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The Effect of Green Energy, Global Environmental Indexes, and Stock Markets in Predicting Oil Price Crashes: Evidence from Explainable Machine Learning

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Abstract: This study aims to predict oil prices during the 2019 novel coronavirus (COVID-19) pandemic by looking into green energy resources, global environmental indexes (ESG), and stock markets. The study employs advanced machine learning, such as the LightGBM, CatBoost, XGBoost, Random Forest (RF), and neural network models. An accurate forecasting framework can effectively capture the trend of the changes in oil prices and reduce the impact of the COVID-19 pandemic on such prices. Additionally, a large dataset with different asset classes was used to investigate the crash period. The research also introduced SHapely Additive exPlanations (SHAP) values for model analysis and interpretability. The empirical results indicate the superiority of the RF and LightGBM over traditional models. Moreover, this new framework provides favorable explanations of the model performance using the efficient SHAP algorithm. It also highlights the core features of predicting oil prices. The study found that high values of GER and ESG lead to lower crude oil prices. Our results are crucial for investors and policymakers in promoting climate change mitigation and sustained economic prosperity through green energy resources.

Keywords: crude oil; crash; COVID-19; machine learning models

1. Introduction

One of the most widely investigated academic subjects involves using innovative modeling frameworks to predict the financial time series. Moreover, stock market crashes and distress' forecasting models can be powerfully applied in business, investment strategies, financial management, insurance, banking, money management, and other sectors. This has driven academic researchers and market agents to focus on predicting financial and economic crises and crashes during the last few decades. This particular period has encountered severe and violent events such as the 2008 Global Financial Crisis (GFC), 2010–2012 Eurozone Debt Crisis, 2014–2015 Russian Financial Crisis (RFC), 2017–2018 North Korea-US Crisis, and the unprecedented 2019 novel coronavirus (COVID-19) pandemic. The oil market is one of the major essential markets which have experienced many shocks since the 1973–1974 crisis. The crude oil price represents nearly 50% of the general commodity index (Bašta and Molnár, 2018). The price rose from USD 52.51 per barrel to USD 145.31 per barrel on July 3, 2008. This increase is considered the most significant daily nominal jump in the history of oil. During this

period, the oil (WTI) price skyrocketed by nearly 287%. However, the oil (WTI) price had decreased from its peak price registered to USD 30.28 per barrel on December 23, 2008. This collapse was nearly 80% of its original price. Thereafter, from mid-2014 to early 2016, the oil price plunged from USD 115 per barrel to USD 26.68 per barrel. This represents a dramatic plunge of nearly 68%.

The oil (WTI) price fell to the negative price of USD 37.63 per barrel on April 20, 2020, due to the spread of the COVID-19 pandemic. This pandemic emerged in December 2019 in Wuhan, Hubei Province, China. Furthermore, the price drop was brought about by the price war between Saudi Arabia and Russia, both oil giants, in early March 2020. These oil spikes and crashes have affected the global economy. This is mainly because crude oil is considered a leading and strategic energy source for the global economy (Yuan et al., 2014; Gu and Zhang, 2016). Moreover, it plays a key overriding role in the real-world economy. It is also the preponderant energy resource for expansion, growth, and industrialization in countries seeking sustainable and stable development (Leng and Li, 2020). The crude oil market is complex and involves significant amounts of information. As such, oil price affects the prices of goods in several markets. Similarly, oil prices' volatility significantly influences economic growth and the economy's future stability. Therefore, forecasting oil price crashes and spikes has received significant attention from scholars, policymakers, and investors, particularly in the last two decades. Such a period is notable for its various political conflicts, financial and economic crises, upheavals, international wars, pandemics, and other events.

Several strands of literature have focused on oil prices' modeling and forecasting. One group of studies has utilized classical approaches (Aromi and Clements, 2019; Dutta et al., 2020). This includes univariate and multivariate Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, cointegration techniques (i.e., Error Correction Models [ECM]), simple and multiple linear regression processes, and long memory and simple stochastic models. In this strand, the frameworks capture only the linear features for time series analysis. They do not provide information about the nonlinear structure. The second strand has focused on the time series' nonlinear characteristics by encompassing advanced econometric and statistical frameworks, enclosing, wavelets, neural network analysis, and machine learning and its related tools (Yıldırım et al., 2020; Zolfaghari et al., 2020). Moreover, using data science techniques to

forecast oil price crashes might contribute beneficial information to market agents and investors as they attempt to make good strategy decisions. We expect that predicting oil price crashes through machine learning tools will offer crucial advantages and contribute significantly to the present literature.

Lin et al. (2020) implemented a novel hybrid tool and time-frequency analysis to predict crude oil's price. The authors discussed the oil price's linear and nonlinear characteristics by considering the extended memory, asymmetry, tail distribution, and denoising framework. They found significant forecasting results during periods of extreme events. Aboura and Chevallier (2016) analyzed the oil market's spikes and crashes by combining extreme value theory and quantile regression frameworks. Their main results documented tail risk behavior's existence in the WTI crude oil market. They suggested that policymakers and investors should consider volatility shocks through various swaps to construct a favorable hedging strategy decision toward market risk. Additionally, Demirer et al. (2020) analyzed the forecasting power of oil demand, the oil supply, and risk-driven shocks across the realized volatility for high-frequency data. Thus, the authors used a Heterogeneous Autoregressive Realized Volatility (HAR-RV) approach introduced by Corsi (2009) and the framework established by Ready (2018) to fragment oil price shocks into three shock components: oil demand shocks, oil supply shocks, and risk shocks related to financial market risk. Their results showed that all shock components, on their own, significantly produce extended forecasting completion of the HAR-RV process. Furthermore, Demirer et al. (2020) provided crucial information for investors and market agents when controlling for oil market volatility. Other recent researchers have also examined the forecasting structure of the realized volatility for oil price returns by implementing the HAR-RV approach (Prokopczuk et al., 2016; Degiannakis and Filis, 2017; Wen et al., 2019; Liu et al., 2019; Chen et al., 2019; Yang et al., 2019; Bonato et al., 2020; and Gkillas et al., 2020b).

Several other studies have employed different econometric tools to predict the crude oil price. For example, Leng and Li (2020) examined the dynamic forecasting structure of crude oil prices, employing econophysics and Bayesian frameworks. Their comparative analysis results showed that both approaches effectively quantified crude oil's predictability information. Moreover, the Bayesian approach demonstrated superiority over classical modeling techniques. Algeri and Leccadito (2019) found significant interconnectedness between energy commodities

and equity markets. They used a Conditional Autoregressive Logit (CARL) framework to forecast the probability of the excess returns for crude WTI oil, Brent crude oil, heating oil, and natural gas. Similarly, Hui et al. (2020) investigated dynamic forecasting for crude oil prices under a market crash risk using an asymmetric mean to revert fundamental shocks. They showed that there was a breach in the boundary condition when the oil price sharply decreased in the 2008 GFC and 2014 RFC.

Literature that focuses on predicting oil price crashes and distress using machine learning approaches is scant, particularly during the COVID-19 pandemic. To the best of our knowledge, this empirical research is the first to forecast oil market price crashes during the COVID-19 pandemic using advanced machine learning techniques. These include neural networks, and the random forest (RF), LightGBM, XGBoost, and CatBoost algorithms. A novel hybrid modeling technique was introduced by Abdollahi and Babak (2020) for forecasting purposes to capture the nonlinear characteristics, lags, and interconnectedness of oil prices. The authors used different metrics to quantify errors in the following models when predicting the Brent oil price: the Adaptive Neuro Fuzzy Inference System (ANFIS), the Autoregressive Fractionally Integrated Moving Average (ARFIMA), and Markov-switching. The empirical results showed that efficient predictions of crude oil prices might assist producer and importer economies. A comparative analysis using neural network and vector autoregressive techniques was employed to predict oil prices. Moreover, it provided evidence for the superiority of the neural network method (Ramyar and Kianfar, 2019). Additionally, the same machine learning technique used by Ramyar and Kianfar (2019) was implemented by Ignacio et al. (2017) to forecast oil prices. The predictive analysis revealed the reliability of the artificial neural network framework. A few empirical studies forecasting other commodity prices and stock market prices have documented the superiority of machine learning models in its forecasting structure (Parisi et al., 2008; Khashei and Bijari, 2010; Kim and Ahn, 2012; Sánchez Lasheras et al., 2015; Kristjanpoller and Minutolo, 2015, 2016, 2018; Fan et al., 2016; Fischer and Krauss, 2018; Aziz et al, 2017; Ewees et al., 2017; Nguyen-ky et al., 2018; Alameer et al., 2019; and Alameer et al., 2020).

Against this backdrop, the key objective of this empirical study is to extend the narrowed literature on the forecastability of oil price crashes. Moreover, this study seeks to forecast oil price crashes and distress multi-steps using suitable machine learning models. Therefore, our key

challenge is to obtain a convenient forecasting machine learning model for oil price crashes. Accordingly, crucial information and rapid signaling for policymakers, investors, and authorities when making good strategic decisions may be obtained through sophisticated machine learning techniques to forecast oil price crashes. The same may be achieved by exploring the interconnectedness of the oil market with various markets. These markets include gold, silver, platinum, copper, S&P 500, dollar index, euro-dollar exchange rate, Bitcoins, soybeans, and volatility index. On this ground, several machine learning techniques are employed in our study to forecast oil price crashes and examine the connectedness for the following price couples: oil-gold, oil-silver, oil-platinum, oil-copper, oil-S&P 500, oil-dollar index, oil-euro-dollar exchange rate, oil-Bitcoin, oil-soybeans, and oil-volatility index.

The principal novelty in our empirical study consists of (i) the use of advanced machine learning techniques to forecast oil price crashes, specifically during the COVID-19 pandemic. This includes (ii) the implementation of the LightGBM, XGBoost, CatBoost, and RF algorithms. To the best of our knowledge, this is the pioneering study to attempt such implementation. The present study includes (iii) the use of LightGBM and XGBoost algorithms and the RF process that are expected to exhibit strong forecasting performance. Lastly, (iv) our research study corroborates the power of the following predictor determinants for the forecastability of oil price crashes: gold, silver, platinum, copper, Bitcoin, soybeans, S&P 500, euro-dollar exchange rate, dollar index, and volatility index. Our findings demonstrated that machine learning can effectively predict oil price crashes and help policymakers make appropriate decisions during crises. Therefore, the artificial intelligence methods used in the present study have a “black box” nature. The Shapley Additive Explanations (SHAP) technique can be easily used as a method to reveal “black box” machine learning algorithms and to validate the best model. Table 1 displays some recent research studies on the link between oil and several stock markets.

(Insert Table 1 here)

This paper contributes to the empirical literature related to oil price behavior in three ways. First, we examine the advanced machine learning models’ advantages and contributions.. To the best of our knowledge, this is the first study that used the XGBoost, CatBoost, and LightGBM in predicting oil price crashes. Compared to previous studies, many approaches have been used to

detect crashes and bubbles in oil prices. These approaches include the Log-Periodic Power Law (LPPL) model (Fantazzini, 2016), the switching regression approach (Liu et al., 2020), and the Generalized Supremum Augmented Dickey-Fuller (GSADF) (Gharib et al., 2021; Zhao et al., 2021). These methodologies detect oil price bubbles' existence. However, none of them forecast crash time. Second, our findings provide essential implications for financial institutions, regulators, and investors to prevent systematic risk. This will also diversify portfolios based on more sophisticated artificial intelligence techniques. Third, explainable machine learning framework emphasizes the relative importance of the green and environmental variables on predicting oil prices (Chakraborty et al., 2021). Investors avoid adopting machine learning models because of the lack of explainability and dependability. However, the SHAP value method used in this study, combined with the accurate machine learning models, may be used by more experts in making certain real-world decisions (Chakraborty et al., 2020).

We structured the rest of the paper as follows: In section 2, we present the machine learning algorithms that we implement in our study. The data and variables are then described in section 3. We summed up our results in section 4 and finally concluded the paper in section 5.

2. Machine learning models

2.1. Discriminant analysis

Discriminant analysis pertains to the classification of an observation into one or many populations. It is a classification approach that uses various factors to classify objects into two or more groups. We need to divide the variables into a few categories, to find their linear combinations that are better distinguished in the findings to design the classification rule. The score is calculated as follows:

$$\hat{Y} = \mu_0 + \sum_{i=1}^N \mu_i x_i \quad (1)$$

In the equation above, μ represents the vector of estimated coefficients, and x_i indicates the independent variables. Vector μ will be estimated using a technique that maximizes the discrepancy between each group's average values by combining parameters.

This method has been criticized for not holding in the case of real applications because of its unrealistic assumptions, such as linear separability and multivariate normality (Geng et al., 2015). Other methods have been proposed in earlier studies to overcome such limitations.

2.2. Logistic regression

Logistic regression (LR) models are used to forecast binary outcomes. The scientific community in economics, finance, sociology, and other social sciences has already widely adopted this toolkit (Ben Jabeur, 2017; Zhang et al., 2020). The logistic regression model typically estimates the probability that an occurrence happens from a series of predictors. The logistic regression's predicted output is as follows:

$$\hat{Y} = \text{Log}\left(\frac{P(x)}{1-P(x)}\right) = \beta_0 + \beta_1x_1 + \dots + \beta_kx_k \quad (2)$$

Here, $P(x)$ is the predicted probability of the event, x is the k vector of explanatory variables, and β is the estimated value by the maximum likelihood function.

LR suffers from various statistical drawbacks. These include multicollinearity and lower performance accuracy. For example, Ben Jabeur (2017) reported that LR eliminates most explanatory variables strongly correlated to the analysis' outcome. He explained that the maximum likelihood estimation fails to converge toward the optimal solution.

2.3. Neural networks

Neural networks, such as logistic regression or discriminant analysis, are widely used methods of classification problems. According to Du Jardin and Séverin (2012), the relationship between the explanatory variables and outcome is expressed as a matrix. It contains values representing the strength of connections between neurons. A multilayer perceptron (MLP) was used in this analysis to conduct the classification task. The estimated function can be expressed as follows:

$$\hat{Y} = f\left(f\left(\sum_{i=1}^N \mu_{ij}x_i + b_i\right) * \left(\sum_{j=1}^k \mu_j\right) + b\right) \quad (3)$$

In this equation, μ is the network weight matrix, f is the activation function of neurons, n is the number of features, and k is the number of neurons of the hidden layer.

Neural networks do not include the independent variables' distribution assumptions. Moreover, they are capable of modeling all forms of nonlinear functions between the model's input and output (Du Jardin and Séverin, 2012).

2.4. *Random Forest*

The Random Forest (RF) is a well-known machine algorithm for solving the classification problem. This is a popular algorithm with a rapidly increasing use in various business disciplines such as finance (Ben Jabeur and Fahmi, 2017), environmental protection (Ozigis et al., 2020; Kamińska, 2018), and marketing (Ładyżyński et al., 2019; Salminen et al., 2019). The RF is based on a set of trees. It is accompanied by a measure of the projection's mean value obtained at the end of each tree, removing a single tree's lack of robustness. In this method, each tree is grown by using a subset of randomly chosen independent variables. The estimated model can be expressed as follows:

$$\hat{Y} = \frac{1}{q} \sum_{i=1}^q g_k(X) \quad (4)$$

Here, $g(x)$ is a set of k^{th} learner random trees, and x is the vector of the input features. The RF's final estimation is the average of all the outcomes of each tree. Therefore, each individual tree affects the RF estimation at such weights. According to Yeşilkanat (2020), the RF algorithm is better than other algorithms for machine learning. This is because of the former's capacity to automatically receive training data from subsets and shape trees with random algorithms. Additionally, the RF algorithm preserves the overfitting amount because training is achieved by using bootstraps on randomly chosen separate sub-datasets.

2.5. *XGBoost algorithm*

The XGBoost (eXtreme Gradient Boosting) effectively implements the gradient boosting algorithm by Chen and Guestrin (2016). It is a commonly used modular end-to-end tree boosting method that has achieved state-of-the-art classification and efficiency (Ma et al., 2020). The XGBoost is an ensemble of regression trees used to generate the final output. The final score is obtained using the following equation:

$$\hat{Y} = \sum_{h=1}^H g_h(X_i) \quad (5)$$

In this equation, H reflects the number of trees, and K is the score for the leaf of h trees. As an additional advantage, the XGBoost is not influenced by multicollinearity.

Several parameters need to be chosen in XGBoost to optimize the model performance. Parameter tuning is necessary for the XGBoost to avoid overfitting and too much confusion. However, this can be difficult because the XGBoost uses several parameters. We used a grid search cross-validation in our study to optimize the hyper-parameter values.

2.6. CatBoost algorithm

The CatBoost is a novel version of the gradient-boosting decision tree algorithm. It has powerful learning capabilities to manage extremely nonlinear data (Prokhorenkova et al., 2018). The CatBoost executes a random permutation of the sample and computes the dataset. For example, the average label value of the same category value is put in the permutation before the given one. Moreover, it has fewer parameters and less training time. The predicted function is described as follows:

$$h^t = \arg \min \frac{1}{N} \sum (-f^t(X_k, Y_k) - h(X_k))^2 \quad (6)$$

In such an equation, $h(X)$ is the decision tree function and $f^t(X_k, Y_k)$ is the gradient's conditional distribution.

In the classic algorithm, referred to as structured boosting, the CatBoost uses a different approach to modify the gradient estimation system. This approach will resolve the prediction change induced by gradient bias. Moreover, the approach further increases the model's generalization ability.

2.7. LightGBM algorithm

The LightGBM is another effective and scalable implementation of a tree-based gradient boosting machine learning approach (Ke et al., 2017). It utilizes network connectivity algorithms to maximize parallel learning. Additionally, it develops trees that are leaf-wise instead of level-wise. LightGBM incorporates many T regression trees $\sum_{t=1}^T g_t(X)$ to estimate the final model which may be expressed as follows:

$$\hat{Y} = \sum_{t=1}^T g_t(X) \quad (7)$$

Here, the regression trees may be represented as $w_{p(x)}$, where $p \in \{1, 2, \dots, M\}$. The variable M is number of tree leaves, p is the decision rule of trees, and w is the leaf nodes' sample weights.

The LightGBM algorithm is commonly used in broad areas of big data analytics. Additionally, studies have shown that the LightGBM can achieve linear acceleration by utilizing several machines for specific training. Therefore, this algorithm's benefits can be expressed in several aspects. These include quick training time, poor use of memory, and the model's strong accuracy.

3. Data and variables

The data used in this study involved the closing daily price of WTI crude oil in the past ten years, from January 1, 2010, to April 20, 2020. We used a Yahoo finance dataset to extract the data. In this work, the training and test data were divided using an 80:20 ratio. As pointed out by Alameer et al. (2019), a crucial step in developing an accurate prediction model is the selection of input variables. Therefore, this analysis defines 13 predictor variables to boost the efficiency of the forecasting models — green energy resources and global environmental indexes (i.e., environmental, social, and governance [ESG] index) including companies whose primary source of income is products and services that lead to a more environmentally sustainable economy. The environmental, social, and governance (ESG) index is procured by the S&P Dow Jones index, the pioneering index. In terms of environmental measure, this may include the company's energy use, waste, pollution, natural resources, and animal treatment. On the other hand, the social measure is related to the company's business relationships. Regarding the governance side, the ESG index indicates that companies use appropriate and clear frameworks, avoid conflicts of interest, and do not delve into political and illegal exercise. The Green Energy Resources company provides the Green Energy Resources (GER) index. It is a green bio-energy company that provides biomass and woodchips for direct energy and gasification. The GER includes renewable energy linked to wind power, solar power, and biogas. Furthermore, we used the following indices: gold, silver, S&P500, platinum, copper, dollar index (DIX), volatility index (VIX), soybeans, euro-dollar exchange rate (EUR/USA), copper, and Bitcoin.

This paper focuses on the forecasting performance of machine learning techniques whilst forecasting the price level. The original data of the outcome need to be transferred into a typical dichotomy problem in machine learning, even though any classification problem needs labels (Sun et al., 2020). We also established a threshold to classify a “sharp” day so that the likelihood of returns is smaller than the threshold for every window (i.e., 30, 21, 14, and 7 days). This threshold may be established based on investor risk tolerance. Any returns smaller than the respective threshold in the two windows would be labeled as 1; otherwise, it will be labeled as 0. Besides the lagged returns, we added a combination of simple and exponential moving averages to the existing variables space. Table 1 presents the descriptive statistics. On the other hand, Figure 1 provides the pairwise correlation coefficients between the original variables in our study. We considered the following statistics: mean, standard deviation, minimum, maximum, and the first, second, and third quartile (refer to Table 2).

Regarding the mean statistic, we have highlighted a positive average for all the variables. This indicates that the average returns for the time series enhance the forecasting performance. We computed the standard deviation statistic to show how volatile the time series was. It was found that Bitcoin is the most important volatile stock compared to other variables. It is followed by the S&P 500, platinum, soybeans, and gold. However, Bitcoin, S&P 500, platinum, and soybean stocks are riskier in terms of standard deviation. Figure 1 depicts a graphical illustration of the correlation between the interest variables. This present study aimed is to generate a synopsis for the connection between the primary variables under concern. The correlation coefficients revealed that the oil market is highly connected with all other variables, except the volatility index (-0.04) and Bitcoin (-0.34). This finding suggests a higher co-movement between the oil and other markets.

(Insert Table 2 here)

(Insert Figure 1 here)

(Insert Figure 2 here)

In Figure 2, we used a chord diagram to visualize all examined markets’ dynamic connectedness. The circle is split up into 13 variables with each feature’s arc length. A chord is a link that connects two arcs together. Its width represents the strength of the interaction between the two

connected nodes. The broader the chord, the stronger the interaction. The percentages along the outer rim of the chord diagram represents the share-per-market. Figure 2 shows that the most important chords are those connecting the oil market with the dollar index, euro-dollar exchange rate, copper, and platinum. This may explain the high spillover effect of the aforementioned markets on the oil market during the COVID-19 pandemic. Furthermore, chord intensities connecting the GER with the oil market are more pronounced than chord strengths linking the ESG with the oil market. This indicates the prominent effect of the green energy and environmental indices on the oil market during the COVID-19 pandemic.

We estimated and forecasted all the models using the Python software (version 3.7) by the Pycaret package (<https://pycaret.org>). A hyperparameter tuning in PyCaret was done through the random grid search method for all machine learning models.

4. Results

4.1. General Performance of the Models

This section provides a comparison of the different machine learning models' forecasting performance. In this work, a validation procedure was adopted to determine the individual model's efficiency. Thirty percent of the data were used as validation results (Ben Jabeur et al., 2020). The correspondence between the initial features and the labels is reconstructed by inserting a lag time of one week, two weeks, three weeks, and one month to compare the models' prediction accuracy over various forecast times. We used two different measures to estimate model performance.

(Insert Table 3 here)

Table 3 shows the classification performance measured by accuracy. This can be calculated as follows:

$$ACC = \frac{TP+TN}{TP+TN+FN+FP} \quad (8)$$

In this equation, the variables P and N indicate the falling and not falling numbers, respectively.

Several conclusions can be drawn from the results in Table 3. First, both models are susceptible to shifts that have arisen within the macro-economic climate. This is because the error rises one week before the crash and hits a limit three weeks and one month before the sharp day. Second, among all the models, the XGBoost leads, as a whole, obtaining the best results (mean = 96.73%). The XGBoost model was followed by the NN, LightGBM, and RF models. On the other hand, the logistic regression and discriminant analysis led to the worst results. This reveals that advanced machine learning models have the edge over conventional optimization techniques.

(Insert Table 4 here)

We computed the AUC indicator, which is the area under the ROC curve, to deepen the analysis. According to Jabeur et al. (2021), the AUC indicator is a common metric for assessing a model's overall discriminatory power. Measuring a model's performance based on classification accuracy may be deceptive because oil price crash is such an uncommon occurrence. Therefore, the AUC indicator is a more flexible performance metric, since it is calculated from the Receiver Operating Characteristic (ROC) curve (Mai et al., 2019). Table 4 provides the results calculated with the advanced machine learning models and those estimated with all other models by period. It may be confusing to use classification accuracy to calculate a model's efficiency because falling is a rare event (Mai et al., 2019). Hence, the AUC is a more robust performance measure, especially in analyzing unbalanced data which is used in the present study. Table 4 summarizes the out-of-sample prediction results over different periods. We first note that the AUC values are consistently above 0.7. Additionally, the value of AUC slightly changes from one period to another. The average AUC ranges from 0.954 to 0.996 at the one-month horizon, from 0.872 to 0.948 at the three-week horizon, from 0.742 to 0.943 at the two-week horizon, and 0.761 to 0.935 at the one-week horizon. When one performs an in-depth analysis by models and period of the findings, one can see that the RF and XGBoost are more accurate than the traditional models. This clearly demonstrates that advanced machine learning will boost model efficiency when the forecast horizon is low. Moreover, a part of these results was attributed to the new models' potential to substantially minimize type-I errors, relative to standard ones, while the horizon is rising. These findings confirm the value added by the RF, LightGBM, XGBoost, and CatBoost. This is because they greatly enhance model efficiency, regardless of its measure. It also improves

the capacity of the models to correctly predict the oil price's fate. Therefore, the models offer reliable predictability for financial institutions and oil-exporting countries confronted by the present COVID-19 pandemic.

4.2. Variable importance

In forecasting oil crashes, it is helpful to know all variables' relative contribution on the final prediction outcome. Recently, the SHAP was proposed by Lundberg et al. (2018) to measure certain features' importance. In summary, the SHAP assigns each function based on the game theory. This can be useful in maintaining a compromise between black box machine learning models' accuracy and interpretability. Specifically, the interpretable model g is a linear function of the binary variables, which may be expressed as follows:

$$g(X') = \phi_0 + \sum_{i=1}^N \phi_i X_i' \quad (9)$$

Here, $X' \in \{0, 1\}^M$ is equal to 1 when a variable is observed. Otherwise, it is equal to 0. The variable N is the number of input variables.

(Insert Figure 3 here)

In Figure 3, we show the variable importance measures for the 20 most important features. Figure 3.a displays the most important variables at one week ahead. Here, we can see that the most significant feature is crude oil's simple moving averages during the past 180 days. This is also intuitive because if oil prices have significantly increased in the past, they are more apt to fall or be corrected, and vice versa. Higher values of this variable result in higher SHAP values. Therefore, this corresponds to a higher probability that a crash has occurred. The following four features are returns from green energy resources over 250 days, crude oil returns over 180 and 250 days, and gold over 250 days. Oil, green energy resources, and gold are the three most widely traded and correlated features. The findings are consistent with the studies by Ding et al. (2016) and Li et al. (2012). They found significant long-term causality between stock returns and oil prices.

Moreover, Morema and Bonga-Bonga (2020) showed the significance of the relationship between markets, gold, and oil, which is essential for portfolio management. Niu (2021) reported that there is a more vital linkage of clean energy and crude oil. Understanding the complex

relationship between oil prices and renewable energy is essential for fostering the renewable energy industry's growth and the shift from fossil fuels to renewable energy. Such a move will preserve the climate in the long run (Guo et al., 2021). Additionally, we can see that Bitcoin seems to explain the oil prices. These findings align with the study by Dutta et al. (2020). They indicated positive relationships between crude oil and Bitcoin most of the time. Figure 3.b shows the most important variables at two weeks before the prices fall. We can notice that the gold and oil returns are the most influential features. Additionally, silver and copper appear to explain oil price returns. Lower values of these features correspond to a higher probability that a crash has occurred. The results are consistent with the work of Yildirim et al. (2020). They documented a bidirectional volatility spillover effect between oil and silver returns. Moreover, the ESG also appears in Figure 3.b. This means that high values for the ESG lead to lower crude oil prices. This finding is in contrast with that of Dutta et al. (2020b). They documented an insignificant connection between clean energy stock and crude oil prices. Figures 3.c and 3.d show a feature importance at three weeks and one month before prices fall. We can also show that the volatility index, dollar index, and soybeans appear to be vital in forecasting oil price. These findings establish a strong basis for the assessment of the global variables' importance. Moreover, it offers sufficient information for the models' interpretations.

5. Conclusion

Financial and commodity markets have shown tremendous losses since the onset of the COVID-19 pandemic. Inevitably, the pandemic has culminated in systemic improvements to pricing patterns for multiple markets. It concentrates on commodity markets because of their interlinking with the real economy. Therefore, developing an accurate warning system for oil price fluctuations and oil prices, whether or not they are falling, can provide stakeholders the practical knowledge to make correct choices in avoiding crashes. Research on improving the performance accuracy continues to rise, despite the availability of many forecasts. In the present paper, we proposed advanced machine learning models (RF, LightGBM, CatBoost, and XGBoost) for forecasting oil price crashes.

In terms of empirical findings, we found that among the different machine learning models for predicting oil prices, the RF and LightGBM provide the highest performance, accuracy, and AUC. The RF and LightGBM models have improved accuracies compared to the traditional

models, such as discriminant analysis and logistic regression. Moreover, these models are a promising methodology for oil price forecasting. Using the powerful SHAP, this new framework also provides powerful interpretations regarding the model performance. It highlights the most important variables for oil price fluctuations during the COVID-19 pandemic. The findings provided significant correlations among oil prices and all the predictor variables. In fact, understanding the causal interaction between oil prices and green energy is beneficial for encouraging the renewable energy industry's growth. It also advocates for the shift from fossil fuels to renewable energy, which would ultimately preserve the atmosphere.

The results drawn by the machine learning models in this paper may have various realistic policy consequences for importing and exporting countries, investors, policymakers, and market regulators. Policymakers and investors should also pay attention to risk spillovers between the oil and equity markets. This is true particularly during major crises. The governments of oil-importing and oil-exporting countries should set up an information-sharing framework for risk connectivity. Moreover, they should create a mutual monitoring structure to increase the energy sector's performance. Furthermore, this will help encourage them to adopt alternative risk-avoiding steps during a particular time frame. Finally, future research can explore more interpretable machine learning algorithms and more predictive macroeconomic variables.

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Table 1. Some recent studies on the connectedness between oil and stock markets

Author (s)	Stock market (s)	Method	Sample period
Aromi and Clements, (2019)	Crude oil, S&P 500	Heterogeneous autoregressive (HAR)	January 3, 2007 to December 31, 2016: 5-min daily frequency
Dai et al. (2020)	Crude oil, gold, US dollar foreign exchange	Wavelet analysis, time-varying vine-copula	January 3, 1997 to September 21, 2018: daily frequency
Das et al. (2020)	Crude oil, Bitcoin, gold, US dollar	GARCH, quantile regression, SVAR	July 20, 2010 to June 30, 2019: monthly frequency
Dutta et al. (2020)	Crude oil, gold, Bitcoin	DCC-GARCH	December 2014 to March 2020: daily frequency
Gkillas et al. (2020a)	Crude oil, gold, Bitcoin	Granger causality, VAR	December 2, 2014 to June, 10 2018: 15-min daily frequency
Hau et al. (2020)	Crude oil, soybean, corn, strong wheat, bean pulp, cotton, natural rubber	Quantile-on-quantile, TVP-SVM	December 1999 to December 2019: weekly frequency
Mensi et al. (2020)	Crude oil, gold	Asymmetric Multifractal Detrended Fluctuation Analysis (A-MF-DFA)	April 23, 2018 to April 24, 2020: 15-min daily frequency
Mokni et al. (2020)	Crude oil, gold	TVP-VAR	January 2, 1997 to January 30, 2019: daily frequency
Naeem et al. (2020)	Crude oil, gold, BRICS stock index (IBOV, IMOEX, NIFTY, SHSZ 300, JALSH)	Quantile-on-quantile, quantile coherency	January 2002 to December 2018: daily frequency
Roh et al. (2020)	Crude oil, gold, equity markets	Downside realized variance	January 2010 to June 2018: daily frequency
Salisu et al. (2020)	Crude oil, gold	Asymmetric VARMA-GARCH	January 2016 to August 2020: daily frequency
Singhal et al. (2019)	Crude oil, gold, Mexican Stock Exchange index	ARDL Bound testing cointegration	January 2016 to April 2018: daily frequency
Tiwari et al. (2020)	Crude oil, gold	Time-varying Markov switching copula, multiresolution analysis	January 2, 1985 to November 30, 2017: daily frequency
Yıldırım et al. (2020)	Crude oil, gold, silver, platinum, palladium	Causality-in-variance, GARCH, EGARCH, APARCH, FIGARCH	January 1990 to December 2019: daily frequency
Y. Zhang et al. (2020)	Crude oil, gold, China Securities Index (CSI) 300, CSI aggregate bond index	VAR-CCC-GARCH, VAR-DCC-GARCH	January 9, 2008 to January 4, 2019: daily frequency
Zolfaghari et al. (2020)	Crude oil, natural gas, coal, EUR/USD Exchange rate, S&P 500	VAR-Diagonal BEKK, VARMA-GARCH, VARMA-AGARCH	January 4, 2011 to January 31, 2020

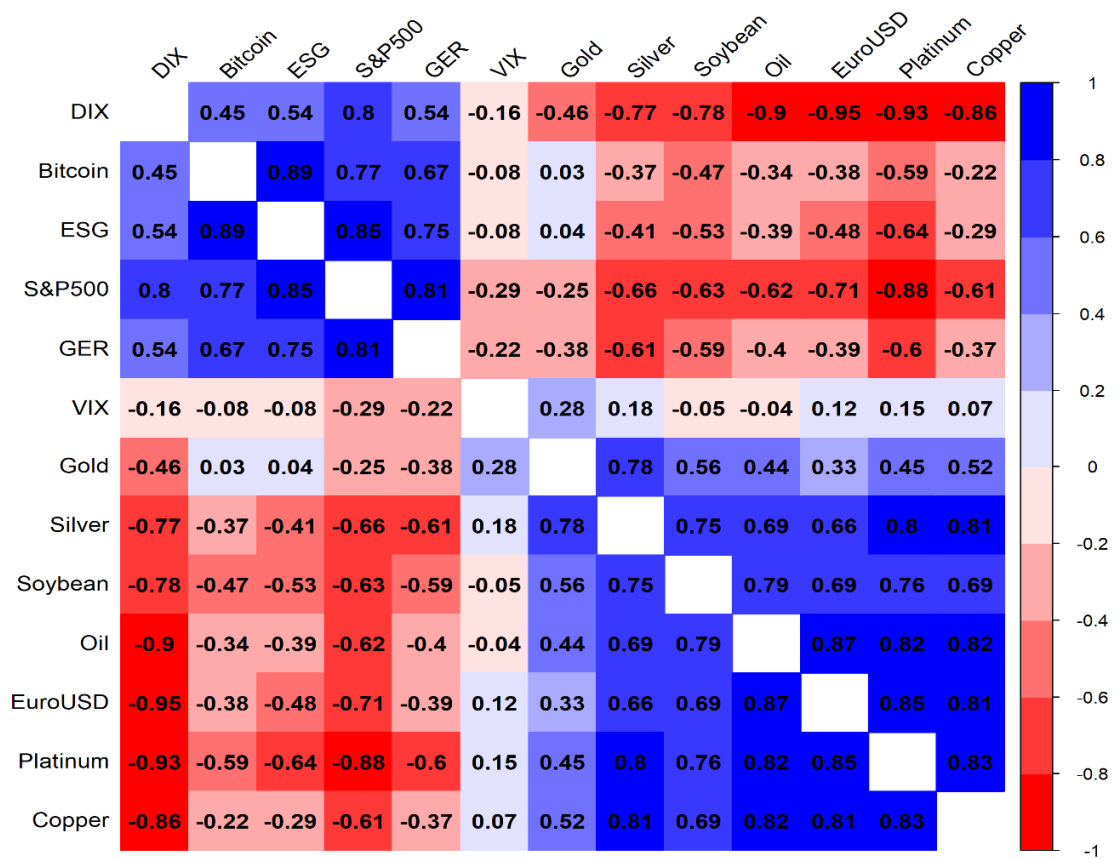


Figure 1. Correlation matrix.

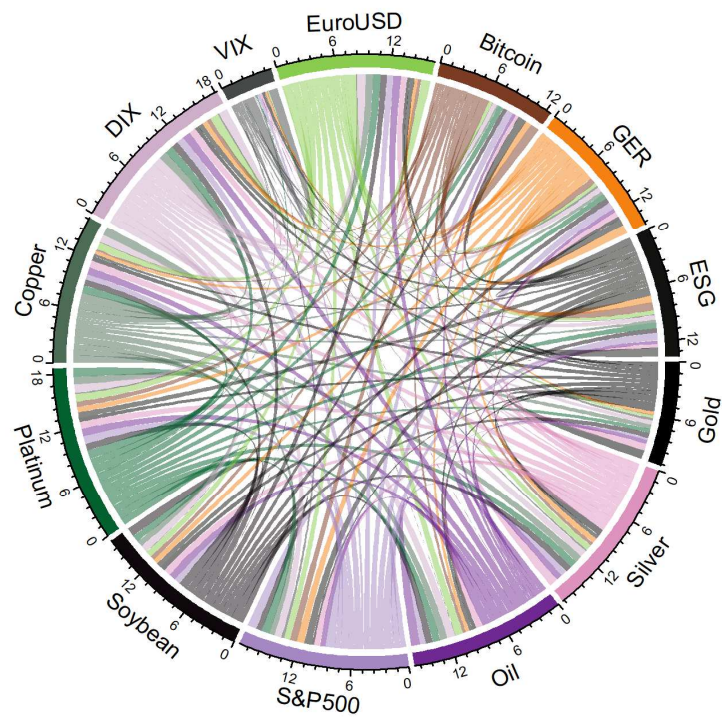


Figure 2. Chord diagram. The abbreviation used in the diagram are as follows. DIX: the dollar in dex, VIX: the volatility index, EuroUSD: the Euro dollar exchange rate, GER: the green energy r esources index, ESG: the environment, social, and governance index.

Table 2. Descriptive statistics.

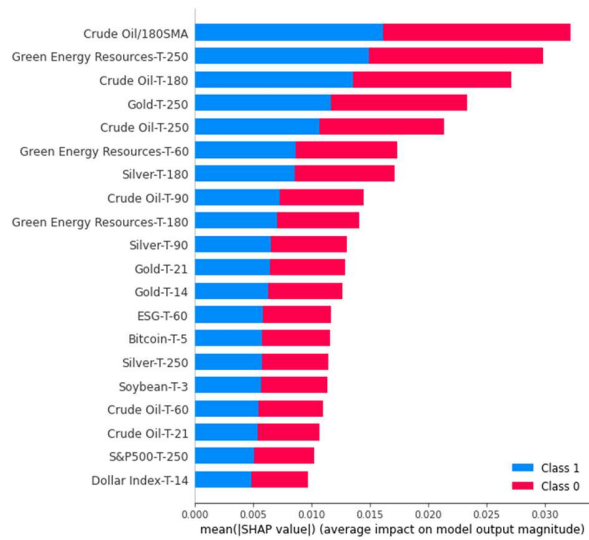
	Gold	Silver	Crude Oil	S&P500	Soybean	Platinum	Copper	Dollar Index	Volatility Index	Euro USD	Bitcoin	Green Energy Resources	ESG
N	2687	2687	2687	2687	2687	2687	2687	2687	2687	2687	2687	2687	2687
Mean	1354.13	20.96	71.58	1992.82	1114.35	1238.11	3.05	88.62	17.32	1.22	2377.26	15.78	51.46
Std	182.05	7.01	22.32	609.01	230.44	330.98	0.56	8.34	7.09	0.11	3420.16	4.02	8.30
Min	1050.8	11.7	18.3	1022.6	791	595.9	1.9	73.1	9.1	1	178.1	7.6	46.2
25%	1225.8	16.3	51.9	1398.5	929.35	933.6	2.6	80.5	13.1	1.1	457.3	13.6	46.4
50%	1296.9	17.8	69.1	2002.3	1017	1180	3	89.9	15.5	1.2	457.3	15.6	46.4
75%	1477.9	23.5	93.3	2476.7	1331.65	1532.75	3.4	96.5	19.1	1.3	3642.95	18.8	55.5
Max	1888.7	48.6	113.9	3386.1	1771	1905.7	4.6	103.6	82.7	1.5	19114.2	30.9	79.6

Table 3. Performance accuracy (ACC %) of different prediction models by period of testing datasets

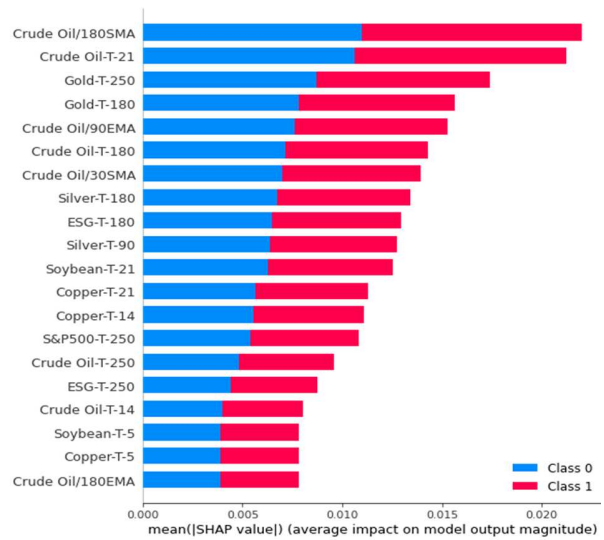
Forecasting period	DA	LR	NN	RF	LightGBM	XGBoost	CatBoost
1-week	91.72	91.72	93.9	93.03	92.81	94.12	93.68
2-week	95.41	94.1	95.41	96.29	96.51	96.29	95.41
3-week	95.86	95.86	97.39	97.39	97.39	98.04	97.82
1-month	96.51	91.48	98.47	97.6	98.25	98.47	98.03
Mean	94.87	93.29	96.29	96.07	96.24	96.73	96.23

Table 4. Area under the ROC curve (AUC) calculated by type of model and by period of testing datasets

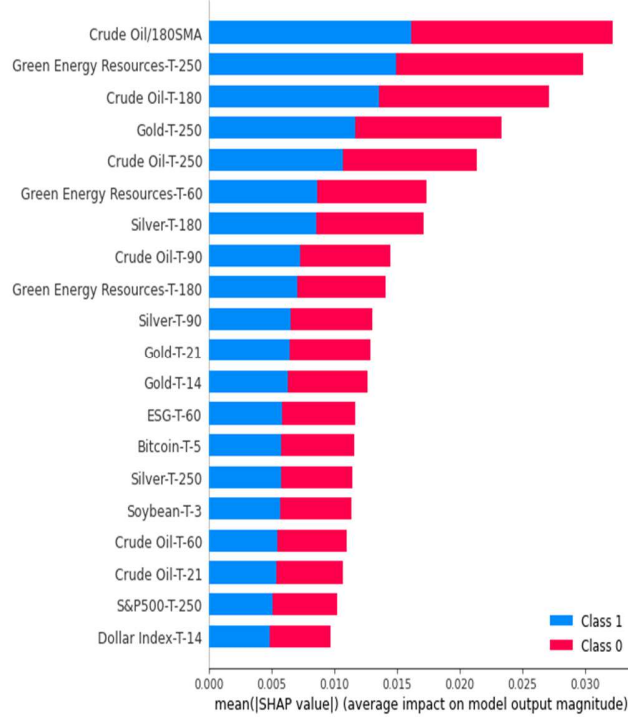
Forecasting period	DA	LR	NN	RF	LightGBM	XGBoost	CatBoost
1-week	0.761	0.698	0.922	0.935	0.910	0.929	0.933
2-week	0.835	0.742	0.900	0.943	0.915	0.932	0.893
3-week	0.872	0.881	0.9232	0.948	0.911	0.908	0.931
1-month	0.954	0.988	0.991	0.996	0.993	0.996	0.991
Mean	0.85	0.82	0.93	0.95	0.93	0.94	0.93



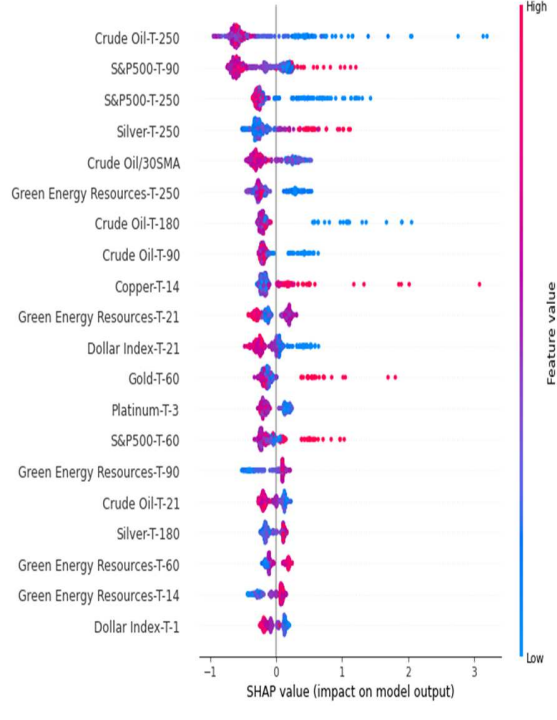
(a)



(b)



(c)



(d)

Figure 3. Contribution of input variables to the oil prices. The “x” axis has the Shapley values. On the other hand, the variables are presented in decreasing order of feature importance on the “y” axis. The high (or low) feature value at that specific data point is shown by the red (or blue) color. Here, (a) features the importance analysis performed using the RF one week before crash; (b) features the importance analysis performed using the RF two weeks before crash; (c) features the i

importance analysis performed using the RF three weeks before crash 3; and (d) features the importance analysis performed using the XGBoost one month before crash.