5. THE EFFECT OF CLIMATE POLICY SHOCKS AND GLOBAL FINANCIAL SHOCKS ON OIL PRICE SHOCKS: EVIDENCE FROM SOUTH AFRICA

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Abstract

While oil consumption is more visible in rich economies, it is also increasing in emerging economies. Yet South Africa, as a large oil importer, keeps facing growing oil consumption and it is projected to remain vulnerable to oil price fluctuations irrespective of the stage of their economic cycle. As such, the purpose of this paper is to investigate the relationship between various uncertainty measures and oil price fluctuations in South Africa from 2000M1 to 2020M3. Our uncertainty indicators recognized numerous points of view, including climate policy uncertainty (CPU), financial globalization uncertainty (FGU), and economic policy uncertainty (EPU). The Quantile Auto Regressive Distributive Lag (QARDL) model is applied to assess the quantile-based relationship of the variables. Besides, the non-linear autoregressive distributed lag (NARDL) is also applied to investigate the asymmetric effect. The QARDL results point out that the CPU, FGU, and EPU contribute to the different quantiles of oil price shocks. Precisely, the CPU has substantially and persistently become an essential determinant influencing oil price shocks in South Africa. The NARDL results aligned with the positive relationship of all the determinants on OPS. Policymakers should consequently pay greater attention to climate policy uncertainty and financial globalization uncertainty, given their significant influence on oil price shocks.

Keywords: oil price shocks, quantile ARDL, NARDL, Uncertainties, climate policy, economic policy

JEL Classification: F64, F65

1. Introduction

Uncertainty over energy pricing is the most significant risk not only for enterprises in the oil industry, but globally too. This makes calculating the financial gains of investments across the life span of a project challenging and may influence economic activity. The distinctive link between

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oil prices and macroeconomic uncertainties remains among the most important, disputable, and unresolved topics in energy economics (Bashar, Wadud, and Ahmed, 2013). Since the early 1970s, and even until recently, international changes in the cost of oil have long been seen as a key cause of macroeconomic uncertainty around the globe. At the beginning of the decade and the late seventies, most industrialized countries had sluggish growth, higher prices, and unemployment, rendering oil price swings a substantial source of worry for policymakers alike (Blanchard and Gali, 2007; Rafiq, Salim, and Bloch, 2009). In addition to the changes caused by fluctuations in oil prices, the uncertainty induced by volatile oil prices generates modifications in a country's economy. Substantial variations in oil prices influence many economic activities, based on the level of uncertainty caused by volatile oil prices and the perceptions of economic entities towards uncertainty (Ebrahim, Inderwildi, and King, 2014). The majority of the recognized causes of fluctuation in oil prices include wars, terrorist attacks, Middle Eastern conflicts, and political disturbances involving OPEC countries (Bloom, 2009; Guo and Kliesen, 2005). The uncertainty that follows significant shocks like the OPEC spike in oil prices is caused by factors outside of the economy (Hamilton, 1983; Plante and Traum, 2012).

While oil consumption is higher in advanced economies, it is also increasing in emerging ones (Birol, 2007). In comparison to other African countries, the South African economy enjoys an excellent record of development from privatization and significant expansion of trade. Its region's use of both gasoline and all forms of energy remains dominated by the economy (Nkomo, 2006). Nevertheless, as a major oil importer, South Africa is projected to be vulnerable to volatile oil prices irrespective of the stage of its economic model (Kilian, 2008). Variations in oil prices influence the consumption and supply sides of the real economy of oil-importing nations (Khan and Ahmed, 2011). An upsurge in oil prices increases energy expenses, lowering actual financial balances owned by families and, eventually, diminishing overall demand (Elder and Serletis, 2010). Firms confront a rise in production costs, leading to a decrease in output, and this in turn has a negative impact on job opportunities, overall inflation, and investments (Lescaroux and Mignon, 2008). Because oil prices influence a mix of productivity and consumption choices, they alter the conditions of trade with oil-importing nations. The major goal of this article is to describe how various uncertainties impact oil price shocks in an open country like South Africa.

Oil is recognized as a crucial component in propelling economic and financial development. As a result, research into the oil industry is gaining a lot of attention. Given the recent expansion in the oil sector's financial matters market fear is predicted to increase and spread. Sudden catastrophic events, such as the 2017-2018 economic recession and the worldwide COVID-19 epidemic, have raised concerns in the oil business. The expected instability index created by Christiane Baumeister, senior Energy Administrator in the United States, is a widely used indicator of market worry (Salisu and Gupta, 2020). The fluctuating nature of volatile oil prices suggests that amid the global crisis of 2008, the degree of fear in the crude oil business increased from approximately 30 to over 90% (Xiao and Liu, 2023). Shortly, the 2019 COVID-19 outbreak caused enormous turmoil in world economic and financial systems. The recent epidemic appears to have increased panic among oil market participants, as the proportion of OPS increased dramatically from around 30% to around 160% during this period. Market panic is always accompanied by an emotional reaction that cannot be accurately foreseen, compounding the risk (Yaya *et al*., 2021). Undoubtedly, oil prices fell during the financial crisis of 2008 and the newest COVID-19 pandemic. Given that significant anxiety and uncertainty in the oil industry are detrimental to oil activities, asset distribution and risk management, as well as having negative monetary and economic effects, it is critical to investigate the factors that are likely to have contributed to oil market fear. The goal of this paper is to investigate the effects of climate policy uncertainty, financial globalization uncertainty, economic policy uncertainty and economic performance uncertainty on oil price shocks in South Africa.

The following are the main inspirations for our quest. Several studies have found that swings in oil prices are impacted by a variety of factors, including crude oil production, real GDP, currency rates, financing, and investment patterns (Chatziantoniou *et al*., 2021; Xiao and Wang, 2021; Wen *et al*., 2018). The commencement of the 2008 financial catastrophe, which happened during the economic downturn, heightened concerns about possible unpredictability. Uncertainty decreases investments, spending by customers, and a variety of other economic activities, harming the broader economy and finance businesses. Uncertainty is an important factor in oil prices since it can impact the fundamental principles of the world's crude trade. Nonetheless, adequate measurement of uncertainty for the majority of relevant empirical investigations may be challenging. To their honour, Baker *et al.* (2016) present a news-based uncertainty measure. Several research studies explored the effects of various forms of uncertainty on the volatile oil price (Qin *et al*., 2020a; Zhang and Yan, 2020; Liu *et al*., 2021, and Wang *et al*., 2022). In particular, contingent on the data, uncertainty measures can have a wide range of effects on the oil market. As a consequence, economic policy uncertainty (EPU) may influence the consumer side of the oil market; financial globalization uncertainty (FGU) may have an impact on the supply side of the oil market owing to oil financing; and climate policy uncertainty (CPU) may have an impact on the supply side of the oil market and influence oil prices due to broad participation in firms and financial operations.

However, the influence of various sorts of instabilities on the volatile oil price has received little study consideration. Wen *et al.* (2019) and Huang *et al.* (2021) focused on contrasting economic and financial uncertainty measures. Li *et al.* (2020) and Liang *et al.* (2020) investigated the diverse effects of economic, financial and location-based uncertainty measures. Gu *et al.* (2021) study the influence of macro-variables on geographical vulnerability. Despite increased interest in the link between instabilities and oil price shocks, previous research focused mostly on the influence of climatic uncertainty factors in relation to oil price shocks (Guo *et al*., 2022). Climate change is still among the most contentious socioeconomic concerns (Bartram *et al*., 2022). The Paris Agreement, signed in 2015, gives further motivation to implement the required legislation to reduce greenhouse gas emissions.

As a result, a variety of variables, including unexpected environmental change, public outrage, technological advances, and economic circumstances. have contributed to tremendous uncertainty surrounding climate policy. In principle, climate policy uncertainty may affect the oil price shocks along three different avenues. While oil is one of the major fossil energy sources, its usage contributes greatly to the existing carbon dioxide excess in the climate. It is vital to develop renewable energy corporations and enhance energy-use techniques that minimize the amount of fossil fuels used in the atmosphere to reduce ambient CO2 emissions and ameliorate the detrimental consequences of global warming. Significant uncertainty in environmental legislation may lead to crucial decisions on renewable energy supply along with effective energy technologies to be stopped or modified, influencing oil demand predictions and, as a result, raising oil market concern and volatility. Second, the impacts of ecological footprint and transitory concerns have had a significant impact on investment and commerce (Zhang, 2022). Climate change policy uncertainty may emerge in an unstable economy if environmental standards are imprecise and conflicting in the middle of harsh climatic conditions as well as the transition to an environmentally friendly system, generating oil market fear and volatility. Finally, in terms of natural hazards and financing for carbon dioxide reduction, global warming risks may be connected to the financial framework via insurance firms (Hong *et al*., 2020). Global warming has been identified as a key factor influencing institutional investors' property holdings (Krueger *et al*., 2020). The growth of oil funds has increased the relationship between oil and the stock market, and oil has grown into critical asset management for financial organizations. As a result, climate risk associated with legislation and rules may impact oil market fears and volatility via this financial mechanism. The fact that climate policy uncertainty can be related to the oil market in several ways, makes it critical to explore how climate policy uncertainty causes oil market fear.

Furthermore, past research on the factors driving oil price volatility relied heavily on GARCH models and observable variance. Such variance estimates are ex-post and do not take into account future market data projections (Ji and Fan, 2016; Bildirici and Ersin, 2014). Oppositely, the US administrator's developed oil price volatility index evaluates market estimates for 30-day swings in oil prices, suggesting that it is a prediction indicator. The index depends on investor projections. While investors become more anxious, their perception of market uncertainty changes, as do their trading patterns. As such, the OPS index is frequently used as a measure of the volatile oil price which shows the level of fear in the market (Baumeister and Hamilton, 2019). Given the two major advantages described above, employing the OPS index would offer deeper insight and larger economic repercussions to the study of oil price shocks. Presently the OPS index is being increasingly applied to study as an indicator of the fear in the oil market in place of conventional fluctuation indicators (Salisu and Gupta, 2020), as well as the relationship between financial markets and oil prices (Xiao *et al*., 2018; Li, 2022). Regardless of this, a limited number of studies have been conducted on the relationships between various uncertainty indicators and OPS.

This paper provides three significant contributions to the existing literature. Although the link between uncertainties and oil market volatility is gaining scrutiny, to the best of our understanding, no prior work has been conducted to investigate the influence of different categories of uncertainty on oil price shocks using South Africa as a case study from 2000M1 to 2020M3. The oil price shocks index (OPS) is more informative than oil volatility metrics based on previous price data. More crucially, the OPS measures fear perception in the oil market, which might show investors' psychological shifts in the context of unforeseen shocks. As a result, the application of OPS to investigate the reactions of volatile oil prices to various uncertainty shocks is an important addition to this research. Second, in recent years, one of the greatest themes has been the repercussions of climate danger. Climate risk, according to academics, investors and politicians, has a significant impact on energy arrangements, the economy and financing. Therefore, climate risk is expected to have an impact on the oil price shocks. This problem, however, is largely unresolved. Guo *et al.* (2022) mainly focus on the influence of climate policy uncertainty (CPU) on oil price fluctuations. This article expands on previous studies by concentrating on the link between CPU, EPU, FGU and income on oil price shocks employing the oil price shocks index. Finally, while more study has been done on the link between various types of uncertainties and oil price shocks, there has been very little research done on merging several uncertainty measures in a single framework to explore how they influence the volatility of oil prices. Previous research (for example, Wen *et al*., 2019; Li *et al*., 2020) has only compared the impacts of economic, financial, and geopolitical instability. The Quantile autoregressive distributed lag (QARDL) and non-linear autoregressive distributed lag (NARDL) models are used in this study to examine the impact of uncertainty assessments on oil price shocks.

2. Literature Review

Volatility is often used in research to describe oil price instability (Elder and Serletis, 2010), and new data shows that oil prices are volatile (Baumeister and Kilian, 2016; Demirbas, Al-Sasi, and Nizami, 2017). This assessment of the literature concentrates on research that looked at the impact of oil price volatility. The exchange rate, as determined by Wen *et al.* (2018), has a short-run negative influence on oil price movements. Chatziantoniou *et al.* (2021) explore the effects of oil accessibility, consumption and economic factors on oil price variations and discover that financial indicators exert a bigger impact. According to Xiao and Wang (2021), investor attentiveness has a primarily favourable influence on poor volatility in the oil market. In addition to the previously mentioned variables, uncertainty has emerged as a new component in oil market analysis in recent years. By this stage, estimating uncertainty is a critical issue for conducting an

uncertainty study. Baker *et al.* (2016) use this information to calculate a news-based economic policy uncertainty (EPU). Baker *et al.* (2016); Dai and Zhu (2023), and several more studies bring solid proof that economic policy uncertainty has a significant influence on monetary and economic parameters. It is often assumed that swings in oil prices are closely related to economic factors. As a result, several research employs this EPU index and category to explore the influence of economic uncertainty over the oil price shock. Wei *et al.* (2017), for instance, show that data from basics and expectations is incorporated by the EPU indices when employing the GARCH-MIDAS model to forecast oil price changes, showing the importance of EPU measures in affecting oil variations. Ji *et al.* (2018) show that EPU has a minimal impact on oil price yields using the stochastic copula-based CoVaR technique. According to Qin *et al.* (2020a), the influence of EPU on oil prices changes over time, with taxation and trade EPU having a larger relationship with oil prices when Trump takes office. Zhang and Yan (2020) show that the EPU indicator affects oil price returns differently based on duration and acceleration, but the effect of multiple EPU indices on oil price returns increases with large happenings. Lin and Bai (2021) show that EPU among nations that produce oil has a bigger impact on rising oil prices than EPU in petroleum-importing states. Wang *et al.* (2022) use the contraction technique to show that the forecasting precision of key EPU factors for oil fluctuations in various markets is asymmetrical, owing to the underlying EPU trend concerning state debt and exchange instability being very often projected.

Several studies have been carried out as well to study the impact of various forms of uncertainty on the crude oil market. Wen *et al.* (2019), for example, discovered that when utilizing HAR-RV modelling, EMV instead of EPU may give more information to estimate the actual instability of oil contracts. Liang *et al.* (2020) employ several statistical techniques to study the relationships between global EPU, US EPU, EPU, GPR, and OPS via oil accomplished variance and discover that global EPU and OPS play a larger role in forecasting oil reached variance. Li *et al.* (2020) utilize the GARCH-MIDAS framework to study the forecasting power of news-based instability indicators for oil fluctuations, discovering that EPU in America might improve forecasts of large oil fluctuations. Gu *et al.* (2021) employ the VAR technique to argue that EPU has a higher impact on the oil price than GPR. Huang *et al.* (2021) employ the TVP-VAR technique to analyse the effects of EPU, and economic instability on oil price shocks and discover that EPU has greater effects on oil prices.

Climate uncertainty is presently creating widespread concern, prompting an increase in study interest. For instance, Hong *et al.* (2020) outline the climate danger and look at some related research. According to Krueger *et al.* (2020), environmental risk is a crucial factor influencing broad investors' investment decisions. According to Huynh and Xia (2021), changing environmental data threats may have an impact on corporate bond rates. Firms that are more exposed to environmental hazards have wider bank credit growth, according to Javadi and Masum (2021). Roncoroni *et al.* (2021) explore the influence of environmental transition risk and market framework on finance and discover that tough climate objectives may be met while the economy remains strong. According to Bartram *et al.* (2022), business regulation arbitrage has several ramifications for ecological policy. Bouri *et al.* (2022) show that CPU has a substantial influence on the effectiveness of green equities over brown stocks. *et al.* (2022) offer a framework for investigating the relationships between energy consumption and environmental threats. Ren *et al.* (2022a) show that CPU has a large nonlinear influence on corporate expenditures using data from the Chinese energy industry. Ren *et al.* (2022b) discovered that CPU has a detrimental influence on firm-level general effectiveness in Beijing. Tian *et al.* (2022) employ the NARDL approach to show that the CPU might have an asymmetric influence on the green bond formation in the near run in the case of China. Zhang and Kong (2022) give convincing proof that prices react negatively to alleged fluctuations in ecological hazards. As mentioned by Dai and Zhang (2023), environmental unpredictability has a substantial impact on the risk that banks face. However, as reported by Guo *et al.* (2022), there exists little study on the influence of climate-

related volatility on the price of oil. Guo *et al.* (2022) utilize the TVP-VAR model to demonstrate that the influence of CPU on oil prices changes from positive to negative regularly.

Moshashai *et al.* (2020) looked into the influence of fluctuating oil prices on the economic expansion in Saudi Arabia by assessing dependence on the oil commodities sector as emphasized in the National Transformation Programme (Saudi Vision 2030) to determine how much the equity-energy expenditure responsibility would encourage economic expansion in Saudi Arabia. The findings of the study support the oil sector's role in Saudi prosperity. Furthermore, they proposed that the oil-Saudi economic link exhibits nonlinear behaviour and threshold implications. This is explained by the reality that the cost of oil changes from time to time-based on the situation of the crude market. Oil prices are projected to have a favourable and considerable influence on Saudi Arabia's economy under the Vision 2030 strategy. Mukhtarov *et al.* (2020) evaluated the influence of the price of crude on economic expansion, exports, inflation, and the foreign exchange rate of Azerbaijan using the co-integration of Johansen and VECM techniques with data gathered between January 2005 and January 2019. The research findings show that the co-integration of the Johansen approach supports the presence of a long-term link between factors. Thus, for the instance of Azerbaijan, it is evident from the impulse-response and decomposition of variance tests that economic development, export and inflation have a positive and statistically significant impact on oil prices. However, given that oil prices have an impact on exchange rates, policymakers should evaluate the impact of shocks to oil prices on the economies of emerging nations like Azerbaijan which are rich in oil. Mohaddes *et al.* (2020) created a quarterly macroeconometric model for the Saudi economy covering the years 1981Q2–2018Q2, which they then included into a compact model of the global economy that took the global oil market into account. They are permitted to remove the amount and pace of economic shock distribution from the United States, China, and the rest of the globe to Saudi Arabia. They have the opportunity to investigate the effects of global financial uncertainty, lower oil prices and local budgetary reform on the Saudi economy. The results of the research show that advances influence more Saudi Arabia's economy in China than fluctuations in the United States, as they heavily rely on the trajectory of emerging trade trends and China's expanding position in the global oil market. Furthermore, the analysis found that a 10% drop in oil prices and volatility in the international financial system will hurt the Saudi economy. Yet, given Saudi Arabia's prevailing societal agreement, their influence is balanced by budgetary relief. As a result, domestic budgetary reform in Saudi Arabia has no detrimental influence on economic development. The impact on productivity would be determined by the quality of budgetary adjustments and whether or not structural changes were implemented.

Despite increased interest in the relationship between uncertainties and the oil market, previous research has mostly focused on the relationships of uncertainty accompanying yields based on historical data. The oil shock index (OPS), calculated from choice prices, includes historical data as well as investors' forecasts of future market changes. The OPS is seen to be a more precise sign of crude oil market fluctuations, which may signify fear in the market.

3. Data and Methodology

3.1 Data

Considering the limitations of data, we use South Africa's monthly time series dataset from 2000M1 to 2020M3. The Chicago Board Options Exchange (CBOE) oil price shock index is used as a proxy for oil price shocks. This indicator represents market estimates for 30-day fluctuation in the cost of oil, and since it is the most trustworthy. While some rely on the British Petroleum (BP) Statistical Review of World Energy database (Ersin and Bildirici, 2019) to create the financial globalization uncertainty measure, researchers first generated the Chinn and Ito (2020) KAOPEN

index, known as a measure of financial globalization. With that, we created the uncertainty series by employing an ordinary least squares (OLS) residual-based approach. This residual technique was widely employed by previous investigators such as Ahmad *et al.* (2018), Danlami *et al.* (2018), and Farouq and Sulong (2021, 2023).

We acquire information on the CPU index produced by Gavriilidis (2021). This indicator is designed to assess the level of uncertainty in US climate policy developments. Considering the United States has the world's greatest economy, we may use the US CPU index to reflect global climate risk, which additionally affects South Africa's economy and growth. The data may be accessed at http://www.policyuncertainty.com/climate_uncertainty.html. Many academics utilize it as well (Apergis *et al*., 2022; Ren *et al*., 2022; Isik *et al*., 2023). Baker *et al.* (2016) developed a news-based EPU index that uses scaled frequency counts of several newspaper items to measure economic policy uncertainty. Because yearly data is accessible to other factors, the CPU and EPU monthly statistic series were transformed to annual periodicity for analysis of time series. The income is the control variable that measures a country's economic performance. This data comes from World Development Indicators (WDI).

Table 1 summarises the statistics for all factors evaluated. We utilized the natural log of the variables chosen for econometric analysis. The mean of income (4.471) is found to be the greatest among all variables, while the mean of climate policy uncertainty (1.721) is found to be the lowest. Nevertheless, the SD indicates that income appears to be more variable than the oil price, financial globalization uncertainty, climate policy uncertainty and economic policy uncertainty. Except for income, all factors are negatively skewed. Furthermore, we utilize Jarque-Bera statistics to assess the normality associated with these variables, having the null hypothesis implying that the information in it is normally distributed. The evaluation in Table 1 reveals that the null hypothesis of normalcy is rejected, showing that the data is still not normally distributed. Given that the data in Table 1 is not normal, employing basic linear models may result in inaccurate results. As a result, for the statistical evaluation, the present research uses non-linear autoregressive distributed lag and quantile ARDL. These sophisticated econometrics approaches can provide robust conclusions regardless of data distribution since they assess the influence not only on the conditional average along on the data's left-right tail scales.

Table 1: Descriptive Summary

Variables	Mean	Standard deviation	Skewness	Kurtosis	Jarque-Bera
$lnOPS_t$	1.881	0.792	-0.765	3.021	9.211* (0.000)
$lnFGU_t$	3.298	2.060	-1.715	1.617	3.791** (0.073)
$lnCPU_t$	1.721	0.590	-0.185	2.032	3.384 (0.000)
$lnEPU_t$	3.626	1.903	-2.274	3.174	5.216 (0.000)
$lnINC_t$	4.471	2.537	0.721	2.771	10.038 (0.000)

3.2 Model specification

A lot of research found that oil activity, real GDP, the currency rate, financial measures, investment behaviours, and a range of other economic factors influence oil market fear (Chatziantoniou *et al*., 2021; Xiao and Wang, 2021). Yet, there is little literature that focuses on analysing uncertainty to estimate the fear of the oil trade. As previously said, numerous uncertainties may have a good or negative impact on a country's oil market fear, considering that

uncertainty is also viewed as a primary determinant of oil prices owing to how it may alter the fundamental components of the oil market. Furthermore, evidence implies that financial prosperity is an important factor in volatile oil prices (Kilian and Vigfusson, 2011). As a result, in line with the existing literature, we present our framework as:

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

OPS indicates oil price shocks, 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:

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

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 technique has grown into one of the most popular approaches for analysing the relationship between economic factors. Furthermore, we contribute to the previous study by using Cho *et al.* (2016) Quantile ARDL approach. This model is an upgraded form of the ARDL technique that investigates the short- along long-run impacts of the factors that explain the variable over various quantiles. The QARDL model has various variants. First, it investigates the explained variable's short and long-run impacts across multiple quantiles. Second, it may be used with a modest size. Finally, it may be employed when the variables have an interacting order of 0 I (0) or 1 I (1) (Bhutto and Chang, 2019). In contrast to the ARDL and NARDL models, this technique has a limitation: we cannot apply the QARDL technique if the parameters have such a level of integration as I (2). To summarise, we cannot apply this model if the variables become stable after their second difference. As a result, before applying the QARDL in conjunction with ARDL models, we conduct ADF and KPSS tests to examine the amount of convergence across every parameter. After defining the order of convergence, we employ the QARDL model presented by Cho *et al.* (2016). We characterize our formulation in a quantile-based manner of the QARDL paradigm within the framework proposed by Cho *et al.* (2016) as follows:

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

Where $e_t(\tau) = OPS_{t-i} - QOPS_t \binom{r}{\delta_{t-1}}$ 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:

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

The QARDL-ECM form of the above-generalized formulae (equation9) can be shown below:

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

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:

$$H_0: w * (0.05) = w * (0.1) = w * (0.2) = \cdots = w * (0.95) \quad (6)$$

The alternate hypothesis is:

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

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	1.216*	2.531*	-2.051	-51.325*
FGU_t	0.062	5.733*	-1.683	-42.683*
CPU_t	1.630*	1.829*	-23.184*	-61.202*
EPU_t	0.371	4.285*	-13.483*	-44.042*
INC_t	1.083**	5.152*	-2.582	-66.207*

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

Additionally, in this study, the NARDL model is employed to reveal the asymmetric link between CPU, EPU, FGU, INC, and oil price shock. The uncertainty over financial globalization, uncertainty over economic policy, uncertainty over climate policy, and income level may all play an important role in oil price shocks. Shin *et al.* (2014) suggested the nonlinear equation for creating the nonlinear ARDL as follows:

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

Notably, the long-term coefficients are represented by c1 through c7. Variable variation, on the other hand, represents short-term aspects. Furthermore, employing the NARLD model specified in Equation (9), the bound test was used to explore factor cointegration. Pesaran *et al.* (2001) developed and recommended the bound testing technique to study the long-term relationship between components. The NARDL takes into account the potential asymmetrical effects caused by positive and negative changes in different portions of the explanatory factors. This is widely used by many researchers such as Gong *et al.* (2023); Yacouba and Altintas (2019).

3.5 Diagnostic tests

Interestingly, we employed diagnostic analyses to evaluate the models' strength and other criteria for the models employed in this study. The Ramsey RESET test determines whether the models are appropriately formed, while the serial correlation test determines whether our models contain no autocorrelation. Lastly, an adjusted R square is determined to see if the models are of good fit. Table 3 shows the results of the co-integration test.

3.6 The ARDL bounds tests for cointegration.

Table 3: Bound Test Results

Function	*F*-statistics QARDL		*F-statistics* NARDL	
$F_{lnOPS}(lnCPU_t, lnEPU_t, lnFGU_t, lnINC_t)$	28.742		20.059	
C value bounds				
Level of significance	I(0)	I(1)	I(0)	I(1)
At 10%	5.43	6.13	3.97	5.11
At 5%	3.69	4.97	6.39	7.16
At 1%	5.98	7.79	3.16	4.28
Diagnostic test				
R^2	0.625		0.651	
Adj-R^2	0.453		0.484	
F statistic	4.017		3.408	
Prob (*F* statistic)	0.000		0.000	
LM	1.202		1.091	
ECM	-0.381**		-0.421*	
$Wald_{LR}$	4.135*		5.362*	
$Wald_{SR}$	0.426*		0.453**	

Table 3 summarises the findings of the cointegration bound test assessment for the parameters. At a 5% significance level, the derived F-statistics are 28.742 and 20.059, which exceeds the greatest analytical limit. This demonstrated the presence of a long-term association between climate policy uncertainty, economic policy uncertainty, financial globalization uncertainty, income, and oil price shocks.

4. Results discussion and analysis

Our study examines the influence of financial globalization uncertainty, economic policy uncertainty, climate policy uncertainty and income on several quantiles of South African oil price shocks. Our research adds to the existing literature by comparing the estimations of the quantile ARDL (QARDL) (Cho *et al*., 2016) approach with those of the NARDL approach. The QARDL technique has the distinct benefit of investigating the influence across multiple quantiles of the explanatory variable. The QARDL approach, on the other hand, has a drawback in that it cannot be used if any parameter remains stationary at the next second differencing. As a result, in this study, we use the ADF and KPSS tests to determine stationarity estimates. Table 2 shows the outcomes of the ADF and KPSS tests. The ADF test estimates demonstrate that all variables were either stationary at level or first difference. Likewise, KPSS test findings show that parameters either remain stable at I(0) or I(1). Overall, the ADF and KPSS stationarity tests match the models' requirements. Following that, in Table 3, we analyse the bound test computations for co-integration. In addition, the bound test results suggest the presence of cointegration amongst variables in each of the QARDL and NARDL models.

Table 4 summarises the quantile ARDL model outcomes from this investigation. The Q0.05-Q0.95 matched the distinct quantiles of oil price shocks, where Q0.05 and Q0.95 signify the lower and higher quantiles of the oil shock series, respectively. Based on the results of the QARDL evaluation, we can observe that in the 5th quantile, the fluctuations from CPU, FGU, and EPU explain around 45%, 41%, and 12% of the variation in oil price shock, respectively. While income explained 15% of the variance in the long term. The impact of CPU on the volatility of oil price shock is greatest in this first period. Similarly, the impact of climate policy uncertainty in the lower tenth quantile is larger than the FGU and EPU. When viewed alongside the CPU coefficient of 65%, the contributions of FGU, EPU, and INC are quite minor. We also discovered that the volatility from CPU had the greatest contribution to explaining the oil price shocks in South Africa in both the 20th, 30th, 40th, 50th, 60th, 70th, and 80th quantiles and explaining about 65%, 66%, 61%, 58%, 57%, 60%, 47%, and 51% of the variability in oil price shocks, correspondingly. Nevertheless, in the 90th and 95th upper quantiles, financial globalization uncertainty appears to have the greatest share of variation in oil price shock. Notably, the short-run outcomes of the different quantiles were consistent with the long-run outcomes.

A growing EPU, in particular, typically has an immediate adverse effect on real economic growth by lowering spending and investment, cutting oil demand, and raising market volatility. As such, EPU increases are more likely to instil panic in the oil market, since market participants expect a drop in oil consumption and price decreases as a result of the probability of EPU shocks. In contrast, the influence of EPU on oil price shock evolves and is most noticeable during times of catastrophic disasters causing economic contraction (e.g., the 2018 financial crash and the most recent COVID-19 outbreak). This might signal that market participants in the oil industry are more concerned about EPU shocks amid an economic downturn.

The connection between financial globalization uncertainty and oil price shock is founded not just on economic concepts, but also on oil financing. Because of this close link, oil market participants have cited financial globalization uncertainty as a major source of concern at various periods. As such, the FGU has a consistently favourable and considerable impact on oil market panic. There is an inverse relationship between income and oil price shock.

Table 4: QARDL Results

Quantiles	Constant	ECM	Long-run estimates				Short-run estimates				
[ ]	[ ]	*	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Q_5	0.011*	-0.028*	0.450*	0.225**	0.422*	0.162*	0.013	0.511**	0.017*	0.316*	0.021*
Q_{10}	0.021	-0.051*	0.652*	0.074**	0.526*	0.031*	0.057**	0.581*	0.043*	0.016*	0.201*
Q_{20}	0.053*	-0.033*	0.662*	0.028**	0.482*	0.114*	0.153*	0.262*	0.045*	0.013*	0.053*
Q_{30}	0.033**	-0.022*	0.617*	0.165**	0.519*	0.091*	0.034*	0.358*	0.130*	0.041*	0.015*
Q_{40}	0.026**	-0.072*	0.582*	0.155**	0.561*	0.072*	0.052*	0.411*	0.074*	0.021*	0.061*
Q_{50}	0.011	-0.038*	0.572*	0.015**	0.566*	0.140*	0.116*	0.351*	0.108*	0.210*	0.011*
Q_{60}	0.053	-0.051*	0.607*	0.105	0.336*	0.021*	0.017**	0.191*	0.113*	0.012**	0.010*
Q_{70}	0.067	-0.028*	0.471*	0.301*	0.282*	0.017*	0.018*	0.241*	0.110*	0.042	0.021*
Q_{80}	0.271*	-0.047*	0.512*	0.321*	0.152	0.206*	0.041*	0.321	0.024*	0.173**	0.011*
Q_{90}	0.259	-0.260*	0.011*	0.159**	0.561*	0.065**	0.131*	0.014*	0.068	0.371*	0.012*
Q_{95}	0.101*	-0.128*	0.131*	0.120*	0.395*	0.217**	0.071*	0.024*	0.011*	0.210*	0.026*

This is possible because, as an oil-importing country, South Africa would be relieved if economic activity increased, decreasing the risk of oil price shocks due to the growing oil demand. Expansion of the economic system is one significant aspect that the nation is always attempting to achieve to realize its prosperity and transition to renewable energy consumption.

We found that one of the major elements influencing oil price shock is the CPU. The CPU can be related to oil price concerns in general via the paths described below. First, a significant amount of CO2 emissions from oil usage are directly tied to climate change. To address the negative consequences of climate change, vital initiatives such as energy restructuring and energy efficiency advancements, as well as oil consumption regulation, are required. Policy formulation and implementation, on the contrary, are plagued with uncertainty (Nodari, 2014). Oil market participants will be concerned about the likelihood of climate policy uncertainty events since increased climate policy uncertainty makes projecting oil demand more difficult.

Second, climate change typically raises physical and transfer hazards, which may harm businesses and even the whole economy (In *et al*., 2022; Zhang, 2022). When policy solutions to global warming are uncertain, the physical and transfer threats presented by climate change are poorly addressed, generating economic volatility and rising oil market fear. Finally, climate risk has an influence on real productivity growth and, obviously, financial markets. As reported by Krueger *et al.* (2020), institutional investors have given a special focus on climate risk volatility. Zhang (2022) argues that climate risk has a negative influence on stock prices. Because of oil financing, the oil market is increasingly tightly tied to the financial market. Because of the duo's strong link, climate risk spikes caused by policy uncertainty might potentially boost the level of anxiety in the oil market. Nonetheless, the empirical findings highlight the need for more research into the link between environmental policy uncertainty along oil price shock across multiple quantiles.

Our results might be elaborated further by looking into the many factors that lead to the growth in environmental policy uncertainty and public concern over climate threat. The frequency of important climate policy initiatives, including the Paris Climate Change Conference on December 12, 2015, is a crucial contributing factor. Almost 200 parties joined this meeting and signed the Paris Agreement, which aimed to reduce carbon dioxide emissions and slow global temperature rise. The Paris Agreement eventually became law in November 2016. The Paris Agreement became law in November 2016. However, the US withdrew from the Paris Agreement in June 2017. As noted by Battiston *et al.* (2021), since the Paris Agreement in 2015, the finance sector has been heavily involved in talks on climate change, and economic regulatory bodies now clearly acknowledge that global warming is a growing cause of financial danger.

As stated by Diaz-Rainey *et al.* (2021), the adoption of the Paris Agreement, as well as the proclamation of the United States' departure from the Paris Agreement, has a significant negative impact on the fossil fuel industry. Because of the significant increase in climate policy uncertainties around the Paris Agreement, both financial and economic volatility have created fear in the oil sector. In addition, the government's efforts to develop an ecologically friendly economy have increased the public's understanding of climate risk. Fahmy (2022) uses a search engine index to show that investors have become more concerned about climate change following the Paris Agreement. This increased public concern about global warming may exacerbate CPU's beneficial influence on fluctuations in oil prices beyond 2016.

Table 5: NARDL Results

Variable	Short-run	SE	t-statistic
ΔCPU^{+}	0.026*	0.009	2.89
ΔCPU^{-}	0.047*	0.011	4.27
ΔFGU^{+}	0.041	0.021	1.95
ΔFGU^{-}	0.216*	0.046	4.69
ΔEPU	0.411*	0.120	3.42
ΔINC	0.066	0.082	0.80
$ECT(-1)$	-0.524*	0.176	-2.97
Variable	**Long-run**	**SE**	**t-statistic**
C	0.117*	0.053	3.33
CPU^{+}	0.157**	0.048	3.27
CPU^{-}	0.129*	0.036	3.58
FGU^{+}	0.521*	0.075	6.94
FGU^{-}	0.366**	0.148	2.47
EPU	0.069**	0.015	4.61
INC	0.302	0.291	1.04

However, the NARDL test findings in table 5 begin by distinguishing the negative and positive aspects of the climate policy uncertainty and financial globalization uncertainty parameters. The findings show that the estimations are positive for both CPU and FGU appreciations and for depreciations. This means that a 1% increase in CPU increases the short-run and long-run oil price shock by 2% and 15%, respectively. The negative shock reveals that a 1% decrease in CPU reduces oil price shocks by 4% in the near term and 12% in the long run. Notably, the FGU positive shock is statistically significant but inconsequential in the near term. In the long term, it turns statistically significant, and the coefficient is at 4%. Because the negative shock of FGU is statistically positive and substantial, a 1% drop in FGU decreases the oil price shocks by 21% in the short run and 12% in the long run. The NARDL results back up our QNARDL findings, revealing favourable correlations between FGU, CPU, EPU, and INC concerning oil market panic. However, the asymmetric NARDL results show that the coefficient of FGU rise is insignificant in the short run but significant in the long run. Based on the varied statistical results and the direction of the estimated elasticities, change in CPU and FGU appears to have an asymmetric influence on South Africa's oil price shocks in both the short and long term. Our findings agreed with the findings of Salisu *et al.* (2023), who discovered that CPU, particularly in the United States, might increase uncertainty in the world's crude oil market. However, contrary to our findings, Hailemariam *et al.* (2019); and Apostolakis *et al.* (2021) discovered that economic policy uncertainty had a detrimental impact on oil price shocks in G7 nations. Furthermore, Yang *et al.* (2021) discovered a similar positive link between financial globalization uncertainty and oil price shock in China. This suggests that rising financial uncertainty dampens economic activity, resulting in decreased energy consumption and lower oil prices (Ratti and Vespignani, 2016; Kang *et al*., 2020). Speaking about our gross domestic product variable, which represents income in our study, the negligible finding is consistent with many other studies, such as Gbatu *et al*., (2017); and Akinsola and Odhiambo (2020).

5. Conclusion

More recently, with a clear increase in external uncertainty, fear in the oil market has intensified, and oil prices have displayed significant fluctuations. This study examines how economic policy uncertainty, climate policy uncertainty, financial globalization uncertainty, and economic performance impact oil price shock in South Africa between 2000M1 and 2020M3. Notably, because the relationships of CPU, FGU, EPU, and INC with OPS may have quantile-varying properties, we conduct our empirical study largely using the quantile ARDL model. Furthermore, we used the NARDL evaluation model to demonstrate the existence of an asymmetric link between CPU FGU and OPS. Based on the results of our research, CPU, FGU, EPU, and INC have quantile-varying effects on OPS. The QARDL model highlights the significance of climate policy uncertainty in shaping South Africa's oil market fear. This is verified in all quantiles tested, except the higher quantile, where FGU has a substantial influence. The NARDL model confirmed the positive link revealed by the QARDL estimation model between all components regarding the oil price shock in South Africa.

Excessive fear and uncertainties in the oil market are detrimental to oil transactions, investment, and risk minimization. Our findings have significant implications for coping with the current state of the oil market. To reduce oil market volatility and concern caused by climate policy uncertainty shocks, governments should take specific actions to accelerate the process of moving energy, while investors should broaden their portfolios of investments by investing in various clean energy sources. Second, lawmakers and investors must acknowledge that climatic, economic, and financial uncertainty all have different effects on the oil market, and they must employ various tactics to manage these uncertainty waves based on their informational content. Finally, during the pandemic, regulators and investors must remain aware of inconsistencies related to climate, economics, and finance, since these unforeseeable events can significantly raise investor concern in the oil market. Decision-makers may provide economic stimulus to keep up oil demand and avoid a price drop, while also reducing fear speculation via more transparency and restrictions. During a pandemic, investors may need to mitigate their risks through various financial strategies or minimize their direct engagement in the oil sector.

Given that this country imports enormous volumes of oil, its influence on productivity is rapidly noticeable. Although changes in global oil prices cannot be regulated at the local level, South Africa should implement measures to mitigate the negative consequences of oil price uncertainty shocks. Policymakers must be vigilant in the face of oil price unpredictability to control economic agents' expectations and influence the South African economy's expected results. More focus will be placed on smart macroeconomic policies to deal with output increases while oil price uncertainty arises.

Research limitations and Future research

This research has several drawbacks. To calculate oil price volatility, the study examined only one major proxy of oil price shocks. There are several other measurements from other sources, but they are not included in this research. Furthermore, the timeframe covered in this analysis is constrained by the availability of data on the South African economy (particularly data on climate policy uncertainty and economic policy uncertainty). Future researchers should pay attention to the other indicators and broaden the scope of the study by taking into account other aspects. This study is based on a small sample of one net African oil importer to examine the implications of various macroeconomic uncertainties on oil market shocks in South Africa. This country can only give a restricted data set, however, the findings might be applied to a few similar countries. Getting data from other parts of the world, on the other hand, might increase the study's universality and dependability.

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