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EXPLORING THE ASYMMETRIC EFFECTS OF ECONOMIC POLICY UNCERTAINTY AND IMPLIED VOLATILITIES ON ENERGY FUTURES RETURNS: NOVEL INSIGHTS FROM QUANTILE-ON-QUANTILE REGRESSION

Ahmed BOSSMAN[1], Ştefan Cristian GHERGHINA[2*], Emmanuel ASAFO-ADJEI[1], Anokye Mohammed ADAM[1], Samuel Kwaku AGYEI[1]

[1]*Department of Finance, University of Cape Coast, Cape Coast, Ghana*
[2]*Department of Finance, Bucharest University of Economic Studies, Bucharest, Romania*

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Abstract. This study examined the asymmetric effects of major uncertainty and volatility indices (economic policy uncertainty, Chicago Board Options Exchange crude oil volatility, CBOE volatility index, CBOE VIX volatility, and NASDAQ 100 volatility target) on the returns of global energy and its constituents (global energy index, Brent, heating oil, natural gas, and petroleum). The causality-in-quantiles test and the quantile-on-quantile regression technique were employed on daily data covering the period between April 2012 and March 2022. The findings evidenced asymmetries and heterogeneity in the causal effects of global uncertainty and market volatilities on energy markets. For all uncertainty and volatility measures, we found strong negative relationships with energy commodities at stressed conditions, signalling some hedging benefits for market participants. The current research is among the first investigations to explore the asymmetric relationships between major uncertainty and volatility indices, as well as global energy and its constituents. Essential portfolio implications of our findings are discussed.

Keywords: energy commodities, energy markets, uncertainty indices, volatility indices, causality-in-quantiles, quantile-on-quantile regression.

JEL Classification: G01, G10, G18, Q40, Q41.

Introduction

Market uncertainties play a pivotal role in the price- and return-generating process for commodities (Liu et al., 2018). Due to the unpredictability of the market, risk-averse investors are striving to reduce the likelihood that they might lose their invested capital (Vukovic & Prosin, 2018). Therefore, commodity-based investment has gained attention in recent periods (Umar et al., 2019, 2022c; Zaremba et al., 2021) owing to the high integration among traditional

*Corresponding author. E-mail: *stefan.gherghina@fin.ase.ro*

markets (Asafo-Adjei et al., 2021a; Owusu Junior et al., 2021, 2022) and the associated need for effective portfolio/risk management (Umar et al., 2022a). According to Skapa (2013), direct commodity investing using commodity investable indexes may provide advantages of portfolio diversification since it may enhance return, lessen the risk, or even both. Also, Kurach (2012) emphasized that typically, commodities are regarded as effective diversifiers of equity portfolios. This rekindles the commodity financialisation hypothesis (CFH) originally put forth by Domanski and Heath (2007). Owing to market uncertainties, the fundamental conclusion concerning the CFH has witnessed some contentions based on empirical findings (Adams & Glück, 2015; Z. Huang et al., 2021; Tang & Xiong, 2012; Yin et al., 2021). Of the major commodity classes (i.e., agricultural, energy, and industrial), Umar et al. (2022c) underscore the leading role of energies over time. Dragomirescu-Gaina and Philippas (2022) document the relative merit of global uncertainty factors on asset prices and returns as opposed to local factors.

Meanwhile, the relationship between major global uncertainty measures and energy commodities, which are leading and drive global productivity, has not yet been scrutinized, with the exception of the recent contribution of Antonakakis et al. (2023), who merely examine the relationship between several uncertainty measures and oil prices. The oil sector has one of the most unstable markets and one of the largest environmental implications of any industry (Filimonova et al., 2020). Qiao et al. (2022) found that there is an interaction between economic policy uncertainty (EPU) and high-risk assets using time-varying parameter vector autoregression. According to Zhu et al. (2021), the interconnection among EPU, crude oil, and commodities futures increases as the scale expands but decreases in the ultralong horizon.

Further, given the leading role of energy commodities, examining the relationship among these commodities and implied volatilities is essential for at least three reasons. First, implied volatilities present a set of forward-looking measures of uncertainty and, hence, could effectively gauge investor fear. From a worldwide standpoint, Osei and Adam (2021) demonstrated that US EPU have a significant impact on both advanced and emerging market economies, and it is more prevalent in the literature. Second, they are a key determining variable in option pricing. Third, volatility trading by investors is hinged on the information possessed by implied volatility. Therefore, the link between anticipated uncertainty and energy commodities across various conditions of the market improves the understanding of financial investors concerning (i) the future trends of fundamental asset prices, which is particularly important for devising risk management strategies, (ii) the accuracy of option pricing, and (iii) asset allocation and portfolio management strategies.

To this end, we examine the influence of major uncertainty variables on the returns of energy commodities. We acknowledge that the intense complexities in the global economy cause the relationship between financial markets asymmetric across market conditions (Alsubaie et al., 2022; Armah et al., 2022; Assifuah-Nunoo et al., 2022; Umar et al., 2022b). Consequently, we formulate the following research hypothesis:

H_1: the relationship between market uncertainties and energy markets is asymmetric.

By empirically testing the postulated relationship, this study adds two main contributions to the existing evidence. First, we employ five major and widely-noted (Antonakakis et al., 2023) uncertainty measures (i.e., the US economic policy uncertainty (EPU), CBOE Crude Oil Volatility (OVX), CBOE Volatility Index (VIX), CBOE VIX Volatility (VVIX), and DWS NASDAQ 100 Volatility Target (GVNF)) to assess their impact on the aggregate global energy market and its constituents (i.e., global energy index, Brent, heating oil, natural gas, and petroleum). EPU can provide an outlook for policy uncertainty within the global economy. Ma et al. (2019) proved that the US EPU index exhibit the most accurate long-term predicting ability for the volatility of crude oil return. Also, Huang et al. (2022) reinforced through time-domain analysis the strong connection between the gold and crude oil markets and EPU. Olubusoye et al. (2021) reported that EPU drives the majority of the energy price uncertainty during the pandemic, followed by VIX, COVID-Induced Uncertainty (CIU), Misinformation Index of Uncertainty (MIU), and Global Fear Index (GFI). He et al. (2021) showed that positive associations exist between China's energy sector stock volatility and EPU shocks, while a negative relationship was found between adverse volatility and EPU. OVX is instrumental in forecasting oil market volatility, which drives major global activities. Lv (2018) found that the effect of OVX on future volatility is statistically significant, demonstrating that OVX can amplify price fluctuations for crude oil futures. In the same vein, Lu et al. (2020) proved that regime change is effective in addressing the structural break in the energy market and that OVX contains information that is estimating of oil realized volatility. Also, Niu et al. (2022) showed that the volatility of crude oil is most affected by OVX. Benedetto et al. (2020) noticed that there was less information exchange between OVX and the spot variance of WTI returns, while there was more information exchange with Brent. VIX and VVIX are particularly important to gauge global market uncertainty based on the changes in the stock market of the US. Chen et al. (2021) noticed that natural gas spot, natural gas futures, WTI oil futures and spot, and Brent oil spot are all considerably influenced favorably by VIX. As well, through the GVNF, the volatility of top-listed markets on NASDAQ can be anticipated to influence investment choices. Adekoya et al. (2022) found that in both the causality-in-mean and causality-in-variance models, EPU has the greatest impact on the stock returns of energy companies regardless of the market conditions, although under the causality-in-mean model, VIX has a stronger impact than OVX, and the opposite is true for the causality-in-variance. Hence, taking into account all uncertainty measures may provide valuable insights. To the best of our knowledge, no prior study has covered all the aforementioned variables. The assessment of the impact of these uncertainty factors will provide insights into their respective influence on the price and returns generating mechanism. This is instrumental for effective asset allocation and risk management.

Second, in our analysis, the impact of each uncertainty is envisaged from diverse market conditions, viz. bullish, bearish, and normal market states rather than an average market condition. To achieve this, the quantile-on-quantile regression (QQR) technique proposed by Sim and Zhou (2015) is employed. The QQR approach yields more robust results in the relationship between the dependent and independent variables relative to classic methods like ordinary least squares and simple quantile regressions. Thus, relative to other methods, the QQR approach helps us to assess the effect of the quantiles of a single explanatory variable on distinct quantiles of energy market returns. We employ several tests to confirm the use of the QQR approach and the robustness of our findings.

From our findings, the effect of various uncertainty indices evidences the heterogeneous impact of global uncertainty indices on energy markets' returns across normal, bullish, and bearish market conditions. EPU's effect on energy markets is more pronounced than other volatility indices such as crude oil volatility, CBOE volatility index, CBOE VIX volatility, and DWS NASDAQ 100 volatility target. We document significant Granger-causality from uncertainty and volatility indices across different quantiles of energy markets' returns. We contribute to the strand of works that examine the impact of various uncertainties on commodity markets by providing fresh evidence from nonparametric estimators.

The remainder of the study is outlined as follows. Section 1 covers a brief literature review; Section 2 details the methods; we present the results and their implications in Section 3 and conclude the last section.

1. Literature review

The literature on energy commodities has gained increasing attention. We review two major strands of literature, particularly on energy commodities and market uncertainties, to situate our study.

The first strand of works modeled the dynamic interrelations between commodity uncertainties and/or macroeconomic uncertainties, and relative assessments of energy and non-energy markets. For instance, El-Karimi and El-Ghini (2020) claimed that through a number of direct and indirect means, the rising global commodity prices could increase domestic consumer prices. Balli et al. (2019) explored the network structure of 22 globally traded commodity markets' uncertainties and reveal substantial connectedness between commodity markets in the long run. Liu et al. (2018) also report that news implied volatility on commodity futures' long-term volatilities has heterogeneous impacts on energy and non-energy commodity futures. Z. Huang et al. (2021) find a consistent predictive power of macroeconomic uncertainties on commodity futures' volatilities.

The second strand of literature point to the time-varying and heterogeneous links between commodity-based uncertainties and/or commodity markets, and nonlinear relationships between commodity markets and market uncertainty. Reiterating Reboredo and Uddin's (2015) conclusion that uncertainties from general stock market returns are insignificant to predict commodity market dynamics, we note that the emphasis on the significance of uncertainty indices' effect on commodity markets cannot be shelved. This partly draws attention to an emerging strand of works that examine market uncertainties on commodity investments.

Assaf et al. (2021) model the dynamic linkages between energy markets and selected market uncertainties (EPU, equity market uncertainty, geopolitical risk, and international trade uncertainty). Among the studied market uncertainties, the authors document that EPU's contribution to system spillovers is the highest. After introducing investor sentiment to the system, the authors further divulge that the consumer sentiment index is positively related to the net connectedness of energy markets. J. Huang et al. (2021) examine the time-varying connectedness of varied uncertainty measures on commodities. Except for macroeconomic uncertainty, all other uncertainty measures possessed time-varying effects on commodity markets. With evidence from the COVID-19 pandemic era, the information transmission dynamics between global commodities and uncertainties were modeled by Asafo-Adjei et al. (2022) and Qabhobho et al. (2022) in a transfer entropy framework.

The asymmetric interrelations between financial markets have been underscored (Agyei et al., 2022a, 2022b; Asafo-Adjei et al., 2021b; Bossman & Agyei, 2022a, 2022b; Bossman et al., 2022a; Hazgui et al., 2021; Roy & Sinha Roy, 2022; Shah & Dar, 2022; Umar et al., 2019) but from the emerging strand of works on commodity markets, the asymmetric relationships between uncertainty indices and commodity markets across bullish, bearish, and normal market conditions are yet to be documented. We provide this evidence among energy markets, which have seen huge investments in recent periods and have taken a leading role among other commodity classes.

Note that from the new literature strand, the commonly used econometric techniques are spillover techniques (Assaf et al., 2021; J. Huang et al., 2021), which analyze the overall and directional connectedness between a set of variables, and transfer entropy (Asafo-Adjei et al., 2022; Qabhobho et al., 2022), which quantifies the intrinsic information between markets. These techniques may not adequately assess the asymmetric effects of market uncertainty on energy markets. As a result, this study employs the QQR technique, which helps us to assess the effect of different conditions of market uncertainty on various return distributions of energy commodities. This feature is provided by the QQR technique and, hence, justifies its use in the current study.

2. Data and econometric framework

2.1. Data

From 25 April 2012 to 31 March 2022, our datasets include daily indices for global energy and its constituents (i.e., global energy index – GEnergy, Brent, heating oil – HOil, natural gas – NGas, and petroleum), and daily uncertainty indices for the US economic policy uncertainty (EPU), CBOE Crude Oil Volatility (OVX), CBOE Volatility Index (VIX), CBOE VIX Volatility (VVIX), and DWS NASDAQ 100 Volatility Target (GVNF). A total of 2182 common data points (in terms of daily returns) were generated for each variable. Consistent with the literature (e.g., Antonakakis et al., 2023; Owusu Junior et al., 2021) we utilize returns to adequately assess changes in market dynamics, which are of importance for risk management. For instance, for a given market return on the VIX, we can assess changes in investor fear, as depicted by the change in the economic and stock market activity of the US. This measure is pivotal for financial analysts – in providing adequate analysis and market trends – and portfolio managers – in devising cross-market and cross-asset diversification strategies. The statistical properties of the datasets are shown in Table 1 with pictorial trajectories in Figure 1. All data were sourced from the EquityRT database.

The descriptive statistics indicate negative mean returns for all energy indices and positive averages (nearly zero) for all uncertainty indices. Except for natural gas, the negative skewness for the energy indices suggests that more negative returns were recorded over the sample period. For the uncertainty indices, more positive returns were recorded for EPU, GVNF,

Table 1. Descriptive statistics and pairwise correlations

Panel A: Descriptive statistics										
	Brent	HOil	NGas	Petroleum	GEnergy	EPU	GVNF	OVX	VIX	VVIX
Min	−0.2699	−0.1771	−0.192	−0.2478	−0.2564	−2.9039	−0.6223	−0.4368	−0.2848	−0.0654
Max	0.1352	0.1026	0.1664	0.146	0.1373	3.2156	0.8577	0.7682	0.3732	0.0557
Mean	−0.0004	−0.0004	−0.001	−0.0005	−0.0005	0.0002	0.0003	0.0001	0	0.0007
Std. dev.	0.0225	0.0198	0.0263	0.0223	0.0209	0.5026	0.0595	0.0815	0.0536	0.0113
Skew	−1.1489	−0.4437	0.1471	−1.1041	−1.2224	0.1782	1.8263	1.212	0.9206	−0.644
Kurt	18.151	8.1509	3.9652	17.525	20.2331	2.0263	32.1556	7.3479	5.5704	3.2845
Norm	0.8804[a]	0.9246[a]	0.9661[a]	0.8765[a]	0.8654[a]	0.9844[a]	0.834[a]	0.9222[a]	0.9326[a]	0.9524[a]
ADF	−48.8536[a]	−48.8535[a]	−49.1758[a]	−49.3771[a]	−48.2805[a]	−26.5766[a]	−49.062[a]	−47.2662[a]	−51.2659[a]	−49.2704[a]
PP	−48.8983[a]	−48.8626[a]	−49.2708[a]	−49.4676[a]	−48.3764[a]	−443.073[a]	−49.2938[a]	−47.6552[a]	−55.4464[a]	−62.0142[a]
Panel B: Correlation matrix										
Brent	1.0000									
HOil	0.9380[a]	1.0000								
NGas	0.1409[a]	0.1581[a]	1.0000							
Petroleum	0.9875[a]	0.9412[a]	0.1465[a]	1.0000						
GEnergy	0.9782[a]	0.9356[a]	0.2520[a]	0.9894[a]	1.0000					
EPU	−0.0052	−0.0203	−0.0471[b]	−0.0081	−0.0142	1.0000				
GVNF	−0.4786[a]	−0.4280[a]	−0.0680[a]	−0.4867[a]	−0.4887[a]	0.0657[a]	1.0000			
OVX	−0.2709[a]	−0.2507[a]	−0.0126	−0.2654[a]	−0.2542[a]	0.0272	0.3749[a]	1.0000		
VIX	−0.1908[a]	−0.1747[a]	0.0076	−0.1850[a]	−0.1748[a]	0.0252	0.3018[a]	0.8436[a]	1.0000	
VVIX	0.2231[a]	0.2061[a]	−0.0006	0.2213[a]	0.2114[a]	−0.0227	−0.3010[a]	−0.7676[a]	−0.6674[a]	1.0000

Notes: This table presents the summary statistics and correlation matrix for the sampled variables. [a] and [b] denote significance at 1% and 5%, respectively.

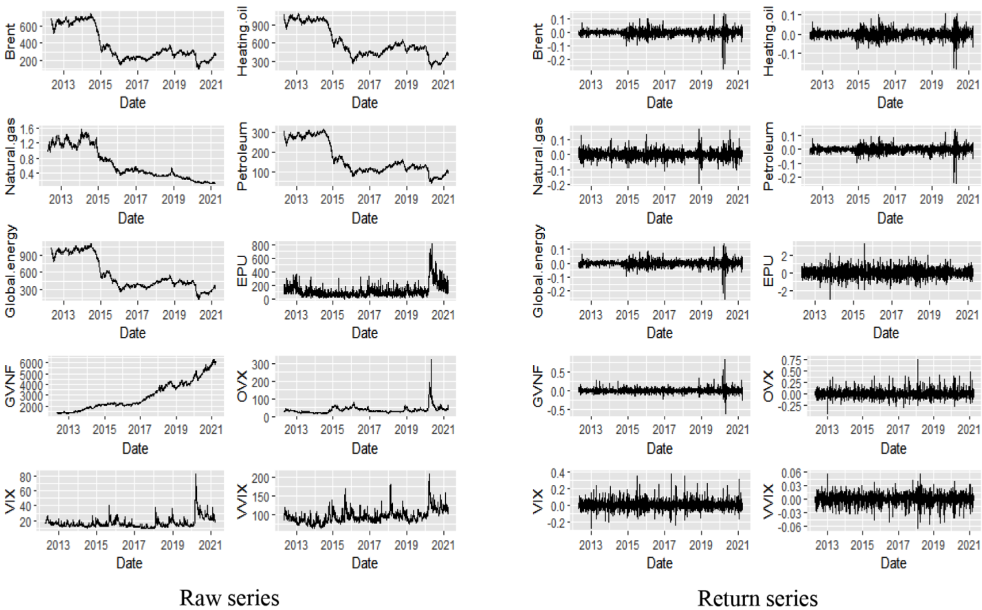


Figure 1. Time series plots

OVX and VIX but negative for VVIX. The leptokurtic behavior of all the series is evidenced by the kurtosis statistics. All series are non-normally distributed. Meanwhile, at the first difference, the Augmented Dickey-Fuller (ADF) and Phillips Perron (PP) test statistics suggest that all returns series are stationary. The QQR approach works well with non-normally distributed and stationarity time series (Adebayo et al., 2022) and, thus, justifies the choice of the econometric approach.

The correlation statistics divulge high positive connectivity between global energy and its constituents. Natural gas' correlation with global energy is the lowest relative to other constituents. The energy indices are mainly negative correlated with uncertainty indices except for Brent and VVIX, heating oil and VVIX, natural gas and VIX, petroleum and VVIX, and global energy and VVIX. All uncertainty indices are positively correlated except for the correlations with VVIX.

The trajectories in Figure 1 indicate drops in energy indices but hikes in uncertainty indices across stressed market states. These reveal corresponding clusters for the return series.

2.2. Econometric framework

2.2.1. Non-parametric causality-in-quantiles

As a preliminary analysis, we assess whether there exist any causal relations between uncertainty indices and energy markets' returns across quantiles. We follow the non-parametric approach of Jeong et al. (2012) and Balcilar et al. (2016) to ascertain the extent to which uncertainty indices cause the mean returns of energy commodities across quantiles. The method is recently expatiated by Jena et al. (2019).

The simplified hypothesis is tested as:

H_0: Uncertainty index does not Granger energy markets' returns.

This hypothesis is tested under a 95% confidence interval (i.e., at the 5% level of significance). This test is undertaken for both signal and decomposed data series to assess the predictive power of uncertainty indices on energy markets. This would help establish the predictive power of uncertainties on energy markets across the bullish, bearish, and normal market states.

2.2.2. The QQR approach

The QQR technique is a nonparametric variant of the classic quantile regression (QR) method. The QQR method experimentally justifies the conditioned quantile connection between multiple variables. Under the QQR technique, one of the QR and one of the nonparametric estimates are merged. Because quantiles may represent asymmetry of low and high market price and return dynamics, the QQR is appropriate for analysing the bearish/bullish connections between energy and uncertainty returns.

To begin with, the connections between energy indices and global uncertainties are looked at to argue for a causal relationship between global uncertainty indices and energy markets' returns. The basic equation is specified as:

$$Y_t = \beta^{\theta}\left(X_t\right) + u_t^{\theta}, \tag{1}$$

where Y_t and X_t represent the changes in the energy indices' returns and global uncertainty returns, respectively in period t; $\beta^{\theta}\left(\bullet\right)$ is the slope of the relationship between the two variables at any conditional level; the θth quantile of Y_t in Eq. (1) with a conditional distribution is represented by θ, and u_t^{θ} is the error term conditioned on θth quantile.

Following the specifications of Sim and Zhou (2015), we define the bandwidth for the quantiles as $h = \left[0.05 \text{ to } 0.95\right]$. This bandwidth is also in line with recent works such as Bossman et al. (2022b) and Umar et al. (2022a). Using QR and QQR, we capture the dynamic and nonstationary effect of changes in uncertainty indices and energy returns as well as also deduce the effect during bearish, normal, and bullish market returns. QQR reveals these qualities better than traditional QR and ordinary least squares approaches.

Furthermore, note that the QQR approach is nonparametric and to ascertain the significance of QQR estimates, it is customary to compare them to their QR equivalents to see if the QQR connections can be inferred from the QR connections. This procedure provides a means of ascertaining the robustness of the QQR coefficients (Adebayo et al., 2022; Bossman et al., 2022b).

3. Empirical results

The main results are presented in this section. Two preliminary assessments of the nonlinear character of the returns series and the quantile causality between uncertainty indices and energy markets are first presented followed by the QQR results.

3.1. Linearity test

To ascertain the nonlinear character of the variables, we use the Broock Dechert Scheinkman (BDS) test advanced by Broock et al. (1996). The Z-stats from the BDS test (see Table 2) lead to the rejection of the linearity hypothesis for all sampled variables. Impliedly, the returns series for global energy markets and uncertainty indices are nonlinear, justifying the application of the quantile-on-quantile regression technique, which is appropriate for the nonlinear data type (Adebayo et al., 2022).

Table 2. Z-statistics from BDS test of linearity

	Panel A: Global energy and constituents				
Dimension	GEnergy	Brent	HOil	NGas	Petroleum
2	11.30962***	11.70856***	10.3586***	5.289849***	11.72386***
3	13.98357***	14.29678***	13.14445***	6.622084***	14.45201***
4	16.16915***	16.53825***	15.29003***	7.957761***	16.58823***
5	17.91597***	18.18688***	16.75844***	9.41609***	18.16196***
6	19.84437***	20.26178***	18.33655***	10.73424***	20.11466***
	Panel B: Uncertainty indices				
Dimension	EPU	GVNF	OVX	VIX	VVIX
2	15.57903***	10.34153***	8.439222***	8.363304***	9.411039***
3	15.79117***	12.25872***	9.97084***	11.28604***	11.91828***
4	16.16782***	13.75539***	10.91596***	12.7213***	12.89406***
5	16.29223***	14.82964***	11.54816***	13.92506***	13.62918***
6	16.58038***	15.75735***	12.08715***	14.66864***	14.00702***

Notes: This table presents the Z-statistics from the Broock Dechert Scheinkman (BDS) test of linearity. [***] denotes the significance of Z-statistics at 1%.

3.2. Causality tests

The quantile causal relations between uncertainties and energy markets are examined in this part. This analysis is needed to establish that indeed there is a causal relationship between global uncertainty indices and energy markets across conditional distributions of energy markets' returns. Relative to the traditional Granger causality test, which only examines the average, the nonparametric causality in the quantiles technique captures all quantiles in the distribution (Bossman et al., 2022b; Jena et al., 2019; Umar et al., 2022a). Therefore, this method may demonstrate how causality works in both low and high energy returns.

The results from the quantile causality test are pictorially shown in Figure 2 and numerically backed by the test statistics in Table 3. From Figure 2, the test statistics are matched against the vertical axis with the quantiles on the horizontal axis in each plot. The 5% significance level, which corresponds to a critical value (CV) of 1.96, is depicted by the horizontal solid line. As such, the null hypothesis states that a change in global uncertainty indices does not Granger-cause a change in energy returns. E.g., the null hypothesis of no Granger-causality from EPU to Brent is rejected (CV > 1.96; p < 0.05) over the quantile range 0.20–0.70.

Table 3. T-statistics from causality-in-quantiles tests

Panel A: Global energy					
τ	EPU		OVX	VIX	VVIX
0.05	1.25680	1.07588	1.07723	1.13078	1.03053
0.10	1.57659	1.22218	1.51555	1.79070*	1.57994
0.15	1.80822*	1.60741	1.85890*	2.23615**	2.22116**
0.20	2.27686**	26107**	1.98006*	2.60306***	2.61313***
05	2.49609**	2.51234**	2.55193**	2.71347***	2.49962**
0.30	2.97401***	30285***	3.26445***	3.27570***	2.53313**
0.35	3.08829***	3.14010***	2.91337***	3.50813***	2.70314***
0.40	2.88090***	3.27682***	3.07864***	3.52796***	2.74534***
0.45	2.89697***	2.79909***	2.97489***	3.40510***	2.59641***
0.50	2.96694***	2.95497***	2.88529***	3.88572***	2.79282***
0.55	2.54484***	2.55687**	2.48836**	3.26496***	2.77137***
0.60	2.19851***	2.25448**	2.74372***	3.29772***	2.66056***
0.65	2.10229***	2.13976**	2.71446***	3.02675***	3.01260***
0.70	2.36179**	2.71609***	2.40163**	3.35174***	3.12180***
0.75	1.81744*	2.36862**	2.05514**	3.00116***	2.53024**
0.80	1.79956*	1.83417*	1.99942*	2.76792***	2.69333***
0.85	1.66182*	1.66843*	1.60823	1.78791*	2.05221**
0.90	1.49703	1.45082	1.34311	1.39171	1.30143
0.95	0.83771	0.76211	0.67489	0.85147	0.85556
Panel B: Brent					
τ	EPU	GVNF	OVX	VIX	VVIX
0.05	1.12107	1.05603	1.27797	1.10631	1.19668
0.10	1.77362*	1.26815	1.76920*	1.83313*	1.76194*
0.15	2.28904**	1.84926*	2.11155**	2.31599**	1.94523*
0.20	2.50259**	2.35166**	2.74491***	2.98219***	2.10205**
0.25	2.59622***	2.66773***	3.56402***	3.36692***	2.42891**
0.30	2.86345***	3.07776***	3.50530***	3.11659***	2.59845***
0.35	3.39973***	3.59995***	3.37647***	3.27413***	3.25436***
0.40	3.39716***	3.75073***	3.12553***	4.05371***	3.10747***
0.45	3.11483***	3.10188***	2.68132***	3.61777***	3.35800***
0.50	2.79361***	2.55530**	2.26313**	3.49732***	3.27942***
0.55	2.62130***	2.68427***	2.39018**	2.83975***	3.09858***
0.60	2.14643**	2.33140**	2.20423**	3.35506***	3.18668***
0.65	2.07488**	2.32874**	2.08299**	2.53688**	3.16987***

Continued Table 3

Panel B: Brent					
τ	EPU	GVNF	OVX	VIX	VVIX
0.70	2.10509**	2.10078**	2.49068**	2.12008**	3.14310***
0.75	1.77120*	1.94675*	2.25825**	2.36274**	2.84084***
0.80	1.61230	2.06370**	2.25177**	2.15903**	2.42264**
0.85	1.42361	1.95254*	1.75348*	2.03883**	2.61684***
0.90	1.12165	1.55273	1.12131	1.67147*	2.04475**
0.95	0.73413	0.84925	0.80338	0.83132	1.05786
Panel C: Heating oil					
τ	EPU	GVNF	OVX	VIX	VVIX
0.05	0.91657	0.69661	1.11505	0.98432	0.98021
0.10	1.29557	1.05484	1.81488*	1.55671	1.39211
0.15	1.67551*	1.23947	2.31174**	1.49850	1.50377
0.20	2.01211**	1.54438	2.48503**	1.84375*	1.65778*
0.25	2.38248**	1.79144*	2.49323**	2.10998**	2.44019**
0.30	2.57521***	2.10336**	2.92197***	2.44342**	2.44316**
0.35	2.82545***	2.24159**	2.84955***	2.52820**	2.52131**
0.40	3.01926***	2.51261**	2.43358**	2.25720**	2.26202**
0.45	2.80342***	2.62727***	2.43473**	2.48332**	2.31204**
0.50	2.55029**	2.72546***	2.54132**	2.47320**	2.25963**
0.55	2.56858***	2.30914**	2.33388**	2.45182**	2.35748**
0.60	2.09244**	2.52170**	2.31744**	2.56825***	2.14389**
0.65	1.91951*	2.56753***	2.01324**	2.43097**	2.31364**
0.70	1.74396*	2.25663**	1.92031*	2.48851**	2.64901***
0.75	1.59656	2.44534**	1.89059*	2.42749**	2.40398**
0.80	1.46495	1.98434**	1.79725*	2.25411**	2.10403**
0.85	1.47288	1.40240	1.51770	1.73639*	1.83990*
0.90	1.40042	1.07696	1.04447	1.41221	1.30942
0.95	0.94760	0.59121	0.68431	0.94135	1.13546
Panel D: Natural gas					
τ	EPU	GVNF	OVX	VIX	VVIX
0.05	0.56574	0.51396	0.50585	0.43991	0.54093
0.10	0.98683	1.03001	0.94370	0.78403	0.79835
0.15	1.20819	1.38907	1.02614	1.44558	1.78693*
0.20	1.34566	1.12215	1.42284	1.48855	1.75581*
0.25	1.70049*	1.53900	1.65045*	1.56261	2.15280*
0.30	1.84512*	1.75613*	1.98355**	1.58383	1.91970*
0.35	1.87780*	1.73633*	2.04654**	1.71269*	1.63718
0.40	1.60012	1.62430	1.77278*	1.58577	1.98368*

End of Table 3

Panel D: Natural gas					
τ	EPU	GVNF	OVX	VIX	VVIX
0.45	1.71102*	1.68792*	1.81867*	1.72645*	1.86541*
0.50	1.84099*	2.12700**	1.80747*	1.65588*	1.66724*
0.55	2.13001**	1.83864*	2.05655**	1.66985*	2.22394**
0.60	1.87551*	1.61057	1.97048**	1.80594*	2.51336**
0.65	2.03881**	1.59300	1.95581**	1.61389	2.22116**
0.70	1.81981*	1.73851*	1.86296*	1.50161	2.20129**
0.75	1.74505*	1.61953	1.42242	1.23596	1.56309
0.80	1.61785	1.45734	1.45291	1.30443	1.45503
0.85	1.30344	1.21221	1.52484	1.08206	1.34444
0.90	0.85897	0.91704	0.94555	0.86599	0.63645
0.95	0.83163	0.43144	0.47503	0.47568	0.45530
Panel E: Petroleum					
τ	EPU	GVNF	OVX	VIX	VVIX
0.05	1.31103	0.98925	1.25818	1.10827	1.04894
0.10	1.71291*	1.25096	1.37281	1.65440*	1.53931
0.15	2.00785**	1.83971*	1.72164	2.29010**	2.16631**
0.20	2.32006**	2.02884**	2.31151**	2.57701***	2.45556**
0.25	2.44502**	2.48559**	2.49059**	2.80999***	2.23821**
0.30	2.76899***	2.72047***	3.10315***	2.50308**	2.25896**
0.35	2.85796***	3.00365***	3.21632***	2.90551***	2.55818*
0.40	3.14060***	2.70132***	3.34746***	3.23271***	2.72346***
0.45	3.12043***	2.51300**	2.71257***	3.48025***	2.90833***
0.50	3.10254***	2.42868**	2.80422***	3.19759***	2.86531***
0.55	3.01921***	2.82413***	2.73551***	2.81713***	2.84157***
0.60	3.07367***	2.47132**	2.66964***	3.22720***	3.31871***
0.65	2.78888***	2.40038**	2.24015**	3.15504***	3.04786***
0.70	1.67557*	2.20096**	2.67343***	3.43237***	2.98936***
0.75	1.69049*	2.31908**	2.18133**	2.78195***	2.44910**
0.80	1.60250	2.22244**	1.82399*	2.29100**	2.44403**
0.85	1.46724	2.08358**	1.45456	2.06063**	2.39920**
0.90	1.29817	1.63791	1.21713	1.79604*	1.80301*
0.95	0.78312	0.76359	0.71490	1.04796	1.00527

Notes: τ denotes quantiles; the significance levels for the critical values of 1.645, 1.96, and 2.567 are denoted by [*], [**], and [***], respectively.

Generally, the causal effect of uncertainty indices on the returns of commodity markets has a high predictive power across the quantile range 0.20–0.80. Except for the most extreme quantiles, we find a strong predictive power of uncertainty indices on energy returns. The exceptional energy market is natural gas for which the predictive power of uncertainty indices is relatively low across quantiles. This is unsurprising since natural gas' correlation with global energy was the lowest. It seems decoupled from the broader index and, hence, the general conclusions that apply to the other constituents may be seemingly different from natural gas. Notwithstanding, the causal effect of uncertainties on energy markets is established across most of the quantiles. We probe into the asymmetric relationships under the QQR approach.

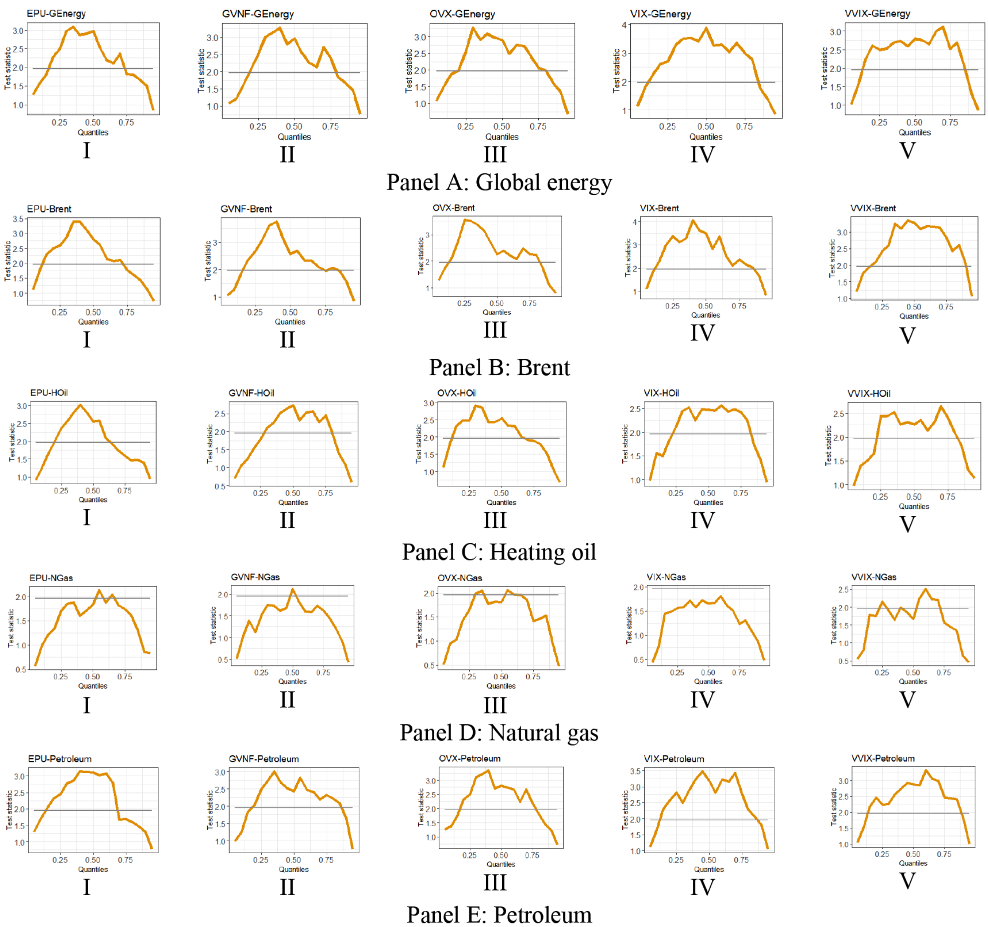


Figure 2. Causality-in-means test

Notes: This figure reveals the causality in means plots for the causal effect from world uncertainty indices and global energy markets. For each panel, plots I, II, III, IV, and V are for EPU, GVNF, OVX, VIX, and VVIX, respectively.

3.3. QQR

For a more simplified QQR analysis, we classify quantiles into market conditions. We attribute the quantile range 0.05–0.35 as the bearish market state (i.e., lower quantiles), 0.40~0.70 as the normal market state (i.e., median quantiles), and 0.75~0.95 as the bullish market state (i.e., upper quantiles). Figure 3 displays the slope coefficients $\beta_1(\theta,\tau)$, represented by the effect of the τ_{th} quantile of uncertainties on the θ_{th} quantile of energy returns. The effect of the various uncertainty indices (i.e., EPU, GVNF, OVX, VIX, and VVIX) on the global energy index (GEnergy) is shown in panel A; Brent in panel B; heating oil (HOil) in panel C, natural gas (NGas) in panel D, and petroleum in panel E.

From Panel A of Figure 3, the slope coefficients range between 0 and 15 for the effect of EPU on GEnergy. The impact of EPU on GEnergy is positive but nearly zero across all quantiles of EPU and GEnergy except across the median to upper quantiles (0.30–0.95) of EPU and lower quantiles (0.05–0.10) of GEnergy where EPU's effect is strongly positive. Similar observations hold for the effects of OVX, VIX, and VVIX on GEnergy but with varying slope coefficients. The slope coefficients range from –3 to 5 for OVX and VIX, and from –1.5 to 1.5 for VVIX. For GVNF, the slope coefficients range from –0.5 to 0.2. GVNF's impact on GEnergy is positive across all quantiles except for the lowest quantile (0.05) of GEnergy and the lower to median quantiles (0.05–0.60) of GVNF.

For Brent (i.e., Panel B of Figure 3), the slope coefficients – for EPU's effect – range from –20 to 0. The impact of EPU on Brent is positive across all quantiles of EPU and Brent except across the lower quantiles (0.05–0.85) of EPU and lower quantiles (0.05–0.10) of Brent where EPU's effect is strongly negative. Similar observations hold for the effect of VIX on Brent but with varying slope coefficients which range from –6 to 0. OVX's impact on Brent is positive across the upper quantiles (0.80–0.95) of Brent and the median to upper quantiles (0.25–0.95) of OVX. It is worth noting that the strong negative impact of EPU on Brent across the lower quantiles (0.05–0.85) of EPU and lower quantiles (0.05–0.10) of Brent is similar to the impacts of OVX, VIX, and VVIX on Brent. Across the median quantiles (0.45–0.75) of both Brent and OVX returns, OVX mildly negatively impacts Brent. For GVNF, the slope coefficients range from 0 to 0.5. GVNF's impact on Brent is almost zero across all quantiles except for the lowest quantile (0.05) of Brent and the median to upper quantiles (0.25–0.95) of GVNF.

For heating oil (i.e., Panel C of Figure 3), with scale coefficients ranging between –4 and 2, the effect of EPU is recorded as negative across median and high quantiles of heating oil and all quantiles of EPU. Across the median and upper quantiles (0.50–0.95) of heating oil and the lowest quantile (0.05) of EPU, the impact of EPU on heating oil is positive. Meanwhile, across the lower quantiles (0.05–0.15) of heating oil and the lower and upper quantiles (specifically, between 0.05–0.20 and 0.60–0.90) of EPU, the impact of EPU on heating oil is highly negative. The scale coefficient of GVNF's impact on heating oil ranges from 0.05 to 0.25. GVNF's impact on heating oil is mildly positive across the median and upper quantiles (0.40–0.95) of GVNF and all quantiles of heating oil but at lower quantiles of EPU and almost all quantiles of heating oil, the magnitude of the effect is stronger. Across the upper quantiles (0.80–0.95) of heating oil and median to upper quantiles (0.35–0.95) of OVX, OVX's impact on heating oil is almost negligible (i.e., zero). This is similar across the median quantiles (0.30–0.60) of heating oil and lower quantiles (0.05–0.10) of OVX. Whereas the OVX's effect is mildly negative across the median quantiles of both OVX and heating oil, it is strongly negative across the lower quantiles of heating oil and all quantiles of OVX. VIX has a mild positive effect on heating oil across all quantiles of heating oil and VIX except across the lower to median quantiles (0.75–0.95) of heating oil and the upper quantile (0.95) of VIX. The effects of VIX and VVIX are comparable, but VIX has magnitudes ranging between –3 and 0.5 whereas VVIX has magnitudes ranging from –1.2 and 0.

From Panel D of Figure 3, the impact of EPU on natural gas ranges from –6 to 4. EPU strongly negatively affects natural gas across the upper and lower quantiles of both EPU and natural gas returns. Conversely, across the upper (lower) quantiles of natural gas (EPU), EPU's impact is positive. Across the median quantiles (0.35–0.75) of both returns series, EPU's impact is mildly negative. With a scale coefficient ranging from –0.15 to 0.05, GVNF has a mildly positive impact on natural gas across all quantiles except at lower quantiles (0.75–0.95) of both GVNF and natural gas returns where the impact turns negative. The impact of OVX on natural gas ranges between –1 and 0.6. OVX's effect is mildly positive across the median and upper quantiles (0.45–0.95) of both natural gas and OVX but strongly positive across the lower quantiles (0.05–0.30) of natural gas and all quantiles of OVX. Meanwhile, across the median and lower quantiles (0.05–0.50) of natural gas (OVX) and median and upper quantiles (0.60–0.90) of OVX (natural gas), the impact of OVX on natural gas is strongly negative. VIX and VVIX have generally negative impacts on natural gas across all quantiles of both natural gas and either VIX or VVIX but across the lower quantiles (0.05–0.10) of natural gas and the upper quantiles (0.75–0.95) of either VIX or VVIX, the impact of either volatility index on natural gas is positive. The only difference is that the magnitude of effect for VIX is in higher magnitudes (ranging from –0.5 to 1) relative to that of VVIX which ranges between –0.1 and 0.8.

Panel E of Figure 3 shows the impact of uncertainty indices on petroleum. The impact of EPU on petroleum ranges from –4 to 2. EPU's impact is mildly positive across the median and upper quantiles of both petroleum and EPU returns. Across the lower quantiles (0.05–0.10) of EPU and upper quantiles (0.75–0.95) of petroleum, EPU exerts a positive impact on petroleum. Meanwhile, across the upper and lower quantiles (i.e., 0.60–0.95 and 0.05–0.15, respectively) of EPU and lower quantiles (0.05–0.20) of petroleum, EPU's effect is strongly negative. This effect is positive at the median (lower) quantiles of EPU (petroleum). GVNF's impact on petroleum is generally positive (ranging from 0 to 0.25) across all quantiles of either asset. However, the magnitude of the effect becomes stronger across the median quantiles of petroleum and lower quantiles of GVNF. For OVX, except for the upper quantiles of petroleum and the median and upper quantiles of OVX, which reveal nearly zero effect, the effect of OVX on petroleum is generally negative across all other quantiles of either asset. The magnitude of the negative effect reaches a maximum of –3. VIX and VVIX have a mild positive impact (ranging from –3 to 0.5 for VIX and –1.5 to 0.5 for VVIX) on petroleum. The respective impact of VIX and VVIX on petroleum is highly negative across the lower to median quantiles (0.05–0.55) of petroleum and upper quantiles (0.90–0.95) of either VIX or VVIX.

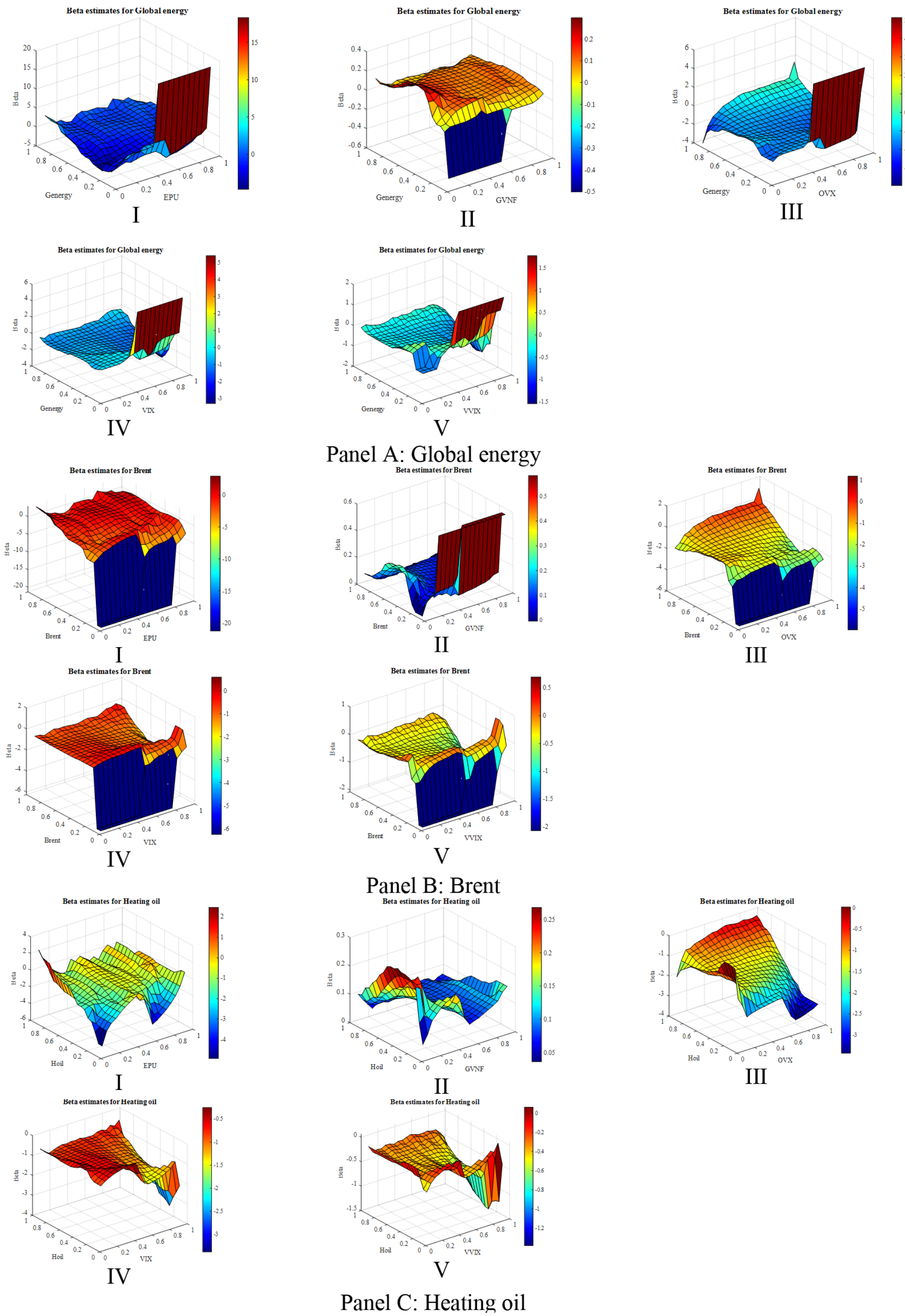
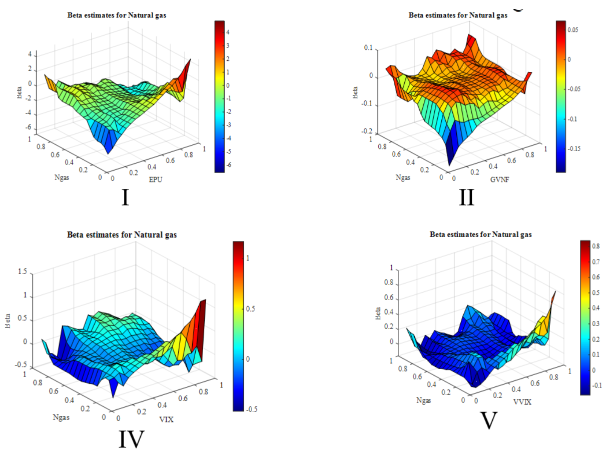
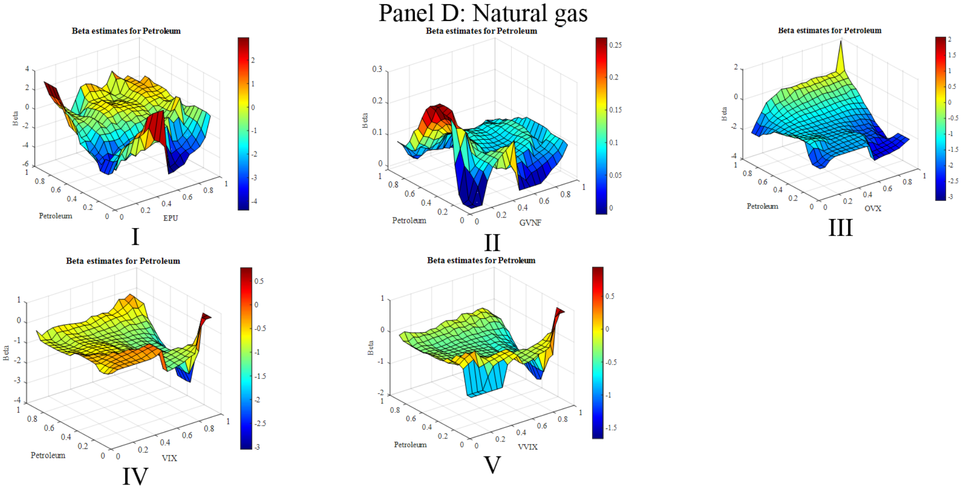


Figure 3. *To be continued*



Panel D: Natural gas



Panel E: Petroleum

Figure 3. 3D analysis of QQR estimates

Notes: This figure reveals the 3-dimensional plots of the QQR estimates between world uncertainty indices and global energy markets. For each panel, plots I, II, III, IV, and V are for EPU, GVNF, OVX, VIX, and VVIX, respectively.

Our results communicate that the effect of various uncertainty factors on energy markets' returns is heterogeneous. This is supported by existing works (Liu et al., 2018; Wang & Lee, 2022) that identified heterogeneous effects of market uncertainties and volatility measures on commodity markets either on the aggregate market level or country level. For instance, Wang and Lee (2022) reported varied impacts of Chinese policy uncertainties on local and international crude oil prices. Liu et al. (2018) also reported that news uncertainty heterogeneously affects energy and non-energy markets.

Indicatively, we report that relative to other market uncertainty and volatility indicators, the effect of EPU on commodities records the highest magnitude and particularly manifests across bearish quantiles. This finding supports the existing literature (Assaf et al., 2021) that provides evidence that EPU's effect on net commodity markets' connectedness is more intense relative to other market uncertainties and volatilities. This observation is not surprising given how interconnected and interdependent the energy markets and market uncertainties are (Qin et al., 2020; Wang & Lee, 2020), and how bearish conditions may affect their dependency.

The findings on EPU are similar to those for other market volatilities (GVNF, OVX, VIX, and VVIX), although the magnitude of the effect may be relatively lower. That is, generally, for all volatility measures, we find that at stressed conditions of either energy markets' returns or market volatility returns, a strong negative effect is found with few peculiarities for some energy markets. The varied and intense effect of uncertainties and volatilities on energy markets has intuitive support. Stressed market conditions may heighten trade, geopolitical, and equity market volatilities, causing unfavorable shifts in investor sentiment. In effect, investment decisions and the long-term dynamics of energy prices stand a high chance of being affected, although they may be unsuspected by market participants. Such unanticipated market shocks will alter investors' risk appetite and investment opportunities (Assaf et al., 2021; Bossman, 2021).

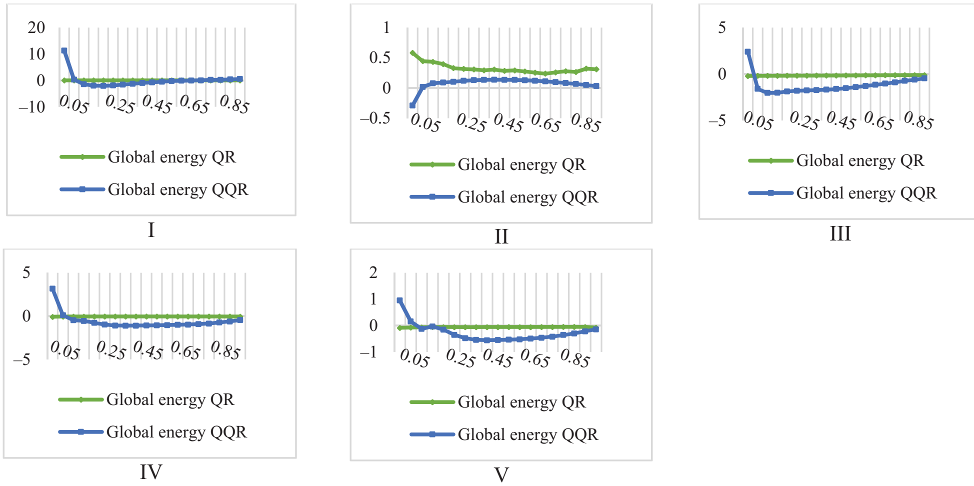
Furthermore, it is worth noting that the findings also indicate mild effects of market uncertainty and volatility on energy markets. This communicates the potential for diversification with energy commodities. Our findings lend support to those emphasized by Asafo-Adjei et al. (2022) that premised on the information flow between uncertainty and commodity markets, commodity volatilities in commodity markets' returns could be hedged against using policy uncertainty and market volatilities.

3.4. Robustness of QQR estimates

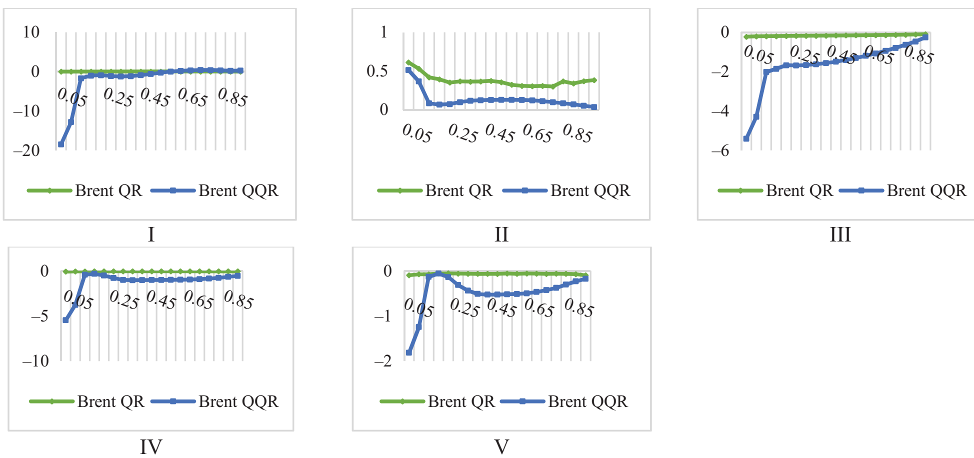
We compare QQR estimates to their QR equivalents to see if the QQR connections can be inferred from the QR connections. Because the QQR method is a nonparametric model, it is impossible to determine the significance of the coefficients obtained. Because the QQR estimations are deconstructed estimates of QR into defined quantiles of the regressors, they may be verified by comparing their coefficients to those of QR (Adebayo et al., 2022; Agyei, 2022; Bossman et al., 2022b, 2023; Umar et al., 2023). The QR and QQR coefficients line graphs in Figure 4 indicate this.

For two reasons, line graphs are useful. To begin with, they graphically represent the QR estimations by depicting the trend of rising and/or falling uncertainty indices, as well as the associated trends in energy market returns. Second, by comparing the QQR to the QR estimations, the line graphs confirm the QQR (Adebayo et al., 2022; Bossman et al., 2022b). The quantiles (QR/QQR estimates) are shown by the horizontal (vertical) axis in the plots; blue and green lines or spots correspond to QQR and QR estimates, respectively, across quantiles.

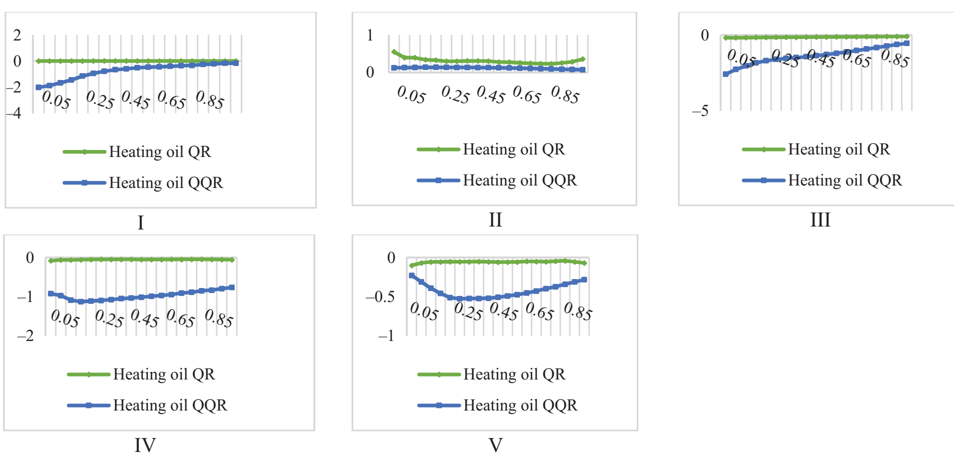
We can see from the graphs in Figure 4 that the QR and QQR estimates for all quantiles agree. The only variation is the amount of the effect at particular quantiles, which is in the same direction as the quantile estimates. Nonetheless, the QRR estimations are corroborated by the QR method.



Panel A: Global energy

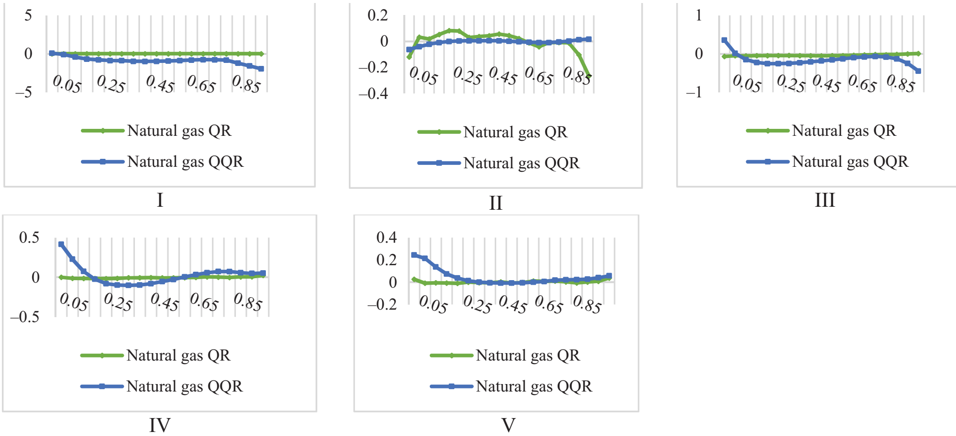


Panel B: Brent

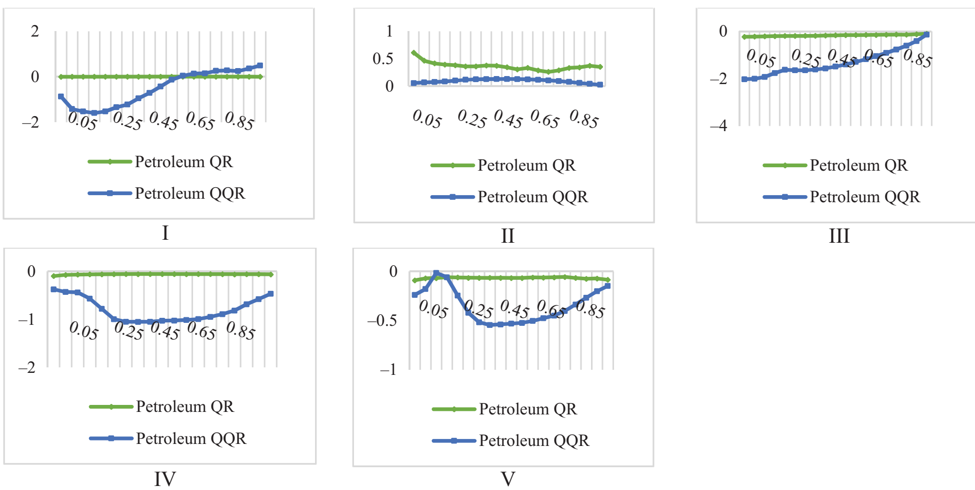


Panel C: Heating oil

Figure 4. *To be continued*



Panel D: Natural gas



Panel E: Petroleum

Figure 4. Line graphs of QR and QQR slopes

Notes: This figure reveals the line graphs of the QR and QQR estimates for the relationship between world uncertainty indices and global energy markets. For each panel, plots I, II, III, IV, and V are for EPU, GVNF, OVX, VIX, and VVIX, respectively.

Conclusions

We examined the asymmetric effects of market uncertainties and volatilities on energy markets. From 25 April 2012 to 31 March 2022, our datasets include daily indices for global energy and its constituents (i.e., global energy index, Brent, heating oil, natural gas, and petroleum), and daily uncertainty indices for the US economic policy uncertainty (EPU), CBOE Crude Oil Volatility (OVX), CBOE Volatility Index (VIX), CBOE VIX Volatility (VVIX), and DWS NASDAQ 100 Volatility Target (GVNF). We employed the quantile-on-quantile regression (QQR) technique after satisfying the requirements from preliminary analysis covering the Broock Dechert Scheinkman (BDS) linearity test and the causality-in-quantiles test.

We confirmed the nonlinear character of the datasets under the BDS test. Our causality-in-quantiles test suggested that generally, the uncertainty indices largely Granger-cause energy markets' returns across the quantile range 0.20–0.70. The QQR results revealed asymmetric effects of uncertainty and volatility indices on energy markets' returns. These results confirmed the hypothesized relationship (H_1) that the relationship between market uncertainties and energy markets is asymmetric. Notably, EPU's impacts on energy markets have the highest magnitudes across the bullish and bearish market states. The findings on EPU are qualitatively similar to those for other market volatilities (i.e., GVNF, OVX, VIX, and VVIX). Specifically, for all volatility measures, we found that at stressed conditions of either energy markets' returns or market volatility returns, a strong negative effect is generally found. This communicates some hedging benefits for market participants.

Our findings have important policy and portfolio implications in some instances. First, in terms of policy, we have discovered that economic policy, crude oil volatility, CBOE volatility, CBOE VIX Volatility, and NASDAQ 100 volatility concerns all have a significant effect on energy markets and can significantly undermine energy prices. Following this, we suggest that policymakers should pay close attention to how energy prices respond to shocks from policy uncertainty, which might manifest as a significant rise or fall in energy prices. As a result, authorities' interference – concerning decision-making – in energy markets should take into account the degrees of uncertainty in economic policy and essential market volatilities such as those relating to crude oil, NASQAQ top-100, VIX, and VVIX. To stabilize energy prices, many sorts of uncertainty and market volatilities should be applied, with policy uncertainty in the US being the most important category that determines the price and returns dynamics of energy markets.

As long as our findings clearly illustrate the significance of market uncertainty and volatilities for energy price and return dynamics, market participants should consider policy uncertainty and market volatilities when designing portfolios and managing risks as they relate to investment decisions. As financialization relates to the increasing interest of market participants' use of energy commodities in financial investments, market participants are advised to pay extra attention not only to policy uncertainty of the US but also consider market volatilities such as volatilities in crude markets and top equities markets. Investors should take advantage of the mid and negative effects of policy uncertainty and market uncertainties on energy commodities to diversify and hedge against volatilities in commodity returns during normal market conditions whilst keeping them as safe havens during stressed market conditions. However, the tendency for high positive effects in some market states should be carefully incorporated into asset allocation and portfolio management decisions.

We acknowledge the potential shortcomings of our analysis and recognize that they could be improved upon in future contributions. The nature of the empirical problem, which influenced our analysis led us to employ a bivariate technique, which to some extent might be restricted. Hence, future works could envisage this problem from a broader perspective and employ multivariate techniques to capture more uncertainty and volatilities which may have significant impacts on energy markets.

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Author contributions

Conceptualization, Ahmed Bossman (A.B.), Ştefan Cristian Gherghina (Ş.C.G.), Emmanuel Asafo-Adjei (E.A-A), Anokye Mohammed Adam (A.M.A) and Samuel Kwaku Agyei (S.K.A.); methodology, A.B., Ş.C.G., E.A-A., A.M.A and S.K.A.; software, A.B., Ş.C.G., E.A-A., A.M.A and S.K.A.; validation, A.B., Ş.C.G., E.A-A., A.M.A and S.K.A.; formal analysis, A.B., Ş.C.G., E.A-A., A.M.A and S.K.A.; investigation, A.B., Ş.C.G., E.A-A., A.M.A and S.K.A.; resources, A.B., Ş.C.G., E.A-A., A.M.A and S.K.A.; data curation, A.B., Ş.C.G., E.A-A., A.M.A and S.K.A.; writing–original draft preparation, A.B., Ş.C.G., E.A-A., A.M.A and S.K.A.; writing–review and editing, A.B., Ş.C.G., E.A-A., A.M.A and S.K.A.; visualization, A.B., Ş.C.G., E.A-A., A.M.A and S.K.A.; supervision, A.B., Ş.C.G., E.A-A., A.M.A and S.K.A.; project administration, A.B., Ş.C.G., E.A-A., A.M.A and S.K.A.; funding acquisition, A.B., Ş.C.G., E.A-A., A.M.A and S.K.A. All authors have read and agreed to the published version of the manuscript.

Disclosure statement

The authors declare that they have no competing interests.

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