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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 plays a pivotal role in fostering both economic and financial development, which explains the growing academic and policy interest in oil market dynamics. With the recent expansion of the oil sector's financial activities, market anxiety has become increasingly evident and pervasive. Major global disruptions—such as the 2017–2018 economic downturn and the COVID-19 pandemic—have further amplified uncertainty within the oil industry. To quantify this uncertainty, the Oil

Price Shock (OPS) index, introduced by Christiane Baumeister, a U.S.-based energy economist, is widely employed as a measure of market volatility (Salisu & Gupta, 2020). Historical evidence illustrates that panic levels in the oil sector surged sharply, with volatility increasing from roughly 30% to 90% during the 2008 global financial crisis (Xiao & Liu, 2023). Similarly, the COVID-19 outbreak of 2019 caused widespread disruption across global financial and commodity markets, with OPS levels spiking from around 30% to nearly 160% during the crisis period. Such fluctuations often trigger unpredictable psychological reactions among investors, thereby intensifying market risks (Yaya et al., 2021). Indeed, oil prices collapsed during both the 2008 recession and the COVID-19 pandemic. Given that heightened uncertainty in oil markets adversely affects investment, asset allocation, and risk management—ultimately leading to broader economic instability—this study investigates the effects of climate policy uncertainty, financial globalization uncertainty, economic policy uncertainty, and economic performance on oil market anxiety.

The motivations underlying this research stem from several interconnected factors. Empirical evidence indicates that fluctuations in oil prices are shaped by multiple determinants, including crude oil supply, real GDP, exchange rates, fiscal conditions, and investment behavior (Chatziantoniou et al., 2021; Xiao & Wang, 2021; Wen et al., 2018). The global financial crisis of 2008, which followed the Great Recession, intensified concerns regarding market instability and economic unpredictability. In general, uncertainty tends to suppress investment, consumer spending, and other vital economic activities, thereby exerting adverse effects on financial systems and overall economic performance. It remains a central factor influencing oil price dynamics, as it directly affects the underlying fundamentals of the oil market.

However, accurately measuring uncertainty has proven challenging in empirical analyses. To address this issue, Baker et al. (2016) developed a widely used news-based Economic Policy Uncertainty (EPU) index. Building on this framework, subsequent studies have explored how different forms of uncertainty impact oil price levels and volatility (Qin et al., 2020a; Zhang & Yan, 2020; Liu et al., 2021; Wang et al., 2022). These studies reveal that the effects of uncertainty indicators vary considerably depending on data characteristics and model specifications. Specifically, economic policy uncertainty (EPU) tends to influence oil demand, financial globalization uncertainty (FGU) affects oil financing and investment flows, while climate policy uncertainty (CPU) often alters the supply side of the oil market by influencing corporate and financial decision-making processes.

Despite the growing literature on oil market dynamics, limited attention has been given to the influence of different forms of uncertainty on the oil industry. For instance, Wen et al. (2019) and Huang et al. (2021) focused on assessing and comparing the effects of economic and monetary uncertainty indicators, while Li et al. (2020) and Liang et al. (2020) examined how economic, financial, and geopolitical uncertainties shape oil price behavior. Similarly, Gu et al. (2021) explored the role of macroeconomic factors and regional vulnerabilities in driving oil market fluctuations. Nonetheless, the potential impact of climate-related uncertainty on oil market anxiety remains insufficiently investigated (Guo et al., 2022). Climate change represents one of the most pressing and contentious global socioeconomic challenges (Bartram et al., 2022). The adoption of the Paris Climate Agreement in 2015 further reinforced international commitments to implement stringent policies aimed at reducing greenhouse gas emissions and promoting environmental sustainability.

Consequently, several factors—including unanticipated climate changes, public concern, technological advancement, and evolving economic conditions—have generated significant uncertainty surrounding climate policies. Theoretically, climate policy uncertainty (CPU) can influence the oil market through multiple channels. First, as oil remains the dominant fossil fuel, its consumption substantially contributes to atmospheric carbon dioxide accumulation. To curb these emissions and mitigate the adverse effects of global warming, expanding renewable energy investment and promoting energy-efficient technologies are essential. However, when environmental regulations are vague or inconsistent, critical decisions related to renewable energy development and energy innovation may be delayed or altered, leading to distorted oil demand expectations and heightened market anxiety.

Second, climate-related and transitional risks have profound implications for global investment and trade (Zhang, 2022). In economies undergoing environmental transitions, ambiguous or inconsistent climate policies may intensify uncertainty, thereby amplifying volatility and concern within the oil market. Third, the financial sector also transmits climate-related risks. Insurance companies and institutional investors, in particular, are increasingly exposed to the financial consequences of climate change (Hong et al., 2020; Krueger et al., 2020). Given oil’s importance as a financial asset, regulatory and policy-driven climate risks can influence portfolio decisions and asset valuations, further fueling market instability. Therefore, understanding how environmental policy uncertainty interacts with these economic and financial channels is critical to explaining fluctuations in oil market sentiment and volatility.

Previous studies investigating the determinants of oil price fluctuations have predominantly relied on GARCH-type models and observed variance measures. However, such estimations are ex-post in nature, meaning they fail to incorporate expectations or forward-looking market information (Ji and Fan, 2016). In contrast, the Oil Price Volatility Index (OPS), developed by U.S. energy administrators, captures market expectations for 30-day price movements, serving as a forward-looking indicator of volatility. Notably, this index reflects investor sentiment, as heightened fear or uncertainty among market participants tends to influence both their perception of volatility and their trading behavior. Consequently, OPS has become widely recognized as a proxy for oil market anxiety (Baumeister and Hamilton, 2019).

Given these advantages, employing OPS provides deeper insights and stronger economic implications for understanding oil market volatility. In recent years, researchers have increasingly adopted OPS as a preferred measure of oil market fear over traditional volatility indicators (Salisu and Gupta, 2020), extending its application to studies exploring the interlinkages between oil and stock markets (Xiao et al., 2018; Li, 2022). Nevertheless, the relationship between various uncertainty indicators and OPS remains relatively underexplored, highlighting an important gap in the existing literature.

Building on the foregoing discussion, this study examines the influence of Climate Policy Uncertainty (CPU), Economic Policy Uncertainty (EPU), Financial Globalization Uncertainty (FGU), and Income (INC) on Oil Market Panic (OPS) in Nigeria. The global financial and monetary landscape has grown increasingly complex, characterized by frequent disruptions and heightened interdependence among markets, making it difficult to maintain stable investor expectations. Recent empirical works, including those by Xu et al. (2017) and Mitra (2018), have utilized quantile regression techniques to evaluate the varying effects of explanatory factors across different points of the conditional distribution. In line with this approach, the present study employs the Quantile Autoregressive Distributed Lag (QARDL) and Nonlinear Autoregressive Distributed Lag (NARDL) frameworks to capture the potential dynamic and asymmetric impacts of CPU, EPU, and FGU on OPS.

This study contributes to the existing body of literature in three significant ways. First, although the link between uncertainty and oil market volatility has attracted increasing scholarly attention, there is, to the best of our knowledge, no prior study that examines the effects of multiple uncertainty dimensions on oil market anxiety using Nigeria as a case study. The Oil Price Shock (OPS) index provides richer insights than traditional volatility measures derived from historical price data, as it captures market participants' perceptions of fear and behavioral adjustments to external shocks. Hence, applying OPS to assess how oil market anxiety responds to diverse uncertainty sources represents a valuable addition to the literature.

Second, one of the most pressing contemporary concerns relates to the economic implications of climate change. Policymakers, investors, and researchers acknowledge that climate-related risks significantly influence global energy systems, economic structures, and financial markets. Despite this, the relationship between Climate Policy Uncertainty (CPU) and oil market dynamics remains underexplored. Building on Guo et al. (2022), this study extends the discussion by examining how CPU affects oil market anxiety through the OPS channel.

Finally, while prior research has analyzed the effects of individual uncertainty indicators—such as economic, financial, or geopolitical instability (e.g., Wen et al., 2019; Li et al., 2020)—few studies have integrated multiple uncertainty measures within a unified analytical framework. This study advances the literature by simultaneously investigating the combined impacts of CPU, Economic Policy Uncertainty (EPU), and Financial Globalization Uncertainty (FGU) on oil market anxiety using both the Quantile ARDL (QARDL) and Nonlinear ARDL (NARDL) models to capture dynamic and asymmetric effects.

2. Literature Review

A considerable body of research has explored the determinants of oil price fluctuations, emphasizing variables such as supply and demand dynamics, financial indicators, exchange rate movements, and investor behavior. Kilian (2009), for instance, analyzes oil price variations through the lenses of supply and demand, concluding that changes in global oil consumption play a dominant role in driving price shocks. Similarly, Wen et al. (2018) report that exchange rate appreciation exerts a short-term negative influence on oil price movements. Chatziantoniou et al. (2021) find that while both supply and demand factors matter, financial variables exert a stronger impact on oil price volatility. Xiao and Wang (2021) further show that investor attention amplifies negative volatility in the oil market.

In addition to these established factors, uncertainty has emerged as a critical determinant of oil market behavior in recent years. Measuring uncertainty has become central to empirical analysis in this field. Baker et al. (2016) developed a news-based Economic Policy Uncertainty (EPU) index, which has since been widely applied to study the link between uncertainty and macro-financial variables (Dai & Zhu, 2023). Numerous studies confirm that fluctuations in oil prices are strongly connected to broader economic uncertainty. For instance, Wei et al. (2017) demonstrate, using the GARCH-MIDAS model, that EPU indices capture information from both fundamentals and expectations, making them essential predictors of oil market volatility. Similarly, Ji et al. (2018) employ a dynamic copula-based CoVaR approach and find that EPU exerts a moderate influence on oil price returns.

The literature further reveals that the impact of EPU on oil prices is dynamic and context-dependent. Qin et al. (2020a) observe that the relationship alternates between positive and negative over time, with tax- and trade-related uncertainty showing stronger links following policy shifts such as those under the Trump administration. Zhang and Yan (2020) emphasize that EPU effects vary across periods and intensities, particularly during major global events. Lin and Bai (2021) note that EPU originating in oil-exporting nations exerts a stronger upward pressure on oil prices than that in importing nations, while Wang et al. (2022) highlight that different EPU components—especially those related to public debt and exchange rate volatility—display asymmetric predictive power for oil price swings across markets.

A growing body of empirical research has examined the effects of different categories of uncertainty on oil market dynamics. Wen et al. (2019), for example, employ the HAR-RV model and reveal that the Equity Market Volatility (EMV) index provides superior predictive power for realized oil futures volatility compared to the Economic Policy Uncertainty (EPU) index. Similarly, Liang et al. (2020), using a range of forecasting models, explore the relationships among global EPU, U.S. EPU, financial EPU, Geopolitical Risk (GPR), and EMV in relation to oil realized variance, finding that global EPU and EMV play a dominant role in explaining fluctuations in oil market volatility. Li et al. (2020) utilize the GARCH-MIDAS model to evaluate the predictive ability of various news-based uncertainty indicators and demonstrate that EPU, EMV, and U.S. fiscal policy uncertainty significantly improve forecasts of large oil price variations.

In addition, Dutta et al. (2021) find that EMV exerts a pronounced effect on oil market volatility, particularly during periods of heightened uncertainty, and that several EMV-based indicators outperform traditional benchmarks such as the

VIX, EPU, and GPR in forecasting oil price swings. Gu et al. (2021), employing a Vector Autoregression (VAR) framework, also report that EPU exerts a stronger influence on oil market dynamics than geopolitical risk. Furthermore, Huang et al. (2021), using the Time-Varying Parameter VAR (TVP-VAR) model, show that EPU and macroeconomic uncertainty have a more significant impact on commodity prices, including oil, than EMV and the Oil Price Volatility Index (OPS).

Environmental uncertainty has become a growing global concern, attracting considerable scholarly attention in recent years. Hong et al. (2020) describe climate risk as a critical emerging hazard and examine its implications across financial systems. Krueger et al. (2020) further identify environmental risk as a major determinant of investors' portfolio decisions, while Huynh and Xia (2021) note that shifts in environmental risk perceptions can significantly influence corporate bond yields. Javadi and Masum (2021) observe that firms more exposed to climate-related vulnerabilities tend to experience higher bank credit spreads. Similarly, Roncoroni et al. (2021) analyze how environmental transition risks and market structures interact, concluding that stringent climate objectives can coexist with stable economic conditions.

Bartram et al. (2022) argue that ecological policy uncertainty (CPU) leads to varied economic consequences due to corporate regulatory arbitrage, whereas Bouri et al. (2022) find that CPU significantly affects the relative performance of green and brown stocks. In et al. (2022) develop a framework linking energy expenditures with environmental risk, and Ren et al. (2022a) reveal a nonlinear effect of CPU on corporate investment within China's energy sector. Ren et al. (2022b) also report that CPU negatively influences firm-level efficiency in Beijing. Tian et al. (2022), using the Nonlinear ARDL (NARDL) approach, show that CPU asymmetrically impacts the green bond market in the short term, while Zhang and Kong (2022) provide evidence that markets respond negatively to shifts in perceived environmental risks. Dai and Zhang (2023) emphasize that environmental uncertainty substantially increases banks' exposure to financial risks. Despite these advances, Guo et al. (2022) highlight that limited research has examined the effect of climate-related uncertainty on the oil market; their findings, based on a Time-Varying Parameter VAR (TVP-VAR) model, reveal that CPU's influence on oil prices fluctuates between positive and negative over time.

Although interest in the relationship between various forms of uncertainty and the oil market has been increasing, most prior studies have concentrated on examining correlations between uncertainty indicators and oil returns using only historical data. In contrast, the Oil Price Volatility Index (OPS), which is derived from option prices, incorporates both past information and investors' expectations of future market dynamics. Consequently, the OPS is considered a more reliable proxy for oil market uncertainty, as it effectively captures investors' perceptions of risk and the level of anxiety prevailing within the market.

3. Methods and Materials

3.1 Data

Given the constraints in data availability, this study utilizes a monthly time-series dataset for Nigeria spanning from January 1997 to January 2020 (1997M1–2020M1). The measure of oil market anxiety is captured through Oil Price Shocks (OPS), while the explanatory variables include Financial Globalisation Uncertainty (FGU), Climate Policy Uncertainty (CPU), and real GDP, which serves as a proxy for economic performance (INC). The dependent variable is OPS, and the independent variables comprise FGU, CPU, and INC.

The study adopts the environmental policy uncertainty index developed by Gavriilidis (2021), which applies a text-mining approach to quantify economic policy uncertainty using data extracted from leading national newspapers. Specifically, CPU is derived from the frequency of key media articles containing phrases such as climate risk, environmental uncertainty, and greenhouse gases. The monthly CPU index is sourced from policyuncertainty.com.

Additionally, updated data on oil price shocks are obtained from Baumeister's database, as applied in Salisu and Gupta (2020), with original datasets drawn from the U.S. Energy Information Administration (EIA). The Economic Policy Uncertainty (EPU) index is also freely accessible from policyuncertainty.com. The Financial Globalisation Uncertainty (FGU) variable is constructed using the Chinn and Ito (2007) KAOPEN index, incorporating a one-period lag (FGU_{t–1}). Finally, real GDP data representing national income are retrieved from the World Bank's World Development Indicators (WDI) database.

Table 1 presents the descriptive statistics for all variables, where OPS denotes oil market fear, FGU represents financial globalisation uncertainty, CPU refers to climate policy uncertainty, EPU stands for economic policy uncertainty, and INC captures economic performance. The Jarque–Bera (JB) statistic is employed to test for data normality under the null hypothesis that each series follows a normal distribution. The results indicate that the null hypothesis is rejected for all variables, suggesting that the data deviate from normality. Given this non-normal distribution, the application of traditional linear models could lead to biased or inefficient estimates. Consequently, the study employs advanced econometric techniques—specifically the Quantile ARDL (QARDL) and Nonlinear ARDL (NARDL) models—which account for asymmetries and distributional heterogeneity. These methods allow for a more comprehensive assessment of the relationships across the entire conditional distribution, capturing both lower and upper tail dynamics of the data and ensuring more robust and reliable results.

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

Several studies have identified factors such as oil production activity, real GDP, exchange rates, financial indicators, and investor behavior as key determinants influencing volatility and anxiety in the oil market (Chatziantoniou et al., 2021; Xiao and Wang, 2021). However, only a limited number of studies have explicitly examined the role of uncertainty in shaping oil market anxiety. As highlighted earlier, different types of uncertainty can exert either positive or negative effects on oil market dynamics, given their capacity to influence the fundamental structure and expectations within the energy sector. Moreover, empirical evidence underscores that macroeconomic and financial performance remain significant determinants of oil market stability (Kilian and Vigfusson, 2011). In line with the existing literature, this study proposes a conceptual framework that integrates various dimensions of uncertainty—economic, financial, and climate-related—alongside macroeconomic performance indicators to better explain the drivers of oil market anxiety.

$$lnOPS_t = f(lnCPU_t, lnEPU_t, lnFGU_t, lnINC_t) \tag{1}$$

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:

$$lnOPS_t = \beta_0 + \beta_1 lnCPU_t + \beta_2 lnEPU_t + \beta_3 lnFGU_t + \beta_4 lnINC_t + \varepsilon_t \tag{2}$$

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

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

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

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

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 (At Level) lm-stat [C-value]	KPSS (At First Diff.) lm-stat [C-value]	ADF (At Level) t-stat [p-value]	ADF (At First Diff.) [p-value]
OPSt	0.52* (0.739)	0.18* (0.739)	-6.98* (0.000)	-11.84* (0.000)
FGUt	0.47* (0.739)	0.09* (0.739)	-0.83 (0.792)	-9.57* (0.000)
CPUt	1.26 (0.739)	0.31* (0.739)	-4.02* (0.001)	-10.28* (0.000)
EPUt	1.42 (0.739)	0.28* (0.739)	-2.31 (0.162)	-11.67* (0.000)
INCt	1.39 (0.739)	0.07* (0.739)	-1.83 (0.372)	-6.03* (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 the oil market fair. It is noteworthy to understand that one of the advantages of NARDL is that is a more robust and popular approach due to its flexibility, which means that it can be used irrespective of the 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 to c7 denote the long-run coefficients, while the changes in the variables capture the short-run dynamics. Furthermore, the bounds testing procedure is employed to examine the existence of a long-term relationship among the variables within the framework of the Nonlinear Autoregressive Distributed Lag (NARDL) model presented in Equation (9). The bounds testing approach, developed by Pesaran et al. (2001), is designed to assess cointegration among variables regardless of whether they are integrated of order zero or one. The NARDL model also accounts for the asymmetric effects arising from positive and negative variations in the explanatory variables, thereby allowing a more comprehensive understanding of their differential impacts.

3.5 Diagnostic Tests

It is important to note that several diagnostic tests were conducted to evaluate the adequacy and reliability of the estimated models. The Ramsey RESET test was employed to verify the correctness of the model specification, while the serial correlation test was used to check for the absence of autocorrelation in the residuals. Additionally, the adjusted R-squared statistic was computed to assess the overall goodness of fit of the models. The outcomes of these diagnostic evaluations are reported alongside the cointegration test results in Table 3.

3.6 The ARDL Bounds Tests for Cointegration

The outcomes of the cointegration bounds test are presented in Table 3. The computed F-statistic, valued at 17.127 and significant at the 5% level, exceeds the upper critical bound, thereby confirming the presence of a long-run equilibrium relationship among 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 and Discussion

This study examines how financial globalisation uncertainty, economic policy uncertainty, climate policy uncertainty, and economic performance influence different quantiles of Nigeria's oil market anxiety. It extends the existing literature by comparing results from the Quantile Autoregressive Distributed Lag (QARDL) model (Cho et al., 2016) with those from the Nonlinear Autoregressive Distributed Lag (NARDL) framework. The QARDL model's main advantage lies in its ability to capture heterogeneous effects across various quantiles of the dependent variable, providing a more nuanced understanding of the relationships. However, one limitation of the QARDL approach is that it cannot be applied when any variable is stationary at the second difference. To ensure model validity, this study employs both Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests to determine the stationarity properties of the variables. As shown previously in Table 1, the ADF results reveal that all variables are stationary either at level or at first difference, while the KPSS test confirms stationarity at I(0) or

I(1). These findings satisfy the preconditions for applying both models. The results of the bound cointegration tests, presented in Table 3, further confirm the existence of long-run relationships among the studied variables under both the QARDL and NARDL frameworks.

Table 4 presents the results of the Quantile ARDL (QARDL) model, covering quantiles ranging from Q0.05 to Q0.95, which represent the lower and upper ends of the oil market fear distribution, respectively. The findings reveal that at the 5th quantile, shocks originating from climate policy uncertainty (CPU), financial globalization uncertainty (FGU), and economic policy uncertainty (EPU) account for approximately 85%, 50%, and 9% of the variations in oil market fear, while economic performance (INC) explains about 17% in the long run. At this stage, CPU exerts the greatest influence on oil market fear compared to other variables. Similarly, in the 10th quantile, CPU continues to have a stronger impact than FGU, EPU, and INC, contributing roughly 74% of the observed variation. Across the 20th to 80th quantiles, CPU consistently demonstrates the most significant explanatory power, accounting for about 74%, 71%, 66%, 64%, 61%, 70%, 73%, and 63% of the variation in oil market fear, respectively. However, in the 90th and 95th upper quantiles, FGU emerges as the dominant factor influencing oil market fear. Overall, the short-run outcomes across quantiles show a consistent pattern with the long-run estimates.

In particular, an increase in economic policy uncertainty (EPU) often exerts a direct negative effect on real economic activity by discouraging investment and consumption, which subsequently reduces oil demand and heightens market volatility. Consequently, surges in EPU tend to amplify fear within the oil market, as investors and traders anticipate a decline in oil demand and potential price drops resulting from such shocks. However, the influence of EPU on oil market anxiety is not constant—it fluctuates over time and becomes especially pronounced during major crises that trigger economic downturns, such as the 2018 financial crisis or the recent COVID-19 pandemic. This suggests that market participants exhibit heightened sensitivity to EPU shocks during periods of economic instability.

The relationship between financial globalization uncertainty (FGU) and oil market anxiety is shaped not only by economic fundamentals but also by the financial nature of the oil sector. Due to this close connection, fluctuations in global financial conditions often heighten market apprehension, making FGU a key determinant of oil market fear over time. Accordingly, FGU consistently exhibits a positive and significant impact on oil market volatility and investor sentiment. Conversely, economic performance (as measured by INC) shows a negative relationship with oil market anxiety. This inverse link suggests that as Nigeria—an oil-producing and oil-dependent nation—experiences stronger economic activity, market participants become less apprehensive about potential oil price shocks because increased domestic demand provides a stabilizing effect. Moreover, Nigeria's ongoing efforts to diversify its economy aim to mitigate this dependence on oil revenues, thereby reducing the broader economic and psychological vulnerabilities associated with oil market fluctuations.

Our findings indicate that climate policy uncertainty (CPU) is one of the strongest drivers of oil market anxiety. Broadly, CPU influences oil market behavior through several interconnected channels. First, a significant share of global carbon dioxide emissions stems from oil consumption, directly linking the sector to climate change. To mitigate these adverse effects, governments must implement energy restructuring, improve efficiency, and regulate fossil fuel use. However, the design and enforcement of such policies often involve considerable uncertainty (Nodari, 2014). When policy directions are unclear or inconsistent, oil market participants face difficulty in predicting future demand patterns. This uncertainty amplifies their anxiety, as fluctuating climate regulations introduce additional risks into investment decisions and market expectations.

Second, climate change often amplifies both physical and transition risks, which can negatively impact firms and broader economic stability (In et al., 2022; Zhang, 2022). When policy measures to mitigate global warming are uncertain or poorly defined, these risks remain inadequately managed, heightening economic volatility and intensifying anxiety within the oil market. Furthermore, climate-related risks also influence real economic activity and financial markets. Krueger et al. (2020) emphasize that institutional investors increasingly consider climate shocks in their decision-making, while Zhang (2022) finds that climate risks exert a negative effect on stock valuations. Given the deep financial integration of the oil market, such risks quickly transmit through investment channels, linking fluctuations in financial sentiment with oil price instability. Consequently, uncertainty surrounding climate policies can magnify market apprehension and volatility. Overall, the empirical evidence underscores the importance of understanding how climate policy uncertainty shapes oil market anxiety across different quantiles and market conditions.

Our findings can be further extended by exploring the underlying factors driving the rise in climate policy uncertainty and the broader apprehension surrounding climate-related risks. One major catalyst is the frequency of significant global climate policy events, such as the Paris Climate Change Conference held on December 12, 2015. The conference brought together nearly 200 parties that endorsed the Paris Agreement, committing to reduce greenhouse gas emissions and limit global temperature increases. The Agreement officially came into force in November 2016, marking a landmark step in international climate governance. However, the subsequent withdrawal of the United States from the Agreement in June 2017 heightened global uncertainty regarding the stability and enforcement of climate policies. As Battiston et al. (2021) note, the period following the Paris Agreement saw increased involvement of the financial sector in climate-related discussions, with monetary and regulatory authorities recognizing climate change as an emerging systemic financial risk.

Diaz-Rainey et al. (2021) report that both the ratification of the Paris Agreement and the subsequent announcement of the United States' withdrawal had a markedly negative impact on the fossil fuel industry. These developments contributed to a sharp rise in climate policy uncertainty, which in turn fueled volatility across economic and financial markets—intensifying anxiety within the oil sector. Additionally, government initiatives aimed at transitioning toward greener, low-carbon economies have raised public awareness of environmental risks and climate-related threats. Fahmy (2022), using the Google Search Index, finds that since the adoption of the Paris Agreement, investor attention to climate-related issues has grown significantly. This heightened public concern over climate risks likely magnified the positive relationship between climate policy uncertainty and oil market fear in the post-2016 period.

The NARDL estimation results presented in Table 5 distinguish between the positive and negative components of climate policy uncertainty (CPU) and financial globalization uncertainty (FGU). The findings indicate that both increases and decreases in these variables exhibit positive estimated coefficients. Specifically, a 1% rise in CPU leads to a 3% increase in oil market anxiety in the short run and a 14% increase in the long run. Conversely, a 1% decline in CPU results in a 3% reduction in oil market fear in the short term and an 11% decrease in the long term.

Regarding FGU, the positive shock is statistically positive but insignificant in the short run, while in the long run, it becomes statistically significant with a coefficient of 0.71. The negative shock of FGU, however, is statistically positive and significant, suggesting that a 1% decrease in FGU reduces oil market fear by 14% in the short run and 24% in the long run.

Overall, the NARDL results reinforce the findings of the QNARDL model, confirming positive associations between FGU, CPU, EPU, and INC in explaining oil market anxiety. Nevertheless, the asymmetry evident in the NARDL results highlights that FGU's short-run effects are insignificant, whereas long-run effects are substantial. These findings imply that variations in CPU and FGU exert asymmetric influences on Nigeria's oil market fear over both short- and long-term horizons.

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

Note: * Shows statistical significance at the 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 the 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

In recent times, amid heightened global uncertainties, anxiety in the oil market has intensified, accompanied by significant fluctuations in oil prices. This study employs the oil price shocks (OPS) index to analyze how economic policy uncertainty (EPU), climate policy uncertainty (CPU), financial globalization uncertainty (FGU), and economic performance (INC) influence oil market fear in Nigeria. Recognizing that the relationships between these variables and OPS may vary across quantiles, the study primarily adopts the Quantile ARDL (QARDL) model for empirical analysis. Additionally, the Nonlinear ARDL (NARDL) model is applied to test for potential asymmetric effects between CPU and FGU on OPS.

The empirical results reveal that CPU, FGU, EPU, and INC exert quantile-dependent impacts on oil market anxiety. The QARDL findings underscore the dominant role of climate policy uncertainty in shaping Nigeria's oil market fear across most quantiles, except at the upper quantile, where financial globalization uncertainty becomes more influential. Furthermore, the NARDL results confirm the positive associations observed in the QARDL estimations, reinforcing the presence of asymmetric relationships among the variables and their collective influence on oil market fear in Nigeria.

High levels of fear and uncertainty in the oil market negatively affect trade, investment, and effective risk management. The findings of this study provide essential insights for addressing the current volatility in the oil sector. Specifically, climate-related instability—alongside economic, financial, and performance-related uncertainties—can intensify market anxiety, particularly within the framework of the Paris Agreement. To mitigate oil market volatility stemming from climate policy uncertainty, policymakers should accelerate the shift toward cleaner and more sustainable energy systems. Likewise, investors are encouraged to diversify their portfolios by incorporating renewable energy investments.

Furthermore, governments and investors must recognize that climate, economic, and financial uncertainties influence oil market behavior in distinct ways, requiring targeted and context-specific responses. During crises such as pandemics, both authorities and market participants should remain vigilant to these overlapping sources of uncertainty, as they can significantly heighten investor apprehension. Policymakers can stabilize demand and prevent sharp price declines by implementing economic stimulus measures and strengthening transparency and market regulations. At the same time, investors may need to hedge against risks through alternative financial instruments or temporarily reduce their exposure to the oil sector to safeguard their assets.

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