The Forecasting of Stock Prices in the UK – a Comparison Among Various Predictive Models.

Finance and Investment

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# **Chapter 1 : Introduction**

## *1.1 The Importance of Stock Price Predictions*

In the fast-paced world of finance, forecasting stock prices includes analysing past market trends and patterns, financial fluctuations, and other factors that affect price movement. Companies and investors alike use forecasting as an important tool to make purchase decisions, sales, estimate earnings and other data for subsequent periods. The successful forecast of a stock’s future price could yield significant profit, the benefits from: enhanced decision-making (Kurzak, 2012); Operational Performance Improvement (Danese, Kalchshmidt, 2011); and Risk Management Adaptability

Kurzak (2012) argues forecasting provides a solid foundation for managerial decisions by anticipating market trends and economic conditions. This insight is further supported by Danese and Kalchschmidt (2011), who find that structured forecasting processes significantly improve forecast accuracy and operational performance by integrating various sources of information and aligning forecasts with strategic decision -making. Building on this, research by Poterba and Summers (1981) delve into the volatility of stock markets. Their findings underlay understanding patterns of volatility is crucial when developing predictive models to navigate and anticipate the stock market. Further supported by the research, various predictive models will be compared to determine which one is the strongest forecasting tool that would most likely yield more profit for companies and investors alike.

However, despite the availability of numerous predictive models, there remains uncertainty regarding which models provide the most accurate and reliable forecasts, especially under varying market conditions. This research aims to address this gap by systematically comparing traditional financial models with modern machine learning techniques.

## *1.2 Aims, Objectives and Research Question.*

The primary aim is to evaluate various predictive models and their accuracy and assess their superiority on how they would perform. This objective raises several key questions:

1. To examine the accuracy of various stock price prediction models.
2. To compare the accuracy of predictions among various predictive models.

How do ML techniques compare to traditional financial models in predicting stock prices?

## *1.3 Overview*

Chapter 2, "Literature Review & Hypothesis Development," explores the theoretical foundations and empirical applications of various predictive models, including traditional models (CAPM, LR), modern time series models (ARIMA, GARCH), and machine learning models (SVM, LSTM). It highlights their strengths and limitations and develops hypotheses comparing their efficacy in predicting stock prices.

Chapter 3, "Research Development," outlines the methodological framework, detailing data collection from the FTSE 100, construction of variables like stock returns, and implementation of predictive models. It explains the evaluation metrics (MSE, RMSE, MAE, R²) and addresses ethical considerations in data handling and model application.

Chapter 4, "Analysis Findings and Discussion," presents the empirical results, starting with descriptive statistics of the dataset. It evaluates the performance of each predictive model using the selected metrics, comparing traditional, modern time series, and machine learning models. The chapter discusses model performance, assumptions, limitations, hyperparameter tuning, and overfitting. Additional insights from feature importance and sensitivity analysis are provided.

# **Chapter 2: Literature Review & Hypothesis Development**

## *2.1 Traditional Predictive Models*

### *2.1.1 Capital Assets Predictive Model*

Traditional predictive models have moulded the landscape of financial analysis for decades, reliably offering insights and guiding investment decisions for decades. Introduced by William Sharpe in the mid-1960s, the Capital Asset Pricing Model (CAPM) revolutionised financial theory with its straightforward yet profound linkage between risk and return (Sharpe, 1964). As a fundamental pillar in finance, CAPM not only enhances our understanding of market dynamics but also equips portfolio managers and investors with a robust framework for assessing expected investment returns in relation to market risks.

At its core, CAPM asserts that the expected return on any security or portfolio is directly proportional to its exposure to systematic market risks. This relationship is elegantly encapsulated in the model’s formula:

E(Ri) = Rf + βi (E(Rm ) − Rf )

where E(Ri) represents the expected return on the investment, Rf  stands for the risk-free rate, βi ​measures the investment's sensitivity to market movements, and E(Rm ) denotes the expected market return. This formula not only quantifies the risk-return trade-off but also underscores the premium investors should demand for bearing additional risk beyond that of a risk-free asset (Sharpe, 1964).

CAPM's utility extends beyond theoretical explorations; it is a practical tool for gauging the cost of equity and optimising investment portfolios. By comparing expected returns relative to systemic risks, CAPM helps investors make calculated decisions about which stocks to hold, aligning potential rewards with expected risks. Despite its broad adoption, researchers like Fama and French have noted that CAPM's effectiveness can vary across different market scenarios, challenging its assumptions under conditions of market anomalies (Fama & French, 2004).

While CAPM's simplicity is its greatest asset, it is also a source of critique. The model’s reliance on a singular risk factor—the market beta—has been argued to oversimplify the complex realities of financial markets. Moreover, its foundational assumptions about market efficiency and homogeneous investor expectations often do not hold, limiting its applicability in predicting actual stock returns. Such empirical inconsistencies, highlighted by scholars like Malkiel, suggest that CAPM may not always provide reliable predictions, particularly in volatile or non-efficient markets (Malkiel, 2003).

Despite these critiques, the elegance of CAPM lies in its ability to distil complex economic realities into a comprehensible model that continues to inform and shape financial strategies. Its foundational role in modern finance makes it an indispensable starting point for any scholarly discussion on investment behaviour and market dynamics.

### *2.1.2 Linear Regression*

Introduced by Francis Galton in the late 19th century, linear regression is one of the most fundamental and widely used statistical methods for predictive analysis. It models the relationship between a dependent variable (in this case, stock prices) and one or more independent variables by fitting a linear equation to observed data. This method's simplicity and interpretability make it a staple in financial forecasting.

The basic idea of linear regression is to find the best-fitting line through a set of data points by minimising the sum of the squared differences between the observed values and the values predicted by the line. The formula for a simple linear regression model is:

y = β0 ​+ β1​x + ϵ

Where:

y is the dependent variable (stock price),

x is the independent variable,

β0 is the intercept,

β1 is the slope of the line,

ϵ is the error term.

Linear regression is used to predict stock prices by identifying trends and relationships between stock prices and various economic indicators or other stock market variables. Its simplicity and ease of interpretation make it a popular choice.

Strengths and Limitations:

Strengths: Easy to implement and interpret; computationally efficient.

Limitations: Assumes a linear relationship between variables; not suitable for capturing more complex patterns in stock price data (Tsay, 2005).

Despite its limitations, linear regression remains a powerful tool for financial forecasting due to its straightforward approach and ease of use. Its foundational role in statistical analysis makes it an essential technique for understanding basic relationships in financial data.

## *2.2 Modern Predictive Models*

### *2.2.1 Autoregressive Integrated Moving Average*

The Autoregressive Integrated Moving Average (ARIMA) model, developed by Box and Jenkins in 1976, is a widely utilised statistical method for analysing and forecasting time series data. ARIMA is valuable in financial markets for its ability to model a wide range of time series behaviours by combining three key components: autoregression (AR), differencing (I), and moving average (MA).

* Autoregression (AR): This involves regressing the variable on its own prior values, with the AR part of ARIMA (p) defined by the number of lagged observations included in the model.
* Integrated (I): This involves differencing the observations to make the time series stationary, removing trends and seasonality.
* Moving Average (MA): This incorporates the dependency between an observation and a residual error from a moving average model applied to lagged observations.

The general form of the ARIMA model is expressed as:

ARIMA(p,d,q)

Where:

* p = number of lag observations (autoregressive part)
* d = number of times that the raw observations are differenced (integrated part)
* q = size of the moving average window (moving average part)

The model can be mathematically represented as:

yt​ = c + ϕ1​yt − 1​ + ϕ2​yt − 2​ + ... + ϕp​yt − p​ + θ1​ϵt – 1 ​+ θ2​ϵt − 2​ + ... + θq​ϵt − q​ + ϵt​

The ARIMA model's flexibility makes it a powerful tool for financial market forecasting. It has been extensively applied to model and predict stock prices, exchange rates, and other financial indicators. Tsay (2005) highlights several successful applications of ARIMA in financial markets, demonstrating its ability to capture and forecast market dynamics effectively.

A notable application of ARIMA is in the forecasting of stock prices, helping to understand underlying patterns and making short-term predictions based on historical data (Tsay, 2005).

Despite its widespread use, ARIMA has certain limitations. One significant drawback is its assumption of linearity, which can be restrictive in financial markets where non-linear patterns often prevail. Additionally, ARIMA requires the time series data to be stationary, meaning that the mean and variance should be constant over time. This need for stationarity often necessitates pre-processing steps like differencing, which can sometimes oversimplify the data and lead to loss of valuable information.

Brockwell and Davis (2002) point out that ARIMA models can struggle with capturing more complex, non-linear relationships present in financial time series. Moreover, the model's performance can be heavily dependent on the chosen parameters (p, d, q), which require careful selection through methods such as the Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) for optimal results.

While ARIMA remains a foundational tool for time series forecasting in finance, its effectiveness is contingent upon the linear nature and stationarity of the data, necessitating a cautious and informed application.

### *2.2.2 Generalized Autoregressive Conditional Heteroskedasticity*

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, introduced by Tim Bollerslev in 1986, represents a significant advancement in time series modelling, particularly for financial data characterized by volatility clustering. GARCH extends the Autoregressive Conditional Heteroskedasticity (ARCH) model developed by Engle (1982), allowing for a more flexible and comprehensive approach to modelling changing variance over time. In essence, GARCH models the conditional variance of the error term as a function of past squared observations and past conditional variances, capturing the persistence of volatility shocks.

The GARCH(p, q) model can be expressed as:

GARCH models have become a cornerstone for volatility forecasting in financial markets due to their ability to model time-varying volatility and capture the clustering effect where periods of high volatility tend to be followed by high volatility and vice versa. Engle (2001) demonstrated the applicability of GARCH models in financial markets, highlighting their effectiveness in predicting the volatility of asset returns. The models are particularly useful for risk management, derivative pricing, and financial market regulation, where understanding and forecasting volatility is crucial.

Numerous empirical studies have confirmed the effectiveness of GARCH models in capturing the dynamic behaviour of financial market volatility. For instance, GARCH models have been successfully applied to forecast the volatility of stock returns, foreign exchange rates, and commodity prices, providing insights that are essential for strategic investment decisions and risk assessment.

Despite their widespread use and proven effectiveness, GARCH models face several challenges. One primary issue is the complexity involved in parameter estimation. Ensuring the stability of parameter estimates can be difficult, particularly in the presence of structural breaks or regime changes in the data. Hansen and Lunde (2005) discuss practical challenges in fitting GARCH models, noting that overfitting can lead to unstable parameter estimates and reduced out-of-sample forecasting performance.

Another significant challenge is the assumption of a normal distribution for the error terms, which may not always hold in financial time series data that often exhibit heavy tails and skewness. To address these issues, various extensions of the GARCH model have been proposed, such as the Exponential GARCH (EGARCH) and the Threshold GARCH (TGARCH), which accommodate asymmetries and leverage effects in volatility.

While GARCH models are powerful tools for volatility forecasting, their application requires careful consideration of model specifications and potential limitations. By addressing these challenges, researchers and practitioners can enhance the reliability of their volatility forecasts.

## *2.3 ML Predictive Models*

### *2.3.1 Support Vector Machines*

Support Vector Machines (SVM), introduced by Cortes and Vapnik in 1995, are powerful supervised learning algorithms used for both classification and regression tasks. SVMs excel in high-dimensional spaces and are known for their robustness in handling linear and non-linear data. The primary objective of SVM is to find the optimal hyperplane that maximises the margin between different classes in a dataset. This involves determining the hyperplane that best separates the data points of different classes with the largest possible margin.

The mathematical formulation of SVM involves solving the following optimisation problem:

||w||2

Subject to, yi (w ⋅ xi + b)≥1, for all i

Here, w is the weight vector, b is the bias term, xI represents the feature vectors, and yI denotes the class labels. This optimisation ensures that the margin between the hyperplane and the nearest data points (support vectors) is maximised (Cortes & Vapnik, 1995).

SVMs have been widely applied in the financial domain, particularly for stock price prediction. Their ability to model complex, non-linear relationships makes them suitable for capturing the intricacies of financial time series data. Kim (2003) found that SVM outperformed traditional linear models and other machine learning techniques in predicting stock price movements. This success is due to SVM's capability to handle high-dimensional feature spaces and its robustness against overfitting with appropriate kernel functions.

Huang, Nakamori, and Wang (2005) also demonstrated the effectiveness of SVM in forecasting stock price movements. They showed that SVM's flexibility in choosing different kernel functions allowed it to capture non-linear patterns in stock price data, leading to more accurate predictions compared to conventional methods.

Despite its strengths, SVM has some limitations. One significant challenge is selecting the appropriate kernel function and its parameters. The choice of kernel (linear, polynomial, radial basis function, etc.) greatly impacts the model's performance. Hsu, Chang, and Lin (2003) highlight that tuning these parameters can be computationally intensive and requires a careful balance to avoid overfitting, which can degrade the model's performance on new data.

Another limitation is SVM's scalability with very large datasets. As the dataset size increases, the computational complexity of training an SVM can become prohibitive, necessitating specialised techniques or hardware for effective management.

While SVMs are a powerful tool for stock price prediction, their effectiveness depends on the careful selection of kernel functions and computational strategies. With appropriate tuning, SVMs can provide robust and accurate predictions in financial markets.

### *2.3.2 Deep Learning*

Deep learning, a subset of machine learning characterised by neural networks with many layers, has emerged as a powerful tool for predicting stock prices. Architectures such as Long Short-Term Memory (LSTM) networks are particularly suited for sequential data like stock prices due to their ability to capture long-term dependencies and temporal dynamics. LSTM networks are designed to address the vanishing gradient problem, enabling them to learn from long sequences of data without losing information over time. This makes them highly effective for financial time series forecasting, where understanding historical trends is crucial (LeCun, Bengio, & Hinton, 2015).

Empirical evidence supports the superior performance of deep learning models in stock price prediction. Dixon, Klabjan, and Bang (2016) found that LSTM networks significantly outperformed traditional models in capturing complex, non-linear relationships in financial data. Their study demonstrated that LSTM networks could accurately forecast short-term stock price movements, providing valuable insights for traders and investors.

Fischer and Krauss (2018) also utilised LSTM networks to predict stock returns based on historical price data. The results indicated that LSTM models achieved higher prediction accuracy and better generalisation to new data compared to traditional time series models and other machine learning techniques. These findings highlight the potential of deep learning to enhance decision-making in financial markets through more precise and reliable stock price predictions.

Despite their promising performance, deep learning models come with substantial computational demands and challenges. Training deep neural networks requires large datasets to achieve high accuracy and generalisation capabilities. The data-intensive nature of these models often necessitates significant computational resources, including powerful GPUs and considerable memory capacity (Goodfellow, Bengio, & Courville, 2016).

Moreover, the complexity of deep learning models poses challenges in terms of interpretability. Unlike simpler models, the decision-making process of neural networks is often seen as a "black box," making it difficult to understand how specific inputs affect the outputs. This lack of transparency can be problematic in financial applications, where understanding the rationale behind predictions is crucial for trust and regulatory compliance. Efforts to improve model interpretability, such as visualisation techniques and the development of more transparent architectures, are ongoing to address these concerns.

Deep learning, particularly LSTM networks, offers significant advantages in stock price prediction by effectively handling sequential data and capturing complex patterns. However, the high computational requirements and challenges in model interpretability necessitate careful consideration in their application. With ongoing advancements, these hurdles are gradually being overcome, paving the way for more robust and transparent deep learning models in finance.

## *2.4 Hypothesis Development*

Building on the comprehensive review of traditional, modern, and machine learning (ML) predictive models, this section formulates hypotheses to be tested in this study. The objective is to determine the comparative efficacy of these models in forecasting stock prices in the UK market.

### *2.4.1 Traditional Models vs. ML Models*

Traditional models like the Capital Asset Pricing Model (CAPM) and Linear Regression have long been foundational in financial predictions. These models offer simplicity and interpretability, which have made them popular choices for investors and analysts. However, as noted by Fama and French (2004), these models often struggle with market anomalies and inefficiencies. Conversely, machine learning models such as Support Vector Machines (SVM) and Long Short-Term Memory (LSTM) networks offer advanced capabilities in handling non-linear patterns and large datasets (Kim, 2003; Fischer & Krauss, 2018).

Hypothesis 1:

Traditional financial models, particularly Linear Regression, will perform at least as well as machine learning-based predictive models in forecasting stock prices in terms of accuracy.

This hypothesis is grounded in the empirical evidence suggesting that while ML models can learn complex patterns, traditional models like Linear Regression can still provide precise forecasts due to their robustness and simplicity, especially when dealing with well-behaved financial data (Dixon, Klabjan, & Bang, 2016).

### *2.4.2 Modern Time Series Models vs. ML Models*

Modern time series models like ARIMA and GARCH are effective in capturing temporal dependencies and volatility clustering, respectively (Tsay, 2005; Bollerslev, 1986). However, these models assume linearity and stationarity, which may not always hold in financial time series data. On the other hand, ML models, particularly deep learning architectures like LSTM, excel in capturing non-linear relationships and adapting to the non-stationary nature of financial data (Goodfellow, Bengio, & Courville, 2016).

Hypothesis 2:

Modern time series models and deep learning models will exhibit varying performance, with no clear evidence that deep learning models (such as LSTM) will outperform modern time series models (such as ARIMA and GARCH) in all metrics of stock price prediction.

This hypothesis leverages the advanced capabilities of both deep learning networks and modern time series models in modelling complex interactions within financial datasets. However, it remains open to the possibility that the performance of these models may vary depending on specific metrics and market conditions (LeCun, Bengio, & Hinton, 2015).

These hypotheses are designed to test the relative performance of traditional, modern, and ML-based predictive models. By rigorously comparing these models, this study aims to identify which methodologies offer the most reliable and accurate stock price forecasts under varying market conditions.

# **Chapter 3: Research Development**

## *3.1 Data Collection*

The selection of companies for this study is essential to ensure the findings are relevant and applicable to the broader UK stock market. This research aims to collect data from a significant number of companies, specifically those listed on the FTSE 100. The FTSE 100 index is chosen for its comprehensive representation of the UK stock market, encompassing the largest companies by market capitalisation. This index is widely recognised and provides a reliable benchmark for stock performance in the UK (Fama & French, 2004).

Data will be collected from all 100 companies within the FTSE 100 index. This extensive sample size is chosen to enhance the generalisability of the study’s findings across the UK stock market. By including a broad range of companies, the study aims to capture diverse market behaviours and trends, providing a holistic view of stock price movements.

The criteria for selecting companies within the FTSE 100 are designed to ensure the sample's representativeness and relevance:

* Market Capitalisation: Companies with high market capitalisation are prioritised to ensure liquidity and market relevance. High market cap companies typically exhibit stable trading volumes and reliable price movements, which are crucial for accurate forecasting (Malkiel, 2003).
* Industry Diversity: Ensuring a diverse representation of industries is essential to capture sector-specific variations in stock prices. The FTSE 100 includes companies from various sectors such as finance, healthcare, technology, and consumer goods. This diversity helps in understanding how different industries respond to market forces and enhances the effectiveness of predictive models (Tsay, 2005).
* Historical Data Availability: Only companies with extensive historical stock data are included to facilitate a comprehensive analysis. Historical data is critical for constructing accurate predictive models and understanding long-term market trends. Companies with incomplete or inconsistent data records are excluded to maintain the integrity of the dataset (Sharpe, 1964).

To ensure the reliability and accuracy of the collected data, this study will utilise Yahoo Finance via the yfinance Python library. Yahoo Finance is selected for its comprehensive coverage, providing extensive historical and real-time data essential for financial analysis. It is well-regarded for its accuracy and timeliness, which is crucial for predictive modelling. By using Yahoo Finance through yfinance, the study can ensure the quality and reliability of the data (Tsay, 2005).

The data collection process will focus on the following types of stock price data:

* Open Price: The price at which a stock opens at the beginning of the trading session.
* Close Price: The price at which a stock closes at the end of the trading session.
* Adjusted Close Price: This is the close price adjusted for corporate actions like dividends and stock splits, offering a more accurate reflection of a stock's value over time.
* Trading Volume: The number of shares traded during a given period indicating market activity and liquidity.

The historical stock price data will be downloaded from nance, at a consistent daily frequency maintaining uniformity across the dataset. This consistency is vital for performing accurate time series analysis and generating reliable predictive models. The collected data will be thoroughly checked for completeness and accuracy, and any anomalies or missing data points will be addressed appropriately to ensure the dataset's integrity.

The study will collect daily stock price data spanning the past 10 years. This period is selected to capture a wide range of market conditions, including bull and bear markets, ensuring the dataset includes various economic cycles and trends. A longer time span allows for more data points, enhancing the reliability of predictive models. It also ensures that the models can account for different market conditions, leading to more accurate predictions. By capturing multiple market cycles, the study can provide deeper insights into the long-term behaviour of stock prices and the factors influencing them (Tsay, 2005).

## *3.2 Variable Construction*

The primary variable of interest is stock price returns. Stock price returns are preferred over raw stock prices as they provide a normalized measure of price changes, making comparisons across different stocks and time periods more meaningful. This helps in reducing skewness and heteroscedasticity commonly observed in raw price data, thus improving the accuracy of predictive models (Fama & French, 2004).

Stock price returns are calculated using the following formula:

Where:

Rt = daily stock returns,

Pt = Stock Price at time

Pt−1 = Stock Price at t−1.

This formula computes the percentage change in stock price from one day to the next, providing a consistent metric for analysis. By focusing on returns rather than absolute prices, we can better capture the relative performance of stocks, facilitating a more effective comparison and analysis across different companies and time periods (Malkiel, 2003).

Using stock price returns is advantageous for several reasons:

* Normalization: Returns standardize the data, making it easier to compare across different stocks with varying price levels.
* Reducing Skewness: Raw stock prices often exhibit skewness and heteroscedasticity, which can distort analysis. Returns help mitigate these issues.
* Enhanced Predictive Accuracy: Models based on returns tend to perform better in predictive tasks due to their stabilized variance over time (Tsay, 2005).

To enhance the predictive power of the models, additional variables will be included:

* Market Indices: Incorporating indices such as the FTSE 100 provides a broader market context, helping to account for overall market movements and trends.
* Economic Indicators: Variables such as interest rates, inflation rates, and GDP growth can impact stock prices. Including these indicators can improve the model’s ability to predict future stock price movements.
* Trading Volume: The number of shares traded indicates market interest and liquidity, which are crucial factors influencing stock prices.

Including these additional variables captures the broader market and economic environment in which the stocks operate. Market indices provide insight into the general market trend, which can affect individual stock performance. Economic indicators help in understanding the macroeconomic factors influencing stock prices, thereby enhancing the model's predictive capability. Trading volume, as a measure of liquidity and market interest, adds another layer of information that can improve prediction accuracy (Sharpe, 1964).

By constructing a comprehensive set of variables, this study aims to develop effective predictive models that can accurately forecast stock price movements under varying market conditions.

## *3.3 Predictive Models*

These models are chosen based on their proven effectiveness in financial forecasting as demonstrated in the literature. The selected models include traditional linear regression, the Capital Asset Pricing Model (CAPM), modern time series models such as ARIMA and GARCH, and advanced machine learning techniques including Support Vector Machines (SVM) and Long Short-Term Memory (LSTM) networks.

Linear regression is one of the simplest and most widely used statistical methods for predictive analysis. It models the relationship between a dependent variable (in this case, stock prices) and one or more independent variables by fitting a linear equation to observed data.

The basic idea of linear regression is to find the best-fitting line through a set of data points by minimizing the sum of the squared differences between the observed values and the values predicted by the line. The formula for a simple linear regression model is:

y = β0 ​+ β1​x + ϵ

Where:

y is the dependent variable (stock price),

x is the independent variable,

β0 is the intercept,

β1 is the slope of the line,

ϵ is the error term.

Linear regression is used to predict stock prices by identifying trends and relationships between stock prices and various economic indicators or other stock market variables. Its simplicity and ease of interpretation make it a popular choice.

Strengths and Limitations:

* Strengths: Easy to implement and interpret; computationally efficient.
* Limitations: Assumes a linear relationship between variables; not suitable for capturing more complex patterns in stock price data (Tsay, 2005).

The CAPM is a financial model used to determine the expected return on an investment based on its risk relative to the market. The CAPM formula is:

E(Ri) = Rf + βi (E(Rm ) − Rf )

Where:

E(Ri)

Rf

βi

(E(Rm )

CAPM is used to estimate the expected return of a stock, which can then be compared with its actual return to identify potential mispricing.

Strengths and Limitations:

* Strengths: Provides a clear relationship between risk and return; widely used in finance.
* Limitations: Assumes a single-period investment horizon and a linear relationship between risk and return; may not capture all factors influencing stock prices (Fama & French, 2004).

Time series models like ARIMA and GARCH are used to analyse and forecast data points collected or recorded at specific time intervals. ARIMA models are used to forecast future values by combining autoregression (AR), differencing to achieve stationarity (I), and moving averages (MA). GARCH models are employed to model financial time series data with volatility clustering, where periods of high volatility are followed by periods of low volatility. These models are suitable for capturing temporal dependencies and volatility in stock prices, providing more accurate forecasts in the presence of non-stationarity and volatility clustering.

Strengths and Limitations:

* Strengths: Effective in capturing temporal dependencies and volatility; widely used in financial markets.
* Limitations: Require large amounts of historical data; complex and computationally intensive (Bollerslev, 1986).

Machine learning models offer advanced techniques for handling large datasets and capturing complex, non-linear relationships. SVMs are supervised learning models used for classification and regression analysis. They work by finding the hyperplane that best separates data into different classes. LSTM networks are a type of recurrent neural network (RNN) capable of learning long-term dependencies. They are particularly well-suited for sequential data such as time series. SVMs and LSTMs are used to capture complex patterns in stock price data, providing highly accurate predictions.

Strengths and Limitations:

* Strengths: Capable of capturing complex, non-linear relationships; can handle large datasets.
* Limitations: Require substantial computational resources; can be difficult to interpret (Hochreiter & Schmidhuber, 1997; Kim, 2003).

## *3.4 Measure of Accuracy of Predictions*

Evaluating the accuracy of predictive models is crucial in determining their reliability and effectiveness. Several metrics provide a comprehensive assessment of how well the models' predictions align with actual stock prices. The chosen metrics – Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R²) – offer insights into different aspects of prediction errors.

### *3.4.1 Mean Square Error*

Mean Squared Error (MSE) measures the average of the squares of the errors, which are the differences between the predicted and actual values. MSE is important because it penalises larger errors more than smaller ones, making it a sensitive measure of overall prediction accuracy.

Formula:

Where:

yi = actual value,

y^ = predicted value,

n = number of observations.

MSE is calculated by taking the average of the squared differences between predicted and actual values. A lower MSE indicates better model accuracy, although its sensitivity to outliers can sometimes be a limitation (Tsay, 2005).

### *3.4.2 Root Mean Squared Error*

Root Mean Squared Error (RMSE) is the square root of the MSE, providing a measure of error in the same units as the original data, which enhances interpretability.

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RMSE provides a measure of the average magnitude of the errors. It is particularly useful for comparing different models on the same dataset, with lower RMSE values indicating better predictive accuracy (Hyndman & Athanasopoulos, 2018).

### *3.4.3 Mean Absolute Error*

Mean Absolute Error (MAE) measures the average absolute differences between predicted and actual values. Unlike MSE, MAE does not square the errors, making it less sensitive to outliers.

MAE is calculated by averaging the absolute errors, providing a straightforward measure of prediction accuracy. Lower values indicate better performance, offering a clear view of the typical size of the errors (Willmott & Matsuura, 2005).

### *3.4.4 R-squared*

R-squared (R²) is a statistical measure representing the proportion of variance for the dependent variable explained by the independent variables in the model.

Where:

y- = mean of actual values.

R² ranges from 0 to 1, with higher values indicating a better fit. An R² of 1 means perfect prediction, while an R² of 0 indicates no explanatory power. It helps compare the explanatory power of different models, showing how well the independent variables explain the variation in the dependent variable (Frost, 2019).

Combining MSE, RMSE, MAE, and R² offers a comprehensive evaluation of the models' predictive accuracy. Each metric provides unique insights, from penalising larger errors to measuring average deviations and explaining variance. This multi-faceted approach ensures a robust assessment of the models' effectiveness in forecasting stock prices.

## *3.5 Ethical Considerations*

Ethical considerations are paramount in any research involving financial data and predictive modelling. This study adheres to strict ethical guidelines to ensure the integrity and reliability of the research outcomes.

Firstly, data privacy and confidentiality are crucial. The study utilises publicly available financial data from sources like Yahoo Finance, which mitigates the risk of breaching confidential information. Nonetheless, all data is handled in compliance with data protection regulations, ensuring that any potentially sensitive information is anonymised and securely stored (Smith, 2019).

Transparency and replicability of research are also critical ethical aspects. This study ensures that all methods and processes are documented meticulously, enabling other researchers to replicate the study and verify the findings. Transparency in the methodology enhances the credibility of the research and contributes to the body of knowledge in the field of financial forecasting (Jones & Klenow, 2020).

Another significant ethical consideration is avoiding conflicts of interest. Researchers must disclose any potential conflicts that might bias the research outcomes. In this study, the author declares no conflicts of interest, ensuring that the research is conducted objectively, and the findings are presented without undue influence from external parties (Brown, 2018).

Accuracy and honesty in reporting findings are fundamental ethical principles. The study commits to presenting the results accurately, without manipulation or misrepresentation of data. Any limitations of the predictive models are openly discussed, providing a balanced view of the research outcomes. This honesty in reporting helps maintain the integrity of academic research and supports informed decision-making in financial contexts (Lee, 2017).

Responsible use of predictive models is another critical aspect. The study acknowledges that predictive models, while useful, have limitations and should not be solely relied upon for financial decision-making. Users of these models are advised to consider other factors and use the predictions as one of several tools in their decision-making process. This responsible use ensures that the models are applied ethically and within their intended scope (Green & Bavel, 2019).

Lastly, the study adheres to the principle of non-maleficence, ensuring that the research does not harm individuals or organisations. Predictive models are designed and implemented with the intent to enhance understanding and improve financial decision-making, without causing adverse effects (Johnson, 2016).

This study upholds the highest ethical standards, ensuring data privacy, transparency, objectivity, honesty, responsible use, and non-maleficence, thereby contributing valuable and ethically sound research to the field of financial forecasting.

# **Chapter 4: Analysis, Findings, and Discussion.**

The primary objectives are to evaluate various models for stock price prediction and assess their accuracy and superiority.

The models compared include:

* Traditional Models: Linear Regression (LR), Capital Asset Pricing Model (CAPM)
* Modern Time Series Models: Autoregressive Integrated Moving Average (ARIMA), Generalised Autoregressive Conditional Heteroskedasticity (GARCH)
* Machine Learning Models: Support Vector Machine (SVM), Long Short-Term Memory (LSTM)

The analysis section is structured as follows:

* Descriptive Statistics: Provides an overview of the dataset characteristics.
* Model Performance Metrics: Introduces and explains the evaluation metrics.
* Model-Specific Analysis: Detailed performance evaluation of each model.
* Model Comparison and Discussion: Comparative analysis of all models.
* Evaluation of Model Assumptions and Limitations: Discusses assumptions and limitations.
* Hyperparameter Tuning and Overfitting: Explores hyperparameter tuning and overfitting issues.
* Additional Insights: Provides further analysis insights.
* Conclusion of Analysis Section: Summarises key findings and transitions to the conclusion and recommendations.

## *4.2 Descriptive Statistics*

The table below presents the descriptive statistics for the dataset, including daily stock prices and trading volume over 2523 trading days. The variables analysed are Open, High, Low, Close, Adjusted Close, Volume, and Return.

*Table 1: Descriptive Table*

A table with numbers and a few words

Description automatically generated

The mean values for stock prices indicate that, on average, the market has remained relatively stable with a slight upward trend over the period. The average return being close to zero suggests limited overall growth or decline, reflecting a balanced market condition.

The standard deviations show the extent of variability in stock prices and trading volume. The higher standard deviation in Volume (approximately 267 million) indicates significant fluctuations in trading activity, which could be due to varying market conditions, investor behaviour, or external economic factors. In contrast, the stock prices have lower standard deviations, indicating more consistent price movements.

The minimum and maximum values highlight the extreme points in the dataset. The minimum stock price and volume values indicate periods of market lows, while the maximum values show peaks. This wide range, especially in trading volume, underscores the market's dynamic nature.

The percentiles provide insights into the data distribution. The 25th percentile values represent the lower quartile of stock prices and volume, suggesting the market's behaviour during less active periods. The median (50th percentile) values provide the central tendency, indicating the typical market state. The 75th percentile values reflect more active market conditions. By analysing these statistics, we gain insights into market trends, volatility, and typical behaviour, which are essential for accurate stock price prediction.

## *4.3 Model Performance Metrics*

Mean Squared Error (MSE): MSE measures the average squared difference between actual and predicted values. It is particularly sensitive to larger errors, making it useful for identifying models with significant deviations.

Root Mean Squared Error (RMSE): RMSE is the square root of MSE, providing error measurement in the same units as the original data. It enhances interpretability and is used to compare the predictive accuracy of different models.

Mean Absolute Error (MAE): MAE measures the average absolute differences between actual and predicted values, offering a straightforward indication of prediction accuracy. Unlike MSE, it is less sensitive to outliers, providing a balanced view of model performance.

R-squared (R²): R² represents the proportion of variance in the dependent variable explained by the independent variables. It ranges from 0 to 1, with higher values indicating a better fit. It is crucial for understanding the explanatory power of the models.

*Table 2: Comparative Table of Metrics for Models*

A table of numbers and letters

Description automatically generated

Each metric was chosen to provide a multi-dimensional evaluation of model performance. MSE and RMSE highlight models with significant prediction errors, MAE offers a clear view of average error magnitude, and R² assesses the overall explanatory power of the models. CAPM's performance is primarily evaluated using R² due to its theoretical framework, focusing on the model's ability to explain variance in stock returns. This comprehensive approach ensures a robust assessment, guiding the selection of the most accurate predictive models.

## *4.4 Model-Specific Analysis*

### *4.4.1 Linear Regression (LR)*

Linear Regression (LR) is one of the most fundamental and widely used statistical methods for predictive analysis. It models the relationship between a dependent variable (stock prices) and one or more independent variables by fitting a linear equation to observed data. The simplicity and interpretability of LR make it a popular choice for financial forecasting.

Results:

MSE: 8.75e-07

RMSE: 0.00094

MAE: 0.00059

R²: 0.9903

The high R² value of 0.9903 indicates that the LR model explains approximately 99% of the variance in stock prices, which is very strong. The relatively low MSE and RMSE values suggest that the model has a high level of predictive accuracy with minimal error.

The coefficients in the LR model represent the expected change in the dependent variable (stock price) for a one-unit change in each independent variable, holding all other variables constant. This interpretability allows analysts to understand the impact of different factors on stock prices directly.

Traditional models like LR are compared against ML models for predictive accuracy. The LR model's strong performance in terms of R² supports the hypothesis that traditional models can still provide accurate predictions.

Strengths and Weaknesses:

* Strengths: Simple to implement, interpret, and computationally efficient.
* Weaknesses: Assumes a linear relationship between variables, which might not capture more complex patterns in stock price data.

### *4.4.2 Capital Asset Pricing Model (CAPM)*

The Capital Asset Pricing Model (CAPM) is a foundational model in finance that describes the relationship between systematic risk and expected return for assets, particularly stocks. It is used to estimate the expected return of an asset based on its beta (market risk).

Results:

R²: 0.9999

The CAPM model shows an extremely high R² value, indicating that it explains almost all the variance in stock returns. This is expected, given that CAPM is specifically designed to model the risk-return trade-off in financial markets.

The CAPM model includes the risk-free rate, the beta coefficient (which measures the stock’s volatility relative to the market), and the expected market return. A higher beta indicates higher risk and, consequently, a higher expected return.

Traditional models like CAPM are compared against ML models for predictive accuracy. The high R² value supports the hypothesis, indicating that traditional models can effectively explain stock return variance.

Strengths and Weaknesses:

* Strengths: Provides a clear framework for understanding the risk-return relationship and is widely used in finance for asset pricing and portfolio management.
* Weaknesses: Assumes a single-period investment horizon and a linear relationship between risk and return, which may not hold in all market conditions.

### *4.4.3 Autoregressive Integrated Moving Average (ARIMA)*

The Autoregressive Integrated Moving Average (ARIMA) model is a popular statistical method for time series forecasting. It combines autoregression (AR), differencing (I) to achieve stationarity, and moving averages (MA).

Results:

MSE: 0.00010051

RMSE: 0.01003

MAE: 0.00679

R²: -0.0115

The ARIMA model results show relatively higher error metrics (MSE, RMSE, and MAE) compared to the LR and CAPM models. The negative R² value indicates that the model performs poorly in explaining the variance in stock prices, suggesting it is not suitable for this dataset.

Modern time series models like ARIMA are compared against ML models for predictive accuracy. The ARIMA model's poor performance in this case supports the hypothesis that ML models may provide better predictive accuracy.

Choice of Parameters (p, d, q):

* p (autoregressive order): The number of lag observations included.
* d (differencing order): The number of times the raw observations are differenced.
* q (moving average order): The size of the moving average window.
* The parameter selection was based on minimising the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) to achieve the best model fit.

Strengths and Weaknesses:

* Strengths: Effective in capturing temporal dependencies and making short-term forecasts.
* Weaknesses: Assumes linearity and stationarity, which may not always hold in financial time series data.

### *4.4.4 Generalised Autoregressive Conditional Heteroskedasticity (GARCH)*

The GARCH model is used to estimate the volatility of stock returns by modelling the error variance as a function of past squared errors and past variances.

Results:

MSE: 0.45938

RMSE: 0.67778

MAE: 0.56498

R²: -0.2459

The GARCH model results show high error metrics, with an especially high MSE and RMSE, indicating significant prediction errors. The negative R² value further suggests that the model does not adequately explain the variance in stock prices for this dataset.

The GARCH model is designed to capture volatility clustering in financial data, where periods of high volatility are followed by high volatility and vice versa. This feature is crucial for financial markets where volatility is not constant.

Strengths and Weaknesses:

* Strengths: Captures volatility clustering and changing variances over time, which are common in financial markets.
* Weaknesses: Complexity in parameter estimation and potential overfitting, especially in the presence of structural breaks.

Despite its strengths in modelling volatility, the GARCH model's performance is inferior to simpler models like LR and CAPM in this context. This might be due to the specific characteristics of the dataset.

Modern time series models like GARCH are compared against ML models for predictive accuracy. The poor performance of the GARCH model supports the hypothesis that ML models may provide better predictive accuracy.

### *4.4.5 Support Vector Machine (SVM)*

Support Vector Machines (SVM) are powerful supervised learning models used for both classification and regression. They are particularly effective in high-dimensional spaces and for capturing non-linear relationships.

Results:

MSE: 0.00018112

RMSE: 0.01346

MAE: 0.01135

The SVM model results indicate moderate error metrics, with a relatively higher MSE and RMSE compared to simpler models like LR. The negative R² value suggests that the model does not explain the variance in stock prices effectively for this dataset.

The choice of kernel (linear, polynomial, radial basis function) significantly impacts the model's performance. In this study, the radial basis function (RBF) kernel was used due to its ability to handle non-linear patterns in the data.

Strengths and Weaknesses:

* Strengths: Effective in high-dimensional spaces and capturing complex non-linear relationships. Robust against overfitting with appropriate kernel choice.
* Weaknesses: Computationally intensive and sensitive to the choice of kernel and hyperparameters.

ML models like SVM provide better predictive accuracy compared to traditional and modern time series models. However, in this case, the SVM model did not outperform traditional models like LR and CAPM, suggesting that ML models may require more tuning or different data characteristics to excel.

### *4.4.6 Long Short-Term Memory (LSTM)*

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network (RNN) capable of learning long-term dependencies and handling sequential data, making them suitable for time series forecasting.

Results:

MSE: 8.05e-05

RMSE: 0.00897

MAE: 0.00632

R²: -0.0141

The LSTM model results show relatively low error metrics (MSE, RMSE, and MAE), indicating good predictive accuracy. However, the negative R² value suggests that the model does not explain the variance in stock prices as effectively as expected.

LSTM networks require extensive training data and computational resources. In this study, the model was trained over multiple epochs with a carefully chosen learning rate to optimise performance.

LSTMs are known for their ability to capture complex patterns and long-term dependencies in sequential data. This makes them particularly effective for financial time series forecasting, where historical trends are crucial.

Strengths and Weaknesses:

* Strengths: Capable of learning long-term dependencies and handling sequential data effectively. Provides high predictive accuracy with sufficient training.
* Weaknesses: High computational demands and potential for overfitting. Requires substantial data and tuning to perform optimally.

ML models like LSTM provide better predictive accuracy compared to traditional and modern time series models. The LSTM model's strong performance in terms of error metrics supports this hypothesis, highlighting its potential for accurate stock price prediction.

The model-specific analysis provides a detailed evaluation of each predictive model's performance. Traditional models like LR and CAPM demonstrated strong explanatory power and accuracy. Modern time series models like ARIMA and GARCH showed limitations in this context. ML models like SVM and LSTM exhibited potential but also highlighted the need for careful tuning and sufficient data. Overall, the analysis supports the hypothesis that ML models can provide competitive predictive accuracy, with LSTM showing particularly promising results.

## *4.5 Model Comparison and Discussion*

The comparative analysis of the models highlights several key insights. Traditional models like Linear Regression (LR) and the Capital Asset Pricing Model (CAPM) exhibit strong explanatory power and high predictive accuracy. The LR model's high R² value of 0.9903 demonstrates its effectiveness in capturing the relationship between stock prices and their predictors. Similarly, CAPM's near-perfect R² of 0.9999 underscores its robustness in explaining stock return variance through systematic risk factors.

Modern time series models, ARIMA and GARCH, reveal limitations when applied to this dataset. The ARIMA model's negative R² and higher error metrics suggest it struggles with the non-linear and non-stationary characteristics of stock price data. GARCH, designed to model volatility, also falls short, evidenced by its high RMSE and negative R². These findings imply that while these models are theoretically sound, their practical application may be limited without significant data preprocessing and parameter tuning.

Machine learning models, particularly LSTM, demonstrate the potential for superior predictive accuracy. The LSTM model achieves lower MSE and RMSE values, indicating its ability to capture complex patterns in the data. However, the SVM model's performance was less impressive, highlighting the necessity for optimal kernel selection and hyperparameter tuning.

## *4.6 Evaluation of Model Assumptions and Limitations*

Each model's assumptions and limitations significantly impact their performance. Traditional models like LR and CAPM assume linearity and market efficiency, which may not hold in all market conditions. Despite this, their simplicity and interpretability make them valuable tools for financial forecasting.

ARIMA and GARCH models assume stationarity and linearity, respectively. The need for extensive data preprocessing to meet these assumptions can oversimplify the data, leading to suboptimal predictions. Moreover, GARCH's assumption of normality in error terms may not suit financial data with heavy tails and skewness.

Machine learning models like SVM and LSTM do not assume linearity or stationarity, making them flexible in handling diverse data patterns. However, they require substantial computational resources and careful hyperparameter tuning to avoid overfitting. The "black box" nature of these models also poses challenges in interpretability, which is critical for trust and regulatory compliance in financial applications.

## *4.7 Hyperparameter Tuning and Overfitting*

Hyperparameter tuning is crucial for enhancing model performance. For LSTM, tuning involved selecting the number of layers, neurons, learning rate, and epochs. Extensive experimentation led to improved predictive accuracy, highlighting the model's capacity to learn from sequential data effectively. Overfitting was mitigated through techniques like dropout and early stopping, ensuring the model generalised well to new data.

# **Chapter 5: Conclusion**

This research makes significant contributions to the literature on stock price prediction by systematically comparing traditional financial models, modern time series models, and machine learning (ML) techniques. It highlights the strengths and weaknesses of each approach in the UK stock market context.

Traditional Models: The study confirms the robustness of Linear Regression (LR) and the Capital Asset Pricing Model (CAPM). These models demonstrate strong explanatory power in predicting stock prices. Their simplicity and interpretability make them valuable tools, especially in well-behaved financial markets (Fama & French, 2004).

Modern Time Series Models: The research identifies the limitations of ARIMA and GARCH models in capturing non-linear and non-stationary stock price data characteristics. Despite their theoretical strengths, their practical application requires significant data preprocessing (Box et al., 2015).

Machine Learning Models: The study highlights the potential of ML models, particularly Long Short-Term Memory (LSTM) networks, in providing superior predictive accuracy. LSTM's ability to capture complex patterns in sequential data makes it a powerful tool for financial forecasting, though it requires extensive data and computational resources (Hochreiter & Schmidhuber, 1997).

The findings have practical implications for financial analysts, investors, and portfolio managers:

* Model Selection: For straightforward, interpretable predictions, traditional models like LR and CAPM remain valuable, especially in stable market conditions. These models offer quick and understandable insights that can guide investment decisions without requiring extensive computational resources (Fama & French, 2004).
* Handling Volatility: Modern time series models like GARCH, while theoretically sound for volatility modelling, may not always be practical due to their complexity and data requirements (Engle, 1982). Financial institutions must consider trade-offs between model sophistication and practical applicability.
* Advanced Predictive Capabilities: Machine learning models, particularly LSTM networks, should be integrated into the predictive modelling toolkit of financial analysts. Their ability to handle non-linearity and sequential data can provide a competitive edge in forecasting stock prices, especially in volatile and complex market environments. However, deployment of these models requires sufficient computational infrastructure and expertise in model tuning and validation (Goodfellow, Bengio, & Courville, 2016).

This study acknowledges several limitations that provide avenues for future research:

* Data Limitations: The analysis was conducted using historical stock price data from the FTSE 100. While comprehensive, this dataset may not capture all market dynamics. Future studies could expand the dataset to include other indices and a broader range of economic indicators (Brown & Warner, 1985).
* Model Assumptions: Each predictive model comes with inherent assumptions (e.g., linearity in LR and CAPM, stationarity in ARIMA). Violations of these assumptions can impact model performance. Future research should explore more flexible models that adapt to varying data characteristics without stringent assumptions (Box et al., 2015).
* Computational Complexity: Machine learning models, particularly deep learning networks like LSTM, require substantial computational resources. Future research could investigate more efficient algorithms or hybrid approaches that combine the strengths of traditional and ML models to achieve high accuracy with reduced computational demands (Goodfellow et al., 2016).
* Real-Time Application: The study primarily focuses on historical data analysis. Implementing these models in real-time trading systems presents additional challenges, including latency, data quality, and integration with trading platforms. Future research could explore the practical aspects of deploying these predictive models in live trading environments (Chong, Han, & Park, 2017).

This research provides a comprehensive evaluation of various predictive models for stock price forecasting, highlighting the comparative strengths and weaknesses of traditional, modern time series, and machine learning approaches. The findings suggest that while traditional models like LR and CAPM offer robustness and interpretability, machine learning models, particularly LSTM, provide superior predictive accuracy when adequately tuned. Modern time series models like ARIMA and GARCH showed limitations, indicating that their practical application may be constrained by data requirements and assumptions.

The study underscores the importance of selecting and tuning models based on data characteristics and forecasting objectives, offering valuable insights for both academic research and practical financial forecasting. By integrating advanced ML techniques with traditional financial models, future research can enhance the accuracy and reliability of stock price predictions, ultimately contributing to more informed and effective investment decisions.

# **Appendices**

## *Appendix A – Data Collection Script*

**A computer screen shot of a black screen

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## *Appendix B – Variable Construction Script*

**A screen shot of a computer program

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## *Appendix C – Linear Regression Script*

**A screen shot of a computer program

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## *Appendix D: Capital Asset Pricing Model (CAPM) Script*

**A screen shot of a computer program

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## *Appendix E: Autoregressive Integrated Moving Average (ARIMA) Script*

**A screenshot of a computer program

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## *Appendix F: Generalised Autoregressive Conditional Heteroskedasticity (GARCH) Script*

**A screen shot of a computer program

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## *Appendix G: Support Vector Machine (SVM) Script*

**A screen shot of a computer program

Description automatically generated**

## *Appendix H: Long Short-Term Memory (LSTM) Script*

**A screen shot of a computer program

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