The Impact of Russia-Ukraine conflict on Global Commodity Brent Crude Prices

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15 August 2023

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First Submission: August 15, 2023
Revision: May 21, 2025
Report Date: February 10, 2024

Abstract

This study investigates the impact of the Russia- Ukraine conflict on Brent Crude commodity pricing using World Bank time series data. The conflict's influence on global oil and gas markets, characterized by intricate supply and demand dynamics, is analyzed through advanced time series techniques and machine learning modeling. Univariate models such as Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are employed to discern temporal patterns in Brent Crude prices. Additionally, Seasonal Autoregressive Integrated Moving Average (SARIMA) and Exponential Smoothing State Space (ETS) models are utilized to capture complex seasonality and trends in the data. Moving beyond traditional methods, multivariate models are leveraged to comprehensively grasp the multifaceted impact of the conflict. Principal Component Analysis (PCA) and Factor Analysis are applied to uncover latent variables influencing Brent Crude pricing in the context of global trade disruptions, inflation, and diplomatic negotiations. These extracted components are then integrated with ensemble machine learning algorithms, including Random Forest, Extra Tree Classifier, Gradient Boosting, K-Nearest Neighbors, and Decision Trees. The fusion of multivariate time series analysis and machine learning empowers a holistic understanding of the conflict's intricate repercussions on commodity prices.The analysis reveals that not only direct factors related to geopolitical tensions but also indirect economic data are crucial in determining Brent Crude prices. Factors such as declining industrial demand for precious metals like silver, disruptions in vehicle production due to supply chain breakdowns, reduced demand for automotive autocatalysts, weak copper demand from China, and unexpected changes in steel consumption have contributed to the observed fluctuations in Brent Crude prices.Through a comprehensive exploration of time series data and advanced machine learning modeling, this research contributes to a a clearer understanding of the complex connections between the crisis in Russia and Ukraine and the price of commodities globally. The findings offer valuable insights for policy-makers, industry stakeholders, and investors seeking to navigate the complex landscape of commodity markets during periods of geopolitical instability.
Keywords: **Brent Crude Prices, Univariate Models, Multivariate Models, Ensemble Machine Learning, PCA, SARIMA, ETS** etc.

By utilizing data science and analytics techniques, the research has analyzed the effects of the conflict between Russia and Ukraine on brent crude pricing. The research study is detailed and unique examination of the relationship between the war and commodity prices, shedding light on the potential long-term consequences for stakeholders worldwide. This unique analysis will appeal to economists, analysts, policymakers, and investors who seek to better understand the complex dynamics of geo-political conflicts and their impact on commodity markets.The analysis has been presented in a detailed manner to appeal to all audiences, whether their intent is qualitative, or driven by quantitative data science.

1 Introduction

In today's interconnected global economy, understanding the intricate relationship between geopolitical events and commodity prices has become more crucial than ever. The ongoing conflict between Russia and Ukraine has emerged as a poignant example of how geopolitical tensions can reverberate across financial markets, impacting vital commodities such as Brent Crude oil. This study delves into the multifaceted dynamics at play, utilizing a blend of traditional time series analysis and advanced machine learning techniques to unravel the impact of the Russia-Ukraine conflict on Brent Crude commodity pricing [7, 20].

The Russia-Ukraine war has unleashed a wave of disruptions that have rippled through supply chains and caused seismic shifts in the energy sector. Notably, Brent Crude prices, a key benchmark for global oil markets, have been significantly affected. The fallout encompasses a spectrum of factors including supply chain bottlenecks, production delays, amplified market uncertainty, and economic turbulence within major oil-producing and consuming nations [23, 12, 15].

To comprehensively explore the intricate interplay of these factors, this study harnesses a suite of technical tools. Concepts like Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF), Seasonal Autoregressive Integrated Moving Average (SARIMA), and Exponential Smoothing State Space (ETS) models are employed to dissect the underlying time series data. This enables us to unravel the temporal patterns and inherent structures that have driven fluctuations in Brent Crude prices during this pivotal period [3].

In tandem with these classical methodologies, the study seamlessly integrates modern machine learning algorithms. Random Forest, Extra Tree, Gradient Boosting, K-Nearest Neighbors, and Decision Tree algorithms are harnessed to tease out intricate relationships between Brent Crude prices and a suite of crucial variables. By enlisting these algorithms, we aim to capture complex nonlinearities that might elude traditional statistical approaches [4].

The scope of this study extends beyond Brent Crude alone. It encompasses a broad spectrum of interconnected commodities that collectively shape the global economic landscape. The profound ripple effects stemming from shifts in commodities like silver, platinum, copper, iron ore, and gold are meticulously scrutinized. By pinpointing the impact of these commodities on Brent Crude prices, we gain an enriched understanding of the intricate web of interdependencies that characterizes the global commodity market. In 2021, the EU bought 42 percent of Russian oil production [33, 23].

As this study unfolds, it aims to illuminate how various factors have collectively sculpted the trajectory of Brent Crude prices amidst the Russia-Ukraine conflict. The declining industrial demand for silver, disruptions in vehicle production due to supply chain interruptions, weakened demand for copper from China, and suboptimal steel consumption in China collectively underscore the depth of influence that geopolitical upheavals can exert on commodity markets [7, 8, 15].

In summary, this research embarks on a multifaceted journey, weaving together time-honored analytical techniques with cutting-edge machine learning methodologies. By delving into the heart of the Russia-Ukraine conflict's impact on Brent Crude prices, we endeavor to unearth nuanced insights that empower stakeholders, economists, and policymakers to navigate the evolving contours of a world where geopolitical events and economic forces intertwine in unprecedented ways [5, 20, 34].

2 Literature Review

The research study has been performed after a methodical literature review based on Industry Reports, Research Papers, Research Articles, Books, Case Studies and News Media. Based on the literature review of the World Bank's Commodity Data Analysis, it is evident that the review did not identify specific forecasting methods for the industrial commodity pricing in the volume of studies that have been conducted so far. However, much effort is being made to improve the accuracy of the forecast [34].

The forecasting of industrial commodity prices, such as those of metals and energy sources like Brent Crude, has gained significant attention in recent years due to the volatility of global markets and the increasing complexity of economic interdependencies. Accurate forecasting is crucial for stakeholders, including policymakers, investors, and businesses, as it informs decision-making processes regarding production, pricing, and risk management [34].

2.1 The Evolution of Commodity Price Forecasting Methods

Forecasting commodity prices has evolved significantly over the past few decades, moving from simpler methods like univariate models and futures pricing to more sophisticated approaches that leverage multivariate models and machine learning algorithms. Early methods relied heavily on futures prices to predict spot prices for commodities. However, as more complex economic relationships were uncovered, research began to shift toward model-based approaches that incorporate a wider range of data, including economic indicators, inventory levels, and currency exchange rates [3].

According to the literature, futures prices often fail to provide accurate long-term predictions due to their inability to account for unforeseen economic shifts and market disruptions. Studies by various scholars emphasize that models incorporating additional information, such as global economic conditions and petroleum inventories, outperform futures prices in forecasting accuracy [3, 34]. The work of Vochozka et al. (2023), for instance, highlights that composite forecasting models, which combine several approaches, are particularly effective in improving prediction reliability by accounting for both short-term market trends and long-term economic conditions [87].

2.2 Multivariate Time Series Models and Machine Learning

Multivariate time series models have emerged as a powerful tool in forecasting industrial commodity prices. These models, which analyze multiple variables simultaneously, are better equipped to capture the complex interrelationships between commodities and other economic factors. For example, Brent Crude prices can be influenced by numerous variables, including exchange rates, global trade flows, and production levels [3].

Several studies, such as those by Vochozka et al. (2022), have demonstrated the effectiveness of multivariate models in forecasting industrial commodities like oil and metals [86]. These models leverage techniques such as autoregressive integrated moving average (ARIMA), exponential smoothing state space models (ETS), and more advanced machine learning methods like random forests and gradient boosting [4].

Machine learning models, particularly those using deep learning techniques, have gained traction in recent years due to their ability to process vast amounts of data and uncover hidden patterns that traditional models might overlook [4]. In the context of commodity price forecasting, machine learning models such as neural networks, decision trees, and ensemble methods like random forests have been successfully applied to predict price movements with high accuracy. However, the literature emphasizes the need for careful data preparation and feature engineering to ensure that machine learning models perform optimally. Data quality, selection of appropriate features, and validation processes are critical to achieving accurate and reliable forecasts [4].

2.3 The Role of Economic Variables in Enhancing Forecast Accuracy

One of the key insights from the literature is that the inclusion of additional economic variables in forecasting models significantly enhances predictive accuracy. Several studies have shown that adding data on global economic conditions, industrial production levels, and currency exchange rates improves the performance of both statistical and machine learning models [67, 66].

The real effective exchange rate (REER) of the U.S. dollar, for example, plays a crucial role in shaping the price of globally traded commodities like oil and metals. When the U.S. dollar strengthens, the cost of commodities typically rises in other currencies, leading to reduced demand and lower prices. By accounting for such macroeconomic variables, forecasting models are better equipped to anticipate price movements in response to currency fluctuations and other global factors [66].

Vochozka et al. (2023) also explored how world output gaps—an indicator of global economic health—affect commodity prices. Their findings suggest that incorporating measures of global economic activity into forecasting models improves their ability to predict long-term trends in industrial commodities like platinum [86].

2.4 Machine Learning and Time Series Data

Machine learning techniques are becoming increasingly prominent in commodity price forecasting, particularly for time series data. Unlike traditional statistical models, machine learning algorithms can adapt to changing data patterns and are capable of processing large datasets with high dimensionality. This adaptability makes them particularly well-suited to forecasting in volatile and complex markets [4].

One of the main advantages of using machine learning for time series analysis is the ability to incorporate non-linear relationships between variables. Traditional time series models like ARIMA and SARIMA are linear by design, meaning they assume that future values of a time series are a linear function of past values. However, commodity prices are often influenced by a wide range of non-linear factors, such as geopolitical tensions, technological advancements, and environmental policies. Machine learning models, such as neural networks and decision trees, are better equipped to capture these non-linear relationships, leading to more accurate forecasts [4].

However, while machine learning models hold great promise, the literature emphasizes the importance of model validation and performance comparison. Vochozka et al. (2022) point out that while standalone machine learning algorithms can provide high-accuracy predictions, their performance should be compared with other traditional models, such as multivariate time series models, to determine the most effective approach for a given dataset [86].

2.5 Composite Forecasting Methods

Composite forecasting methods, which combine multiple models, have been shown to outperform single-model approaches in many cases. These methods leverage the strengths of different models to provide more accurate and reliable forecasts. For example, a composite model might combine a traditional time series model, such as SARIMA, with a machine learning model like a random forest to capture both linear trends and non-linear relationships in the data [4].

Research suggests that composite forecasting methods are particularly useful in volatile markets, where commodity prices are influenced by a wide range of factors that are difficult to predict using a single model. By combining multiple models, researchers can account for both short-term fluctuations and long-term trends, leading to more robust predictions [87].

In addition to improving accuracy, composite forecasting methods also enhance the transparency and interpretability of forecasts. By using a combination of models, researchers can provide stakeholders with a more comprehensive understanding of the factors driving commodity prices, which can inform better decision-making [4].

Future Research Directions based on Literature Review

The literature on industrial commodity price forecasting highlights the importance of using model-based approaches and incorporating additional economic data to improve forecast accuracy.

While futures prices have traditionally been used to predict commodity prices, the evidence suggests that multivariate models and machine learning techniques generally outperform futures prices, particularly when additional information is included in the models [3, 86].

Future research in this area could explore novel machine learning techniques, such as deep learning and reinforcement learning, as well as the integration of real-time data from sources like social media and news reports. Additionally, further research is needed to evaluate the performance of different forecasting methods across a wider range of commodities and economic conditions [4].

In conclusion, the evolving landscape of commodity price forecasting presents numerous opportunities for innovation, particularly through the application of machine learning and composite forecasting methods. By incorporating more data and leveraging advanced models, researchers and practitioners can improve the accuracy and reliability of commodity price forecasts, ultimately supporting better decision-making in global markets.

3 Research Methods / CRISP-DM Process Methodology

This research follows the systematic methodology based on the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework. The primary objective is to analyze Brent Crude pricing and explore the impact of global trade disruptions, inflation, and diplomatic negotiations on price trends. This study incorporates advanced machine learning algorithms and time series models to derive meaningful insights [85].

The CRISP DM methodology consists of six stages: business understanding, data understanding, data preparation, modeling, evaluation, and deployment. The steps involved in this study are detailed as follows [85]

3.1 Business Understanding

The first phase focuses on defining the business or research objective. In this study, the primary objective is to explore temporal patterns in Brent Crude pricing and identify underlying economic factors that contribute to price fluctuations, especially in the context of global disruptions. The analysis aims to support stakeholders, such as policymakers and investors, in decision-making regarding commodity market trends. The methods applied in this phase are largely qualitative, grounded in identifying global economic factors that influence the dependent variable—Brent Crude prices [85].

3.2 Data Understanding

Relevant data sources include the World Bank [66], public reports, news articles and academic journals. The World Bank provides time series data on Brent Crude prices, inflation rates, and other economic indicators. News articles and public reports are used to track events affecting global commodity markets. Data understanding is achieved through exploratory data analysis (EDA) using Pandas [4] and NumPy [100] libraries in Python to identify trends, outliers, anomalies, and missing data [4].

3.3 Data Preparation

Data preprocessing is crucial for ensuring the data is clean and suitable for machine learning algorithms. This phase includes the following steps [4]:

- **Handling Missing Data**: Missing values are imputed using mean, median, or mode values.
- **Feature Engineering**: Lag features and differencing techniques are applied to capture temporal dependencies in the time series data.
- **Normalization and Scaling**: Methods such as Min-Max scaling and z-score normalization are used to standardize the data for modeling.
- **Heatmap and Correlation Analysis**: Correlation matrices and heatmaps are generated to identify relationships between variables, aiding feature selection.

3.4 Modeling

This study employs a variety of univariate, multivariate, and ensemble machine learning models to analyze Brent Crude pricing dynamics [1,3,4].

3.4.1 Univariate Models

- Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analyze temporal dependencies in Brent Crude pricing data.
- Seasonal Autoregressive Integrated Moving Average (SARIMA) captures seasonal trends in the time series.
- Exponential Smoothing State Space (ETS) models account for trend and seasonal patterns.

3.4.2 Multivariate Models

- Principal Component Analysis (PCA) reduces dataset dimensionality and identifies latent variables influencing Brent Crude pricing.
- Factor Analysis uncovers hidden economic factors affecting price fluctuations, such as global trade disruptions and inflation.

3.4.3 Ensemble Machine Learning Algorithms

- Random Forest builds an ensemble of decision trees to improve predictive performance.
- Gradient Boosting iteratively corrects errors to enhance model accuracy.
- K-Nearest Neighbors (KNN) classifies data points based on proximity to neighbors.

- Multi-Layer Perceptron (MLP), a neural network, models nonlinear relationships among features.

3.5 Evaluation

Models are evaluated using metrics such as accuracy, Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE). Cross-validation techniques, including k-fold validation, ensure the models generalize well on unseen data. Feature importance is assessed using SHAP (SHapley Additive exPlanations) values to identify which features most influence Brent Crude pricing[4].

3.6 Deployment

The models are used to simulate scenarios exploring the effects of economic conditions on Brent Crude pricing. Data visualization techniques—such as line plots, heatmaps, and bar charts—present the findings clearly. Visualization libraries Matplotlib[98] and Seaborn are utilized to create insightful graphics[4].

This research integrates advanced machine learning techniques, time series models, and econometric analysis to uncover patterns in Brent Crude pricing. The structured methodology ensures transparency, repeatability, and robust insights for stakeholders. Models ranging from SARIMA to ensemble methods like Random Forest and Gradient Boosting enable deep analysis of complex economic relationships, supporting informed decision-making in commodity markets [1, 2, 4].

4 Research Questions and Discussion

4.1 Impact of the Russia-Ukraine War

The impact of the Russia-Ukraine War has brought considerable advantages to oil and gas producing countries like Russia and Saudi Arabia, who have used the war situation for price manipulation. However, the war has also exposed these countries to global risks caused by supply chain disruptions [7]. For oil-consuming countries like India and Ghana, the war has led to increased energy prices and fears of inflation [6][35]. Many of these economic disruptions have prompted government interventions and policy measures [34][38]. Top oil and gas companies such as Exxon and Chevron experienced a decline in earnings, and Brent Crude prices dropped to USD 75/barrel after peaking at USD 100/barrel following the war's onset on February 24, 2022 [11]. According to a journal article in the Journal of Energy and Social Sciences Research, Nigeria may benefit from higher oil prices through increased oil exports, possibly boosting its economic growth [21].

According to Wood Mackenzie, the war has changed the market in five ways [12]:

1. Increased geopolitical tension risks and disruptions in global oil supply.
2. Higher oil and gas prices have altered consumer spending and raised inflation.
3. Greater focus on energy diversification and renewable efforts.

4. Long-term concerns about oil and gas sustainability have intensified.
5. Projects with greater environmental impact are under increased scrutiny.

Furthermore, The Times reported that Saudi Arabia threatened to cut production output amid rising geopolitical tensions, increasing oil prices [29]. This, alongside record outflows from the world's largest exchange-traded commodity (ETC), has led to heightened market volatility [30][40]. Oil marketing companies (OMCs) face greater uncertainty due to increased volatility, rising prices, reduced earnings, and growing risks [8].

As per Mark Einseberg and Cheryl Tessell, oil price hikes are largely driven by the fear of supply disruptions. The associated risk premium has further escalated crude oil prices. Overall, the war has had a significant impact on Brent Crude prices, resulting in price surges, volatility, and supply security concerns, affecting all stakeholders across the oil and gas spectrum.

4.2 Supply Chain Disruptions

Supply-demand uncertainty, price volatility, and geopolitical instability have posed serious challenges to both consumers and corporations, impacting company earnings [27]. Saudi Arabia's recurring threats to cut production levels have worsened volatility [29]. Russia's supply reduction following extensive sanctions led to market imbalances and shortages, further inflating prices. Saudi Arabia's extended production cuts exacerbated oil market challenges.

According to Wood Mackenzie [12], the war triggered a domino effect—disrupting logistics, transportation, infrastructure, production, and refining—causing sharp market fluctuations. The largest commodity ETF saw record outflows post-war, reflecting a shift in investor sentiment [30]. For oil-importing economies like Ghana and India, the result has been costlier imports and sustained inflationary pressures [35][36]. These disruptions have broader implications for global politics, diplomacy, and economic stability.

4.3 Production Delays

Production delays and supply disruptions have become common among oil-producing nations, leading to global insecurity. To mitigate these issues, stakeholders should enhance security, diversify energy sources, and stabilize oil-producing regions. The extension of Saudi production cuts exerts pressure on suppliers, logistics partners, and contractors operating on annual contracts. Disruptions have significantly hindered optimal production levels, particularly in the Russia-Ukraine region.

Despite sanctions, Russian energy revenues exceeded pre-war levels by over one billion USD year-on-year [33]. However, the Russian market suffered from NATO sanctions, affecting its trade with neighboring nations. Ukraine, meanwhile, faced labor shortages, infrastructure destruction, production setbacks, and severe security risks. These production-related uncertainties continue to fuel price volatility and geopolitical instability, adversely impacting investments and earnings.

4.4 Market Uncertainty:

The geopolitical tensions and conflicts lead to disruption of the market and enhanced market uncertainties, leading to less confidence in the market and the investors taking their investments off the market. Apart from the unanimous sanctions, the onset of war led to more than 1000 multinational companies to pack their bags and investments from Russia. The war has caused a potential unrest in the minds of traders, because of the concerns over oil supply disruptions and the impact on the trade routes. More and more companies are adjusting their trading strategies to absorb these market uncertainties and pricing volatility. [37].

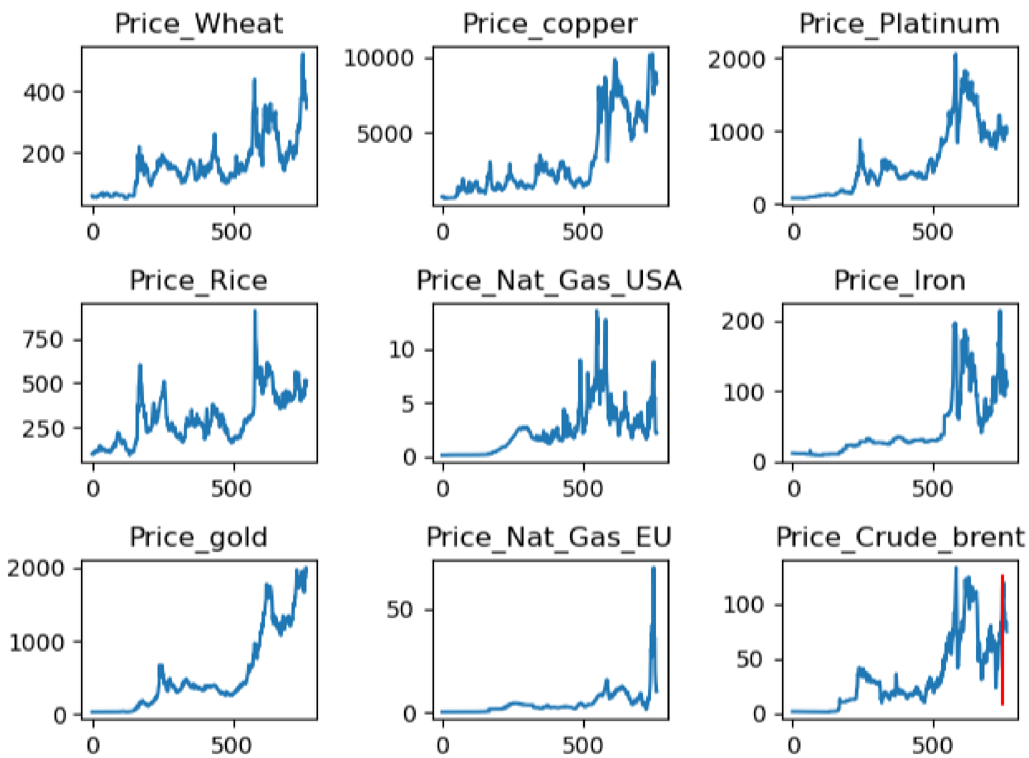

Figure 1: Brent Crude Price Fluctuations

In the international market dynamics all these factors lead to increase in the prices of the Brent Crude Oil. To mitigate market instability, countries like the UK and US implemented price caps and embargoes on Russian oil [16][45]. Though controversial, these policies help manage consumer anxiety. In the early stages of the war, countries built up strategic inventories to buffer against shocks, pushing Brent crude prices upward. Although, the market pundits and economists debate such market moves, however, it is a measure to absorb some uneasiness from the mind of consumers. After the start of the Ukraine - Russia war, like any other war, countries tend to build on their stockpile of inventories to absorb the market shock and not be affected by the market vagaries of the war in another region. This leads to surge in Brent crude prices, Market uncertainties cause the investors to re-evaluate their investment options, more level of caution leads to hedging the risks by investing in some more markets which are not subjected to the risks of war. Hence, the overall market sentiment towards investments in Oil and Gas companies and products, becomes more cautious, leading to a downward pressure on the Brent Oil Prices.

4.5 Options for Russia and European Nations:

Although the ongoing Russia-Ukraine conflict has had far-reaching effects globally, Russia and European nations still have several options to mitigate the crisis. Some of the key strategies include diversification and investment in renewable energy sources, implementing price caps, and increasing domestic production capacity. Both Russia and the European Union (EU) should reduce their reliance on Russian conventional energy resources. Diversifying their energy portfolios by investing in alternatives such as renewable energy, nuclear power, and liquefied natural gas (LNG) would reduce the EU's vulnerability to disruptions in Russian oil and gas supply and could help stabilize global Brent crude prices [5, 44].

European nations can also enhance domestic production through investments in exploration and development, improved extraction techniques, and incentivizing local production to decrease supply uncertainties arising from dependence on Russian imports [43, 18]. The implementation of price caps by European nations and the US aims to protect markets from excessive price surges and prevent stockpiling behaviors that lead to volatility [16, 45].

Moreover, investing in renewables like wind, solar, biogas, and hydro will reduce dependence on conventional fossil fuels, including Russian oil and gas [65, 48]. Supportive policies such as market subsidies, tax incentives, and robust regulatory frameworks for renewable projects will foster energy security and political stability across Europe [38, 54]. International cooperation remains essential to mitigating the broader impacts of the war and fostering a more resilient and stable Brent crude market [10, 34].

4.6 Diplomatic Negotiations

Diplomatic negotiations are essential for reducing uncertainties in the global crude oil market caused by the Russia-Ukraine war. Diplomatic dialogue around production levels, price controls, and international cooperation, involving all key stakeholders, can help stabilize Brent crude markets [64, 55].

This conflict has caused supply disruptions and trade uncertainties, prompting countries like Saudi Arabia to engage in extended production cuts based on diplomatic negotiations, aimed at supporting global crude prices [29, 40]. Agreements between the UK, coalition nations, and the US on sanctions and price caps on Russian oil were introduced to mitigate consumer price shocks and promote market stability [37, 42].

Price caps have been particularly instrumental in maintaining public confidence and ensuring a level of control over volatile oil markets [16]. Despite significant sanctions, including the exit of over 500 foreign firms from Russia, especially in the Moscow region, these developments were largely achieved through diplomatic channels [45, 12].

Diplomacy remains pivotal in easing tensions, promoting dialogue, and establishing pathways to peaceful resolution. Strengthened international relations—even post-conflict—can significantly help in recovering trade and market equilibrium. Global collaboration among oil producers, consumers, and traders is vital for effective communication and conflict resolution, ultimately fostering a more stable energy market environment [66, 19]. Market volatility leads investors to reassess and diversify into less exposed assets, creating downward pressure on oil prices. Consequently, market sentiment toward oil and gas investments has grown more cautious.

4.7 Diversification of Energy / Investment in Renewable:

Diversification of renewable energy which is mostly domestically produced and not subjected to geopolitical tensions and vagaries / uncertainties of the global market can be a good option for reducing reliance on conventional resources specifically Russian Oil, and thus mitigate the disruptions caused due to sanctions, restrictions and embargoes on Russian Oil Products. A shift towards solar, wind, hydro, geothermal can mean less reliance on imported oil and gas.[10, 44] Thus by exploring more options for domestic production, promoting energy efficiency and alternative suppliers can help in lesser reliance on Russian Oil and Gas. However, these options are mostly relevant for EU Countries, Ukraine, the US and the UK. Also, greater energy security and stability amidst supply disruptions. The diversification to renewables is inline with the Global Climate 2050 goals [18, 65, 75]. The move toward renewables contributes to greater energy security and fosters sustainability even in post-conflict periods. Furthermore, it opens economic opportunities—such as job creation in green sectors and the attraction of investments in clean technology and infrastructure [19, 53]. By reducing exposure to global oil price shocks driven by geopolitical events, these strategies enhance market stability [38, 39].

4.8 Regional and Global Cooperation:

Regional and global cooperation among energy-importing and exporting nations is essential for mitigating price volatility and supply chain disruptions caused by geopolitical conflicts and natural disasters [64, 49]. Mechanisms like shared oil reserves, production quotas, and export coordination can help create a more resilient and stable global oil market [40, 12].

By promoting transparency and timely data exchange on oil markets, these alliances can reduce uncertainty and speculative trading [62, 66]. Moreover, strategic partnerships—such as the peace talks between Ukraine and Russia, facilitated by global actors—underline the importance of diplomacy in restoring stakeholder confidence and ensuring market functionality [37, 15]. Regional and Global partners can agree on energy security agreements for ensuring mutual support and cooperation in the times of crisis. By employing these factors Russia and Europe can ensure market stability and respond to market fluctuations in a more proactive manner.

4.9 The role of top oil-producing and consuming countries:

The top oil-producing countries—United States, Saudi Arabia, Russia, Canada, and China—along with top consuming countries like the US, China, India, Russia, and Japan, exert significant influence on global oil dynamics [48, 24]. These nations account for a major share of oil production and consumption, highlighting their capacity to influence energy security, pricing, and geopolitical strategies [68, 67]. The Top 5 Oil Producing Countries are the United States, Saudi Arabia, Russia, Canada, China, and the top 10 oil production countries account for 73 percent of the global yearly oil production. The Top 5 Oil Consuming Countries are United States, China, India, Russia and Japan, with top 10 most consumption countries accounting for 62 percent of the global yearly oil consumption.

Policies from these countries shape the strategic direction of the global energy landscape, making their cooperation vital for implementing effective energy transition and stabilization strategies during conflicts [70, 52].

4.10 Comparison of Crude Oil Prices in 2021 and 2023?

It can be inferred that the crude oil prices before the war, at the peak of the conflict, and in the current scenario (2021 to 2023) have experienced significant fluctuations and impacts due to the Russia-Ukraine war. The war has caused disruptions in global oil markets, leading to fluctuating crude oil prices. Crude oil prices experienced dramatic fluctuations between 2021 and 2023, largely driven by the Russia-Ukraine war [28, 27].
Here is a brief summary of the crude prices during this period:

1. Pre-War: Before the Russia-Ukraine war, crude oil prices were influenced by various factors such as supply-demand dynamics, OPEC+ agreements, and global economic conditions. However, tensions and expectations of the war already impacted oil prices, leading to some volatility. [69].

2. Peak Price: The peak price of crude oil was reached after the start of the conflict, as Russia's invasion of Ukraine heightened geopolitical tensions and raised concerns over potential supply disruptions. This resulted in a significant surge in oil prices, with Brent crude oil surpassing USD 100 per barrel. [30, 15].

3. Current Scenario: The current scenario is characterized by ongoing geopolitical uncertainties and market volatility. Despite efforts to stabilize the market, crude oil prices remain impacted by the war. While there have been fluctuations in prices, they have generally remained elevated compared to the pre-war period. [46].

It is important to note that crude oil prices are influenced by multiple factors, including supply and demand dynamics, geopolitical events, market sentiment, and global economic conditions. The Russia-Ukraine war has introduced significant uncertainties and disruptions to the market, resulting in fluctuating crude oil prices. [16, 20].

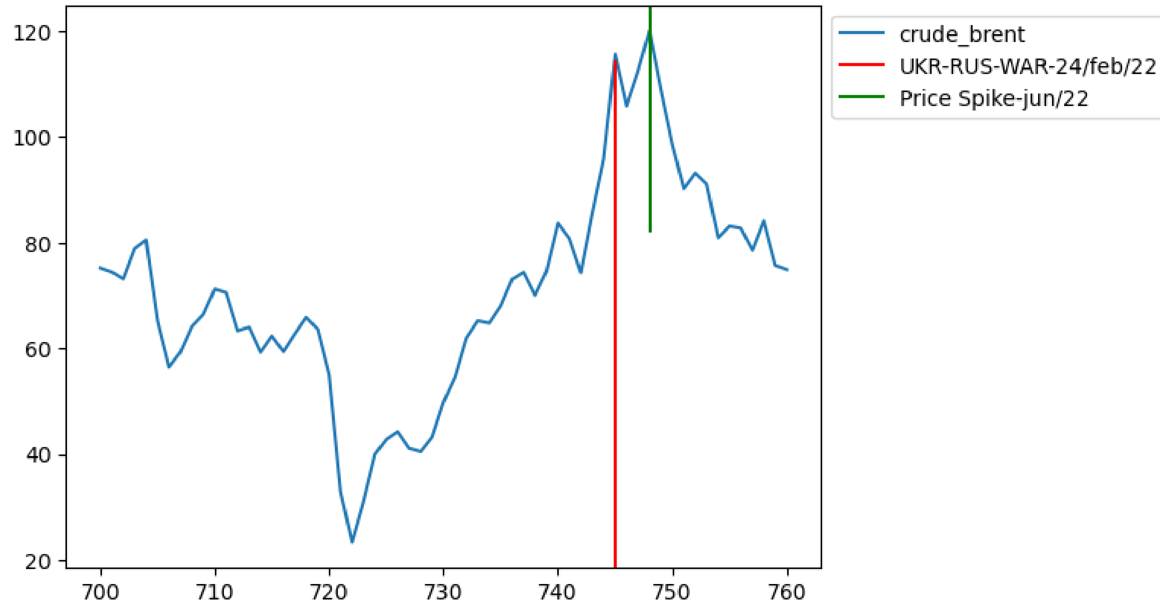

Figure 2: Price Time Series - 3 Years Brent Crude, Red Line Onset of War

4.11 Role of OPEC in the current Russia-Ukraine War

The role of OPEC in the current Ukraine-Russia war scenario is complex. OPEC, or the Organization of the Petroleum Exporting Countries, is a group of oil-producing nations that work together to coordinate and manage oil production and prices. [64, 17].
OPEC has monitored the conflict closely and adjusted production levels to counterbalance the market shocks and maintain price stability [5, 50]. However, internal member differences and Russia's independent policies have constrained OPEC's full intervention capacity [14, 7].

4.12 Ukraine's ENERGY Strategy as of 2023

As of 2023, Ukraine's energy strategy in response to the disruptions caused by the war with Russia and plans of partnership with India and China includes various initiatives and changes:

1. Diversification of energy sources: Ukraine aims to reduce its dependence on Russian energy imports, particularly natural gas. The country is focused on diversifying its energy mix by increasing domestic production, promoting renewable energy sources, and exploring partnerships with other countries for alternative energy supplies [5] [17] [42].

2. Development of renewable energy: Ukraine has been actively promoting the development of renewable energy sources, such as solar and wind power. The government has implemented policies and provided incentives to attract investment in renewable energy projects, aiming to increase the share of renewables in the country's energy mix [18] [44] [48].

3. Enhanced energy efficiency measures: Ukraine has recognized the importance of improving energy efficiency to reduce energy consumption and enhance energy security. The country is

implementing measures to increase energy efficiency in various sectors, including industry, residential buildings, and transportation [54], [58].

4. Strengthening energy cooperation with India: Ukraine has been exploring energy partnerships with India, focusing on areas such as oil and gas exploration, renewable energy projects, and technology transfer. The aim is to enhance bilateral energy trade and cooperation between the two countries [6, 22].

5. Cooperation with China: Ukraine is also seeking energy partnerships with China, particularly in the areas of natural gas and infrastructure development. The country aims to leverage China's expertise and investment to develop its energy sector and enhance energy security [13, 59].

Overall, Ukraine's energy strategy in response to the disruptions caused by the war and plans of partnership with India and China is focused on reducing dependence on Russian energy imports, diversifying the energy mix, promoting renewable energy, improving energy efficiency, and exploring partnerships with other countries for energy cooperation [10, 55, 40].

5 Data Visualization and Analysis for Brent Crude Oil Pricing

The research report includes data visualization illustrating global commodity pricing across various sectors, including agriculture, energy, and precious metals. These visualizations provide a comprehensive overview of price fluctuations and trends in these markets before and during the Russia-Ukraine war [5, 34, 7, 15].

The Commodity Pricing dataset, downloaded from the World Bank's website, contains pricing data on commodities classified as Agriculture Produce, Energy, Precious Metals, and Minerals [34, 66]. Due to the presence of missing values, which can compromise data quality and lead to erroneous insights, variables with incomplete records were dropped from the analysis to maintain data integrity [4, 1].

Further investigation revealed high correlations between crudebrent and variables such as crudeavg and crudedubai, introducing multicollinearity, which can distort regression results. To mitigate this issue, we employed feature engineering techniques to eliminate redundant variables [1, 3].

Additionally, Principal Component Analysis (PCA) was used to assess dataset complexity and reduce dimensionality, facilitating better visualization and model performance in machine learning applications [4, 83, 90]. PCA transforms high-dimensional correlated variables into a set of uncorrelated components, preserving the variance while reducing complexity [1, 93, 96].

Visualization and preprocessing were conducted using Python libraries such as Matplotlib for plotting, Pandas for data manipulation, and NumPy for numerical computation [98, 99, 100].

This approach helps in modeling oil pricing trends and evaluating the economic impact of geopolitical events, such as the Russia-Ukraine conflict, on the energy sector [81, 11, 85, 89].

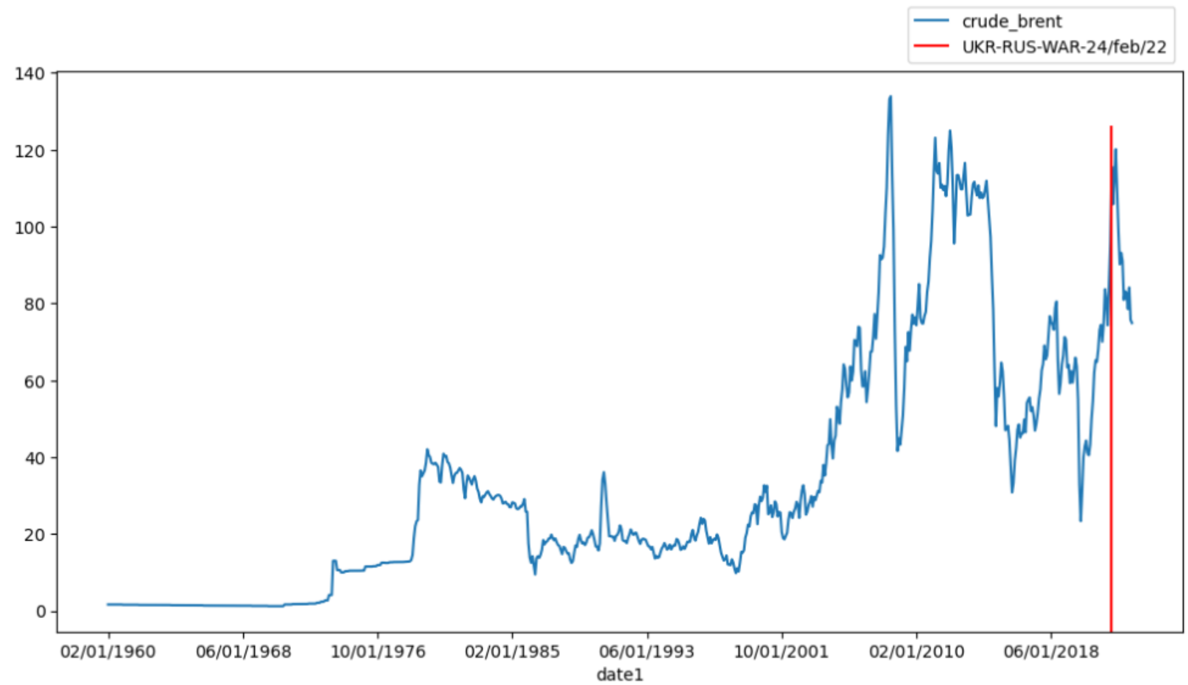

Figure 3: Price Time Series - 63 Years Brent Crude, Red Line Onset of War

5.1 ARIMA Model for Brent Crude Price Forecast Generation

For the purpose of forecasting time series, the ARIMA (Autoregressive Integrated Moving Average) is a frequently employed statistical modeling technique. It combines autoregressive (AR), differencing (I), and moving average (MA) components to capture the different patterns and trends present in the data [3].

The AR component of the model captures the relationship between the variable and its own lagged values. It represents how the variable's current value is linearly related to its past values. The AR component is denoted by the parameter p, denoted by the number of included lagged terms [3].

The differencing component (I) is the integer representing the number of times the time series is differenced to achieve stationarity, for removing the trend and seasonality from the series. Stationarity is important for forecasting because many time series models assume the series to be stationary [90]. The differencing component is denoted by the parameter d, which determines the order of differencing required to make the series stationary.

The MA component captures the relationship between the variable and its past forecast errors. It represents how the variable's current value linearly represents the errors made by the previous forecasts. The MA component is included by the parameter q, denoted by the number of included past forecast errors [3].

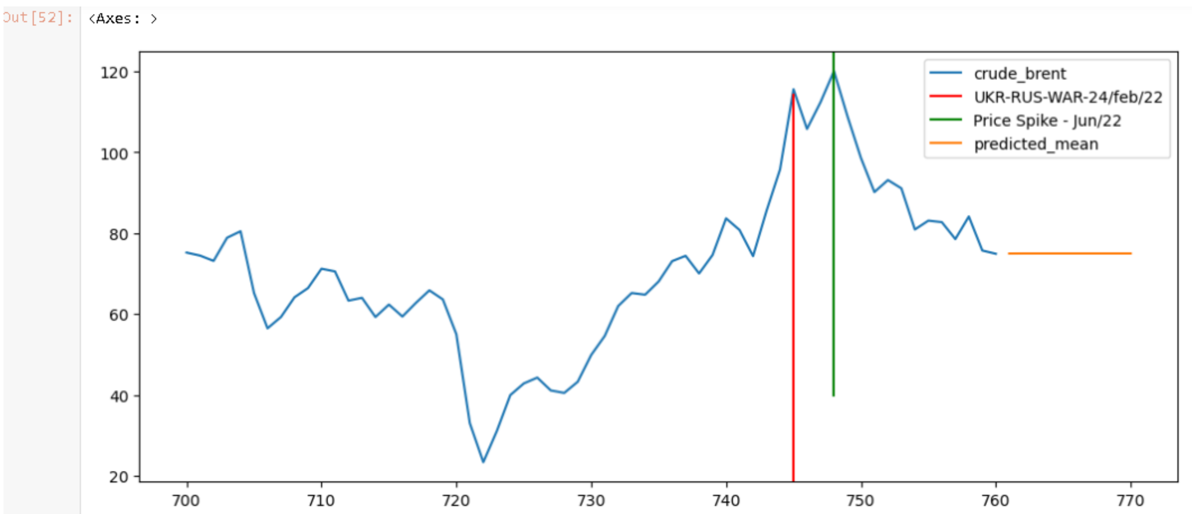

Figure 4: Forecast - Classical Forecasting Model

The Seasonal data is separated into Residual, Trend, Error and Seasonality, which is why this kind of seasonal data decomposition is referred to as ETS (Error-Trend-Seasonality) decomposition [4]. Since the decomposition indicates that our data is not stationary, ARIMA modeling is a more appropriate technique for forecasting such a time series. Generally, for government policy decisions, classical regression, exponential smoothing, or the Box-Jenkins ARIMA forecasting approach is used [3, 1].

5.1.1 ARIMA Decomposition: Error-Trend-Seasonality

The ARIMA model decomposes a time series into three main components: Error, Trend, and Seasonality [3]. The decomposition can be represented as follows:

$$\text{Original Time Series} = \text{Trend} + \text{Seasonality} + \text{Error}$$

5.1.2 Components

1. Trend ($Td_t t$): The underlying pattern or long-term movement in the data.
2. Seasonality ($Sy_t t$): The repeating pattern that occurs at regular intervals.
3. Error or Residual ($Er_t t$): The random fluctuations that cannot be explained by the trend and seasonality.

5.1.3 Mathematical Representation

Mathematically ARIMA decomposition can be represented as follows:

$$y(t) = T(t) + S(t) + Er(t)$$

Out[46]:

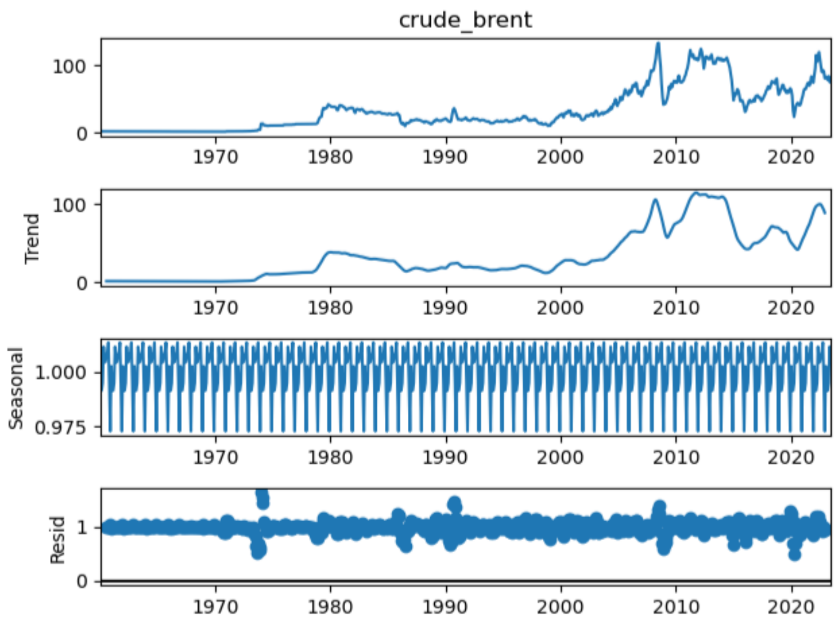

Figure 5: ARIMA Decomposition performed on actual dataset

Where:

$$y(t): \text{ is the observed time series at time } t$$
$$T(t): \text{ is the trend component at time } t$$
$$S(t): \text{ is the seasonal component at time } t$$
$$Er(t): \text{ is the residual component at time } t$$

In some instances, rather than being multiplicative, trend and seasonality could be additive. The additive components can be represented as:

$$y(t) = T(t) \cdot S(t) \cdot Er(t)$$

5.1.4 ARIMA Model

The ARIMA(p,d,q) model can be represented mathematically as:

$$(1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p)(1 - B)^d X(t) equals (1 + \theta_1 B + \theta_2 B^2 + \ldots + \theta_q B^q)\epsilon_t$$

where: - $X(t)$ is the time series
- B is the backshift operator, which shifts the time series by one lag $(BX_t = X_{t-1})$
- ϵ_t is white noise
- p is the order of the autoregressive part of the model
- d is the degree of differencing (integer representing the number of times the time series is differenced to achieve stationarity)

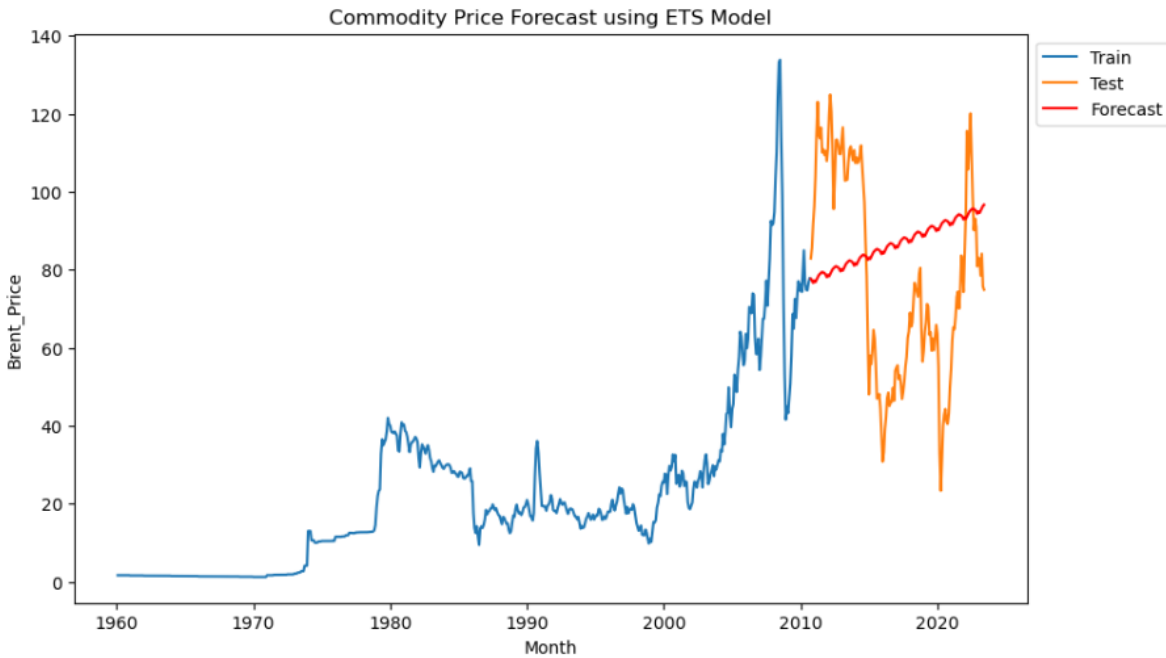

Figure 6: Forecast based on ETS modeling.

- q is the order of the moving average part of the model
- $\phi_1, \phi_2, \ldots, \phi_p$ are the autoregressive coefficients
- $\theta_1, \theta_2, \ldots, \theta_q$ are the moving average coefficients

5.2 Correlation Heatmap

A correlation heatmap is a graphical representation of the correlation coefficients between different variables in a data set. It provides a visual summary of the relationships between variables, helping to identify patterns or dependencies.[1].

Correlation is interpreted as a measure of linear association derived from covariance. Covariance is the strength of linear association between two numerical variables. Thus we can derive correlation from covariance as

$$\text{corr}(x, y) = \frac{\text{cov}(x, y)}{S_x S_y}$$

where $S_x S_y$ is the product of standard deviations. Properties of Correlation to remember -
1. Measures the strength of linear association.
2. It is always between -1 and +1: -1 $\leq \text{corr}(x, y) \leq +1$
3. It does not have any units

Here is the correlation heatmap generated using Python:

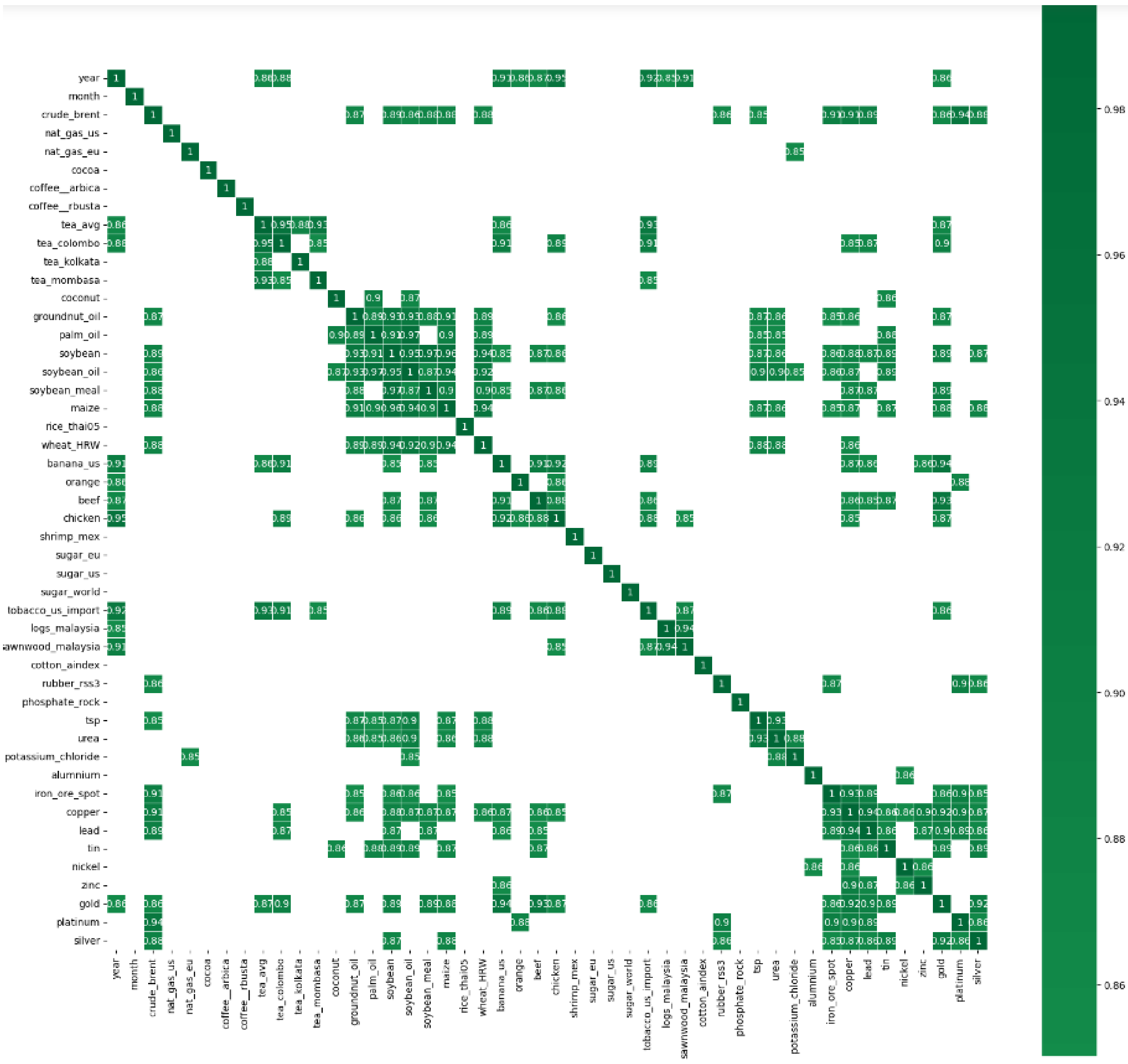

Figure 7: Correlation Heatmap

6 Feature Engineering, Model Selection, Model Training and Validation, Analysis

Our raw dataset has more than 50 features or commodity products,the raw dataset contains monthly pricing data on each feature from year 1960 to current month. Hence, by doing feature engineering we have done the process of selecting, manipulating and transforming raw data for our machine learning modeling. Since, we are interested in finding the reasons for the change in prices of crude-oil, hence, crude-avg variable is our output variable and the rest of the variables can be considered as input variables.

In our feature engineering exercise we have mostly performed operations around imputation, replacing values, removal of missing values, scaling, standardization, normalization etc. By doing these feature engineering tasks we have achieved two goals in our research, as listed -

1. Preparing the dataset for doing our machine learning exercise, hence we have achieved compatiblity of our dataset with the chosen machine learning algorithms.
2. By comparing the machine learning model performance on our data we have achieved a benchmark of machine learning models and pathways to improve the machine learning models performance.

As per Forbes Survey, Data Scientists spend 80 percent of their time in massaging the data for data preparation and analysis. Data is the new oil and money of 21st Century AI Age.

The mathematical representation of Root Mean Square Error (RMSE) in Machine Learning is given by:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

where N is the number of samples, y_i is the true value of the target variable, and $\hat{y}_i$ is the predicted value of the target variable.

The mathematical representation of Accuracy in Machine Learning is given by:

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \times 100$$

where the number of correct predictions is the count of correctly predicted samples, and the total number of predictions is the count of all samples.

6.1 Analyzed Scenarios for Feature Engineering

This section discusses the different approaches used for feature engineering to enhance model performance.

6.1.1 Adaboost Regressor [4]

The Adaboost regressor is used to improve the prediction accuracy by combining weak learners into a strong learner. This feature engineering exercise yielded Platinum, Iron Ore Spot and Silver as top three features. The prediction accuracy was 93.28 percent, MAE was 6.61 and R Squared Value was 94.54 percent. The top three features selected by our machine learning model are- platinum - 34.83 percent, silver - 24.17 percent and iron-ore-spot -11.32 percent.

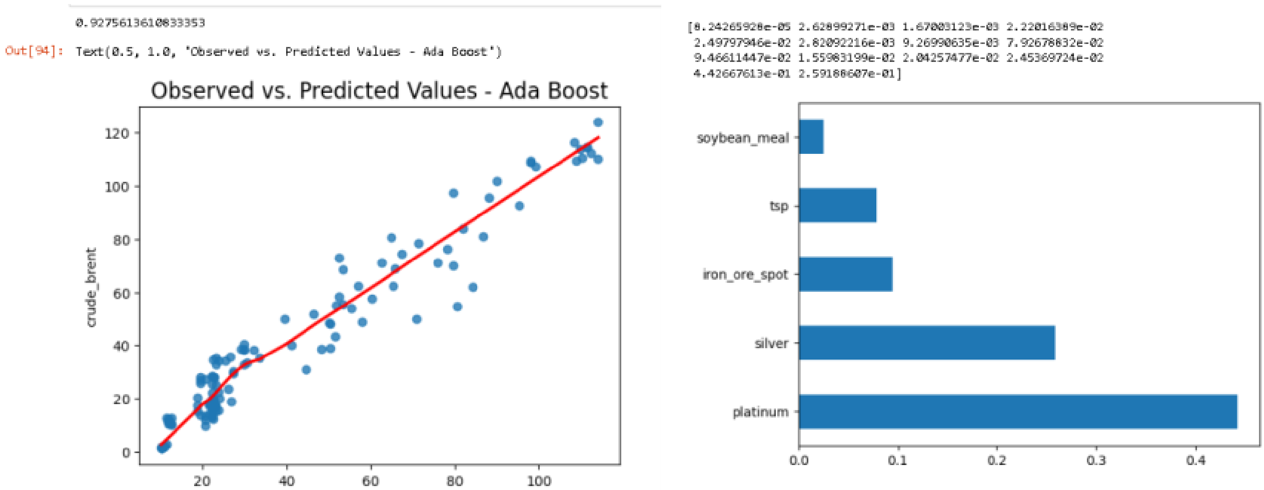

Figure 8: Scenario 1 - Adaboost Algorithm

6.1.2 Extra Tree Regressor

The Extra Tree Regressor is an ensemble learning method that uses multiple decision trees and randomizes split points for improved predictions. This feature engineering exercise yielded Platinum, Iron Ore Spot, Copper, Gold and Silver as top features. The prediction accuracy was 98.33 percent, MAE was 2.23276 and R Squared Value was 99.07 percent. The top features selected by our machine learning model are - iron ore spot - 17.96 percent, platinum - 16.01 percent, copper - 15.24 percent , silver - 10.75 percent and gold - 10.69 percent

6.1.3 Decision Tree Regressor

This algorithm creates a decision tree model to predict the target variable based on input features. This feature engineering exercise yielded Platinum, Iron Ore Spot 95.47 percent accuracy as top features. The top two features selected by our machine learning model are - platinum - 74.88 percent , iron ore spot - 14.38 percent

6.1.4 Random Forest

The Random Forest regressor is an ensemble learning method that builds multiple decision trees and merges them to get more accurate and stable predictions. This feature engineering exercise yielded Platinum, Silver and Iron Ore Spot as top features. The prediction accuracy was 97.29

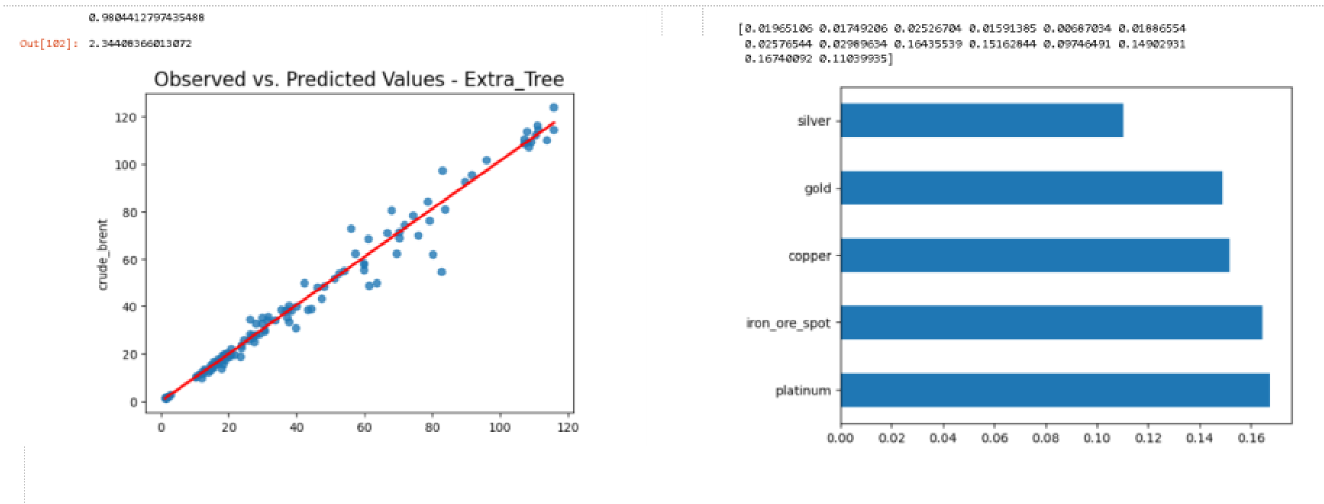

Figure 9: Scenario 2 - Extra Tree Algorithm

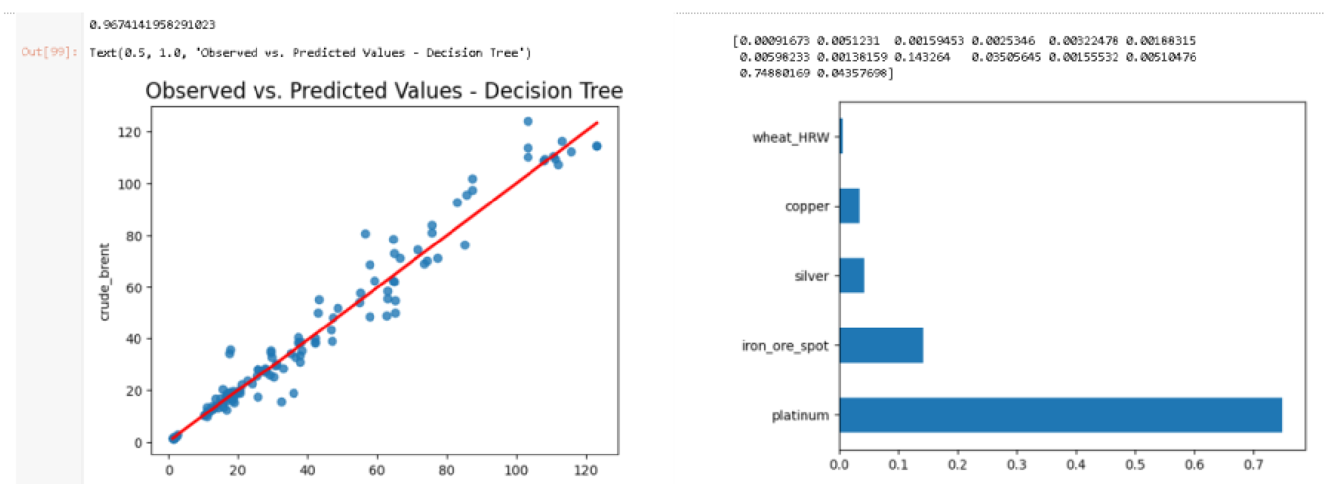

Figure 10: Scenario 3 - Decision Tree Algorithm

percent, MAE was 2.8794 and R Squared Value was 97.49 percent. The top features selected by our machine learning model are - platinum - 38.19 percent, silver - 35.01 percent, iron ore spot - 9.82 percent.

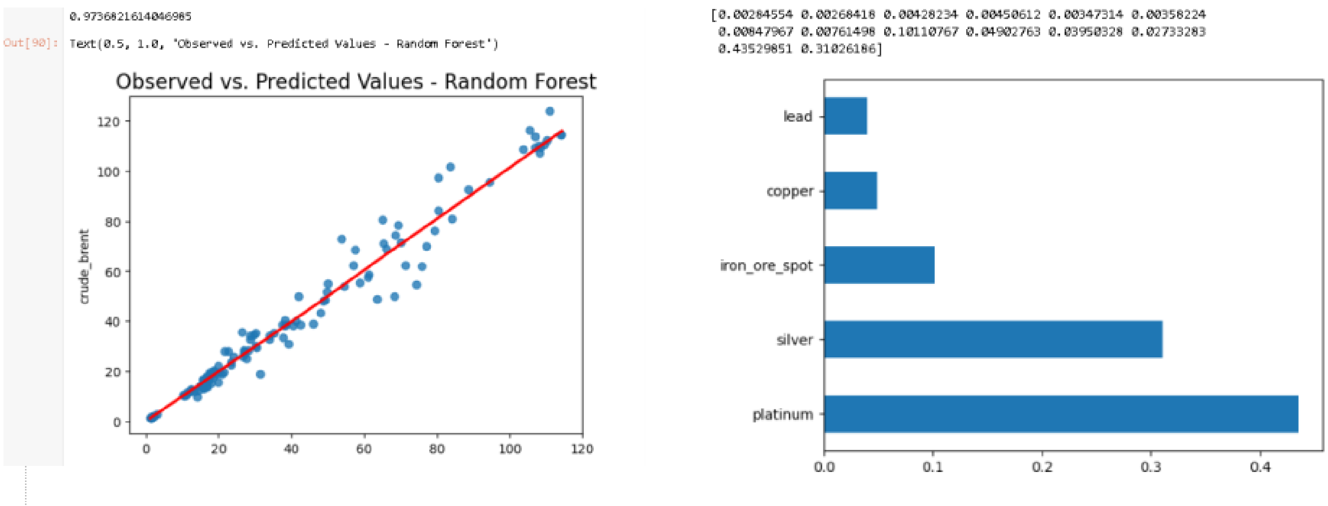

Figure 11: Scenario 4 - Random Forest Algorithm

6.2 Key Inferences from Factor Analysis

Factor analysis is applied to identify underlying relationships between observed variables, which are used to improve model performance. Explanation of Brent Crude price spike with these features -

6.2.1 Silver [86, 85]

1. Silver prices slumped due to waning industrial demand.
2. More than 50 percent of the Silver yearly consumption is driven by industrial demand.
3. Silver is used in electronics , solar panels and photographic equipment.
4. Consumer Electronic output was lowest in November 2022.
5. China's Purchasing Manager Index was lowest in April 2022, while USA's PMI rating took a deep plunge in June 2022.
6. Investment Demand of Silver Fell Sharply, which is the second highest demand of silver after industrial applications.

6.2.2 Platinum [87]

1. Palladium and Platinum are widely used in Automotive Industry.

2. The war has hit the vehicle production which was already reeling due to disruption of supply chains during COVID-19 and although the Russia's Norlisk Nickel which is the largest producer of palladium did not let the Ukraine-Russia war to disrupt it's production and delivery of palladium. European car makers have been hit due to the shortage of wiring harness supply from Ukraine, It's due to the war.

3. Decline in the demand of the Autocatalyst in the Auto Industry has led to downward pressure on palladium and platinum prices.

4. Platinum's use in electrolyzers, carbon free hydrogen, production and fuel cells.

6.2.3 Copper

1. The decline in Copper prices due to weak demand from China since the April 2022.

2. China accounts for approximately 57 percent of Global Copper Consumption.

3. Copper is consumed in Electric Vehicles, renewable power and associated electric grid infrastructure.

6.2.4 Iron ore

1. Iron ore imports have been under a lot of pressure in China, due to lower than expected steel consumption. Iron ore purchases in China slumped to 10 month low in April.

2. Chinese Officials are considering an official cut by 2.5 percent to the steel production output in the year 2023.

3. Experts say that peak Iron Ore demand in China has already been reached in the year 2020.

4. Market Pundits consider the price of iron ore and crude oil maintain a complex relationship, hence our machine learning algorithms are able to extract complex relationships between oil price movement and precious metals and minerals.

6.2.5 Gold [83]

1. The Prices of Gold follow the trends in Oil Prices. Generally, Oil exporting countries hedge their risks in Oil by buying more gold from the revenues generated from the Oil exports. [54]

2. Gold is considered as Safe Haven investment in most parts of the world, and rising oil prices lead to inflation but investments in gold are considered as a counter for rising inflation.

3. Oil prices can be used non-linearly to predict the gold prices but not vice versa.[54]

4. The work on relationship between oil prices and gold prices is however limited.[54]

6.3 Drivers of Brent Crude Oil Prices -

1. Disruption in Oil Supplies from Russia. [7, 5].
2. Steep rise in Inflation in North America after the onset of war and throughout Year 2022.[10].
3. Strong exchange rate of USD , compared to other currencies. [32].
4. Market Volatility, Drop in demand of Precious Metals, Iron Ore, Copper and overall Weak industrial and economic activity, [6, 11].
5. Record Number of Sanctions against Russia by Global Companies

Our four features namely Platinum, Silver, Iron Ore Spot and Copper account for the best accuracy in our prediction results.

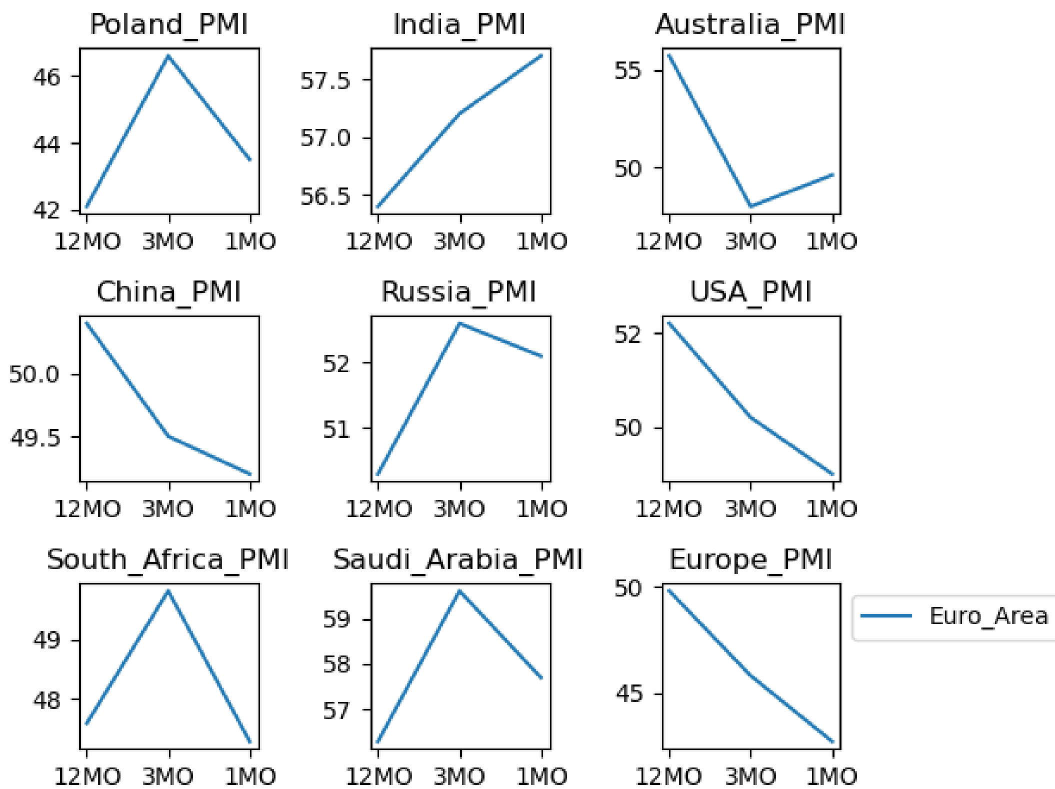

Figure 12: Plot of PMI Index

6.4 Country Level PMI Index

From the PMI index plot, it is clearly evident that except India and Australia, there is a drop in manufacturing activity all over the world in the countries which are under consideration, based on factor analysis.

A comparison of Purchasing Manager Index (PMI Index) based on 12 months average, 3 months average and 1 month average of data is showing a downward trend in the past 3 months for the manufacturing sector. Platinum, Sliver, Copper and Iron Ore are all used in Industrial Applications as discussed in the section on inferences based on factor analysis. Russia, Poland, South Africa and Saudi Arabia had a positive PMI trend 3 months ago, but they have shown a downward trend in comparison of 3 month and 1 month data. Europe, the USA, China, have shown a consistent downward trend in their PMI Index in the past 12 months based on 12 month, 3 months and 1 month average score.

7 Principal Component Analysis (PCA) - Introduction and Mathematical Formulation

PCA is a dimensionality reduction technique that transforms the original variables into a new set of uncorrelated variables known as principal components. It is a technique in machine learning wherein a dataset with high dimensionality is converted into a dataset with low dimensionality, while retaining as much of the variance as possible.This is achieved by finding a new set of orthogonal axes, called principal components, along which the data varies the most. By doing this exercise, we are able to extract a small number of important features which can explain the hidden properties in our dataset. The PCA technique uses simple and intuitive mathematics from matrix algebra.[4]

- Variance and Covariance

- Eigen Values and Eigen Factors.

Given a dataset $\mathbf{X}$ with n samples and d features, the goal of PCA is to find a new orthogonal basis $\mathbf{U}$ such that the projected data $\mathbf{Z}$ along these components has maximum variance. The first principal component is the direction along which the variance is maximized, the second principal component is orthogonal to the first and maximizes the remaining variance, and so on.

Let $\mathbf{X}$ be centered by subtracting the mean along each feature:

$$\mathbf{X}_{\text{centered}} = \mathbf{X} - \bar{\mathbf{x}},$$

where $\bar{\mathbf{x}}$ is the mean vector.

The covariance matrix of the centered data is obtained as follows:

$$\mathbf{C} = \frac{1}{n-1}\mathbf{X}_{\text{centered}}^T \mathbf{X}_{\text{centered}}.$$

The eigenvectors $\mathbf{u}_i$ and eigenvalues λ_i of the covariance matrix satisfy:

$$\mathbf{C}\mathbf{u}_i = \lambda_i \mathbf{u}_i,$$

where $\mathbf{u}_i$ are the principal components and λ_i are the corresponding variances along each component. The transformed data $\mathbf{Z}$ along the principal components can be obtained by:

$$\mathbf{Z} = \mathbf{X}_{\text{centered}}\mathbf{U},$$

where $\mathbf{U} = [\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_k]$ for k principal components.

7.1 Dimensionality Reduction

To reduce the dimensionality of the data while preserving most of the variance, and to simplify the model without losing critical information. we can retain the top k principal components that correspond to the largest eigenvalues.The reduced dataset is given by:

$$\mathbf{X}_{\text{reduced}} = \mathbf{Z}[:, 1:k]\mathbf{U}^T[:, 1:k] + \bar{\mathbf{x}},$$

where $\mathbf{Z}[:, 1:k]$ contains the first k columns of $\mathbf{Z}$ and $\mathbf{U}^T[:, 1:k]$ contains the first k columns of $\mathbf{U}^T$. Based on the ACF and PACF plots, we can choose the PDQ values as follows:

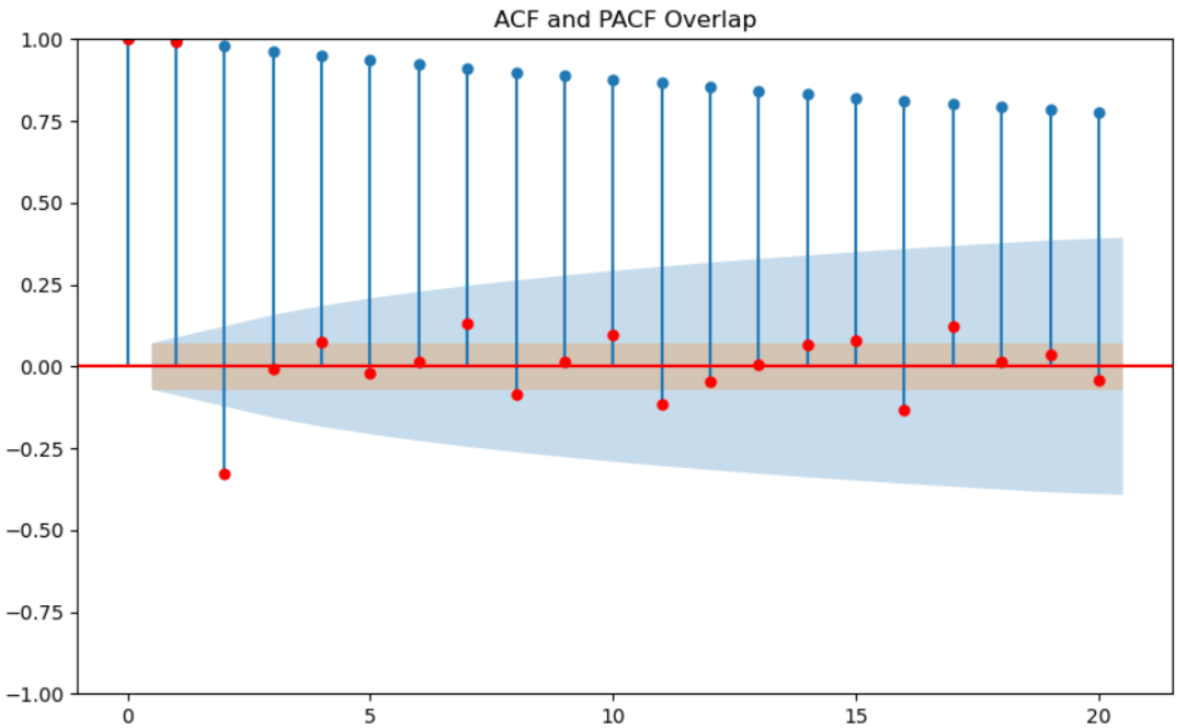

Figure 13: Overlapping ACF and PACF plots

- P (Auto-Regressive Order): The lag value where the PACF cuts off.
- D (Differencing Order): The order of differencing needed to make the time series stationary.
- Q (Moving Average Order): The lag value where the ACF cuts off.

Based on ACF and PACF,In this case, the chosen values are P=1, D=1, and Q=2.

7.2 Results and Discussion

SARIMAX (Seasonal Autoregressive Integrated Moving Average with Exogenous Variables) is a time series model that incorporates both autoregressive and moving average components, as well as exogenous variables. It is widely used for forecasting and modeling time series data. SARIMAX Results on our dataset are depicted in Figure 11 and explained in detail.

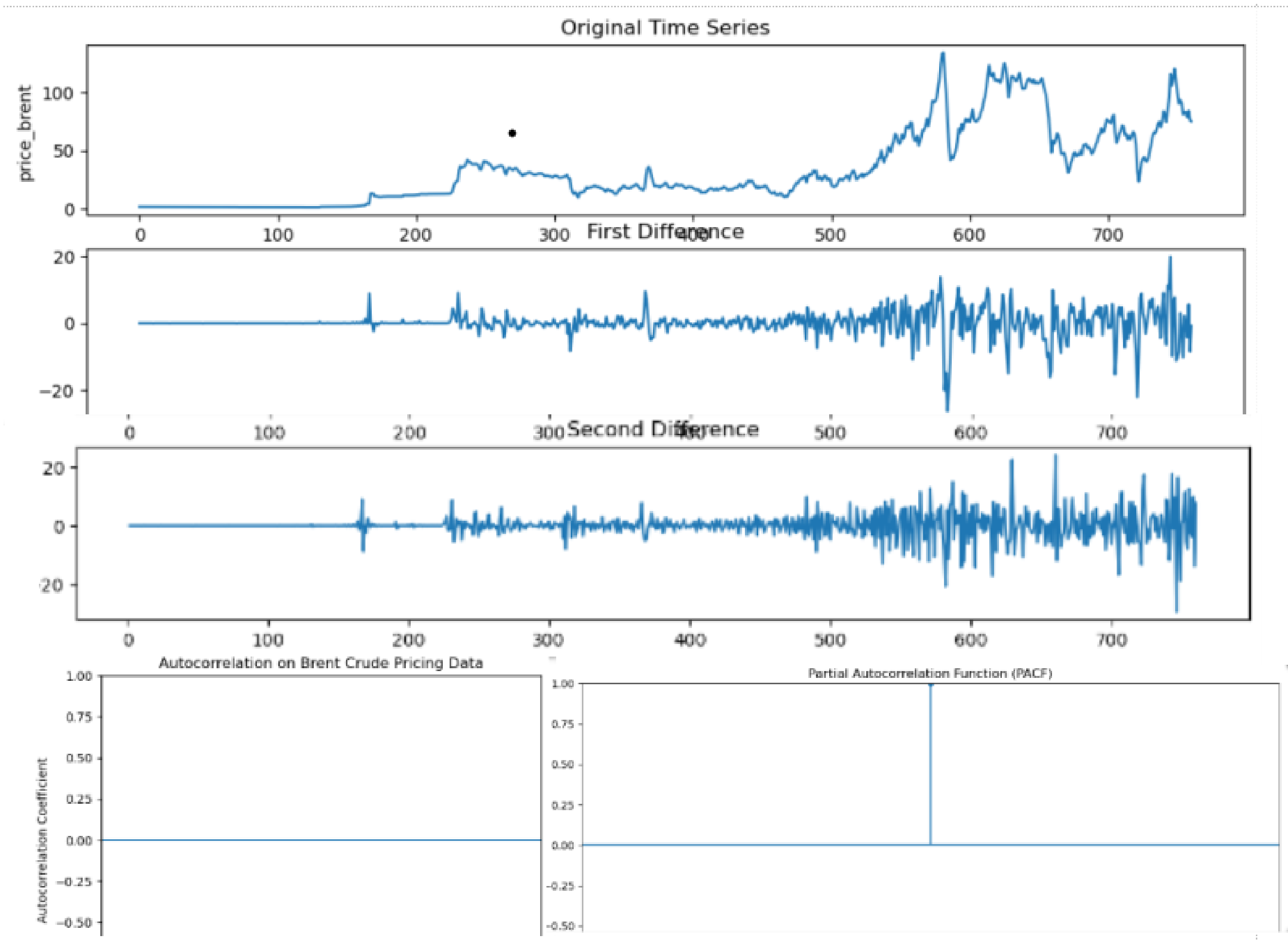

Figure 14: Differential ACF and PACF plots

- Dep. Variable: crude brent dependent variable (exogenous time series) used in the model.
- Model: ARIMA (1,1,2), based on the ACF / PACF (p,d,q) model presented earlier in the PCA Analysis.
- Date: The date and time when the model was fitted.
- Sample: The range of data used for model fitting (e.g., "1970-01-01 01:00:00" to "2023-07-01 01:00:00").
- AIC (Akaike Information Criterion): A measure of the model's goodness of fit, accounting for both model complexity and fit quality. Lower AIC indicates a better model fit.
- BIC (Bayesian Information Criterion): Similar to AIC, but penalizes model complexity more heavily. It is used to compare different models, with lower values being preferred.
- Log-Likelihood: The logarithm of the likelihood function, which measures how well the model explains the observed data.

```
                               SARIMAX Results
==============================================================================
Dep. Variable:            crude_brent   No. Observations:                  761
Model:                 ARIMA(1, 1, 2)   Log Likelihood               -2039.775
Date:                Thu, 10 Aug 2023   AIC                           4087.549
Time:                        17:48:58   BIC                           4106.083
Sample:                             0   HQIC                          4094.686
                                - 761
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -0.0125      0.194     -0.064      0.949      -0.393       0.368
ma.L1          0.3648      0.198      1.838      0.066      -0.024       0.754
ma.L2          0.1031      0.068      1.514      0.130      -0.030       0.236
sigma2        12.5506      0.306     41.065      0.000      11.952      13.150
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):              1781.93
Prob(Q):                              1.00   Prob(JB):                         0.00
Heteroskedasticity (H):              30.95   Skew:                            -0.85
Prob(H) (two-sided):                  0.00   Kurtosis:                        10.31
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
```

Figure 15: SARIMAX Results

- LLR p-value: The p-value associated with the likelihood ratio test, comparing the current model to the null model. A low p-value indicates that the current model is better.
- Scale: The estimated scale parameter, which is often related to the variance of the residuals.
- Cov Type: The type of covariance estimator used in parameter standard errors and confidence intervals.
- Covariance Matrix: Displays the estimated covariance matrix for the model parameters.
- Ljung-Box (Q): A test for residual autocorrelation. It tests the null hypothesis, Q Value less than .05 denotes non- stationery data, which is a fact as shown in the earlier section of ETS decomposition of the data.
- Prob(Q): The p-value associated with the Ljung-Box test. Low p-values indicate the presence of significant autocorrelation in the residuals.
- Heteroskedasticity (H): A test for heteroskedasticity in the residuals.
- Prob(H): The p-value associated with the heteroskedasticity test. Low p-values suggest the presence of heteroskedasticity in the residuals.

7.3 Comparison of Factor Analysis and PCA

From our analysis, we can easily compare PCA and Factor Analysis and draw inferences, based on different scenarios and datasets. We compare the results and performance of Factor Analysis and PCA in terms of dimensionality reduction and their effect on the model's accuracy. Hence, the study can be useful for researchers, industry practitioners, academicians, consultants, students etc. in different domains of data science.

Principal Component Analysis (PCA):
Principal Component Analysis (PCA) aims to transform the original variables into a new set of orthogonal variables called principal components.

Factor Analysis (FA): FA, on the other hand, is used to identify underlying latent factors that might explain the observed correlations between variables.

1. **Funadamental Differences:**
   PCA: Analyzes Variance and assumes no underlying structure in the data.
   FA: Analyzes Covariance and assumes that the observed variables are influenced by latent factors(Tab Achnick and Fidell, 2013)

   PCA: Includes all the variance in the dataset,
   (a) Variance of each variable.
   (b) Variance common among variables
   (c) Error variance (Gorsuch 1983, Kline 2002, Tab Achnick and Fidelb, 2013)

   FA: Error Variance, and the variance unique to each variable are excluded from the analysis. Only the variance in the correlation coefficient is considered.

2. **P**CA: No differentiation between common and unique variance but EFA does.

3. **Applications:**

   PCA: Often used for data compression, visualization, noise reduction.

   FA: Used for understanding the underlying structure of observed correlations, e.g., in psychology or social sciences.

From our analysis, As shown in figure 17, two component PCA Analysis is able to explain 80 percent of variance, which is pretty good, hence, we have been able to execute the 2 component PCA Analysis on our dataset. Similarly, 12 components are able to account for 95 percent of the explained variance. Hence, we can see that out of 50 variables, we have done data reduction to 2 components by performing PCA Analysis on the dataset. Similarly with Factor Analysis we were able to separate top 5 features based on the different machine learning algorithms. However, it is recommended to do both the analysis, in these turbulent and uncertain times, requiring more indepth reasoning in our decision making and to prevent any problems arising in the analysis due to hidden correlation and multicollinearity.

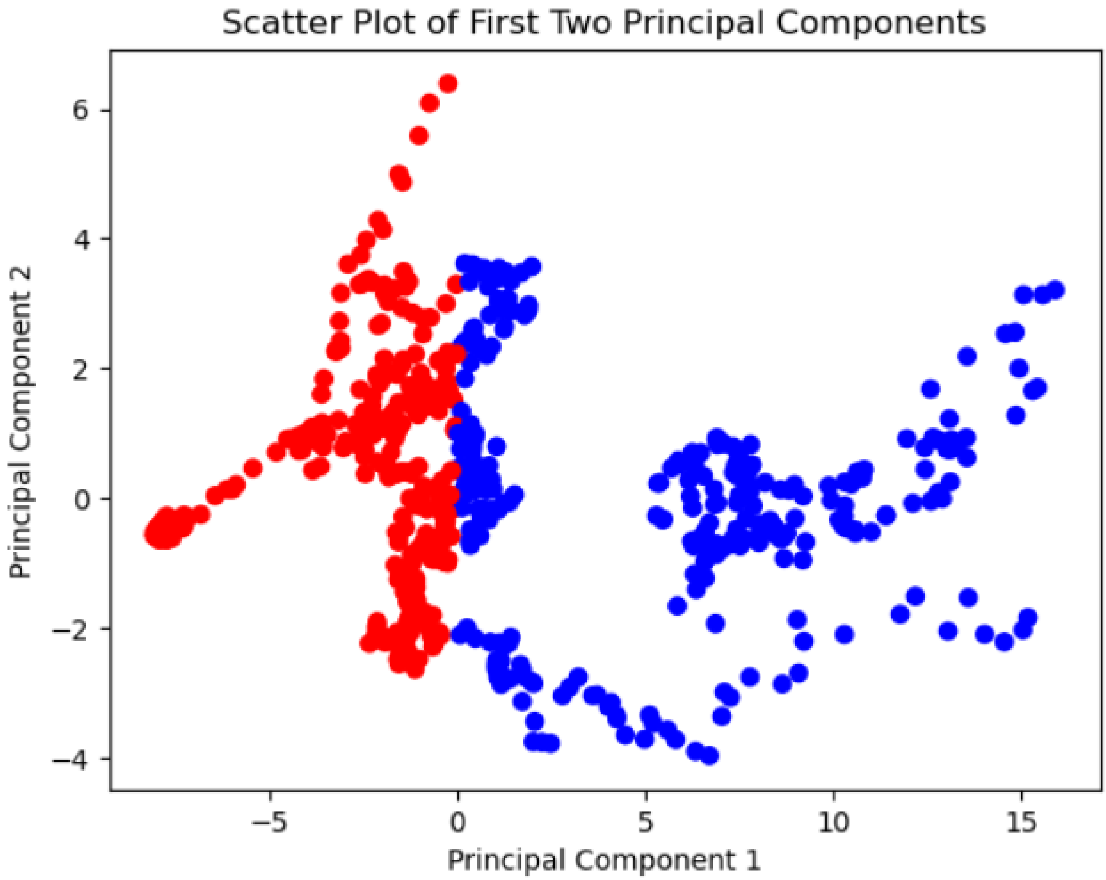

Figure 16: Scatter Plot of PC1 vs PC2

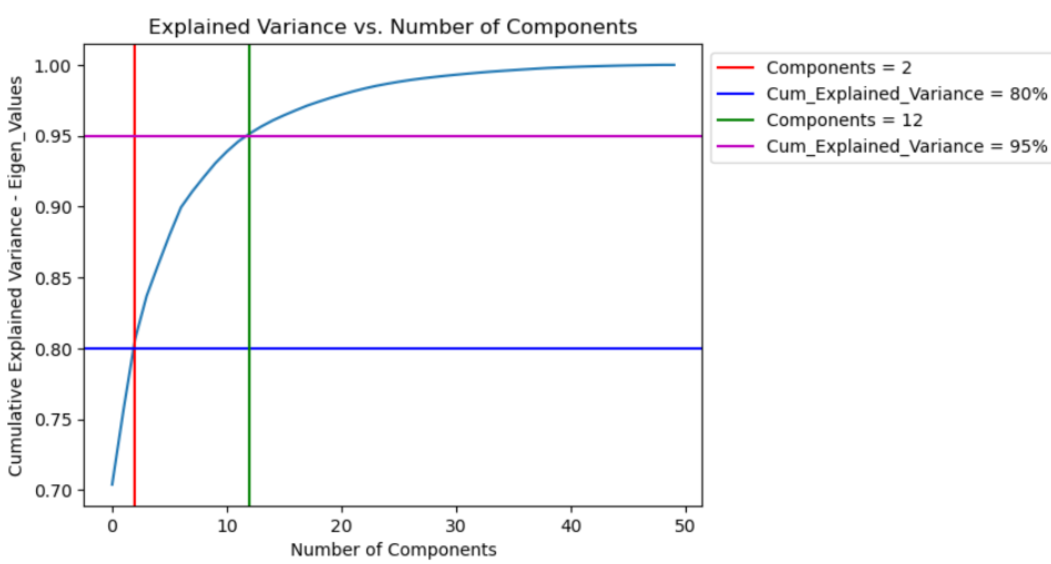

Figure 17: Explained Variance vs. Number of Components

Out[112]:

	Name	Train_Time	Train_R2_Score	Test_R2_Score	Test_RMSE_Score
0	<<Lasso>>	0.101363	0.930908	0.943597	7.602921
1	<<Ridge>>	0.363591	0.931117	0.943390	7.616866
2	<<KNeighborsRegressor>>	0.054314	0.980567	0.970962	5.455171
3	<<SVR>>	0.053461	0.834235	0.843520	12.663624
4	<<MLP_Regressor>>	0.333897	0.868320	0.865409	11.744542
5	<<Extra_Tree_Regressor>>	0.630111	1.000000	0.990728	3.082566
6	<<Gradient_Boosting_Classifier>>	0.708772	0.995676	0.985651	3.834760
7	<<Random_Forest>>	1.334107	0.997231	0.983380	4.127108

Figure 18: Algorithms Performance Table

8 Results-Algorithms

Top Machine Learning Algorithms for Crude Brent Forecasting based on Accuracy and RMSE - Fig 14
Machine Learning Models Accuracy and RMSE

1. Extra Tree Algorithm
   Accuracy - 99.07 Percent, RMSE - 3.083
2. Random Classifier Algorithm
   Accuracy - 98.34 Percent, RMSE - 4.127
3. Gradient Boost
   Accuracy - 98.565 Percent, RMSE - 3.834
4. MLP Regressor (Neural Network)
   Accuracy - 86.54 Percent, RMSE - 11.744
5. KNearest Neighbor
   Accuracy - 97.09 Percent, RMSE - 5.455

Summary of different Machine Learning Models. Top Algorithms based on our machine learning modeling for Crude Brent Pricing Data.

1. Extra Tree Classifier
2. Random Classifier
3. Gradient Boost Accuracy
4. KNearest Neighbor

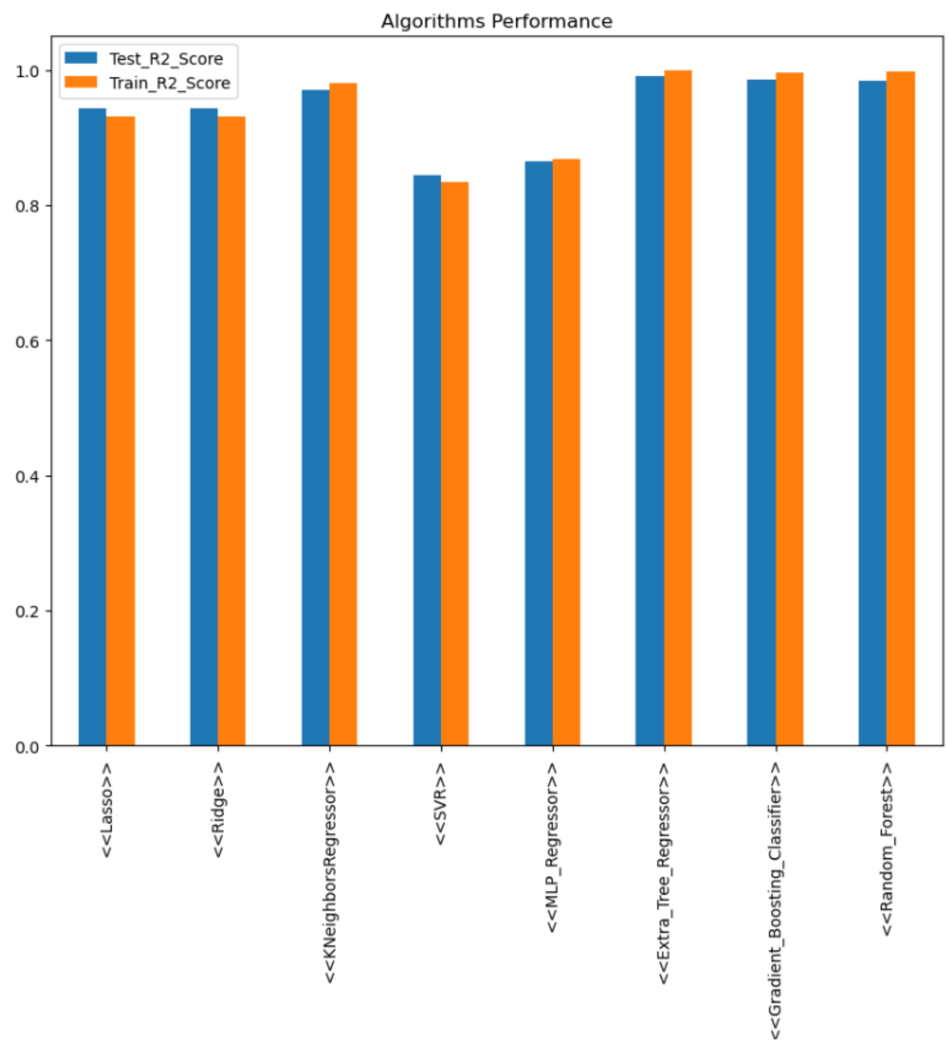

Figure 19: Algorithms Summary

9 Conclusion

The analysis of the impact of the Russia-Ukraine conflict on Brent Crude commodity pricing using World Bank Time Series data [34, 66] reveals a complex relationship among the factors influencing the fluctuations in Brent Crude prices. The ongoing war has disrupted global supply chains, causing production delays and market uncertainty [7, 19, 38]. This has led to a ripple effect on the economies of major oil-producing and consuming countries [34, 30, 66].

Through a comprehensive approach, while marrying traditional time series analysis techniques such as Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF), Seasonal Autoregressive Integrated Moving Average (SARIMA), Run Sequence Plot, and Exponential Smoothing State Space (ETS) [3, 93], with advanced machine learning algorithms like Random Forest, Extra Tree, Gradient Boosting, K-Nearest Neighbor, and Decision Tree [4, 94, 96], we have identified the key drivers of Brent Crude prices.

Notably, factors such as declining industrial demand for silver, disruption in vehicle production, weak demand for copper from China, and lower steel consumption have contributed to the observed changes in Brent Crude prices [15, 19]. These factors underline the intricate relationship between commodities and energy resources [1, 85, 92]. The decline in industrial demand for silver speaks to the broader industrial slowdown, which has been shown in a plot of PMIs by countries; this decline in demand has disrupted various sectors and subsequently affected crude oil consumption [34, 66].

Furthermore, our analysis showcases the significance of multivariate modeling techniques, including Principal Component Analysis (PCA) and Factor Analysis [1, 3], in understanding the intricate relationships between different commodities and their collective impact on Brent Crude prices. These methodologies have allowed us to extract crucial insights from a complex set of latencies in the interconnected variables [85].

As the global economic landscape continues to evolve, diplomatic negotiations, supply chain disruptions, and shifts in global trade dynamics will continue to play a pivotal role in shaping commodity prices, particularly for energy resources like Brent Crude [5, 47, 54]. A holistic understanding of these dynamics, supported by both time-tested statistical methods and cutting-edge machine learning approaches, is essential for accurate forecasting and informed decision-making in the realm of commodity trading and energy markets [3, 4, 94, 96].

For policymakers, we have also reached the root causes of the problems for decision-making, with reduced computational complexity, time, and costs [4, 85]. At the same time, we have been able to integrate multivariate time series analysis and machine learning for a holistic global approach in policy analysis and decision-making [85, 91]. By reaching the underlying cause of complex issues, for long-term solutions and evidence-based decision-making, we can prioritize the resources, prevent policy failures, and increase stakeholder engagement for more effective policies [85].

For corporate entities, by following these time-tested statistical and engineering studies, we can reach strategic decisions which can be the drivers of a company's bottom line and profitability [85]. Root-cause analysis is the lifeblood of engineering decision-making in day-to-day life, from manufacturing processes, quality improvements, productivity studies, and fault diagnostics [1, 4]. Hence, organizations can take decisions on quality, safety, and productivity, making the research useful for engineering and manufacturing.

In essence, the research study not only sheds light on the multifaceted nature of the Russia-Ukraine conflict's influence on Brent Crude pricing but also underscores the significance of integrating various analytical tools and methodologies to gain a comprehensive perspective on the intricate forces driving commodity price fluctuations in a rapidly changing world [19, 30, 85]. This analysis emphasizes the need for a multidimensional approach that considers geopolitical, economic, and industrial factors in tandem to truly grasp the complexities of Brent Crude pricing [85, 92]. As the global landscape continues to evolve, this holistic approach will remain vital for anticipating and responding to the ever-changing dynamics of the energy market [65, 67, 73].

10 Recommendations

Based on the findings, we recommend the following actions for various stakeholders:

1. Russia: Ensure the stability of oil supplies and minimize disruptions to global markets. Explore diplomatic solutions to the conflict and strengthen trade relationships with other countries.

2. European nations: Diversify energy sources to reduce reliance on Russian oil and gas imports. Invest in renewable energy and promote regional cooperation to enhance energy security.

3. Oil-producing countries: Monitor the situation closely and adjust production levels accordingly to mitigate the impact on global oil prices. Collaborate with other oil-producing nations to stabilize the market.

4. Oil-consuming countries: Diversify energy sources and reduce dependence on fossil fuels. Promote energy efficiency measures and support the development of renewable energy technologies.

5. Investors: Monitor market volatility and consider diversifying investment portfolios to include other commodities and industries. Stay informed about geopolitical developments and their potential impact on global markets.

In addition, we recommend using machine learning algorithms such as Extra Tree, Random Forest, Gradient Boost, KNearest Neighbor, and Decision Tree for better forecasting and analysis of Brent Crude prices. These algorithms can help identify complex relationships between oil price movements and precious metals and minerals.

Overall, it is crucial for all stakeholders to remain vigilant, adapt to changing market dynamics, and explore sustainable energy solutions to mitigate the impact of the Russia-Ukraine war on Brent Crude prices and global commodity markets.

List of Abbreviations

1. Akaike Information Criterion (AIC)
2. Auto Regressive (AR)
3. Autoregressive Integrated Moving Average (ARIMA)
4. AutoCorrelation Function (ACF)
5. Bayesian Information Criterion (BIC)
6. CRoss Industry Standard Process for Data Mining (CRISP-DM)
7. Exchange Traded Commodity (ETC)
8. Exponential Smoothing State Space (ETS)
9. Exploratory Factor Analysis (EFA)
10. European Union (EU)
11. Factor Analysis (FA)
12. K-Nearest Neighbor (KNN)
13. Log-Likelihood Ratio (LLR)
14. Moving Average (MA)
15. Multilayer Perceptron (MLP)
16. North Atlantic Treaty Organization (NATO)
17. Oil Marketing Companies (OMC)
18. Partial Auto-Correlation Function (PACF)
19. Principal Component (PC)
20. Principal Component Analysis (PCA)
21. Purchasing Manager Index (PMI)
22. Root Mean Squared Error (RMSE)
23. Seasonal Autoregressive Integrated Moving Average(SARIMA)

Discussion on Importance of Forecasting Research in Commodity Pricing

The ongoing Russia-Ukraine war has significantly influenced global commodity prices, particularly Brent Crude [6, 7]. Although forecasting techniques such as regression models, futures analysis, artificial intelligence, and machine learning have been applied to commodity pricing for several decades, this research makes a unique contribution by employing time series data sourced from the World Bank to explore enhanced forecasting approaches [34].

The study leverages augmented forecasting techniques specifically tailored to commodity time series data, enriching the field with methodological diversity. A suite of advanced machine learning models—including Lasso Regression, K-Nearest Neighbors (KNN), Support Vector Regressor (SVR), Multi-Layer Perceptron (MLP) Regressor (a form of neural network), Gradient Boosting, Random Forest Regressor, AdaBoost Regressor, and Decision Tree Regressor—has been deployed to model the behavior of commodity prices over time [4, 81]. These models were selected to detect underlying patterns and uncover the primary drivers of Brent Crude price volatility during a period of heightened geopolitical instability.

Despite the widespread use of futures prices in commodity markets, they are often unreliable as predictors. Research shows that futures frequently yield substantial prediction errors [89]. In fact, mixed-model approaches—where forecasts from various models, including futures, are combined—have demonstrated greater accuracy in oil price forecasting [89, 85]. Similarly, improved directional accuracy and reduced bias were reported when combining forecasts from multiple models compared to relying solely on futures data [85].

Integrating a broader set of macroeconomic indicators into forecasting models has also been shown to improve performance. For instance, including variables such as global economic conditions, petroleum inventories, the world output gap, and the U.S. dollar exchange rate enhances predictive accuracy [85, 86]. Moreover, studies found that including external regressors—such as industrial production, commodity currencies, and international metal stock indices—significantly improved the forecasting of metal prices [86, 87, 88].

Multivariate time series models further offer an edge by capturing interdependencies between variables. These models enable a more holistic understanding of the forces that influence commodity pricing, as they account for dynamic relationships across economic, financial, and geopolitical indicators [1, 3]. By integrating such comprehensive data-driven insights, this research contributes toward developing more reliable forecasting mechanisms for navigating volatile commodity markets.

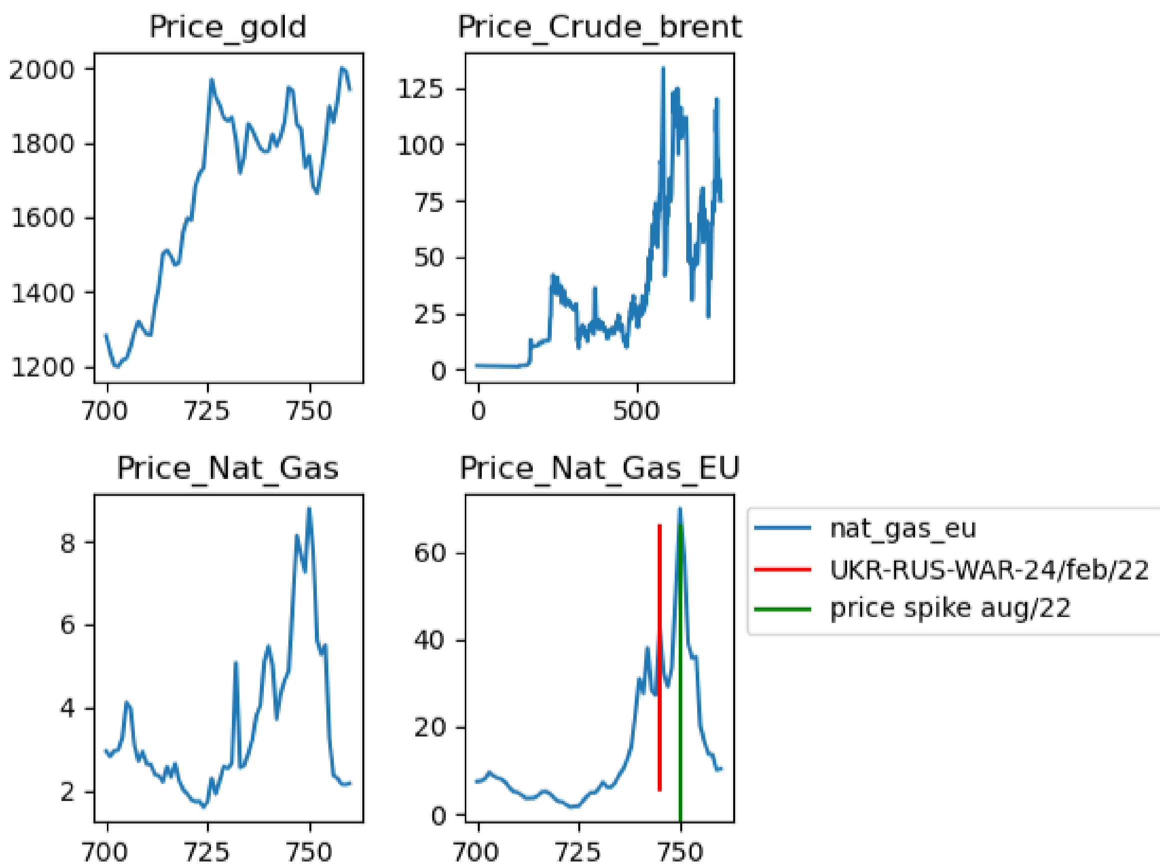

Figure 20: Price/Month, Plot for Energy and Gold

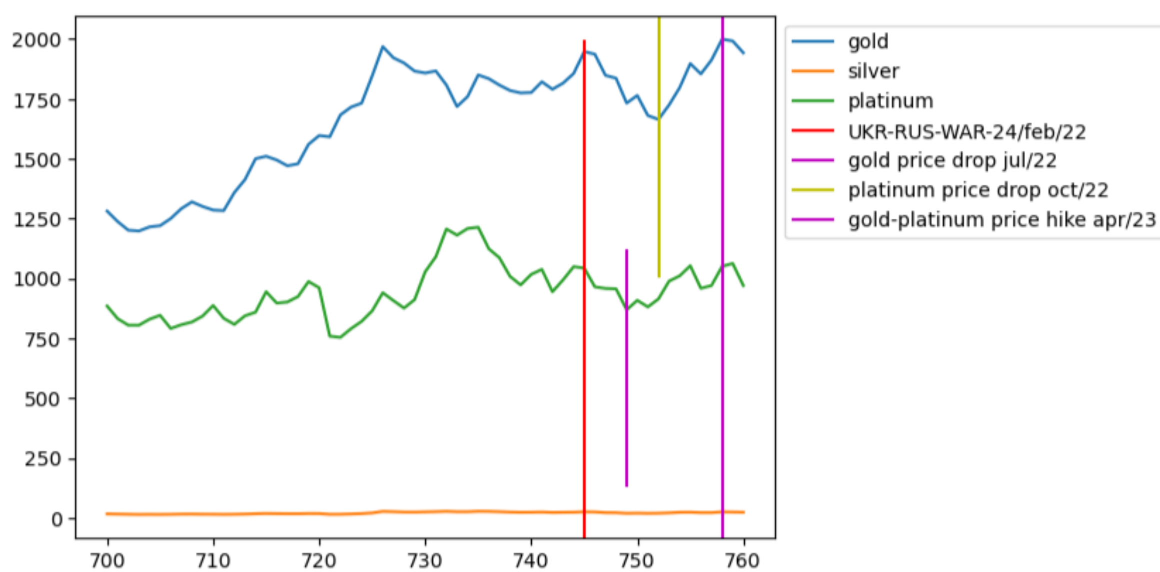

Figure 21: Price/Month,Plot for Precious Metals

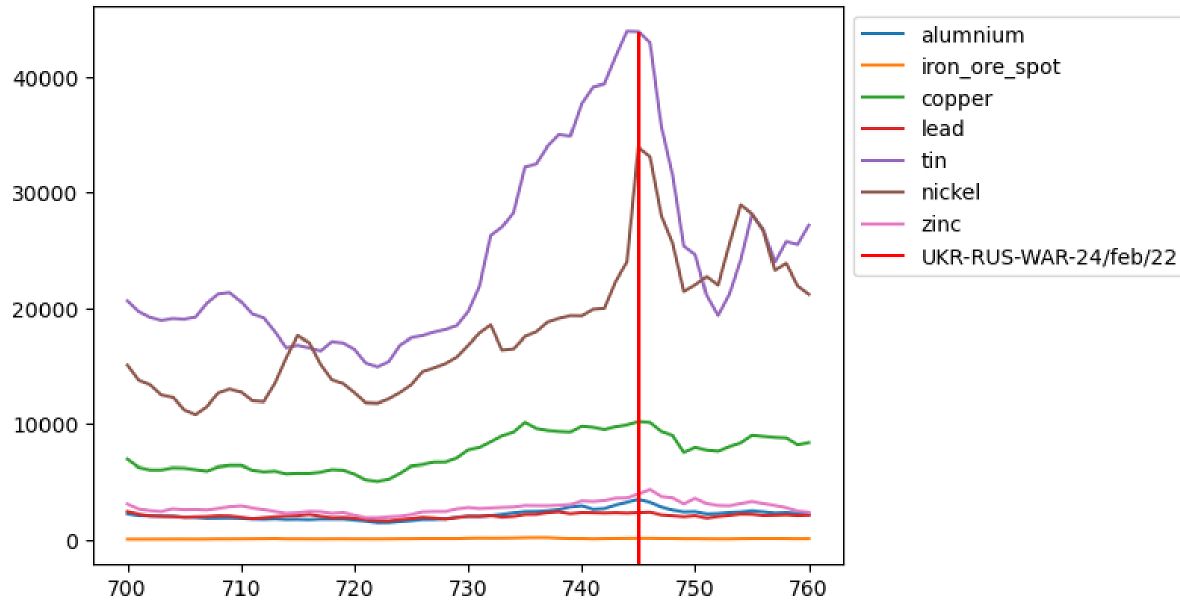

Figure 22: Price/Month,Plot for Metals

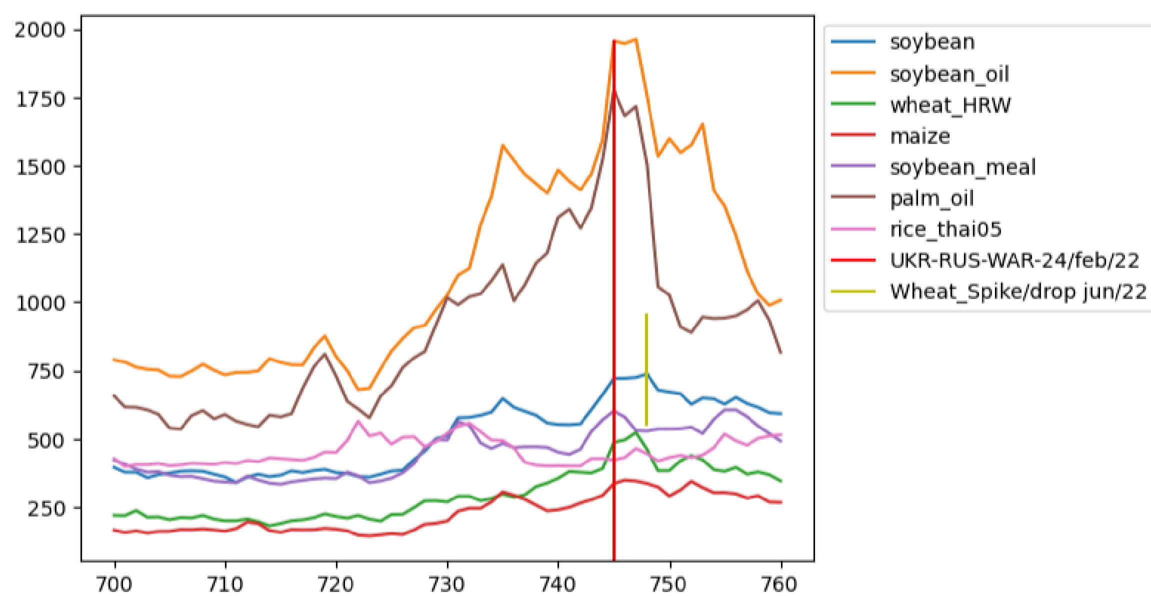

Figure 23: Price/Month, Plot for Agriculture Produce

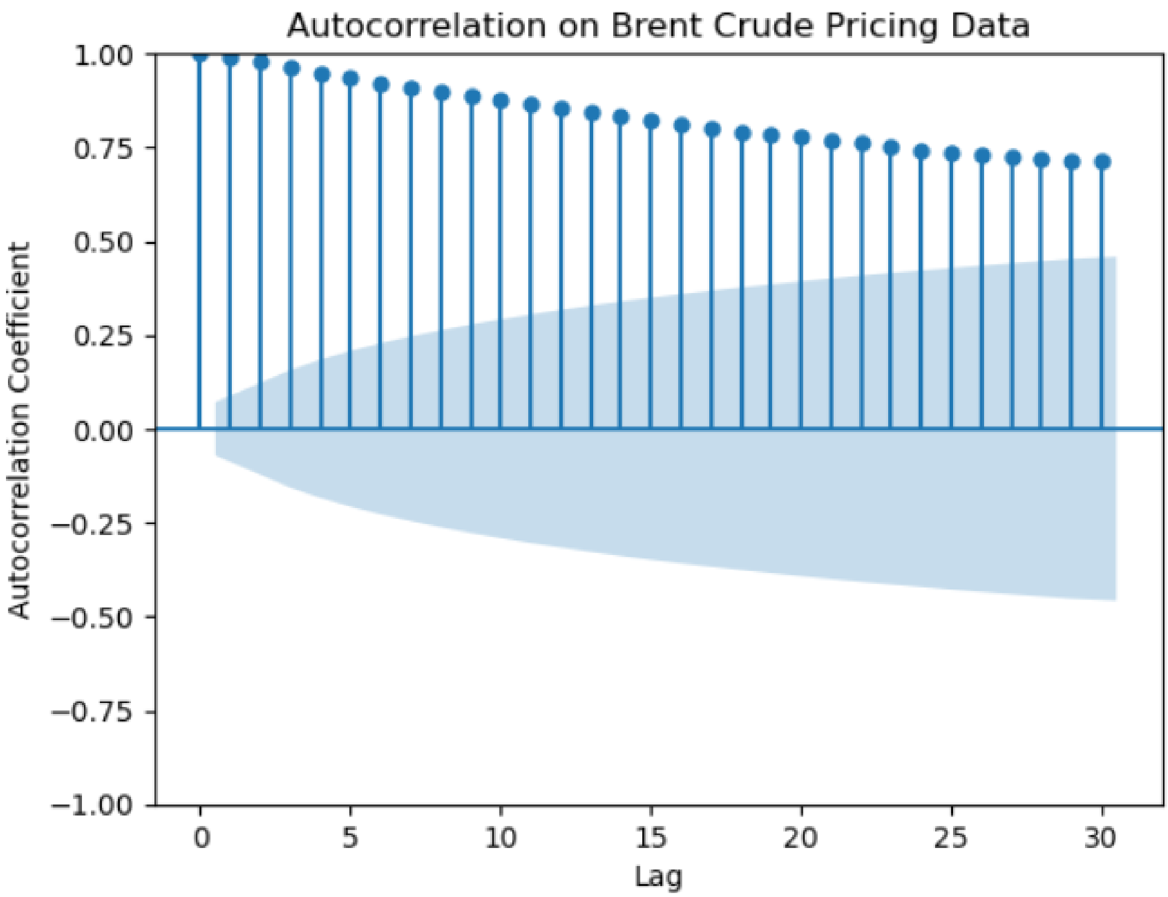

Figure 24: ACF Plot, Autocorrelation Coefficient/Lag

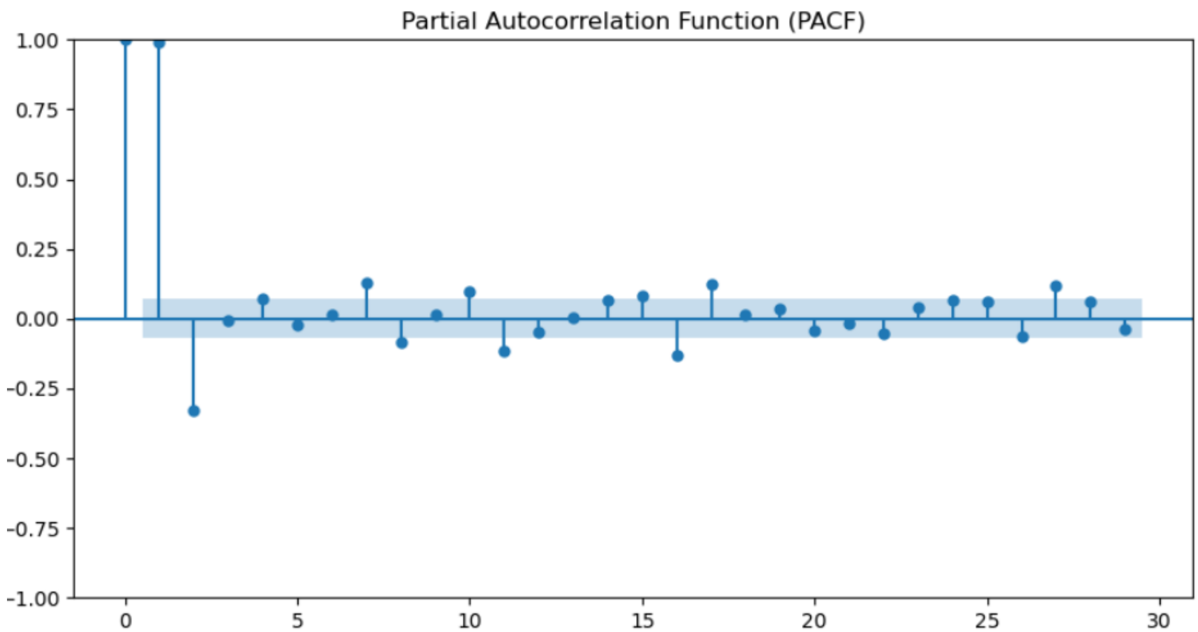

Figure 25: Partial Autocorrelation Function(PACF)

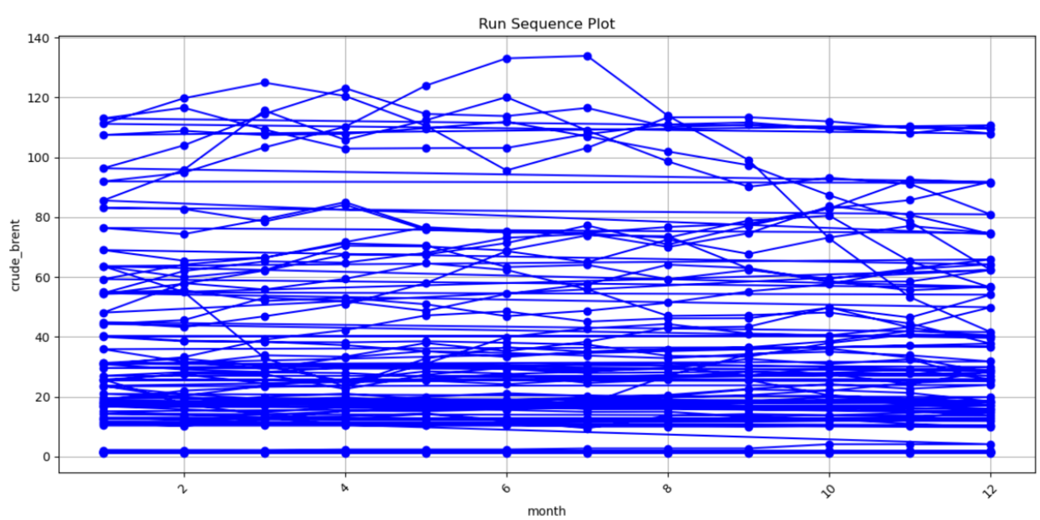

Figure 26: Run Sequence Plot

11 Declarations

Availability of data and material:
- As of July 28 2023, the data was available online in World Bank Real Time Dataset. - To the best of my knowledge as an author/researcher/analyst/director there were no restrictions on the usage of data for research, policy decision making, peace progress or academic purposes.
Competing interests: - There are no potential conflicts of interest in this research and there is no external influence that has been made to conduct or influence the research and the results produced in writing. - Author has graduated from India, the USA and the UK from some prestigious degree granting colleges/universities, because of the propensity of the USA and the UK towards NATO, the research paper might be received differently in different parts of the world. However, extreme care has been taken to prevent any personal or professional relationships to create any bias in the research and its findings and presentation.
Funding:
- The Author is a founder of ALTREICH THINKTANK, the research has been done after balancing time and resources from the organization's role as a founder and director. - As a Senior Director of a Global Thinktank, which works on the several causes including peace progress, knowledge dissemination and awareness towards the negative consequences of the war, this research is a valuable document amidst the turmoil of Russia-Ukraine war, which has lasted over 18 months.
Author' contributions:
- Mr. Hemendra Pal is an individual contributor in the research. The timing and delivery of the research paper necessitated an individual contribution with utmost clarity and transparency, with minimal and optimal resources needed to coordinate the research and plan it's delivery in required time. - As a Founder of a Global Strategic Thinktank as well as a former Assistant Professor of Business and Practitioner of Ethics, Author is in a situation to do justification to the research with a focus on research, knowledge dissemination and full transparency.
Acknowledgements:
- Hemendra Pal, ALTREICH THINKTANK, D/G 004 Moti Residency, Raj Nagar Extension, Near Morta, NH58, Ghaziabad, 201003, India, hpal00001@gmail.com

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