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

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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.

List of Figures

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.

The Russia-Ukraine war has unleashed a wave of disruptions that have rippled through supply chains and caused seismic shifts in the energy sec- tor. 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.

To comprehensively explore the intricate inter- play 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 Smooth ing 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.

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.[30]

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 inter-dependencies that characterizes the global commodity market. In 2021, the EU bought 42 percent of Russian oil production.

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.

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 in- sights that empower stakeholders, economists, and policymakers to navigate the evolving contours of a world where geopolitical events and economic forces intertwine in unprecedented ways.

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.[30]

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.[30] This literature review provides an overview of the methods and models employed in forecasting industrial commodity prices, drawing insights from industry reports, research articles, books, case studies, and news media. The review focuses on machine learning models, multivariate time series models, composite forecasting methods, and the importance of incorporating additional economic variables to enhance predictive accuracy.

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.[30]

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.[30] 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 .

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. By incorporating these variables into a multivariate framework, researchers have been able to improve the accuracy of price forecasts.[30]

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. 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 . The ARIMA and ETS models are particularly useful for capturing time-series trends and seasonal variations, while machine learning models excel at handling large datasets and identifying complex, non-linear patterns.

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. 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.[30]

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. For instance, the inclusion of external regressors such as commodity currency dynamics, international metal stock indexes, and petroleum inventory levels has led to more accurate predictions of metal prices, particularly under conditions of market volatility.[30]

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.

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 . The integration of these variables helps capture the effects of economic cycles, geopolitical events, and other external factors on commodity pricing, resulting in more accurate and robust predictions.

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 . Additionally, the inclusion of additional data on relevant economic variables has been shown to further improve the performance of machine learning models.

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.[61]

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.[30]

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.[61]

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. Machine learning models, in particular, hold great promise for improving forecast accuracy, but they require careful data preparation and validation.

Composite forecasting methods, which combine multiple models, have also been shown to provide more accurate and reliable forecasts than individual models. These methods leverage the strengths of different models to capture both short-term and long-term trends in commodity prices.

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.

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.[4]

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: [4]

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**.[4]

3.2 Data Understanding

Relevant data sources include the **World Bank**, **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** and **NumPy** 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: [4]

- **Handling Missing Data**: Missing values are imputed using mean, median, or mode values.[4]
- **Feature Engineering**: Lag features and differencing are created to capture temporal dependencies for time series modeling.[4]
- **Normalization and Scaling**: Techniques such as **Min-Max scaling** and **z-score normalization** ensure the data is standardized for modeling.[4]
- **Heatmap and Correlation Analysis**: Correlation matrices and heatmaps are generated to identify relationships between variables, helping in feature selection.[4]

3.4 Modeling

The study employs a variety of univariate, multivariate, and ensemble machine learning models:

3.4.1 Univariate Models

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

3.4.2 Multivariate Models

- **Principal Component Analysis (PCA)** reduces the dimensionality of the dataset and identifies latent variables affecting Brent Crude pricing.[4]
- **Factor Analysis** uncovers hidden economic factors influencing the price, such as global trade disruptions and inflation.[4]

3.4.3 Ensemble Machine Learning Algorithms

- **Random Forest** builds decision trees and aggregates them for better predictive performance.[4]
- **Gradient Boosting** improves model accuracy by iteratively correcting errors from previous models.[4]
- **K-Nearest Neighbors (KNN)** classifies data points based on their proximity to other points.[4]
- **Multi-Layer Perceptron (MLP)** is a neural network that models non-linear relationships between features.[4]

3.5 Evaluation

Models are evaluated using metrics such as **accuracy**, **RMSE (Root Mean Squared Error)**, and **MAE (Mean Absolute Error)**. Cross-validation techniques like **k-fold validation** ensure that the model generalizes well on unseen data. Feature importance is assessed using **SHAP values** to determine which features most influence Brent Crude pricing.[4]

3.6 Deployment

The models are used to simulate scenarios that explore the effects of economic conditions on Brent Crude pricing. Data visualization techniques, such as **line plots**, **heatmaps**, and **bar charts**, are employed to present the findings. **Matplotlib** and **Seaborn** are utilized for creating insightful visualizations.[4]

This research combines 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. The models, from **SARIMA** to ensemble methods like **Random Forest** and **Gradient Boosting**, allow for deep analysis of complex economic relationships, supporting informed decision-making in commodity markets.

4 Discussion and Research Questions

4.1 Impact of the Russia-Ukraine War:

The Impact of Ukraine Russia War has been some considerable advantages to Oil and Gas producing countries like Russia and Saudi Arabia, who have used the war situation for price manipulations, however, the war has also exposed these countries to global risks caused due to supply chain disruptions[32]. For oil-consuming countries like India and Ghana, the war has led to increased energy prices and scare of increased inflation. In many countries, these economic situations have led to government intervention and policy measures. [20][31] Top Oil and Gas companies such as Exxon and Chevron have seen a drop in their earnings, and subsequently the Brent Crude has reached a level of USD 75 / Barrel after hitting the USD 100 / Barrel, after the onset of the war on 24 February 2022. The overall profitability as well as the decision making in the Oil and Gas Industry has been affected by the war. [35]. As per a Journal Article in Journal of Energy and Social Sciences Research, Nigeria might take advantage of higher oil prices through its oil exports. Hence. the war might be advantageous for Nigeria's economic growth and revenues from oil exports. [22] As per Wood Mackenzie a Global Consulting Firm, The war has changed the market in five ways [8] firstly, the risks of geopolitical tensions has increased leading to disruptions in global supply of oil, secondly, the rise in oil and gas prices has changed the consumer spending patterns as well as increased inflation rates. thirdly, the energy diversification and renewable energy efforts have increased due to increased awareness of energy security, fourthly, the real long term concerns of oil and gas sustainability have been increased to all time high, Finally, the scrutiny on projects with more environmental impact has been on all time high. As per another article from The Times, amidst increased geopolitical tensions, Saudi Arabia threatened to decrease it production output, leading to increase in oil prices. Increased concerns on the future energy security and oil supplies has increased the market volatility. Record outflows from the world's largest exchange traded commodity (ETC) has led to increased volatility. [3][4] Oil Marketing Companies (OMC's) have been subjected to greater oil uncertainty crude pains after the war due to increased volatility, increased prices, drop in earnings and increased risks. [6] According to Mark Einseberg and Cheryl Tessell, in their article, the rise in oil prices have been greatly caused by scare of disruption in Oil and Gas Supplies. The Risk Premium associated with Crude Oil Production, storage and supplies has further exacerbated the increase in oil prices. Overall, the Russia-Ukraine war has had a significant impact on Brent Crude prices. It has led to increases in oil prices, greater price volatility, and concerns about future oil supply. These developments have affected various stakeholders, including oil-producing countries, oil-consuming countries, and oil companies. It is crucial for these stakeholders to closely monitor the situation and develop strategies to mitigate the risks associated with the war.

4.2 Supply Chain Disruptions:

The supply and demand uncertainty, increased volatility and prices have led to elevated challenges to the consumers and corporate companies, the earnings have affected company's performance. The Price Volatility has been further worsened due to Saudi Arabia's continued threats on cutting oil production levels[25]. The reduction in supply by Russia, after the record number of sanctions has resulted in market imbalance and supply shortages, thereby increasing the prices. Saudi Arabia's decision to extend production cuts just exacerbated the oil market woes. As per Wood Mackenzie(2022) [8], the war has triggered a domino affect resulting in disruption in logistics, transportation and infrastructure, Oil production, transportation and refining have resulted in market fluctuations. ETFS (The world's largest ETF), has seen record outflows after the war [41], hence there is a clear shift in the investor's sentiment, after the war. Oil consuming economies of Ghana and India have faced higher oil prices in their imports, leading to an increase in the price and sustained inflationary pressures. [19] Thus Supply Chain Disruptions post war have resulted in increased volatility, supply shortages and imbalance between Supply and demand, causing an impact on international relations, global geopolitics and overall global economy.

4.3 Production Delays:

Production delays, supply disruptions and price fluctuations have become a global phenomena, for the oil producing countries. This had resulted in an atmosphere of global insecurity and uncertainty. The market stakeholders can respond by enhancing security measures, diversifying the energy resources and promoting stability in oil producing nations. Production delays and uncertainties have resulted in increase in oil prices, the increase in duration of production cuts by Saudi Government also puts pressure on suppliers, contractors and transportation/logistics companies who allocate their resources based on annual contracts. The disruption in supply chains have caused increased level of risks, and the ability to maintain optimal levels of production has been greatly reduced. Oil Supply Chains have been disrupted in the region of Russia and Ukraine. However, due to production delays and market uncertainties globally, Russian Energy and gas year on year revenues were one Billion USD's more compared to the pre-war levels. Russian market has been hit hard due to sanctions from NATO Countries, this has affected the oil and gas business with the neighboring countries too. However, Ukraine has faced labor shortages, infrastructure damages, production delays and security concerns. Price volatility due to market concerns, global uncertainties has led to increased geopolitical risks. Investments and Earnings of Oil Producing companies has reduced and due to price hike both the producers and consumers have been affected.

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.

In the international market dynamics all these factors lead to increase in the prices

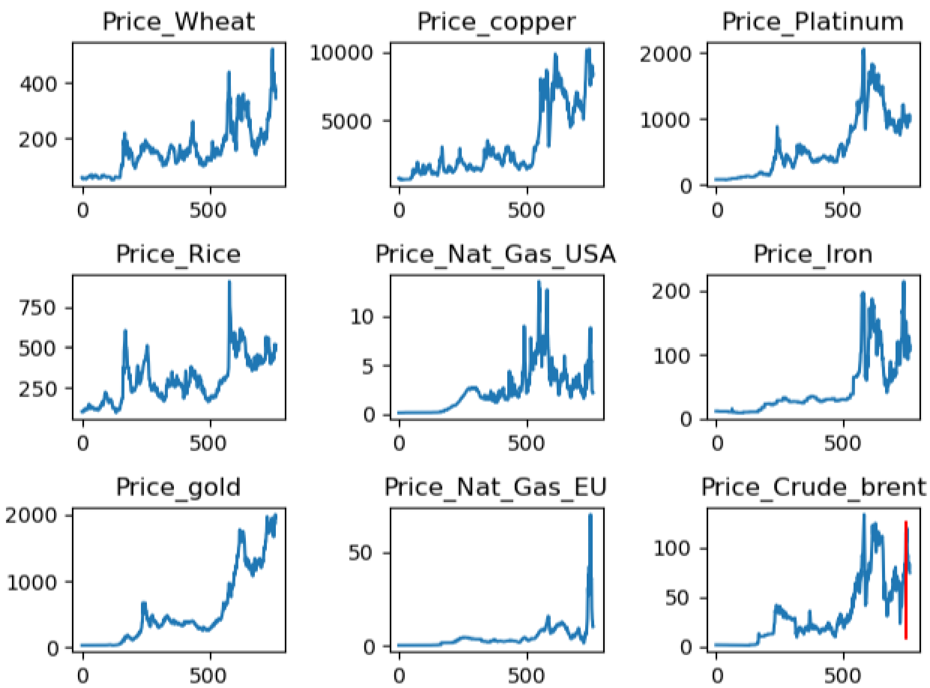

Figure 1: Price / Month, Plots of Commodity Pricing, Red Line Onset of War

of the Brent Crude Oil. To mitigate the risks and market uncertainties due to the volatility in Brent crude prices, some nations such as the UK and the US, have put a price cap and embargoes on Russian Oil products.[33][38] 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 had a far reaching affects globally. Russia and European nations have several options, some of the mitigating strategies include, diversification and investments in renewable energy sources, implementing price caps, and increasing the domestic production. Both Russia and EU should have less reliance on Russian Conventional Energy resources, and the diversification of portfolio should be achieved by investing in alternative energy such as renewable energy, nuclear power, and liquefied natural gas (LNG). The diversification would in-turn decrease the vulnerability of the EU by not relying on Russian Oil and Gas Supplies and would help stabilize the global prices of Brent crude prices.[10] European nations can enhance their domestic production. This strategy entails investments in exploration and research development. improving extraction techniques, and incentivizing the domestic production, for less supply uncertainties due to Russian imports. European Nations and the US have announced price caps to protect the markets from excessive price increases.[38][41] This kind of policy is made to prevent stockpiling of inventory, and reduce the risks of price fluctuation subjected to the market uncertainties and risks. Investing in renewable energy such as wind, solar, biogas, hydro can help the reliance of conventional energy resources including Russian Oil and Gas. Similarly, market subsidies to the new and old users, tax incentives and regulatory framework that supports renewable energy plans will create a more stable political environment for both Russia and the EU. International Cooperation can also help in mitigating the impact of Russia Ukraine War and it's affect on the Brent Crude Oil prices.

4.6 Diplomatic Negotiations:

Diplomatic negotiations continue to play a crucial role in stabilizing the uncertainties in the crude oil market caused due to Russia- Ukraine War. Diplomatic negotiation on production levels, price controls, international relations and while keeping the stakeholders in the loop can lead to a stable environment for the Brent Crude market. This conflict has resulted in supply and trade disruptions in oil industry, Saudi production cut for a longer duration was based on international relations and diplomatic negotiations and was done with the aim of supporting the crude oil prices globally. Production Levels or Production Cuts / Restrictions can lead to stability in the Brent crude oil markets. Diplomatic negotiations between the UK, the coalition countries and the US, led to a price cap and embargoes on the Russian Oil Products. This move was done to prevent the consumers from excessive price increases and market shocks due to this price increase. Measures such as Price Cap is meant to restore confidence of the people in their government. Even after the sanctions on Russian companies and closures of foreign businesses in Russia especially Moscow region where more than 500 companies were closed, was possible only through negotiations. Diplomatic negotiations help to ease tensions, facilitate dialogue and open the doors towards peaceful resolution. Improved international relations even after the war helps to regain the trade and market stability after the end of war. Cooperation between the oil producing, oil consuming, oil trading stakeholders is of extreme importance for collaboration, cooperation and communication for finding a peaceful solution for easing of geopolitical conflict and towards a more stable environment. These negotiations can help in stabilizing the Brent Crude Market and can help to minimize the damages caused due to extreme uncertainties and vagaries of the global oil market. Thus, agreements on production levels, price control, stakeholder engagement, International cooperation and International relations are all important for not-only keeping Brent crude prices under check but also for finding a long term peaceful solution to the conflict.

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. 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, Reduction in green house gas emissions, greater participation in sustainable development and mitigation of climate change are some intangible benefits even in peaceful times after the war.[44] There are significant economic opportunities, generate green jobs, attract investments in green energy, green technologies,and sustainable infrastructure. Thus, accelerated diversification towards long term sustainable green energy goals and deployment of renewable energy solutions can help in mitigating the market risks and price fluctuations associated with geopolitical tensions associated with conflicts.

4.8 Regional and Global Cooperation:

Regional and Global cooperation can be harnessed between strategic partner countries to have a check and balance on supply and demand. This practice of maintaining and sharing the oil reserves can stabilise the price fluctuations and supply disruptions due to conflicts and natural disasters. Thus by doing this exercise we are ensuring a consistent supply and absorbing the market shocks. Cooperation between regional and global partners can help in diversifying the energy portfolio as well as reduce reliance on a single source or a single region. With these practices, we can create a more resilient market with decreased vulnerability to geopolitical conflicts. Cooperation among oil producing countries through production coordination and export measures. This can be achieved by implementing market mechanisms such as production quotas and export controls. Regional and Global Cooperation can help in timely, accurate and transparent information on the oil market data and thus reducing uncertainty and reduce speculation. Thus sharing of timely information can lead to enhanced market stability. Consistent regional and global market diplomatic cooperation towards peace,and can restore the stakeholders confidence in the market. Although, the war did not stop until the end of 2022, but as a peacemaking measure, six peace talks were held between the ministries of Ukraine and Russia. Regional and Global partners can facilitate economic and financial support in the most affected regions of the conflict for mitigating the impact of conflict on the oil industry. 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 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. The above statistics portray the well defined supply and demand countries for the Brent Crude Oil, and hence the strategies written in this paper can be implemented practically. Overall, the top oil-producing and consuming countries wield considerable influence over global economy dynamics due to their role in shaping oil prices, energy security, and geopolitical relations. Their actions and policies can have far-reaching implications for the stability and sustainability of the global economy.

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. 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. 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. 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. 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.

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. In the context of the Ukraine-Russia war, OPEC has been closely monitoring the situation and its potential impact on global oil markets. The conflict has the potential to disrupt oil supplies and

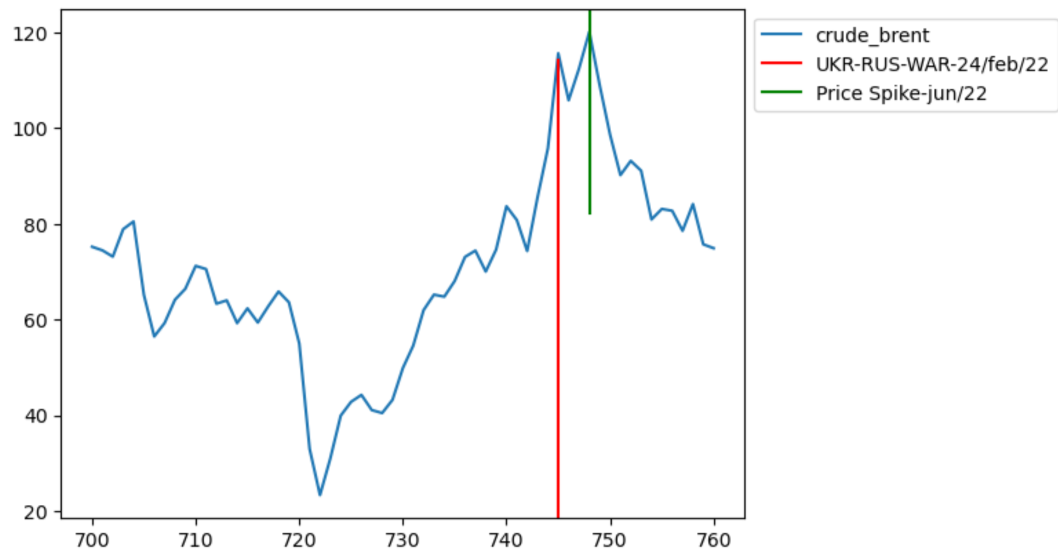

Figure 2: Price Time Series - 3 Years Brent Crude, Red Line Onset of War

increase market volatility. OPEC may intervene to stabilize oil prices and ensure adequate supply if necessary. However, the extent to which OPEC can influence the situation is limited, as Russia is not a member of OPEC and has its own oil production and export policies.

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.

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.

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.

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.

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.

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.

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 prior and during the Russia-Ukraine war. The Commodity Pricing dataset which has been downloaded from the World Bank's website has pricing data on commodities classified as Agriculture Produce, Energy, Precious Metals and Minerals. It is evident that missing values can lead to poor data quality and data corruption. For actionable insights with complete clarity, we have dropped the variables with missing values. Further, crudeavg and crudedubai have very high correlation with crudebrent. In order to remove the hidden multicollinearity in our features, we use feature engineering, it's recommended that we remove these variables for our machine learning analysis. PCA or Principal Component Analysis can also be used to drop the less important features in the high dimensional data set to convert it into lower dimensionality. We have also performed Principal Component Analysis (PCA) to see the complexity of our dataset.

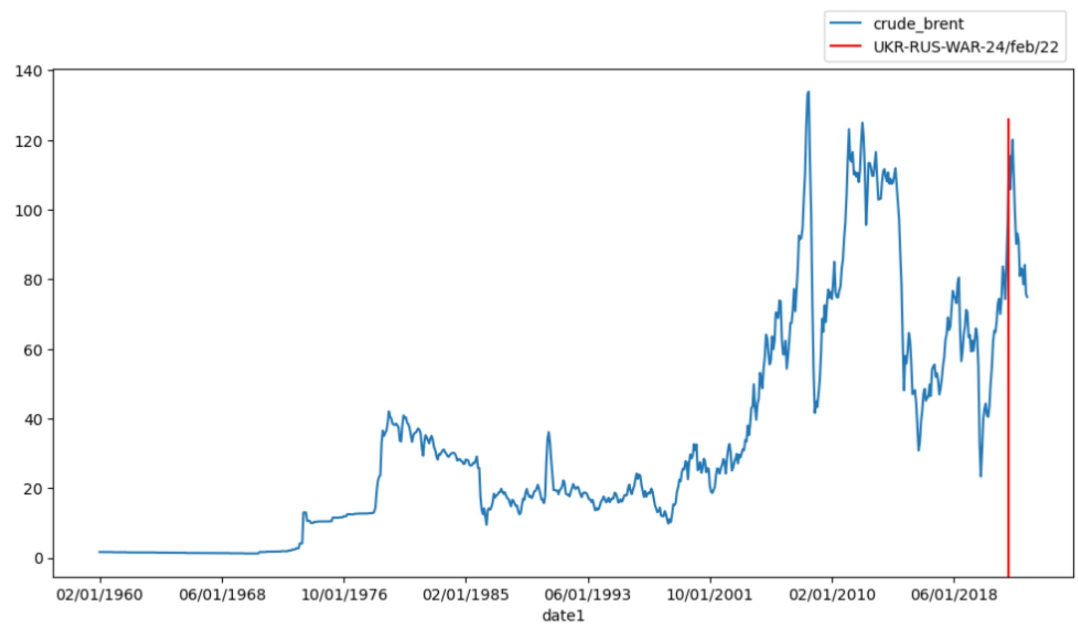

Figure 3: Price Time Series - 63 Years Brent Crude, Red Line Onset of War

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.

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.

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. 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.

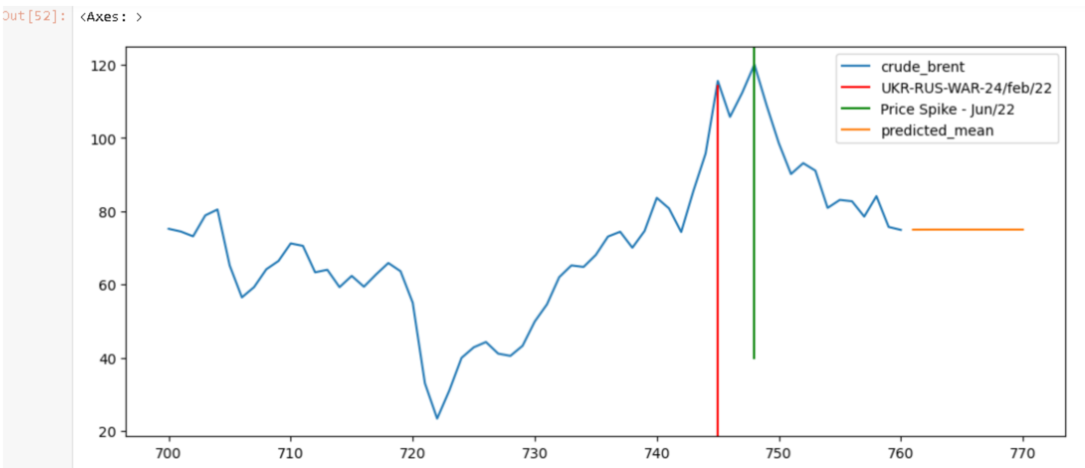

Figure 4: Forecast - Classical Forecasting Model

The Seasonal data is separated into Residual, Trend, Error and Seasonality, that's the reason that such kind of seasonal data decomposition is called as ETS Decomposition. Since, from the decomposition of data, it is clear that our data is not stationary, hence, Auto Regressive Integrated Moving Averages is a better technique for doing forecasting of this time series data. Generally, for government policy decisions, either the classicial, regression, exponential smoothing or Box Jenkins method of ARIMA Forecasting Modeling is used,

5.1.1 ARIMA Decomposition: Error-Trend-Seasonality

The ARIMA model decomposes a time series into three main components: Error, Trend, and Seasonality. 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.

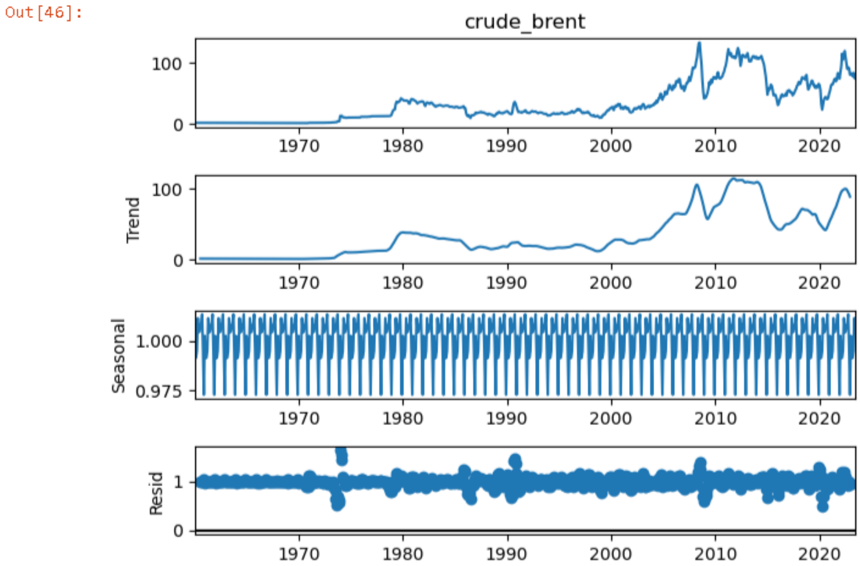

Figure 5: ARIMA Decomposition performed on actual dataset

5.1.3 Mathematical Representation

Mathematically ARIMA decomposition can be represented as follows:

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

Where:

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

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

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

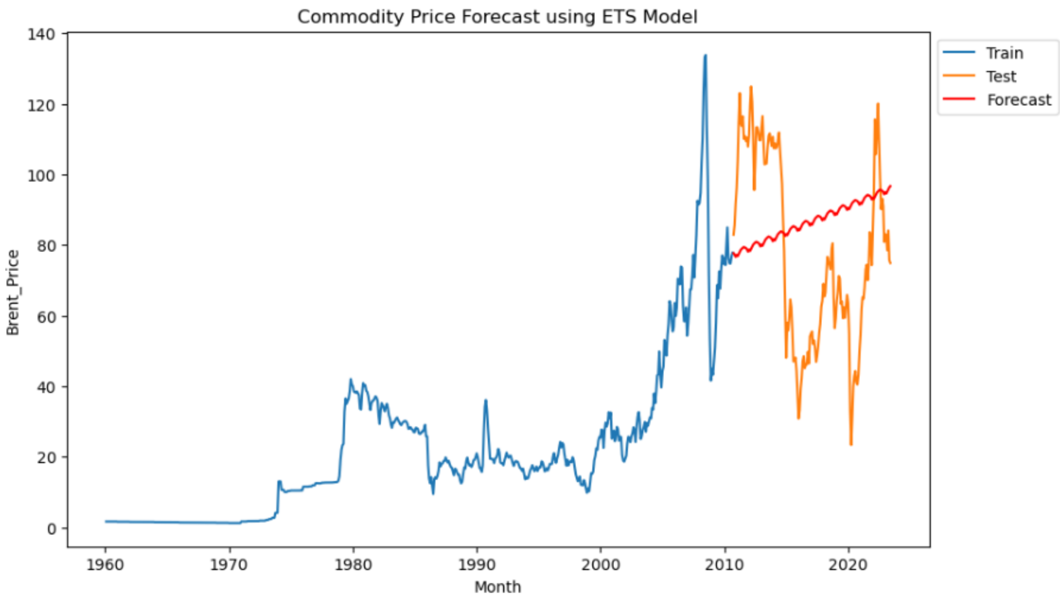

Figure 6: Forecast based on ETS modeling.

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)
- 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.

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 $\leq$ corr$(x, y) \leq$ +1
3. It does not have any units

Here is the correlation heatmap generated using Python:

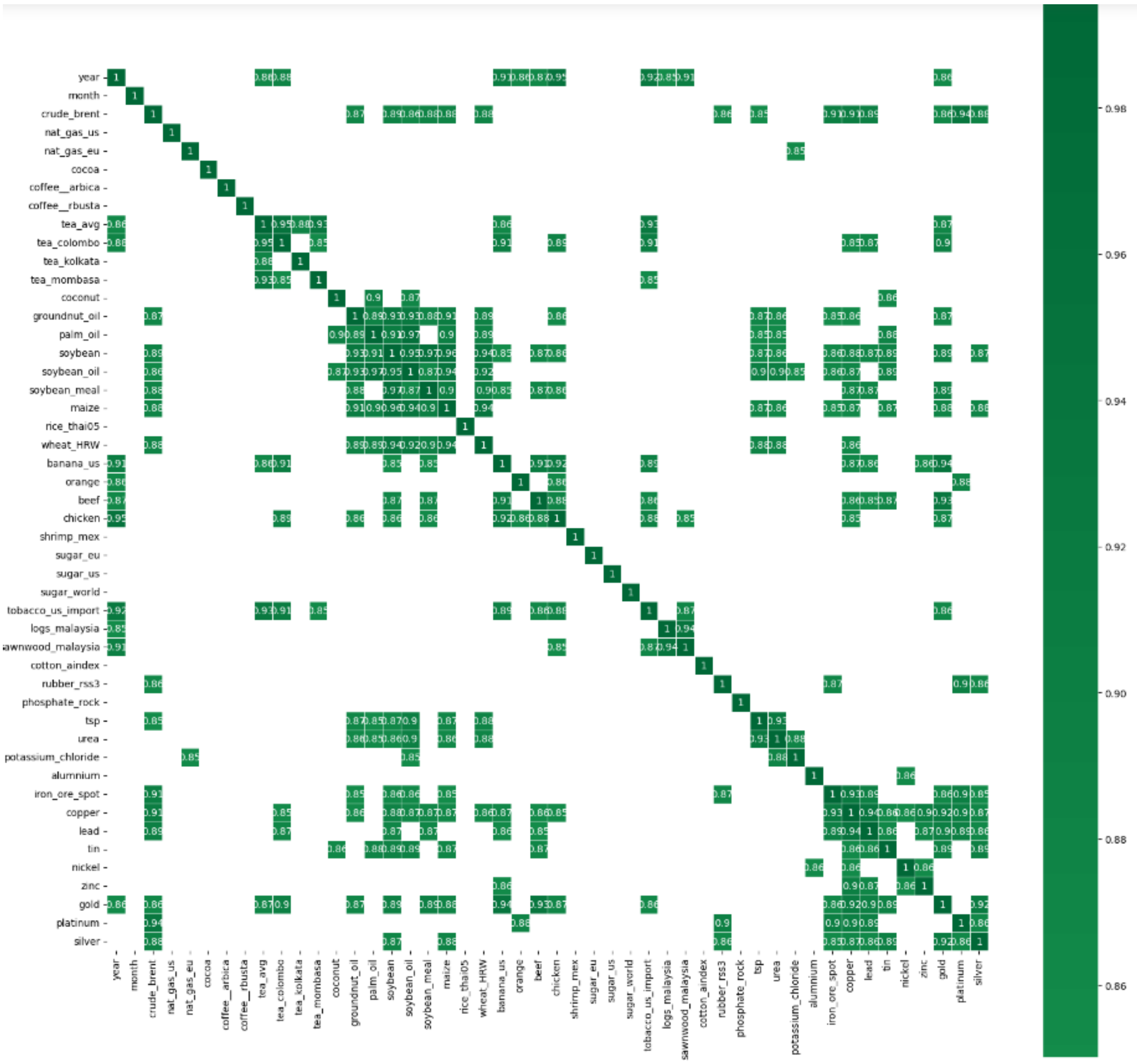

Figure 7: Correlation Heatmap

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

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.

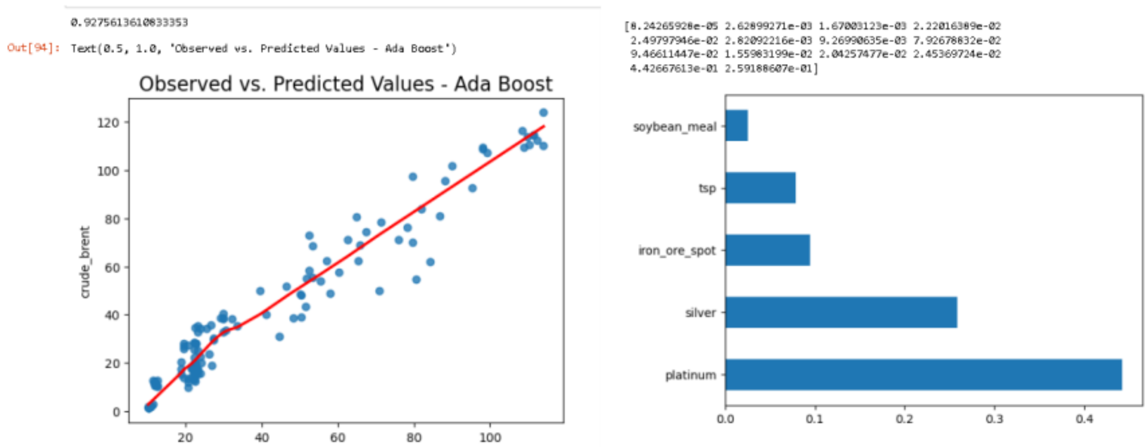

Figure 8: Scenario 1 - Adaboost Algorithm

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

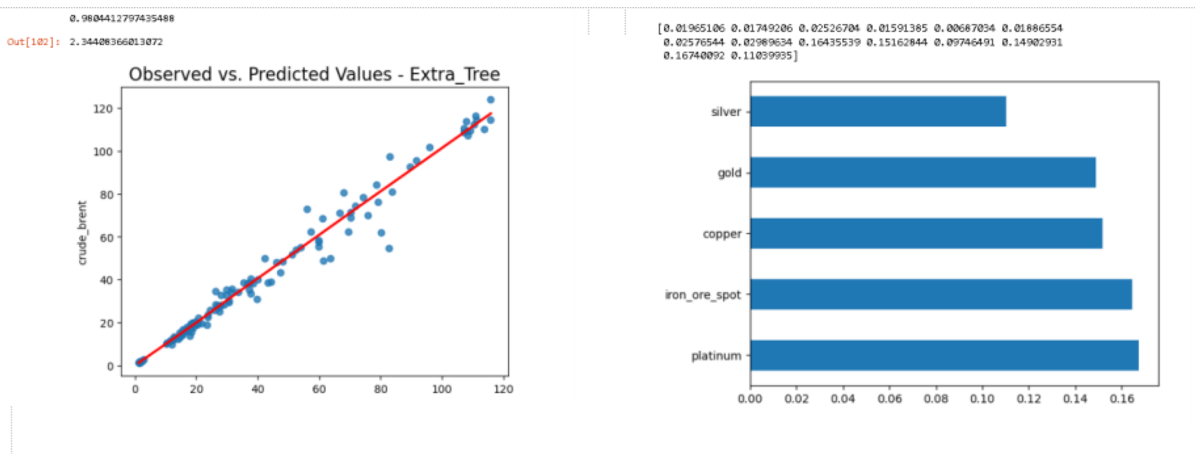

Figure 9: Scenario 2 - Extra Tree Algorithm

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

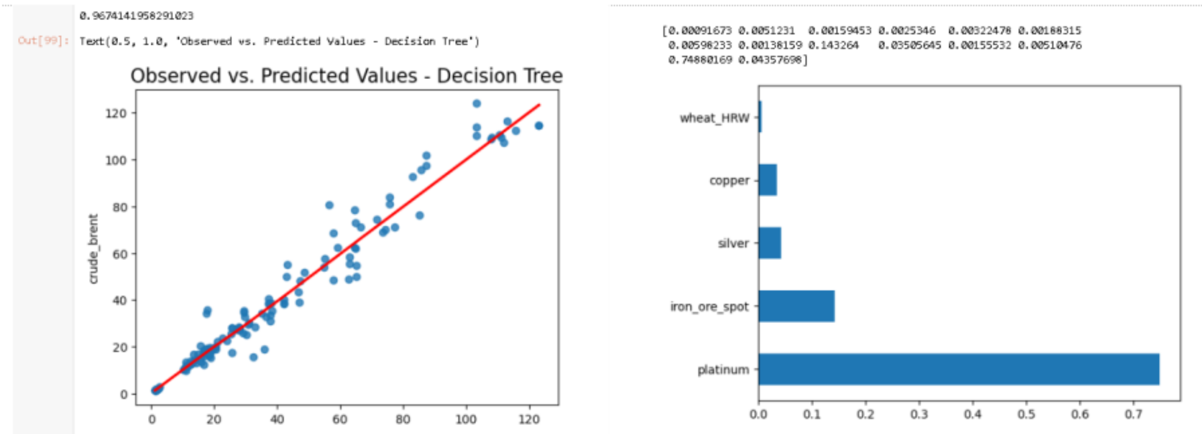

Figure 10: Scenario 3 - Decision Tree Algorithm

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 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.

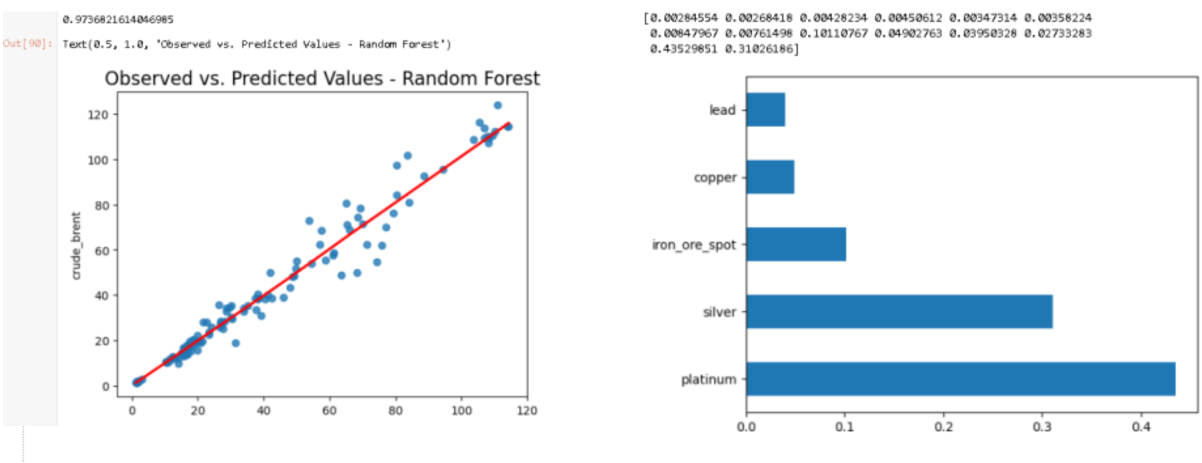

Figure 11: Scenario 4 - Random Forest Algorithm

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

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

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

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.

2. Steep rise in Inflation in North America after the onset of war and throughout Year 2022.

3. Strong exchange rate of USD , compared to other currencies.

4. Market Volatility, Drop in demand of Precious Metals, Iron Ore, Copper and overall Weak industrial and economic activity,

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.

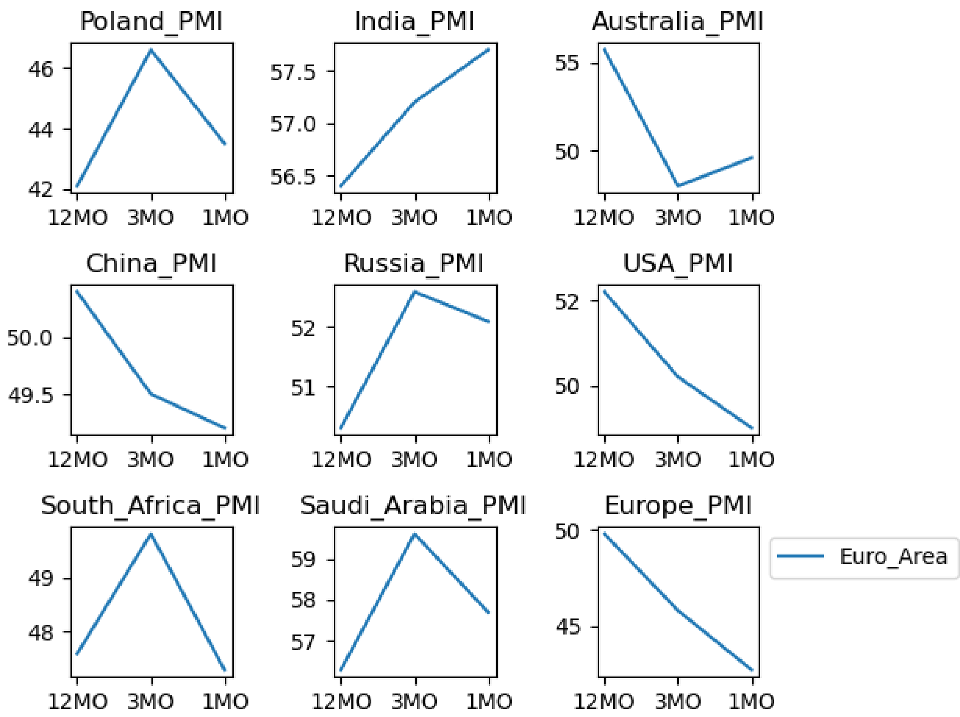

Figure 12: Plot of PMI Index

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:

- 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.

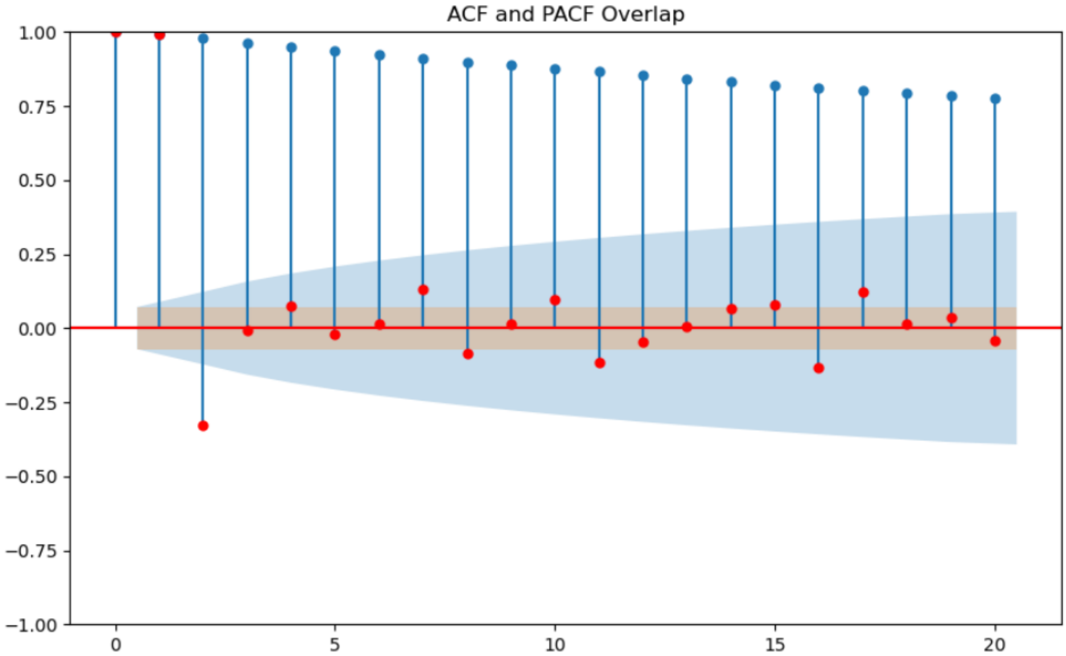

Figure 13: Overlapping ACF and PACF plots

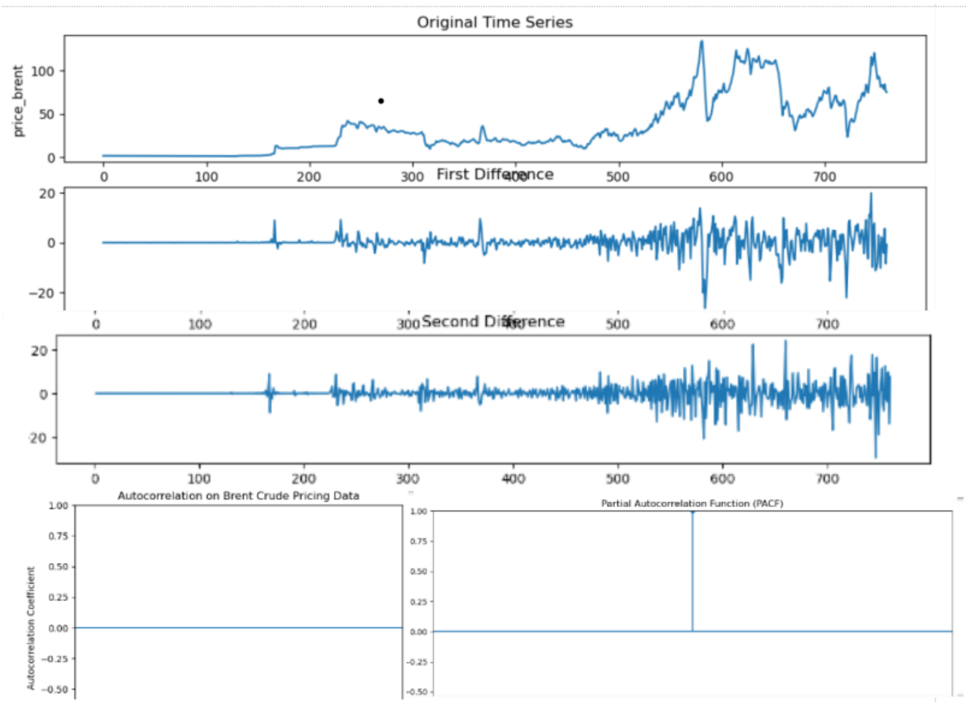

Figure 14: Differential ACF and PACF plots

7.2 Results and Discussion

```
                               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

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.

- 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.
- 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

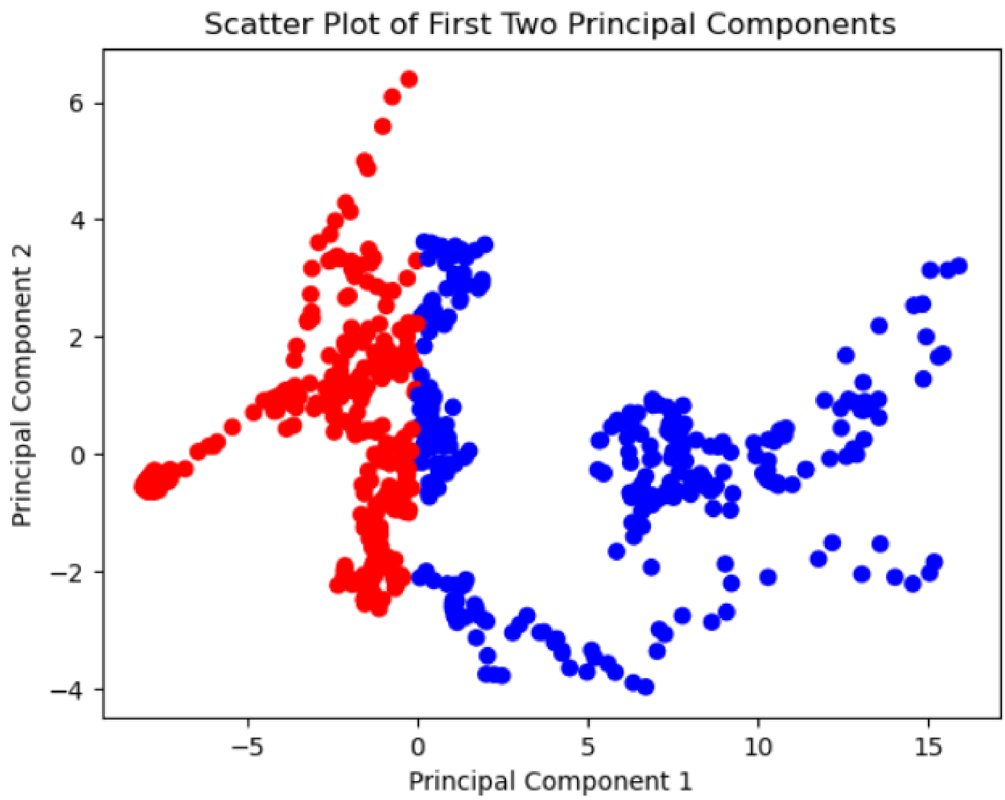

Figure 16: Scatter Plot of PC1 vs PC2

(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.

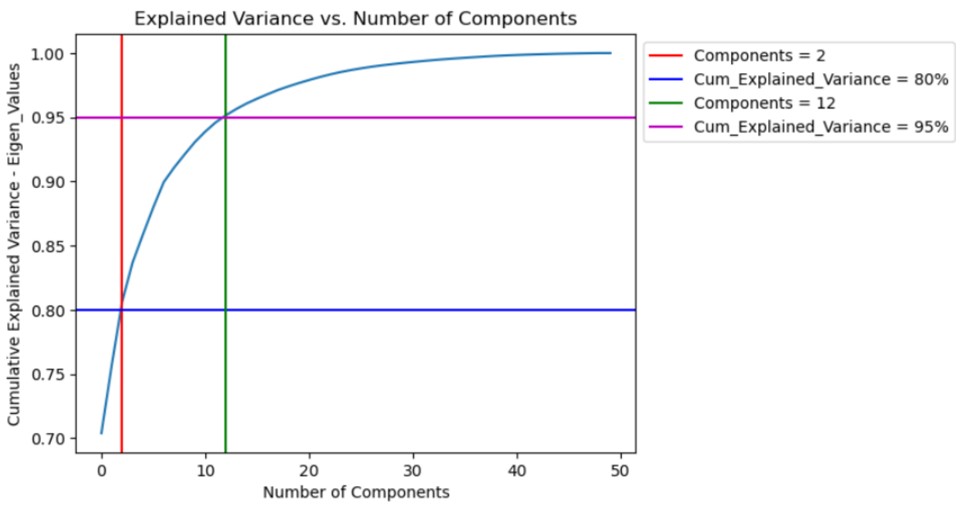

Figure 17: Explained Variance vs. Number of Components

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

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

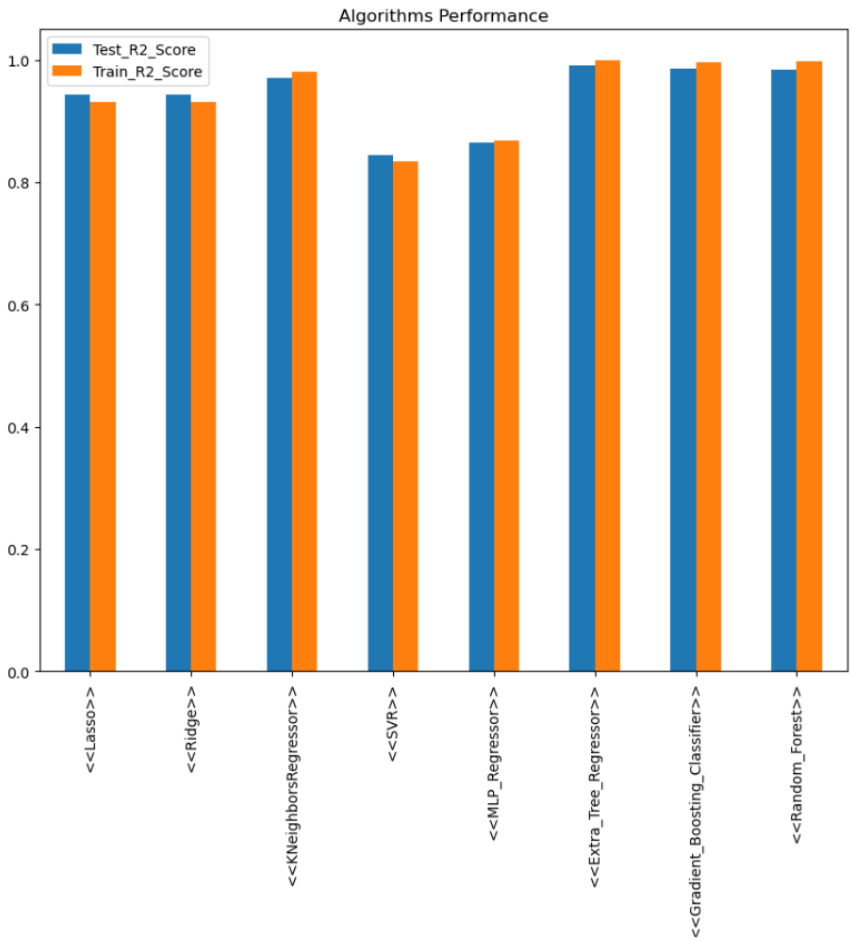

Figure 19: Algorithms Summary

9 Conclusion

The analysis of the impact of the Russia-Ukraine conflict on Brent Crude commodity pricing using Worldbank Time Series data 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. This has led to a ripple effect on the economies of major oil-producing and consuming countries.

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) with advanced machine learning algorithms like Random Forest, Extra Tree, Gradient Boosting, K-Nearest Neighbor, and Decision Tree, 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. These factors underline the intricate relationship between commodities and energy resources. The decline in industrial demand for silver speaks to the broader Industrial slowdown which has been shown in a plot of PMI's by countries, this decline in demand has disrupted various sectors and subsequently affected crude oil consumption.

Furthermore, our analysis showcases the significance of multivariate modeling techniques, including Principal Component Analysis (PCA) and Factor Analysis, 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.

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. 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.

For Policy makers, We have also reached the root causes of the problems for decision making, with reduced computational complexity, time and costs. 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. By reaching the underline cause of complex issues, for long term solutions and evidence based decision making, we can prioritize the resources, prevent policy failures, increase stakeholder engagement for more effective policies. Hence, This research can be a valuable asset in the area of public policy decision making.

For Corporate entities, by following these time tested statistics and engineering studies, we can reach strategic decisions which can be the drivers of companies bottom line and profitability, Root-cause Analysis is the life and blood of engineering decision making in day to day life, from manufacturing processes, quality improvements, productivity studies and fault diagnostics. Hence, organizations can take decisions on quality, safety and productivity. Thus 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. 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. 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.

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 had a significant impact on global commodity prices, including Brent Crude. Although, Regression Models, Futures,

Artificial Intelligence and Machine Learning have been used for several decades in forecasting the commodity pricing data, but this research has used a time series dataset from the worldbank site for doing this analysis. The research focuses on augmented forecasting techniques on commodity pricing time series data, for addition to this field of research.[30].

Machine Learning methods such as Lasso, KNN, Support Vector Regressor, MLP Regressor (Neural Network), Gradient Boosting Classifier, Random Forest Regressor, Adaboost Regressor, Decision Tree Regressor have been used on commodity pricing time series. The analysis in this study is to discover the root cause of the fluctuation in the market prices of brent crude and the underlying causes. The most widely used forecasting method, even if it is not fair, is the futures price, which has made huge predicition errors [30].Additionally, Baumeister and Kilian (2015) found that mixed forecasting combining forecasts from different models, including futures prices, resulted in more accurate reporting of the model as is found useful for the fuel price forecast.

Similarly, Manescu and Van Robays (2017) found that forecast combination approaches improved directional accuracy and unbiasedness over futures prices. Studies have shown that combining more data in different models can improve performance. For example, accounting for global economic conditions, petroleum inventories, world output gap, the U.S. dollar exchange rate, and the possibility of speculation has been shown to improve oil price forecasts (Baumeister, Korobilis, and Lee 2022; Kaufmann et al. 2008; Lalonde, Zhu, and Demers 2003).

Similarly, the inclusion of significant external regressors such as industrial production, exchange rate dynamics, commodity currencies and international metal stock indices improved the forecasting performance of some metal prices (Gong and Lin 2018; Issler, Rodrigues and Burjack 2014; Pincheira, Brown and Hardy 2019). Multivariate time series models also have the advantage of capturing the interactions and relationships between variables. They can account for the dynamics and dependencies among different variables, allowing for a more comprehensive understanding of the underlying factors driving commodity prices.

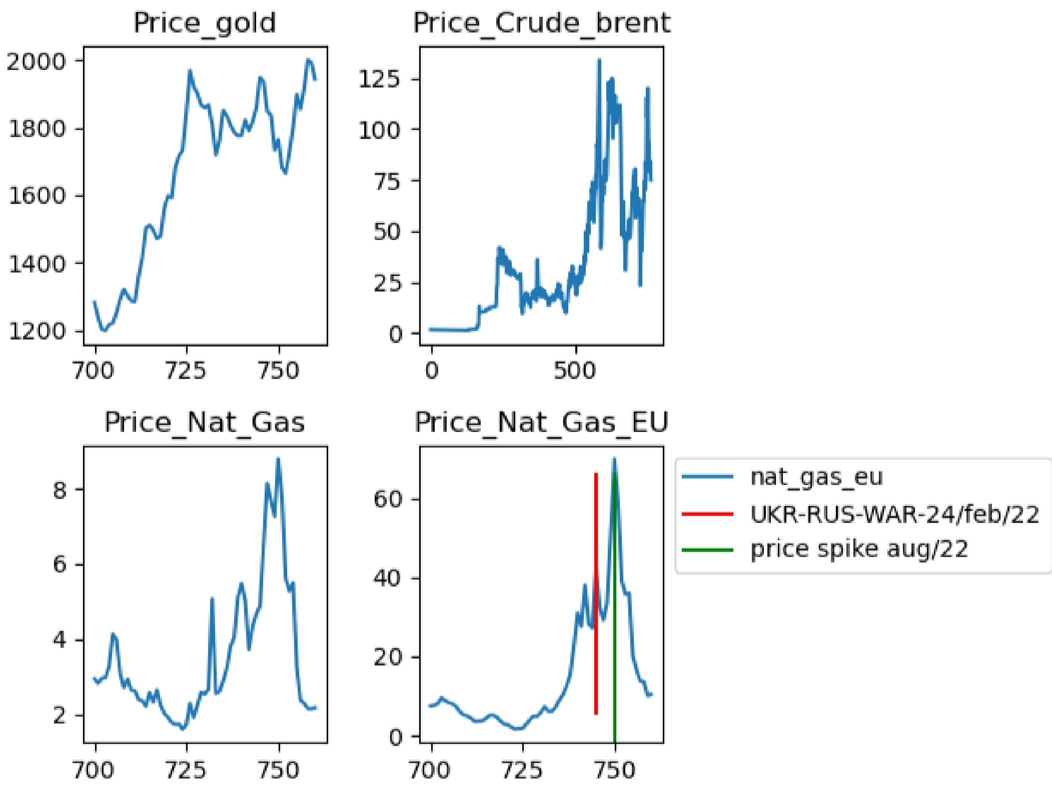

Figure 20: Price/Month, Plot for Energy and Gold

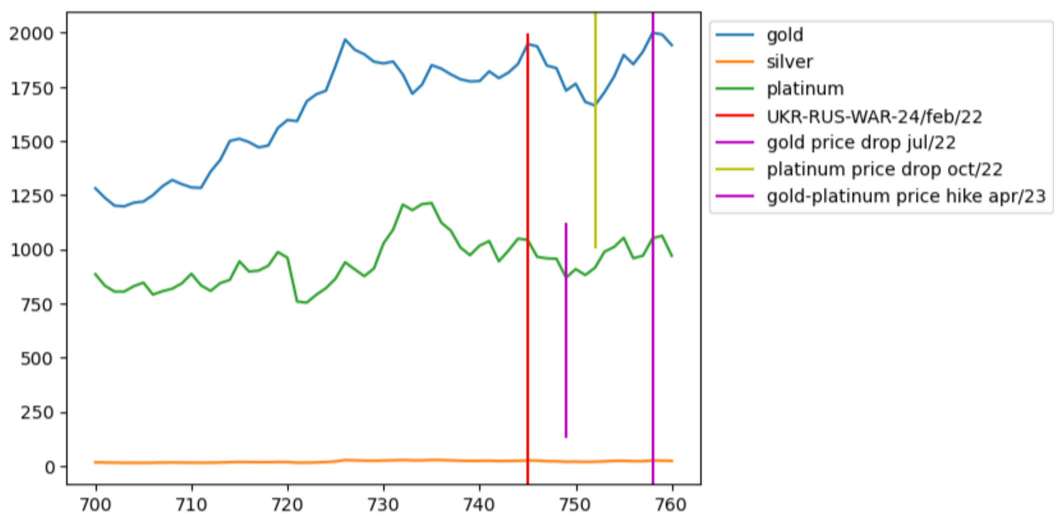

Figure 21: Price/Month,Plot for Precious Metals

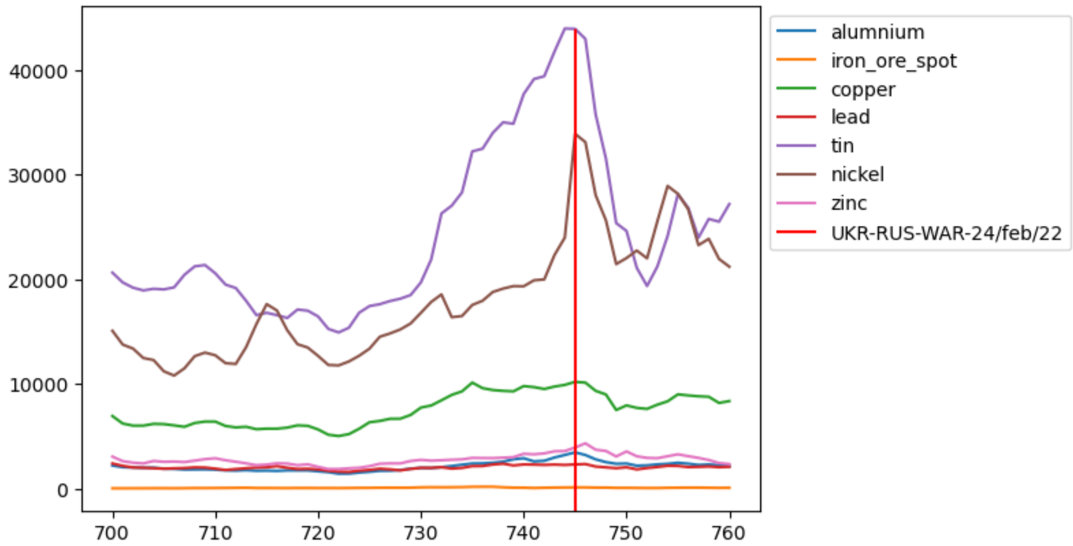

Figure 22: Price/Month,Plot for Metals

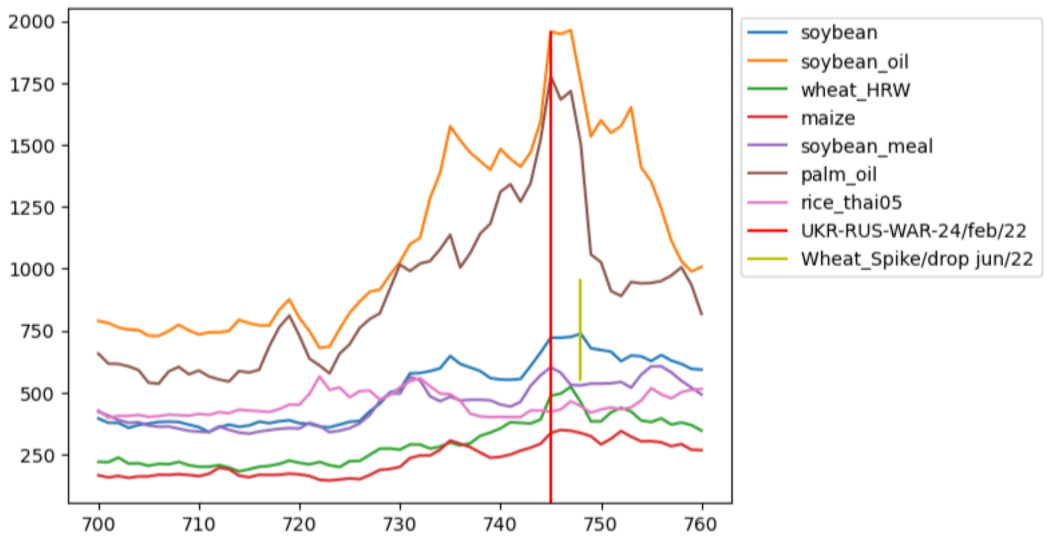

Figure 23: Price/Month, Plot for Agriculture Produce

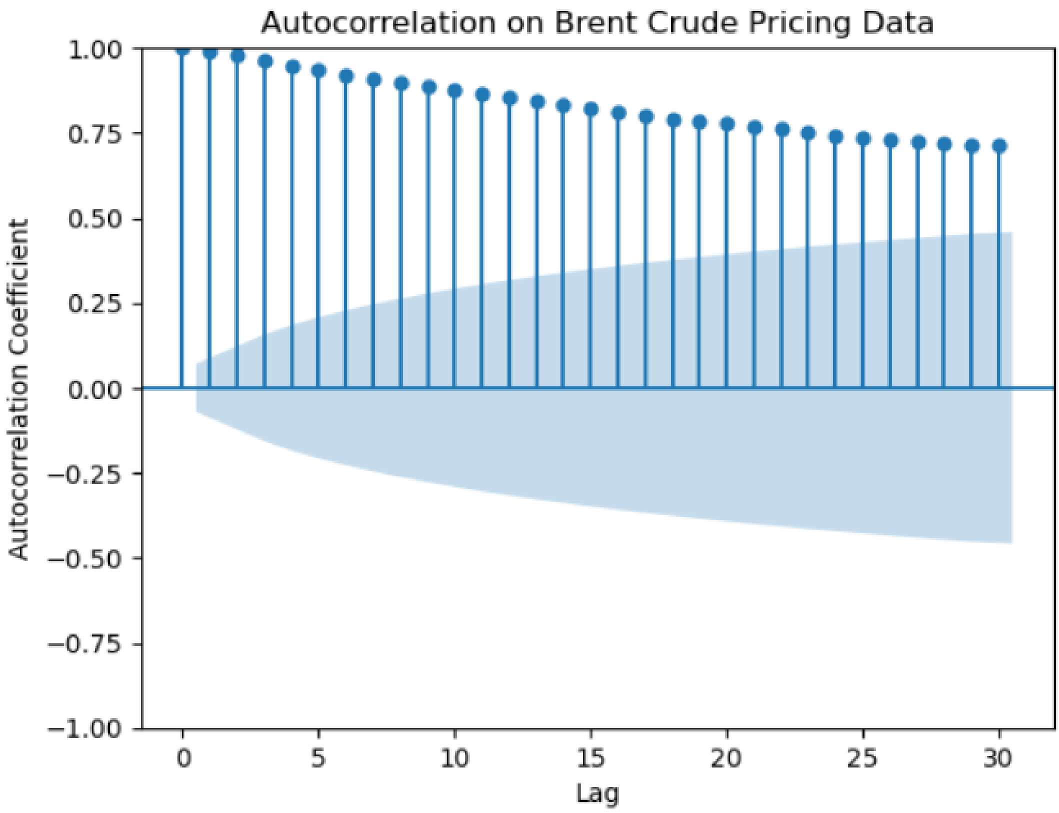

Figure 24: ACF Plot, Autocorrelation Coefficient/Lag

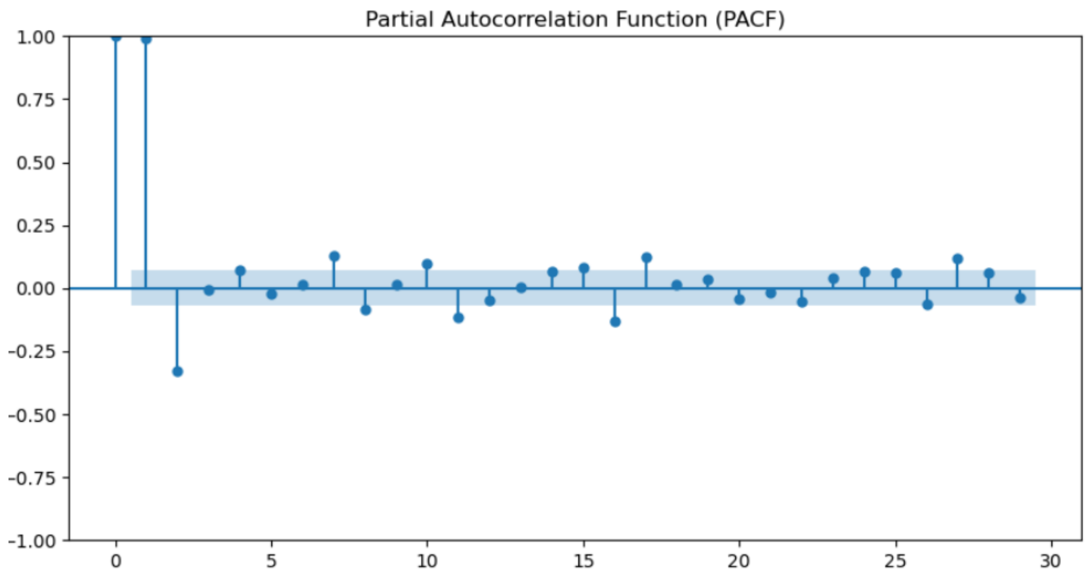

Figure 25: Partial Autocorrelation Function(PACF)

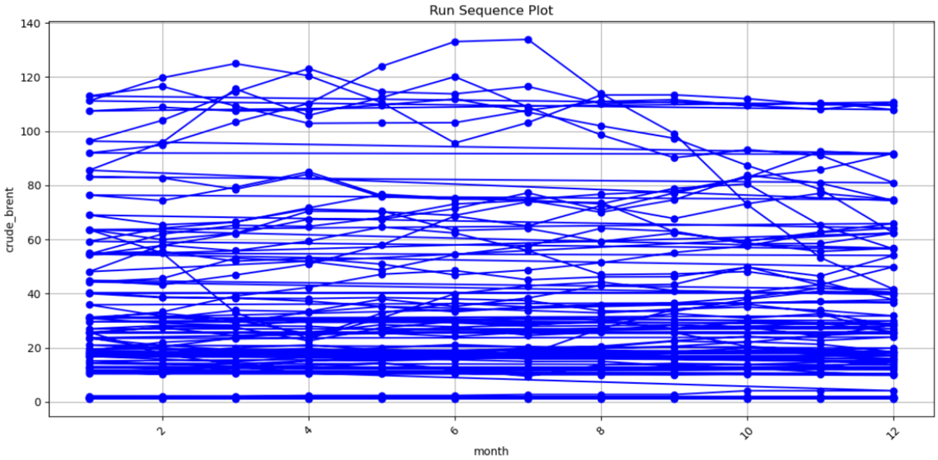

Figure 26: Run Sequence Plot

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.

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- 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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