An Information-Based Index of Uncertainty and the predictability of Energy Prices

Olubusoye, Olusanya E and Yaya, OlaOluwa S. and Ogbonna, Ahamuefula

University of Ibadan, University of Ibadan, University of Ibadan

February 2021

An Information-Based Index of Uncertainty and the predictability of Energy Prices

Olusanya E. Olubusoye
Laboratory for Interdisciplinary Statistical Analysis, Department of Statistics, University of Ibadan, Ibadan, Nigeria & Computational Statistics Unit, Department of Statistics, University of Ibadan, Nigeria
& Centre for Econometric and Allied Research, University of Ibadan, Ibadan, Nigeria & Centre for Petroleum, Energy Economics and Law, University of Ibadan, Ibadan, Nigeria
Email address: busoye2001@yahoo.com

OlaOluwa S. Yaya
Computational Statistics Unit, Department of Statistics, University of Ibadan, Nigeria
& Centre for Econometric and Allied Research, University of Ibadan, Ibadan, Nigeria & Centre for Petroleum, Energy Economics and Law, University of Ibadan, Ibadan, Nigeria
Email address: o.s.olaoluwa@gmail.com

Ahamuefula E. Ogbonna
Centre for Econometric and Allied Research, University of Ibadan, Ibadan, Nigeria & Economic and Statistics Unit, Department of Statistics, University of Ibadan, Ibadan, Nigeria & Centre for Petroleum, Energy Economics and Law, University of Ibadan, Ibadan, Nigeria
Email address: ogbonnaephraim@yahoo.com

Ahamuefula E. Ogbonna
Economic and Statistics Unit, Department of Statistics, University of Ibadan, Ibadan, Nigeria

ABSTRACT

We develop an index of uncertainty, the COVID-19 induced uncertainty (CIU) index, and employ it to empirically examine the vulnerability of energy prices amidst the COVID-19 pandemic using a distributed lag model that jointly accounts for conditional heteroscedasticity, autocorrelation, persistence, and structural breaks, as well as day-of-the-week effect. The nexus between energy returns and uncertainty index is analyzed, using daily price returns of eight energy sources (Brent oil, diesel, gasoline, heating oil, kerosene, natural gas, propane, and WTI oil) and four news/information-based uncertainty proxies [CIU, EPU, Global Fear Index (GFI) and VIX]. The CIU and alternative indexes are used, respectively for the main estimation and sensitivity analysis. We show the outperformance of CIU over alternative news uncertainty proxies in the prediction of energy prices. News (aggregate) and bad news are found to negatively and significantly impact energy returns, while good news has a significantly positive impact. Imperatively, energy variables lack hedging potentials against the uncertainty occasioned by the COVID-19 pandemic, while we find no strong evidence of asymmetry. Our results are robust to the choice of news variables, forecast horizons employed, with likely sensitivity to energy prices.

Keywords: Distributed lag Model, Energy, Google Trends, Hedging Potential, Uncertainty
JEL Classification: C22, C32; Q41; Q47

1. INTRODUCTION

Coronavirus disease (COVID-19) is yet another crisis that has affected virtually every sector of the global economy. As the outbreak began to affect nearly all economies from late February to early March 2020, the World Health Organization (WHO) declared the disease as a pandemic on 11 March 2020 (WHO, 2020). The pandemic, within the first 3 months of the outbreak in Wuhan city, China on December 31 hit approximately one (1) million infected cases globally, while just a few weeks following, the confirmed cases reached approximately 2 million. As of 25 August 2020, the number of confirmed cases has hit approximately 23 million with almost 1 million deaths.[1]

Some recent studies have revealed that COVID-19 lockdown is impacting differently on different environment. The rapid spread and rate of increase in the number of recorded positive cases appear connected to regional climatic conditions. According to Iqbal et al. (2020), the rate of increase and spread was found to be faster in countries with relatively cooler climatic conditions than in countries with warmer climatic conditions, despite differences in socio-economic conditions. To curtail the spread of the virus, many countries imposed some measures such as the closure of shops, malls, event centres, market places, public transports, airports, etc. These restrictive measures resulted in general low economic output/productivity, and as relating to the energy sector, low energy demands. The low demand for oil and other energy sources; occasioned by the imposed restrictions – lockdown of businesses and international travels, among others; had some positive impacts as it led to some improvement in air quality with the reduction in the levels of air pollutants such as particulate matter, carbon dioxide, Sulphur dioxide, ozone, and aerosol concentration, in most major cities and highly industrialized areas of the world, especially, highly polluted cities like Kolkata, India (see Chowdhuri et al., 2020; Dang and Trinh, 2021; among others). Also, the improvement in the air quality in most megacities during the intense pandemic period was attributed to the reduction in vehicular emission as a result of fewer vehicles on the roads (Keremray et al., 2020; Xuelin et al., 2021; among others).

The pandemic, however, triggered an oil price shock at the three international oil markets,[2] as oil demand was ridiculously lowered amidst the pandemic in April 2020. The sharp drop in energy demand and wholesale energy prices resulted in an unprecedented increase in per-unit costs

[1] https://www.worldometers.info/coronavirus/?

[2] The West Texas Intermediate (WTI), UK Brent and the Organization of Petroleum Exporting Countries (OPEC) markets.

of energy. The disruption in the demand for oil and gas led to a decline in the prices of energy. IEA (2020) showed that in mid-April 2020, countries in full lockdown experienced a 25% decline in energy demand, while countries with partial lockdown experienced about an 18% decline in energy demand. It has been estimated that by the end of 2020, energy investment is set to fall by one-fifth; with larger effects on investments coming from oil and petroleum products as a result of restrictions on the movement of people as well as goods and services.

We are motivated by the development of indexes for monitoring global uncertainty as has been done previously with the prominent Economic Policy Uncertainty (EPU) indices for some G20 countries in the world (see https://www.policyuncertainty.com). Development of similar indexes relating to the current ravaging pandemic is still ongoing; given its unprecedented rate of spread across the globe. Therefore, drawing from (Salisu and Akanni, 2020) that recently used the number of confirmed COVID-19 positive cases and the number of recorded deaths to develop a Global Fear Index [GFI], we herein develop a similar index but differ on the method and the comprising variables considered. Extant indexes have been based on reported infection and mortality figures, causing anxiety levels of individuals to rise. However, the level of awareness and the quantity/quality of information that individuals have about the virus are not factored into the extant developed indexes. Such information, if and when available, is likely to affect an individual's decision more than just the news of rising figures, and provide a decision support mechanism that could reduce investment risks (Norouzi et al., 2020). Google Trends provides relevant search volumes relating to information being sought from web sources. We harness the wealth of information in Google Trends, on the COVID-19 pandemic and subsequently develop an information-based index of uncertainty – COVID-19 induced uncertainty [hereafter, CIU]. Investment decisions are mostly dependent on available market information; hence, the relevance of the Google Trends features. The CIU and GFI are similar to the prominent volatility index (VIX)[3] and the economic policy uncertainty (EPU).

We subsequently examine the vulnerability of energy prices using the uncertainty index herein developed as well as other uncertainty proxies. The choice of energy variables is not only informed by its wide usage (residential, commercial/industrial, among others) and the important role of energy in economic development, with its demand cutting across different socio-economic divides; but also that the movement restriction during the peak of the unprecedented pandemic in April 2020, affected the global energy price dynamics. Modelling these price dynamics is

[3] http://www.cboe.com/index/

fundamental to improving the economic prospects of global energy. The literature is therefore replete with diverse methodological studies (see Esfahani and Ramirez, 2003; Guo and Luh, 2004; Che and Wang, 2010; Ghadimi, 2015; Yaya et al., 2017; Basel et al., 2018; Salisu and Ogbonna, 2019; Sharif et al., 2020; Salisu et al., 2020a; among others). Recent studies have revolved around the COVID-19 pandemic, with several papers focusing on examining the impact of the pandemic on commodity markets, especially the energy markets (Akintande et al., 2020; Aloui et al., 2020; Karaca and Dincer, 2020; Sharif et al., 2020; Wang et al., 2020; Salisu et al., 2020a; and Narayan, 2020; among others), and greenhouse gases emission (Le Quéré et al., 2020 and Mahato et al., 2020; among others).

The contributions of this paper are five-fold. First, we develop an information-based index of uncertainty induced by the COVID-19 pandemic from the wealth of information embedded in the daily Google search volumes. Second, we employ the index 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. This aligns with extant researches that have shown the relevance of the Google Trends data to facilitate predictability of financial and economic series (see Salisu et al., 2020b & c; among others). Third, we account for salient data features, such as structural breaks, persistence, conditional heteroscedasticity, and autocorrelation, as well as day-of-the-week effect following (Zhang et al., 2017; Yaya and Ogbonna, 2019), within a single predictive model, following Westerlund and Narayan (2012, 2015). These features characterize most high-frequency series like the daily energy prices herein considered and could yield misleading results if neglected.

Fourth, we test for asymmetric effect in the developed index, to ascertain if good news and bad news are to be modelled differently or assumed similarly, with no need to decompose the index into positive and negative partial sums. Ignoring asymmetry when it exists could lead to unreliable estimates. Finally, we adopt a rolling, rather than fixed, window framework to account for the plausible time-varying parameter(s), while evaluating the forecast performance for in-sample and out-of-sample periods, to ascertain if results are sensitive to the data sample period. In summary, the results obtained here would be of policy relevance to energy market stakeholders, who are keen on the hedging or safe-haven or diversifier properties of energy prices amidst the current period of the pandemic.

Following the introductory section of this paper, the remaining part of the paper is structured as follow: Section 2 focuses on the materials and methods detailing the construction of the information-based index of uncertainty, the empirical model, and an exploration of the data issues along with some preliminary analyses; Section 3 presents and discusses the empirical results; while Section 4 concludes the paper.

2. MATERIALS AND METHODS

The study framework adopted in this study is four-fold: First, we construct the new information-based index and provide a detailed explanation of the features in subsection 2.1; Second, we specify the distributed lag model to be used in the estimation of the energy-uncertainty nexus in subsection 2.2; third, we examine the data feature using statistical summaries along with some preliminary analyses in subsection 2.3; and fourth, we thereafter estimate and evaluate the model fitness as well as the preference of one of the indexes of uncertainty over the other contending proxies.

2.1 Construction of the COVID-19 Index of Uncertainty

In obtaining the information-based index - ciu, the global daily Google search volumes of keywords, single words or phrases, relating to the COVID-19 pandemic were used. These keywords were chosen given the increased frequency of usage following the outbreak of the epidemic-turned-pandemic. The keywords include: "Coronavirus", "nCov2", "Severe acute respiratory syndrome", "Covid - 19", "COVID-19", "COVID", "Pandemic COVID-19", "COVID-19 Pandemic" "Pandemic", "Vaccine", and "COVID Vaccine". The search volumes for any given item/topic is scaled to range between 0 and 100, where the latter and the former indicate the least and highest search frequency. Having obtained the daily volumes of word-search for the specified keywords, forming time series spanning the set period, the principal component analysis was used to combine the variables into an index, i.e. COVID-19 Induced Uncertainty [CIU]. The obtained index is therefore the first principal component factor of the linear combination of the eleven (11) daily time series of volumes of searched words. We subsequently normalized the index to values between 0 and 100, using $ciu_{scaled} = (b-a)\times\left[\frac{ciu_{unscaled} - min(ciu_{unscaled})}{max(ciu_{unscaled}) - min(ciu_{unscaled})}\right] + a$, such that $ciu_{unscaled}$ is the obtained index, and *a* and *b* correspond to 0 and 100, respectively, that is the least and the highest levels of uncertainty. Imperatively, the higher the index value, the higher the investor's uncertainty about the market; while an index value of 50 indicates a moderate level of uncertainty. The index facilitates the concept of parsimony in the model, by pooling the information in the different searched words in one variable.

2.2 The Empirical Model

We construct a predictive model to assess the vulnerability of energy prices to the uncertainty induced by the COVID-19 pandemic, while also accounting for inherent salient data features, following Westerlund and Narayan (2012, 2015) approach. This approach adequately circumvents the proliferation of parameters and simultaneously resolves inherent bias, and has been widely applied in many recent studies (see Narayan and Gupta, 2015; Narayan, Phan, Sharma, 2018; Salisu et al., 2019; among others). In a bid to ascertain the most appropriate model to adopt, the data trends and features are analytically examined for the presence of salient features such as persistence, endogeneity, autocorrelation, and conditional heteroscedasticity (see Bannigidadmath and Narayan, 2015; Narayan and Gupta, 2015; Phan et al., 2015; Narayan et al., 2016, Devpura et al., 2018; Narayan et al, 2018; Salisu and Oloko, 2015; Salisu et al., 2019; among others).

We specify a distributed lag model that comprises five lags of our index of uncertainty (news) variable, as well as a break dummy variable, and pre-weight the model variables with the standard deviation of an ordinary least squares [OLS] regression model residuals; in a bid to account for inherent data characteristics. The included lags are informed by the need to account for the day-of-the-week effect,[4] which usually characterizes the daily financial series and are likely to bias the results if ignored when modelling such high-frequency series (Zhang et al., 2017; Yaya and Ogbonna, 2019). The inclusion of a break-dummy is informed by the need to account for the plausible structural shift from the natural path. We pre-weight our predictive model with the inverse of the standard deviation of the residuals $\left(\hat{\sigma}_{\varepsilon}\right)$ to account for the conditional heteroscedasticity effect that is inherent in the high-frequency data. The predictive model is as given in equation (1),

$$r_t = \alpha + \sum_{i=1}^{k} \beta_i ciu_{t-i} + \gamma\left(ciu_t - ciu_{t-1}\right) + \phi brk_t + \varepsilon_t \qquad (1)$$

[4] Day-of-the-week effect was preliminarily confirmed for all the energy prices except gasoline and natural gas, as Monday appears to be statistical significant.

where $r_t = \ln\left(P_t / P_{t-1}\right)$ represents returns on energy prices P_t at the time t; α denotes intercept; ciu_{t-i} denotes the i^{th} lag of the predictor variable – index of COVID-19 induced uncertainty $\left(ciu_t\right)$, $i = 1, 2, \ldots, k$ and $k = 5$; β_i is the slope coefficient associated with the i^{th} lag of the predictor variable; the term, $\gamma\left(ciu_t - ciu_{t-1}\right)$ is incorporated to correct for plausible endogeneity bias and persistence (unit root problem) that may be inherent in the predictor variable; brk_t is an exogenously determined dummy variable that is used to capture the period of the shift from the natural trend, such that it takes value 0 for the period before WHO declaration and value 1 afterward; ϕ denotes the break dummy coefficient; and ε_t denotes the error term. The CIU in equation (1) is replaced by other uncertainty proxies - GFI, EPU, and VIX, as the case may be.

Equation (1) specifies energy price returns as a function of the lags of the index of uncertainty (CIU, GFI, EPU, and VIX) and an exogenously determined structural break dummy. Although the estimated coefficients associated with the lags of the predictor as well as the break dummy are examined for statistical significance, the joint significance of these lags, which translates to ciu predictability for energy prices is of greater importance. The joint significance is examined under a null hypothesis of no predictability (that is, $H_0 : \sum_{i=1}^{k} \beta_i = 0$) using the Wald test statistic. Failure to reject the stated null hypothesis implies no joint significance of the lags of ciu. However, if the joint significance for the lags of ciu is ascertained, then the relationship between energy price returns and ciu is expected to be negative. A rolling window, rather than a fixed window, the framework is adopted to forecast the selected energy price returns, given that the former accounts for plausible time-variation in the parameters. The model is used, also with partially decomposed sums in a bid to examine the asymmetric effect. The COVID-19 induced uncertainty $\left(ciu_t\right)$ is decomposed into positive and negative partial sums, which are defined as $ciu_t^{+} = \sum_{j=1}^{t} \Delta ciu_j^{+} = \sum_{j=1}^{t} \max\left(\Delta ciu_j, 0\right)$ and $ciu_t^{-} = \sum_{j=1}^{t} \Delta ciu_j^{-} = \sum_{j=1}^{t} \min\left(\Delta ciu_j, 0\right)$, respectively (see Narayan and Gupta, 2015; Salisu et al., 2019; Salisu et al., 2020b & c; among others).

A historical average model is also estimated for each energy price returns to serve as a benchmark model, with which the forecast performance of our predictive model is compared using relative root mean square error (RMSE). The relative RMSE value is computed as a ratio of the

RMSE of our predictive model (with each proxy of uncertainty) and the historical average model. Consequently, we expect a value less than one for our predictive model to out-perform the historical average, and greater than one for the latter over the former. A unity value will indicate no difference in the forecast of our predictive model and the historical average model. We also consider a pairwise comparison statistic – Diebold and Mariano [DM, 1995] test, which is considered the most appropriate when the contending models are non-nested; to compare the forecast performance of our predictive model with the different uncertainty proxies. The test provides a formal framework to tests whether the observed difference, in the forecast errors of the paired contending non-nested models, is not statistically different from zero. The test statistic is specified as:

$$DM\ Stat = \frac{\bar{d}}{\sqrt{V(d)/T}} \sim N(0,1) \tag{6}$$

where the sample mean of the loss differential $d_t \equiv g(\varepsilon_{it}) - g(\varepsilon_{jt})$ is defined as $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$, with $g(\varepsilon_{it})$ and $g(\varepsilon_{jt})$ representing the loss functions of the contending models' forecast errors, ε_{it} and ε_{jt}, which are associated with the two forecasts, say $\hat{r}_{it}$ and $\hat{r}_{jt}$, respectively, while $V(d_t)$ is the unconditional variance of d_t. The null hypothesis tests for the equality of the forecast errors of the paired competing models, such that $E[d_t] = 0$. A rejection of the null hypothesis would imply a statistically significant difference in the forecast precision of the two competing models. We expect a significantly negative DM statistic for our predictive model with our new index to out-perform the predictive model with any of the other uncertainty proxies; otherwise, the latter would be preferred over the former. In any case, the preferred predicts the energy price returns more precisely with few errors compared to the contending paired model. In the case of asymmetry, we also require a significantly negative DM statistic to confirm the presence of the asymmetric effect.

2.3 Data Issues and Some Preliminary Analyses

In this study, daily prices of eight different energy sources (oil and petroleum products), uncertainty index (ciu) computed based on the principal component analysis (PCA) of Google search volumes relating to COVID-19 pandemic, and Global Fear Index [hereafter, GFI] were analyzed. Prices of energy sources such as Brent crude, diesel, gasoline, heating oil, kerosene, natural gas, propane, and West Texas Intermediate [WTI] crude oil obtained from the website https://www.investing.com; the Google search volume data were obtained from Google Trend search engine; the daily implied volatility on the S&P500 index [VIX] from the Chicago Board of Options Exchange was obtained from https://fred.stlouisfed.org/series/VIXCLS; while the economic policy uncertainty [EPU] (see Baker, Bloom, and Davis, 2016) was obtained from www.policyuncertainty.com/media/All_Daily_Policy_Data.csv. The energy prices, Google search volume data, and the uncertainty proxies (EPU and VIX) span a period between January 2, 2020 and July 17, 2020. The GFI data, which spanned a period between February 9, 2020 and July 17, 2020, was sourced from Salisu and Akanni (2020) [5]. The data sample interval was chosen to include periods before and after the WHO declaration of COVID-19 as a pandemic.

On the transformation of variables, except for the uncertainty proxies (CIU, GFI, EPU, and VIX), that were logged, all the energy prices were transformed into returns. Table 1 presents the summary statistics of the data employed in this study, and some preliminary tests, which include unit root tests, the ARCH test, autocorrelation, persistence, and endogeneity tests. The results of the data feature and tests serve as a pre-requisite for the adoption of the estimation approach used in the paper.

Table 1: Summary Statistics and Preliminary Analysis

	BRENT	DIESEL	GASOLINE	HEATING_OIL	KEROSENE	NGAS	PROPANE	WTI	CIU	GFI	EPU	VIX
Mean	-0.306	-0.361	-0.291	-0.382	-0.426	1.802	0.060	-0.291	45.243	310.924	58.105	30.257
Std. Dev.	9.457	4.904	8.559	4.840	6.008	0.152	4.758	8.408	30.536	183.403	15.439	13.666
Minimum	-64.370	-20.430	-41.080	-18.460	-28.104	1.420	-16.959	-34.542	1.690	22.250	9.909	12.100
Maximum	41.202	15.079	29.469	11.186	15.346	2.170	15.645	31.963	100.000	807.660	91.190	76.450
Skewness	-1.693	-0.626	-1.159	-0.702	-0.747	0.022	-0.612	-0.451	-0.153	0.303	0.693	1.387
Kurtosis	20.267	6.394	10.078	5.553	6.628	2.704	6.033	8.570	1.729	2.084	3.363	5.213
J-B Statistic	1818.947***	76.874***	325.942***	49.896***	90.460***	0.531	62.850***	187.062***	10.112***	7.134***	9.843**	74.544***
N	141	141	141	141	141	142	141	141	142	115	142	142
ADF	-10.687***	-11.223***	-12.346***	-11.148***	-11.644***	-3.600***	-11.802***	-10.914***	-12.400***	-4.602***	-19.137***	-10.894***
PP	-10.764***	-11.224***	-12.344***	-11.150***	-11.771***	-3.282**	-11.828***	-10.914***	-12.424***	-16.481***	-23.044***	-10.883***
ARCH(3)	5.130***	3.858**	2.662*	2.106	1.434	0.994	5.542***	15.417***	1.694	6.267***	2.685**	3.997***
ARCH(6)	2.439**	2.366**	3.974***	2.529**	1.484	1.246	3.139***	8.191***	0.841	5.638***	1.822*	1.909*
ARCH(12)	1.29	1.215	1.843**	1.537	0.816	2.832***	3.209***	3.847***	0.578	12.955***	0.951	1.665*
Q(3)	2.7536	1.4457	3.6319	0.3528	1.3786	2.7865	13.924***	7.461*	3.5031	25.654***	22.424***	5.3851
Q(6)	4.9866	2.455	6.8007	3.4964	10.175	4.3183	17.745***	15.008**	12.608*	31.052***	23.901***	7.0648
Q(12)	18.958*	9.2243	17.77	13.895	15.287	9.9238	37.736***	20.070*	21.251**	80.433***	44.529***	19.843*
$Q^2(3)$	14.266***	12.126***	9.853***	8.426**	5.6672	3.487	16.686***	50.707***	6.1776	13.740***	7.723*	13.174***
$Q^2(6)$	14.272**	20.842***	26.492***	25.534***	15.064**	6.9955	21.413***	61.701***	6.258	15.24**	11.237*	14.605**
$Q^2(12)$	17.577	25.454**	35.836***	36.617***	23.239**	30.795***	59.584***	69.914***	8.6479	54.627***	14.491	30.328***
Persistence	-0.048	0.065	-0.153*	0.073	-0.049	0.840***	-0.046	0.077	0.971***	0.862***	0.879***	0.957***
Endogeneity												
CIU	-0.108	-0.075	-0.317***	-0.096	-0.136*	1.58E-05	-0.078	-0.012	-	-	-	-
GFI	-0.098	-0.082	-0.059	-0.080	-0.108	-4.02E-04	-0.046	-0.119	-	-	-	-

[5] Details of computation of GFI index is found in Salisu and Akanni (2020).

EPU	0.006	0.006	-0.003	0.005	0.006	-2.56E-04***	0.004	0.002	-	-	-	-
VIX	0.050	0.099	0.327*	0.059	0.133	0.003	0.135	0.079	-	-	-	-

Note: ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

From the results in Table 1, the average returns on energy variables; apart from natural gas and propane, for the sampled period is positive. The returns on Brent oil are more volatile than those of WTI oil and the other energy variables, judging from the standard deviation results. Returns on propane are least volatile compared to the other energy variables. As consistent with returns series, we find all the energy prices, except natural gas, to be negatively skewed. These energy prices are leptokurtic (exhibiting kurtosis values greater than the normal threshold of 3). On the predictors, CIU is negatively skewed, GFI is positively skewed, and both are platykurtic. From the foregoing, all the energy prices and predictors – CIU, GFI, EPU, and VIX, are not normally distributed, judging from the Jarque-Bera statistic.

On the stationarity of the variables, we find all the energy prices, except natural gas, to be non-stationary at levels, hence the need to transform using differenced log transformation; and the predictor variables are found to be integrated of order 1, as revealed by the ADF and PP unit root tests. The presence of the ARCH effect is also confirmed in all the energy prices and GFI, EPU, and VIX but not in CIU, while we find the variables to exhibit some level of autocorrelation up to lag 12. Persistence is evidenced in the two predictor variables (CIU, GFI, EPU, and VIX), which conforms to their non-stationary stance at levels as observed from the ADF and PP unit root tests. These predictors do not exhibit any significant evidence of endogeneity across the model, pairing each predictor with any of the energy returns series. This translates to the fact that while the evidence of persistence may portend some challenges, we do not have to worry about endogeneity bias.

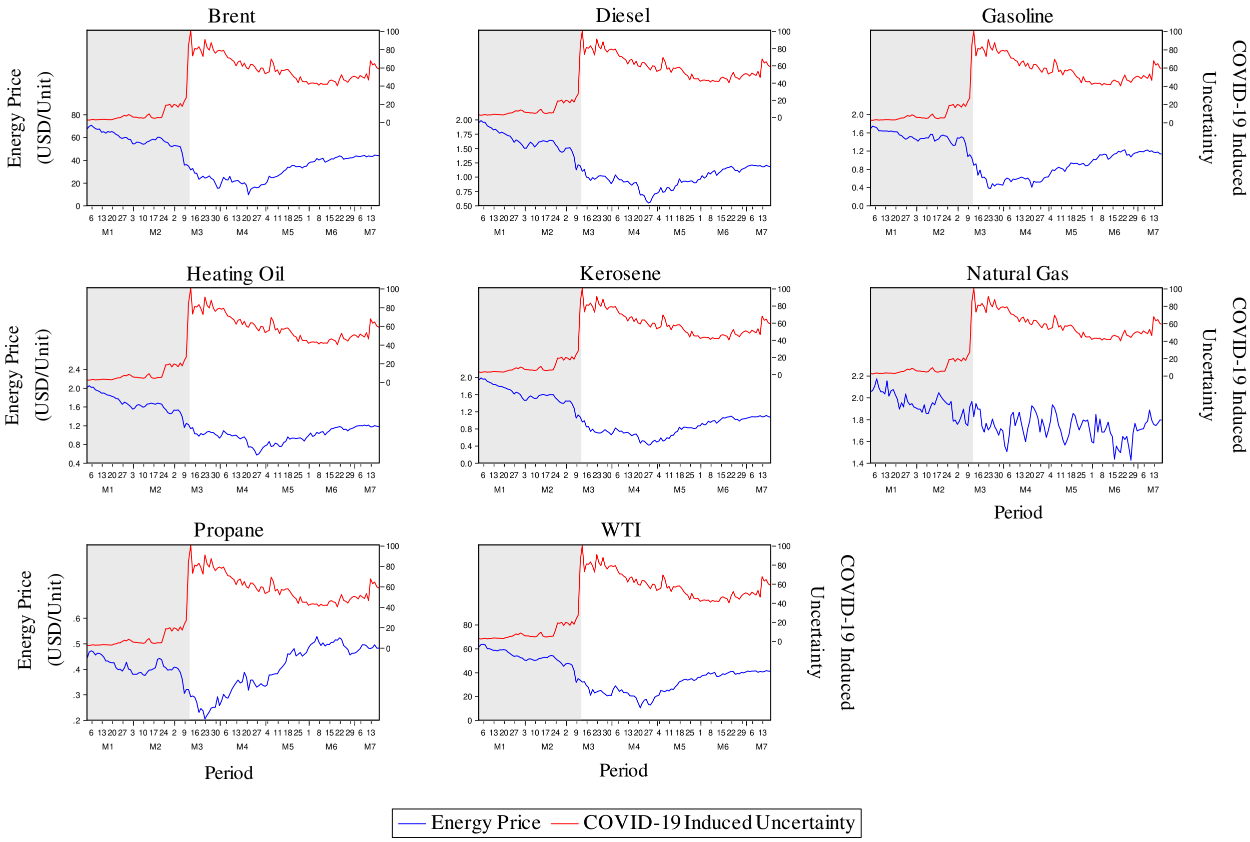

Figure 1: Bivariate Plot of Energy Prices and COVID-19 Induced Uncertainty

The graphical illustration in Figures 1 - 4 show pairs of each energy price variable with each uncertainty proxies (CIU, EPU, GFI, and VIX, respectively) and can be seen that although the prices are trending downwards, there appears to be relative stability in the prices before the WHO declaration of the COVID-19 as a pandemic. The announcement appears to have triggered a structural shift in the natural path of the prices and more prominently in the level of uncertainty. Interestingly, the highest level of uncertainty coincides with the WHO declaration of COVID-19 as a pandemic (see Figures 1 and 3). It would, therefore, be necessary to account for structural breaks in the predictive model of these energy prices. The evidence featured in the data suggests that the most appropriate model would be one that accounts for conditional heteroscedasticity, autocorrelation, the persistence as well as a structural break; hence, the adoption of the distributed lag model specification in equation (1).

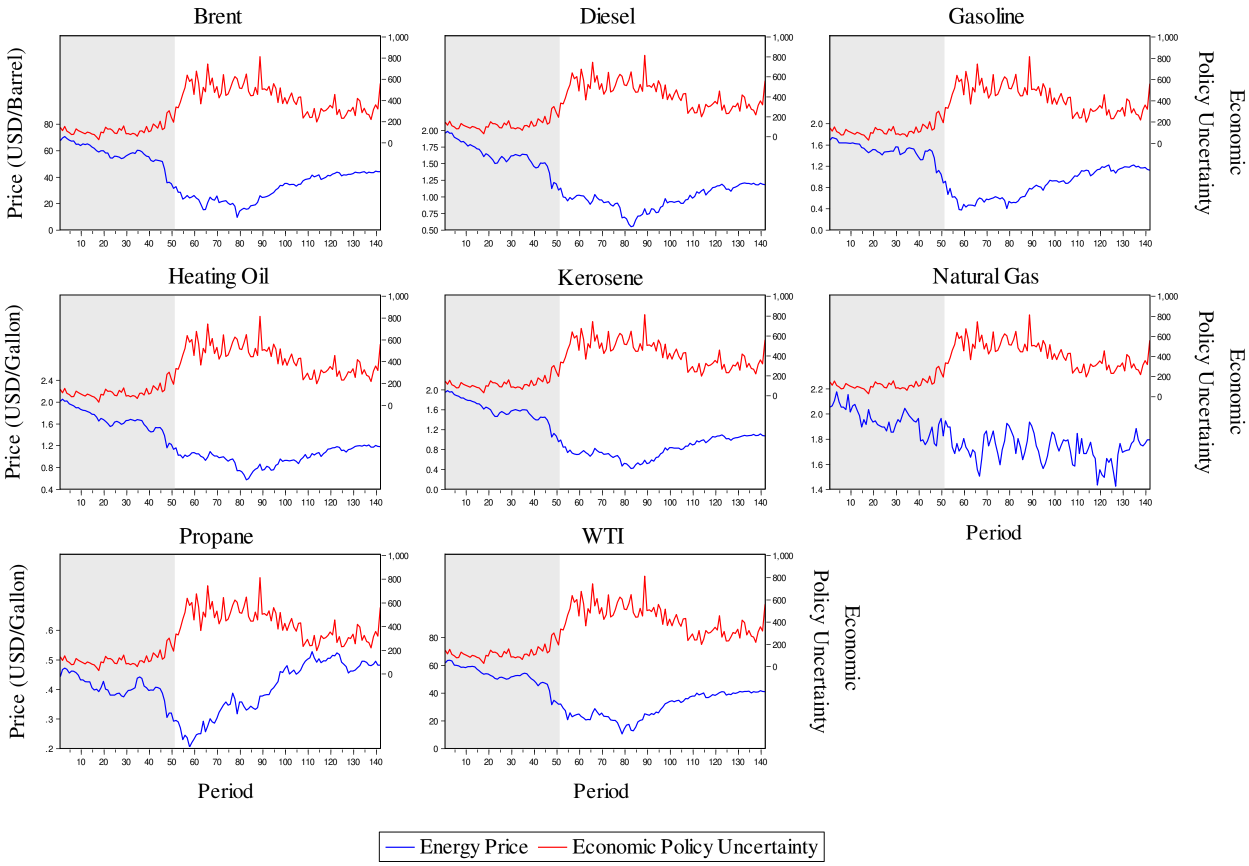

Figure 2: Bivariate Plot of Energy Prices and Economic Policy Uncertainty

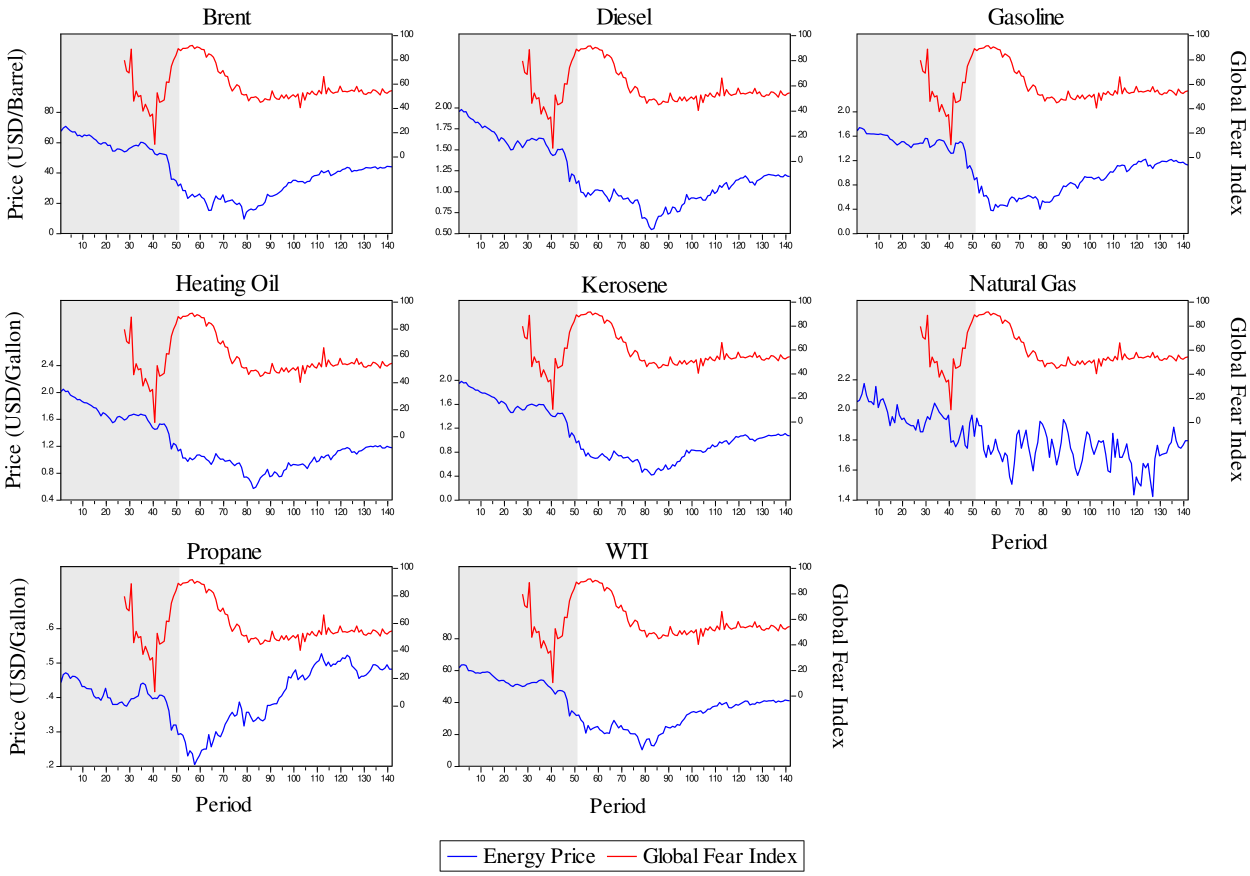

Figure 3: Bivariate Plot of Energy Prices and Global Fear Index

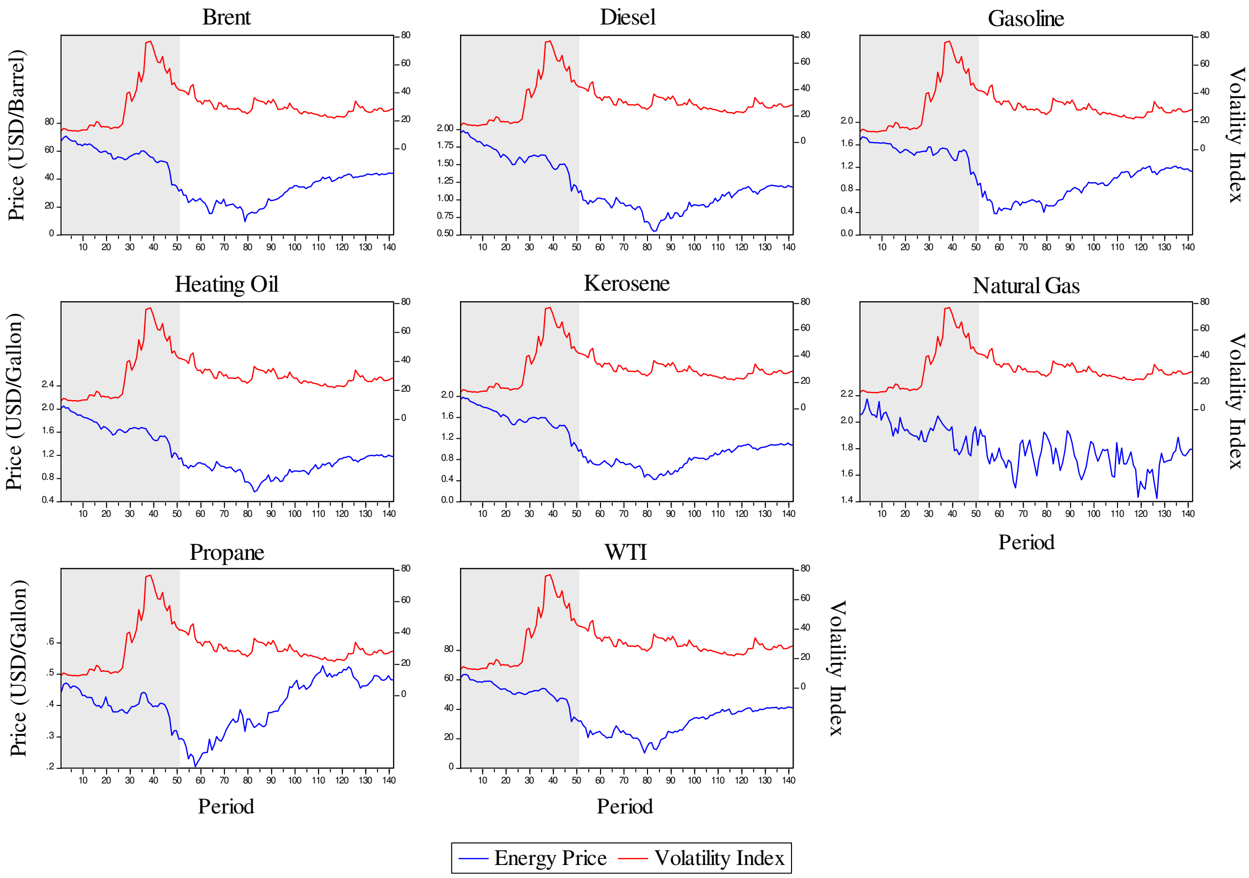

Figure 4: Bivariate Plot of Energy Prices and Volatility Index

3. RESULTS AND DISCUSSIONS

3.1 Main Estimation

Here, we present the empirical findings of our analysis using the distributed lag model specified in equation (1). We begin this section by ascertaining the predictability of each energy price returns using the developed index of uncertainty – CIU, and thereafter, examine the impact of accounting for asymmetry in the predictive model for each of the energy price returns (Table 2). In a bid to evaluate the model adequacy, we employ both the relative RMSE and the DM test (Diebold and Mariano, 1995) in a pairwise comparison of a benchmark and the paired contending models; and examine both the in-sample and out-of-sample (*h=5, h=10,* and *h=20*) forecast performance of our predictive model (see Tables 3 and 4). We also conduct a sensitivity analysis using extant uncertainty proxies (GFI, EPU, and VIX) and discuss the results for the predictability (see Tables 2) and forecast performance (see Tables 3 and 4), as in the main estimation.

Table 2 presents the predictability results for energy returns, using the aggregate (news) as well as the positively (good news) and negatively (bad news) decomposed partial sums of CIU index, separately, as predictors. The CIU index is generated by summarizing the information in Google search volumes on several keywords relating to the COVID-19 pandemic, using PCA. Five (5) lags of CIU index are then included in the model, as a way to account for the day-of-the-week effect, which characterizes most daily frequency series (Zhang et al., 2017; Yaya and Ogbonna, 2019; among others). While the statistical significances of the lags of CIU are as well important; the predictability stance is ascertained from the joint coefficient that combines the coefficients of the five lags of CIU, with the statistical significance, or otherwise, of the joint coefficient estimate determined using the conventional Wald statistic. Consequently, a statistically significant joint coefficient estimate[6] would suggest that the index of uncertainty is a good predictor for the corresponding energy price.

The results across the energy variables, except for natural gas and propane that are positive and statistically significant, reveal that CIU impacts energy returns negatively and significantly. This is consistently evidenced in six of the eight energy returns measures considered in this study. The significantly negative relationship between energy price returns and CIU implies that energy prices have no hedging potential against the uncertainty occasioned by the COVID-19 pandemic. This finding contradicts the stance of Salisu et al., (2020a) that found a positive relationship between commodity prices and uncertainty. Imperatively, investors in the energy market who do not seek alternative assets to invest in, are likely to incur losses during the COVID-19 pandemic.

Table 2: Predictability of Energy Prices using CIU

Energy	Aggregate	Asymmetry	
		Negative	Positive
Brent	-5.63E-02***[1.83E-02]	-4.16E-02***[1.25E-02]	2.28E-02***[4.91E-03]
Diesel	-3.32E-02***[5.23E-03]	-1.87E-02***[5.35E-03]	1.60E-02***[5.58E-03]
Gasoline	-6.02E-02***[6.44E-03]	-7.15E-02***[1.05E-02]	3.54E-02***[1.17E-02]
Heating oil	-4.64E-02***[6.81E-03]	-1.79E-02***[3.82E-03]	1.81E-02***[5.78E-03]
Kerosene	-1.54E-02[1.40E-02]	-4.46E-02***[4.16E-03]	1.97E-02*[1.02E-02]
Natural gas	4.46E-04*[2.34E-04]	6.74E-04***[7.55E-05]	-3.69E-04**[1.72E-04]
Propane	2.38E-02**[1.14E-02]	-3.09E-02***[3.67E-03]	-3.79E-02***[6.48E-03]
WTI	-5.46E-02***[9.23E-03]	-1.12E-02***[1.04E-02]	3.58E-03[1.68E-02]

Note: ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively. Figures in square brackets are the standard errors of the estimated coefficients.

[6] We only report the joint coefficient estimates to conserve space, however the results are available on request.

In the same vein, bad news (negative decomposed partial sum of CIU) impacts negatively and significantly on energy returns in all but one case – natural gas. This largely follows the stance with the news (aggregated) results. On the other hand, the good news (positively decomposed partial sum of CIU) appears to have mixed impacts on the energy returns, with more evidence of significant positive impacts than significant negative impacts. While it had a significantly positive impact on brent, diesel, gasoline; heating oil, and kerosene; it significantly negatively impacted on prices of natural gas and propane. From the foregoing, it appears that bad news and good news do not impact equally energy returns. This informs the need to test for asymmetric effect in the information-based variable (see results in Tables 4 and 5), in addition to our predictive model's performance compared with the contending models, using DM statistic.

3.2 Predictability of energy prices using alternative measures of uncertainty

Here, we consider alternative measures of uncertainty to ascertain the role of uncertainty in the predictability of energy price returns amidst the COVID-19 pandemic. This could in a way be considered a sensitivity analysis of the results earlier obtained in the main estimation. The alternative measures of uncertainty include EPU, GFI, and VIX. The predictive model specification and estimation procedures are still the same as those of the main estimation with CIU lag as predictors, except for the change in the uncertainty proxy. The results of the predictability of the different energy prices are presented in Table 3. The stances and conclusions here are largely similar to those observed in the main estimation, where CIU lags were used instead. We observed a more significantly positive relationship between energy prices and EPU, while a more significant negative relationship is observed for GFI and VIX, under the aggregated data (second column of Table 3). However, under the negative and positive asymmetry column, the stance across uncertainty proxies are quite similar to those earlier observed in the case of CIU. Imperatively, while we could say that uncertainty and negatively decomposed partial sum of uncertainty measures (bad news) impact energy prices significantly negatively and positively decomposed partial sum of uncertainty measures (good news) impacts energy prices significantly positively, the result may be sensitive to the energy and uncertainty pairs being considered (see Table 3).

Table 3: Predictability of Energy Prices using alternative measures of uncertainty

	Aggregate	Negative	Positive
		EPU	
Brent	6.02E-03***[5.81E-04]	-8.40E-04***[7.13E-05]	1.02E-03***[6.62E-05]

Diesel	-2.96E-03***[5.70E-04]	-5.62E-04***[7.13E-05]	8.90E-04***[1.04E-04]
Gasoline	1.28E-02***[1.59E-03]	-1.01E-03***[2.30E-04]	1.36E-03***[1.27E-04]
Heating oil	-2.94E-03***[3.64E-04]	-5.10E-04***[9.51E-05]	6.50E-04***[1.21E-04]
Kerosene	2.42E-03***[8.03E-04]	-1.05E-03***[1.31E-04]	1.16E-03***[8.96E-05]
Natural gas	1.19E-04***[4.06E-05]	2.82E-05***[3.05E-06]	-4.75E-05***[2.42E-06]
Propane	1.01E-02***[8.77E-04]	-4.65E-04***[6.17E-05]	3.03E-04***[8.13E-05]
WTI	2.48E-03***[9.80E-04]	-2.26E-04[1.87E-04]	6.45E-04*[3.48E-04]
GFI			
Brent	-7.11E-02***[1.74E-02]	-8.00E-03**[3.56E-03]	1.48E-02***[2.05E-03]
Diesel	-3.60E-02***[4.09E-03]	-1.59E-02***[7.50E-04]	7.33E-03***[2.13E-03]
Gasoline	-8.28E-02***[1.01E-02]	-2.01E-02***[4.70E-03]	1.51E-02***[1.55E-03]
Heating oil	-1.01E-02[6.63E-03]	-1.02E-02***[3.09E-03]	1.00E-02***[2.74E-03]
Kerosene	-4.62E-02***[1.38E-02]	-1.99E-02***[3.06E-03]	2.16E-02***[1.72E-03]
Natural gas	2.35E-04[2.34E-04]	8.80E-04***[8.81E-05]	-1.21E-03***[5.45E-05]
Propane	-2.68E-02**[1.16E-02]	-1.51E-04[1.27E-03]	-8.44E-03***[2.52E-03]
WTI	-8.97E-02***[9.87E-03]	-4.02E-03[5.55E-03]	1.52E-02***[1.98E-03]
VIX			
Brent	-1.28E-02[1.25E-02]	-2.67E-02***[4.49E-03]	1.32E-03[9.63E-04]
Diesel	4.09E-05[7.64E-03]	-2.53E-02***[4.41E-03]	1.19E-02***[8.86E-04]
Gasoline	-4.88E-02***[4.48E-03]	-4.12E-02***[1.01E-02]	1.20E-02***[4.70E-03]
Heating oil	7.10E-03***[5.02E-03]	-1.89E-02***[5.20E-03]	1.03E-02***[1.01E-03]
Kerosene	-6.31E-03[1.15E-02]	-3.10E-02***[8.30E-03]	1.64E-02***[9.52E-04]
Natural gas	-3.36E-04[3.25E-04]	2.11E-03***[1.47E-04]	-1.42E-03***[1.63E-04]
Propane	-1.81E-03[8.20E-03]	3.41E-03[6.98E-03]	-2.25E-03[2.27E-03]
WTI	-5.45E-02***[1.33E-02]	-1.73E-02***[1.40E-03]	-5.80E-04[5.19E-03]

Note: ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively. Figures in square brackets are the standard errors of the estimated coefficients.

3.3 Forecast Evaluation

Having established the in-sample predictability of energy prices using the different uncertainty proxies, we here examine the out-of-sample forecast performance of all the model constructs. We employ the conventional RMSE and the Diebold and Mariano (1995) test statistic. The results are presented in Tables 4 and 5, respectively. The results in Table 4 are the relative RMSE pairwise comparison between the forecast of an unrestricted (our predictive distributed lag) model comprising separately the lags of the different uncertainty measures (CIU, EPU, GFI, and VIX) and the restricted (benchmark historical average) model. Relative RMSE values that are less than one indicate a preference for the lag distributed over the historical average. In addition to the established in-sample predictability in Tables 2 and 3, we examine the out-of-sample forecast performances under three forecast horizons (*h=5, h=10,* and *h=20*), as another form of robustness check. Across the out-of-sample forecast periods and energy prices (except Brent, under longer out-of-sample forecast horizon), our distributed lag model with CIU lags as predictors and incorporates all evidenced data features (conditional heteroscedasticity, autocorrelation, and structural break) outperformed the benchmark historical average model that ignores same. This shows that the incorporation of an information-based (news) variable in the predictive model for energy prices does improve the forecasts of the returns series than when ignored.

The stance of outperformance of the distributed lag model that incorporates any of the alternative proxies is dependent on the energy variable being considered. While the forecast performance results for EPU are quite similar to those of CIU, the distributed lag model incorporating GFI and VIX differ markedly, with less proportion of outperformance over the historical average model. The consistency of outperformance across the out-of-sample periods shows that results are not sensitive to the forecast periods chosen, especially in the case of CIU. However, the model incorporating the decomposed partial sums of lags of the corresponding uncertainty proxy, separately, as predictors may not outperform the historical average model as the case incorporating the aggregate. Put differently, the predictive model (with CIU lags as predictors) is preferred over the benchmark historical average model across energy markets (Brent, diesel, gasoline, kerosene, propane, WTI oil) returns as well as across forecast horizons. Furthermore, we adopt the DM test statistic to formally ascertain the performance of the different constructs of the non-nested distributed lag model.

Table 4: Relative RMSE test results using alternative measures of uncertainty

Energy	Aggregate			Asymmetry					
				Negative			Positive		
	$h=5$	$h=10$	$h=20$	$h=5$	$h=10$	$h=20$	$h=5$	$h=10$	$h=20$
CIU									
Brent	0.998	1.001	1.002	0.988	1.013	1.062	1.063	1.089	1.142
Diesel	0.979	0.984	0.983	0.982	1.003	1.045	1.017	1.039	1.082
Gasoline	0.964	0.970	0.973	0.932	0.951	0.994	0.990	1.010	1.057
Heating Oil	0.977	0.982	0.981	1.014	1.036	1.078	1.038	1.060	1.104
Kerosene	0.973	0.977	0.978	0.962	0.984	1.028	1.026	1.050	1.097
Natural Gas	0.856	0.882	0.901	0.800	0.761	0.747	0.778	0.740	0.727
Propane	0.907	0.913	0.915	0.950	0.969	1.009	1.012	1.033	1.076
WTI	0.970	0.971	0.974	0.993	1.017	1.066	1.039	1.063	1.115
EPU									
Brent	0.988	0.988	0.989	0.998	1.001	1.016	0.988	0.992	1.000
Diesel	1.006	1.010	1.009	1.017	1.036	1.048	0.991	1.000	1.005
Gasoline	0.959	0.960	0.967	0.953	0.955	0.958	0.978	0.988	1.005
Heating Oil	0.997	1.002	1.001	1.029	1.046	1.050	0.977	0.986	0.990
Kerosene	0.983	0.988	0.995	0.958	0.975	0.991	0.972	0.985	1.000
Natural Gas	0.919	0.939	0.949	0.899	0.916	0.912	0.860	0.841	0.833
Propane	0.969	0.972	0.975	0.944	0.949	0.957	0.976	0.985	0.999
WTI	0.980	0.982	0.983	0.999	1.007	1.012	0.992	0.996	1.004
GFI									
Brent	1.003	1.003	1.001	1.042	1.051	1.062	1.030	1.032	1.035
Diesel	1.003	1.004	1.000	1.019	1.026	1.028	1.015	1.021	1.023
Gasoline	0.997	0.999	0.997	1.036	1.043	1.049	1.020	1.023	1.023
Heating Oil	1.028	1.030	1.025	1.041	1.046	1.044	1.035	1.039	1.036
Kerosene	1.013	1.014	1.011	1.051	1.091	1.152	1.020	1.026	1.029
Natural Gas	0.912	0.916	0.920	0.922	0.904	0.892	0.888	0.870	0.857
Propane	0.991	0.994	0.994	0.984	0.987	0.988	1.030	1.032	1.035
WTI	1.015	1.015	1.013	1.048	1.049	1.050	1.032	1.035	1.038
VIX									

Brent	0.992	0.992	0.992	0.981	0.983	0.984	1.007	1.008	1.008
Diesel	1.006	1.009	1.005	0.966	0.971	0.970	1.006	1.012	1.013
Gasoline	0.980	0.981	0.980	0.924	0.936	0.943	1.007	1.009	1.008
Heating Oil	1.000	1.003	0.999	0.973	0.979	0.978	1.033	1.037	1.039
Kerosene	1.006	1.009	1.006	0.951	0.962	0.969	1.040	1.046	1.050
Natural Gas	0.890	0.900	0.911	0.882	0.864	0.846	0.879	0.884	0.894
Propane	0.983	0.987	0.993	0.981	0.987	0.989	1.000	1.002	1.006
WTI	1.000	1.002	1.002	0.987	0.991	0.995	1.002	1.004	1.005

Note: Figures less than one indicate a preference for our predictive model over the benchmark historical average model.

The results in Table 5 are the DM test statistics that provide a pairwise comparison between non-nested models. Here, we compare our predictive distributed lag model that incorporates CIU lags as predictors with the other model variants that incorporated the alternative uncertainty measures (EPU, GFI, and VIX). Under the column titled, “aggregate”, the null hypothesis asserts that both contending models do not differ markedly, one from the other. Negative and statistically significant DM statistics would imply preference of the model incorporating CIU over the models incorporating other uncertainty proxies (EPU, GFI, and VIX), while positive and statistically significant DM statistics would imply preference of the other uncertainty proxies over CIU. Similarly, the distributed lag models incorporating, separately, positively and negatively decomposed partial sums of the corresponding uncertainty measure are compared, to ascertain formally if asymmetry exists. The null hypothesis here asserts that asymmetric effect does matter, which implies that forecast from a model incorporating positive partial sum of corresponding uncertainty measure does not differ markedly from a model incorporating negative partial sum of corresponding uncertainty measure. In all cases, we consider three different out-of-sample forecast horizons.

Table 5: Diebold and Mariano Test Results

Energy	Aggregate			Asymmetry		
	$h=5$	$h=10$	$h=20$	$h=5$	$h=10$	$h=20$
			CIU			
Brent	-	-	-	0.492	0.493	0.493
Diesel	-	-	-	-0.939	-0.939	-0.940
Gasoline	-	-	-	-0.090	-0.090	-0.090
Heating oil	-	-	-	0.121	0.121	0.121
Kerosene	-	-	-	-1.040	-1.041	-1.041
Natural Gas	-	-	-	0.479	0.479	0.479
Propane	-	-	-	-0.276	-0.276	-0.276
WTI	-	-	-	0.286	0.286	0.287
			EPU			
Brent	-6.331***	-6.265***	-6.158***	0.713	0.876	1.621
Diesel	-9.245***	-9.461***	-9.654***	1.435	1.953*	2.637***
Gasoline	-7.913***	-7.770***	-7.564***	-0.319	-0.708	-1.514
Heating oil	-9.562***	-9.292***	-8.865***	0.842	0.999	1.045
Kerosene	-9.942***	-10.175***	-9.610***	0.403	0.371	0.194
Natural Gas	-1.911*	-2.927***	-3.941***	0.605	1.417	1.694*
Propane	-8.975***	-9.282***	-9.825***	-0.306	-0.306	-0.306
WTI	-7.805***	-8.032***	-8.112***	1.162	1.162	1.162
			GFI			
Brent	-6.383***	-6.316***	-6.206***	1.616	1.615	1.615
Diesel	-9.576***	-9.741***	-9.897***	0.475	0.556	0.651
Gasoline	-7.973***	-8.095***	-7.863***	1.690*	1.938*	2.430**
Heating oil	-9.796***	-9.837***	-9.880***	-0.018	-0.018	-0.018
Kerosene	-9.365***	-9.096***	-8.672***	1.040	1.889*	1.887*
Natural Gas	-2.119**	-2.118**	-2.115**	0.961	1.077	1.112
Propane	-8.847***	-8.668***	-8.383***	-0.198	-0.164	-0.164
WTI	-7.634***	-7.519***	-7.333***	1.021	1.021	1.022
			VIX			
Brent	-6.283***	-6.219***	-6.114***	-0.964	-0.934	-0.580
Diesel	-9.792***	-9.960***	-10.035***	-0.513	-0.555	-0.439
Gasoline	-8.133***	-7.979***	-7.756***	-1.150	-0.791	-0.126
Heating oil	-10.200***	-9.879***	-9.380***	-0.378	-0.378	-0.378
Kerosene	-9.881***	-9.573***	-9.091***	-1.700*	-1.475	-1.475
Natural Gas	-1.336	-1.336	-1.336	-0.711	-0.712	-0.712
Propane	-8.834***	-9.019***	-8.699***	0.534	0.554	0.507
WTI	-7.999***	-8.065***	-8.085***	-0.534	-0.534	-0.535

Note: ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively. Figures in square brackets are standard errors of the estimated coefficients.

We find consistently across energy variables and out-of-sample forecast horizons the distributed lag model that incorporates CIU lags significantly outperformed the distributed lag model that incorporates the alternative uncertainty measures (see results in Table 5, under the column titled "Aggregate"). Imperatively, the newly developed index of uncertainty appears to have better predictive capacity over the extant variants (EPU, GFI, and VIX), hinging on the wealth of information from the Google trends database. Its outperformance transcends all three out-of-sample forecast horizons (*h=5, h=10,* and *h=20*), thus, it is not sensitive to the choice of the sample period. . On the confirmation of asymmetric effect, the results are presented under the column titled "Asymmetry" in Table 3. In testing formally the relevance of disaggregating the news effect into positive and negative values, we find, mostly, no evidence of asymmetry across the energy price variables, except in the case of EPU (diesel), GFI (gasoline and kerosene), and VIX (kerosene). Asymmetry may be dependent on the energy price variable and sample period, and should only be incorporated whenever they exist.

Generally, energy prices are vulnerable to the uncertainty induced by the COVID-19 pandemic, as they exhibit little or no hedging potential against uncertainty. While the relevance of news cannot be ignored when modelling energy price returns, failure to account for salient data features in the predictive model would bias the results and lead to unreliable conclusions.

4. CONCLUSION

In this study, we set out to develop an information-based index of uncertainty (the COVID-19 induced uncertainty) and empirically apply it to assess the vulnerability of energy prices to market uncertainties using a distributed lag model that appropriately accounts for conditional heteroscedasticity, autocorrelation, persistence, and structural breaks. Eight energy sources (Brent, diesel, gasoline, heating oil, kerosene, natural gas, propane, and the WTI oil) prices and four uncertainty proxies (CIU, GFI, EPU, and VIX) were analyzed. The first uncertainty proxy, the CIU index was developed in this study by summarizing the information in Google search volumes on several keywords relating to the COVID-19 pandemic, using the PCA, and used the same in the main estimation, while the other three alternative indices – GFI, EPU, and VIX, are drawn from extant literature and used to ascertain the robustness of results to news proxy. In addition to the computation of relevant summary statistics, some preliminary analyses were conducted, which informed the choice of the predictive model. Hence, we specified a distributed lag model (with five lags of the news variable, meant to account for the day-of-the-week effect and autocorrelations) that properly accounted for the observed salient data features. A break dummy that indicated the structural shift occasioned by the WHO declaration of COVID-19 as a pandemic was also incorporated into the predictive model. The conditional heteroscedasticity was taken care of by pre-weighting the model with the inverse of the standard deviation of the residuals.

We ascertained the predictability of each energy price returns using the aggregate (news), as well as the positively (good news) and negatively (bad news) decomposed partial sums of our index of uncertainty – CIU, as well as those of the three alternatives. While we found that news and bad news negatively and significantly impacted energy prices; good news impacted significantly positively. These outcomes revealed the lack of hedging potential of energy returns against the uncertainty that is occasioned by the COVID-19 pandemic. We showed the relevance of incorporating news as a predictor for energy prices by comparing our predictive model with the benchmark historical average model. The former outperformed the latter in most of the cases, across the specified forecast horizons (*h=5, h=10,* and *h=20*). We also found that the predictive model incorporating CIU performs better than the variants incorporating the three other alternatives. We further examined the relevance of accounting for asymmetry by comparing models that incorporated, separately, the good and bad news; and seldom found evidence of asymmetric effect across forecast horizons and energy prices being modelled. By implication, energy prices were vulnerable to the uncertainty occasioned by the COVID-19 pandemic, and this stance was not sensitive to the uncertainty proxy employed, given that the conclusions from the main estimation were upheld in the sensitivity analysis that used EPU, GFI, and VIX in place of CIU.

Meanwhile, investors in the energy market who do not seek alternative assets to invest in, are likely to incur losses during the COVID-19 pandemic. In furtherance of attempting to understand how commodity markets react to pandemics, research into improving the uncertainty index could be pursued, concerning accommodating more dynamics that are inherent in different sources of uncertainty. Also, this could be extended to other macroeconomic variables, other than energy prices.

References

Akintande, O.J., Olubusoye, O.E., Adenikinju, A.F., and Olanrewaju, B.T. (2020). Modeling the determinants of renewable energy consumption: Evidence from the five most populous nations in Africa. Energy, 117992

Aloui D., Goutte S., Guesmi K., and Hchaichi R. 2020. COVID 19'S Impact on Crude Oil and Natural Gas S & P GS Indexes. HAL Working Paper 02613280.

Baker, S. R., Bloom, N. and Davis, S. J. (2016). Measuring Economic Policy Uncertainty, The Quarterly Journal of Economics, 131 (4), 1593–1636, https://doi.org/10.1093/qje/qjw024

Bannigidadmath, D., and Narayan, P. (2015). Stock return predictability and determinants of predictability and profits. Emerg. Market. Rev. 26, 153–173.

Basel, A., Farrukh, J., Aktham, M. and Nader, V. (2018). Time-varying transmission between oil and equities in the MENA region: New evidence from DCC-MIDAS analyses Review of Development Finance 8, 116–126

Che, J., and Wang, J. (October 2010). Short-term electricity prices forecasting based on support vector regression and auto-regressive integrated moving average modeling. Energy Conversion and Management, 51(10), 1911–1917.

Chowdhuri, I., Pal, S. C., Saha, A., Chakrabortty, R., Ghosh, M. and Roy, P. (2020). Significant decrease of lightning activities during COVID-19 lockdown period over Kolkata megacity in India. Science of the Total Environment. December 10; 747: 141321. doi: 10.1016/j.scitotenv.2020.141321.

Clark, T.E. and West, K.D. (2007). Approximately normal tests for equal predictive accuracy in nested models. Journal of Econometrics 138, 291–311.

Conlon, T., McGee, R., 2020. Safe haven or risky hazard? Bitcoin during the COVID-19 bear market. Finance Res. Lett. 35.

Corbet, S., Larkin, C., Lucey, B., 2020. The contagion effects of the COVID-19 pandemic: Evidence from gold and cryptocurrencies. Finance Res. Lett.

Dang, H. and Trinh, T. (2021). Does the COVID-19 lockdown improve global air quality? Newcross-national evidence on its unintended consequences. Journal of Environmental Economics and Management, 105, 102401

Devpura, N., Narayan, P. K. and Sharma, S. S. (2018). Is stock return predictability time varying? J. Int. Financ. Market. Inst. Money 52, 152–172.

Diebold F, Mariano R. (1995) Comparing predictive accuracy. J Bus Econ Stat;13:134-144.

Esfahani, H. S. and Ramirez, M. T. (2003). Institutions, infrastructure, and economic growth. Journal of Development Economics, 70, 443–477.

Ghadimi, N. (2015). A new hybrid algorithm based on optimal fuzzy controller in multimachine power system. Complexity, 21(1), 78–93.

Guo, J. J. and Luh, P. B. (2004). Improving market clearing price prediction by using a committee machine of neural networks. IEEE Transactions on Power Systems, 19, 1867–1876.

IEA (2020). Global Energy Review 2020: The impacts of Covid-19 crisis on global energy demand and CO2 emissions. https://www.iea.org/reports/global-energy-review-2020. Retrieved on 25.08.2020.

Iqbal, M. M., Abid, I., Hussain, S., Shahzad, N., Waqas, M. S., & Iqbal, M. J. (2020). The effects of regional climatic condition on the spread of COVID-19 at global scale. The Science of the total environment, 739, 140101. https://doi.org/10.1016/j.scitotenv.2020.140101

Kerimray, A., Baimatova, N., Ibragimova, O. P., Bukenov, B., Kenessov, B., Plotitsyn, P. and Karaca, F. (2020). Assessing air quality changes in large cities during COVID-19 lockdowns: The impacts of traffic-free urban conditions in Almaty, Kazakhstan. Science of The Total Environment, Volume 730, 2020, 139179, https://doi.org/10.1016/j.scitotenv.2020.139179.

Le Quéré, C., Jackson, R.B., Jones, M.W. et al. (2020). Temporary reduction in daily global CO2 emissions during the COVID-19 forced confinement. Nat. Clim. Chang. 10, 647–653. https://doi.org/10.1038/s41558-020-0797-x

Mahato, S., Pal, S., & Ghosh, K. G. (2020). Effect of lockdown amid COVID-19 pandemic on air quality of the megacity Delhi, India. Science of the Total Environment, 139086. doi:10.1016/j.scitotenv.2020.139086

Narayan, P. K. and Gupta, R. (2015). Has oil price predicted stock returns for over a century? Energy Economics, 48, 18–23.

Narayan, P., Phan, D., Sharma, S. (2018). Does Islamic stock sensitivity to oil prices have economic significance? Pac. Basin Finance J. 53, 497–512.

Narayan, P.K., Phan, D.H.B., Sharma, S.S. and Westerlund, J. (2016). Are Islamic stock returns predictable? A global perspective. Pac. Basin Finance J. 40 (A), 210–223.

Norouzi, N, Zarazua de Rubens, GZ, Enevoldsen, P, Behzadi Forough, A. (2020). The impact of COVID- 19 on the electricity sector in Spain: An econometric approach based on prices. Int J Energy Res., 1– 13. https://doi.org/10.1002/er.6259

Salisu, A. A. and Akanni, L. O. (2020). Constructing a Global Fear Index for the COVID-19 Pandemic. Emerging Markets Finance and Trade, Accepted, DOI:10.1080/1540496X.2020.1785424.

Salisu, A. A. and Ogbonna A. E. (2019). Another look at the energy-growth nexus: New insights from MIDAS regressions. Energy (2019), doi:10.1016/j.energy.2019.02.138

Salisu, A. A. and Oloko, T. F. (2015). Modeling oil price-US stock nexus: A VARMA-BEKK-AGARCH approach. Energy Economics, 50, 1-12.

Salisu, A. A., Akanni, L., and Raheem, I. (2020a). The COVID-19 global fear index and the predictability of commodity price returns. Journal of behavioral and experimental finance, 27, 100383. https://doi.org/10.1016/j.jbef.2020.100383

Salisu, A. A., Ogbonna, A. E. and Adewuyi, A. (2020b). Google trends and the predictability of precious metals. Resources Policy 65, https://doi.org/10.1016/j.resourpol.2019.101542

Salisu, A. A., Ogbonna, A.E. and Adediran, I. (2020c). Stock- induced Google trends and the predictability of sectoral stock returns. *Journal of Forecasting*. doi:10.1002/for.2722.

Salisu, A. A., Swaray, R., Oloko, T. F. (2019). Improving the predictability of the oil–US stock nexus: The role of macroeconomic variables. Economic Modelling, 76, 153-171.

Sharif A., Aloui C., Yarovaya L. (2020). COVID-19 pandemic, oil prices, stock market, geopolitical risk and policy uncertainty nexus in the US economy: Fresh evidence from the wavelet-based approach. Int. Rev. Financ. Anal.;70

Wang, J., Shao, W., Kim, J., 2020. Analysis of the impact of COVID-19 on the correlations between crude oil and agricultural futures. Chaos Solitons Fractals 136.

Westerlund, J., Narayan, P. K. (2012). Does the choice of estimator matter when forecasting returns? J. Bank. Finance 36, 2632–2640.

Westerlund, J., Narayan, P. K. (2015). Testing for predictability in conditionally heteroscedastic stock returns. J. Financ. Econom. 13, 342–375.

WHO (2020). Archived: WHO Timeline - COVID-19**.** https://www.who.int/news-room/detail/27-04-2020-who-timeline---covid-19WHO

Xuelin, T., Chunjiang, A., Zhikun, C. and Zhiqiang, T. (2021). Assessing the impact of COVID-19 pandemic on urban transportation and air quality in Canada, Science of The Total Environment, Volume 765, 144270, ISSN 0048-9697, https://doi.org/10.1016/j.scitotenv.2020.144270

Yaya, O. S. and Ogbonna, A. E. (2019). Do we Experience Day-of-the-week Effects in Returns and Volatility of Cryptocurrency? MPRA Paper 91429, University Library of Munich, Germany.

Yaya, O. S., Luqman, S., Akinlana, D. M., Tumala, M. M. and Ogbonna, A. E. (2017). Oil Price-US Dollars Exchange Returns and Volatility Spillovers in OPEC Member Countries: Post Global Crisis Period's Analysis. African Journal of Applied Statistics, 4(1): 191-208.

Yaya, O. S., Ogbonna, A. E. and Olubusoye, O. E. (2019). How Persistent and Dynamic Inter-Dependent are pricing Bitcoin to other Cryptocurrencies Before and After 2017/18 Crash? Physica A, Statistical Mechanics and Applications. doi.org/10.1016/j.physa.2019.121732

Yaya, O.S., Ogbonna, A.E., Mudida, R. and Abu, N. (2020). Market Efficiency and Volatility Persistence of Cryptocurrency during Pre- and Post-Crash Periods of Bitcoin: Evidence based on Fractional Integration. International Journal of Finance and Economics, 1–18. https://doi.org/10.1002/ijfe.1851

Zhang, J., Lai, Y. and Lin, J. (2017). The day-of-the-Week effects of stock markets in different countries. Finance Research Letters, 20, 47-62.