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Forecasting G7 Stock Markets During the Russia-Ukraine Conflict: A Comparison of Machine Learning and Time Series Models

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RESEARCH ARTICLE

Abstract

Machine learning methods are increasingly used for financial time series forecasting. However, their performance during major geopolitical events remains less explored. This study examines the performance of five forecasting models: ARIMA, Facebook Prophet, Random Forest, elastic GLMNet, and XGBoost to predict the stock markets of G7 countries during the Russia-Ukraine conflict. The techniques include two time series models (ARIMA and Prophet) and three machine learning algorithms (Random Forest, GLMNet, and XGBoost). We used daily closing prices of major stock indices from each G7 country (FTSE 100, S&P 500, DAX, FTSE MIB, S&P/TSX Composite, Nikkei 225, and CAC 40) covering February 24, 2022 to October 25, 2024. Forecast accuracy was evaluated using RMSE, MAE, and MAPE. ARIMA performed best in stable markets (UK, France, Italy), while GLMNet was the top machine learning model overall. All models struggled with Japan's volatile market. Germany and Italy showed the highest price fluctuations. These findings suggest that model selection should consider market stability, and that traditional time series models remain competitive in certain contexts.

Keywords: Stock market, ARIMA, Machine learning, Facebook Prophet, Forecast

1. Introduction

Russia-Ukraine conflict can be traced back to February 24, 2022 when Russian military entered the territory of Ukraine under the auspices of a special military operation aimed at political intervention in Ukraine. Since the beginning of the conflict, 2,155,326 people have fled Ukraine to its neighboring countries, with Poland hosting most of the refugees (UNHCR, 2022). The conflict has clearly affected global businesses, as well as consumers. There is clear evidence from the stock market that firms with strong ties to Russia, through trade or ownership, experienced a substantial fall in share prices following the invasion. For instance, Izzeldin et al (2023) reported that stock markets and commodities respond most rapidly to the Russian invasion; and post-invasion crisis intensity is noticeably smaller compared to both the Covid-19 and the GFC while Steinbach (2023) noted that the Russia-Ukraine conflict has caused major price hikes, with notable heterogeneity across product groups and regions of the World.

Many researchers have studied the impact of the Russia-Ukraine conflict on the financial market (Assaf et al., 2023; Boungou & Yatié, 2022; Fang & Shao, 2022; Gheorghe & Panazan, 2023; Joshipura

& Lamba, 2024; Umar et al., 2022). These authors have all highlighted different level of uncertainties of Russia-Ukraine conflict on financial markets. For instance, Assaf, *et al*. (2023) find out that the trade-to-GDP ratio negatively impacts the abnormal returns in the post-event window during Russia-Ukraine conflict, indicating that countries with more percentage of the trade in their GDP have been affected to a greater extent. Joshipura and Lamba (2024) also examine the impact of the Russia-Ukraine conflict on global stock markets. The results show that the conflict had a significant negative impact on global stock markets, particularly in the short term. However, the impact was asymmetric, with countries geographically close to the conflict and those heavily reliant on Russian and Ukrainian exports experiencing more significant losses. Robus, *et al* (2024) looks at how the Russian conflict in Ukraine affected global stock market sectors in 2022, showing that when the conflict began, most sectors experienced negative abnormal returns, followed by varied changes in cumulative abnormal returns over time.

The use of machine learning to forecast financial time series techniques has gained popularity due to its potential to provide valuable insights for investment decisions and risk management in financial markets. Qian (2017) compares the performance of traditional time series models (ARIMA) and machine learning models (logistic regression, multilayer perception, support vector machine, and denoising autoencoder in predicting financial time series. The study found that machine learning models generally outperform traditional time series models, demonstrating their potential for more accurate and reliable predictions. Iqbal et al. (2013) reviews various machine learning techniques for stock price prediction, including time series models, neural networks, and hybrid approaches. The authors conclude that neural networks, particularly when combined with denoising techniques, are the most effective method for predicting stock prices. They also compare the performance of different neural network architectures, such as Layered Recurrent Neural Networks (LRNN) and Feedforward Neural Networks (NN), on real-world datasets. The study by Hossain et al. (2013) compared GARCH, neural networks, and support vector machines for financial time series prediction. Their findings suggest that GARCH and SVM models outperformed standard backpropagation neural networks in forecasting stock market indices. Sardar et al. (2023) proposed a framework combining machine learning (ML) and statistical methods to forecast COVID-19 cases in SAARC countries. The study compared the performance of ARIMA, Prophet, Extreme Gradient Boosting, GLMNet, and Random Forest models. Results indicated that ARIMA was the most suitable model for Afghanistan, Bangladesh, India, Maldives, and Sri Lanka, while Prophet was better for Bhutan. GLMNet outperformed other models for Nepal and Pakistan, and Random Forest was excluded due to poor performance. The paper "A Review of ARIMA vs. Machine Learning Approaches for Time Series Forecasting in Data Driven Networks" (Kontopoulou et al., 2023) reviews the application of ARIMA models and machine learning techniques for time series forecasting. It finds that machine learning models often outperform ARIMA, especially in complex scenarios. However, hybrid models combining ARIMA, and machine learning techniques can further improve prediction accuracy. The study emphasizes the need for careful evaluation and selection of the appropriate method based on the specific characteristics of the time series data. Sen et al. (2023) evaluated the performance of various time series, econometric, statistical, and machine learning models, including Holt-Winters, ARIMA, OLS, Random Forest, KNN, CNN, and LSTM, on a dataset of ten industry leaders and NIFTY50 to predict stock prices and their direction across different sectors. The study by Noorunnahar et al. (2023) compared the performance of ARIMA and XGBoost models for predicting annual rice production in Bangladesh. The ARIMA model, a statistical time series method, was used to capture temporal patterns in the data. On the other hand, XGBoost, a powerful machine learning algorithm, was employed to learn complex relationships between variables. The results indicated that the XGBoost model outperformed ARIMA in terms of various performance metrics, including Mean Absolute Error (MAE), Mean Percentage Error (MPE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Based on the better performance of XGBoost,

the authors forecasted an increasing trend in rice production in Bangladesh over the next decade. Arata et al. (2023) demonstrated improvements in Prophet's stock price forecasting accuracy by refining change-point selection and incorporating competitor data, reducing forecast error by 90.2% in some cases. Wu (2023) found that Random Forest was effective for stock prediction due to its ability to capture non-linear patterns, performing better than simpler models but sometimes less accurately than XGBoost, which can handle more complex features. Zheng et al. (2024) compares six machine learning models to see how well they predict small-sample, multi-feature time series data. Results show that ridge regression has the best overall performance, SVR works well for nonlinear data, random forest (an ensemble model) outperforms single models in generalization, and MLP is effective for linear data. Tong, *et al*. (2023) found that using a hybrid model, combining ARIMA with machine learning methods like XGBoost, improves accuracy, especially in complex markets, as this approach captures a wider range of patterns than ARIMA alone.

More studies examined these models in various stock market contexts. Humairah and Agustina (2024) applied Random Forest to predict the Jakarta Islamic Index and achieved MAPE values below 3%, which indicate a very good prediction accuracy. Yin et al. (2023) showed that optimized Random Forest effectively captures non-linear patterns in stock trend prediction, while Abraham et al. (2022) combined genetic algorithms with Random Forest for stock trend forecasting. For XGBoost, Liu (2024) found that the model performs well in moderately fluctuating markets when combined with multi-objective optimization on Chinese A-shares. However, Halul and Kamil (2022) compared XGBoost with SVM on 28 Malaysian stocks and found that SVM performed better in their sample, suggesting that model performance may vary by market context. For regularized regression methods, a global study by Azevedo, et al. (2023) confirmed that Elastic Net and Lasso produce significant positive returns when applied to stock market anomalies across multiple countries. Multi-model comparisons also support the use of these techniques. Akyüz et al. (2024) evaluated Random Forest, KNN, and gradient boosting on the BIST Forestry Index and found that all machine learning methods performed successfully, with KNN achieving the highest accuracy. Similarly, Lachaab and Omri (2024) compared multiple models on the French CAC 40 index during the COVID-19 pandemic and found that machine learning approaches outperformed traditional time series models.

The Group of Seven (G7) consists of seven advanced economies: Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States. Several studies have shown that the Russia-Ukraine conflict affected the economies of G7 countries. For example, Sobhy (2024) applied an EGARCH model to examine the conflict's impact on stock market volatility in G7 countries. The study found that four countries (Canada, France, Germany, and the UK) were negatively affected, while three countries (Japan, the US, and Italy) showed no significant impact. This study provides a systematic comparison of time series and machine learning models for forecasting G7 stock markets during the Russia-Ukraine conflict. The main contribution of this work is not only comparing the performance of these algorithms across G7 countries, but also offering a cross-country perspective that is lacking in studies focused on single markets. This approach helps identify which modeling techniques are more suitable for different market conditions and provides a foundation for future research on forecasting during geopolitical crises. The findings also highlight limitations to be addressed and suggest directions for adopting machine learning models in other financial time series forecasting applications.

The rest of the paper is structured as; Section 2 gives the methods used for analysis. Following that, the data and results in this study are discussed in detail in Sections 3 and 4, respectively. Lastly, the concluding section includes the overall research implications, study limitations, and the final conclusion.

2. Materials and methods

The data were pre-processed accordingly for each model type. In the time series models (ARIMA and Prophet), dates were set as the primary index to maintain the temporal structure necessary for time series forecasting. For the machine learning models, lagged values were created as features. Specifically, lags of one day, three days, and five days were generated to introduce temporal dependency in the models, allowing them to capture recent price trends and dependencies. These lagged features serve as inputs to the machine learning algorithms, enabling them to make future price predictions based on historical patterns. The flowchart of the proposed methodology is shown in Figure 1.

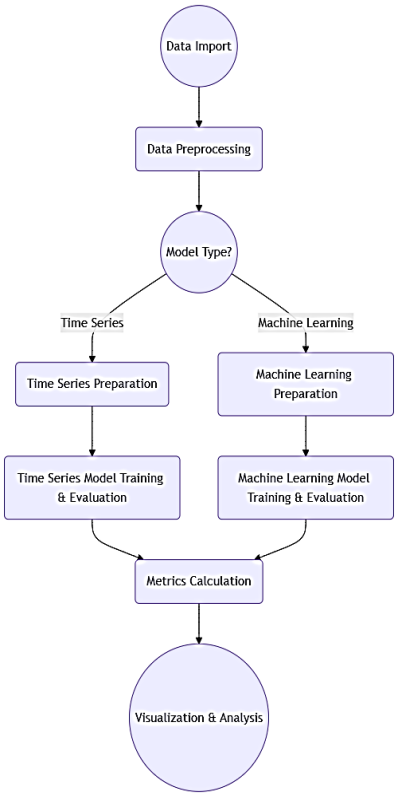

Figure. 1: Flowchart of the proposed methodology

The techniques used are classified into two groups: basic time series models (ARIMA and Facebook Prophet) and machine learning algorithms (Random Forest, elastic GLMNet, and XGBoost). The following subsections illustrate the theory behind each algorithm.

2.1 ARIMA

ARIMA model, known as Autoregressive integrated moving average is one of the oldest forecasting models. The model was developed in the 1970s by George Box and Gwilym Jenkins (Brockwell and Davis (1991)). It has become one of the most common approaches to time series modeling as they take both long-term trends and sudden shocks into account. It can also perform well with moderate amounts of data. The Lags of the stationarized series in the forecasting equation are called "autoregressive" terms, lags of the forecast errors are called "moving average" terms, and a time series which needs to be differenced to be made stationary is said to be an "integrated" version of a stationary series. There are so many special cases of ARIMA models which include Random-walk and random-trend models, autoregressive models, and exponential smoothing models. Thus, an ARIMA model can be written as

ARIMA (p, d, q) model where **p** is the number of autoregressive terms, **d** is the number of nonseasonal differences needed for stationarity, and **q** is the number of lagged forecast errors in the prediction equation.
Hence, the general form of ARIMA is given as:

$$X_t = \mathrm{c} + \emptyset_1 X_{t-1} + \emptyset_2 X_{t-2} + \ldots + \emptyset_p X_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \quad (1)$$

(Brockwell & Davis, 1991)

2.2 Facebook Prophet

Prophet model was introduced by Facebook data science team in 2017 (Taylor and Letham, 2018). It is a procedure for forecasting time series data based on an additive model where non-linear trends are fit with yearly, weekly, and daily seasonality. The presence of a trend also add more color to its usage because its component enables it to handle long-term evolutions, while the seasonality model helps capture periodic variations. It works best with time series that have strong seasonal effects and several seasons of historical data. Prophet is also robust to missing data and shifts in the trend and typically handles outliers well. Annapoorna *et al* (2024) explores the use of the Facebook Prophet model for predicting stock prices, demonstrating its effectiveness in providing accurate forecasts and visualizations, despite the inherent challenges of stock market volatility influenced by various factors.

Also, Kaninde *et al.* (2023) utilizes Facebook Prophet to predict stock prices. The model effectively captures various factors influencing stock prices, including seasonal patterns and holiday effects. The results show that Facebook Prophet can provide accurate long-term stock price predictions. Prophet is considered as non-linear regression model of the form:

$$y_t = g(t) + \mathrm{S(t)} + h(t) + \varepsilon_t \quad (2)$$

(Taylor & Letham, 2018)
where
$g(t)$ describes a piecewise-linear trend (or "growth term"),
$h(t)$ captures the holiday effects,
S(t) describes the various seasonal patterns, and
ε_t is a white noise error term.

2.3 Random forest

The first algorithm for random decision forests started with the work of Ho (1995) using the random subspace method. Random forest is a supervised Machine learning algorithm that is widely used in regression and classification problems. It is composed of different decision trees, each with the same nodes, but using different data that leads to different leaves. It merges the decisions of multiple decision trees in order to find an answer, which represents the average of all these decision trees. It is the most used algorithm because of its simplicity. It builds a number of decision trees on different samples and then takes the majority.

2.4 Elastic GLMNet

GLMNet is a package that fits generalized linear and similar models via penalized maximum likelihood. The algorithm is extremely fast and can exploit sparsity in the input matrix x. It can also fit multi-response linear regression, generalized linear models for custom families, and relaxed lasso regression models. It is good for prediction and plotting, and functions for cross-validation.

2.5 XGBoost

XGBoost simply stands for Extreme Gradient Boosting. It is a scalable, distributed gradient-boosted decision tree (GBDT) machine learning library. It provides parallel tree boosting and is among the leading machine learning library for regression, classification, and ranking problems. In the last few years, XGBoost has been gaining significant favor as a result of helping individuals and teams win virtually every structured data competition. It also has wide range usage of applications, including solving problems in regression, classification, ranking, and user-defined prediction challenges. XGBoost is popular for its computational efficiency, insightful feature importance analysis, and seamless handling of missing values. This technique has three steps outlined as follows:

(a) Initialize model with constant value as:

$$F_{(o)}(\mathrm{x}) = \underset{\theta}{\operatorname{argmin}} \sum_{i=1}^{n} L(y_i,\ \theta) \tag{3}$$

(b) Compute the gradient of the loss function iteratively using the expression given as:

$$g_m\ (x_i) = [\frac{\partial\ L\ y_i, F(x_i)}{\partial f(x_i)}]_{F(\mathrm{x})=F_{m-1}(\mathrm{x})} \tag{4}$$

(c) Update the model as defined by:

$$F_m(\mathrm{x}) = F_{m-1}(\mathrm{x}) +\ \theta_m\ h_m(\mathrm{x}) \tag{5}$$

3. Data presentation

This analysis evaluates stock price trends in G7 countries following the start of the Russia-Ukraine conflict in February 2022, using both time series models and machine learning models. The time series models applied include ARIMA and the Prophet model (developed by Facebook), while the machine learning models comprise Random Forest, Elastic Net (GLMNET), and XGBoost. Each of these methods is applied consistently across all seven countries to capture distinctive patterns and forecast future stock price trends.

For each country, the most representative and actively traded stock index was selected. These indices include:

- FTSE 100 for the UK – comprises the 100 most highly capitalised blue-chip companies listed on the London Stock Exchange (Ögel & Temizel, 2021).
- S&P 500 for the US – includes 500 leading companies and covers approximately 80% of US market capitalization (Wilson & Jones, 2002).
- DAX for Germany – tracks the 40 largest and most actively traded companies on the Frankfurt Stock Exchange (Schmidhammer et al., 2014).
- FTSE MIB for Italy – tracks the 40 largest and most liquid stocks listed on the Borsa Italiana (Ögel & Temizel, 2021).
- S&P/TSX Composite for Canada – the principal broad market measure for the Canadian equity markets (Alam et al., 2016; Shams, 2015).
- Nikkei 225 for Japan – a price-weighted index of 225 highly liquid stocks traded on the Tokyo Stock Exchange (Nikkei Industry Research Institute, as cited in FRED, n.d.).
- CAC 40 for France – comprises the 40 largest and most actively traded multinational companies on Euronext Paris (Ögel & Temizel, 2021).

These indices were chosen as they offer a comprehensive reflection of each country's stock market performance. The daily closing prices for each of these indices, covering the period from February 24, 2022, to October 25, 2024, were gotten from MarketWatch.

4. Results and Discussion

Table 1 presents a summary of the daily stock price statistics for each G7 country since the beginning of the Russia-Ukraine conflict in February 2022, this includes the average price, standard deviation (volatility), and the minimum and maximum closing prices observed over the period. For the United Kingdom, the index had an average closing price of 7,660.31 GBP, with a standard deviation of 365.79 GBP which shows a moderate price variability. The lowest closing price during this period was 6,826.15 GBP, and the highest was 8,445.80 GBP, which reflects a stable market performance throughout this period.

However, there is an average price of 4,519.14 USD for United States index, with a standard deviation of 599.26 USD, a higher price fluctuation compared to other markets. The minimum and maximum closing prices were 3,577.03 USD and 5,864.67 USD. In Japan stock market, there is an average price of 31,893.23 JPY, with a high standard deviation of 4,823.32 JPY, this indicates the significant price movement over the period. The minimum and maximum prices observed were 24,717.53 JPY and 42,224.02 JPY, which indicate a broader range of volatility.

Also, Germany had an average price of 15,766 EUR, with a standard deviation of 1,918.76 EUR, this shows a considerable fluctuation. The lowest recorded price was 11,975.55 EUR, while the highest was 19,657.37 EUR, this shift in market is likely affected by the conflict's impact on the European economy.

Italy displayed an average price of 27,994.63 EUR with high volatility (standard deviation of 4,274.80 EUR). Stock prices fluctuated between a low of 20,352.98 EUR and a high of 35,410.13 EUR, this shows Italy's economic sensitivity to regional geopolitical shifts and European market trends. In France, there is an average price of 7,795.90 EUR and a standard deviation of 616.76 EUR, this shows less price variability compared to some of the other European markets. The stock market ranged from a low of 5,676.87 EUR to a high of 8,239.99 EUR, which is considered moderate during this period.

Lastly, Canada recorded an averaged 20,750.78 CAD, with a standard deviation of 1,340.41 CAD, indicating moderate volatility. The lowest and highest prices recorded during this period were 18,206.28 CAD and 24,822.54 CAD, which is considered a relatively stable market performance.

The descriptive statistics reveal clear differences in how G7 markets responded to the conflict. Japan and Italy show the highest volatility (SD of 4,823.32 JPY and 4,274.80 EUR respectively), which suggest greater sensitivity to the geopolitical shock. In contrast, the UK and Canada show more stable markets with lower standard deviations and narrower price ranges. Germany's wide price range (from 11,975.55 to 19,657.37 EUR) reflects considerable fluctuation, likely due to its energy dependence and exposure to European supply chain disruptions. These differences suggest that the impact of the conflict varied based on each country's economic structure, energy reliance, and trade linkages with Russia and Ukraine.Also, it can be seen from the grid time plot that the data are roughly constant in size over time, which show that stock markets in the G7 countries have generally grown since the start of the Russia-Ukraine conflict in February 2022, though with different patterns.

The UK and US markets show overall growth, with the US having a few sharp drops around mid-2022 and mid-2023. Japan's stock market has a clear upward trend, showing steady growth since early 2022 without major declines. In Europe, markets in Germany, Italy, and France have been more volatile, with significant dips in 2022 but gradual recovery afterward. Canada's market has been relatively stable, with a slow upward trend and minor drops.

In summary, most G7 markets have shown resilience and growth since the conflict began, although European markets appear more sensitive to economic pressures.

Table 1: Descriptive statistics

	N	Mean	SD	Min	Max
UK	676	7,660.31	365.79	6,826.15	8,445.80
US	672	4,519.14	599.26	3,577.03	5,864.67
Japan	656	31,893.23	4,823.32	24,717.53	42,224.02
Germany	684	15,766.00	1,918.76	11,975.55	19,657.37
France	671	7,095.90	616.76	5,676.87	8,239.99
Italy	685	27,994.63	4,274.8	20,353.98	35,410.13
Canada	682	20,750.78	1340.41	18,206.28	24,822.54

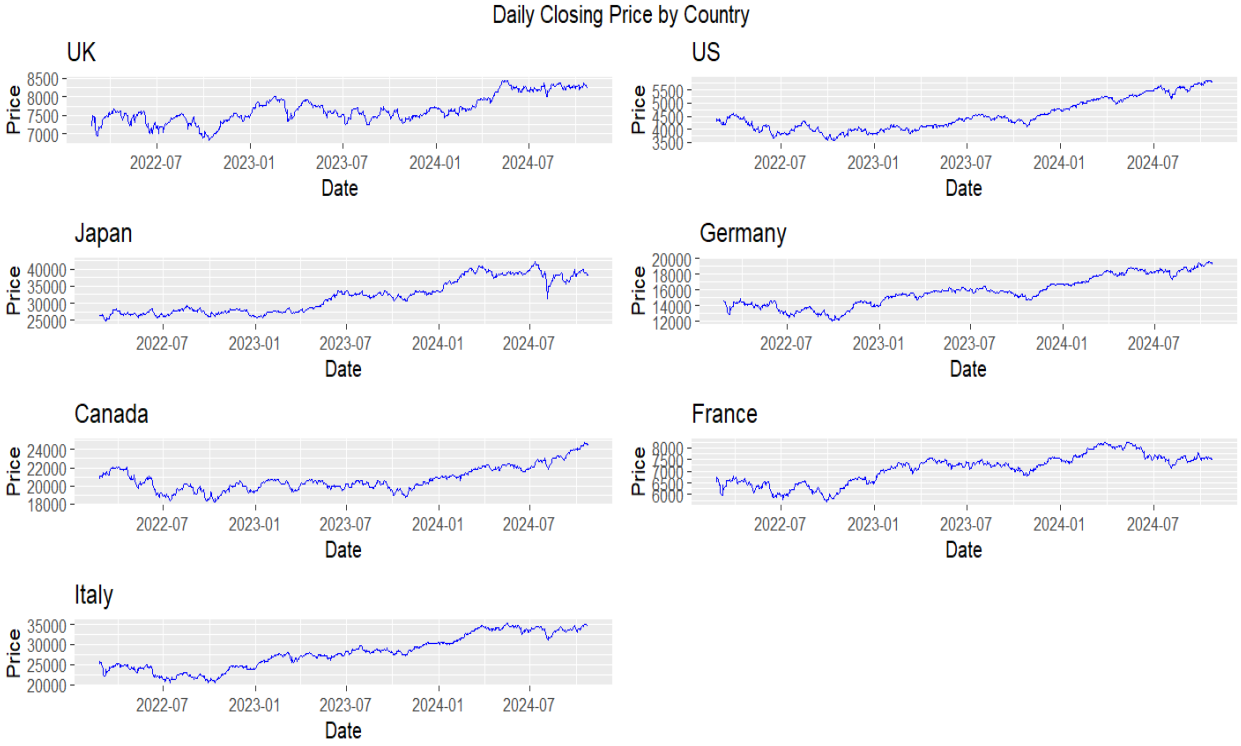

Figure 2: Plots showing daily closing price by Country

Model Evaluation

In this section, traditional time series models, specifically ARIMA and Prophet were applied alongside machine learning algorithms such as Random Forest, GLMNet, and XGBoost to forecast stock prices for G7 countries. The first step involved data preprocessing, during which we excluded outliers to enhance the quality of our analysis. We then split the dataset into training and testing subsets, with the last 60 days designated as the test set for an in-sample forecasting. To compare the performance of these models, we evaluate their effectiveness using metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE).

Time series Models

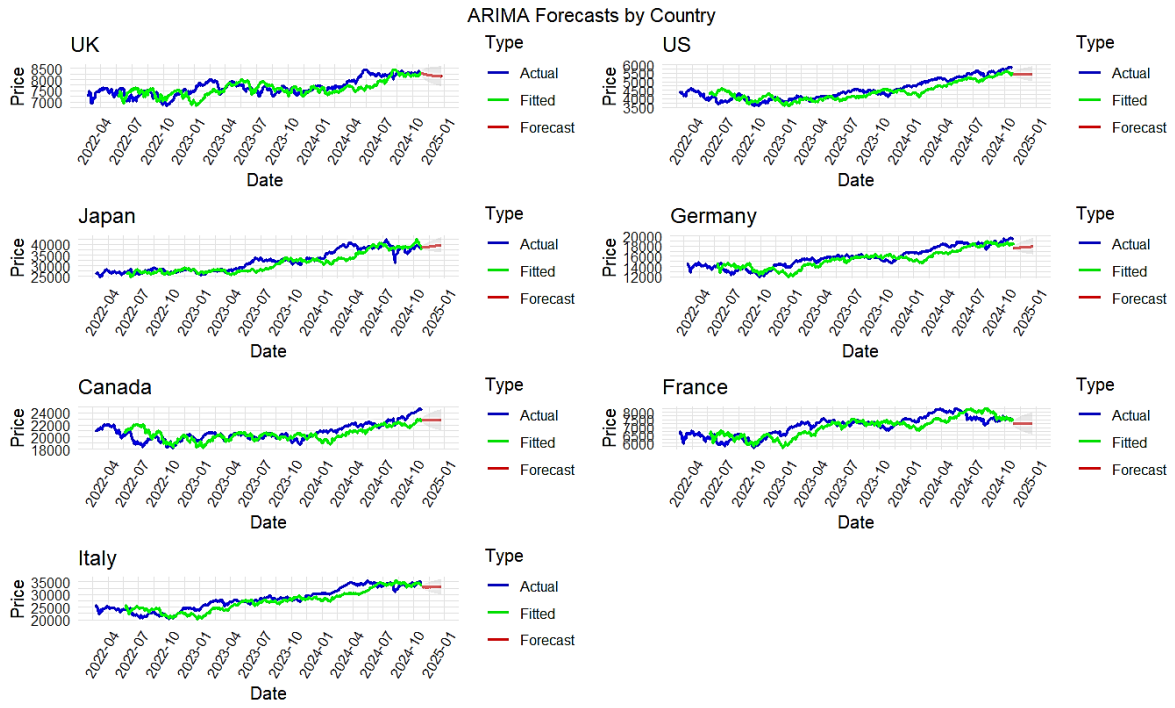

Figure 3: Plot showing ARIMA forecasts by Country

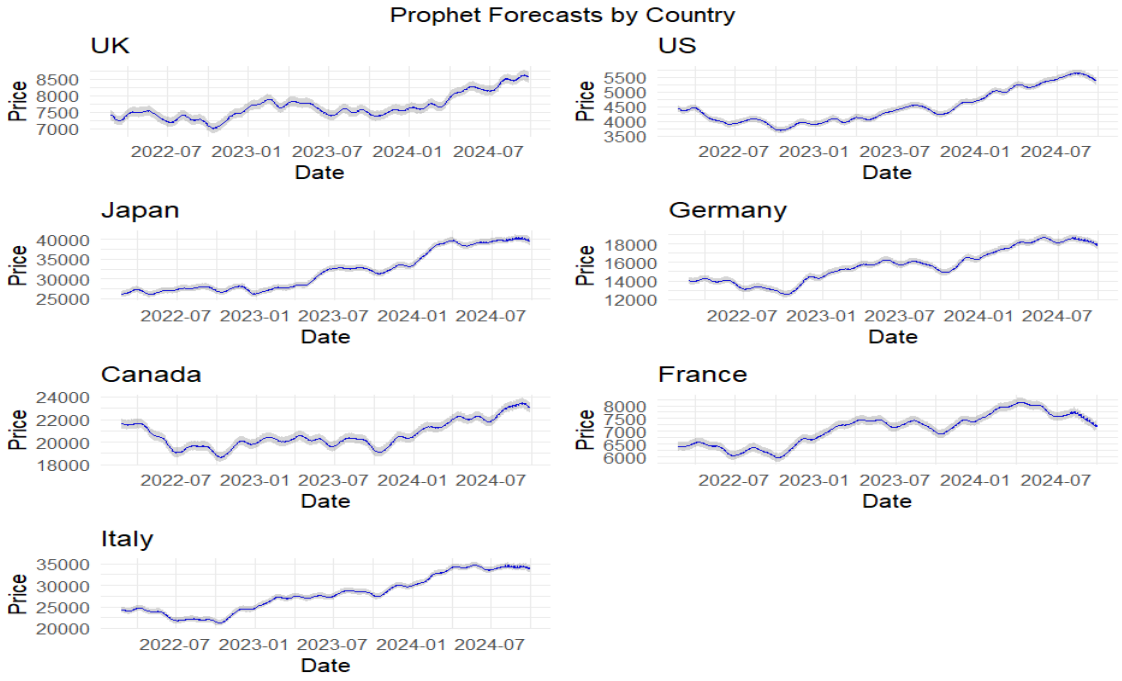

Figure 4: Plot showing Prophet forecasts by Country

The performance of the ARIMA and Prophet models in forecasting G7 stock prices varies across countries, as indicated in their metrics.

For the UK, the ARIMA model, with a RMSE of 123.32 GBP, demonstrates good accuracy with an MAE of 110.02 GBP and a MAPE of only 1%, this indicates that its forecasts are very close to the

actual prices. The Prophet model for the UK has a higher RMSE of 291.11 GBP with an MAE of 285.85 GBP and a MAPE of 3%, though reasonably accurate, but not as precise as ARIMA.

In the US, the ARIMA model shows moderate performance with a RMSE of 224.38 USD and an MAE of 216.40 USD, giving a MAPE of 4%, while the Prophet model performs a bit better with a RMSE of 254.36 USD, a smaller MAE of 206.57 USD, but the same MAPE of 4%, which shows similar accuracy between the two models.

Japan's forecasts show significant challenges, While the ARIMA model reported a very high RMSE of 19,992.02 JPY and MAE of 1,502.30 JPY, which led to a MAPE of 4%, the Prophet model struggles as well, showing a RMSE of 2,835.07 JPY, MAE of 2,388.60 JPY, and a higher MAPE of 7%, this shows there is the need to improve tools and methods in forecasting for this market.

In Germany, the ARIMA model shows a RMSE of 1,117.71 EUR and MAE of 1,015.92 EUR, leading to a MAPE of 5%, while the Prophet model provides slightly better results with a RMSE of 881.82 EUR, an MAE of 713.33 EUR, and a MAPE of 4%, which indicate a better predictive performance.

For Canada, the ARIMA model has a RMSE of 1,031.07 CAD and an MAE of 855.63 CAD, with a MAPE of 4%. However, the Prophet model performs even better, with a lower RMSE of 725.04 CAD, MAE of 563.15 CAD, and MAPE of 2%, which indicate better precision.

In France, the ARIMA model shows reasonable performance with a RMSE of 278.00 EUR, a MAE of 254.41 EUR, and a MAPE of 3%, while the Prophet model maintains similar accuracy with a RMSE of 286.59 EUR, an MAE of 222.70 EUR, and a MAPE of 3%.

Finally, in Italy, the ARIMA model reports a RMSE of 1,183.69 EUR and an MAE of 1,057.06 EUR, resulting in a MAPE of 3%, which indicates moderate accuracy, while the Prophet model's RMSE of 1,260.61 EUR and MAE of 955.30 EUR, with a MAPE of 3%, suggests a similar level of performance.

Overall, ARIMA generally performs better for the UK, France, and Italy, while Prophet outperforms ARIMA in the US, Canada, and Germany. Both models struggle with Japan, which indicates that that local economic conditions significantly affect forecasting effectiveness.

Table 2: Performance of ARIMA and Prophet models

Countries	ARIMA			PROPHET		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
UK [ARIMA (3,1,3)]	123.32	110.02	0.01	291.11	285.85	0.03
US [ARIMA (2,1,2)]	224.38	216.40	0.04	254.36	206.57	0.04
Japan [ARIMA (0,1,0)]	19992.02	1502.30	0.04	2835.07	2388.60	0.07
Germany [ARIMA (5,1,3)]	1117.71	1015.92	0.05	881.82	713.33	0.04
Canada [ARIMA (2,1,2)]	1031.07	855.63	0.04	725.04	563.15	0.02
France [ARIMA (2,1,2)]	278.00	254.41	0.03	286.59	222.70	0.03
Italy [ARIMA (2,1,3)]	1183.69	1057.06	0.03	1260.61	955.30	0.03

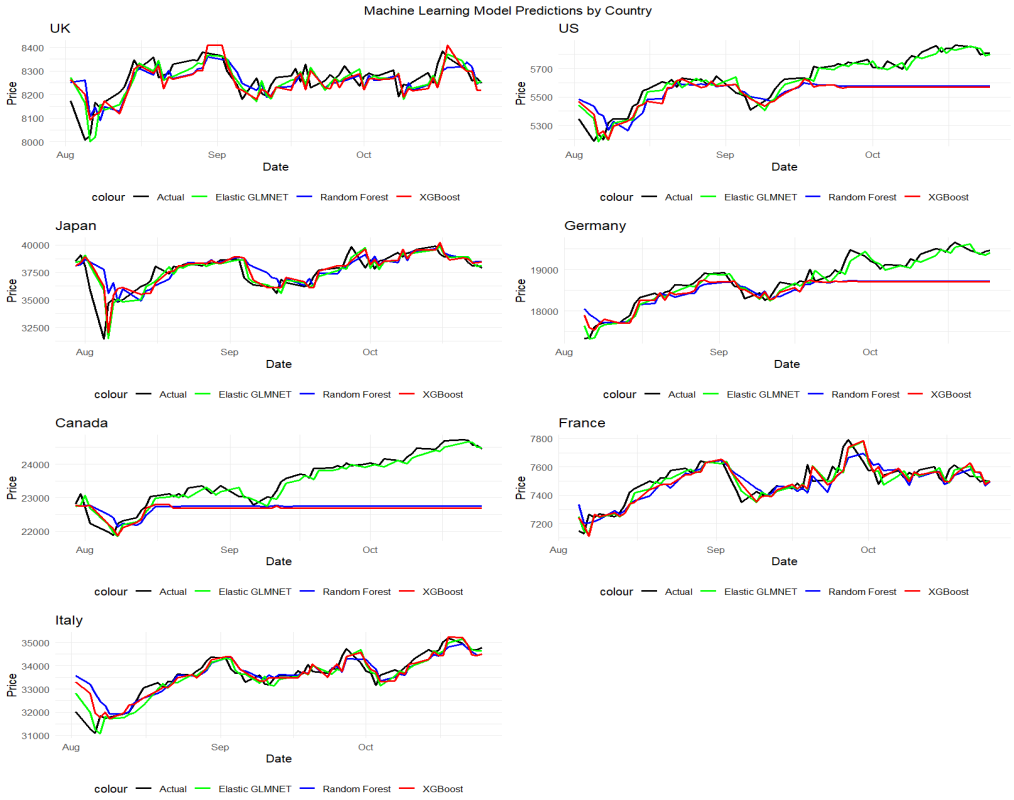

Figure 5: Plot showing Machine learning models forecasts by Country

In the analysis of the machine learning forecast performance for G7 stock prices, each of the models exhibit different accuracy across countries.

In the UK, the GLMNet algorithm performs best with the lowest RMSE of 54.56 GBP and MAE of 43.27 GBP, achieving a MAPE of 1%. The Random Forest model follows closely with an RMSE of 59.33 GBP and MAE of 47.04 GBP, while XGBoost shows a slightly higher RMSE of 57.36 GBP and MAE of 47.51 GBP.

For the US market, GLMNet again stands out, with a significantly lower RMSE of 52.09 USD and MAE of 39.13 USD, resulting in a MAPE of 1%. Random Forest has an RMSE of 151.76 USD and MAE of 127.11 USD, while XGBoost closely mirrors Random Forest's performance with an RMSE of 151.92 USD and MAE of 123.78 USD, both having less effective forecasting compared to GLMNet.

In Japan, all models show relatively high RMSE values, while GLMNet still offers the best performance with an RMSE of 966.41 JPY and MAE of 594.14 JPY, maintaining a MAPE of 2%. Random Forest and XGBoost show RMSE values of 1,168.67 JPY and 1,017.72 JPY, respectively, which indicate a significant forecasting challenge.

The German stock market is best predicted by GLMNet, which has an RMSE of 150.69 EUR and an MAE of 120.36 EUR, leading to a MAPE of 1%. The Random Forest model and XGBoost show RMSE values of 430.08 EUR and 420.39 EUR, respectively.

In Canada, GLMNet again, with an RMSE of 175.82 CAD and MAE of 138.19 CAD, achieving a MAPE of 1%. The Random Forest model shows a much higher RMSE of 1,033.26 CAD, while XGBoost also struggles with an RMSE of 1,070.49 CAD.

For France, GLMNet maintains its position with the lowest RMSE of 64.44 EUR and MAE of 49.86 EUR, resulting in a MAPE of 1%. Random Forest and XGBoost show slightly higher RMSE values of 74.45 EUR and 69.77 EUR, respectively, this is comparable but slightly less accurate forecasts.

In Italy, GLMNet again leads with an RMSE of 318.70 EUR and MAE of 249.41 EUR, both achieving a MAPE of 1%. The Random Forest model shows a higher RMSE of 489.40 EUR, while XGBoost presents an RMSE of 394.63 EUR.

Overall, GLMNet consistently outperforms the other machine learning models across the majority of countries, particularly in the UK, US, Germany, Canada, France, and Italy. However, in Japan, all models, including GLMNet, face significant challenges, as indicated by their relatively high RMSE values. While Random Forest and XGBoost generally lag behind GLMNet in predictive performance across most markets.

Table 3: Performance of Machine learning models

Countries	Random Forest			GLMnet			XGBoost		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
UK	59.33	47.04	0.01	54.56	43.27	0.01	57.36	47.51	0.01
US	151.76	127.11	0.02	52.09	39.13	0.01	151.92	123.78	0.01
Japan	1168.67	734.08	0.02	966.41	594.14	0.02	1017.72	655.75	0.02
Germany	430.08	345.15	0.02	150.69	120.36	0.01	420.39	326.87	0.02
Canada	1033.26	852.25	0.04	175.82	138.19	0.01	1070.49	879.31	0.04
France	74.45	56.85	0.01	64.44	49.86	0.01	69.77	55.24	0.01
Italy	489.40	319.38	0.01	318.70	249.41	0.01	394.63	283.57	0.01

5. Conclusion

This study compared the forecasting performance of ARIMA, Prophet, Random Forest, GLMNet, and XGBoost on G7 stock markets during the Russia-Ukraine conflict. ARIMA generally performed well in stable markets such as the UK, France, and Italy, where stock prices exhibited predictable trends. Prophet demonstrated better performance in more complex and volatile markets, such as the US and Canada, where stock prices are influenced by seasonal trends and policy changes. Among machine learning models, Elastic GLMNet exhibited the strongest performance across most G7 countries, including the UK, US, Germany, Canada, France, and Italy. Random Forest and XGBoost, while powerful for capturing non-linear relationships, faced challenges in smaller datasets characterized by high volatility, such as Japan's market. Regarding regional patterns, European markets like Germany and Italy exhibited higher fluctuations, likely driven by the conflict's economic impact on energy-reliant sectors.

The results align with existing literature on model performance under different market conditions. ARIMA's strength in stable markets supports Hou (2023), who emphasized that ARIMA is particularly effective when historical patterns repeat without major disruptions. Prophet's flexibility in accommodating seasonal shifts proved beneficial in the US and Canada, consistent with Taylor and Letham's (2018) description of its strengths in handling abrupt changes. GLMNet's consistent performance across most countries reflects its regularization benefits, which reduce overfitting and enhance stability in markets with linear or straightforward trends, as noted in recent studies. The difficulties faced by complex models like XGBoost in Japan's volatile market suggest that model complexity alone does not guarantee better forecasts, particularly when data availability is limited.

For investors and financial practitioners, these findings highlight the importance of matching forecasting models to market conditions. In stable markets with clear trends, simpler models like

ARIMA or regularized regression methods such as GLMNet may provide reliable predictions with lower computational cost. In markets subject to policy shifts or seasonal patterns, Prophet offers greater adaptability. For highly volatile markets, the results suggest that complex machine learning models require larger datasets to perform effectively. Policymakers and analysts monitoring geopolitical impacts should also consider that European markets may be more sensitive to regional conflicts due to energy dependence and trade linkages.

This study has several limitations. First, it uses daily closing prices only, which may not capture intraday volatility or high-frequency trading patterns. Second, the forecasting horizon was fixed at 60 days; longer or shorter horizons may yield different results. Third, the study does not incorporate exogenous variables such as macroeconomic indicators, policy announcements, or news sentiment, which could improve forecast accuracy. Fourth, the dataset period (2022-2024) may not generalize to other crisis periods. Future research should explore hybrid models combining time series and machine learning approaches, incorporate external predictors, and test these models on other emerging markets or different crisis events to assess generalizability.

6. References

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