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Role of Economic Policy Uncertainty in Energy commodities prices forecasting: Evidence from a hybrid deep learning approach

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Abstract

Amidst a dynamic energy market landscape, understanding evolving influencing factors is pivotal. Accurate forecasting techniques are indispensable for effective energy resource management. This study focuses on illuminating insights into economic uncertainty and commodity price forecasting. A meticulously curated dataset spanning January 2000 to December 2022 forms the foundation, incorporating diverse economic and financial uncertainty metrics. Through an innovative research framework, we discern influential factors and forecast their trajectories. Three deep learning models - Short-Term Memory, Gated Recurrent Units, and Multilayer Perception Network - are deployed. The Multilayer Perception model emerges as the standout, showcasing exceptional predictive capability rooted in its adeptness at decoding intricate market patterns. This finding holds significance for policymakers, industry experts, and energy economists. The Multilayer Perception model's supremacy offers a robust tool for decision-making in crafting economic policies and navigating volatile markets.

JEL Classification: O14, Q56

Keywords: Oil Price; Natural Gas; Economic uncertainty; Deep Learning; Forecast; commodity prices

1 – Introduction

Energy policies play a critical role in the current global economy, as energy is a vital resource to lead economic growth and development (Kasman and Uman, 2015; Tiba and Omri, 2017; Wang et al., 2018). Remarkably, the global economy is sensitive to energy price changes; hence policies can help to ensure that it remains stable. An appropriate energy program based on diversification to reduce dependence on a single supplier could promote and ensure energy security by preventing potential energy supply disruptions (Zakeri et al., 2022; Zhou et al., 2023). The current geopolitical situation has contributed to the rise in global inflation levels due to the energy crisis that is a consequence of the war in Ukraine. Roughly, the increased political uncertainty level can converge into price spikes that significantly impact the real economy. Therefore, governments and policymakers may be interested in preventing energy price tools that can help to address the more appropriate economic policies, such as the European price cap.

According to Herrera et al. (2019) and Al-Thaqeb and Algharabali (2019), the role of economic policy uncertainty is crucial to determine energy prices. Recent literature has examined how uncertainty shocks impact the economy. For example, Baker et al. (2016) created an index of economic policy uncertainty based on word frequency in U.S. newspaper articles. Similarly, Knotek and Zaman (2018) developed a historical index for energy price news using New York Times articles. They used a Bayesian approach to model energy inflation, excluding food and energy prices, and consumption growth. Notably, consumer responses to positive and negative energy shocks are nonlinear, with larger shocks showing more pronounced differences. While heightened uncertainty could lower investments and employment (Baker et al., 2016), Knotek and Zaman (2018) propose that consumers closely follow energy price news during major oil shocks. If high oil prices coincide with policy uncertainty, future economic activity might decline.[1]

Forecasting oil and gas prices is extremely important because of their central role in the global economy (Alquist and Kilian, 2010). They are crucial components in the production of many goods and services, thereof changes in prices can significantly impact different industries and economies. Accurate energy price forecasts can help businesses and governments make informed decisions about their operations and investments. For example, governments can use them to formulate ad hoc energy and economic policies. Many methods have been used in the

[1] Several papers investigated the relevance of economic uncertainty in the context of energy prices, see, among others, Kang and Ratti (2013), Kang et al. (2017) and Herrera et al. (2018).

literature to forecast oil and gas prices, ranging from standard econometric techniques (Lee and Huh, 2017; Hendrawaty et al., 2020) to deep learning methods (Shiri et al., 2015; Zhao et al., 2017).

There exists a plethora of factors that can affect commodity prices, including geopolitical events (Coleman, 2012), changes in global supply and demand (Kilian, 2009; Barsky and Kilian, 2010; Baumeister and Kilian, 2012), and technological advances (Dees et al., 2007; Ravazzolo and Vespignani, 2015). Lu et al. (2020) demonstrated the relevance of Google Trends research in influencing the rapid instability of commodity prices, highlighting the importance of the speculative component. As such, their forecasting can be a complex and challenging task. Several methods have been proposed for forecasting oil prices, including statistical models, fundamental analysis, and expert opinion. In recent years, machine and deep learning approaches have also gained popularity in forecasting oil prices (Gabralla and Abraham, 2013; Sehgal and Pandey, 2015; Zhang et al., 2015). Miao et al. (2017), through a Least Absolute Shrinkage and Selection Operator (LASSO), concluded the crucial role of political factors in forecasting crude oil prices.

The US Energy Information Administration (EIA), which formally produces monthly and quarterly forecasts of commodity prices for up to two years, is one of the most closely watched energy price forecasters. While the EIA's short-term estimates help influence business investment and resource use decisions, they are difficult to reproduce and occasionally inaccurate. The lack of comprehensive information on the forecasting approach makes replication difficult. Price estimates based on futures provide a market-based expectation. Although, in theory, the futures market should be a reliable predictor of future spot prices, actual data do not support this (Alquist and Kilian, 2010).

Given the difficulties of previous forecasting methods, several scholars investigated the motivations for the hardness in fossil fuel price prediction. The literature provides fascinating insights (Hamilton, 2009). A wide range of dynamic and multidimensional elements influence oil and gas prices, including physical market factors, financial market factors, and trade factors, all of which are difficult to anticipate and may have opposing effects. Further, perfect predictability is hampered by unforeseen movements in global demand, supply disruptions, changes in oil and gas production and storage requirements, geopolitical events, and other considerations. Such events raise concerns about the future supply curve, which can lead to increased price volatility. Unexpected events, such as refinery outages or pipeline failures, add to the unreliability. As a result, market participants constantly analyse the prospect of future events and their potential impact on prices, considering the history of oil and gas supply and demand shocks resulting from various events. Agents examine existing stocks and the ability of producers to compensate for a possible supply and demand shock, as well as the extent and duration of the potential disruption.

Besides, the forward-looking behaviour of speculators and the measurement of theoretical fuel demand shocks can sometimes invalidate standard econometric models. According to Kilian and Lee (2014), if investors and hedge funds react quickly to the missing forecasters' information, the detached purpose of demand and supply shocks using historical data may be irrelevant. To further complicate matters, the reverse causality issue (Chatrath et al., 2016) from macro aggregates to oil prices makes it difficult to link fluctuations in effective oil and gas prices to macroeconomic outcomes. Despite all these issues, forecasting efforts have allowed researchers to expand the range of potential factors influencing oil and gas prices (Tissaoui et al., 2022). This paper aims to determine the role of global political uncertainty factors in predicting commodity price trends. The above elements have also been shown to be of considerable importance with the recent financial crises brought on by COVID-19 and the Russian-Ukrainian war (Ding et al., 2022). In addition, using hybrid deep learning models, we incorporate relevant economic factors such as general inflation, the relative dollar index, and the financial uncertainty indicator considered by the Chicago Board Options Exchange (CBOE) into the forecasting context.

In details, the predictive analysis can help formulate energy and economic policies. In particular, according to Ahmad et al. (2021) and Ahmad et. al (2022), accurate energy price predictions enable governments and businesses to allocate resources more efficiently. For example, if predictive analytics suggest a future rise in oil prices, policymakers can prioritize investments in renewable energy sources or energy-efficient technologies. In addition, according to Song et al. (2019), forecasting price fluctuations helps countries plan for energy security. Governments can adjust their strategic reserves of crude oil and natural gas based on anticipated price trends, ensuring a stable supply during periods of volatility. Finally, according to Khan et al (2021), predictive analytics can guide policymakers towards more sustainable energy choices. If the analysis points to a rise in fossil fuel prices, governments could speed up the rollout of renewable energy projects or enact tougher environmental regulations. Accordingly, we highly contribute the literature in forecasting fossil fuels prices.

This study examines and forecasts the effects of oil prices using advanced deep-learning methodologies. As part of this investigation, we use a cutting-edge algorithm that integrates multiple variables to forecast oil price fluctuations. In contrast to traditional econometric forecasting models, deep learning approaches generate predictions that are not based on pre-established assumptions(Chen et al., 2023; Guliyev & Mustafayev, 2022; Zhao & Hastie, 2021). Notably, the Deep Learning methodology in macroeconomic data forecasting has grown and become significant in macroeconomic series forecasting and prediction (Dieudonné et al., 2023; Magazzino et al., 2022). Empirical evidence suggests that these techniques outperform traditional statistical methods, mainly when dealing with non-parametric, non-linear challenges and large datasets required for short-term and long-term forecasting. In this context, the treatment of non-linearity, a domain in which machine learning excels, is profoundly shaped by the dynamics of economic uncertainties and the richness of the data model, highlighting the ability to encapsulate intricate macroeconomic interconnections(Guliyev & Mustafayev, 2022; Shahzad et al., 2023; Zhao & Hastie, 2021). Furthermore, while alternative linearization strategies such as Lasso and Ridge are notable, they do not outperform the factor model, reinforcing that a component-based representation of the macroeconomy is an effective dimensionality reduction tool. Understanding that deep learning, a subset of machine learning, is distinguished by its inherent ability to learn autonomously, eliminating the need for human-annotated labelling is critical. Furthermore, deep learning optimization techniques within artificial neural networks mimic the structural complexities of the human neural framework.

This paper contributes to the literature using a relatively new methodology that optimally weights the factors underlying oil and gas price movements. We aim to innovate the current oil and gas forecasting literature in three ways. First, we consider several measures of economic policy uncertainty to improve the forecasting performance of our model. In particular, we consider the different categories of Economic Policy Uncertainty (EPU) discussed in Baker et al. (2016), the geopolitical risk index of Caldara and Iacovello (2021), and the climate policy uncertainty index of Gavriilidis, K. (2021). The EPU is a daily index that contains several measures of uncertainty: monetary policies, taxes, tax policies and government spending, health care, national security, entitlement programs, regulation, financial regulation, trade policy and sovereign debt, and currency crises (the detailed list is shown in Table 1). Second, by examining the current uncertain environment, we can establish the predictive quality of models when turbulent economic situations arise. Furthermore, we can understand how the data generation process underlying the estimated processes affects the generality of our results and thus conclude possible viable economic policies. Third, the heterogeneity of variables considered allows us to infer the contribution of each factor to the prediction of commodity prices considered. Finally, we analyse the series' short- and long-term forecasting ability through different deep-learning methods. Based on the accuracy metrics, we found that the Multilayer Perception (MLP) network has the best forecasting ability to predict trends and peaks. We believe this work provides insights from a policy perspective, as it allows for action to reduce price rises and falls.

The rest of the article is organised as follows. Section 3 provides a brief literature review of the topic. Section 2 describes the deep learning methods used. Section 3 presents the dataset. Section 4 describes the results, and Section 5 concludes.

2 – Literature Review

Many methods have been used in the literature to forecast oil and gas prices, ranging from standard econometric techniques (Lee and Huh, 2017; Hendrawaty et al., 2020) to deep learning methods (Shiri et al., 2015; Zhao et al., 2017).

There exists a plethora of factors that can affect commodity prices, including geopolitical events (Coleman, 2012), changes in global supply and demand (Kilian, 2009; Barsky and Kilian, 2010; Baumeister and Kilian, 2012), and technological advances (Dees et al., 2007; Ravazzolo and Vespignani, 2015). Lu et al. (2020) demonstrated the relevance of Google Trends research in influencing the rapid instability of commodity prices, highlighting the importance of the speculative component. As such, their forecasting can be a complex and challenging task. Several methods have been proposed for forecasting oil prices, including statistical models, fundamental analysis, and expert opinion. In recent years, machine and deep learning approaches have also gained popularity in forecasting oil prices (Gabralla and Abraham, 2013; Sehgal and Pandey, 2015; Zhang et al., 2015). Miao et al. (2017), through a Least Absolute Shrinkage and Selection Operator (LASSO), concluded the crucial role of political factors in forecasting crude oil prices.

Besides, the forward-looking behaviour of speculators and the measurement of theoretical fuel demand shocks can sometimes invalidate standard econometric models. According to Kilian and Lee (2014), if investors and hedge funds react quickly to the missing forecasters' information, the detached purpose of demand and supply shocks using historical data may be irrelevant. To further complicate matters, the reverse causality issue (Chatrath et al., 2016) from macro aggregates to oil prices makes it difficult to link fluctuations in effective oil and gas prices to macroeconomic outcomes. Despite all these issues, forecasting efforts have allowed researchers to expand the range of potential factors influencing oil and gas prices (Tissaoui et al., 2022). This paper aims to determine the role of global political uncertainty factors in predicting commodity price trends. The above elements have also been shown to be of considerable importance with the recent financial crises brought on by COVID-19 and the Russian-Ukrainian war (Ding et al., 2022). In addition, using hybrid deep learning models, we incorporate relevant economic factors such as general inflation, the relative dollar index, and the financial uncertainty indicator considered by the Chicago Board Options Exchange (CBOE) into the forecasting context.

According to Bernanke (1983), Economic Policy Uncertainty (EPU) has played an important role in shaping economic cycles and guiding investment decisions, including oil markets. Despite its importance within economic paradigms, previous studies frequently overlooked uncertainty's role in predicting oil prices owing to a lack of reliable and quantifiable metrics to assess policy uncertainty. In response to this gap, Baker et al. (2016) developed an EPU index based on newspaper data, a methodology that has received widespread acclaim in the academic community. This index has since been used by academics worldwide to investigate the effects of EPU on oil price dynamics. (Y. Zhang et al., 2023) investigated the role of EPU in oil price predictability. According to their findings, increased global economic uncertainty can accurately forecast crude oil market volatility within the sample and in extrapolated scenarios. It is worth noting that, as (He et al., 2022; Sen et al., 2023; S. Zhang et al., 2023)point out, the adoption of deep learning techniques, a subset of Machine Learning, is still in its infancy when compared to traditional time-series econometric approaches, despite their demonstrable empirical prowess in forecasting oil prices. The intricate web of global economic and financial linkages suggests that geopolitical events can impact the oil market (Si Mohammed et al., 2023). The effects of the COVID-19 pandemic have been particularly severe on US businesses, prompting predictions of oil prices based on Healthcare Uncertainty(Al Mustanyir, 2023; Tissaoui et al., 2022). Furthermore, fluctuations in energy prices strongly impact the global economic landscape, emphasizing the importance of consistent policies. Oil price oscillations, caused by monetary and fiscal policy uncertainties, are now recognized as primary determinants in changes in oil prices (Bashar et al., 2013; Su et al., 2020).

3 – Methodology

Machine learning and deep learning approaches can produce accurate forecasts because they can analyse large amounts of data and learn patterns. The learning-based mechanism on historical patterns allows the model to adapt to changes in data over time, which is often a key challenge in forecasting. A crucial advantage of machine learning and deep learning approaches is that they can handle complex, non-linear relationships in the data, which can be difficult for traditional statistical models to capture. In addition, these approaches can handle large amounts of data, including data that may be noisy or incomplete, and learn from the data in real-time as it becomes available. Overall, the learning ability of machine learning and deep learning approaches from data is a powerful tool for forecasting and decision-making in a variety of applications.

Recursive Neural Network (RNN) approach

In typical neural network applications, there are only complete layer connections between neighbouring, but not between nodes in the same layer. Since in a temporal-spatial network, there are continuous exchanges between components, this type of network can fail when it comes to temporal-spatial challenges. Considering Graves' (2013) famous discourse, unlike conventional networks, the hidden units of RNNs (Recursive Neural Networks) receive input from the past state to the present one. Figure 1 shows a basic RNN architecture with a delay line deployed in the time domain for two-time steps.

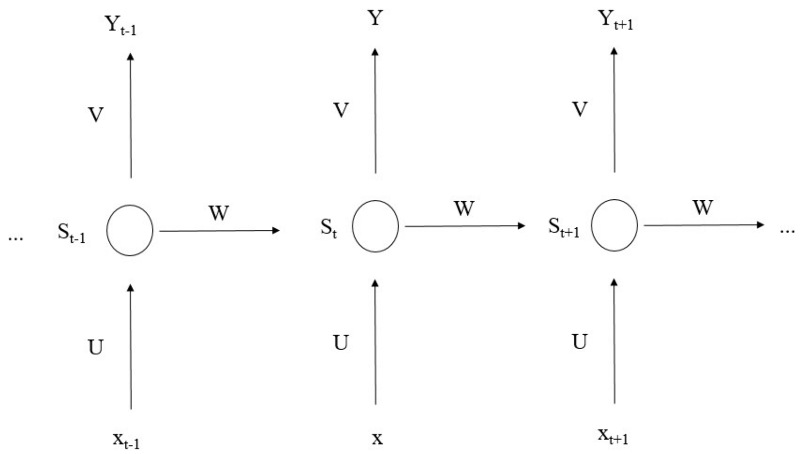

Figure 1: RNN structure

Instead of using a combination of multiple vectors like typical network designs, the input parameters are supplied to the RNN once at a time. In addition, this design can use all input data accessible up to the present time. The RNN depth can be defined according to the actual conditions. The outcome depends not only on the input sequence but also on the result of the previously hidden layer.

Let x_i be the input variable, W_{rx} W_{rr} W_{or} weight matrices, b_r and b_y bias vectors, σ and η sigmoid functions, the mathematical representation of the RNN model in Figure 1 is as follows:

$$t_i = W_{rx}x_i + W_{rr}x_{i-1} + b_r \qquad (1)$$

$$r_i = \sigma(t_i) \qquad (2)$$

$$s_i = W_{\square}r_i + b_y \qquad (3)$$

$$\hat{y}_i = \eta(s_i) \qquad (4)$$

Where t_i, r_i, and s_i, are the temporary variables, and y hat is the expected output. The cost function is the modular difference between the sum of the expected output and its actual value. Consequently, the result at t+1 is a function of both the input at t+1 and the previous data. The RNN model correlation in the time series, along with the thickness of the network, is determined by the time interval. However, due to the curse of dimensionality and the inflation gradient problem, the accuracy of the RNN model decreases as the time interval increases, affecting the final output.

Long short-term memory (*LSTM*) algorithm

The LSTM network is a type of RNN. Using convolutions as the cache memory, the LSTM network can handle both short- and long-term time series correlation. Figure 2 illustrates the structure of the memory unit. The red circle represents a memory cell in the center. The available data is the input, and the expected result Y_t is the output. The memory unit has three ports, illustrated by the green circles: input, forget and output. In addition, D_t represents the state of the cell, the input of each gate is pre-processed data, and D_{t-1} represents the previous state of the memory. The blue dots represent confluences, and the dotted lines represent the function of the previous level. The status update and output of the memory unit can be summarised as follows according to the information flow in the memory unit structure:

$$i_t = \sigma\left(W^i X_t + U^i S_{t-1}\right) \qquad (5)$$

$$o_t = \sigma(W^o X_t + U^o S_{t-1}) \qquad (6)$$

$$y_t = \sigma(W^y X_t + U^y S_{t-1}) \qquad (7)$$

$$\tilde{S} = tanh(W^s X_t + W^s S_{t-1}) \quad (8)$$

$$S_t = o_t \circ S_{y-1} + i_t \circ \tilde{S}_t \quad (9)$$

$$Y_t = y_t \circ tanh(S_t) \quad (10)$$

where ∘ is the Hadamard product. The first three equations are the outputs of the separate gates, the fourth is the new state of the memory cell, the fifth is the final state of the memory cell, and the last is the final output of the memory unit. LSTM memory units can record complex correlation information within short- and long-term time series using the separate port function, which is a significant advantage over RNNs.

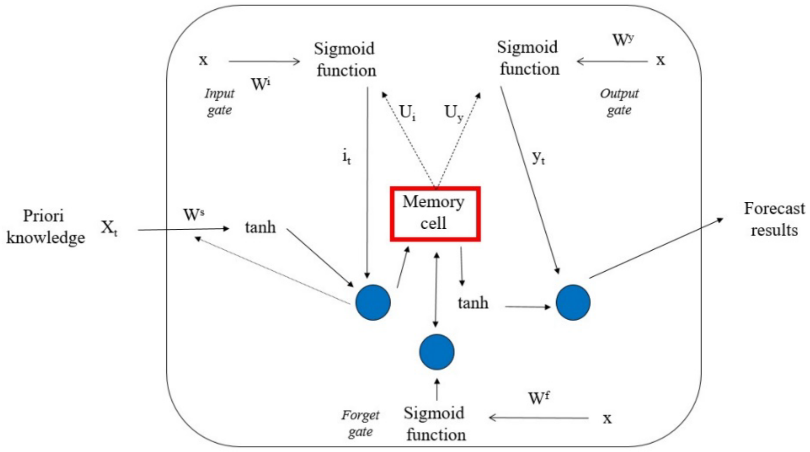

Figure 2: LSTM memory procedure

Gated Recurrent Units (*GRU*) method

According to Cho et al. (2014), Gated Recurrent Units (GRUs) are a filtering method in an RNN structure like LSTMs. It has fewer parameters than LSTMs, as it lacks an output gate. GRUs do not have an additional memory cell to store information, so they can only control it within the unit. The structure of the equations is like that of LSTMs and can be summarised as follows:

$$u_t = \sigma(W^u X_t + U^u S_{t-1}) \quad (11)$$

$$r_t = \sigma(W^r X_t + U^r S_{t-1}) \quad (12)$$

$$\tilde{y}_t = tanh(W^{r_t} + W^{S_{t-1}} + X_t) \quad (13)$$

$$Y_t = (1 - u_t) \circ y_{t-1} + u_t \circ \tilde{y}_t \quad (14)$$

In the previous block of equations, u_t decides how much content or information is updated. Then, r_t is a kind of dummy operator, if the gate is set to zero, it reads the input sequences and forgets the previously calculated state. Furthermore, the tilde y_t shows the same functionality as the recurring unit, and y_t of the GRU at time t represents the linear interpolation between the various equations of state.

Multilayer Perceptron (MLP) system

According to Basheer et al. (2000), the Multilayer Perceptron (MLP) is one of the most widely used FeedForward Neural Networks (FFNN). Its structure is as follows. The input layer is the initial layer that feeds the network with input variables, the output layer is the last, and all layers between the input and output layers are called the hidden layer. The neurons in the MLP are one-way connected. The connections between the neurons are expressed by the weights, which are real integers in the range [-1;1].

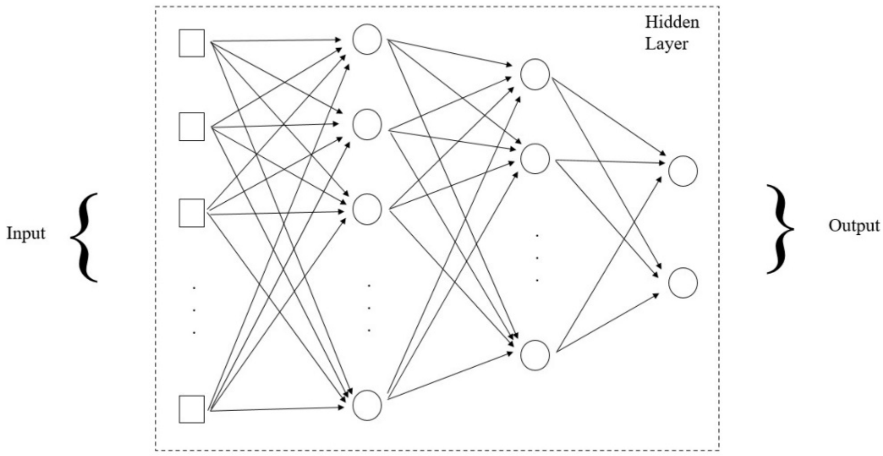

Figure 3: MLP framework.

Each layer in an MLP can be described mathematically, as depicted in Figure 3:

$$O_i^l = \zeta\left(\sum_j O_j^{l-1} k_{j,i} + k_{0,i}\right), \qquad (15)$$

where ζ is the activation function of the layer. It is often designed as a complex hyperbolic tangent function for the hidden units and a linear function for the output layer results. The index 'l' identifies the real layer in a structure of L non-input layers, and n_l denotes the number of neurons in layer O_l indicating the output of neuron I in real layer l. In addition, $k_{j,i}$ are the weights relative to the connections of neuron I in layer l, and $k_{0,i}$ is the bias of neuron i in the real layer. The output vector coincides with the input feature vector, and the final output vector corresponds to the network results.

4 – Data Specification

The dataset we used includes several market indicators. First, we aim to predict crude oil and natural gas prices. All deep learning methods described in Section 2 aim to forecast them. Furthermore, we use several indicators to enable good forecasting. According to Tissaoui et al. (2022), who demonstrated the relevance of policy indicators in energy price forecasting, we use the categorical policy indicators of Baker et al. (2016). The categorical data include some sub-indices based solely on journalistic data. These are extracted from the Access World News database, which contains over 2,000 US newspapers. We detailed in Table 1 the variables used.

Furthermore, due to the recent clash between Russia and Ukraine, we include the geopolitical risk indicator of Caldara and Iacovello (2021) to account for the occurrence of the recent energy crisis. Furthermore, given the fossil nature of the dependent variables, we include the Climate Policy Uncertainty index by Gavriilidis, K. (2021) to establish a possible link to this framework. Given the relevance exploited in the literature, we include several financial measures such as the CBOE volatility index (VIX), the Dow Jones Industrial Average (DJIA), the median consumer price index, and the US dollar index. While the uncertainty measures are directly downloadable from the specific web page (https://www.policyuncertainty.com/index.html), the financial data are obtained via Datastream. The period is from January 2000 to December 2022, with variables observed monthly according to sample availability.

Figure 4 shows the time series of the dependent variables, while Figure 5 shows the explanatory variables. Table 2 shows the descriptive statistics. Deep Learning methods allow us to use non-stationary prices, so we do not report Unit Root tests here. The mean value of the WTI is higher than that of the NG and indicates a potentially higher expectation of the former. Both dependent variables show a more volatile behavior in the second part of the sample, being significantly influenced by different economic events. Several EPU categories, such as Trade Policy, Aid Programme, and Sovereign Debt, Uncertainty of Currency Crises, show higher peaks in the different periods considered. These preliminary statistics highlight the role of time-varying uncertainty in this context.

Variable	**Label**
Crude Oil Price West Texas Intermediate	WTI
Natural Gas	NG
US Field Production of Crude Oil (1000 per barrel)	CRUDE_PROD
Economic Policy Uncertainty index (EPU)	EPU
Monetary policy uncertainty index (MPU)	MPU
Fiscal Policy Uncertainty Index (Taxes OR Spending)	FISCAL
Taxes Uncertainty	TAX
Government spending Uncertainty	GOV
Health care Uncertainty	HEALTH
National security Uncertainty	NS
Entitlement programs Uncertainty	EP
Regulation Uncertainty	RU
Financial Regulation Uncertainty	FRU
Trade policy Uncertainty	TPU
Sovereign debt, currency crises Uncertainty	SCU
Geopolitical Risk Index (GPR)	GPR
Climate Policy Uncertainty Index (CPU)	CPU
CBOE Volatility Index (VIX)	CBOE
Dow Jones Industrial Average (DJIA)	DJIA
Median CPI	CPI
US Dollar Index	USD

Table 1: Variables and respective token.

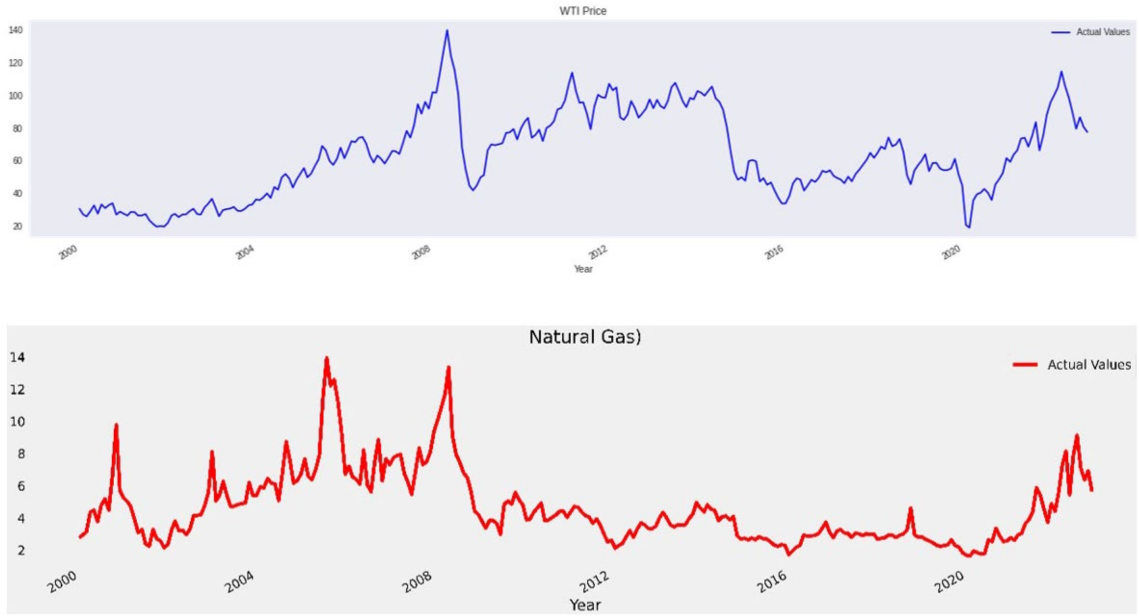

Figure 4: Dependent variables

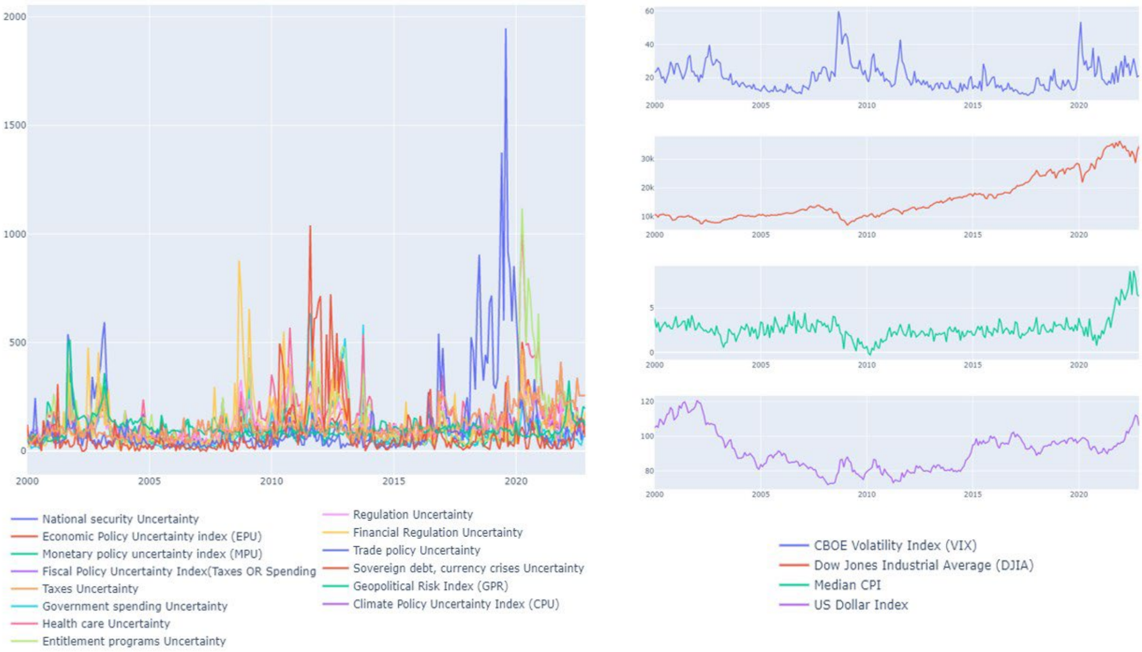

Figure 5: Explanatory variables

	Mean	Max	Min	Std. Dev.	Skew	Kurt	JB	N
WTI	62.87	140	18.84	26.05	0.3	2.22	11.004***	275
CBOE	20.28	59.89	9.51	8.15	1.62	6.73	280.08	275
CPI	2.67	9.22	-0.29	1.32	1.83	9.18	590.83	275
CPU	116.86	411.29	28.16	64.01	1.52	5.42	172.73	275
CRUDE_PROD	7524.78	13000	3974	2539.07	0.67	1.97	33.11	275

DJIA	16161.96	36338.3	7062.93	7693.49	1.05	2.96	50.84	275
EP	148.13	1118.79	14.38	142.15	3.09	16	2373.86	275
EPU	106.8	503.01	37.27	59.63	2.63	14.05	1715.09	275
FISCAL	114.91	433.29	23.05	72.99	1.58	5.73	199.7	275
FRU	118.48	877.55	0	119.19	2.7	12.94	1465.75	275
GOV	91.82	635.27	5.78	93.6	2.93	13.83	1738.98	275
GPR	104.9	512.53	45.06	53.01	4.29	28.63	8368.41	275
HEALTH	163.5	1030.68	29.97	128.42	2.65	13.88	1677.52	275
MPU	89.49	407.94	17.62	58.64	1.79	7.73	403.69	275
NS	93.99	593.46	23.74	80.7	3.21	16.08	2431.57	275
RU	118.75	384.39	31.06	59.28	1.3	5.21	133.67	275
SCU	83.77	1039.34	0	136.29	3.51	17.64	3021.1	275
TAX	120.2	471.9	24.44	75.76	1.64	6.21	240.88	275
TPU	119.32	1946.68	7.67	209.66	4.53	30.05	9321.58	275
USD	91.52	120.59	72.17	11.39	0.55	2.67	14.89	275

Table 2: Descriptive statistics and normality test (*** means p-value lower than 1%)

5 – Results

The prediction results are primarily shown in Figures 6 and 8, while the metrics are calculated in Tables 3 and 4. We based our prediction results on an 80-20% split of the training and test data, as stated by most of the literature. We include model loss estimates, defined as the penalty for poor prediction. If the model prediction is perfect, the loss is zero; otherwise, the loss is higher. We include some additional variables in the raw dataset, such as the SP 500 Energy index, which we decided to remove due to its high correlation with the dependent variable.

The number of neurons, batch size, and optimizer are chosen in this study via hyperparameter tuning. The number of layer neurons in the models is 64, as is the batch size. The neural network structure was trained using the back-propagation algorithm (BP), with the learning rate, batch size, and epochs set to 0.05, 64, and 100, respectively. The learning rate, which is a function of reducing time, controls the convergence rate. When the number and learning frequency of epochs is respectively set to 100 and 0.05, the training set converges, and the empirical findings tend to be stable, allowing the training set data to be recognized.

Crude oil price forecasts demonstrate the feasibility of MLP when adverse economic situations occur. The model shows a surprising fit for the test set. Since it is involved in 20% of the last data, it includes COVID-19 and the Russian-Ukrainian war. It can predict the negative oil price peak reached in April 2020. However, it can forecast the positive max caused by the energy crisis. These results are confirmed by the three accuracy metrics used. While most of the literature states the predictive power of LSTM models (Lu et al.; 2021), it is not the best in our case. Moreover, looking at the graphical representation, it manages to predict the negative peak reached during the COVID-19 period. What emerged is the difficulty in predicting the direction of prices after a peak is reached, whether negative or positive.

The LSTM deep learning method was often used to forecast the natural gas price. However, our analysis shows the higher predictability power of MLP with respect to the other methods. In this situation, the LSTM forecasting power is significantly lower than the others. Moreover, both LSTM and GRU predict a natural gas increase during the COVID-19 period. Quite the opposite, GRU had a good performance after the widespread pandemic. The MLP forecasts show a greater power, both in peaks and trends, as confirmed by the metrics. We can conclude about the forecasting predictability of MLP.

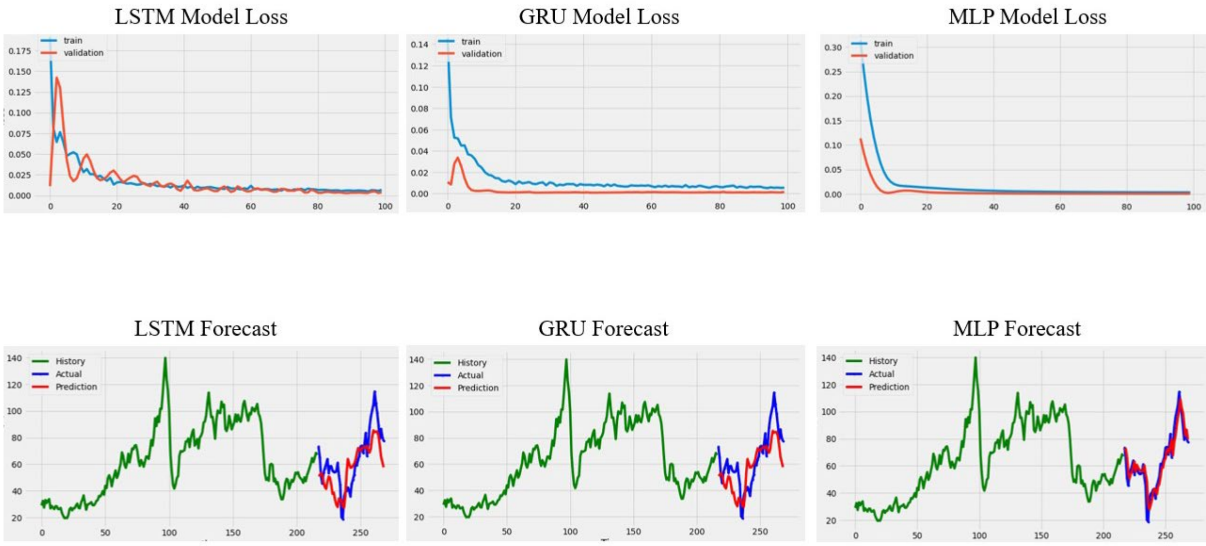

Figure 6: WTI Forecasts

	LSTM	MLP	GRU
MAE	11.479	6.6192	16.625
RMSE	15.22	8.13	20.521
MAPE	23.944	13.005	34.52

Table 3: WTI metrics accuracy

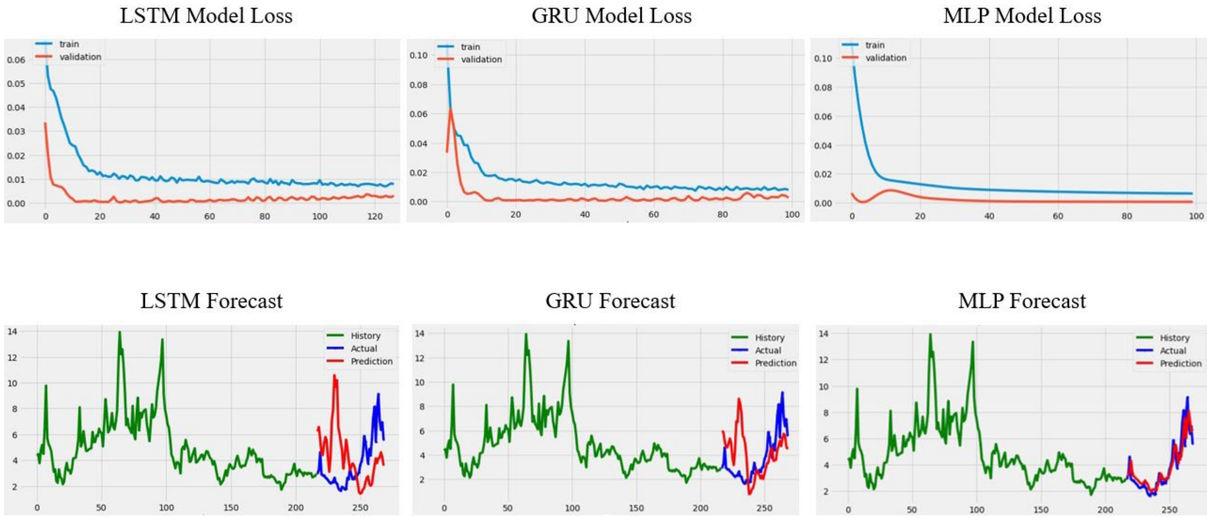

Figure 7: NG Forecasts

	LSTM	MLP	GRU
MAE	2.7961	0.6307	1.9408
RMSE	3.3283	0.8299	2.437
MAPE	94.615	16.555	67.247

Table 4: NG metrics accuracy

5.1 – Discussion of Findings

In this section, we discuss the economic implications of our results. Given the complexity of international fossil fuels price movements and the uncertainty of forecasting results, this paper proposes a new empirical application for natural gas and crude oil price forecasting. With the proposed approaches, we can take into account the nonlinearities of the system together with the temporal dynamics of crude oil prices, which the literature has considered fundamental from a forecasting perspective (Çepni et al., 2022). All these results indicate the excellent predictive ability of the Multilayer Perceptron (MLP) method for forecasting crude oil prices. However, it should be noted that the computational process of the hybrid method is relatively complicated compared to most previous standard methods, although the hybrid method can capture the complex dynamic behaviour of crude oil prices. Overall, our forecasting method definitely provides a decision support tool for investors and analysts involved in the energy markets to assess trends price movements and thus effectively measure the dynamics of extreme risk developments.

Several studies in the literature have highlighted the role of integrating structural disruptions to improve commodity price forecasting (Arouri et al., 2012; Chatzikonstanti and Venetis, 2015; Wang and Hao, 2023). In our case, thanks to the proposed machine learning techniques, we were also able to filter out these events and define hybrid models capable of integrating these situations. The MLP model, which is by far the best in terms of all the metrics used, thus allows us to identify hidden layers capable of explaining the behaviour of the economic variables under study. Given the structure of the sample analysed, two events of global importance, the war in Ukraine and the outbreak of COVID-19, made it possible to understand the predictive power of our models. In this situation, it is crucial to specify that our study is purely predictive of prices, not volatilities, as in much relevant economic literature (Mensi et al., 2014; Qu and Li, 2023). In our case, volatility is an exogenous instrument that is filtered through the use of the proposed measures of uncertainty. The literature on volatility forecasting has been studied extensively. See, for example, Kristjanpoller and Minutolo (2016) and Chen et al. (2022).

We have also been able to show that the inclusion of uncertainty measures improves the performance of out-of-sample forecasts. These results have important policy implications. Macroeconomic policy decisions usually take into account oil price estimates. In terms of policy efficiency, accurate oil price estimates are undoubtedly required. Since oil price shocks significantly affect the real economy, any policy to mitigate their adverse effects must be considered. Baumeister and Peersman (2013) provide supporting evidence by showing the time-varying effects of oil supply shocks on the real side of the economy.

Furthermore, several scholars have affirmed the goodness of forecasting commodity prices in turbulent situations (Baumeister and Kilian, 2014; Wang et al., 2017). We further corroborate these findings by providing a more general model that helps policymakers and traders predict these values in calm and turbulent situations. According to Baumeister and Kilian (2016a), empirical models may fail in predicting real-time oil prices. However, we can affirm the goodness of oil price prediction even if it is based on monthly observations. We use the uncertainty measure as opposed to Baumeister and Kilian (2016b), who employed the oil price decline to predict the financial crisis. Our results are crucial from a policy point of view, as they allow us to make accurate predictions in any occurrence based on the value of economic and financial uncertainty measures.

6 – Conclusions and policy implications

In this paper, we conduct a forecast analysis of natural gas and oil prices. The growing uncertainty in world energy markets, especially in energy importers countries, has led many states to review their energy structure. As several scholars have pointed out, the impact of prices on energy production has been significant and growing over the past decade. While during COVID-19 a general reduction in the price level occurred due to the various national lockdowns imposed, the invasion of Ukraine by Russia saw an increase in fossil prices.

The restriction of energy supplies by Russia, as a reaction to the sanctions adopted, led to a decrease in supply. Moreover, given the persistence on the demand side, the sanctions led to an increase in the prices of fossil fuels and raw materials. In this context, having a model capable of predicting oil price trends based on other economic indicators (leading) is of fundamental importance because it helps states to define their economic policies. Based on the increasing availability of data, we used different measures of uncertainty to build deep learning models. In our dataset, we integrated measures of political uncertainty and measures of financial uncertainty. By comparing the results obtained through the accuracy measures (MAE, MAPE, RMSE), we were able to conclude the predictive power of the MultiLayer Perception (MLP) algorithm. Not only was it the best on average, but from a graphical analysis, we affirm its ability to predict negative and positive price spikes.

We firmly believe that having a model to predict market trends can intervene during the policy-making decision. If energy prices are expected to rise steadily, from the point of view of an energy-importing country, it would be essential to reduce external dependencies. One possible solution to this problem may be to use an energy mix that reduces risk and improves the environment, which is increasingly subject to deterioration. Conversely, for a producer/exporter country, incentive mechanisms for energy purchases are needed. For instance, the elimination of taxes could attract purchasers from abroad.

This paper uses the hybrid method to forecast international natural gas and crude oil prices based on historical data. However, energy markets have proven to be a typical complex system, the movement of which can commonly be influenced by many factors, as mentioned above. Therefore, the forecast accuracy is determined not only by the quantitative results of the hybrid method but also by some random variables that are difficult to quantify. Thus, in the future, we will be able to infer the influence of these qualitative factors, by combining quantitative and qualitative findings.

To conclude, future research prospects can compare model accuracy based on different explicative variables. In addition, through dimensionality reduction mechanisms, scholars could identify whether the loss of information is relevant. As a result of this analysis, researchers could conclude about the applicability of these reduction mechanisms. Finally, given a deep-learning system, possible future studies could compare performance measures with classical econometric forecasting models.

Ethical approval

Ethical approval is not applicable as the data is obtained from different data bases and no questionnaires for animals or humans are used.

Consent to publish: Not applicable

Availability of data and materials: The datasets used during the current study are available from the corresponding or first author on reasonable request.

Competing interests: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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