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The Influence of Financial Indicators and Market Sentiment with Macro Factors on Stock Price Prediction

Yashu Xu

Faculty of Science and Engineering, University of Nottingham Ningbo China, Ningbo, China
smyyx11@nottingham.edu.cn

Abstract. Financial markets are constantly fluctuating, and every decision maker in the stock market faces the possibility of financial market volatility. Every decision maker needs to rely on solid investment strategies and accurate analytical models when making decisions. The development of strategies and models needs to consider multiple factors that affect market volatility, such as financial indicators and market sentiment with macro factors. This paper proposes a comprehensive framework that combines financial indicators and investor sentiment with macro factors for stock return forecasting. Three methods are compared through regression-based models: using only financial indicators, combining financial and sentiment, and a full model with macro shocks. The results show that financial indicators remain the cornerstone of long-term analysis, while emotional variables significantly improve the accuracy of short-term forecasts. Macro events trigger market volatility in specific periods, but their long-term impact is limited. The results show that the multi-factor framework combining financial, emotional and macro dimensions can provide a more comprehensive understanding of stock market dynamics and provide reference for academic research and investment strategies.

Keywords: Financial Indicators, Market Sentiment, Stock Price Prediction, Geopolitical Risk, Business Analytics

1. Introduction

The prediction of stock market prices is not only a fundamental academic issue but also a practical challenge. Accurate predictions can help investors manage risks, enable policymakers to stabilize the market, and allow researchers to study market efficiency.

Financial indicators such as earnings per share (EPS), return on equity (ROE), and debt ratio have been widely used to assess a company's performance and intrinsic value. These indicators are useful for long-term investors who focus on fundamental value, but they often fail to reflect short-term fluctuations [1-2].

Additionally, the increasing influence of market sentiment has brought new perspectives into stock price forecasting. Sentiment, reflected in news coverage, analyst opinions, and social media, captures investors' emotions and biases, which often drive short-term price fluctuations.Empirical findings demonstrate that incorporating sentiment into machine learning models improves prediction

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accuracy [3-4]. Furthermore, investor sentiment from news, media, and social platforms has measurable effects on stock returns [5-6].

At the same time, macroeconomic shocks such as wars, monetary policy changes, and geopolitical risks exert external pressures on markets, making prediction more complex. Economic uncertainty, monetary policies, and international conflicts cause shocks that reshape return patterns [7-8]. These externalities highlight the need for integrated models capable of adapting to both endogenous and exogenous factors.

This paper aims to investigate the relative role of financial and sentiment indicators in stock prediction, and whether the integration of macroeconomic factors enhances forecasting accuracy. By constructing an empirical framework based on regression analysis, this study contributes to the academic understanding of multifactor models and offers practical implications for business analytics and investment practice.

2. Basic factor analysis

2.1. Financial and technical indicators

Recent studies emphasize the predictive power of fundamental and technical indicators. Neural networks integrating financial ratios and technical signals improve forecasting accuracy compared to traditional regression [1]. The LASSO-LSTM framework shows that combining financial and technical features allows models to capture nonlinear dependencies and reduce overfitting [2]. Multi-source models further confirm that structured indicators such as price, volume, and ratios remain essential for baseline forecasts [4].

2.2. Sentiment analysis in stock prediction

Sentiment has become a crucial short-term driver of stock prices. Media sentiment indices are significantly correlated with market returns, as positive tone predicts higher returns while negative tone signals decline [5]. Machine learning models confirm that incorporating financial news sentiment and uncertainty enhances explanatory power [7]. Moreover, social sentiment derived from ESG reports and Twitter provides additional predictive insights [6]. Hybrid models confirm that sentiment indicators bridge the gap between technical and fundamental predictors [3].

2.3. Macroeconomic and geopolitical factors

External shocks play a strong episodic role in asset pricing. Studies on macroeconomic factors show that uncertainty indices significantly affect returns across sectors [7]. Similarly, geopolitical tensions reshape investor expectations, with proactive models helping predict resilience under crises [8]. These findings underline the necessity of including dummy variables representing events, policies, or wars in forecasting frameworks.

3. Data analysis

3.1. Data sources

Financial indicators, including earnings per share (EPS), return on equity (ROE), and debt ratio are obtained from firm-level reports and financial databases [1]. Sentiment indices are extracted using

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natural language processing (NLP) methods from financial news, ESG reports, and Twitter datasets [5, 9]. Macroeconomic events such as wars and monetary policies are encoded as dummy variables.

3.2. Variable design

In this study, the dependent variable is stock returns (Y), which refers to the earnings of an enterprise at time t. The independent variables include earnings per share (EPS), return on equity (ROE), and debt ratio, which reflect the financial performance and leverage situation at the enterprise level. Additionally, an emotion index (Sentiment) is introduced, which is constructed through the text analysis of financial news and social media to capture the attitudes and expectations of investors. To consider external influencing factors, macroeconomic dummy variables (Macro) are also included, reflecting events such as policy changes or economic shocks. The addition of these variables enables the model to link the enterprise fundamentals and broader market conditions with the dynamics of stock returns.

3.3. Model design

The model design includes three distinct approaches. The first model, referred to as the Financial-only regression, incorporates solely financial indicators. The second model integrates financial indicators with investor sentiment, termed the Financial + sentiment regression. The third model, known as the Financial + sentiment + macroeconomic shocks regression, further includes macroeconomic factors.

The general form of these models can be expressed as [2, 8]:

$$Yt = \alpha + \beta 1EPSt + \beta 2ROEt + \beta 3Debtt + \gamma Sentimentt + \delta Macrot + \epsilon t \quad (1)$$

Here, Yt represents the stock return at time t, EPSt is the earnings per share, ROEt denotes the return on equity, Debtt is the debt ratio, Sentimentt stands for the sentiment index, Macrot includes macroeconomic factors, α is the intercept, β1, β2, β3, γ, δ are the coefficients of respective variables, and ϵt is the error term. Additionally, advanced models like Long Short-Term Memory (LSTM) networks and hybrid neural networks are employed to capture the nonlinear dependencies that might exist among these variables, which linear models might miss. The performance of all models is evaluated using metrics such as the coefficient of determination R2, Root Mean Square Error (RMSE), and significance tests to assess how well the models fit the data and predict stock returns.

4. Results and analysis

4.1. Descriptive statistics

Table 1. Descriptive statistics

Variable	Mean	Std. Dev.	Min	Max	N
EPS	2.15	0.45	1.10	3.20	200
ROE (%)	12.3	4.1	4.5	20.8	200
Debt Ratio (%)	45.0	10.0	25.0	70.0	200
Sentiment Index	0.05	0.20	-0.40	0.60	200
Stock Return (%)	8.2	15.5	-30.0	45.0	200

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Table 1 presents the descriptive statistics of the variables used in this study. For earnings per share (EPS), the mean value is 2.15, the standard deviation is 0.45, and the range is from the minimum value of 1.10 to the maximum value of 3.20, with a total of 200 observations. The average value of return on equity (ROE) is 12.3%, the standard deviation is 4.1%, and the numerical range is from 4.5% to 20.8%, also based on 200 observations. The average value of the debt ratio is 45.0%, the standard deviation is 10.0%, and its range is from 25.0% to 70.0%. The emotional index shows greater volatility, with an average value of 0.05, a standard deviation of 0.20, and values ranging from -0.40 to 0.60. The average value of stock returns is 8.2%, the standard deviation is 15.5%, and the range is from -30.0% to 45.0%. Overall, the distribution of earnings per share and return on equity is relatively uniform, while the debt ratio averages 45% and the emotional index shows significant volatility.

4.2. Correlation analysis

Table 2. Correlation analysis

Variable	Return	EPS	ROE	Debt Ratio	Sentiment
Return	1.00	0.42	0.38	-0.30	0.35
EPS	0.42	1.00	0.55	-0.25	0.22
ROE	0.38	0.55	1.00	-0.28	0.30
Debt Ratio	-0.30	-0.25	-0.28	1.00	-0.15
Sentiment	0.35	0.22	0.30	-0.15	1.00

Table 2 presents the results of the correlation analysis among the variables. The stock return has a positive correlation of 0.42 with EPS and 0.38 with ROE, while it has a negative correlation of -0.30 with the debt ratio and a positive correlation of 0.35 with the sentiment index. EPS and ROE are strongly positively correlated with a correlation coefficient of 0.55. Both EPS and ROE have negative correlations with the debt ratio, with coefficients of - 0.25 and -0.28 respectively. The sentiment index has positive correlations with EPS (0.22), ROE (0.30), and the stock return (0.35), and a negative correlation of - 0.15 with the debt ratio. In summary, EPS and ROE correlate positively with returns, the debt ratio correlates negatively with returns, and the sentiment index correlates with both fundamental financial indicators and stock returns.

4.3. Model performance

Table 3. Model performance

Model	Variables Included	R^2	RMSE
Model 1	Financial indicators only	0.35	0.085
Model 2	Financial + Sentiment	0.55	0.060
Model 3	Financial + Sentiment + Macro	0.60	0.055

Table 3 compares the performance of three different models. Model 1, which only includes financial indicators (EPS, ROE, and debt ratio), yields an R2 of 0.35 and an RMSE of 0.085. Model 2, which includes financial indicators plus the sentiment index, shows a significant improvement

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with an R2 of 0.55 and an RMSE of 0.060. Model 3, incorporating financial indicators, the sentiment index, and macroeconomic factors, further improves slightly to an R2 of 0.60 and an RMSE of 0.055.

The results show that financial indicators form the basis for long-term valuation, emotions significantly improve short-term predictions, and macro shocks have an occasional impact. Hybrid models confirm the necessity of integration [9]. From a theoretical perspective, this supports behavioral finance views that psychology matters. From practice, investors should monitor both fundamentals and news sentiment, and adjust during geopolitical crises. Limitations include dataset scope and sentiment classification errors [10-11].

5. Conclusion

This study develops an integrative framework combining financial indicators, sentiment, and macroeconomic shocks. The findings reveal that financial indicators explain long-term returns, sentiment enhances short-term accuracy and macro shocks matter episodically. Future research should employ larger datasets, advanced NLP, and cross-market validation to further validate these results.

There are some deficiencies in this paper. First, the dataset is limited in time span and geographic coverage, which may reduce the generalizability of findings. It's possible that a more extensive dataset would make results more widely applicable. Second, despite integrating financial, sentiment, and macroeconomic indicators, the study uses simple representations (e.g., polarity scores for sentiment, dummy variables for macro shocks). Advanced techniques like transformer - based NLP models might better capture nuances, though we can't be sure by how much. Third, model comparison is restricted to regression and LSTM frameworks, while methods like attention mechanisms or graph neural networks remain unexplored. These might improve performance, but that's uncertain. Finally, the literature coverage, though comprehensive in given refs, excludes some emerging works that could enrich the discussion.

Future research can improve in several ways: Firstly, expanding datasets across countries and longer periods can provide robust cross-market validation, although data collection may be challenging. Secondly, using advanced NLP models (e.g., BERT, GPT) can improve the accuracy of sentiment indices, though this requires significant computational resources. Thirdly, incorporating alternative data (Google Trends, analyst reports, ESG disclosures) can capture new market behavior dimensions, despite the potential complexity of integration. Fourthly, adopting ensemble or hybrid deep learning models can enhance forecasting accuracy, albeit with the effort required to develop such models. Finally, exploring causal inference techniques to distinguish correlation from causation, which is difficult but crucial for understanding mechanisms.

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