Research and Analysis on the Prediction of Google's Stock Price Fluctuations in "Black Swan" Events Using a Deep Learning Model Integrated with a Macro Panic Index

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Abstract: In the 21st century, global economic fluctuations have intensified, and black swan events such as the COVID-19 pandemic occurred frequently in 2020. Traditional financial models are unable to cope with sudden market shocks and the problem of prediction failure has become increasingly prominent. Therefore, this study constructs a deep learning framework integrating the macro panic index (VIX), aiming to improve the accuracy of stock price fluctuation prediction in extreme markets. Using Google stocks as the research object, market data from 2015 to 2020 was selected, and the predictive performance of LSTM, CNN-LSTM, GARCH-LSTM, and LSTM-VIX models was compared. The empirical results show that the LSTM-VIX model significantly reduced the mean square error (MSE) during the 2020 crisis period, demonstrating stronger robustness and predictive ability. The study confirms that the introduction of macro risk factors is of great value for constructing a crisis warning system and optimizing financial risk management tools in the post-pandemic era.

Keywords: Black Swan Event; Stock Market Volatility; Deep Learning; VIX Index

1 Introduction

In the global economic landscape of the 21st century, the volatility and complexity of financial markets have been increasing. Especially since 2020, the outbreak of the novel coronavirus disease (COVID-19) has been widely regarded as a global "black swan" event, causing an unprecedented impact on global stock markets. Such extreme market fluctuations not only exposed the vulnerability of traditional financial risk models in dealing with sudden crises, but also prompted the academic community to re-examine the existing market prediction mechanisms.

In the early stage of the pandemic, the major global stock markets experienced severe fluctuations. Traditional linear prediction models often failed when dealing with such nonlinear and highly dynamic market data. Therefore, how to utilize advanced computing technologies to extract patterns from massive historical data and build robust prediction models in the new normal characterized by frequent "black swan" events has become a core issue in the field of financial engineering.

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Black swan events are characterized by their rarity, strong impact, and post-event explainability, which can cause severe fluctuations in global stock markets [1]. After Taleb proposed this concept, Χατζηκομνίτσας pointed out that traditional models have difficulty capturing their tail risks [2]. Walter believes that traditional financial modeling relies on normal assumptions and tends to underestimate extreme risks [3]. Phadnis et al. defined black swan events as a 7-day extreme value difference of the stock index being $\geqslant$ 10%, and reviewed seven typical events from 1997 to 2020, finding that short-term fluctuations of technology stocks were significant [4]. Ahmad et al. confirmed that technology stocks are more sensitive to crises and emotions [5], and Hanif et al. also pointed out that the financial and technology sectors were the most directly impacted [6].

Traditional forecasting is divided into fundamental analysis and technical analysis. Bhanja and Das believe that both are effective in stable markets, but difficult to deal with extreme shocks [7]. Rehman and Karimullah pointed out that GARCH-type models cannot identify fat-tailed risks, and the failure of predictions was obvious during the 2008 crisis and the COVID-19 pandemic [8]. Topiwala and Dai found that traditional timing models are prone to triggering stampede under black swan shocks [9]. Yadav added that traditional models have data smoothing defects, which filter out tail risks [10].

Deep learning has become the mainstream of nonlinear forecasting. Bhanja and Das constructed a 1D-CNN + Bi-GRU hybrid model, which can simultaneously extract spatio-temporal features [7]. Jin proposed that the model should have anti-fragility and learn from extreme disturbances [11]. Kjoersvik and Bate believed that intelligent automation can efficiently identify rare risks [12]. Yadav reminded that intelligent algorithms should avoid Gaussian smoothing, otherwise, extreme signals will be lost [10].

Macro panic index is a key indicator of extreme volatility. Swamy and Sayyad proved that the panic index can predict in advance and make up for the lag of technical indicators [13]. Rajalakshmi et al. found that panic sentiment amplifies the volatility of technology stocks [1]. Bhanja and Das pointed out that existing deep learning models often ignore the cross-border impact of black swan events and emotional factors [6]. Ahmad et al. emphasized the lack of specialized research on technology stocks such as Google [5].

In conclusion, the current research has revealed the mechanism of black swan shocks, the limitations of traditional models and the advantages of deep learning, and has also confirmed the value of the panic index. However, there are still gaps: first, there is a lack of research on extreme fluctuations of Google stocks; second, the models do not integrate the macro panic index; third, there is a lack of an appropriate model that takes into account both fat tails and emotional transmission. In view of this, this study aims to explore a new framework for stock market volatility prediction that combines deep learning technology (LSTM model) with macro factors (VIX panic index). The paper will systematically evaluate the performance of this framework under the impact of the COVID-19 pandemic and compare it with traditional benchmark models. Through empirical analysis, the paper expects to verify the effectiveness of this new method in improving the accuracy of predictions in Shanghai and major global financial markets,

thereby providing more reliable tools for asset pricing and risk management in the post-pandemic era.

2 Methodology

2.1. Data Sources and Feature Engineering

This paper selects the historical daily trading data of Google stocks as the research object, which is sourced from Kaggle and includes variables such as opening price, highest price, lowest price, closing price, and trading volume. Firstly, missing values and abnormal trading volume data are cleaned and sorted in chronological order. Then, logarithmic returns are calculated, and the 5-day rolling standard deviation is used as the volatility prediction target.

In terms of feature engineering, this paper constructs features such as price fluctuation indicators (HL_PCT, OC_PCT), moving averages (MA5, MA10), rolling standard deviation (STD5, STD10), and trading volume change rate to reflect market trends, risk levels, and trading activity.

The data is divided into a training set (2015-2018) and a test set (2019-2020) based on time, and StandardScaler is used for standardization processing. Finally, by using the sliding time window method, time series samples are constructed using the data of the past 20 trading days to provide input for deep learning models such as LSTM, CNN-LSTM, etc.

All the models adopted MSELoss as the loss function and used the Adam optimizer for training. Finally, the model's prediction performance was evaluated through the MSE, RMSE and MAE indicators.

2.2. Basic Prediction Model

To comprehensively evaluate the effectiveness of deep learning models in predicting stock market volatility, this paper selects three representative models, namely GARCH, LSTM, and CNN, to predict stock market volatility, and compares their prediction results under the impact of the COVID-19 pandemic. Among them, the GARCH(1,1) model is used to describe the conditional heteroscedasticity characteristics of the financial market, and its form is:

$$\sigma_t^2 = \omega + \alpha \mathcal{E}_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{1}$$

σ_t^2 denotes the conditional variance at period t, ω represents the long-term baseline volatility, α is the impact coefficient of new shocks, $\mathcal{E}_{t-1}^2$ stands for the squared residual at period t-1, and β refers to the persistence coefficient of historical volatility.

The LSTM model is a type of recurrent neural network suitable for time series prediction. In this paper, 13-dimensional financial features from the past 20 trading days are used as the input, and a two-layer LSTM network is constructed with a hidden layer dimension of 64. A fully connected layer is combined to output the future volatility:

$$h_t = o_t \cdot tanh(C_t) \tag{2}$$

$h_t$is the hidden state at time t, o_t denotes the output gate weight, tanh represents the nonlinear activation function, and C_t stands for the cell memory state.

CNN model extracts the local fluctuation features in the financial time series by using one-dimensional convolution. It achieves volatility prediction through convolutional layers, pooling layers and fully connected layers. The convolution form is as follows:

$$y_t = \mathrm{f}\left(\sum_{j=1}^{n} w_j x_{t+j-1} + b\right) \tag{3}$$

$\mathrm{y_t}$ denotes the local fluctuation feature extracted by convolution, f is the nonlinear activation function, $\mathrm{w_j}$ represents the convolution kernel weight, $\mathrm{x_{t+j-1}}$ stands for the time-series input data, and b refers to the convolution bias.

2.3. Dynamic Mixing Prediction Mechanism

The GARCH-LSTM model combines traditional financial econometric models with deep learning models. The model first uses GARCH to extract conditional volatility features, and then combines these with returns, technical indicators, etc. to input into the LSTM network. LSTM achieves long-term temporal dependency learning through forget gates, input gates, and output gates, and its core state update is:

$$h_t = f(W_h h_{t-1} + U_h x_t + b_h) \tag{4}$$

h_t is the hidden state integrating volatility features, f denotes the nonlinear activation function, W_h represents the hidden layer weight matrix,h_{t-1}stands for the previous hidden state, U_h refers to the input feature weight matrix, x_t is the current input feature, and b_h denotes the hidden layer bias.

Finally, the volatility prediction values are output by the fully connected layer, achieving the integration of statistical volatility modeling and deep time series learning.

The CNN-LSTM model combines convolutional neural network and long short-term memory network. Among them, the CNN is responsible for extracting local fluctuation patterns and nonlinear features. The convolution process is represented as:

$$c_t = f(W \cdot x_t + b) \tag{5}$$

c_t denotes the local time-series feature extracted by CNN, f is the convolution activation function, W represents the convolution weight matrix, x_t stands for the time-series input window data, and b refers to the convolution bias.

The convolutional layer identifies the local change characteristics of the price sequence by sliding the convolution kernel, and uses the pooling layer to reduce the noise interference. Subsequently, the extracted high-dimensional features are input into the LSTM network to further learn the long-term dynamic dependencies in the financial time series. The hidden state is updated as:

$$h_t = f(W_h x_{t-1} + U_h h_{t-1} + b_h) \quad (6)$$

Finally, the volatility prediction results are output through *the* fully connected layer. This model can simultaneously take into account the local feature extraction ability and the long-term temporal memory ability, thereby improving the nonlinear fitting effect of stock volatility prediction.

2.4. Introduction of Macro Factors in Deep Learning Models

To further enhance the predictive ability of stock volatility, this paper incorporates the VIX index as a macroeconomic risk factor within the deep learning model. The VIX index is regarded as an important indicator for measuring market panic and risk expectations, and its changes can reflect the overall level of market uncertainty.

In the feature construction, the VIX yield is defined as:

$$VIX_{Return,t} = ln\left(\frac{VIX_t}{VIX_{t-1}}\right) \quad (7)$$

$VIX_{Return,t}$ denotes the logarithmic return of VIX at period t, ln represents the logarithmic transformation function, VIX_t stands for the VIX index at period t, and VIX_{t-1} refers to the VIX index at period t-10.

Qmpared with deep learning models that only rely on historical price information, when the VIX macro factor is introduced, the model can more effectively capture changes in market risk sentiment, thereby enhancing its ability to predict extreme volatility and market shocks.

3 Empirical Results and Analysis

3.1. Result Analysis

Table 1. Model prediction error

Modle	2019			2020		
	MSE	RMSE	MAE	MSE	RMSE	MAE
GARCH	0.000169	0.012993	0.009517	0.000257	0.016042	0.012321
LSTM	0.000025	0.004993	0.003320	0.000093	0.009633	0.006314
CNN	0.000045	0.006690	0.004376	0.000083	0.009114	0.006255
CNN-LSTM	0.000029	0.005405	0.003328	0.000061	0.007808	0.005143
GARCH-LSTM	0.000026	0.005060	0.003102	0.000072	0.008512	0.006197
LSTM-VIX	0.000031	0.005540	0.005540	0.000053	0.007281	0.004790

LSTM-VIX, CNN-LSTM, and GARCH-LSTM models were used to compare their predictive abilities for the normal period in 2019 and the crisis period of the COVID-

19 pandemic in 2020, and the effects of different model strategies on market fluctuation predictions were examined.

As shown in Table 1, by adding the VIX panic factor to the LSTM-VIX model, both the prediction accuracy and robustness in the crisis period were improved significantly compared with those of CNN-LSTM and GARCH-LSTM. During the crisis, the MSE of LSTM-VIX (0.000053) was significantly lower than that of CNN-LSTM (0.000061) and GARCH-LSTM (0.000072), and the error increase (70.97%) was considerably smaller than for the other models (CNN-LSTM: 110.34%, GARCH-LSTM: 176.92%); therefore, it is indicated that this model is more suitable for capturing the non-linear fluctuations in the market during a period of panic. In addition, as shown in the above analysis, although CNN-LSTM is able to learn price features effectively through convolutional layers during normal times, it still has shortcomings in the face of "black swan" events, and it only uses historical data; GARCH-LSTM considers volatility clustering but fails to handle sudden macroeconomic shocks properly. Based on the research results above, simple data-driven models or statistical rule-fitting cannot replace the inclusion of macro-risk signals; only by integrating the data-mining capability of deep learning with external factors such as market sentiment can a predictive system be built that is highly accurate in prediction and crisis-resilient.

3.2. Strategic Analysis

Based on the comparison of the three models' performance, CNN-LSTM, GARCH-LSTM and LSTM-VIX, it can be seen that different mixed paths have varying degrees of efficiency in normal and crisis periods and offer different support for financial prediction strategies.

CNN-LSTM extracts local features from the price sequence using a CNN layer to achieve the best performance with an MSE of 0.000029 in the 2019 normal period; thus, it can be seen that feature engineering is effective in a stable market. However, in a crisis period, the MSE increased to 0.000061 (an increase of 110.34%), and solely relying on historical price features cannot address sudden, non-linear market panics, revealing the inherent deficiencies of data-driven models.

GARCH-LSTM combines the property of volatility clustering in GARCH and performs well; the MSE in the normal period is 0.000026, and although it is still relatively stable at 0.000072 during the 2020 crisis, it can learn patterns of volatility according to statistical laws. However, it still performs worse than LSTM-VIX in predicting large jumps triggered by changes in macroeconomic sentiment, indicating that traditional statistical methods are limited in describing sudden systemic risks.

LSTM-VIX directly adds the VIX panic factor to construct a macro factor path, and among them, it shows the best prediction accuracy with an MSE of 0.000053 in the crisis period; in the normal period, it has a relatively small accuracy loss (0.000031) and only a 70.97% increase in error. In short, considering the current market conditions, a mixed-path selection has been made. Feature extraction and statistical laws can improve the accuracy during normal times; at the same time, a large number of factors in a crisis need to be added to make the model more stable.

4 Conclusion

Build a deep learning model that integrates the macro panic index (VIX) to predict fluctuations in Google's stock prices during black swan events in this study. Based on empirical studies, it has been found that adding the VIX significantly increases the sensitivity of the model to extreme risk, and the LSTM-VIX model achieved the lowest MSE during the 2020 crisis; therefore, macro-sentiment is likely one of the reasons for this volatility.

CNN-LSTM, GARCH-LSTM and LSTM-VIX have been compared, and suitable ranges for different modelling strategies have been determined in the paper: data-driven models are appropriate in stable periods but perform poorly during crises; statistical models are stable but fail to respond effectively to sentiment-induced shocks. Based on the above results, it can be seen that a combined deep learning and macroeconomic model is suitable for both normal operation and crisis detection. This study has generally provided some references for managing financial risks and macroprudential regulation in the post-pandemic era.

Although this research has achieved certain results, there is still room for improvement. Firstly, this study mainly focuses on a single VIX index as the macro proxy variable. In the future, more dimensions of macro factors (such as liquidity indicators, policy uncertainty index) or alternative data (such as social media sentiment) can be introduced to build a more comprehensive prediction system. Secondly, the sample in this study only selected Google stocks. In the future, it can be expanded to global major financial markets (such as Shanghai, European markets) for cross-market verification to test the universality of the model. Finally, for the "black box" characteristics of deep learning models that lead to interpretability issues, subsequent research can combine SHAP values and other interpretive AI technologies to further explore the internal logic mechanism of the model, providing more persuasive evidence for investment decisions.

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