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RESEARCH PAPER

The Effect of Climate Policy Uncertainty and Financial Globalization Uncertainty on Oil Market Fear: New Insight from QARDL

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Abstract

The oil implied shocks index of Christiane Baumeist is a prominent measure for market fear. This article adopts the oil implied shocks index (OPS) to examine the impact of various uncertainty indicators and economic performance on oil market fear in Nigeria. Our uncertainty proxies acknowledged multiple viewpoints, particularly the climate policy uncertainty (CPU), financial globalization uncertainty (FGU), and economic policy uncertainty (EPU). Based on the Quantile Auto Regressive Distributive Lag model (QARDL), our empirical findings reveal that the impact of CPU, FGU, EPU, and INC on OPS is quantile-based and heterogeneous by virtue of the productivity growth and these uncertainties. Precisely, the CPU has increasingly become an important determinant sparking oil market fear across the quantiles. CPU play an essential role in deepening oil market fear in Nigeria. The Non-linear ARDL results confirmed the positive relationship of all the determinants on OPS. Policy recommendations are discussed accordingly in the last part of the paper.

Keywords: Baumeist, Environmental Policy, Financial Openness, Instability, Quantile.
JEL Classification: E4, E5, F63, F63, F65.

1. Introduction

Oil is regarded as a critical component in driving economic and financial progress. As such, research on the oil market is receiving a lot of consideration. Given the recent growth in the oil sector's finances, anxiety is expected to intensify and extend throughout markets. Sudden catastrophic incidents, such as the 2017-2018 economic slowdown and global COVID-19 outbreak, have increased the level of anxiety in the oil industry. The anticipated instability index developed by US Lecturer Christiane Baumeist, senior Energy Administrator, serves as a commonly used gauge of market anxiety (Salisu and Gupta, 2020). The volatile nature of oil prices reveals that the level of panic in the oil industry grew from around 30 to around 90% during the global recession of 2008 (Xiao and Liu, 2023). Not too long ago, the 2019 COVID-19 epidemic produced enormous disruption in the global economic as well as financial markets. The latest pandemic seems to have heightened fear amongst oil market players, as percentage of OPS grew drastically from roughly 30% to roughly 160% amid this time. Market fear is continually accompanied by a psychological response that may not be predicted precisely, exacerbating the hazard (Yaya et al., 2021). Certainly, oil prices plummeted amid the 2008 recession and the latest COVID-19 epidemic. Considering severe anxiety and insecurity in oil markets are harmful to oil operations, asset dissemination, and risk control, along with generating negative financial and economic consequences, it is vital to explore the elements probable to contribute to oil market worry. The purpose of this article is to look into the consequences of climate policy uncertainty, financial globalisation uncertainty, economic policy uncertainty, economic performance on oil market anxiety.

The reasons that follows are the specific inspirations behind our quest. Multiple studies have shown that fluctuations in oil costs are influenced by a number of variables such as crude oil supply, real GDP, exchange rates, finances, and investment behaviour (Chatziantoniou et al., 2021; Xiao and Wang, 2021; Wen et al., 2018). The onset of the financial meltdown in 2008, which occurred after Great Recession, heightened fears about potential unpredictability. In its entirety, uncertainty reduces investments, spending among consumers, and numerous other economic activities, damaging the broader economic components and finance industries. Uncertainty remains as an important contributor to oil costs, as it can influence the core values of the oil trade. Nonetheless, proper quantification of uncertainty may be difficult in the most pertinent empirical studies. Baker et al. (2016), to their credit, give a news-based uncertainty index. Citing Baker et al. (2016), several studies have investigated the implications of various types of uncertainty upon oil price appreciation and volatility (Qin et al., 2020a; Zhang and Yan, 2020; Liu et al., 2021, and Wang et al., 2022). Notably, depending on the data material, uncertainty indicators might have an extensive range of impacts on oil trade. As a result, EPU may impact the demand side of the oil trade; FGU may also be related with the oil trade due to finance of oil; and CPU could drive the supply side of the oil industry and tweak oil prices due to widespread engagement in companies and financial processes.

However, the impact of various types of uncertainty upon oil industry has attracted scant research attention. Wen et al. (2019) and Huang et al. (2021) concentrated on comparing economic and monetary uncertainty indicators. Li et al. (2020) and Liang et al. (2020) examined the various impacts of economic, finances and geographical uncertainty indicators. Gu et al. (2021) investigate the effects of macro-variables and regional vulnerability. Despite growing interest in the relationship between uncertainties and the oil market, earlier research largely focused less upon the impact of climatic uncertainty determinants affecting the oil market anxiety (Guo et al., 2022). Global warming remains one of among the most divisive socioeconomic issues (Bartram et al., 2022). The Paris Agreement, reached ln 2015, provides extra impetus to execute the necessary legislation to lower greenhouse gas emissions.

As a result, a number of factors, particularly unplanned climate change, public concerns, technological breakthroughs, and economic conditions, have led to a significant amount of uncertainty regarding climate policy. In theory, environmental policy uncertainty may influence the oil market through no fewer than three channels. For example, because oil is the most important fossil energy site, its consumption contributes significantly to the current surplus of carbon dioxide in the atmosphere. To reduce atmospheric carbon dioxide emissions and mitigate the harmful effects of global warming, it is critical to increase renewable energy firms and improve energy-use technologies that reduce the percentage of fossil energy. Substantial ambiguity in environmental regulations may cause critical choices on clean energy supplies and efficient energy innovation to be stalled or changed, impacting oil demand forecasts and hence increasing oil market anxiety and instability. Second, the environmental and transitional risks offered by climate change have had a substantial influence on investment and trade (Zhang, 2022). If environmental regulations are ambiguous and inconsistent in the midst of severe climatic along with the transition towards an ecologically friendly system, climate change policy uncertainty might occur in a volatile economy, raising oil market concern and turbulence. Finally, for natural risks and finance for greenhouse gas reduction, risks related to climate change may be linked to the financial system through insurance companies (Hong et al., 2020). The threat of climate change has been highlighted as a significant factor impacting the asset holdings of institutional investors (Krueger et al., 2020). The rise of finance of oil has strengthened the bond between oil and the stock exchange, and oil has become a crucial asset allocation for financial institutions. As such, climate risk connected with laws and regulations may influence oil market panic and swings through this financial channel. Given that ecological policy uncertainty may be linked to the oil market through a variety of channels, it is vital to investigate how environmental policy uncertainty drives oil market fear.

Meanwhile, previous research on determinants influencing oil price variability primarily employed GARCH models and observed variance. These variance estimations are ex-post and lack the ability to take into consideration future market information forecasts (Ji and Fan, 2016). From the other hand, the US administrator's established oil price volatility index analyses market projections for 30-day fluctuations in oil prices, indicating that it is a forecasting indicator. The index, on the other hand, is determined based on investor forecasts. When investors get afraid, their impression of market volatility and subsequent trading habits are altered. As a result, OPS is commonly employed as a substitute for fear in the oil market (Baumeister and Hamilton, 2019). Considering the two important benefits mentioned above, utilising OPS will provide greater understanding and higher economic ramifications for the research of oil market volatility. Nowadays, the OPS is being gradually applied to research as a measure for oil market fear in lieu of traditional fluctuation measures (Salisu and Gupta, 2020), as well as the connection between stock markets as well as the oil market (Xiao et al., 2018; Li, 2022). Despite this, only a few studies have been undertaken on the links between different uncertainty metrics and OPS.

Given the aforementioned, this study investigates the impact of CPU, EPU, FGU, and INC on OPS in Nigeria. Particularly, the international monetary and financial environment has become more complicated over time, with significant occurrences happening on a frequent basis. The links between marketplaces and investor anticipations are challenging to sustain. Recent studies, such as Xu et al. (2017) and Mitra (2018), use quantile regression to measure the impact of a variable's motivating factor. The Quantile Auto Regressive Distributive Lag (QARDL) and Non-Linear Auto Regressive Distributive Lag (NARDL) models are used for empirical study to express possible dynamic aspects in the impacts of CPU, EPU, and FGU on OPS.

This work makes three substantial contributions to the present literature. For starters, the relationship between uncertainties and oil market fluctuation is gaining traction. To the greatest of our knowledge, there exists no prior work investigating the impact of different types of uncertainty on oil market anxiety by using Nigeria as an illustration. The OPS provides more information than typically used oil fluctuation predictions based on past price data. More importantly, the OPS monitors fear perception in the oil market, that may reflect alterations to investor conduct in expectation of external disturbances. As such, the application of OPS to explore the responses of oil market concern to diverse unexpected events is an important complement to this work. Also, among the most serious worries in recent times has revolved around the effects of climate change. According to scientists, investors, and policymakers, climate risk has a huge impact on energy frameworks, economies, and financial institutions. As a result, it is realistic to anticipate that climate risk will have a bearing on the oil market. However, this issue is frequently disregarded. Guo et al. (2022) investigate the impact of CPU on oil price fluctuations. This study expands previous research by focusing on the relationship between CPU and oil market worry via OPS. At last, whilst more studies have been conducted on the relationship between various forms of instabilities and the oil market, relatively little research has been conducted on combining multiple uncertainty metrics in a single framework to investigate how they vary on oil market fear. The sole goal of previous studies has been comparing the effects of economic, financial, and geopolitical instability (for example, Wen et al., 2019; Li et al., 2020). This study expands on previous research by evaluating the influence of uncertainty measurements on oil market panic using the Quantile ARDL model and the NARDL model.

2. Literature review

The variables that influence oil prices have garnered a great deal of attention in the literature. Multiple investigations have found that oil prices are influenced by variables involving oil availability and demand, financing, currency rates, and investor habits. For example, Kilian (2009) examines oil prices in terms of supply as well as demand which finds that variations in oil consumption are substantially to blame for the present price shocks. According to Wen et al. (2018), the currency exchange value has a short-run adverse effect on oil price changes. Chatziantoniou et al. (2021) investigate the impacts of oil availability, demand, and monetary variables on oil price fluctuations and find that financial indicators have a greater influence. Based on Xiao and Wang (2021), focus of investors has a predominantly positive impact on bad volatility for oil market. Furthermore, to the beyond listed variables, uncertainty has appeared as a fresh factor for oil market analyses in current years. The estimation of uncertainty, by this point, is a vital topic in undertaking uncertainty research. Baker et al. (2016) establishes a news-based macroeconomic policy uncertainty (EPU) score based on this. Baker et al. (2016), Dai and Zhu (2023), and numerous more research provide solid evidence that economic policy uncertainty has a major impact on financial and economic variables. It is commonly considered that fluctuations in oil prices are directly tied to economic variables. As such, some studies use this EPU metric and categorization to investigate the impact of economic uncertainty upon oil market. For example, Wei et al. (2017) show that information included in fundamentals and anticipation is absorbed by the EPU indexes when using the GARCH-MIDAS model to anticipate oil market fluctuation, indicating the significance of the EPU metrics in influencing oil fluctuations. Using the dynamic copula based CoVaR approach, Ji et al. (2018) demonstrate that EPU has a relatively minor effect on oil price returns. As shown by Qin et al. (2020a), the impact of EPU upon oil prices is positive as well as negative as time passes, with taxes and commerce EPU having a stronger association with oil prices after Trump assumes power. Zhang and Yan (2020) demonstrate that the EPU measure influences oil price yields differently depending on the period and the velocity, whereas the impact of various EPU indexes on oil price yields grows during significant occurrences. Lin and Bai (2021) demonstrate that EPU in oil- producing nations have greater influence on the rise in oil prices compared to EPU in oil-importing countries. Wang et al. (2022) employ the contraction approach to demonstrate that the prediction precision of categorised EPU variables for oil swings in different markets is asymmetric, owing to the EPU trend about public debt and exchange upheaval being particularly frequently forecasted.

Several research have also been conducted to investigate the influence of various types of uncertainty upon oil trade. Wen et al. (2019), for instance, found that when using the HAR-RV simulations, EMV rather than EPU may provide more information to forecast realised volatility of oil futures. Liang et al. (2020) use multiple predictive models to investigate the associations with worldwide EPU, US EPU, financial EPU, GPR, and EMV via oil achieved variance and find that international EPU and EMV fulfil a more major role in predicting oil achieved variance. Li et al. (2020) use the GARCH-MIDAS model to investigate the forecasting capacity of news-based uncertainty measures for oil swings, finding that EPU, EMV, and fiscal policy uncertainty in the United States could enhance predictions of great oil variations. Dutta et al. (2021) demonstrates that EMV exerts a significant influence upon oil market volatility during times of high volatility, and that numerous EMV monitors outperform the VIX, EPU, and GPR to forecast oil volatility. Gu et al. (2021) utilise the VAR approach to suggest that EPU exerts greater effects upon oil market than GPR. Huang et al. (2021) use the TVP-VAR approach to examine the impacts of EPU, macroeconomic uncertainty, EMV, and financial market fluctuations on commodity rates and find that EPU and MU exert a greater impact on oil prices than EMV and OPS.

Environmental uncertainty is currently causing widespread worry and has spurred a rise in research interest. For example, Hong et al. (2020) describes the climate hazard and investigate some associated study. Environmental risk is a major issue impacting broad shareholders' investment choices, as reported by Krueger et al. (2020). In line with Huynh and Xia (2021), altering environmental data risks may influence commercial bond yields. In the words of Javadi and Masum (2021), firms that are more vulnerable to climate change have bigger bank credit spreads. Roncoroni et al. (2021) investigate the impact of environmental transition danger and market structure on finances and find that stringent climate targets can be achieved with robust economic circumstances. In the words of Bartram et al. (2022), ecological policy generates a variety of implications as a result of corporate regulatory arbitrage. Bouri et al. (2022) demonstrate that CPU exerts a significant impact on the efficacy of green against brown stocks. In et al. (2022), a framework for examining the linkages between energy spending and environmental risks is developed. Using information gathered from Chinese energy industry, Ren et al. (2022a) demonstrate that CPU has a significantly nonlinear impact on company expenditures. Ren et al. (2022b) find that in Beijing, CPU has a negative effect on firm-level overall efficiency. Tian et al. (2022) use the NARDL method to demonstrate that over the short term, the CPU may exert an asymmetric impact upon the green bond structure in China. Zhang and Kong (2022) provide compelling evidence that markets react adversely to purported changes in environmental risk. Environmental uncertainty, as stated by Dai and Zhang (2023), has a significant effect on the threat that banks confront. Nonetheless, according to Guo et al. (2022), there has been minimal research into the impact of climate-related uncertainty on the oil market. Guo et al. (2022) use the TVP-VAR model to show that the impact of CPU on oil prices flips from favourable to adverse periodically.

Despite growing curiosity in the association between uncertainties and oil market, past research primarily focused on the correlations of uncertainty alongside yields based on past information. The oil shocks index (OPS), computed from option prices, contains both historical data and investors' projections of future market movements. The OPS is regarded to be a more accurate indication of oil market uncertainty, and it may represent oil market panic.

3. Data and Methodology

3.1 Data

Given the limited data available, we employ monthly time-series Nigeria's dataset running from the start month of 1997 to the third month of 2000 (1997M1-2020M1). Oil market fear is quantified as oil price shocks (OPS), financial globalisation uncertainty (FGU), climate policy uncertainty (CPU), and real GDP, with real GDP serving as a proxy for economic performance (INC). The explained variable is oil price shocks, while the explanatory factors include financial globalisation uncertainty, economic performance, and climate policy uncertainty. While the evaluation employs Gavriilidis's (2021) environmental policy uncertainty measure. It is interesting to note that Gavriilidi uses a text-mining strategy to estimate economic policy uncertainty leveraging on data from leading daily newspapers. As such, Gavriilidis computes CPU based on the prevalence of eight major media pieces that include terms like climate danger, ecological instabilities, and greenhouse gases. The CPU indices utilised is available on a monthly basis at policyuncertainty.com. Furthermore, from Baumeister's internet site, an updated version of the isolated oil shocks statistics, recently examined by Salisu and Gupta (2020), was developed. Baumeister received the data used from the US Energy Information Administration (EIA), and its raw form is publicly available on the web. The Economic Policy Uncertainty Index is available for free generated at policyuncertainty.com. Significantly, financial globalisation is generated from the Chinn and Ito (2007) KAOPEN indexes. As such, we construct the financial globalisation uncertainty using the FGUit-1 index, which measures the financial globalisation lag of one period. Finally, income is acquired from the World Bank database via the real GDP measure.

Table 1 shows the descriptive statistics of all parameters, where OPS stands for oil market fear, FGU stands for financial globalisation uncertainty, CPU stands for environmental policy uncertainty, EPU stands for economic policy uncertainty, and INC stands for economic performance. In addition, we use Jarque-Bera statistics to evaluate the normality of the dataset, with the null hypothesis being that the dataset is normally distributed. The analysis in Table 1 shows that the null hypothesis of normality is rejected, indicating that the data is still not normally distributed. Considering the information in Table 1 is not normally distributed, using basic linear models may yield incorrect findings. Being so, sophisticated methods including the Quantile ARDL method and the Non-linear ARDL experiments are necessary. Since these sophisticated methodologies examine the effect not just on the conditional mean but also on the information's right and left tail ranges, they can offer robust results regardless of the data distribution.

Table 1. Descriptive Summary

Variables	Mean	Standard deviation	Skewness	Kurtosis	Jarque-Bera
$lnOPS_t$	3.743	0.525	-0.995	6.134	18.341* (0.000)
$lnFGU_t$	7.521	1.389	-0.279	2.726	5.437** (0.073)
$lnCPU_t$	1.692	0.890	-0.915	4.041	6.315 (0.000)
$lnEPU_t$	6.361	2.102	-3.329	5.218	27.375 (0.000)
$lnINC_t$	6.309	1.357	0.457	2.831	31.803 (0.000)

Source: Policy Uncertainty (2023); Energy Information Administration (2023); Chinn and Ito (2007) and World Development Indicators (2023).
Note: * shows statistical significance at 1 percent level, while ** signifies the 5 percent significance level.

3.2 Model Specification

Many studies identify oil activity, real GDP, the currency rate, financial measurements, investor habits, and a variety of other aspects of the economy to be determinants impacting oil market anxiety (Chatziantoniou et al., 2021; Xiao and Wang, 2021). However, there is minimal literature that mainly analyses uncertainty to assess the anxiety of the oil market. As mentioned before, several uncertainties could positively or adversely affect a nation's oil market anxiety given that uncertainty is also seen as a major determinant of oil prices due to how it may impact the fundamental structure of the oil market. Evidence further suggests that financial prosperity is an essential determinant in oil market fairness (Kilian and Vigfusson, 2011). Therefore, in accordance with the current literature, we offer a framework as below:

$$lnOPS_t = f(lnCPU_t, lnEPU_t, lnFGU_t, lnINC_t) \quad (1)$$

OPS indicates oil market fair, CPU indicates climate policy uncertainty, EPU shows economic policy uncertainty and INC shows economic performance. Moreover, all variables are used with the natural logarithm. Finally, f denotes the functional representation. The specification in equation (1) is transformed into the econometric specification showing stochastic error term as presented below:

$$lnOPS_t = \beta_0 + \beta_1 lnCPU_t + \beta_2 lnEPU_t + \beta_3 lnFGU_t + \beta_4 lnINC_t + \varepsilon_t \quad (2)$$

Other notations are described earlier; ϵt is the stochastic error term which includes other determinants not taken into account in our study.

3.3 Quantile ARDL

The quantile approach has become one of the most commonly used models for assessing the association between economic parameters. In addition, we contribute to the existing research by adopting Cho et al. (2016)'s Quantile ARDL model. This model is an improved variant of the ARDL approach that examines the short- and long-run effects of the parameters that provide explanation across several quantiles of the explained variable. There are several options for the QARDL model. First, it explores the short and long-run effects of the explained variable over different quantiles. Second, it is applicable with a small sample size. Finally, it can be used when the variables possess an interaction order of 0 I (0) or one I (1) (Bhutto and Chang, 2019). In contrast to the ARDL and NARDL frameworks, this method has a limitation: we cannot use the QARDL method if the variables have a degree of integration as I (2). In summary, we can't use this model if the variables evolve into stationary after the second differencing. As such, before employing the QARDL together with ARDL models, we use the ADF and KPSS analyses to assess the level of integration across all variables. When the order of integration is defined, we use the QARDL model proposed by Cho et al. (2016). Following Xiao and Liu (2023), we describe our model in a quantile-based approach of the QARDL model in the framework presented by Cho et al. (2016) as:

$$\begin{aligned} QOPS_t = a(r) &+ \sum_{i=1}^{n1} b_i\,(r)\Delta lnCPU_{t-i} + \sum_{i=0}^{n2} c_i\,(r)\Delta lnEPU_{t-i} \\ &+ \sum_{i=0}^{n3} d_i\,(r)\Delta lnFGU_{t-i} + \sum_{i=0}^{n4} e_i\,(r)\Delta lnINC_{t-i} + e_t(r) \end{aligned} \tag{3}$$

where $e_t(\tau) = OPS_{t-i} - QOPS_t\left(\frac{r}{\delta_{t-1}}\right)$ and $0 > \tau < 1$ indicates each quantile where its values can be shown as below: $\tau \in \{0.05 \text{ to } 0.95\}$. The QARDL is specified as:

$$\begin{aligned} QOPS_t = a &+ \gamma lnOPS_{t-1} + \beta_{cpu} lnCPU_{t-1} + \beta_{epu} lnEPU_{t-1} \\ &+ \beta_{fgu} lnFGU_{t-1} + \beta_{inc} INC_{t-1} + \sum_{i=1}^{p} b_i\,(r)\Delta lnCPU_{t-i} \\ &+ \sum_{i=0}^{q} c_i\,(r)\Delta lnEPU_{t-i} + \sum_{i=0}^{r} d_i\,(r)\Delta lnFGU_{t-i} \\ &+ \sum_{i=0}^{s} e_i\,(r)\Delta lnINC_{t-i} + e_t(\tau) \end{aligned} \tag{4}$$

The QARDL-ECM form of the above generalized formulae (Equation 9) can be shown below:

$$
\begin{aligned}
QOPS_t = a(r) + \gamma(r)(lnOPS_{t-1} - \beta_{cpu}(r)lnCPU_{t-1} \\
- \beta_{epu}(r)lnEPU_{t-1} - \beta_{fgu}(r)lnFGU_{t-1} \\
- \beta_{inc}(r)INC_{t-1}) + \sum_{i=1}^{p} b_i\,(r)\Delta lnCPU_{t-i} \\
+ \sum_{i=0}^{q} c_i\,(r)\Delta lnEPU_{t-i} + \sum_{i=0}^{r} d_i\,(r)\Delta lnFGU_{t-i} \\
+ \sum_{i=0}^{s} e_i\,(r)\Delta lnINC_{t-i} + e_t(r)
\end{aligned}
\tag{5}
$$

The long-run determinants for CPU, EPU, FGU and INC are specified as $\beta_{cpu} = -\frac{\beta_{cpu}}{p}$, $\beta_{epu} = -\frac{\beta_{epu}}{p}$, $\beta_{fgu} = -\frac{\beta_{fgu}}{p}$, $\beta_{inc} = -\frac{\beta_{inc}}{p}$.

Notably, the ECM element *w* has to be significant with negative coefficient. Also, to examine the estimation result of CPU, EPU, FGU and INC on the oil market fear, we apply the Wald test to estimate the null hypothesis shown below:

$$H_0: w * (0.05) = w * (0.1) = w * (0.2) = \cdots = w * (0.95) \tag{6}$$

The alternate hypothesis is:

$$H_0: xi \neq \frac{j}{w(i)} \neq w(j) \tag{7}$$

Table 2. Stationary Estimates

Variables	KPSS		ADF	
	At level lm-stat [C-value]	At first different lm-stat [C-value]	At level t-stat [p-value]	At the first diff [p-value]
OPS_t	0.46* (0.739)	0.23* (0.739)	-7.49* (0.000)	-12.25* (0.000)
FGU_t	0.49* (0.739)	0.03* (0.739)	-0.76* (0.827)	-9.93* (0.000)
CPU_t	1.34 (0.739)	0.26* (0.739)	-4.416* (0.000)	-10.724* (0.000)
EPU_t	1.38 (0.739)	0.32* (0.739)	-2.24 (0.189)	-12.159* (0.000)
INC_t	1.46 (0.739)	0.04* (0.739)	-1.69 (0.436)	-5.72* (0.000)

Source: Policy Uncertainty (2023); Energy Information Administration (2023); Chinn and Ito (2007) and World Development Indicators (2023).
Note: * shows statistical significance at 1 percent level, while ** signifies the 5 percent significance level.

Table 2 above checks the stationarity of the variables using KPSS and ADF test statistics at the level and first difference. ***,** and * indicate that rejection of the null hypothesis at 10%, 5%, and 1% significance levels, respectively.

3.4 Non-Linear ARDL

Furthermore, the NARDL model is used in this work to uncover the asymmetric relationship between CPU, EPU, FGU, INC, and oil market fair. It is noteworthy to understand that on of the advantages of NARDL is that is more robust and popular approach due to its flexibility that it can be used irrespective of nature of variables, i.e., I(0), I(1), or a mixture of both. However, it cannot be applied if the order of integration is above I(1) (like I(2) process as this will nullify the entire model (Biyase and Naidoo, 2023; Khanday et al., 2024; Jakada et al., 2023; Sehrawat, 2021; Vasichenko et al., 2020 and many others). Uncertainty about financial globalisation, economic policy uncertainty, climate policy uncertainty, and income level all have an essential role to play in oil price shocks. Shin et al. (2014) proposed the following nonlinear equation for constructing the nonlinear ARDL:

$$\begin{aligned}\Delta OPS_t = \omega_1 &+ \sum_{j=1}^{no} \omega_{2j} \Delta FGU^{+} + \sum_{j=1}^{np} \omega_{3j} \Delta FGU^{-} t - j \\ &+ \sum_{j=1}^{nq} \omega_{4j} \Delta CPU^{+} t - j + \sum_{j=1}^{nr} \omega_{5j} \Delta CPU^{-} t - j \\ &+ \sum_{j=1}^{ns} \omega_{6j} \Delta EPU_{t-j} + \sum_{j=1}^{nu} \omega_{7j} \Delta INC_{t-j} + \gamma_1 OPS_{t-1} \\ &+ \gamma_2 FGU^{+}{}_{t-1} + \gamma_3 FGU^{-}{}_{t-1} + \gamma_4 CPU^{+}{}_{t-1} \\ &+ \gamma_5 CPU^{-}{}_{t-1} + \gamma_6 EPU_{t-1} + \gamma_7 INC_{t-1} + \mu_t\end{aligned} \tag{8}$$

Notably, c1 through c7 represent the long-term coefficient. Whereas the variation in variables represents short-term elements. In addition, the bound test has been utilised to investigate factor cointegration using the NARLD model described in Equation (9). The bound testing approach was created and advocated by Pesaran et al. (2001) to investigate the long-term connection among factors. The NARDL considers the possibility of asymmetrical impacts generated by positive and negative fluctuations in the distinct parts of the explaining variables.

3.5 Diagnostic Tests

Notably, we performed diagnostic analyses to assess the models' goodness of fit and other requirements for the models used in this work. The Ramsey RESET test is used to determine whether the models are correctly established, and the serial correlation test is used to determine whether the models have no autocorrelation. Finally, an adjusted R square is calculated to determine whether the models are of good fit. The results are presented under the co-integration test results in Table 3.

3.6 The ARDL Bounds Tests for Cointegration

The results of the evaluation of cointegration bound tests for the parameters are reported in Table 3. The estimated F-statistics at a significance level of 5% is 17.127, which surpasses the highest analytical limit. This established the existence of long-term equilibrium linkages between climate policy uncertainty, economic policy uncertainty, financial globalisation uncertainty, economic performance, and oil market fear.

Table 3. Bound Test Results

Function	*F*-statistics QARDL		*F*-*statistics* NARDL	
$F_{lnOPS}(lnCPU_t, lnEPU_t, lnFGU_t, lnINC_t)$	17.127		12.425	
C value bounds				
Level of significance	I(0)	I(1)	I(0)	I(1)
At 10%	2.02	3.09	2.84	3.10
At 5%	2.56	3.49	3.73	3.61
At 1%	3.29	4.37	4.02	5.52
Diagnostic test				
R^2	0.518		0.610	
Adj-R^2	0.502		0.521	
F statistic	7.531		8.24	
Prob (*F* statistic)	0.000		0.000	
LM	1.153		1.55	
ECM	-0.435**		-0.571*	
$Wald_{LR}$	5.85*		6.233*	
$Wald_{SR}$	0.562*		0.583**	

Source: Policy Uncertainty (2023); Energy Information Administration (2023); Chinn and Ito (2007) and World Development Indicators (2023).

Note: * shows statistical significance at 1 percent level, while ** signifies the 5 percent significance level.

4. Results Discussion and Analysis

Our research looks at the impact of financial globalisation uncertainty, economic policy uncertainty, climate policy uncertainty, and economic performance across various quantiles of Nigeria's oil market fear. Our study contributes to the past literature by comparing the quantile ARDL (QARDL) (Cho et al., 2016) model's estimations to those of the NARDL technique. The key advantage of the QARDL method is that it examines the impact across different quantiles of the explained variable. One downside of the QARDL technique, on the other hand, is that we cannot apply it if any variable is stationary at the following second differencing.

As such, in this work, we apply the ADF and KPSS tests to figure out stationarity values. The results of the ADF and KPSS tests are shown in Table 1 earlier presented. The ADF test estimations show that all variables have either been stationary at level or first difference. Similarly, KPSS test results demonstrate that variables either remain stationary at I(0) or I(1). In general, the ADF and KPSS stationarity tests meet the models' criteria. Following that, in Table 3, we discuss the bound test estimations for co-integration. Furthermore, the bound test outcomes indicate the existence of cointegration among parameters in both the QARDL and NARDL models.

This study shows the quantile ARDL model findings in Table 4. The Q0.05-Q0.95 matched the different quantiles of the oil market fear, where Q0.05 and Q0.95 denotes the lowest the upper quantile of the oil market fear series respectively. Based on the outcomes of the QARDL analysis, we can see that in the 5th quantile, the shocks from CPU, FGU, and EPU, explain about 85%, 50%, and 9% of the variability in oil market fear, respectively. While the economic performance explained 17%, all in the long run. Clearly, during this initial stage, the contribution of CPU to the variability in oil market fear is the largest. Likewise, the impact of climate policy uncertainty in the lower 10th quantile is also stronger than the FGU, EPU and economic performance. The contribution of FGU, EPU and INC are relatively small compared to the coefficient of CPU at 74%. We further observed that in both the 20th, 30th, 40th, 50th, 60th, 70th, and 80th quantiles, the shock from CPU has the largest contribution in terms of explaining the oil market fear in Nigeria. Explaining about 74%, 71%, 66%, 64%, 61%, 70%, 73%, and 63% of the variability in oil market fear respectively. However, in the 90th and 95th upper quantiles, the financial globalization uncertainty appears to have the largest share of variability in oil market fear. Notably, the short-run results of the various quantiles aligned with the long-run results.

Particularly, a rising EPU frequently has a direct negative impact on real economic activity by decreasing investment and consumption, lowering oil demand and increasing market fluctuation. As a result, EPU spikes have a greater tendency to create oil market fear, because market players anticipate a fall in oil demand and price reductions given the possibility of EPU shocks. Conversely, the effect of EPU on oil market anxiety changes over time and is particularly visible during times of severe catastrophes producing economic contraction (e.g., 2018 financial meltdown and the most recent pandemic of Covid-19). This could imply that market players in the oil market are more worried about EPU shocks amid an economic crisis.

The link between financial globalisation uncertainty and oil market concern is based not just on economic principles but also upon oil finances. Because of this intimate relationship, oil market players have identified financial globalisation uncertainty as a significant source of worry at various times. As a result, FGU has a generally consistent and significant positive influence on oil market fear. However, there is an inverse association between economic activity (INC) and oil market anxiety. This might happen considering that as an oil-producing and largely oil dependent economy, Nigeria would be at ease if economic activity grew, reducing the worry of oil price shocks owing to rising demand for oil. Diversification of the economy is one major feature that this country is always striving to do in order to lessen its over dependence on oil.

We discover that the CPU is one of the most prominent factors causing oil market anxiety. In broad terms, the CPU can be linked to oil market concern via the pathways listed below. First, a major portion of carbon dioxide emissions from oil consumption are directly related to climate change. To deal with the negative repercussions of climate change, critical measures such as energy reorganisation and energy efficiency advances as well as regulating oil consumption, must be done. Policy development and execution, on the other hand, are fraught with ambiguity (Nodari, 2014). Oil market players will worry in the face of climate policy uncertainty events, as heightened climate policy uncertainty makes forecasting oil demand harder.

Secondly, climate change frequently increases physical and transfer risks, which may adversely affect enterprises and even the broader economy (In et al., 2022; Zhang, 2022). When policy responses to global warming are unknown, the physical and transfer hazards posed by climate change are ineffectively addressed, causing economic instability and increasing oil market panic. Lastly, climate risk has an impact on real economic activity and, of course, financial markets. According to Krueger et al. (2020), corporate investors have paid close attention to climate risk shocks. Zhang (2022) discovers that climate risk has a detrimental impact on stock values. Because of oil finance, the oil market is more closely linked to the financial market. As a result of the close relationship between the duo, climate risk spikes resulting from policy uncertainty can potentially increase the amount of concern in the oil market. Nevertheless, the empirical findings indicate the needs to gain insight into the relationship between climate policy uncertainty and oil market anxiety across various quantiles.

Our findings might be expanded upon by investigating the many elements that contribute to the rise in climate policy uncertainty and general concern about climate danger. The frequency of serious climate policy activities, such as the Paris Climate Change Conference on December 12, 2015, is a key contributing element. Almost 200 parties attended this conference and signed off to the Paris Agreement, which intended to cut emissions of greenhouse gases and mitigate global temperature growth. The Paris Agreement was subsequently implemented in November 2016. The Paris Agreement eventually became law in November 2016. But the US withdrew out of the Paris Agreement in June 2017. According to Battiston et al. (2021), following the Paris Agreement in 2015, the financial industry has been actively engaged in discussions about climate change, and monetary regulatory authorities now clearly accept that global warming is an emerging cause of financial threat.

According to Diaz-Rainey et al. (2021), the ratification of the Paris Agreement has a tremendous detrimental influence on the fossil fuel sector, as does the declaration of the US's withdrawal out of the Paris Agreement. As a result of the considerable surge in climate policy uncertainty amid the Paris Agreement, economic and financial market instability has resulted in increased concern in the oil market. Furthermore, the government's move towards establishing an environmentally friendly economy has heightened public awareness of climate hazard. Fahmy (2022) utilises the Google search index to argue that since the Paris Agreement, investors have gotten more cognizant of climate concern. This heightened public worry about climate change may amplify the positive effect of CPU on oil market fear after 2016.

However, the NARDL test results presented in Table 5 starts by differentiating the negative and positive elements of the climate policy uncertainty and financial globalization uncertainty variables in Table 4 below. The results reveal that the estimates are positive for both *CPU* and *FGU* increases as well as their respective decreases. This implies that 1% increase in *CPU* will increase the oil market fear by 3% in the short-run and 14% in the long-run respectively. While the negative shock indicates that a 1% decrease in *CPU* will reduce the oil market fear by also 3% in the short-run and 11% in the long-run respectively. Notably, the *FGU* positive shock in the short run is statistically positive but insignificant. While in the long run, it becomes statistically significant, and the coefficient is at 71%. Since the negative shock of *FGU* is statistically positive and significant, it means that 1% decrease in *FGU* reduces the oil market fear by 14% in the short-run and 24% in the long-run respectively. The NARDL results confirms our QNARDL outcomes, showing positive linkages between FGU, CPU, EPU and INC in relation to oil market fear. However, the asymmetric results of NARDL indicates that the coefficient of *FGU* increase is insignificant in the short-run while in the long-run the coefficient becomes significant. In view of the different statistical results and the direction of the computed elasticities, variation in *CPU* and *FGU* seems to have an asymmetric effect on Nigeria’s oil market fear in both the short and the long run.

Table 4. QARDL Results

Quantiles	Constant	ECM	Long-run estimates				Short-run estimates				
$[r]$	$a[r]$	p^*	$\beta CPU[r]$	$\beta EPU[r]$	$\beta FGU[r]$	$\beta INC[r]$	$w1[r]$	$k0[r]$	$d0[r]$	$y0[r]$	$h0[r]$
Q_5	0.017* (0.005)	0.019* (0.004)	0.850* (0.0817)	0.094** (0.041)	0.503* (0.048)	0.171* (0.038)	0.149 (0.834)	0.691** (0.323)	0.108* (0.041)	0.424* (0.031)	0.1701* (0.067)
Q_{10}	0.014 (0.005)	-0.061* (0.013)	0.740* (0.078)	0.088** (0.045)	0.5168* (0.045)	0.177* (0.036)	0.177** (0.075)	0.438* (0.034)	0.138* (0.051)	0.219* (0.059)	0.127* (0.021)
Q_{20}	0.042* (0.013)	0.034** (0.013)	0.714* (0.079)	0.089** (0.044)	0.482* (0.043)	0.181* (0.036)	0.210* (0.042)	0.243* (0.059)	0.165* (0.058)	0.411* (0.038)	0.108* (0.024)
Q_{30}	0.027** (0.011)	0.020** (0.009)	0.662* (0.078)	0.165** (0.082)	0.519* (0.042)	0.169* (0.032)	0.164* (0.041)	0.331* (0.065)	0.167* (0.019)	0.331* (0.051)	0.944* (0.196)
Q_{40}	0.018** (0.008)	0.019** (0.009)	0.649* (0.079)	0.255** (0.129)	0.561* (0.041)	0.157* (0.029)	0.143* (0.037)	0.317* (0.087)	0.184* (0.019)	0.222* (0.054)	0.753* (0.129)
Q_{50}	0.009 (0.012)	0.026** (0.013)	0.611* (0.080)	0.014** (0.052)	0.566* (0.056)	0.184* (0.027)	0.108* (0.038)	0.154* (0.048)	0.177* (0.019)	0.169* (0.053)	0.612* (0.109)
Q_{60}	0.015 (0.008)	0.015** (0.007)	0.703* (0.089)	0.275 (0.857)	0.336* (0.103)	0.189* (0.026)	0.906** (0.474)	0.188* (0.042)	0.142* (0.023)	0.119** (0.055)	0.690* (0.107)
Q_{70}	0.014 (0.008)	0.017** (0.008)	0.738* (0.075)	0.291* (0.106)	0.282* (0.084)	0.218* (0.028)	0.199* (0.093)	0.148* (0.043)	0.100* (0.023)	0.122 (0.070)	0.689* (0.105)
Q_{80}	0.311* (0.118)	0.346* (0.110)	0.629* (0.098)	0.416* (0.079)	0.152 (0.096)	0.218* (0.037)	0.211* (0.089)	0.124 (0.069)	0.075* (0.023)	0.193** (0.095)	0.790* (0.143)
Q_{90}	0.165 (0.185)	0.285** (0.125)	0.081** (0.041)	0.342** (0.170)	0.441* (0.064)	0.155** (0.095)	0.201* (0.073)	0.112* (0.046)	0.047 (0.025)	0.266* (0.097)	0.813* (0.176)
Q_{95}	0.189* (0.036)	0.209* (0.097)	0.129* (0.234)	0.187* (0.028)	0.425* (0.138)	0.309** (0.133)	0.580* (0.161)	0.786* (0.126)	0.708* (0.123)	0.747* (0.128)	0.800* (0.142)

Note: * Shows statistical significance at 1 percent level, while ** signifies the 5 percent significance level.

Source: Policy Uncertainty (2023); Energy Information Administration (2023); Chinn and Ito (2007) and World Development Indicators (2023).

Table 5. NARDL Results

Variable	Short-run	SE	t-statistic
ΔCPU^{+}	0.038**	0.018	2.13
ΔCPU^{-}	0.036**	0.015	2.415
ΔFGU^{+}	0.007	0.028	0.259
ΔFGU^{-}	0.149**	0.058	2.541
ΔEPU	0.292*	0.060	4.851
ΔINC	0.104	0.061	1.711
$ECT(-1)$	-0.567*	0.104	-5.466
Variable	**Long-run**	**SE**	**t-statistic**
C	0.108*	0.041	2.605
CPU^{+}	0.144**	0.058	2.506
CPU^{-}	0.115*	0.028	4.076
FGU^{+}	0.710*	0.063	11.362
FGU^{-}	0.239**	0.111	2.147
EPU	0.037**	0.017	2.209
INC	0.679	0.372	1.828

Note: * Shows statistical significance at 1 percent level, while ** signifies the 5 percent significance level.
Source: Policy Uncertainty (2023); Energy Information Administration (2023); Chinn and Ito (2007) and World Development Indicators (2023).

5. Conclusion

Just recently, amid the clear surge in external uncertainties, oil market fright has grown, and oil prices have shown extreme swings. This article uses the oil price shocks index to examine how economic policy uncertainty, climate policy uncertainty, financial globalisation uncertainty, and economic performance influence oil market fear in Nigeria. Notably, because the connections of CPU, FGU, EPU, and INC with OPS may have quantile-varying characteristics, we primarily use the quantile ARDL model to conduct our empirical research. In addition, we employed the NARDL estimation model to confirm the occurrence of an asymmetric relationship between CPU and FGU in relation to OPS. According to our empirical findings, CPU, FGU, EPU, and INC have quantile-varying influences on OPS. The QARDL model demonstrates the importance of climate policy uncertainty in determining Nigeria's oil market fear. This is confirmed in all quantiles examined, with the exception of the upper quantile, where FGU plays a significant role. The NARDL model verified the positive association established by the QARDL estimate model between all factors in relation to oil market fear in Nigeria.

The excessive amount of fear and uncertainty in the oil market is harmful to oil trade, investment, and risk mitigation. Our results have crucial implications for dealing with the current status of the oil market. At this point, climate-related inconsistencies are capable of causing oil market fear, alongside economic, global financial, and economic performance, especially in the light of the Paris Agreement. To reduce oil market volatility and concern caused by climate policy uncertainty shocks, authorities should take specific actions to hasten the transition towards a more environmentally friendly energy system, whilst investors ought to diversify their investment portfolios by engaging in various clean energy sources. Second, governments and investors must recognise that climate, economic, and financial uncertainty all have diverse consequences on oil market concern, and they must take different strategies to address these uncertainty waves based on their informative content. Ultimately, during the epidemic, authorities and investors must be attentive about the inconsistencies associated to climate, economy, and finance, as these unforeseen circumstances can considerably increase investor anxiety in the oil market. Decision-makers can give economic stimulation to sustain oil demand and avert a price crash, while also lowering fright speculation by enhancing transparency and regulations. At the time a pandemic, investors possibly need to offset their risks with different financial mechanisms or reduce their direct participation in the oil business.

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