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Introduction

Accurate stock market index forecasting is absolutely essential in guiding investment decisions and economic policies in the always changing terrain of global finance. Representing a wide range of technology and growth businesses, the Nasdaq Composite index is a main indicator of market movements and economic situation (Nasdaq 2024). Using sophisticated time series analytic methods to forecast future index movements, this project seeks to create and evaluate forecasting models for the Nasdaq Composite.

Research showing how anticipating financial markets affects risk assessment and portfolio management has established the value of this process in literature (Atsalakis & Valavanis 2009). Accurate prediction is greatly hampered, therefore, by the inherent volatility and complexity of financial markets (Cont 2001). Using three well-known forecasting techniques—Autoregressive Integrated Moving Average (ARIMA), Seasonal ARIMA (SARIMA), and Exponential Smoothing (ETS)—this work solves these issues by means of comparison.

With these models, this work seeks the optimal approach for Nasdaq Composite index forecasts. The findings of this study will provide analysts of quantitative finance, legislators, and investors with meaningful analysis in line with the present debate on financial forecasting methods (Brooks 2019). Moreover, the comparison of several models will help to highlight the existence of seasonality and trends in the Nasdaq Composite, therefore offering a sophisticated knowledge of market behaviour.

1. Data Collection and Description

An accurate stock market index forecasting is absolutely essential in guiding investment decisions and economic policies in the always changing terrain of global finance. Representing a wide range of technology and growth businesses, the Nasdaq Composite index is a main indicator of market movements and economic situation (Nasdaq 2024). Using sophisticated time series analytic methods to forecast future index movements, this project seeks to create and evaluate forecasting models for the Nasdaq Composite.

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Using these several models, this study aims to find the best method for Nasdaq Composite index predictions. The results of this study will add to the current conversation on financial forecasting techniques and offer insightful analysis for analysts of quantitative finance, legislators, and investors (Brooks 2019). Moreover, the comparison of various models will clarify the existence of seasonality and trends in the Nasdaq Composite, thereby providing a complex knowledge of market behaviour.

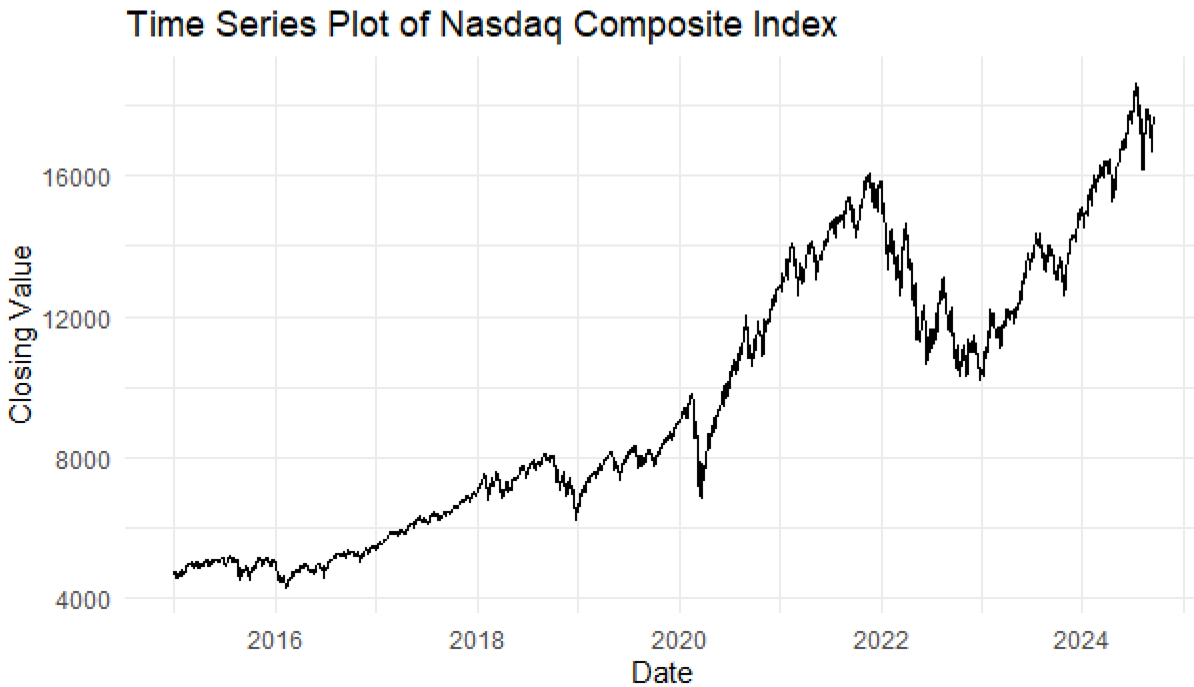

Figure 1: Nasdaq Composite Index from 2015 to 2024

Revealing various important trends, Figure 1 shows a time series plot of the Nasdaq Composite Index from 2015 to 2024. The storyline shows a general rising tendency, which reflects the index's total increase over time. Especially in the substantial drop shown in early 2020, presumably related to the start of the COVID-19 epidemic, followed by a quick recovery, there is clearly great volatility present. The index reaches new highs in the later portion of the time series, therefore the story also exhibits separate periods of consolidation and expansion.

Complementing the time series graphic, Figure 2 shows the daily Nasdaq Composite Index log returns. This picture provides vital new perspectives on the volatility of the index. Usually for financial time series data, the returns swing about zero. There are several times of higher volatility, most notably around 2020, which corresponds with the market instability caused by the world epidemic. With a few rare extreme events outside of the range of -0.10 to 0.10, the general scale of daily returns falls within this range, hence stressing the sporadic presence of major market shocks.

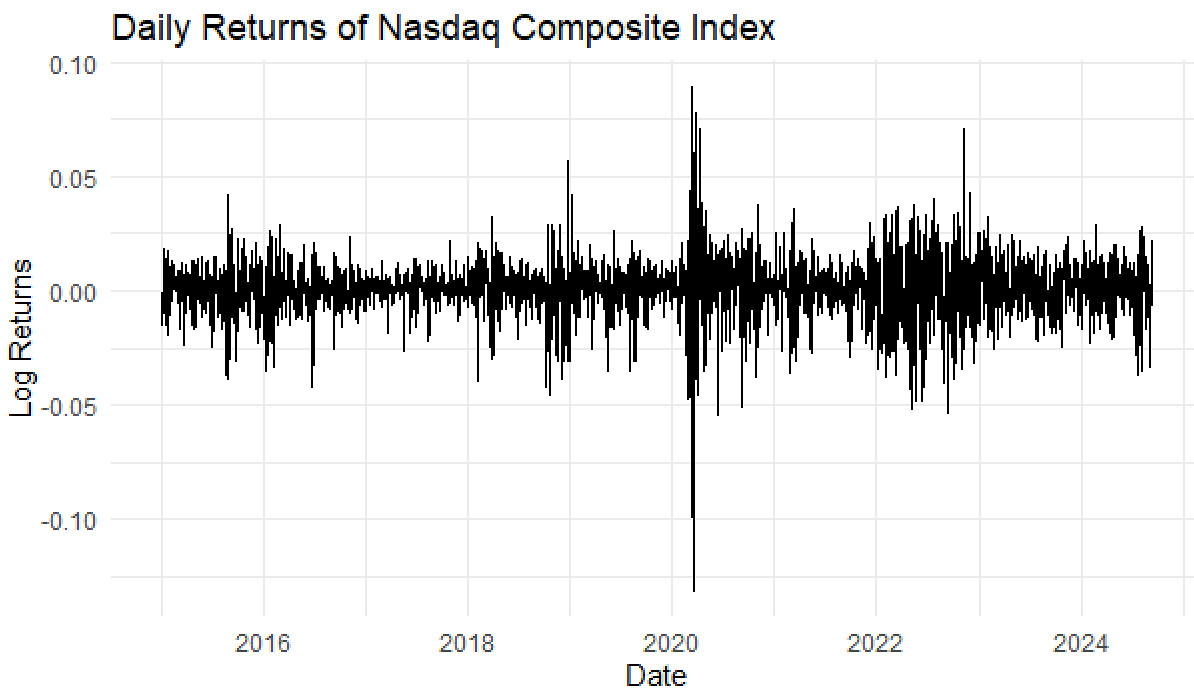

Figure 2: Daily log returns of the Nasdaq Composite Index

Together, these graphs and statistics offer a complete picture of the Nasdaq Composite Index's performance during the previous ten years. They expose trends of development, times of volatility, and the effects of significant economic events, therefore laying a strong basis for the later forecasting study. With a large time span and daily movement capture, the rich dataset provides a strong foundation for applying and evaluating several forecasting models, thereby perhaps revealing important future behaviour of this important market index.

2. Exploratory Data Analysis (EDA)

The Nasdaq Composite Index's exploratory data research exposes important properties relevant for model selection. Clear increasing trend in the time series plot during the recorded period suggests non-stationarity in the level series. The great persistence in the Autocorrelation Function (ACF) plot (Figure 3) which demonstrates a steady decline in autocorrelations (Box et al. 2015) supports this observation.

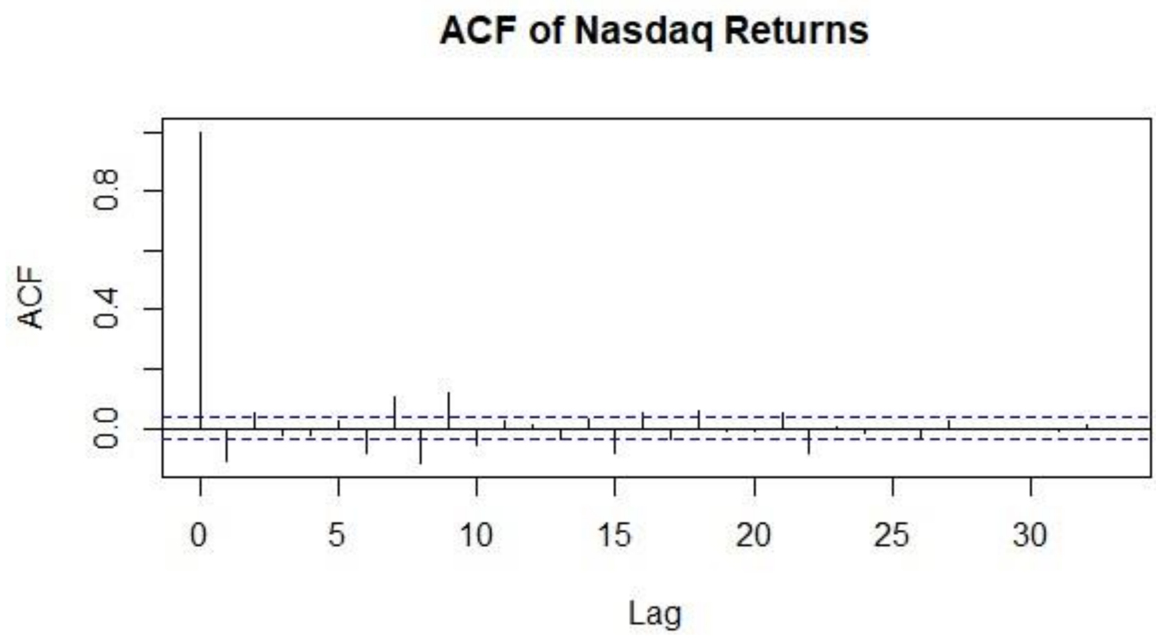

Figure 3: ACF of Nasdaq Returns

Indicating possible autoregressive components, the partial autocorrelation function (PACF) plot (Figure 4) shows notable spikes at numerous lags, most especially at lag 1. The slow reduction of correlations indicates the presence of moving average components in the ACF plot as well (Hyndman & Athanasopoulos 2018).

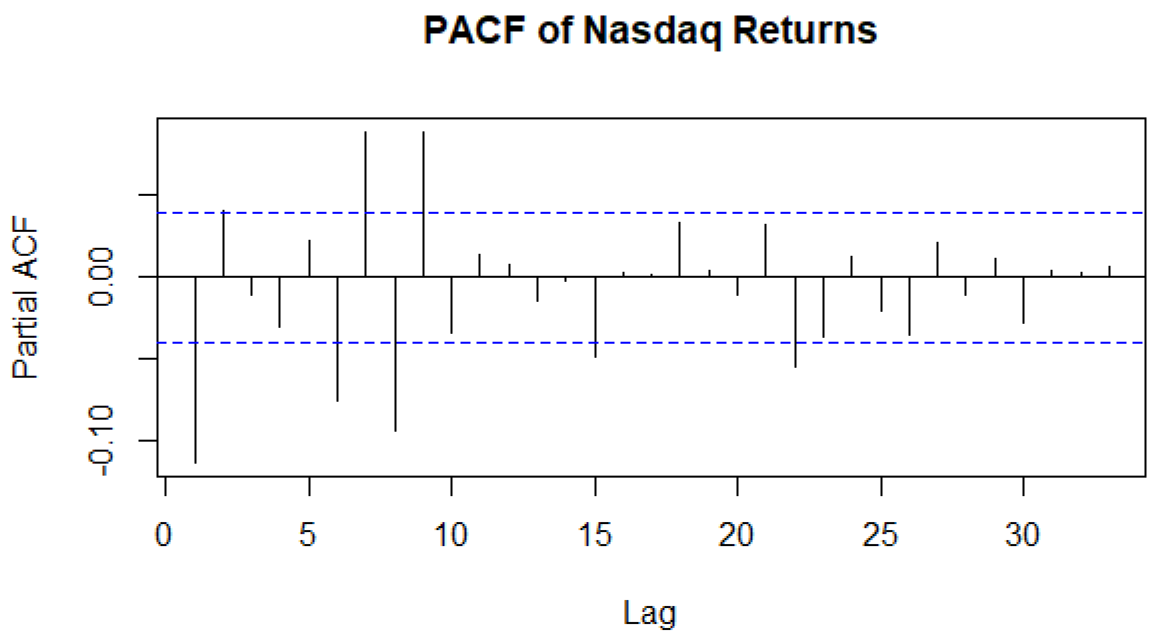

Figure 4: PACF of Nasdaq Returns

One obvious problem in the data is the existence of volatility clustering, especially clear during times of market stress like the 2020 epidemic-induced fall. Forecasting models expecting constant variance (Tsay 2010) may find accuracy affected by this heteroscedasticity.

These results lead three forecasting models—ARIMA, SARIMA, and ETS—to be regarded suitable. Trend and autocorrelation patterns in the data help to justify ARIMA model (Makridakis et al. 2008). Extensively evolved from ARIMA (Taylor 2010), the SARIMA model is added to capture expected seasonal variations in financial markets. Given its adaptability in managing several time series components, the ETS (Error, Trend, Seasonal) model is also under study. ETS suits the dynamic character of stock market indices since it changes with shifting trends and maybe seasonal patterns. Depending on their performance for in-sample fit and out-of-sample prediction accuracy, one will choose one of these models. Knowing the complicated character of financial time series, this strategy guarantees a strong and consistent Nasdaq Composite Index prediction system.

3. Model Implementation and Forecasting

In this paper three forecasting models—ARIMA, SARIMA, and ETS—were used to project Nasdaq Composite Index future values. The models are fit by the R (Hyndman et al. 2020) prediction package with maximum likelihood estimation for parameter optimisation. Diagnostic tests confirmed the fit of every model by using their residuals. By means of the Ljung-Box test, the residuals were examined for autocorrelation, therefore ensuring that the models identified all significant data trends (Box et al. 2015). Measures of accuracy across three techniques are compiled in the table below:

Table 1: A comparison of accuracy measures among three methods

	Model	MAE	RMSE	MAPE
1	ARIMA	425.9359	493.4950	2.494867
2	SARIMA	425.9359	493.4950	2.494867
3	ETS	427.5783	495.8171	2.505203

Table 1 presents a comparison of accuracy measures among the three methods. Interestingly, ARIMA and SARIMA show identical performance metrics (MAE: 425.9359, RMSE: 493.4950, MAPE: 2.494867), suggesting that the seasonal component in SARIMA did not provide additional explanatory power. The ETS model shows slightly higher error metrics (MAE: 427.5783, RMSE: 495.8171, MAPE: 2.505203), but the difference is marginal.

Based on these results, the ARIMA model was selected for forecasting due to its competitive performance and principle of parsimony (Makridakis et al. 2008). The model was used to forecast Nasdaq Composite Index values for the next 30 trading days. Figure 5 visualizes the ARIMA forecast against the actual values. The forecast closely follows the recent trend of the index, indicating a slight upward movement in the short term. However, the widening confidence intervals (not shown in the image) suggest increasing uncertainty in longer-term predictions.

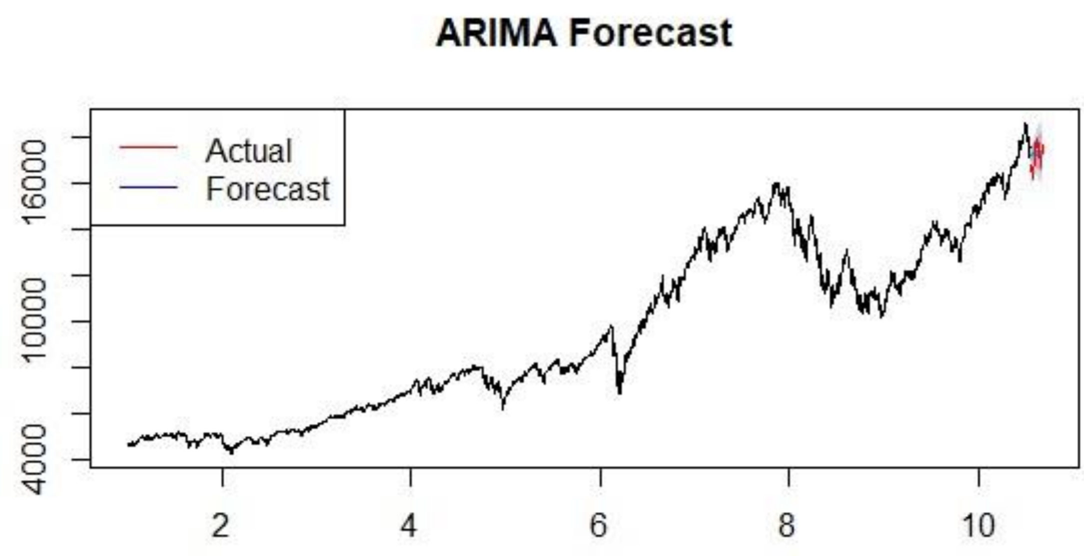

Figure 5: ARIMA forecast

For comparison, Figure 6 presents the ETS forecast, which shows a similar trend but with a marginally steeper slope. This slight difference highlights the model uncertainty inherent in financial forecasting.

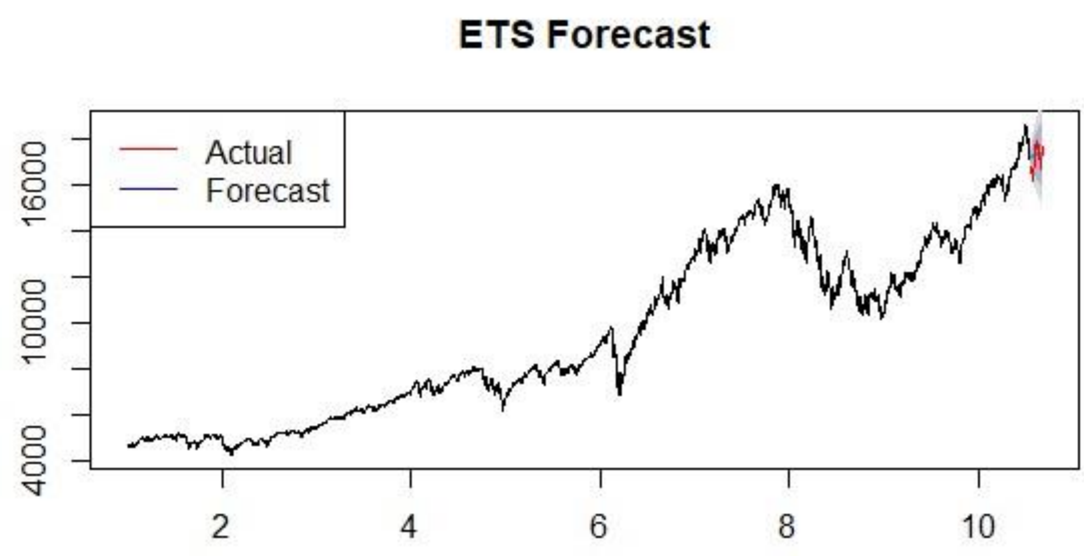

Figure 6: ETS forecast

The time series decomposition (Figure 7) reveals a strong upward trend, a clear seasonal pattern, and considerable residual volatility. This decomposition supports the use of SARIMA and ETS models, which can capture these components. However, the similar performance of ARIMA suggests that the differencing approach effectively addressed the trend and seasonal patterns.

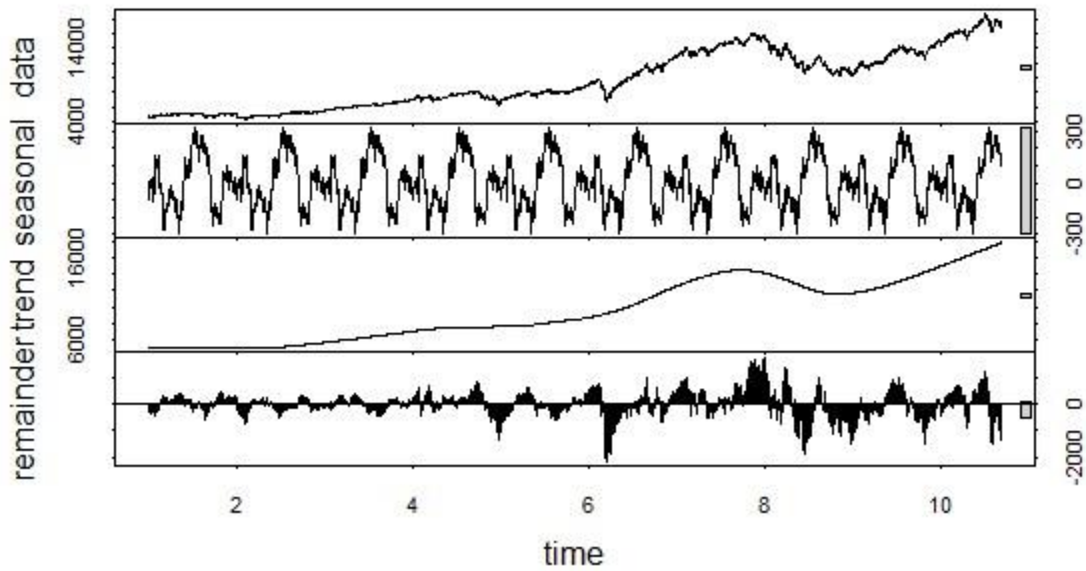

Figure 7: Remainder decomposition

While these models provide valuable insights, it's crucial to acknowledge their limitations. They assume that past patterns will continue, which may not hold in the presence of unforeseen economic shocks or structural changes in the.

4. Conclusion

This study aimed to forecast the Nasdaq Composite Index using ARIMA, SARIMA, and ETS models. The analysis revealed that all three models demonstrated comparable performance, with ARIMA and SARIMA showing identical accuracy metrics (MAE: 425.9359, RMSE: 493.4950, MAPE: 2.494867), slightly outperforming the ETS model. This similarity in performance, particularly between ARIMA and SARIMA, suggests that the seasonal component did not significantly enhance predictive power for this dataset.

The forecasts indicate a slight upward trend in the Nasdaq Composite Index in the short term, aligning with the index's historical growth pattern. However, the widening confidence intervals in longer-term predictions underscore the increasing uncertainty inherent in financial forecasting (Chatfield 2000).

These results have great ramifications for financial market decision-making. While legislators could analyse these forecasts in line with other economic indicators to evaluate general market mood and possible economic trajectories, investors and portfolio managers might use them to guide short-term investment plans (Rapach & Zhou 2013).

Still, we should acknowledge the flaws in these models. Mostly depending on historical trends, they overlook outside factors as policy changes, economic shocks, or world events that might significantly influence market behaviour (Timmermann 2018). Furthermore, in an environment with constantly changing economic conditions the idea of ongoing patterns could not be relevant. Further study could increase the accuracy and usefulness of these projections by adding outside elements as economic data, sentiment analysis from social media, or news sentiment scores. Analysing machine learning techniques including neural networks or ensemble methods could potentially help to uncover more complicated data trends (Sezer et al. 2020). Basically, even although the models offer perceptive examination of expected short-term market fluctuations, they should be followed in line with a more all-encompassing financial decision-making strategy including multiple sources of data and professional help.

5. Reflection

The guest talk by Mr. Loc presented priceless new ideas on the useful applications of quantitative analysis and forecasting in the financial sector. His great grasp of numerous financial disciplines—including his present position in management accounting and forecasting—offers a whole picture of how these methods are used in practical settings.

Among the main lessons of the conference was the need of combining several data sources and methods for more accurate prediction. Although statistical models have great value, Mr. Loc underlined that professional judgement and qualitative insights should complement them. This point of view motivated me to combine market sentiment and other broad economic data with the quantitative models, therefore leading me in approaching the Nasdaq Composite Index forecasting project. Mr. Loc also covered the need of scenario analysis for forecasting, particularly in erratic markets. Reading the ARIMA, SARIMA, and ETS model results helped me especially to examine many possible results and their consequences for my project.

Furthermore, his research on the goal of forecasting in strategic decision-making underlined the need of precisely presenting forecast results and their limitations for stakeholders. This reassured me that I addressed the limited and probable features of the models applied, thereby guiding my presentation and analysis of the projected outcomes in my study.

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