optimism may amplify buying and overvaluation, while fear or anger can precipitate rapid sell-offs, increased volatility, or herding behaviour (Michalak, 2024b). This mechanism links psychological constructs to observable market dynamics, providing a theoretically grounded explanation for departures from EMH and highlighting the role of contextually constructed emotions in shaping financial markets.

While Fama's EMH assumes that investors possess unrestricted cognitive capacity (Fama, 1970), behavioural finance has repeatedly demonstrated that cognitive limitations and emotional influences profoundly shape decision-making. Affective processes—such as mentioned fear, optimism, or anger—can distort attention allocation, risk perception, and valuation judgments, generating temporary mispricings in financial markets (Thaler, 2015).

Despite this, much of the empirical literature treats investor sentiment in a monolithic way, often reducing it to a single polarity index (positive vs. negative). This oversimplification neglects the richness of discrete emotions, which can exert distinct and sometimes opposing effects on trading behaviour and market dynamics (Zobal, 2017).

Consequently, a critical gap remains in understanding how discrete, contextually constructed emotions—rather than aggregated sentiment—interact with market efficiency, volatility, and trading behaviour. Addressing this gap requires an integrative framework that bridges behavioural finance with psychologically grounded theories of emotion, such as Barrett's Theory of Constructed Emotion (2017).

To empirically capture these dynamics, a variety of methodological approaches have been applied to model the relationship between social media communication and stock market variables (Bollen et al., 2011; Michalak & Kruszewski, 2021; Zeitun et al., 2023; Jena & Majhi, 2023). Early studies relied on linear methods, such as Pearson correlation and linear regression, or traditional time-series models like ARIMA and Granger causality, which primarily capture linear dependencies. However, both social media and market data exhibit nonlinear, high-dimensional interactions, motivating the use of more sophisticated models, including GARCH, SOFFN, and Long Short-Term Memory (LSTM) networks (Bollen et al., 2011).

Vector Autoregression (VAR) has been a popular choice due to its ability to model dynamic lead-lag relationships without requiring strict classification of endogenous and exogenous variables (Nofer & Hinz, 2015; Kumari & Mahakud, 2015). VAR also allows for impulse response analysis, assessing how shocks in Twitter activity propagate to market outcomes (Katsafados et al., 2022). Structural VAR (SVAR) extensions have been applied to account for endogenous interdependencies, such as in the TEPU index for monitoring real-time economic policy uncertainty (Yeşiltaş et al., 2022).

Despite its interpretability, VAR has limitations: it struggles with long-term sentiment dynamics, nonlinear interactions, and noisy social media data, which often include spikes, outliers, and memory effects (Azar & Lo, 2016; Michalak, 2021). In contrast, LSTM networks are particularly well-suited for capturing sequential, nonlinear patterns and long-term dependencies. By processing evolving Twitter discussions, LSTMs can detect complex interactions between constructed emotional signals and market responses (Jena & Majhi, 2023; Sawka, 2023). They also demonstrate resilience to noise and adaptability to structural shifts, offering higher predictive accuracy for market outcomes influenced by affective dynamics (Fischer & Krauss, 2018; Rashid & Tanjim, 2021).

In summary, integrating the behavioural finance perspective with a psychologically grounded theory of constructed emotions suggests that discrete affective responses expressed on social media are key drivers of market dynamics. Methodologically, this calls for models capable of capturing both the nonlinear, long-term, and sequential nature of these interactions, positioning LSTM networks as a particularly powerful tool, while VAR remains useful for shorter-term, interpretable analyses.

3. Methods

Following the theoretical framework of constructed emotion (Barrett, 2017), we treat Twitter posts not merely as reflections of sentiment, but as contextually constructed affective signals shaped by cultural, social, and situational factors—with sentiment and emotions labels.

Let $\mathbf{D}$ denote a set of tweets, where each tweet $\mathbf{d}_n$ represents a discrete communicative unit. Let $\mathbf{X}$ be the feature set, composed of sequences of n-grams, and let each tweet $\mathbf{d}_n$ be represented as a sparse vector of length $\mathbf{m}$, with each dimension corresponding to a specific feature (Michalak, 2024b). While this formalisation provides a computationally tractable representation of textual data, from the perspective of Barrett's theory of constructed emotion, each token, phrase, or feature may carry affective significance. That is, the cognitive-affective meaning of a tweet is not intrinsic to single words but arises through the context-dependent construction of emotion. Thus, every feature in $\mathbf{X}$ has the potential to contribute to the affective interpretation that influences investor perception and behaviour.

Sentiment analysis of Twitter data was performed using a structured, four-module pipeline encompassing data collection, preprocessing, feature extraction, and classification. Both machine learning-based (Multinomial Naïve Bayes and Support Vector Machines) and lexicon-based approaches (NRC Emotion Lexicon and VADER) were applied to construct multi-dimensional emotion indices for the target companies affect trends (Liu, 2012; Patil, Wangikar, & Jayamalini, 2017). The full pseudocode, based on Krouska, Troussas, & Virvou, (2016), detailing this procedure is provided in Appendix – A1.

First module included dataset selection – 1.6 million tweets from Senti140 were used to train MNB and SVM models, acknowledging the pseudo-label bias inherent in the dataset (Go et al., 2009; Pedregosa et al., 2011; Krouska et al., 2016; Soni et al., 2021; Skwirowski & Zytkowicz, 2023). Second module – data cleaning – noise reduction involved removing Twitter-specific tokens (#, @, $), repeated letters, URLs, and stopwords, normalizing case, stemming, and handling negations (Agarwal et al., 2011; Effrosynidis et al., 2017). Third, text vectorization – Bag of Words (BoW) and TF-IDF representations were compared using accuracy metrics. Fourth, classification—final sentiment labelling was performed for company-specific tweets.

Naïve Bayes (NB) and Support Vector Machines (SVM) are widely used for short-text classification due to their efficiency and robustness (Bermingham & Smeaton, 2010). NB estimates the probability of a tweet belonging to a specific class, while SVM identifies the optimal separating hyperplane. Both methods operate in high-dimensional feature spaces, where careful feature engineering and parameter optimisation are crucial for performance (Chen et al., 2009; Sindhu et al., 2021).

In parallel, a lexicon-based approach using NRC Emotion Lexicon and VADER captured discrete emotions beyond simple polarity. NRC allowed time-series tracking of emotions derived from Ekman's theory, while VADER was optimised for short social media texts. Domain adaptation and lexicon expansion were applied to account for financial market language (Nascimento & Ferreira, 2019).

Despite these methods, challenges persist, including sarcasm, implicit sentiment, and domain-specific jargon, which can impair classification accuracy (Magliani et al., 2016). Addressing these limitations requires advanced context-aware models and domain-adaptive strategies.

The short-term dynamics between Twitter sentiment and stock market variables were modelled using a Vector Autoregressive (VAR) framework, complemented by Granger causality and impulse response analysis (Appendix F1). The lags of the VAR model were selected based on the information criteria AIC, BIC, and HQC (Appendix A2-A5). The stationarity of the variables was assessed simultaneously using the ADF and KPSS tests. If the variables were found to be non-stationary, their first differences were applied, followed by a subsequent verification of their stationarity.

To capture nonlinear and long-term dependencies, Long Short-Term Memory (LSTM) networks were employed (Keras, n.d.), which are particularly effective for sequential data with extended memory, such as evolving Twitter discussions (Appendix A3).

4. Data

Data for Apple and Amazon was collected from 01/01/2016 to 31/12/ 2017 with cashtag $AAPL and $AMZN. This period was selected because Twitter data was publicly accessible via the API, ensuring completeness and consistency of the dataset. Although the study covers 2016–2017, the methodology is fully replicable and can be applied to other time periods or companies, providing a generalizable framework for examining the relationship between social media activity and stock market dynamics.

During this period, Apple received a total of 808,218 tweets, while Amazon had 405,758 messages. Both companies demonstrated high coefficients of variation indicating significant fluctuations in emotional expression across the dataset (Table A1).

The percentage distribution of emotions and sentiment across the total volume of tweets was examined using three approaches: the NRC lexicon (Ekman labels), the VADER lexicon, and a machine learning model.

Using the NRC lexicon, for Apple, 4.99% of messages were classified as negative, with 1.37% expressing anger, 1.19% sadness, and 1.94% fear, while 10.60% were positive. For Amazon, 4.46% of messages were negative, including 1.08% anger, 0.91% sadness, and 1.69% fear, while 11.55% were positive. These results suggest that both companies had a higher share of positive sentiment compared to negative sentiment, with relatively few negative emotions expressed.

Applying the VADER lexicon, for Apple, 32.67% of the messages were classified as positive, 15.74% as negative, and 51.59% as neutral. For Amazon, 42.94% were positive, 14.21% negative, and 44.44% neutral. This indicates that both companies had a large proportion of neutral tweets, while Amazon showed a notably higher share of positive sentiment compared to Apple.

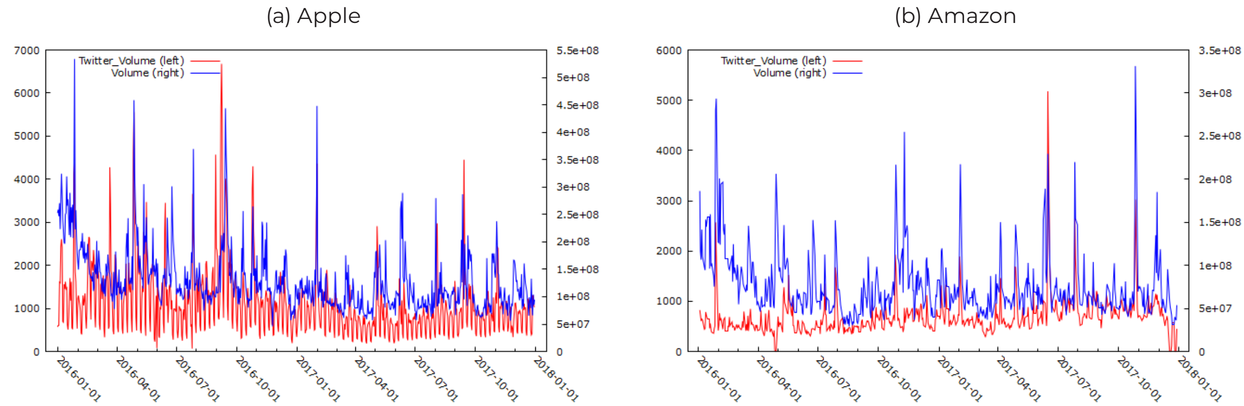

Figure 1 . Time series for Twitter volume and volume of
Source: own preparation

Finally, using the machine learning approach, for Apple, 63.85% of the messages were classified as positive and 36.15% as negative. Similarly, for Amazon, 66.64% of the messages were positive, while 33.36% were negative.

These findings underscore that both companies exhibited a majority of positive sentiment, with Amazon slightly leading in this category.

The feature space defined on the Setiment140 dataset using Bag-of-Words model in the n-gram (1, 2) variant was selected for analysis. Ten-fold cross-validation confirmed the stability of the results across folds, yielding an accuracy of approximately 0.7.

However, several concerns arise, including topic instability, information leakage between companies due to the use of multiple cashtags, and the presence of spam – all of which may reduce the predictive accuracy of Twitter-based models. Considering these challenges, as well as the instability of the VAR model over the entire sample period, the analysis was divided into semi-annual intervals.

Figures 1-2- illustrate the time series for (a) Apple Volume and $aapl Twitter Volume and (b) Amazon Volume and $amzn Twitter Volume, along with their respective close prices. Figure 2 suggests the presence of spurious correlation due to trends in the closing prices. Consequently, a trend decomposition was performed for the close prices (Apple and Amazon) using a linear model estimated via Ordinary Least Squares (OLS) for a quadratic trend. The Pearson linear correlation coefficient was then calculated between the residuals of this model and the standardised sentiment indicators. The correlations were found to be statistically insignificant, leading to the decision to refrain from modelling a linear relationship. However, based on the analysis of the residuals from the trend model for close prices and volume, there is some indication that changes in price and Twitter volume might exhibit certain common patterns during specific periods. In light of these observations, only the Long Short-Term Memory (LSTM) model was computed.

In financial time series, trends may represent a fundamental market characteristic, which reflect long-term movements driven by different economic factors and market dynamics. Including detrended residuals in analysis effects in investigation of short-term fluctuations and potential non-linear correlation that are independent of market's overarching trajectory. Thus, LSTM include residuals as variable.

Due to the significant volatility observed in both Twitter and stock market trading volumes, the entire research period (2016–2017) was segmented into semi-annual intervals, with interdependencies assessed across various configurations, including half-yearly and full two-year periods. This methodological decision was informed by the suboptimal statistical performance of the models estimated over the full sample, particularly the presence of autocorrelation and the instability of impulse response functions.

5. Results

Table 1 presents the results of the Pearson correlation analysis for the volume and sentiment variables. The findings provide evidence that Twitter activity, as measured by various sentiment indicators, is statistically significantly correlated with stock trading volume. Indicators of fear, anger, as well as both

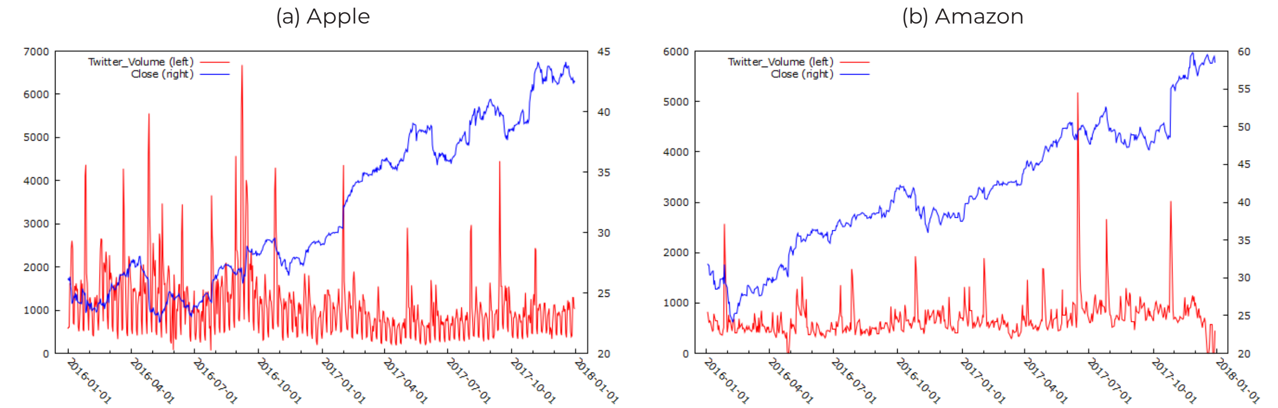

Figure 2. Time series for Twitter volume and close price of
Source: own preparation

positive and negative sentiment, exhibit significant correlations for Amazon and Apple across different time periods. This supports the hypothesis one that there is a statistically significant relationship between Twitter activity and the stock market, when considering trading volume as an outcome variable. In the process of selecting variables for the VAR model and Granger causality analysis, the Pearson correlation was employed as a criterion, given that both methods assess linear relationships between variables. In contrast, for the LSTM model, which captures nonlinear dynamics, all variables were potentially included without prior exclusion based on the results of the correlation analysis.

Tables 2–5 present the results of the analysis conducted using VAR models and LSTM neural networks. The performance of both approaches was evaluated based on the Mean Absolute Error (MAE) calculated on the test dataset. The analysis was carried out in three temporal variants to account for the autocorrelation issue inherent in the VAR model and the short-lived nature of topics trending on Twitter.

The clustering of discussions around specific company related events generated short-term trends. However, changes in discussion dynamics did not consistently correlate with stock price movements, shifts in discussion sentiment, or external events affecting the company. During periods of declining discussion activity following upward trends, conversations often shifted toward general market commentary or spam. Such content frequently included multiple cashtags, resulting in information spillover across different companies.

In the VAR analysis, the full study period exhibited excessive volatility. The models also lacked robustness in their properties, even after introducing additional exogenous variables such as return rates. Granger causality analysis for different study periods primarily shows a unidirectional influence from Twitter on the stock market, with some exceptions. The emotion of sadness did not demonstrate any causal relationship with trading volume in any of the analysed periods. Locally, anger and fear show a unidirectional influence on Twitter. However, identifying consistent patterns across indicator groups is challenging, suggesting that the impact on trading volumes varies depending on influencing factors, leading to different dynamics within the systems.

It should be noted that the causation was primarily observed for indicators associated with a higher volume of tweets (negative and positive sentiment). Indicators of emotions from the NRC lexicon, such as sadness, anger, and fear, demonstrated weaker predictive properties (in Apple's case).

The sadness indicator did not show any predictive capability in the linear analysis for any period. Amazon exhibits weaker linear relationships compared to Apple (in terms of causation). Theoretically, greater discussion on Twitter and a more visible presence on social media should lead to higher dependencies. Apple was mentioned twice as often as Amazon in the performed dataset.

Additionally, Michalak (2024a) demonstrated that the choice of sentiment analysis method affects the final causality results. This is evident in the significance of positive versus negative sentiment, depending on the sentiment analysis method used.

Low MAE values for the 'fear' and 'anger' labels indicate that these variables significantly impact volume forecasts, particularly for Amazon (Tables 5-6).

Table 1. Pearson linear correlation coefficients for sentiment across different research periods (variable: volume)

Indicator	AAPL	AMZN	AAPL	AMZN	AAPL	AMZN
	full period		first half of 2016		first half of 2017	
critical value (5%, two tail)	0,086	0,086	0,172	0,173	0,174	0,174
Fear	0,22	0,38	0,00	0,44	0,30	0,54
Anger	0,21	0,00	0,11	0,05	0,30	0,15
negative VADER	0,57	0,50	0,38	0,46	0,50	0,71
negative NRC	0,49	0,51	0,31	0,65	0,40	0,73
neutral VADER	0,56	0,57	0,29	0,41	0,50	0,77
positive NRC	0,40	0,30	0,26	0,29	0,40	0,59
positive VADER	0,56	0,44	0,36	0,46	0,60	0,70
Sadness	0,29	0,40	0,37	0,53	0,30	0,52
Volume	0,54	0,52	0,36	0,46	0,50	0,74
Machine learning_positive	0,53	0,48	0,14	0,38	0,40	0,72
Machine learning_negative	0,52	0,55	0,16	0,53	0,30	0,74

Source: own preparation

Table 2. Results of the Granger causality analysis for Apple trading volume variable

			Granger causality	
Time period	Model	Twitter variable	Twitter -> Volume	Volume -> Twitter
full period	VAR(5)	Twitter volume	*	*
	VAR(6)	negative VADER	*	
	VAR(5)	positive VADER	*	
first half of 2016	VAR(2)	negative VADER	*	
	VAR(2)	Twitter volume	*	
	VAR(2)	Fear	*	
	VAR(3)	negative NRC	*	
	VAR (3)	positive NRC	*	
	VAR(2)	neutral VADER	*	
	VAR(2)	positive VADER	*	
	VAR(2)	positive ML	*	
	VAR(2)	negative ML	*	
first half of 2017	VAR(2)	negative VADER	*	*
	VAR(1)	negative NRC	*	
	VAR(4)	neutral VADER	*	*
	VAR(1)	Anger	*	
	VAR(1)	positive VADER	*	
	VAR(2)	negative ML	*	*
	VAR(2)	positive ML	*	*

Source: own preparation

Table 3. Results of the Granger causality analysis for the Amazon trading volume variable

			Granger causality	
Time period	**Model**	**Twitter variable**	**Twitter -> Volume**	**Volume -> Twitter**
Full period	VAR(2)	neutral VADER	*	
	VAR(3)	negative ML	*	*
First half of 2016	VAR(2)	Twitter Volume	*	
	VAR(2)	Negative VADER	*	
	VAR(2)	Fear	*	
	VAR(2)	positive NRC	*	
	VAR(2)	neutral VADER	*	
	VAR(2)	positive VADER	*	
	VAR(4)	Anger	*	
	VAR(2)	negative ML	*	
	VAR(2)	negative ML	*	
First half of 2017	VAR(3)	Anger	*	*

Source: own preparation

Although commonly perceived as negative emotions, from a psychological standpoint, they are considered fundamental emotions. According to evolutionary psychology, these emotions have developed as part of adaptive behavioural responses, essential for survival. They increase focus and trigger fight-or-flight responses to stimuli. These are powerful emotions with the potential to influence market trends if experienced by a large enough group of people.

Apple exhibits greater variability in MAE results, suggesting that discussions about Apple are more diverse in terms of topics, tone, and data quality. The 'neutral VADER' and 'positive NRC' variables show higher MAE compared to those related to negative emotions, implying that they have a smaller impact on financial markets. This conclusion aligns with the theory of information asymmetry, where negative news tends to have a more substantial influence on investment decisions.

In the first half of 2016, adding the Twitter variable to the neural network improved the MAE for all Apple indicators and for 9 out of 11 Amazon indicators. However, the results for Apple during this period were not satisfactory, suggesting that Twitter did not significantly enhance the model's ability to predict trading volume. The conclusions for Amazon are similar. Over the full period, Apple did not show satisfactory results, whereas the predictions for Amazon improved significantly.

A baseline model was not constructed for the VAR model as a benchmark; this was a decision made by the author. Comparing VAR would require benchmarking against an AR model, whose estimation results are not dependent on multiple variables. This lack of dependency was the main criterion for its exclusion, as it made the conclusions difficult and unstable to draw.

Table 6 presents the results for closing prices. The findings suggest that incorporating sentiment variables did not consistently demonstrate predictive power. However, negative emotions may be critical for improving forecasts, with their impact varying depending on the period and the company. Negative emotions generally have a greater influence on enhancing predictions for both companies, especially over the full period and in the first half of 2016. For Apple, the inclusion of emotion-related variables does not always improve forecast accuracy, particularly in the first half of 2017. In contrast, Amazon shows more stable results.

The analysis of the impulse response function was conducted with the shock originating from Twitter and affecting trading volume. The trajectory of the function allows us to draw the main conclusion that the duration of impulses is short, lasting a few days. This may correspond with the typical duration of discussions on a given topic. The decline in volume following a shock from Twitter is a complex issue. However, the potential reasons for such a directional

Table 4. MAE results for the Apple and Amazon volume from VAR and LSTM approaches (test dataset)

	Volume Apple		**Volume Amazon**	
	first half of 2016			
	VAR	**LSTM**	**VAR**	**LSTM**
basic model		52084210,079		30415580,280
Fear	6475000	43234472,137	1710000	29134831,193
Anger		44926837,853	2333900	27106026,803
negative VADER		48940743,521	1302400	28507242,885
negative NRC	11669000	47438402,462		27761003,405
neutral VADER	7935700	47392150,783	110190	31538788,185
positive NRC	5272400	46575716,841	1771500	30197920,410
positive VADER		46123079,248	219890	31073486,591
Sadness		45630371,911		27609196,773
Twitter volume	7894500	45452760,479	2821900	29480840,315
ML positive	5065700	48447840,465	201980	28161706,284
ML negative	6480200	45159658,721	748240	29443364,882
	first half of 2017			
basic model		29959620,193		19816644,131
Fear		30032320,014		19610157,993
Anger	27606000	29989363,986	9409900	19193604,890
negative VADER	29061000	29164579,531		19828186,097
negative NRC	26228000	29378243,531		19651018,103
Neutral VADER	28722000	29543515,048		19624056,441
Positive NRC	27437000	29435291,269		19873546,559
positive VADER	29880000	29613845,434		19708110,731
Sadness		29202756,331		19887700,586
Twitter volume	27795000	29200650,234		19666939,683
ML positive	28905000	29288276,166		19862915,138
ML negative		29480424,662		20186129,690
	full period			
basic model		37060274,722		49244981,060
Fear		36283377,928		22495202,131
Anger		37418912,444		22924401,013
negative VADER		37068676,291		22832473,868
negative NRC		37277158,450		22121621,013
Neutral VADER		36841175,338	8603500	23183559,170
Positive NRC		37187736,091		22731837,658
positive VADER	6703500	38351343,147		22735923,064
Sadness		36132565,891		22154059,560
Twitter volume		36132565,891		22725973,268
ML positive		36672397,669		22310880,027
ML negative		35741492,741	9708500	22808249,226

Source: own preparation

Table 5. MAE results for Apple and Amazon closing prices with LSTM approaches (test dataset)

	Full period		First half of 2016		First half of 2017	
Indicators	**AAPL**	**AMZN**	**AAPL**	**AMZN**	**AAPL**	**AMZN**
Base model	131839949	179258627	176138673	274137855	173356700	252350198
Fear	125483563	180665696	164580851	246518980	211031605	302579474
Anger	125998230	188602498	172433139	249338907	171247523	273984994
negative VADER	128457127	183451424	180822334	279399172	176222412	229997950
negative NRC	129982302	181365827	173876262	256298833	174086104	208780619
Neutral VADER	126443868	186080492	180506883	256098881	239225325	256152057
Positive NRC	132827363	180629995	176500689	271267606	193072633	188347131
positive VADER	133481260	183951456	190247008	241919926	149474564	199168532
Sadness	133854686	181299519	186525792	259533810	176089131	209214699
Twitter volume	128999042	186141427	204244861	263932412	166108240	25818537
ML_positive	124848073	180946633	184088680	255719195	169194595	18691250
ML_negative	127055620	178378199	181395180	230176491	1847151434	195771334

Source: own preparation

relationship may include negative perceptions of information and the activation of withholding patterns. The shock could lead to increased caution, resulting in a wait-and-see approach for new information. Nevertheless, the decline in volume is a short-term effect, lasting about 1–2 days. It does not lead to long-term changes and reflects the natural dynamics of the market. The stability of the results indicates that the market tends to absorb the shock and return to normal levels of activity.

The results suggest that incorporating variables representing emotions could have statistically significant implications for improving forecasting accuracy. However, there are no clear patterns indicating which specific variables would be significant. This underscores the necessity of continuous monitoring of social media platforms. The factors influencing the variability of statistical significance over time depend on numerous elements, including those related to the immediate and broader environment of the enterprise, particularly the importance of discussions regarding events within that environment. These findings are consistent with the existing literature. Researchers have demonstrated a connection between stock markets and social media, yet identifying this relationship must occur across multiple dimensions and is often challenging.

VAR class models appear to be better suited for modelling stock trading volume than closing prices. Closing prices and investment returns are categories that are difficult to explain through a linear relationship with the volume of emotions. It is recommended that this relationship be systematised using nonlinear models, such as LSTM or GARCH class models. Consequently, the use of simple models, such as linear regression, in establishing this connection is not recommended, although such approaches are evident in the literature. Issues with time series non-stationarity, long memory processes, and the phenomenon of variance clustering exclude regression as a suitable method.

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Appendix

A1. Pseudocode Twitter sentiment analysis and market modelling

Input: Raw Twitter data D, labelled training dataset for sentiment analysis, stock market data (prices, volumes)

Output: Predicted market variables, classified sentiment indices

1. Data Collection
   - Collect tweets via Twitter API
   - Select relevant hashtags/accounts for target companies
2. Preprocessing
   - Clean text: remove URLs, mentions, hashtags, repeated letters, normalise case
   - Handle negations (e.g., isolate 'not')
   - Remove stop words and perform stemming (Porter algorithm)
   - Optional: remove emoticons if training set does not include them
3. Feature Extraction
   - Transform tweets into feature vectors using:
     - Bag-of-Words (BoW)
     - TF-IDF
   - For lexicon-based methods, assign emotional valence scores using NRC Emotion Lexicon or VADER
4. Sentiment Classification
   - Train classifier on labelled dataset (Senti140) using:
     - Multinomial Naïve Bayes (MNB)
     - Support Vector Machine (SVM)
   - Perform 10-fold cross-validation
   - Evaluate performance using accuracy metrics
5. Construction of Emotion Index
   - Aggregate classified sentiment scores over time for each company
   - Generate multi-dimensional emotion indices (e.g., positive, negative, discrete emotions)
6. Modelling Market Dynamics
   - Align sentiment indices with stock market data (price, volume)
   - Fit models:
     - VAR for short-term linear dependencies and impulse response analysis
     - LSTM for capturing nonlinear, sequential patterns and long-term dependencies
   - Normalise input variables for LSTM (e.g., MinMaxScaler)
7. Prediction & Analysis
   - Predict stock market outcomes based on sentiment indices
   - Compare VAR vs. LSTM performance in capturing market dynamics
   - Evaluate predictive accuracy and ability to capture nonlinear effects

A2. Mathematical specification – VAR model

$$z_t = \sum_{i=1}^{k} A_i z_{t-i} + \varepsilon_t$$

Where:

t=1, 2,…,n;

Z_t is the vector of current observations of all n variables in the model; A_t is the matrix of autoregressive coefficients for each lagged process, where no zero elements are assumed a priori; $\varepsilon_t \varepsilon_t$ is the vector of residual processes, assumed to be contemporaneously correlated but without autocorrelation; K – is the order of the VAR model.

A3. Mathematical specification – LSTM neural network

Forgot gate: $f_t = \sigma\left(w_f \cdot [h_{t-1}, x_t] + b_f\right)$

Input gate: $i_t = \sigma(w_i \cdot [h_{t-1}, x_t] + b_i)$

Candidate cell state: $\tilde{C}_t = tanh(w_c \cdot [h_{t-1}, x_t] + b_c)$

Cell state update: $C_t = f_t \Theta C_{t-1} + i_t \Theta \tilde{C}_t$

Output gate: $o_t = \sigma(w_o \cdot [h_{t-1}, x_t] + b_o)$

Hidden state: $h_t = o_t \Theta tanh(C_t)$

Where: σ is sigmoid activation function, w_f is the weight matrix for the forgot gate, h_{t-1} is the hidden state from previous time step, x_t is the input at the current time step, b_f is the bias for the forget gate, Θ denotes element-wise multiplication and tanh is the hyperbolic tangent function.

Table A1. Descriptive statistics of affective indicators (2016-2017)

Indicator	Mean	Minimum	Maximum	Standard Deviation	Coefficient of Variation
Apple					
Anger	14,83	0	129	16,59	111 %
positive (NRC)	2,94	0	56	4,37	149 %
Fear	20,96	0	188	24,62	117 %
negative (NRC)	54,02	1	692	56,11	104 %
Sadness	12,89	0	426	21,60	167 %
negative (VADER)	170,29	10	1401,0	157,91	93 %
positive (VADER)	353,52	18	1789,0	230,66	65 %
neutral (VADER)	558,32	31	3771	415,12	74 %
negative machine learning	499,15	30	2593	326,07	65%
positive machine learning	863,99	35	4086	495,20	57%
Amazon					
Anger	5,02	0	65	5,90	118 %
positive (NRC)	76,27	0	784	50,38	67 %
Fear	11,18	0	104	8,65	77 %
negative (NRC)	30,40	0	282	22,49	74 %

Continued **Table A1.** Descriptive statistics of affective indicators (2016-2017)

Indicator	Mean	Minimum	Maximum	Standard Deviation	Coefficient of Variation
Sadness	6,22	0	71	6,48	104 %
negative (VADER)	96,43	0	805	64,10	66 %
positive (VADER)	284,50	0	2427	177,23	63 %
neutral (VADER)	296,92	0	1856	143,89	48 %
Positive machine learning	453,88	0	3531	259,43	57 %
Negative machine learning	228,07	0	1647	132,99	58 %

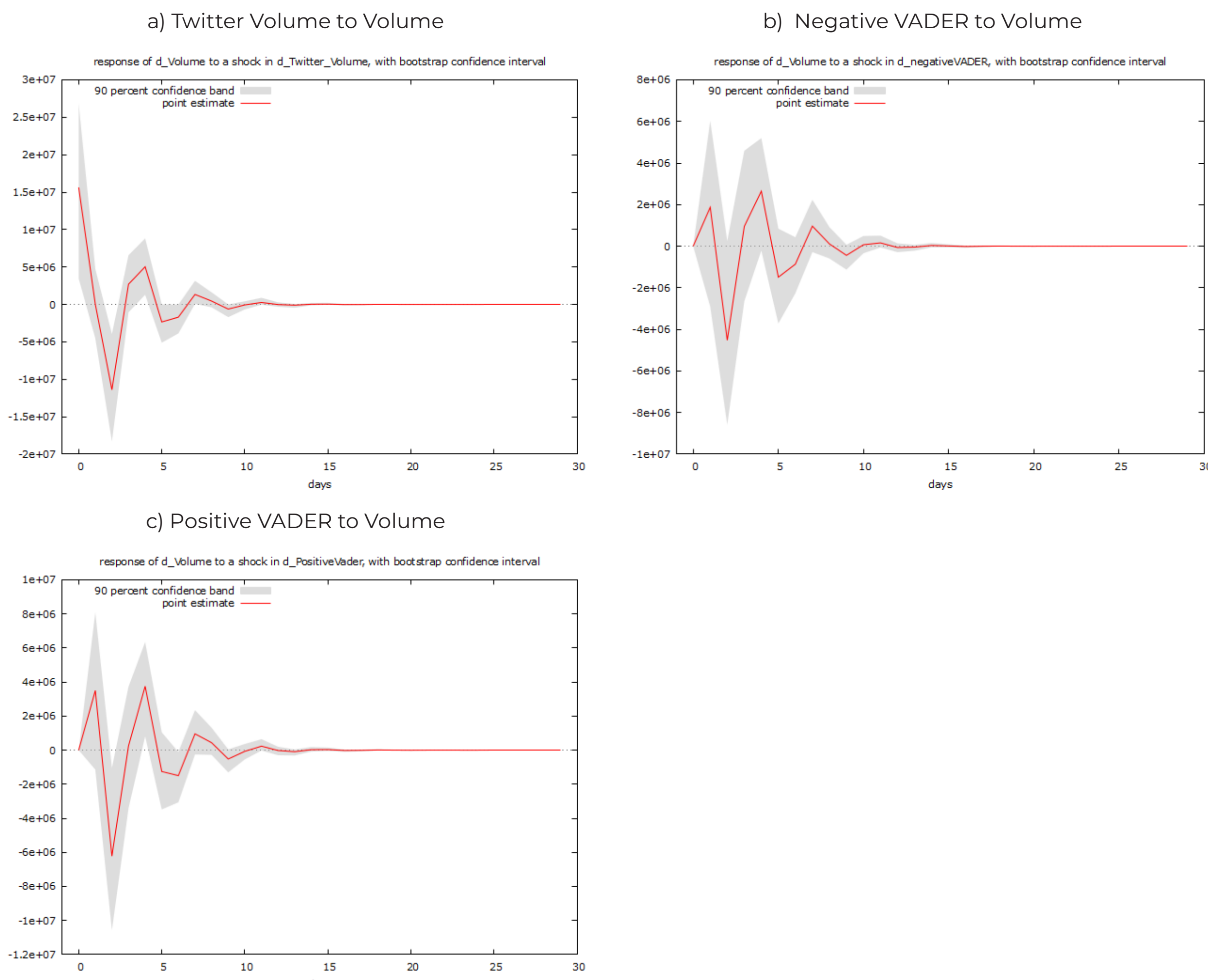

Figure A1. Impulse response function for Apple in the period 01/01/2016–30/06/2016 (VAR (2))
Source: own work

a) Neutral VADER to Volume

b) Negative ML to Volume

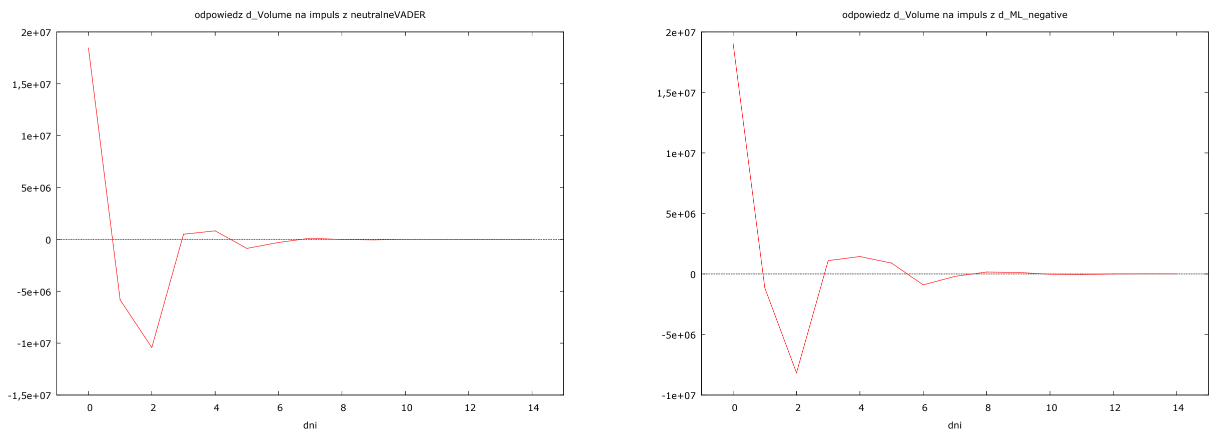

Figure A2. Impulse response function for Amazon in the period 01/01/2016-30/12/2017
Source: own work

Table A2. ADF and KPSS test results for trading volume and the set of Twitter-related explanatory variables for Apple in the period 01/01/2016-31/12/2017

Variable	**ADF test (H0: unit root exists, a=1; process is; proces I(1); α=5%)**			**KPSS test (H0: the process is stationary)**	
	Augmentation	**Test statistic**	**Augmentation**	**Test statistic**	**Augmentation**
anger (NRC)	Levels of the variable	-3,27612	0,01601	3,00692	0,462
	First differences of the variable	-11,99	1,125e-25	0,0161847	0,462
fear (NRC)	Levels of the variable	-3,97906	0,001528	2,54575	0,462
	First differences of the variable	-11,3597	1,285e-23	0,0179549	0,462
negative (NRC)	Levels of the variable	-4,12856	0,0008677	2,18129	0,462
	First differences of the variable	-8,08676	2,779e-13	0,0146701	0,462
positive (NRC)	Levels of the variable	-5,91842	1,878e-07	1,80831	0,462
	First differences of the variable	-8,46602	2,054e-14	0,0106107	0,462
Sadness (NRC)	Levels of the variable	-5,45164	2,222e-06	1,15178	0,462
	First differences of the variable	-10,7283	1,47e-21	0,0104196	0,462
volume - Twitter	Levels of the variable	5,40184	2,727e-05	0,176054	0,462
	First differences of the variable	-9,62749	5,127e-18	0,0134742	0,462
volume	Levels of the variable	-5,26013	5,816e-06	2,54196	0,462
	First differences of the variable	-8,23407	1,018e-13	0,00808336	0,462
negative (VADER)	Levels of the variable	-3,84941	0,002452	3,24397	0,462
	First differences of the variable	-11,0965	9,295e-23	0,0172141	0,462
neutral (VADER)	Levels of the variable	-5,28912	5,038e-06	2,74717	0,462
	First differences of the variable	-3,16272	2,13e-18	0,0160322	0,452

Table A2. ADF and KPSS test results for trading volume and the set of Twitter-related explanatory variables for Apple in the period 01/01/2016-31/12/2017

Variable	ADF test (H0: unit root exists, a=1; process is; proces I(1); α=5%)			KPSS test (H0: the process is stationary)	
	Augmentation	**Test statistic**	**Augmentation**	**Test statistic**	**Augmentation**
positive (VADER)	Levels of the variable	-6,42807	1,046e-08	0,976474	0,462
	First differences of the variable	-11,4848	5,016e-24	0,0120437	0,462
positive (machine learning)	Levels of the variable	-5,87552	2,374e-07	2,07179	0,462
	First differences of the variable	-9,84191	1,064e-18	0,00813973	0,462
negative (machine learning)	Levels of the variable	5,707e-06	-5,26396	2,95298	0,462
	First differences of the variable	-11,0991	9,114e-23	0,00850337	0,462

Source: own work.

Table A3. Information criteria AIC, BIC, and HQC for Apple in the period 01/01/2016-30/12/2017

Variable	AIC	BIC	HQC
volume - Twitter	8	4	4
negative (VADER)	6	4	4
fear (NRC)	7	3	7
negative (NRC)	6	4	4
positive (NRC)	7	4	6
Sadness (NRC)	6	3	6
neutral (VADER)	7	4	6
positive (VADER)	7	4	6
anger (NRC)	9	5	6
positive (machine learning)	8	5	6
negative (machine learning)	7	5	5

Source: own work

Table A4. ADF and KPSS test results for trading volume and the set of Twitter-related explanatory variables for Amazon in the period 01/01/2016-31/12/2017

Variable	ADF test (H0: unit root exists, a=1; process is; proces I(1); α=5%)			KPSS test (H0: the process is stationary)	
	Augmentation	**Test statistic**	**p-value**	**Augmentation**	**Test statistic**
anger (NRC)	Levels of the variable	-3,65442	0,004827	2,02218	0,462
	First differences of the variable	-9,53803	9,85e-18	0,00866198	0,462
fear (NRC)	Levels of the variable	-6,11781	6,205e-08	1,67969	0,462
	First differences of the variable	-14,2471	7,032e-33	0,0111678	0,462
negative (NRC)	Levels of the variable	-6,35963	1,558e-08	2,12338	0,462
	First differences of the variable	-9,1027	2,291e-16	0,0112555	0,462
positive (NRC)	Levels of the variable	-6,93493	4,954e-10	2,31123	0,462
	First differences of the variable	-10,0592	2,144e-19	0,00856802	0,462
Sadness (NRC)	Levels of the variable	-7,34949	3,634e-11	1,82555	0,462
	First differences of the variable	-8,82186	1,694e-15	0,0097475	0,462
volume - Twitter	Levels of the variable	-7,26547	6,221e-11	1,48181	0,462
	First differences of the variable	-10,0402	2,467e-19	0,00921894	0,462
volume	Levels of the variable	-7,95235	6,891e-13	0,932306	0,462
	First differences of the variable	-10,6211	3,279e-21	0,0237538	0,462
negative (VADER)	Levels of the variable	-7,0515	2,401e-10	1,0782	0,462
	First differences of the variable	-9,29976	5,549e-17	0,00935709	0,462
neutral (VADER)	Levels of the variable	-10,1264	1,304e-19	0,233814	0,462
	First differences of the variable				
positive (VADER)	Levels of the variable	-6,5758	4,375e-09	2,66892	0,462
	First differences of the variable	-10,1442	1,143e-19	0,00896029	0,462
positive (machine learning)	Levels of the variable	-9,58592	6,946e-18	1,36072	0,462
	First differences of the variable	-10,0351	2,562e-19	0,00883801	0,462
negative (machine learning)	Levels of the variable	-5,90414	2,03e-07	1,54254	0,462
	First differences of the variable	-9,68659	3,328e-18	0,0110951	0,462

Source: own work

Table A5. Information criteria AIC, BIC, and HQC for Amazon in the period 01/01/2016-31/12/2017

Variable	AIC	BIC	HQC
volume - Twitter	7	3	5
negative (VADER)	7	3	4
fear (NRC)	7	4	5
negative (NRC)	7	3	5
positive (NRC)	7	3	5
Sadness (NRC)	7	4	7
neutral (VADER)	5	2	3
positive (VADER)	7	3	7
anger (NRC)	9	5	7
positive (machine learning)	7	3	5
negative (machine learning)	7	3	5

Source: own work