Energy Pricing during the COVID-19 Pandemic: Predictive Information-Based Uncertainty Indexes with Machine Learning Algorithm

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Abstract

The study investigates the impact of uncertainties on energy pricing during the COVID-19 pandemic using five uncertainty measures that include the COVID-Induced Uncertainty (CIU), Economic Policy Uncertainty (EPU), Global Fear Index (GFI); Volatility Index (VIX), and the Misinformation Index of Uncertainty (MIU). The data, which span between 2-January, 2020 and 19-January, 2021, corresponding to the period of the COVID-19 pandemic. The study finds energy prices to respond significantly to the examined uncertainty measures, with EPU seen to affect the prices of most energy types during the pandemic. We also find predictive potentials inherent in VIX, CIU, and MIU for global energy sources.

Keywords: Coronavirus pandemic; Energy market; Machine Learning; Uncertainty

1.   INTRODUCTION

The SARS-CoV-2 (also known as Coronavirus of 2019 or COVID-19) disease, detected as viral pneumonia in a restaurant in Wuhan city, China; December 2019, transited from an epidemic to a pandemic following the World Health Organization (WHO) declaration on 11-March, 2020.[1] The pandemic caused global economic uncertainty given the rapid rate of spread and death records in most countries of the world (Hallack & Weiss, 2020). Its impact on the energy sector was quite severe, especially on the global prices of oil and petroleum products (Olubusoye et al., 2021). In the early days of COVID-19, when most economic activities were either partially or completely shut down, and various forms of social distancing and isolation measures were put in place, there was a high level of uncertainty that affected both economic production and energy consumption patterns (Hallack & Weiss, 2020).

The restriction of movement during the peak of the pandemic affected the global energy prices, thus modelling energy price dynamics is primary to improving the economic prospects of global energy and ascertaining the predictive potentials of the uncertainty index proxies for energy prices during the global crisis. Fortunately, this study is not in the vacuum of this procedure. Several studies have researched the impact of COVID-19 on the commodity market, (see for instance; Salisu et al., 2020a, and Olubusoye et al, (2021) among others) and other related areas such as misinformation (e.g., Akintande & Olubusoye (2020), Galvão (2020),

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[1] https://www.who.int/news/item/29-06-2020-covidtimeline . Accessed 07/02/2021

among others). Therefore, several extant pieces of literature are detailing different methodological procedures on the subject and COVID-19 related impact on the commodity prices (see Sharif et al., 2020; Salisu et al., 2020; Salisu & Ogbonna, 2019; Yaya et al., 2017; among many others).

In the era of Machine Learning[2] (ML) which is characterized by huge datasets handling with great computational speed, we explore the power of an ML algorithm to examine the volatility of energy prices during the pandemic using the COVID induced uncertainty (CIU) and misinformation induced uncertainty (MIU) indexes as well as other uncertainty proxies such as the global volatility index (VIX), economic uncertainty index (EPU) and the global fear index (GFI). This is premised on the study of Herrera et al. (2019) that empirically showed the outperformance of ML over extant econometric models in the generation of accurate forecasts. The choice of energy variables for this study is informed by its wide usage (residential, commercial/industrial, among others) and the role that energy prices play in economic development since energy adoption cuts across different socioeconomic levels.

By using the power of Google, information searches on the web are harnessed via Google trends. Google trends provide relevant subject-based information from web sources such as web searches. The present study, therefore, harnesses this wealth of information reservoir in Google on the COVID-19 pandemic uncertainty, and subsequently adopts Olubusoye et al., (2021) information-based index of uncertainty (the CIU); and also develops a different variant of MIU. The relevance of these Google trends features (the CIU and MIU) are synonymous with deriving market information on the choice of investment to catalyze decisions making on investment, and related ventures. The MIU could promote disobedience of government guidelines towards controlling or limiting the spreads of COVID-19 leading to continuous lockdown or economic inactivity as evident in the case of the US. The CIU and GFI are considered similar to the VIX and the EPU.

This study employs the aforementioned indexes (the CIU, MIU, VIX, EPU, and the GFI) to examine the vulnerability of energy pricing for different energy proxies (Brent oil, diesel, gasoline, heating oil, kerosene, natural gas, propane, and WTI oil) to COVID-19 pandemic. In

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[2] Several studies (see Herrera et al., 2019; Graf et al., 2020) have adopted different Machine Learning algorithms to model and forecast energy commodity prices, as well as energy systems (see Esen et al. (2017) for a detailed review of ML application to heat pump systems.).

other words, it ascertains whether the adopted and developed uncertainty measures have predictive capabilities for modelling energy prices amidst the COVID-19 pandemic and to what extent they do, as well as the nature of the plausible nexuses between energy prices and uncertainty measures. To achieve this, the study employs the Multivariate Adaptive Regression Spline (MARS) algorithm. This is an ML method that is often used when the relationship of one or more predictor variables to the dependent variable is thought to vary over time. The algorithm accounts for both linear and non-linear relationships of the data features as it provides more predictive power due to its asymmetric structure which induces nonlinearities. Essentially, the adoption of the MARS algorithm is hinged on its characteristic ability to simultaneously account for linearity and non-linearity characteristics of the examined observations, as well as the proven forecast accuracy over econometric models (see Herrera et al., 2019). While it is robust to the presence of outliers, it also incorporates plausible interactions between variables and accounts for important features of the selected best terms. Our study, to the best of our knowledge, is the first study that considers this approach for energy price modelling.

The rest of the paper is sectioned as follows. Section 2 discusses the global energy uncertainty as it is affected by the pandemic. Section 3 describes the MARS algorithm ML method and its application. Section 4 presents the data analysis and the empirical results. Section 5 concludes the paper with some policy recommendations.

2. ENERGY UNCERTAINTY AND COVID-19

Our concern in this paper is the Oil-energy of which prices are subject to the economic forces of supply and demand.[3] Before the COVID-19 outbreak, shale oil and gas has had significant effects on the global oil markets. The rising popularity of renewable energy as alternatives to oil-based energy sources is also putting pressure on the global oil market (Akintande et al., 2020, Olanrewaju et al., 2019, etc.). Thus, the already weakened oil-based energy (oil and gas) was significantly affected by the pandemic and the attendant measures put in place to contain it.

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[3] Crude oil distilled into gas, diesel oil, heating oil, kerosene, propane and other fewer hydrocarbons. These are different oil-based energy sources obtained from crude oil markets.

The pricing of each oil-energy source varies depending on fluctuations in the cost of taking the energy source to the market (Plymouth Rock Energy, 2021). During the COVID-19 pandemic, transportation and industrial energy demand declined to almost zero, although, household energy (especially electricity and) demand increased due to stay-at-home advice. The fall in aggregate energy demand due to movement restrictions and total closure of businesses, international travels, and public & private transportation activities, among many others impacted the environment positively as a result of the reduction in vehicular and industrial emissions of carbon dioxide (CO_2) and other poisonous gases. This led to the improvement of air quality in major cities across the world (Chowdhuri et al., 2020; Keremray et al., 2020; Xuelin et al., 2021; and Dang & Trinh, 2021). While quality air is desirable, economic activities and progress are equally important in many countries, essentially for oil-dependent nations like Nigeria, where the falling oil price imposed significant social and economic costs. There are expectations of global economic recovery in 2021, pushing up oil demand and oil prices. However, the downside risks to the global economic recovery and sustained oil price rally is a resurgence of the pandemic that may result in more lockdowns and less oil demand, low access to vaccines, especially in poorer countries, vaccines hesitancy, and spread of variants of COVID-19. Consequently, some experts suggest that there could be an 8% decline in overall energy demand up to the year 2050, as structural changes, occasioned by COVID-19, impact consumption (Olney, 2021).

From the supply perspective, oil and gas supplies were also affected as the number of oil and gas rigs reduced drastically, with the US experiencing a drop from 805 rigs to 265 rigs between December 2019 and June 2020 (Statista, 2020). The pandemic also affected the major supply chain of both oil and gas (IEA 2020); since twenty-two (22) of the twenty-eight (28) global floating production, storage, and offloading vessels under construction in early 2020 were built at shipyards in China, Korea, and Singapore (Nyga-Lukaszewska and Aruga, 2020). However, natural gas prices only dropped mildly, and IEA (2020) reports that the Henry Hub spot price changed from 1.95 USD/million Btu to 1.65 USD/million Btu between 23-January, 2020 and 30-March, 2020.

The collapse of oil prices amid the pandemic and the economic slowdown forced the Organization of Petroleum Exporting Countries (OPEC),[4] and a group of non-OPEC member

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[4] Other crude oil markets are the Brent market in the North sea, in Europe, and the West Texas intermediate market in the US.

countries, led by Russia to agree on historic production cuts, as a way to stabilize prices and cause a reversal in the significant drop in the price of oil to a 20-year low (OPEC, 2020). Between February and March 2020, oil prices hit the lowest price of $10 per barrel in reaction to the COVID-19 pandemic[5]. Energy prices changed quickly in response to news cycles, policy changes, and fluctuations in the world's markets during the pandemic (Bajpai, 2021). According to Heckman (2017), markets for electricity, natural gas, oil, and renewable energy are complicated and characterized by uncertainties in the global economy. Fundamental economic factors such as supply and demand are relatively predictable; however, energy uncertainties, driven by political and regulatory factors, cum financial speculation, make forecasting energy prices more challenging.[6] Other important factors that affect energy pricing include transportation (both commercial and personal), population growth, and seasonal changes (Bajpai, 2021).

Previous studies on energy have affirmed that energy prices are affected by market forces, gas storage, weather forecasts, generation changes, global markets, imports & exports, government regulation, and financial speculation (Heckman, 2017). The literature on the determinants of energy prices and fluctuation are considerably numerous, but the novel coronavirus has opened the field up for more debates on energy price uncertainty. The introduction of indexes in monitoring global economic activities could be a tool to understanding the new trend of research on energy prices due to the structural changes caused by COVID-19. Interestingly, there are various indexes for monitoring global uncertainty. We are in an era of unprecedented economic uncertainty, and particularly, with the energy sector. Performances of the global economy have been influenced by oil price shocks, health crises such as the Spanish flu and COVID-19, war, and political issues, among others this, therefore, necessitated developing global indices of uncertainty. Salisu & Akanni (2020) developed the GFI by leveraging the ongoing pandemic. They computed the index as a ratio of the number of confirmed COVID-19 cases and the number of recorded deaths. Olubusoye, et al. (2021) developed the CIU index and applied it to examine the vulnerability of energy prices during the pandemic period. In comparison with EPU, GFI, and VIX index, their results showed that energy prices lack hedging potentials against the uncertainty occasioned by the COVID-19 pandemic and the sensitivity of CIU to energy prices.

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[5] In fact, at some point the price of WTI crude oil went into negative territory.
[6] The previous similar case of a global pandemic was the Spanish Flu of 1918.

The importance of energy prices and the decline in demands due to pandemic-associated uncertainties serves as a motivation to investigate how uncertainty indexes impact energy prices. This study develops similar indexes to Salisu & Akanni (2020) but differs in the computational method and the variables under consideration. Many existing indexes (leveraged on the COVID-19) are computed based on reported infection and mortality figures. These indexes are limited. Since access to quality information (Akintande & Olubusoye, 2020) is most likely to affect an individual's perception and decision more than the infection and mortality figures. Thus, misinformation may catalyze the understanding of investment risks (Norouzi et al., 2020). Consequently, the yearnings for quality information about the pandemic forms an essential level of uncertainty.

3. METHODOLOGY

Multivariate Adaptive Regression Spline (MARS) is a form of the regression model (Friedman, 1991) used in Machine Learning. In contrast to other linear techniques, the MARS model is an extension of the linear model technique that explicitly and simultaneously incorporates linearity as well as nonlinearities and interactions between variables. Also, the MARS model is well suited to handle both continuous and categorical observations; that is, categorized output $\{Y_{cat}\}$ as well as continuous output $\{Y_{met}\}$; and is more flexible and quite easy to interpret. It provides interactive plots for model performances and performs important variables selection. Thus, it automatically discards or excludes unimportant variables in the final model. Due to its forward and backward process, it tends to provide a better bias-variance trade-off compared to other linear techniques. Like some methods (e.g., BMA), it can handle fairly large datasets (e.g., 100 predictors and 10^5 observations). Lastly, the presence of outliers in a dataset does not affect the MARS model since it typically partitions the data into disjoint regions.

3.1 MARS Mathematical procedure:

Given X and Y; independent and dependent variables, respectively; MARS relies on a hypothesis of the form:

$$\hat{g}(X) = \sum_{i=1}^{m} k_i \gamma_i(X) \tag{1}$$

where γ_i is the basis function weighted sum, and k_i's are constant coefficients. The basis function γ_i has one of the following forms; (1) a constant, (2) a hinge function, (3) and a product of two or more hinge functions. The hinge function has the form;

$$\text{max}(0, \text{X-constant}) \text{ or max}(0, \text{constant } –X). \tag{2}$$

MARS swiftly picks variables and values of those variables for knots of the hinge function, while the 'basis' functions can model the interactions between two or more variables of interest. Hinge functions are the main component of the MARS models. Thus, the number of hinges is formed to determine the number of linear models for the MARS algorithm. Essentially, if we say we have Y = f(X), then the hinge function is h(X-a), where "a" is the cut-off point value; and for a single knot, the hinge function will result in two linear models for Y, that is,

$$Y = \begin{cases} \gamma_0 + \gamma_1 (a - X) \ X < a \\ \gamma_0 + \gamma_1 (X - a) \ X > a \end{cases} \tag{3}$$

Once the first knot has been obtained, the search continues for a second knot that is obtained at $X = a_2$. This results in three linear models for Y as in (4). This process continues until a potential and highly non-linear prediction equation is achieved. While obtaining several knots is possible, the MARS algorithm introduces pruning, to find the optimal number of knots and removes the insignificant knots to arrive at the best predictive accuracy.

$$Y = \begin{cases} \gamma_0 + \gamma_1 (a - X) \ X < a \\ \gamma_0 + \gamma_1 (X - a) \ X > a \ \ and \ X < a_2 \\ \gamma_0 + \gamma_1 (a_2 - X) \ X > a_2 \end{cases} \tag{4}$$

3.2   MARS model building process

MARS builds a model in two phases namely; the forward and the backward pass. These two stages bear some semblances in recursive partitioning trees (Friedman, 1991). The forward MARS model starts with the intercept term (i.e., the mean of the response values). It then repeatedly sums the basic functions in pairs to the model. In each step, it computes the pair of basic functions (γ_i), which provides the maximum reduction in the sum of squares residual error (sort of greedy algorithm – see Black (2005)). The two basic functions are expected to be identical except that each is on a different part of the mirrored hinge function. Thus, a hinge function is defined by a variable and a knot. MARS searches parent terms, all variables (to pick one for the new, γ_i), and all values of each variable (for the knot of the new hinge function) to compute the coefficient of each term by applying a linear regression over the parents. This term's summation iterates until the change in residual error are reduced. In other words, the process terminates when the maximum number of terms (parents) is reached. Note that the maximum possible terms are usually specified by the users before the MARS iteration starts.

This task is faster if a more rational procedure is adopted (Friedman, 1993). Figure 1 presents an illustration of MARS predictive strength at different knots level.
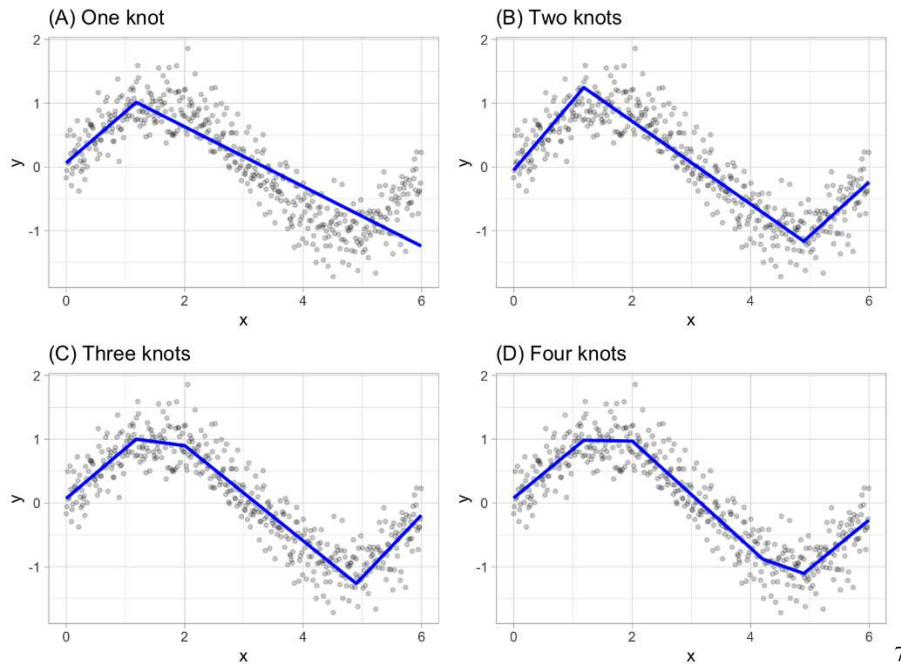
Figure 1: (A) Traditional linear regression approach which captures the little or no nonlinearity content of the distribution. (B) Degree-2 polynomial, (C) Degree-3 polynomial, (D) Step function cutting x into six categorical levels[8]

The backward process proposes to solve the over-fitting problem of the forward process. Hence, the backward process prunes the hypothesis. It removes the terms one after the other, by deleting the least efficient term at each step until it reaches the best sub-hypothesis. The hypothesis subsets are assessed with the generalized cross-validation (GCV) criterion (Craven & Wahba, 1978). Thus, the algorithm for the GCV is given as:

$$GCV = \frac{Residual\ sum\ of\ squares\ (RSS)}{(M\ (1-(E)/M)^2)} \tag{5}$$

where E - efficient number of parameters, and M – number of observations.

and $E = N_m + P\frac{(N_m-1)}{2}$, where N_m – number of MARS terms, and P – penalty. The $\frac{(N_m-1)}{2}$ is the number of hinge–function knots. Note that for the penalty, about 2 or 3 is allowable.

4.   DATA AND RESULTS

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[7] The bend in the graph represents the hinge which accounts for the nonlinearity in the observation. As shown, the predicted line accounts for all the data points, unlike the pure linear trend.

[8] https://bradleyboehmke.github.io/HOML/mars.html

The data employed in this study are daily energy (Brent, Diesel, Gasoline, Heating Oil, Kerosene, Natural Gas, Propane and WTI) prices and uncertainty measures (COVID-Induced Uncertainty – CIU; Economic Policy Uncertainty – EPU; Global Fear Index – GFI; Volatility Index – VIX; and Misinformation Index of Uncertainty-MIU). The dataset spans 2-January, 2020 to January 19, 2021, which corresponds to the period of the COVID-19 pandemic. We extract the energy prices from www.investing.com. The EPU (based on the frequency of usage of economic, policy, and uncertainty-related keywords in major newspapers in the United States) and VIX (measures the global market expectation of near-term volatility conveyed by stock index option prices). We obtained both indices from the Federal Reserve Bank of StLouis Economic Database (FRED) website. The GFI (health news-related index) from Salisu & Akanni (2020) and CIU (based on Google trends search volume) from the procedure described in Olubusoye et al. (2021). It is informed by the perceived connectedness and possible bidirectional causality of uncertainty and misinformation, as the latter is likely to spur the former, while the uncertainty could breed an opportunity for misinformation (see Akintande & Olubusoye, 2020). Hence, we consider search volumes on the Google Trends database relating to misinformation around the COVID-19 pandemic, using keywords such as "COVID-19 Fake news", "Fake news", "COVID-19 Myth", "COVID and Age", "COVID and Race" and "COVID and Bleach". Following Olubusoye et al. (2021) and Salisu et al. (2021), we generate a single factor from the principal component analysis of these search volumes. This factor is re-scaled to range between "a" and "b", using

$$MIU_{scaled} = (b - a) \left[\frac{MIU_{unscaled} - \min(MIU_{unscaled})}{\max(MIU_{unscaled}) - \min(MIU_{unscaled})} \right] + a \qquad (6)$$

such that a = 0 and b = 100 correspond extreme cases of no misinformation and the highest level of misinformation, respectively.

## 4.1 Exploratory Data Analysis on Energy Prices

Between January 2, 2020, and January 19, 2021, the price of Brent fluctuates between 9.12 and 70.25 USD per barrel. The price resonates around 50.88 USD and is valued averagely between 42.34±0.73 and 42.72±0.73 USD per barrel. The WTI price fluctuates between -36.98 (reaching zero USD) and 63.27 USD per barrel. The price around this period resonates at 49.59 USD and is valued between 39.85±0.697 and 40.785±0.697 per barrel. While the lowest price of Brent hit 9.12 USD per barrel, the price of a barrel of WTI during this period cost less than 1 USD.

Also, the diesel price fluctuates between 0.54 USD and 1.97 USD per litre. The price resonates around 1.436 USD per litre and is valued averagely between 1.25±0.017 and 1.178±0.017 USD per litre. The gasoline price fluctuates between 0.364 and 1.729 USD per litre. The price resonates around 1.1145 USD per litre and is valued averagely between 1.1419±0.0183 and 1.1738±0.0183 USD per litre. Table 1 presents the detailed statistics of the energy prices.

Table 1: Statistics on energy prices

Statistics	BRENT	DIESEL	GASOLINE	HEATING_OIL	KEROSENE	NGAS	PROPANE	WTI
Mean	42.3371	1.2125	1.1419	1.2141	1.1167	2.0696	0.4834	39.8560
Stand Error	0.7297	0.0168	0.0183	0.0171	0.0195	0.0252	0.0078	0.6974
Median	42.7200	1.1775	1.1738	1.1585	1.0810	1.9300	0.4930	40.7850
Mode	50.8800	1.4360	1.1140	1.1840	1.4380	1.9300	0.5130	49.5900
Kurtosis	0.0773	0.1071	0.0858	0.4725	0.0637	-0.5078	2.1658	6.6701
Skewness	-0.3247	0.3906	-0.6752	0.7050	0.2869	0.7396	0.9106	-1.4691
Minimum	9.1200	0.5400	0.3640	0.5620	0.4070	1.3300	0.2030	-36.9800
Maximum	70.2500	1.9740	1.7290	2.0390	1.9720	3.1400	0.9580	63.2700

Figure 2 shows the energy price trends during the period under consideration. All the energy sources experience a significant downward trend, falling from their various top prices to the new lowest prices within the study period. Meanwhile, all the energy sources likewise experience peaks from the low trend, trending upward and regaining the previous highs. While (during the study period), the upward trends are evident, and no energy (sources) price has rebound to its initial high as when writing this paper.
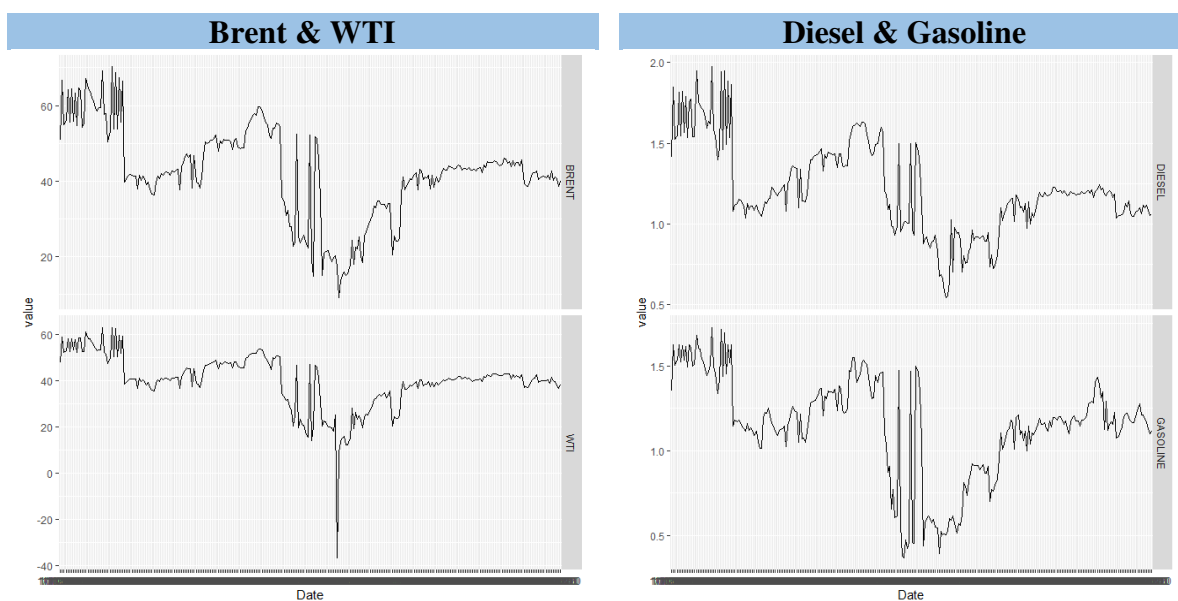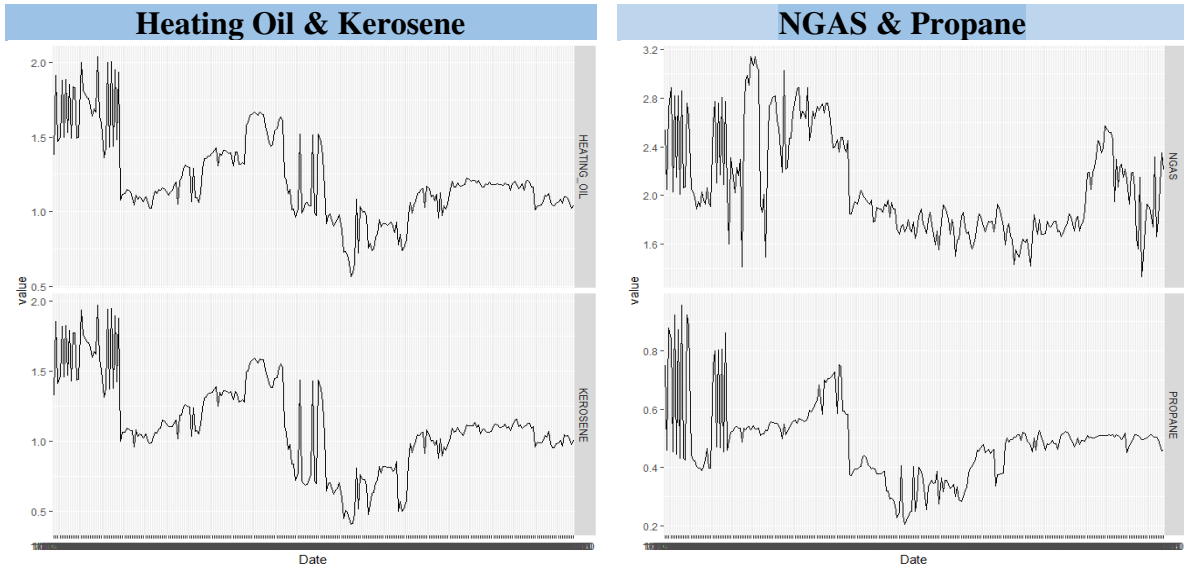
Figure 2: Time plot of the outputs

The crux of this study is to obtain a predictive accuracy of the impact of the uncertainties on various energy prices. We present the predictive hypothesis of the MARS algorithm in Section 3.2. We modelled the algorithm using the K-fold CV scheme, and the best folds are reported based on the RMSE and MAE values. Most importantly, the 10-folds CV is more favorable except for NGAS and Propane, where we adopt the 5-folds CV for the best predictive model. Similarly, this approach facilitated picking the most appropriate prune and degree for the final predictive hypotheses by setting the degree between 1 and 3 and the prune between 2 and 100. Essentially, the best MARS algorithm pruning and degree (to find the optimal number of knots) follows standard algorithmic procedures. And free from authors' bias and influence.

4.2 Results & Discussion

On the resulting figures on the tables (Tables 2 – 9), we obtain the impact of a given uncertainty measure on the considered energy price by taking the product of the knot/hinges (main and interactions) value and the estimated coefficients. It is noteworthy to state that the positively (negatively) signed coefficients will imply that a corresponding uncertainty measure would increase (decrease) in the energy price. We highlighted the model adequacy (GRSq., RSq., RMSE and MAE); and the order of importance for each uncertainty measure. The GRSq. and RSq. Values should be closer to one, and the RMSE and MAE values close to zero for a model are adequate. The order of importance shows the most preferred uncertainty measures among the contending measures. In tandem with the design framework of the algorithm, estimations occur on the relevant variables, and redundant variables are automatically suppressed.

Recall that the number of hinges formed; determine the number of optimal linear hypotheses for the MARS algorithms. Consequently, the optimal hinges for the predictive model in Brent price give fourteen optimal linear models (from seven single feature effects and seven bi-feature interactions). Essentially, the CIU, MIU, and VIX directly influence the price of Brent. In other words, CIU, MIU, and VIX cause a bidirectional effect on the Brent price. In actual term, when the Brent price is bullish, a unit increase in CIU, MIU and VIX lead to a 10.76 increase (i.e., 2.2*4.58, see eq. (1)), 5.70 and 21.52 USD respectively/individually, price recovery of Brent holding "k-1" features constant at every reference. And when the price of Brent is bearish, a unit increase in CIU, MIU and VIX gives 0.704, 1.404, and 44.97USD, respectively/individually, decrease in Brent price holding "k-1" features constant at every reference. Essentially, the effect of these uncertainties (CIU, MIU, and VIX) on Brent price is bidirectional.

Note that the shock (knot) effect gives the true impact of the features (inputs) on the outcome. The higher the knot, the higher the influence of the uncertainty (negative or positive values) given the coefficient value. The result shows that EPU causes the most significant shock leading to a consistent 7.60USD (i.e., 172.45*0.044061) decline in Brent price. Similarly, the shock effect of VIX follows that of EPU, leading to a 44.97USD decrease in Brent price and a 21.80USD increase in Brent price. As observed, unlike the EPU, the VIX has a bidirectional effect. Again, the GFI and EPU jointly have a shock of 66.28. That is, a (7.60 + 0.096) USD consistent decline in Brent price. The effect of both EPU and GFI indices are unidirectional; see Table 2.

Table 2: Brent result

Knot/hinges – nonlinear	Coefficients
(Intercept)	51.002883
h(2.2-CIU)	4.583367
h(CIU-2.2)	-0.323164
h(16.61-MIU)	0.343269
h(MIU-16.61)	-0.084455
h(EPU-172.45)	-0.044061
h(41.38-VIX)	0.526807
h(VIX-41.38)	-1.086791
Interactions	
h(69.08-CIU) * h(EPU-172.45)	0.001151
h(CIU-2.2) * h(VIX-26.87)	0.012514
h(53.68-CIU) * h(41.38-VIX)	-0.007875
h(CIU-53.68) * h(41.38-VIX)	0.040351
h(MIU-16.61) * h(EPU-498.71)	0.001507
h(EPU-172.45) * h(66.28-GFI)	-0.001450
h(EPU-172.45) * h(37.19-VIX)	0.003116
GCV (degree)	14.7747 (2)
GRSq [RSq]	0.8991 [0.9233]
Importance (ordered):	EPU, VIX, GFI, CIU, MIU
CV - RMSE [RSq.]MAE	0.0383[0.9253]0.0284

Model Selection
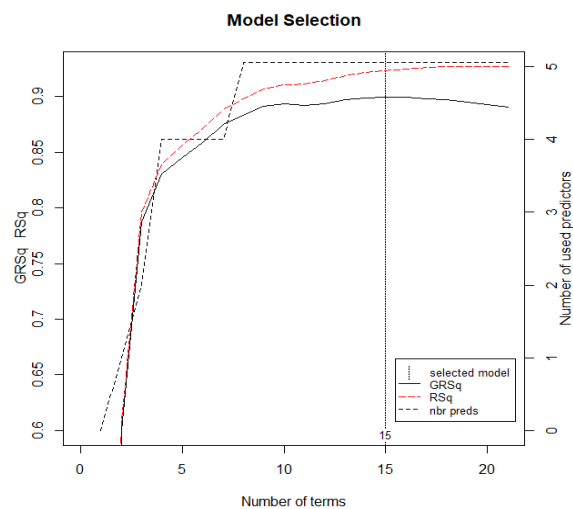
As observed, CIU and EPU result in 78.41 and 596.78 shock effects, respectively, leading to a 0.2346 and 1.7856 USD decline in WTI price. The impact of CIU and VIX leads to a 3.28USD and 1.886USD decrease in WTI price. Similarly, the effect of EPU and VIX leads to a 2.462 and 0.162 USD decline in WTI price. The associative impact of CIU & EPU and EPU & VIX jointly have a bidirectional effect on the price of WTI. The GFI has no significant direct or joint effect on WTI price. Thus, CIU accounts for a 7.76USD increase in WTI price, and MIU accounts for a 5.955USD increase in WTI price. Also, EPU accounts for 23.149USD, and VIX accounts for a 46.140USD increase in the price of WTI. The decline and recovery plot (in Figure 1) and the results (in Table 3).

Table 3: WTI result

Knot/hinges – nonlinear	Coefficients
(Intercept)	-246.474610
h(CIU-2.2)	3.525026
h(69.75-CIU)	3.500012
h(CIU-69.75)	-2.220389
h(66.48-MIU)	0.089574
h(596.78-EPU)	0.067391
h(EPU-596.78)	0.038789
h(43.35-VIX)	1.886762
h(VIX-43.35)	1.064365
Interactions	
h(69.75-CIU) * h(EPU-251.39)	0.002992
h(CIU-78.41) * h(596.78-EPU)	-0.004242
h(CIU-69.75) * h(VIX-40.11)	-0.047026
h(CIU-69.75) * h(40.11-VIX)	-0.029630
h(596.78-EPU) * h(VIX-39.16)	-0.004125
h(596.78-EPU) * h(39.16-VIX)	-0.002490
h(596.78-EPU) * h(VIX-26.87)	0.002657
GCV [degree]	21.1781 [2]
GRSq [RSq]	0.84164 [0.8822]
Importance (ordered):	EPU, VIX, CIU, MIU, GFI-unused
CV - RMSE [RSq.]MAE	0.0264 [0.9462] 0.0215
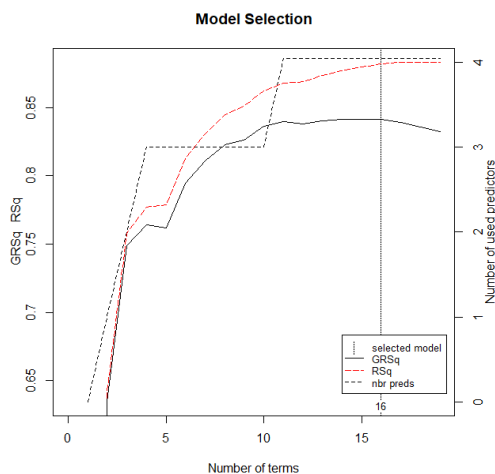
The best predictive algorithm for NGAS price is degree 1 (Brent and WTI are of degree 2). It implies that the effect of the features is insignificant. Thus, CIU has a shock of 62.45, which leads to a 4.1037 USD decline in NGAS and 4.2775USD in NGAS recovery price. The MIU effect leads to 0.3379USD in NGAS recovery. Similarly, the EPU effect leads to a 0.399USD decrease in NGAS price and 0.6806USD NGAS recovery price.

Table 4: NGAS result

| Knot/hinges –nonlinear	Coefficients
(Intercept)	2.54709738
h(62.45-CIU)	-0.02064713
h(CIU-62.45)	-0.06571141
h(CIU-66)	0.06481052
h(42.44-MIU)	0.00796101
h(EPU-157.55)	-0.00253430
h(EPU-329.62)	0.00206467
h(VIX-25.07)	-0.31606312
h(VIX-26.87)	0.80574047
h(27.51-VIX)	0.02801732
h(VIX-27.51)	-0.46427120
h(VIX-38.02)	-0.02823369
GCV [degree]	0.0926 [1]
GRSq [RSq]	0.4692 [0.5513]
Importance (ordered):	EPU, CIU, VIX, MIU, GFI-unused
CV - RMSE [RSq.]MAE	0.00297 [0.4962] 0.0022
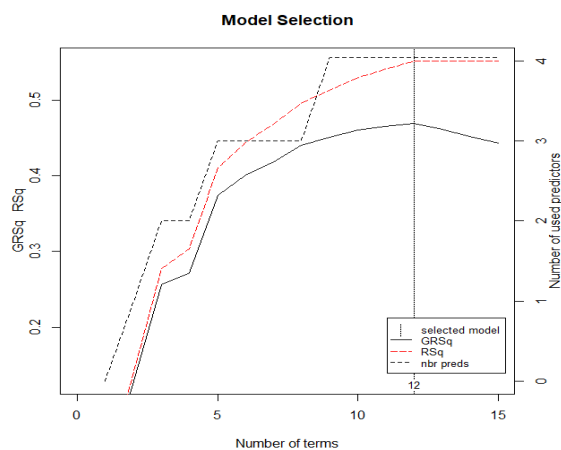
The effect of VIX leads to a 1.0734 USD decline in NGAS price and a 0.7708USD increase or price recovery of NGAS. The GFI has no significant direct influence on NGAS price. The effects of all the uncertainty proxies except MIU are bidirectional (see Table 4).

Diesel price is most affected by VIX, EPU, and MIU, respectively. The EPU index has the most significant (knot) effect of 511.42, causing a 0.5762USD increase/recovery. The CIU has a direct and bidirectional effect on diesel price, causing a 0.2976USD and 0.00601 increase

and decline in diesel price, respectively. The MIU (0.1706 USD) and VIX (2.1288 USD) also have a direct price recovery effect on diesel prices. Similarly, CIU and GFI indices have a price recovery effect on diesel price, and the pairs [CIU & VIX], [MIU & GFI], and [EPU & VIX] have a price decline effect on diesel price. We present the detailed results on the diesel price in Table 5.

Table 5: Diesel result

| Knot/hinges - nonlinear	Coefficients
(Intercept)	1.03277020
h(2.2-CIU)	0.13529324
h(CIU-2.2)	-0.00273221
h(16.61-MIU)	0.01027168
h(511.42-EPU)	0.00112658
h(29.35-VIX)	0.07253306
Interactions	
h(CIU-2.2) * h(GFI-52.14)	0.00005672
h(44.57-CIU) * h(29.35-VIX)	-0.00154725
h(CIU-44.57) * h(29.35-VIX)	-0.00163514
h(MIU-16.61) * h(54.28-GFI)	-0.00058452
h(511.42-EPU) * h(VIX-34.4)	-0.00002310
h(511.42-EPU) * h(34.4-VIX)	-0.00014700
h(CIU-44.57) * h(EPU-348.4) * h(29.35-VIX)	0.00001274
h(48.79-CIU) * h(511.42-EPU) * h(34.4-VIX)	0.00000288
h(CIU-48.79) * h(511.42-EPU) * h(34.4-VIX)	0.00000656
GCV [degree]	0.00961 (3)
GRSq [RSq]	0.8756 [0.9055]
Importance (ordered):	VIX,EPU,MIU,GFI,CIU
CV - RMSE [RSq.]MAE	0.00079[0.9256]0.0005
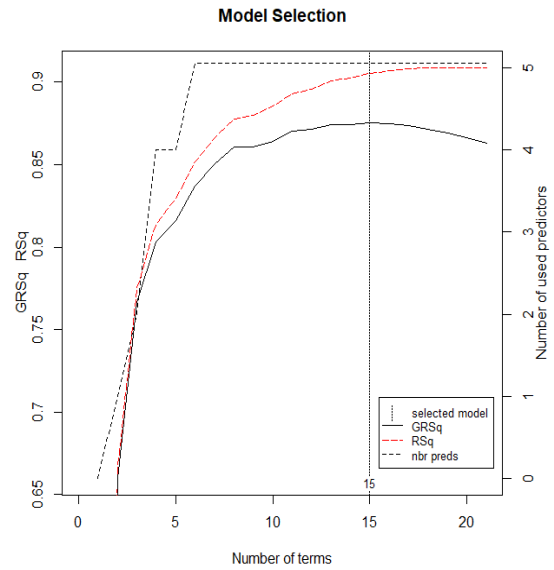
EPU, VIX, CIU, MIU, and GFI, respectively, affect the price of gasoline. Only the CIU index has a bidirectional effect. The CIU & GFI, MIU & VIX jointly cause the decline in gasoline price, and CIU & VIX, EPU & GFI, and EPU & VIX jointly cause the gasoline price recovery. In some senses, CIU leads to a 0.1989USD increase and causes a 0.0199 decline in gasoline price. MIU and EPU cause 0.3824USD and 0.4963USD, respectively, gasoline price recovery. Similarly, the GFI index causes a 0.5285USD decrease in gasoline price. Meanwhile, the pairs [CIU & GFI] and [MIU & VIX] jointly caused 0.02460USD and 0.1034USD, respectively, a decline in gasoline price (see Table 6).

Table 6: Gasoline result

Knot/hinges - nonlinear	Coefficients
(Intercept)	0.88001332
h(3.94-CIU)	0.05047976
h(CIU-3.94)	-0.00505902
h(27.85-MIU)	0.01373142
h(596.78-EPU)	0.00083164
h(88.32-GFI)	-0.00598417
h(54.46-VIX)	0.01534076
Interactions	
h(CIU-50.74) * h(88.32-GFI)	-0.00017693
h(CIU-49.97) * h(54.46-VIX)	0.00051548
h(33.94-MIU) * h(54.46-VIX)	-0.00030487
h(MIU-33.94) * h(54.46-VIX)	-0.00011699

|	
h(440.07-EPU) * h(88.32-GFI)	0.00001830
h(341.68-EPU) * h(54.46-VIX)	0.00004126
GCV [degree]	0.0114 [2]
GRSq [RSq]	0.8759 [0.9017]
Importance (ordered):	EPU, VIX, CIU, MIU, GFI
CV - RMSE [RSq.]MAE	0.00086[0.9319]0.00067

Model Selection
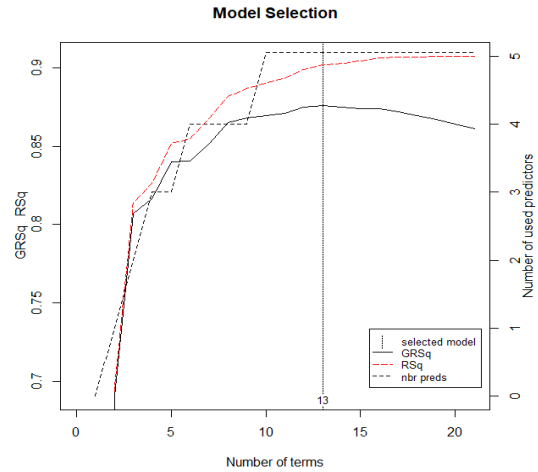
VIX, EPU, MIU, GFI, and CIU respectively affect the heating oil price. Both the CIU and VIX indices have a bidirectional effect. Other uncertainty proxies with direct effects have a unidirectional impact on the heating oil price. Thus, [CIU & VIX], [MIU & GFI], and [EPU & VIX] jointly cause the decline in heating oil price, and the pairs [CIU & GFI] and [CIU, EPU & VIX] impact heating oil price recovery. In actuality, CIU leads to a 0.2501USD heating oil recovery price. VIX leads to a 2.018USD price recovery and 0.1825USD decline in heating oil price. Similarly, EPU causes 0.4495USD in heating oil recovery price. More so, in actual sense, the pairs [CIU & VIX], [MIU & GFI], and [EPU & VIX] jointly cause 0.1013USD, 0.0409USD and 0.1062USD, respectively, decline in heating oil price. Similarly, [CIU & GFI] and [CIU, EPU & VIX] jointly cause 0.00350USD and 0.00253USD, respectively (see Table 7).

Table 7: Heating oil result

Knot/hinges – nonlinear	Coefficients
(Intercept)	-5.2837403
h(CIU-2.2)	0.1136647
h(56.66-CIU)	0.1213670
h(CIU-56.66)	-0.1108185
h(511.42-EPU)	0.0008789
h(28.23-VIX)	0.0714791
h(VIX-28.23)	-0.0064665
Interactions	
h(CIU-2.2) * h(GFI-52.14)	0.0000644
h(53.68-CIU) * h(28.23-VIX)	-0.0012367
h(CIU-53.68) * h(28.23-VIX)	-0.0017166
h(MIU-17.73) * h(54.88-GFI)	-0.0005639
h(511.42-EPU) * h(31.46-VIX)	-0.0001956
h(44.57-CIU) * h(511.42-EPU) * h(31.46-VIX)	0.0000043
h(CIU-44.57) * h(511.42-EPU) * h(31.46-VIX)	0.0000060
GCV [degree]	0.0114 [2]
GRSq [RSq]	0.8759 [0.9017]
Importance (ordered):	VIX, EPU, MIU, GFI, CIU
CV - RMSE [RSq.]MAE	0.00084[0.9246]0.00067

Model Selection
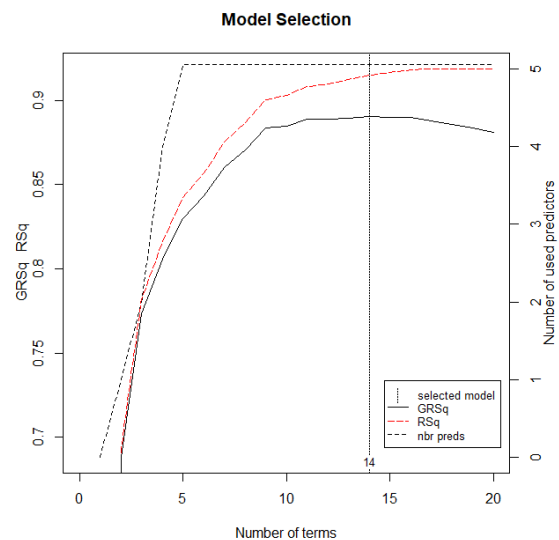
The price of kerosene is affected by EPU, VIX, CIU, MIU, and GFI, with CIU, MIU, and EPU having direct bidirectional effects on kerosene price. Similarly, EPU and GFI jointly have a bidirectional effect on kerosene prices. Other uncertainties have a unidirectional impact on kerosene prices. Thus, while CIU causes a 0.3132USD increase and a 0.016323USD decline in kerosene price, MIU causes a 0.2278USD increase and a 0.03056USD decline in kerosene price, and the EPU causes a 0.3414USD increase (recovery) and 0.6947USD decrease in kerosene price. The impact shows that EPU and GFI indices cause a 0.0458USD decline and a 0.0463USD recovery in kerosene price. The pairs (CIU & VIX) and (EPU & VIX) cause 0.1055USD and 0.01569USD recovery in kerosene price, respectively (see Table 8).

Table 8: Kerosene result

Knot/hinges - nonlinear	Coefficients
(Intercept)	1.44502826
h(2.2-CIU)	0.14236327
h(CIU-2.2)	-0.00741944
h(CIU-48.94)	0.00789137
h(15.17-MIU)	0.01501323
h(MIU-15.17)	-0.00201441
h(EPU-184.25)	-0.00185308
h(EPU-498.71)	0.00139297
Interactions	
h(CIU-44.57) * h(28.23-VIX)	0.00144977
h(EPU-184.25) * h(GFI-52.33)	-0.00019361
h(EPU-184.25) * h(GFI-49.25)	0.00019840
h(EPU-184.25) * h(37.13-VIX)	0.00007088
GCV [degree]	0.01097 [2]
GRSq [RSq]	0.8952 [0.9153]
Importance (ordered):	EPU,VIX,CIU,MIU,GFI
CV - RMSE [RSq.]MAE	0.00069[0.9581]0.00057
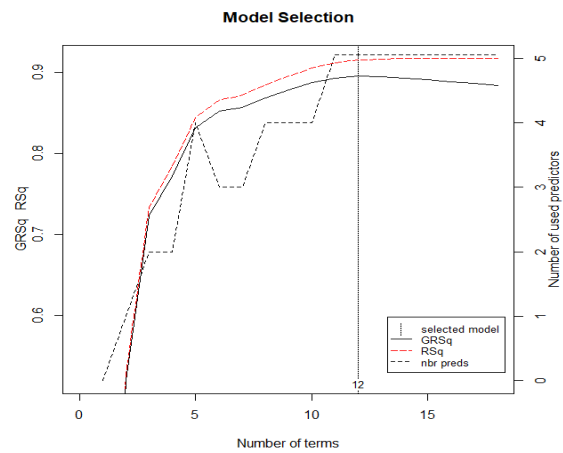
VIX, CIU, EPU, MIU, and GFI, respectively, impact propane price. CIU, EPU, GFI, and VIX have unidirectional and inverse effects on propane prices. On the other hand, the impact of the uncertainty proxies has direct relationships with propane prices. In short, CIU, EPU, GFI, and VIX directly and individually cause 0.3348USD, 0.0892USD, 0.2870USD, and 0.1359USD decline in the propane price.

Table 9: Propane result

Knot/hinges – nonlinear	Coefficients
(Intercept)	0.72536789
h(76.6-CIU)	-0.00437080
h(CIU-76.6)	-0.00478426
h(EPU-161.46)	-0.00055270
h(74.12-GFI)	-0.00387226
h(VIX-21.53)	-0.00631406
Interactions	
h(CIU-66.54) * h(29.11-MIU)	0.00077857
h(76.6-CIU) * h(EPU-108.1)	0.00001626
h(26.15-MIU) * h(74.12-GFI)	0.00019600
h(EPU-498.71) * h(VIX-21.53)	0.00002148
GCV [degree]	0.00584 [2]
GRSq [RSq]	0.6463 [0.7022]
Importance (ordered):	VIX, CIU, EPU, MIU, GFI
CV - RMSE [RSq.]MAE	0.00058[0.810]0.00044
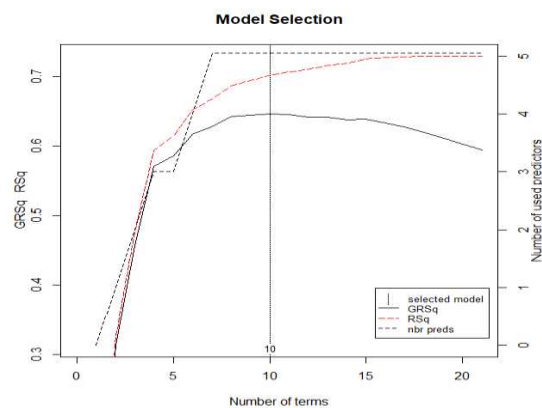
5. CONCLUSION AND POLICY IMPLICATION

The study investigates the effect of uncertainty on energy prices using eight energy prices - Brent oil, Diesel, Gasoline, Heating Oil, Kerosene, Natural Gas, Propane, and WTI oil; and with five different uncertainty measures - COVID Induced Uncertainty (CIU), Economic Policy Uncertainty (EPU), Global Fear Index (GFI), Volatility Index (VIX), and Misinformation Index of Uncertainty (MIU). Given that misinformation spread during the pandemic, we develop the MIU. We formulated the hypothesis using all the uncertainty proxies as input and the energy prices as output. The descriptive statistics of the energy prices reveals

that the trend throughout the study is bidirectional. Imperatively, each energy price has unique characteristics of downward (price decline) and upward (price recovery) movement. Essentially, the hypotheses on the energy prices reveal that uncertainty affects energy prices in both ways.

More formally, we examined the nexus between the energy prices and uncertainty proxies under the ML algorithm. In addition, it reveals the impact of each uncertainty proxy and indicates an ordering of their importance in the predictive model for energy prices. While we find most of the uncertainty measures to have the predictive potential for the energy prices, this is not true for GFI. It may not be unconnected with its health inclination that limits its predictive potential for energy prices. Hence, it should be employed when dealing with health-related phenomena. The order of inherent predictive power in the included uncertainty proxies appears to be sensitive to the energy price under study. As observed, the EPU influences the predictive fluctuations in most of the energy price uncertainty during the pandemic. The VIX, CIU, MIU, and GFI follow the EPU in that order. The contributing influence of the EPU is not surprising because many policies are proffer quickly to arrest the spread of the disease, which may have heightened the uncertainty around economic activities - a characteristic feature that informed the development of the EPU. The other uncertainty proxies are not specific to the energy sector as much as the EPU. Hence their observed position in the ordering of their relevance. Generally, energy prices' responses to economic uncertainties are mostly bi-directional.

In contrast to the findings of Olubusoye et al. (2021) and Salisu et al. (2020) that assume linear nexus between energy prices and economic uncertainty measures; and respectively found negative and positive responses of energy commodity prices to uncertainty measures, ML further beams the light on the non-linear nature of the nexus, as well as the existence of time-varying parameter. Hence, the plausibility of both positive and negative responses that depict a bullish and bearish period in the energy price series. Therefore, given the reaction of energy prices on uncertainty and (more prominently) economic policy uncertainty, our findings bear some implications for policymakers. Policies that affect economic productivity are most likely to affect energy pricing since most products are; either energy-dependent or energy-related. Hence, while attempting to curtail a crisis (epidemic or pandemic), the economic activities should inescapably remain active but not be halted. Efforts such as a virtual working environment and adoption should (from now) remain a viable option.

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