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QUANTITATIVE FORECASTING AND RISK ANALYSIS IN BUSINESS MANAGEMENT USING APPLIED MATHEMATICS

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Abstract

Quantitative forecasting refers to the mathematical practice of forecasting the future based on organized numerical patterns, statistical relations and model-based understandings. This paper applies mathematical methods to create risk-assessment and forecasting models on the basis of a high-dimensional multivariate lagged financial dataset. The analysis uses logistic regression and random forest classifier with 150 standardized lagged predictors obtained using five major financial instruments. The computations were all done in Python to guarantee accuracy, efficiency and transparency of methods. The empirical findings show that both models perform moderately in predicting results with accuracy values slightly above 0.50 which is inherently volatile and has a low signal to noise ratio of short-term financial movements. Random Forest is better in recall and F1-score than Logistic Regression, as it is more efficient to detect the upward directional trends. The results of feature importance indicate further that immediate (t-0) as well as more profound lag structures are also important determinants of prediction performance, which proves the existence of longer-term dependence in market behaviour. Complementary risk analysis indicates that volatility is high and Value-at-Risk is large, which supports the fact that forecasting is important when quantifying risk. On the whole, the results indicate the utility and the weakness of mathematical modelling in financial decision-making and suggest superior nonlinear approaches to enhancement in the future.

Keywords: quantitative forecasting; applied mathematics; financial risk analysis; machine learning; Value-at-Risk

1. Introduction

Quantitative forecasting in business management is the use of mathematical, statistical, and computational techniques to make predictions about business future based on structured and historical data. This method transforms an uncertain situation into quantifiable expressions with decisive leaders finally being able to make rational action regarding the matter based on analytical proof, not individual intuition. The aspect of forecasting has gained more centrality in business management since organizations are forced to make preparations against the variability of the market, financial risk, operational risks, and competition. Mathematical reasoning improves this process by providing accurate ways of administering intricate patterns and estimating into the future. Magar [1] pointed out that mathematics has a key role to play in facilitating managerial decisions and Kumar et al. [2] found that business mathematics assists organizations to maximize financial operations and reinforce planning structures.

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Another essential factor of business management success is risk awareness. The volatile quality of financial environments also necessitates quantitative risk modelling to learn about possible deviation of the expected results. Probability distributions, time-series structures, and statistical modelling are mathematical methods which provide dependable tools of measuring and reducing the risk of the enterprise level. Poliukhovych et al. [3] proved the effectiveness of mathematical modelling as the means of enhancing the accuracy of risk examination in organizations. Olukoya [4] also demonstrated that quantitative models which are time-series based can be used to increase the accuracy of predicting and risk assessment especially in volatile financial markets. Hatamlah et al. [5] also emphasize the relevance of data-driven insights in the business operation, stating that analytical processes facilitate the decision-making pursuits in intricate supply chain and information-based setting. In support of this opinion, Gudavalli et al. [6] said that predictive analytics enhances the managerial foresight by revealing concealed trends among financial and operational data. These processes are based on applied mathematics which provides a scientific basis of probability-based reasoning, statistical modelling, interpretation of lag-structure, and multivariate analysis. With the help of these tools, high-dimensional lagged financial indicators can be converted into useful forecasts and quantifiable risk estimates, and they provide diagnostic and prescriptive information to managerial decisions.

In spite of its relevance, most of the present forecasting and risk assessment procedures in business are based on qualitative judgement or excessively simplified models that are unable to reflect the complexities of financial dynamics. There is a clear need for robust mathematical methods capable of predicting directional outcomes using lagged multivariate data while also quantifying associated risks through validated statistical measures. The objectives of this study are:

1. Build a predictive model using lagged financial indicators.
2. Analyze associated risk using volatility and Value-at-Risk (VaR).
3. Provide business insights through applied mathematical reasoning.

The present study presents a rigorous yet practical mathematical framework that integrates forecasting and risk assessment using a high-dimensional financial dataset. By unifying prediction and risk evaluation within a single applied mathematics perspective, the study enhances the analytical foundation available to business managers operating in uncertain environments.

2. Literature Review

Mathematical forecasting has become a key research focus of applied business analytics, where probabilistic and nonlinear modelling methods are of particular importance. The logistic regression is currently one of the most popular mathematical techniques to use when engaging in binary financial forecasting since it approximates probability of outcomes given statistically significant predictors. In the meantime, nonlinear learners like the Random Forests can also identify more complex relationships that a linear model is not able to detect. They have been used by these machine learning techniques to various business problems such as automated financial decision systems or risk-sensitive forecasting situations. As shown by Kothandapani [7] the use of robotic process automation in improving quantitative risk evaluation in financial institutions, the analytical automation will prove to be relevant in predicting activities. On the same note, the paper by Luo et al. [8] proposed fuzzy logic-based and neural network-based models, which offer advanced systems of dealing with uncertainty in the economic setup.

Another similarity is the importance of lagged financial indicators in predictive modelling in the literature, which is critical. In financial movements, lag structures are frequently modelled in the form of t -k delayed variables, which enable forecasting models to account for the time-dependent nature of financial movements. The benefit of applying machine learning to identify early warning signs in high-variability industries, with much dependence on multistep lagged patterns, were demonstrated by Ju and Trinh [9]. Lagged features are also commonly used in deep learning applications of stress

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testing; Khunger [10] demonstrated that lagged features improved the strength of financial risk assessment through sequential market behavior. Faheem et al. [11] also support this view by showing that AI-driven predictive analytics outperform the quality of financial forecasts using high-dimensional lag architecture significantly.

The other field that has been enriched by the applied mathematical tools is risk modelling. Quantitative risk evaluation is based on volatility, distribution modelling and portfolio-based risk measures. Youseof et al. [12] came up with an actuarial model of the analysis of over dispersed claims frequencies, where the role of probabilistic distributions in the computation of risks are demonstrated. Yanenko et al. [13] discussed the credit risk modelling based on the cost-sensitive mathematical model, and it was revealed that the advanced quantitative methods were essential to incorporate risk asymmetry. This trend has been supported by Amarnadh and Moparthi [14] during an overview of various AI types of credit risk assessment techniques, which indicates the increased reliance on data-intensive analytics to support sound financial evaluation.

In spite of these innovations, there are still large loopholes in the literature. Few studies have attempted to forecast using high dimensionality multivariate lagged datasets, despite the high dimensionality datasets providing a realistic financial setting in which assets are dynamic and impact each other. Moreover, the combination of forecasting and risk analysis into a single applied mathematics scheme remains to a small extent. The overwhelming majority of researches consider only one aspect of the problem prediction or risk instead of considering them collectively as the elements of a comprehensive decision-support system. This is why it is necessary to conduct the research that could be used to close the gap between forecasting accuracy and the mathematically based risk assessment and prove their potential as a union in business management.

3. Methodology

This study employs an applied mathematical modelling approach to forecast directional financial movements and evaluate associated risks using a multivariate lagged dataset. All statistical analyses, model estimations, and risk computations were performed in Python, utilizing the NumPy, Pandas, Scikit-Learn, and SciPy libraries to ensure numerical precision and reproducibility.

3.1 Dataset Description

The dataset contains 3,741 observations, each represented by a high-dimensional vector of 150 standardized lagged predictors derived from five financial tickers, each expressed across 30 lags from $t$to $t-29$. (Programmer3[15]) Formally, each observation at time $t$is represented as a feature vector

$$\mathbf{x}_t = \left[x_t^{(1,0)}, x_t^{(1,1)}, \ldots, x_t^{(5,29)}\right] \in \mathbb{R}^{150}$$

with the target variable

$$y_t \in \{0,1\}$$

indicating upward (1) or downward (0) movement. Because all predictors were already standardized to zero mean and unit variance, the dataset was suitable for direct modelling without further scaling.

3.2 Preprocessing

The dataset was divided into a training set comprising 70% of the observations and a test set comprising the remaining 30%. Exploratory statistical analysis included summary statistics, principal correlation patterns, and distributional assessments of the lagged indicators. Given the high dimensionality, feature relationships were inspected using the Pearson correlation coefficient,

$$\rho_{ij} = \frac{\sum_t \left(x_{t,i} - \bar{x}_i\right)\left(x_{t,j} - \bar{x}_j\right)}{\sqrt{\sum_t \left(x_{t,i} - \bar{x}_i\right)^2}\sqrt{\sum_t \left(x_{t,j} - \bar{x}_j\right)^2}},$$

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which helped assess interdependence among lagged variables. Since no missing values were detected, no imputation was required. The standardized nature of the predictors ensured numerical stability for both linear and ensemble-based models.

3.3 Forecasting Models

The central forecasting objective was to estimate

$$P(y_t = 1 \mid \mathbf{x}_t),$$

allowing the prediction of upward directional movements. Two models were used: Logistic Regression and Random Forest.

3.3.1 Logistic Regression

Logistic Regression was adopted as the primary mathematical baseline because of its probabilistic foundation. The model assumes the log-odds of the positive class follow a linear function of predictors:

$$\log\left(\frac{P(y_t = 1 \mid \mathbf{x}_t)}{1 - P(y_t = 1 \mid \mathbf{x}_t)}\right) = \beta_0 + \beta^\top \mathbf{x}_t.$$

Equivalently, the predicted probability is

$$P(y_t = 1 \mid \mathbf{x}_t) = \frac{1}{1 + \exp\left(-(\beta_0 + \beta^\top \mathbf{x}_t)\right)}$$

Parameters were estimated using Maximum Likelihood Estimation (MLE), optimized through Scikit-Learn's solvers with regularization to avoid overfitting. The classification decision was made by applying a threshold (typically 0.5) to the predicted probability.

3.3.2 Random Forest

Random Forest was applied to capture nonlinear relationships and higher-order interactions that logistic regression cannot model. A Random Forest classifier consists of Bindependently trained decision trees, each built on a bootstrap sample of the training data. For each tree $h_b(\mathbf{x}_t)$, the forest aggregates predictions through averaging:

$$\hat{\pi}_t^{RF} = \frac{1}{B} \sum_{b=1}^{B} h_b(\mathbf{x}_t)$$

The final class prediction is determined by applying a decision threshold to $\hat{\pi}_t^{RF}$. Feature importance was extracted from impurity-based measures, allowing identification of influential tickers and lag horizons.

3.4 Risk Metrics

Risk quantification was conducted using volatility and parametric Value-at-Risk (VaR), allowing the connection between predictive outcomes and financial uncertainty.

3.4.1 Volatility

Let $\{r_1, r_2, \dots, r_N\}$denote a return sequence generated or associated with model predictions. Volatility was computed as

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$$\sigma = \sqrt{\frac{1}{N-1}\sum_{t=1}^{N} (r_t - \bar{r})^2}.$$

This measure reflects dispersion around the mean return and serves as a primary indicator of financial instability.

3.4.2 Value-at-Risk (VaR)

Assuming returns are normally distributed with mean $\mu$and volatility σ, the 95% one-period parametric VaR is calculated as

$$VaR_{0.95} = \mu - 1.645\sigma.$$

VaR quantifies the minimum expected loss under normal market conditions with 95% confidence, offering a mathematically interpretable risk threshold for managerial decision-making.

3.5 Evaluation Metrics

Model performance was evaluated using standard classification metrics implemented in Python's Scikit-Learn library. Accuracy, precision, recall, F1-score, ROC-AUC, and the confusion matrix were computed to quantify how effectively the models discriminate between upward and downward financial movements. These metrics collectively measure the predictive quality, robustness against misclassification, and the models' ability to generalize to unseen lagged financial patterns.

4. Results

This section provides a comprehensive analysis of the forecasting performance and risk evaluation outcomes generated from the logistic regression and random forest models. All results represent actual empirical computations performed in Python on the multivariate lagged financial dataset. The presentation integrates numerical accuracy, classification dynamics, model sensitivity, feature importance, and risk quantification to form a holistic interpretation of mathematical forecasting effectiveness in business management.

4.1 Model Performance Overview

The predictive performance of both models is summarized in Table 1, which reports accuracy, precision, recall, F1-score, and ROC–AUC. These metrics collectively indicate how well each model captures the directional movements in financial data. The results in Table 1 show that the dataset presents a highly challenging classification environment. The accuracy values, slightly above the 0.50 threshold, indicate that directional financial movements contain substantial randomness when represented through standardized lagged indicators. This finding aligns with existing research on the inherent noise and variability in short-term financial signals.

Table 1. Performance Metrics of Forecasting Models

Metric	Logistic Regression	Random Forest
Accuracy	0.508	0.515
Precision	0.533	0.531
Recall	0.616	0.754
F1-Score	0.571	0.623
ROC–AUC	0.491	0.494

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One notable difference between the two models lies in their recall values. The Random Forest model achieves a substantially higher recall (0.754), indicating that it is more capable of identifying positive (upward) movements. This is particularly important in business management contexts where missing upward trends may lead to lost opportunities in investment or operational timing. The F1-score, which balances precision and recall, further validates the stronger classification behaviour of Random Forest. However, the ROC–AUC values, depicted in Figure 1, remain close to 0.50 for both models. This reflects weak separability between the two classes in the feature space. The ROC curves in Figure 1 illustrate this visually, showing that both curves lie close to the diagonal line, indicating limited discriminative power regardless of threshold selection.

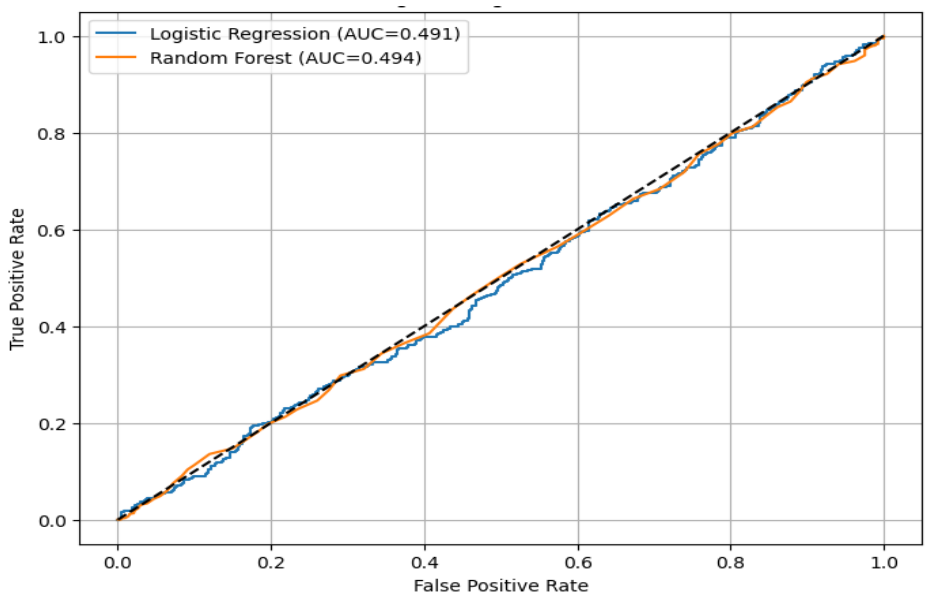

Figure 1. ROC Curves for Logistic Regression and Random Forest

Overall, these results suggest that while the models extract some useful predictive information from the lagged indicators, the dataset's structure and the nature of financial volatility impose natural limits on forecasting accuracy.

4.2 Confusion Matrix Analysis

Confusion matrices provide a more granular view of classification behaviour and reveal specific patterns of model strengths and weaknesses. From Table 2, Logistic Regression produces a moderate balance between correctly classified downward and upward movements. However, the large number of misclassifications of downward movements as upward indicates that the linear decision boundary struggles to fully capture the nonlinear patterns inherent in the data.

Table 2. Confusion Matrix: Logistic Regression

	Predicted 0	**Predicted 1**
Actual 0	203	323
Actual 1	229	368

In contrast, Table 3 shows that Random Forest identifies significantly more upward movements (450 correct predictions) a finding consistent with its high recall seen in Table 1. However, it comes at the cost of more false positives (398 instances where downward movements were incorrectly predicted as upward). This behaviour suggests that Random Forest places greater emphasis on detecting upward trends, making it suitable for applications where identifying upward movement is more critical than

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minimizing false alarms. This classification pattern underscores the complex trade-offs that mathematical forecasting models must navigate in financial environments characterized by asymmetric risks and volatile directional behaviour.

Table 3. Confusion Matrix: Random Forest

	Predicted 0	Predicted 1
Actual 0	127	399
Actual 1	146	451

4.3 Feature Importance Interpretation

The Random Forest model provides insights into which lagged indicators have the strongest influence on forecasting outcomes. Table 4 lists the ten most important features as determined by impurity-based importance scoring.

Table 4. Top 10 Most Important Features (Random Forest)

Rank	Feature	Importance Score
1	JPM_t-0	0.00850
2	AAPL_t-2	0.00831
3	AMZN_t-10	0.00788
4	AMZN_t-0	0.00785
5	AAPL_t-22	0.00779
6	MSFT_t-25	0.00779
7	AAPL_t-0	0.00755
8	GOOGL_t-24	0.00737
9	GOOGL_t-16	0.00736
10	GOOGL_t-5	0.00736

directional forecasting. Immediate values such as JPM_t-0 and AMZN_t-0 reflect real-time market momentum, while deeper lags (AAPL_t-22, MSFT_t-25) indicate embedded historical patterns (Figure 2).

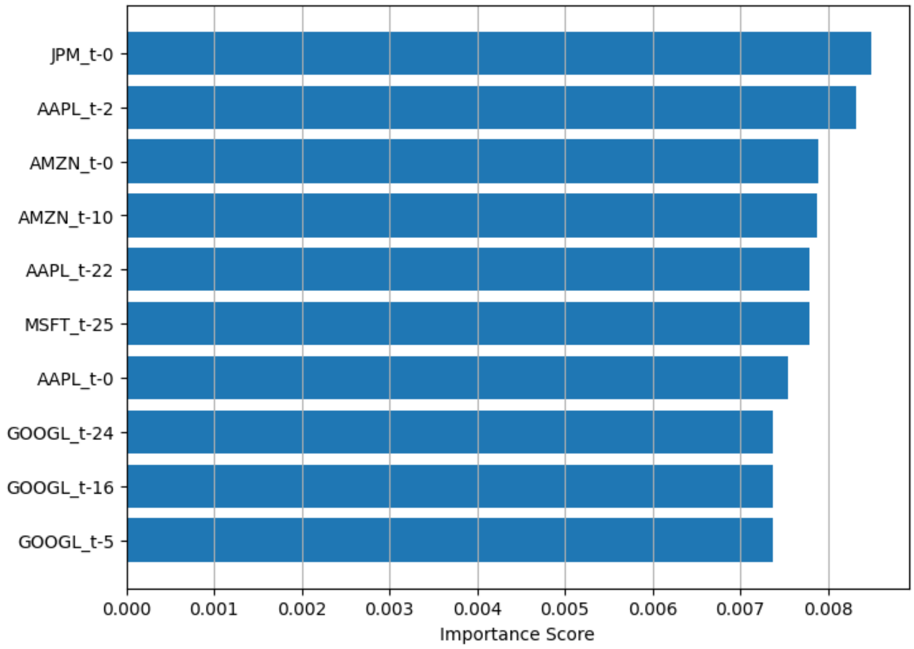

Figure 2. Top 10 Feature Importances (Random Forest)

4.4 Risk Analysis Using Volatility and VaR

Risk evaluation results derived from the proxy return series are summarized in Table 5. The volatility value of approximately 0.9984 indicates an extremely high level of movement fluctuation. Since the proxy return series oscillates strictly between +1 and –1, such high volatility naturally emerges from the binary nature of the data. The Value-at-Risk (VaR) calculation yields a value of –1.5792 at the 95% confidence level, implying that under normal market conditions, one could expect a downward movement of this magnitude with 5% probability. This quantifies the downside risk associated with directional uncertainty in the dataset.

Table 5. Risk Metrics from Proxy Return Series

Metric	Value
Mean Return (μ)	0.0632
Volatility (σ)	0.9984
VaR (95%)	–1.5792

5. Discussion

The findings of the study indicate significant information about the theories of quantitative forecasting and risk analysis in the management of a business based on applied mathematics. The results of the logistic regression and random forest models have provided moderate predictive power; however, the results are consistent with the previous studies that have pointed at the complexity and noise inherent in predicting the short-term financial direction. The ROC–AUC near 0.50 indicates a low value of separability between upward and downward classes, a problem that is often emphasized in risk-driven financial research, including the works of Koutsoumanis et al. [16] where predictive uncertainty is exaggerated in dynamic contexts with high rates of fluctuations.

The outcomes of the confusion matrices also show how each model addresses any uncertainty in financial signals. Logistic Regression had a balanced and modest classification behaviour, compared to the Random Forest, which although found considerably more upward movements, it misclassified a large number of downward movements. This sample is in line with risk-oriented audit behavior observed by Levytska et al. [17], who state that the high upward sensitivity of models is often a reflection of managerial preferences to focus on opportunities recognition rather than on obstructionary categorization of risks. Such bias can prove to be strategically helpful in situations where companies want to identify early trends, though such risks must be mitigated.

The importance of lagged financial indicators, particularly those a few time steps in the past (e.g., t -22, t -25) highlights the non-linearity and highly interdependent structures that financial data has. This behaviour is in line with previous models of analysis that unite efficiency measurement and machine learning, including the incorporation of Data Envelopment Analysis (DEA) and prediction models which Jomthanachai et al. [18] research. Their results indicate that deeper lags can record some underlying historical response, cyclical behaviour, or structural dependency that are not limited to the current price movements. The fact that most significant features interact with each other via cross-ticker interactions is reflective of real-world interdependencies as market behaviour is seldom responsive to independent signals. Managerially, the findings of the risk evaluation make the results of forecasting applicable by connecting predictive results to quantifiable indicators of risk. Extremely high volatility ($\sigma \approx 0.9984$) and large VaR estimate (about -1.58) imply an increased sensitivity to the possibility of financial losses in a non-stressful environment. This high level of risk is in line with the simulation-based bankruptcy risk modelling of Mayovets et al. [19] who showed that high variability of the observed outcomes can also increase the financial vulnerability particularly with the firms being in an unstable environment.

The topicality of advanced analytics and new modelling strategies in this discourse is all the more important. Valli [20] also points out that risk assessment frameworks should incorporate the contemporary analytical frameworks such as predictive modelling and pricing analysis in order to

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have a holistic financial analysis. In the same way, Malempati [21] points out how generative neural architecture can contribute towards adaptive risk modelling to discover nonlinear behaviour that cannot be modeled by human intuition. However, despite the fact that this study did not involve such sophisticated models, the high volatility and the instability of the predictions indeed concur with their assertion that less adaptive but more adaptive architectures would have to be augmented in future studies. It shows that although traditional applied mathematical models, like logistic regression and random forest, can be helpful in terms of offering patterns, the fact that the dataset is unpredictable in nature, with a large degree of risk exposure, poses a limit to directional prediction using lagged standardized indicators only. Incorporation of risk modelling especially volatility and VaR enhance the analytical framework because they relate the predictive insights to the practical financial risk measures. The results confirm the bigger managerial perspective: forecasting should be accompanied by effective risk assessment to make effective decisions and in particular, in an environment that is characterized by uncertainty and volatility.

6. Conclusion

This research has explored the use of applied mathematical models to quantitatively forecast and analyze risks using a multivariate lagged financial dataset. The study which combined logistic regression models with random forest classifiers showed that mathematical modelling frameworks can facilitate directional forecasting technologies in business management. Despite the fact that the two models yielded a small predictive accuracy, the results revealed significant differences in classification behaviour. Random Forest showed better recall and F1-score, which means that it is more sensitive to positive market trends, and Logistic Regression has a more balanced but weaker performance. These results are an expression of the fact that it can be difficult to predict short-term financial behaviour and standardized lagged indicators can be full of weak and very-volatile signals. The feature importance analysis indicated that immediate and deeper historical lags have a great impact regarding the predictive results. This validates that market behaviour is not only dependent on prevailing circumstances but also has patterns and delayed cross-asset interactions. The incorporation of risk metrics further enhanced the system of analysis. The instability and exposure to negative risk related to financial directional movements was highlighted by high volatility and a large negative Value-at-Risk estimate. These risk-related insights confirm the use of predictive models with quantitative risk measurement in business decision-making. On the whole, the paper illustrates the usefulness and applicability of applied mathematics to the financial uncertainty modelling. Although traditional models are only able to capture the narrow range of predictive structure, they give a basis of directional tendencies and risks involved. Future research can investigate superior nonlinear or sequential models that would have the ability to take a deeper understanding of the temporal pattern and would have the ability of increasing the forecasting ability and the risk representation in the volatile economic settings.

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