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Economic activities, dry bulk freight, and economic policy uncertainties as drivers of oil prices: A tail-behaviour time-varying causality perspective

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ABSTRACT

This paper examines the dynamic impact of economic activity, Baltic dry bulk and economic policy uncertainty on oil prices. Drawing on demand-side economic theory, we focus on how economic activity and economic policy uncertainty drive oil prices and subsequently contribute to the formation of market equilibrium. In this context, we first introduce a unidirectional quantile and time-varying Granger-causality mechanism for the drivers of oil prices. Our novel rolling window quantile Granger causality approach reveals that economic activity drives crude oil price fluctuations and highlights their important role in market imbalances. In particular, economic activity and the Baltic exchange rate index emerge as essential drivers of oil prices, confirming our hypothesis of a demand-side effect. Moreover, our robustness wavelet quantile correlation (WQC) analyses reveal that economic activity promotes oil price fluctuations along both long-term equilibrium trends and short-term dynamics. In contrast, economic policy uncertainty has a dampening effect on oil prices. More broadly, economic activity is positively correlated with the Baltic exchange dry index, highlighting its broader impact on global trade indicators. Moreover, we use a bivariate Quantile on Quantile regression method to identify the equilibrium searches of different thresholds and estimate the robustness of the validity of the WQC findings. Analyzing the quantile and frequency connectedness spillovers, we observe that shocks from economic activity are particularly pronounced in the tail quantiles, reinforcing the demand-side narrative. Overall, the increased risk in extreme tails underscores the increased interaction between economic activity, oil prices and economic policy uncertainties. Our findings have important implications for policymakers and highlight the need for adaptive strategies to manage potential oil price shocks. Thus, by adopting a demand-side perspective, policymakers can better anticipate and respond to oil price fluctuations, promoting more resilient economic policies.

1. Introduction

The recurrent surprises in market expectations regarding economic activities contribute to the hump-shaped response in oil prices. In conjunction with the Great Depression in 1929 Keynesian demand-driven economic models' became important. This context underscore the critical importance of comprehending the interaction between economic activities and energy markets, as well as predicting the dynamics of oil prices (Kilian, 2009; Ji, 2012; Güntner, 2014; D'Ecclesia et al., 2014; Juvenal and Petrella, 2015; Baumeister and Kilian, 2016a; Baumeister and Kilian, 2016b; Baumeister and Kilian, 2016c). Recent structural models of the global crude oil market posit that the surge in oil prices from 2003 to 2008 was primarily fuelled by consistent positive shocks in demand for industrial commodities (Coleman, 2012; Figuerola-Ferretti et al., 2020). Furthermore, Kilian (2009) highlights that real oil price shocks can originate from various factors, including shocks in oil supply, global demand shocks for all industrial commodities, or demand shocks specific to the crude oil market. The evidence suggesting that global demand shocks predominantly drove recent oil price increases helps to elucidate why this shock did not lead to a major recession in the United States.

On another note, oil is one of the main drivers of economic growth. It

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is the primary energy for driving production, consumption, and distribution in the economy. Oil price shock is a robust factor affecting economic growth volatility (Maheu et al., 2020). Baumeister and Kilian (2016a) state that oil price shock affects economic decisions. The oil price shock can enter the economy through production channels (Yang et al., 2023). A positive oil price shock increases production costs, impacts firms' production capacity, and shifts the supply curve. Likewise, the negative oil price shock influences the economy via factors triggering uncertainty. For example, the surge in prices of various fossil fuels, such as crude oil, across countries during the financial crisis of 2007–2009, followed by a gradual but uncertain recovery, has become a global concern and focal point (Bloom, 2009). Considering the ability of oil prices to affect an economy through various channels, it is essential to understand how oil prices affect a country's economy through multiple moderators such as economic policy uncertainty (EPU), dry bulk freight, and other economic activities such as consumption or investment. The EPU is postulated by Baker et al. (2016) as comprised the volume of news articles related to economic uncertainty, current and future tax codes, and the forecasts on expected inflation and federal, state, and local expenditures. On the other hand, dry bulk freight is defined as a measure of the average cost to ship dry bulk across twenty ocean routes (Jacks and Stuermer, 2021). The movement of BADI is important as it reflects the changes of commodity prices (Melas and Michail, 2021). Finally, economic activities are widely defined by various economic indicators, such as GDP, inflation, consumption, and investment.

Indeed, since 1960, crude oil prices have been increasing. The Word Bank (2024) shows that the average crude oil prices of BRENT, Dubai, and West Texas Intermediate (WTI) is $80.76 per barrel in 2023, almost four times greater than in 2000 at $28.23 per barrel. The rising oil prices influence the future state of the global economy (Kang and Ratti, 2013; Antonakakis et al., 2014; Su et al., 2018; Hailemariam et al., 2019). Economists believe that oil price dynamics have a predictive power of the future state of the economy (Rehman, 2018; Adeosun et al., 2022). Baumeister and Kilian (2016a) demonstrated that the transmission mechanism of oil price shocks on the economy is linked to economic indicators such as inflation, employment, wages, and output that analyze oil price impact on the economy. However, a couple of studies understand that oil prices have a significant impact on economic activities significantly. For example, some studies demonstrated a positive association between crude oil prices and economic uncertainty (Kang et al., 2017; Maitra, 2023). Nyangarika and Tang (2018) found that higher oil prices correspond to local currency appreciation.

Contradictory, Tunc et al. (2022), Bahmani-Oskooee et al. (2018) demonstrate that oil prices have a negative impact on economic indicators.Baumeister and Kilian (2012, 2014) and Ahmad et al. (2022) found a negative association between oil prices and GDP growth. Indeed, Ilyas et al. (2021) show a negative relationship between oil prices and corporate investment level. According to Taghizadeh-Hesary and Yoshino (2015), the relationship between oil prices and economic indicators is even more substantial during the financial crisis. Further, Rehman (2018) and Kang et al. (2017), contrarily, show that oil price has no significant impact on economic policy uncertainty. Based on the latest novel literature, we identify research gaps as follows. First, we study a set of comprehensive economic indicators by linking oil prices and EPU. Exploring the relationship between new economic indicators with oil prices, and EPU will give a new policy insight for developing and developed economies after the Russian-Ukraine war. Second, there is no consensus regarding this relationship. Thus, further studies confirming the new findings will enrich the literature in the area.

Building on this motivation, our study investigates the demand-side drivers of oil prices considering economic policy uncertainties in this context. Precisely, we investigate the nexus of oil prices, economic activities, dry bulk freight, and economic policy uncertainty. Oil price is approximated using two measures: global spot prices of Brent (BRENT) and WTI crude oil (WTI). Furthermore, economic activity is measured by weekly economic activity (WEI), dry bulk freight is proxied using the Baltic Dry Index (BADI), and economic policy uncertainty is proxied using the economic policy uncertainty (EPU). The BADI serves as a metric for dry bulk freight expenses and also holds significance as a primary economic gauge for oil prices (Ruan et al., 2016), the commodity market (Gu et al., 2019; Melas and Michail, 2021) and trade (Lin and Sim, 2013). Moreover, the BADI offers a comprehensive reflection of fluctuations in shipping transportation (Bijwaard and Knapp, 2009).

To our understanding, no study involves the one-way interaction from economic activities, dry bulk freight, and economic policy uncertainty to oil prices in extreme tail risks. Instead, past studies present the partial interaction among the variables. For example, some studies investigate the interaction between oil price and economic policy uncertainty, such as Apostolakis et al. (2021), Lin and Bai (2021), Bahmani-Oskooee et al. (2018), Tunc et al. (2022), and Maitra (2023), among others. On the other hand, there are also other studies focusing on understanding the relationship between oil price and dry bulk freight, such as Pouliasis and Bentsos (2024), Sun et al. (2014), Sun et al. (2018) and Choi and Yoon (2020), among others. Furthermore, other studies also investigate the interaction between oil prices and some economic activities or indicator such as GDP or consumption. For example, Adeosun et al. (2022), Kilian and Vigfusson (2013) and Taghizadeh-Hesary and Yoshino (2015), investigate the relationship between oil prices and GDP; Herrera et al. (2019) investigating the relationship between oil prices and consumption or investment; and Ahmad et al. (2022) investigating the relationship between oil prices and macroeconomic variables. Nevertheless, despite separate studies, the studies indicate that economic policy uncertainty, dry bulk freight, and economic activities determine oil prices. Thus, this study aims to bridge this literature gap by incorporating these variables into a single analysis framework.

The novel contribution of this research lies in three main aspects. Firstly, it scrutinizes the intricate connections among crude oil prices, EPU, and various economic indicators, aiming to elucidate the mechanisms through which economic activity and EPU impact oil prices considering tail risks. Secondly, it extends the scope by including additional economic indicators such as spot oil prices (WTI/Brent), EPU, BADI, and WEI, drawing from a weekly dataset comprising 842 observations spanning from January 11, 2008, to May 11, 2024, to capture significant events in the post-2007-2009 financial crisis era, such as the collapse of Lehman Brothers, the European debt crisis and the near-collapse of the euro, the implementation of new monetary policy tools by the Federal Reserve including government bond and private security purchases, Brexit, the COVID-19 market crash, and the resurgence of inflation alongside a bear market. Lastly, our study employ advanced methodologies, including Rolling Window Quantile Granger Causality (RWQGC) test (Xiang et al., 2021), Wavelet Quantile Correlation (WQC) (Kumar and Padakandla, 2022), Quantile on Quantile Regression (QQR) (Sim and Zhou, 2015) and a combination of quantile-frequency dynamic connectedness spillover estimation (Ando et al., 2018; Baruník and Křehlík, 2018) to ensure the reliability and robustness of the findings.

We hypothesize the positive association between the economic activity index (WEI) and oil prices. This is primarily based on the understanding that the rise of economic activities should consume energy, which increases the demand of oil prices and hike its prices (Kilian, 2008). Secondly, we select the BADI as a proxy for economic activity, particularly in relation to global trade activity (Lin and Sim, 2013). Besides, rising economic activity and global aggregate demand boosts both commodity prices and BADI rates while declining global aggregate demand causes a decrease in both (Kilian, 2009). Furthermore, with regard to the relationship between oil prices and the economic policy uncertainty index, we predict that their correlation is negative (Antonakakis et al., 2014). While a supply-driven oil price shock tends to increase economic policy uncertainty, heightened economic policy uncertainty can suppress aggregate demand, resulting in a decrease in oil prices (Kang and Ratti, 2013). Finally, the relationship between economic activity and economic policy uncertainty is predicted to be negative. This implies that elevated levels of economic policy uncertainty can significantly disrupt economic activities, potentially leading to adverse outcomes across various sectors of the economy (Bloom et al., 2018).

This study is structured as follows. The first section is introduction. The second section is a systematic literature review and detailed examination of past literature. The third section includes methodology. The final section presents the findings, followed by a discussion and conclusion.

2. Review of related studies

2.1. Oil price dynamics

Oil price is a crucial dynamic component in the economy that fluctuates across sectors of the economy. Herrera et al. (2019) summarized the association between oil price shocks and economic activity in the US economy and found that oil prices and economic activities are linearly related. Kilian (2009) intensively investigated factors behind oil price dynamics during the 1975-2007 period. To be precise, the study has conducted to understand the factors behind the fluctuations in oil prices throughout 1975–2007 (Kilian, 2009), the period of 2003–2008 (Kilian and Hicks, 2013), and June – December 2014 (Baumeister and Kilian, 2016b). These studies show that oil price dynamics are affected by structural shocks of demand or supply. Hence, understanding oil price shocks affected via demand or supply shocks is crucial to formulating an efficacious policy response. During 2003–2008, oil prices experienced a surging growth due to the Asian economic growth (Kilian and Hicks, 2013). Amid the negative effects of the global financial crisis of 2007–09, the rise of oil demand and industrial commodities has increased. Furthermore, from June to December 2014, Baumeister and Kilian (2014) show that global economic slowdown triggers the decline of oil prices. Global economic shocks such as Chinese economic weakening or the Greek debt crisis contribute to rising global oil prices. Baumeister and Kilian (2016a) demonstrated that the transmission mechanism of oil price shocks to the economy is linked to economic indicators like inflation, employment, wages, and output. However, it is not specifically shown that the relationship follows the linear pattern, as shown by Herrera et al. (2019).

2.2. Oil prices and economic policy uncertainty

A couple of literature emphasizes the relationship between oil prices and economic policy uncertainty. Economic policy uncertainty is relevant because the economic decisions of agents are affected by government policy intervention, and oil prices play a vital role in policy formulation. Apostolakis et al. (2021) revealed that oil prices create uncertainty and increase financial stress in G7 economies. Confirming further, Apostolakis et al. (2021) and Lin and Bai (2021) demonstrate that the relationship between oil prices and economic policy uncertainty is bidirectional. On the contrary, Bahmani-Oskooee et al. (2018) found that economic policy uncertainty hurts oil prices, which implies that lower uncertainty corresponds to higher oil prices, which is somehow against Apostolakis et al. (2021) and Bahmani-Oskooee et al. (2018). Maitra (2023) supports Bahmani-Oskooee et al. (2018) by pointing out that economic policy uncertainty and oil prices are negatively associated with the United States. However, Tunc et al. (2022) argued that oil prices and economic policy uncertainty mainly occur only in the short run. Antonakakis et al. (2014) find that economic policy uncertainty negatively impacts on oil prices shocks between 1997 and 2009. Yang (2019) further conclude that economic policy uncertainty influences oil prices shocks across scale of times.

Moreover, a couple of studies show that financial crisis impacts the magnitude of the relationship between policy uncertainty and oil prices. Lyu et al. (2021) examined the relationship between economic policy uncertainty and oil prices during the financial crisis. They found that the impact of economic policy uncertainty on oil shocks is greater during the global financial crisis and debt crisis. Lin and Bai (2021) supported by Lyu et al. (2021) demonstrate that two financial crises, positive shocks in oil prices reduces policy uncertainty, while negative shocks worsen policy uncertainty.

Lin and Bai (2021), supported by Lyu et al. (2021), demonstrate that in two financial crises, positive shocks in oil prices reduce policy uncertainty, while adverse shocks worsen policy uncertainty. Tunc et al. (2022) also demonstrated that the association between economic policy uncertainty and oil prices in Germany becomes positive during oil-related shock such as the Iraq invasion, which echoes the findings from Lyu et al. (2021) and Lin and Bai (2021), emphasizing the role of shock in oil price dynamics. However, Rehman (2018) argued that the economic policy uncertainty and oil prices is only confirmed under oil demand shocks. On the contrary, Kang et al. (2017) investigated oil production shocks on economic policy uncertainty in the US economy. They found that the impact of oil price shocks on economic policy uncertainty is only significant in US oil production shocks, which means from the supply side, which contradicts Rehman (2018) but also at the same time validates that the impact of oil price shocks on economic policy uncertainty can occur either from demand or supply side.

2.3. Oil prices and baltic dry freight

Baltic Dry Index (BADI) is a daily index that measures the average cost to ship dry bulk across twenty ocean routes. The movement of BDI is important as it reflects the changes of commodity prices. The BDI index is a composite of three types of bulk freight ships: Capesize, Panamex, and Supramax/Handymax. Capesize shipping carries 120,000–400,000 deadweight tons of cargo, particularly iron ore and coal. Panamex shipping carries 60,000–120,000 deadweight tons of cargo to traverse the Panama Canal. Finally, Supramax or Handymax is shipping that carries 40,000–60,000 deadweight tons of cargo. There are also some variants of the dry Baltic index. Choi and Yoon (2020) use three measures of Baltic freight: the Baltic Dry Index (BDI), the Baltic Dirty Tanker Index (BDTI), and the Baltic Clean Tanker Index (BCTI).

Some studies show that dry bulk freight is also significantly associated with oil prices. For example, Pouliasis and Bentsos, 2024 investigate the relationship between the Baltic Dirty Tanker Index and oil market uncertainty. The study demonstrates that oil prices and dirty-tankers are negatively associated, implying that the dirty-tanker weight declines when oil prices increase. Similarly, Sun et al. (2014), in support of Pouliasis and Bentsos, 2024, also investigate the dynamic relationship between tanker freight rates and oil prices. The investigation utilizes a sample from August 1998 to September 2011. Oil prices in the study are approximated using WTI and the Baltic Dirty Tanker Index (BDTI), which is similar to those in our study. The study demonstrates that tanker freight rates and oil prices are significantly correlated in the medium and long term but insignificant in the short term. Choi and Yoon (2020) explain that extreme events such as financial crisis or economic boom also affect the relationship between oil prices and dry Baltic freight. The study uses three measures of Baltic freight: the Baltic Dry Index (BADI), the Baltic Dirty Tanker Index (BDTI), and the Baltic Clean Tanker Index (BCTI). Choi and Yoon (2020) explain three channels through which oil price is associated with dry bulk freight. The first channel is related to shipping companies' transportation costs. The second channel is related to crude oil demand due to global economic fluctuation, and the third channel is related to crude oil transport services due to oil supply shocks. Sun et al. (2018) also demonstrate that the cross-market dynamic relationship between the crude oil cost and dry bulk freight rates is a hedging strategy for investors to adjust their portfolio.

2.4. Oil prices and economic activities

To our understanding, no study involves the nexus of oil prices, dry bulk freight, economic policy uncertainty, and economic indicators simultaneously in a single model or a single paper. Therefore, most studies in this area only examine the partial nexus of the variables. For example, some studies investigate the relationship between oil prices and economic indicators. Adeosun et al. (2022) demonstrated that predictive power between oil prices and GDP return varies across countries and forms a bidirectional linkage. Specifically, Adeosun et al. (2022) investigated the relationship between oil prices and GDP in the case of the US, the UK, Germany, Japan, China, Canada, and Australia. They found a significant and bidirectional relationship between GDP return and oil prices across countries. Supporting Rehman (2018) argued that income level status influences a country's sensitivity to oil price shocks, which explains why the strength of the relationship between oil prices and GDP may differ across different countries. Moreover, Rehman (2018) argued that income status influences a country's sensitivity to oil price shocks. Specifically, lower-income countries tend to be more sensitive to oil price shocks. Specifically, lower-income countries tend to be more sensitive to oil price shocks.

Besides affecting GDP, Herrera et al. (2019) demonstrated that consumption and investment are the main channels through which oil prices affect economic growth. This contributes additional information to the literature that oil prices affect other macroeconomic variables besides GDP. Not only on consumption and investment, Nyangarika and Tang (2018) also demonstrate that oil price also affects the economy through the exchange rate. Specifically, the study investigated Russia and concluded that oil prices positively impact the country's real effective exchange rate. Ilyas et al. (2021) confirm this finding in 18 countries. On the other hand, Baker et al. (2016) demonstrated that economic policy uncertainty negatively affects corporate investment. In more general view, Kang et al. (2016) demonstrate that oil price volatility is strongly associated with macroeconomic fluctuations, which support previous studies explaining a significant association between oil prices and macroeconomic variables such as Herrera et al. (2019), Baker et al. (2016), and Nyangarika and Tang (2018), among others. Furthermore, Ahmad et al. (2022) also supported Herrera et al. (2019) and Nyangarika and Tang (2018) by investigating the relationship between critical macroeconomic variables and crude oil prices in the case of the South Asian market. They concluded that world crude oil prices are negative and statistically significant in affecting GDP in South Asian countries.

Some studies show that the relationship between oil prices and economic growth is also conditional on the country's oil reserve level. For example, Taghizadeh-Hesary and Yoshino (2015) investigated the impact of oil prices on GDP and consumer price index in the US, China, and Japan before the global financial crisis (2000–2008) and after the global financial crisis (2008–2013). They found that the impact of oil prices on GDP growth is more substantial in China compared to the US and Japan. This finding most likely occurs because the US and Japan are more developed oil importers than China, so their higher oil reserves can diminish the impact of oil price dynamics on macroeconomic performance. This finding confirms that higher oil reserves in the country can dampen the negative impact of oil price shocks on the local economy. However, another study argues that the relationship between oil prices and GDP is unstable and can only be detected in short period. Gadea et al. (2016) confirmed this finding. They investigated the relationship between oil prices and economic growth in the case of the United States. They indicated that the relationship between the two is either unstable or extremely small, which weakens the statistically significant finding as shown by Adeosun et al. (2022).

3. Methods and data

3.1. Xiang et al. (2021) Time varying quantile granger-causality

First, we apply the Quantile Granger causality analysis with a rolling window approach, obtaining a total of 842 subsamples at 48-weeks intervals. This rolling window procedure proves to be advantageous in capturing instability and structural changes observed in different subsamples. The Granger causality test in quantiles proposed by Chuang et al. (2009) is extended by Xiang et al. (2021) by applying a rolling window procedure. The rolling window procedure provides an opportunity to observe time-varying properties of the relationship between time series. Hence, estimating statistics in different quantiles allows investigating causality in various situations of economic fluctuations. Consequently, this rolling window extension may offer some opportunities to enhance our ability to capture the subtle dynamics of the relationship over time and in different economic conditions.

The test evaluates whether the X_t variable Granger causes the Y_t variable, incorporating the specific condition outlined in Eq. (1) ($Q_{Yt}(\tau|Y,X)_{t-1}) = Q_{Yt}(\tau|Y_{t-1}), \tau \in [a,b]$). Here, $Q_{Yt}(\tau|Y,X)_{t-1})$ represents the τ th quantile of the conditional distribution of the Y_t variable. If the model specified for the τ th conditional quantile function, as explained in Eq. (2) ($Q_{Yt}(\tau|Y,X)_{t-1}) = \alpha(\tau) + Y'_{t-1}\psi(\tau) + X'_{t-1}\vartheta(\tau)$), is accurate, testing Eq. (1) amounts to testing the null hypothesis $H_0 : \vartheta(\tau) = 0$, where $\tau \in [a,b]$. To assess the statistical significance of this hypothesis for a specific $\tau \in [a,b]$, the corresponding Wald statistic is calculated as follows (Eq. 2): $W_T(\tau) = T\hat{\vartheta}_t(\tau)'\hat{\mu}(\tau)^{-1}\hat{\vartheta}_t(\tau)/\tau(1-\tau)$. Here, $\hat{\mu}(\tau)$represents the estimated coefficients, and is the variance–covariance matrix of $\vartheta(\tau)$. Following the methodology introduced by Chuang et al. (2009), the sup-Wald statistic is defined as: $supW_T = \sup_{\tau \in [a,b]} W_T(\tau)$ of null hypothesis. Based on these disaggregated time series, sup Wald statistics are estimated for each sub-sample to capture time-varying causality. Thus, this approach allows us to understand the time-varying causal relationship between variables.

3.2. Kumar & Padkandla (2022)'s wavelet quantile correlation

Next, we employ the recently developed Wavelet Quantile Correlation (Kumar & Padakandla, 2022) for testing the spillover between energy and other market segments. Li et al. (2015) defines the Quantile Correlation (QC) between two variables X and Y in the following way. Let $Q_{\tau,X}$ be the τ^{th} quantile of X and $Q_{\tau,Y}(X)$ be the τ^{th} quantile of Y conditional upon X. Now, $Q_{\tau,Y}(X)$ is independent of X if and only if the random variables $I(Y - Q_{\tau,Y}) > 0$ and X is independent. Here I(.) is the indicator function. For $0 < \tau < 1$, the quantile covariance is defined as:

$$qcov_t(Y,X) = cov\{I(Y - Q_{\tau,Y} > 0), x\} = E(\phi_\tau(Y - Q_{\tau,Y})(X - E(X))$$

Here $\phi_\tau(w) = \tau - I(w < 0)$. We calculate the quantile correlation as:

$$qcor_t(XY) = \frac{qcov_t(YX)}{\sqrt{(var(\phi_\tau(Y - Q_{\tau,Y})var(X)}} \tag{1}$$

we hypothesize that investors exhibit diverse preferences across different timeframes when selecting hedge, haven, or diversifier assets. This can be elucidated by analyzing the dependence structure across various timescales. Our approach involves decomposing asset pairs, denoted as X_t and and Y_t using a maximal overlapping discrete wavelet transform (MODWT).

Consider a signal X_i of length T where $T = 2^j$ for some integer J . Let $h_1[i]$ and $g_1[i]$ be the low-pass filter and the high-pass filter, defined by an orthogonal wavelet. At the first level, $X[i]$ is convolved with $h_1[i]$ to obtain the approximation coefficients $a_1[i]$ and with $g_1[i]$ to obtain the detail coefficients $d_1[i]$. Here, $a_1[i]$ and $d_1[i]$ are of length N. Next, $a_1[i]$ is filtered using the same scheme, but with modified filters $h_2[i]$ and $g_2[i]$, obtained by dyadic up-sampling $h_1[i]$ and $g_1[i]$. This process is continued recursively. For J = 1, 2....J_0–1, where $J_0 \leq J$, we can calculate the approximate and detailed coefficients as:

$$a_{j+1}[i] = h_{j+1}[i]^* a_j[i] = \Sigma_k h_{j+1}[i-k]a_j[i] \tag{2}$$

Table 1
Summary Statistics.

	BADI	WEI	EPU	WTI	BRENT
Mean	−0.002	0.018***	0.000	0.000	0.000
	(0.687)	(0.000)	(0.971)	(0.952)	(0.929)
Variance	0.012	0.001	0.077	0.009	0.002
Skewness	0.118	−0.645***	0.302***	−2.842***	−0.864***
	(0.161)	(0.000)	(0.000)	(0.000)	(0.000)
Ex.Kurtosis	1.879***	4.258***	0.754***	229.552***	11.877***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
JB	125.839***	694.606***	32.704***	1,849,825.071***	5053.427***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	−6.882	−3.784	−16.310	−8.755	−5.262
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q(20)$	182.671***	6284.409***	117.448***	45.172***	91.369***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q^2(20)$	90.805***	4424.883***	35.362***	220.315***	645.552***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kendall's ρ	BADI	WEI	EPU	WTI	BRENT
BADI	1.000***	−0.017	0.001	0.016	0.025
WEI	−0.017	1.000***	0.005	−0.017	0.002
EPU	0.001	0.005	1.000***	−0.045**	−0.056**
WTI	0.016	−0.017	−0.045**	1.000***	0.725***
BRENT	0.025	0.002	−0.056**	0.725***	1.000***

This table provides a comprehensive overview of descriptive statistics for the natural logarithmic returns associated with these variables. Significance levels denoted by ***, **, and * indicate statistical significance at 1 %, 5 %, and 10 %, respectively. Skewness is assessed using the D'Agostino (1970) test, while Kurtosis is examined through the Anscombe and Glynn (1983) test. Normality is rigorously tested employing the Jarque and Bera (1980) method, and the unit-root property is evaluated using the Elliott et al. (1992) test. Additionally, autocorrelation and overall goodness-of-fit in the natural logarithmic returns are scrutinized via the Fisher and Gallagher (2012) weighted Portmanteau test statistics, specifically with lags denoted as $Q(20)$ and $Q^2(20)$.

$$d_{j+1}[i] = g_{j+1}[i]*a_j[i] = \Sigma_k g_{j+1}[n-k]a_j[j] \tag{3}$$

where $h_{j+1}[i] = U(h_j[i])$ and $g_{j+1}[i] = U\left(g_j[i]\right)$.

Here, U is the up-sampling operator. After applying a J level decomposition to X_t and Y_t and obtaining the detail coefficients, we apply QC to the pair of wavelet details $d_j[X]$ and $d_j[Y]$for all J and WQC for each level J is thus obtained. The WQC for two time series X and Y at a given decomposition level J and quantile τ can be then defined as:

$$WQC_\tau(d_j[X], d_j[Y]) = \frac{qcov_\tau(d_j[Y], d_j[X])}{\sqrt{var\left(\phi_\tau\left(d_j[Y] - Q_{\tau,d_j[Y]}\right)\right)var(d_j[X])}} \tag{4}$$

3.3. Data

In this section, we describe weekly dynamics and conceptual frameworks covering the period from January 11, 2008 to May 11, 2024, focusing on key economic metrics. These metrics include the oscillations of essential economic indicators, notably the spot prices of oil (WTI/BRENT), Economic Policy Uncertainty (EPU), the Baltic Dry Index (BADI), and the weekly fluctuations in US economic activity (WEI). The global spot prices of Brent and WTI crude oil, denominated in US dollars, are sourced from the US Energy Information Administration (EIA).[1] Brent and WTI prices serve as pivotal metrics in assessing global energy market dynamics. Economic Policy Uncertainty (EPU) is quantified through the utilization of the daily US EPU quadratic average and its weekly serialized counterpart, renowned as pivotal proxies for gauging economic uncertainty. These metrics are derived from the Baker et al. (2016) News-based EPU database.[2] Originating from the frequency of news articles across various media outlets, Baker et al. (2016) meticulously constructed EPU indices offering nuanced insights into policy-related uncertainties. Moreover, we incorporate developed by Lewis et al. (2024) the US WEI, obtained from the Federal Reserve of Dallas Economic repository.[3] This index offers a comprehensive overview of global economic activity trends, facilitating a deeper understanding of macroeconomic dynamics. The BADI[4] constitutes a pivotal gauge of international trade dynamics by tracking the pricing of dry bulk cargo transportation. Commodities such as cement, coal, iron ore, and grain, pivotal for production processes, are transported via bulk freighters, rendering the BADI a prominent indicator of global economic activity, trade, global aggregate demand, and production trends. Administered by the London-based Baltic Exchange, the BADI serves as a reliable barometer for assessing shifts in global economic conditions. Variables dates are matched according to the BADI.

The returns series of each of these indices are computed using the natural logarithmic difference as part of our analysis. Table 1 depicts results from statistical tests assessing normality, autocorrelation, and stationary property of BADI, WEI, EPU, WTI, and BRENT indices. Statistically significant Jarque and Bera (1980) test statistics indicate that data departure from normality across all series, while the Elliott et al. (1992) unit root test results provide evidence that all log-return series are stationary. Lagrange multiplier tests reveal significant autocorrelation up to lag Q(20) in all indices. We report that while EPU and BADI exhibited a relatively high variance, WEI demonstrates an exceptionally low variance of (0.001), suggesting stability or constrained dispersion with time. Moreover, WTI, and BRENT moderate to low variances, which are reflective of varying volatility inherent with respective time. BADI exhibites skewness close to zero (0.118), implying a distribution tending towards symmetry. WEI displays a notable negative skewness of (−0.645), suggesting a left-tail or a higher frequency of lower values. EPU, WTI, and BRENT demonstrate significant skewness, with WTI manifesting the most pronounced negative skewness at (−2.842), indicative of a prominent leftward skew within its distributional profile. Also, the last five rows in Table 1 we report non-parametric Kendall rank correlation coefficients among the series. In Fig. 1, the trajectory of WTI, BRENT, EPU, BADI, and WEI over time.

[1] https://www.eia.gov/dnav/pet/pet_pri_spt_s1_w.htm.
[2] www.policyuncertainty.com.
[3] https://www.dallasfed.org/research/wei.
[4] https://www.investing.com.

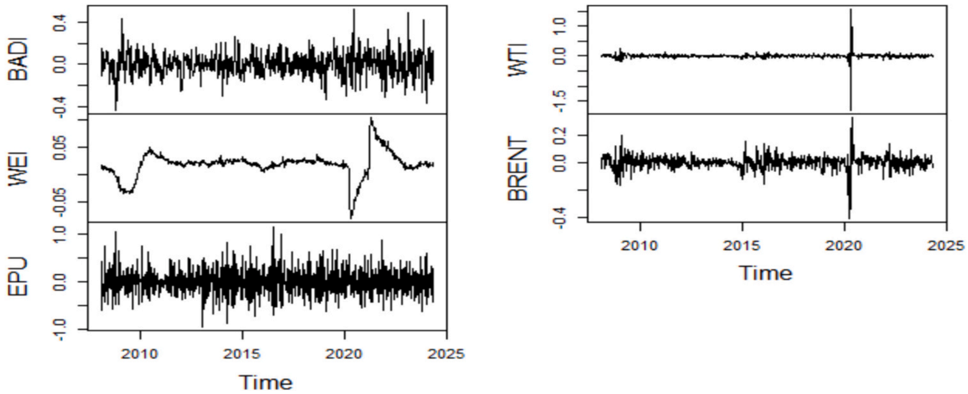

Fig. 1. Variable trajectory.

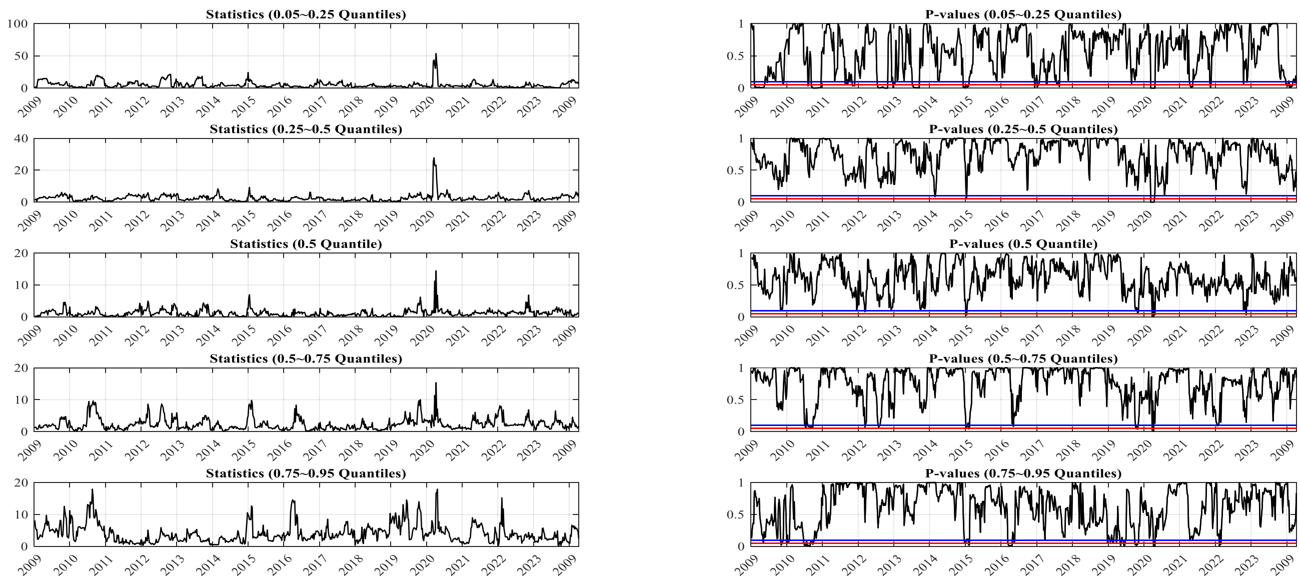

Fig. 2. Rolling window quantile Granger causality from WEI to WTI.

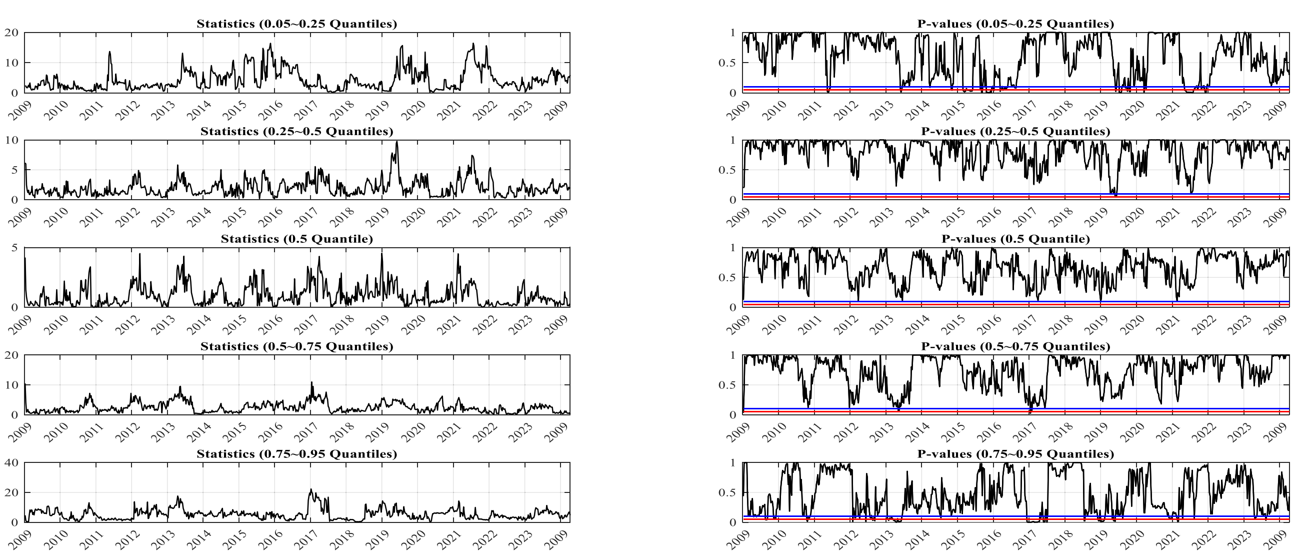

Fig. 3. Rolling window quantile Granger causality from BADI to BRENT.

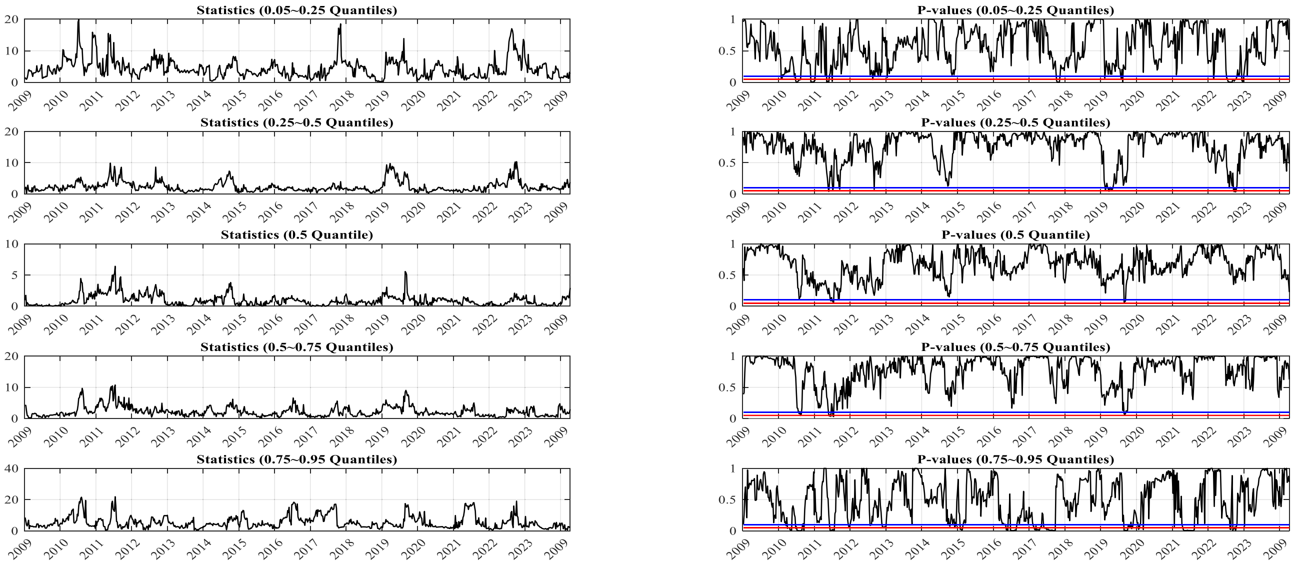

Fig. 4. Rolling window quantile Granger causality from EPU to BRENT.

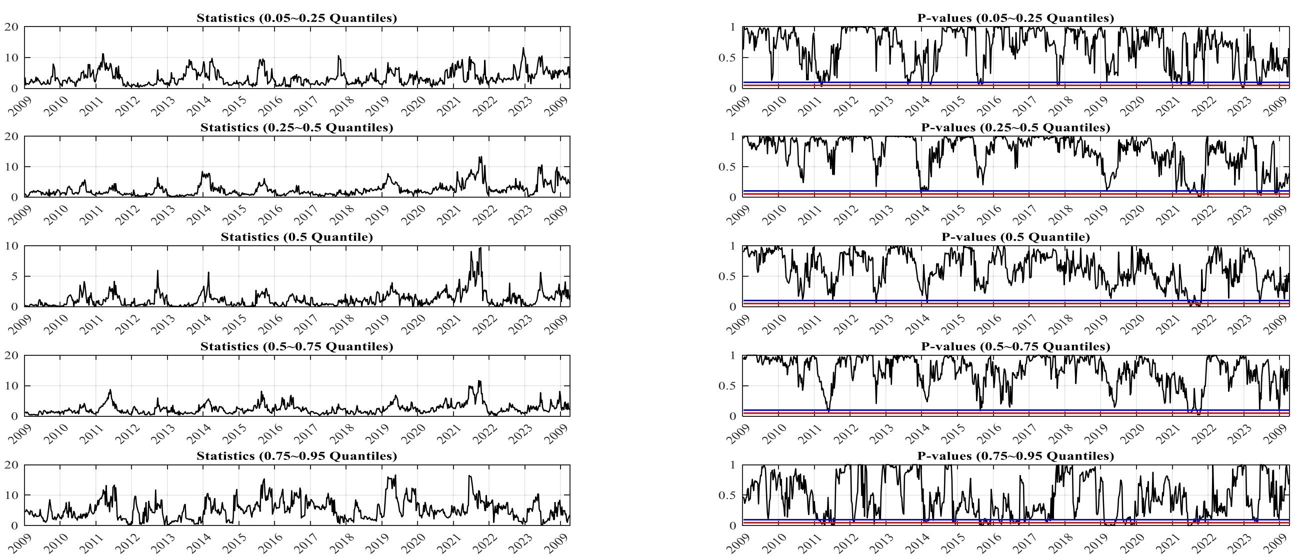

Fig. 5. Rolling window quantile Granger causality from EPU to BADI.

4. Results and discussion

Figs. 2–6 depict the findings of Rolling Window Quantile Granger Causality (RWQGC) analyses, offering a dynamic perspective on various relationships essential for understanding the interaction between WEI, BADI, WTI, BRENT and EPU. In Fig. 2, particularly within tail-risk quantile brackets (0.05–0.25 and 0.75–0.95), we observe granger causality from WEI to WTI, during market disruptions of the Global financial crisis of 2008–2009, the European debt crisis of 2012–2014, and the COVID-19 pandemic outbreaks 2020. This underscores the increased sensitivity of WEI on WTI, especially in extreme macroeconomic environments. In median quantiles, where market risks decrease, the sensitivity of WTI to WEI diminishes. Fig. 3 illustrates the increased sensitivity of rolling window Granger-causality from BADI to BRENT within tail-risk quantiles (0.05 – 0.25 and 0.75 – 0.95). Similarly, Fig. 4 demonstrates the Granger-causal relationships from EPU to BRENT within these tail-risk quantiles (0.05 – 0.25 and 0.75 – 0.95).

In addition, Figs. 5, 6, and 7 demonstrate the RWQGC findings from EPU to BADI, from EPU to WEI, and from WEI to BADI, respectively. The causality linkage from EPU to BADI becomes apparent in left and right tail quantiles. Our findings confirm this increased sensitivity underscores the profound relationship between global aggregate demand, as captured by the BADI, and oil prices, especially during periods of extreme market conditions. When global aggregate demand experiences significant fluctuations, the BADI responds sharply, which in turn amplifies its impact on oil prices. More broadly, this heightened sensitivity in tail-risk scenarios illustrates how oil prices become more reactive to global economic shifts, emphasizing the critical role of aggregate demand in influencing oil market dynamics during times of stress. This result supports the widely accepted view among economists that there is a strong positive relationship between economic activity and freight rates (Beenstock and Vergottis, 1989; Isserlis, 1938; North, 1958; and Klovland, 2002). The prevailing consensus underscores the significant influence of global economic activity as the primary driver of demand for transportation services (Kilian, 2009). Particularly in the years following significant market events, a notable dynamic of granger causality from EPU to WEI emerges, highlighting the sensitivity of WEI to EPU. Essentially, our findings underscore the complex dynamics between WEI, WTI, and EPU, offering detailed insights into the interaction of macroeconomic factors. For detailed findings of RWQGC, please refer

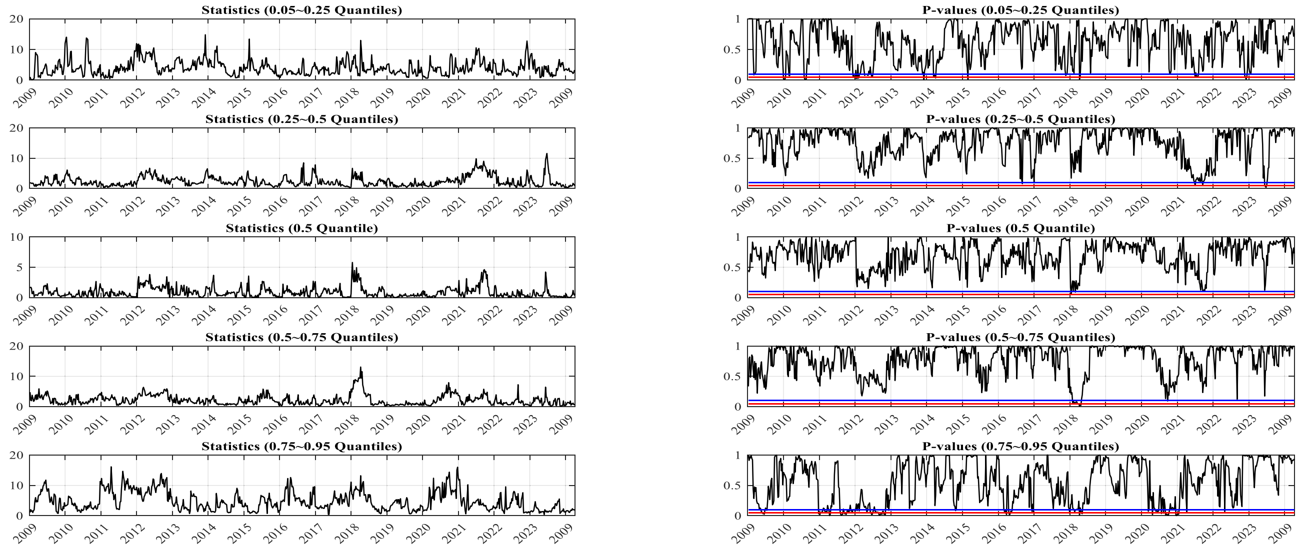

Fig. 6. Rolling window quantile Granger causality from EPU to WEI.

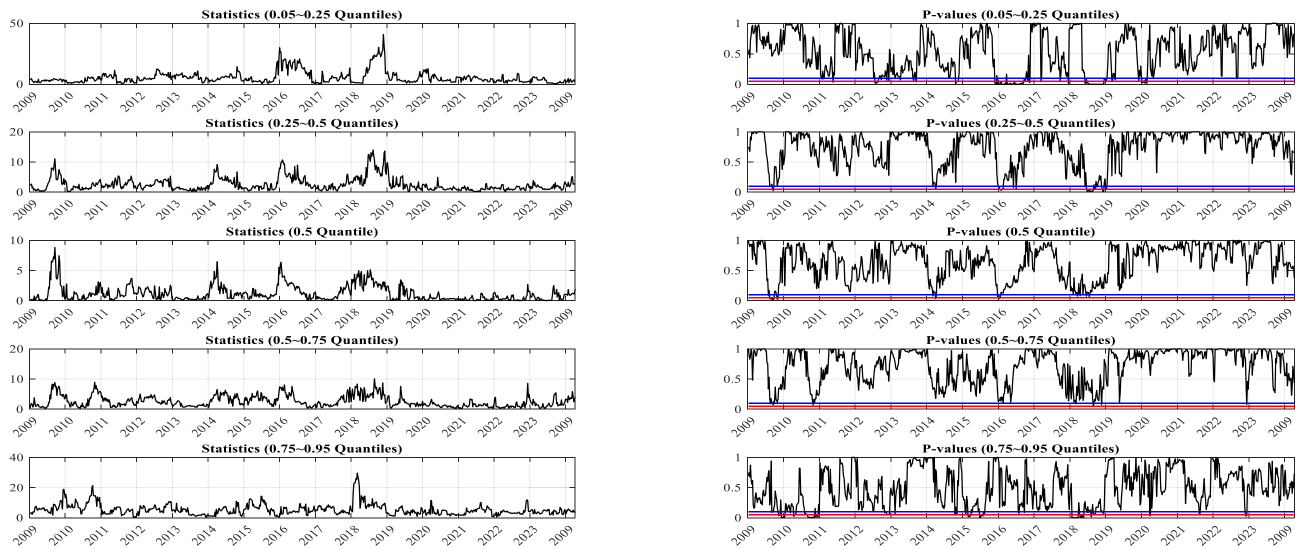

Fig. 7. Rolling window quantile Granger causality from WEI to BADI.
Note: The null hypothesis (H0) for the test is non-causality in quantiles. The rolling windows and step sizes are set to 48 and 1, respectively. The first column includes Sup-Wald statistics for the rolling window quantile granger-causality tests at different quantiles. The second column contains the corresponding *p*-values (black dotted line), the 5 % significance level (red solid line), and the 10 % significance level (blue dashed line).

to the in Supplementary material 1 (Appendix A Table A1; Table A2; Table A3; Table A4; Table A5; Table A6).

Our research findings provide valuable insights into understanding the economic dynamics underlying the declines in oil demand since the global financial crisis of 2008. Set against the backdrop of significant global events such as the European debt crisis of 2012–2014, and the COVID-19 pandemic outbreaks in 2020, our study elucidates how economic crises have contributed to the deceleration of oil demand. Following the turbulent aftermath of the global financial crisis of 2008, the European debt crisis of 2012–2014, exerting additional pressure on global economic stability. This was accompanied by the collapse in oil prices from 2014 to 2016, exacerbated by a supply glut compounded by diminishing aggregate demand expectations. Subsequently, the COVID-19 pandemic outbreaks in 2020 further intensified the economic slowdown, resulting in a noticeable decrease in global oil demand. By delineating the causal relationships between WEI, WTI, and EPU, our research highlights the intricate interplay between macroeconomic factors and fluctuations in oil demand. These findings provide a nuanced understanding of how economic crises have reverberated through the oil market, offering crucial insights for policymakers and industry stakeholders alike. In summary, our study contributes to the development of a robust framework for analyzing and responding to the complex dynamics of oil demand in the face of economic uncertainty, facilitating more informed decision-making in the energy sector and beyond.

5. Robustness checking

5.1. Wavelet quantile correlation (WQC)

In Fig. 8 and in Table 2 we report WQC findings for BRENT/BADI, BRENT/WEI, BRENT/EPU; WTI/BADI WTI/WEI and WTI/EPU.

First, we focus on the dynamics of the relationship between BRENT/BADI and WTI/BADI. The findings suggest a negative correlation between BRENT/BADI and WTI/BADI in the short term (2–4 and 8–16 weeks). However, the findings suggest a positive correlation between BRENT/BADI and WTI/BADI in the long term (16–32 weeks) and high

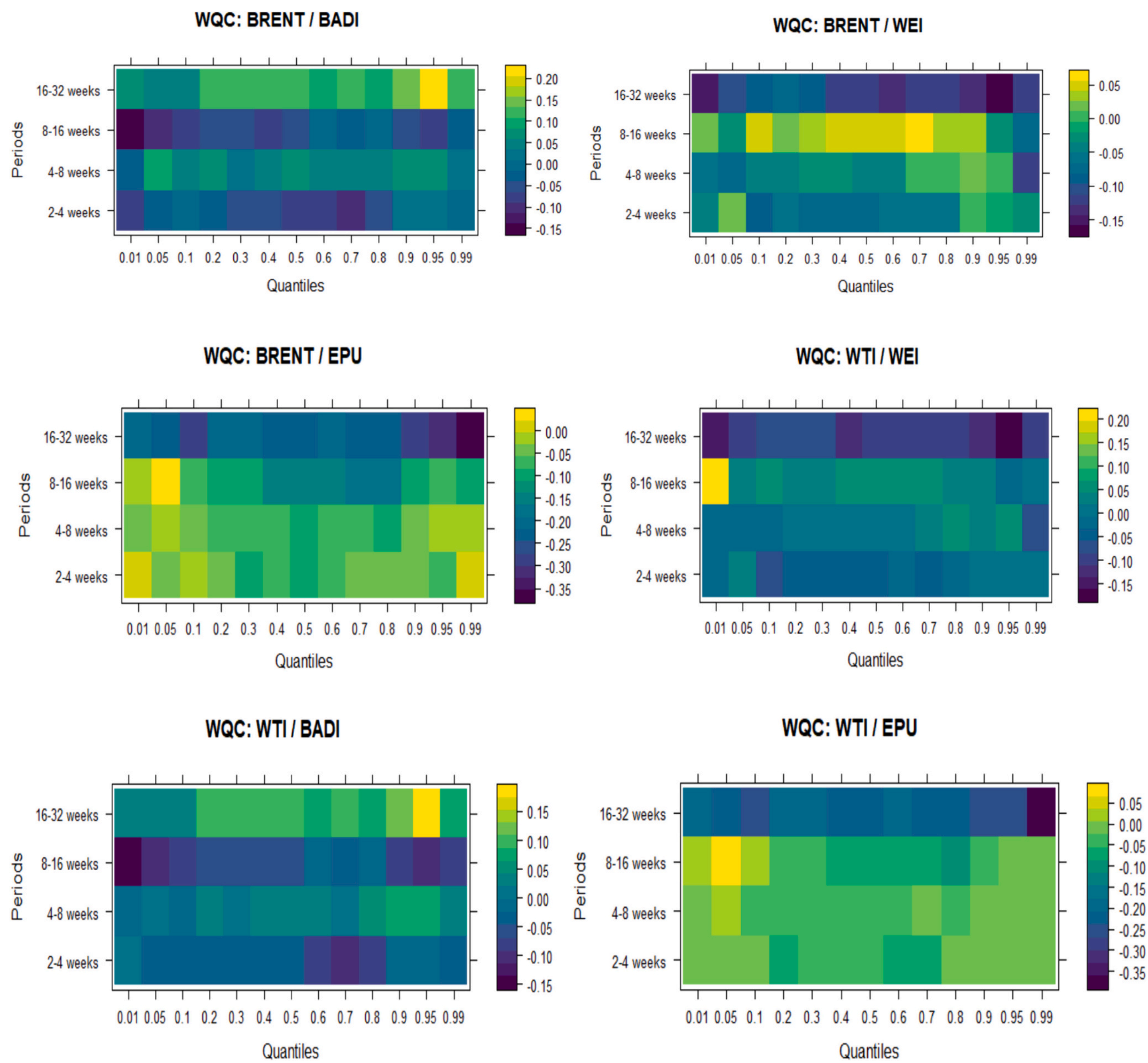

Fig. 8. Wavelet quantile correlation.

quantiles distribution of oil prices. The correlation between BADI and oil prices is asymmetric at low and high quantiles and against long and short-term cyclical fluctuations. As illustrated by Jones et al. (2004), the estimated impact of an oil price shocks on economic activities is listed the negative elasticity between 0.05 and 0.06 %, extending over a two-year timeframe. Notably, this shock threshold is characterized by a price change surpassing a three-year high. This finding is particularly consistent with Dong et al. (2019), indicating a strong correlation between oil prices and global economic activities at high frequencies, while it appears relatively weak at low frequencies.

Next, we investigate the correlations between BRENT/WEI and WTI/WEI. Our findings suggest a positive correlation between economic WEI and oil prices, especially in the 8–16 weeks steps ahead. At frequencies of 2–4 weeks, 4–8 weeks and 16–32 steps ahead, WEI is negatively correlated with oil prices.

Finally, we investigate the correlation between BRENT/EPU and WTI/EPU. We find that there is a strong negative correlation between EPU and oil prices in both frequency and quantile terms. Our findings are in line with the conclusions drawn by He et al. (2010), indicating a significant impact of fluctuations in the Kilian economic index on crude oil prices. This effect remains consistent across both long-term equilibrium trends and short-term dynamics, within a framework rooted in supply-demand dynamics and cointegration theory. Our findings confirm the hypothesis that oil prices fall during periods of uncertainty due to a demand-driven economy. In an environment of heightened uncertainty, slowing economic activity pushes oil prices down.

5.2. Sim and Zhou (2015) Quantile on quantile

WQC focuses only on the quantile distributions of the dependent variable. Capturing the coefficients on the quantile distributions of both the dependent and independent variables will allow us to analyze the demand-side effects on oil prices, especially at higher quantiles of BADI and WEI. Therefore, we also use the Quantile-on-Quantile (QQR) technique proposed by Sim and Zhou (2015) to empirically investigate between BADI and BRENT, WEI and BRENT, EPU and BRENT, BADI and WTI, WEI and WTI, and EPU and WTI. Theoretically, this approach combines the OLS and traditional Quantile Regression (QR) approaches

Table 2
Wavelet quantile correlation coefficients.

	Q_τ	2–4 weeks steps ahead	4–8 weeks steps ahead	8–16 weeks steps ahead	16–32 weeks steps ahead		2–4 weeks steps ahead	4–8 weeks steps ahead	8–16 weeks steps ahead	16–32 weeks steps ahead
	0.01	−0.09021	−0.01754	−0.14113	0.061779		−0.03681	−0.05553	0.02052	−0.15787
	0.05	−0.0414	0.092139	−0.10024	0.047867		0.024411	−0.06826	−0.02447	−0.11012
	0.1	0.006719	0.054	−0.07557	0.04815		−0.09308	−0.04656	0.053915	−0.09376
	0.2	−0.02414	0.072792	−0.05578	0.109599		−0.06592	−0.03696	0.021066	−0.08155
	0.3	−0.05886	0.030644	−0.066	0.114386		−0.08124	−0.0229	0.035813	−0.09699
BRENT /BADI	0.4	−0.04947	0.051909	−0.07021	0.111248	BRENT /WEI	−0.08	−0.03091	0.045148	−0.12845
	0.5	−0.07103	0.067722	−0.05309	0.108347		−0.07828	−0.04189	0.044265	−0.12205
	0.6	−0.06993	0.040779	−0.00389	0.088762		−0.05931	−0.03821	0.05253	−0.13875
	0.7	−0.10383	0.034117	−0.01855	0.122029		−0.06189	−0.00393	0.056247	−0.12462
	0.8	−0.04265	0.057139	0.000596	0.103612		−0.06587	0.007959	0.028979	−0.12513
	0.9	0.015511	0.074536	−0.0547	0.147489		0.009257	0.016384	0.036743	−0.13399
	0.95	0.026973	0.062164	−0.07136	0.205955		−0.00727	−0.00097	−0.02555	−0.15985
	0.99	−0.01654	0.023498	−0.03411	0.11692		−0.02825	−0.12538	−0.08133	−0.12209
	0.01	−0.00192	−0.0426	−0.01253	−0.20365		0.002216	−0.00893	−0.1375	0.028715
	0.05	−0.03208	−0.00548	0.022708	−0.24322		−0.04246	0.013625	−0.10379	0.025785
	0.1	−0.0263	−0.04131	−0.06362	−0.27746		−0.03689	−0.02378	−0.08892	0.039647
	0.2	−0.05092	−0.0785	−0.10124	−0.21192		−0.0329	0.031476	−0.06684	0.093772
	0.3	−0.08714	−0.0763	−0.10928	−0.20631		−0.04193	0.014735	−0.06423	0.086354
BRENT /EPU	0.4	−0.06824	−0.0737	−0.13961	−0.23043	WTI /BADI	−0.04177	0.024305	−0.05904	0.086266
	0.5	−0.09226	−0.08942	−0.15638	−0.22998		−0.04495	0.03736	−0.04946	0.087016
	0.6	−0.08458	−0.06834	−0.15876	−0.20659		−0.0868	0.028428	−0.00651	0.079483
	0.7	−0.05356	−0.0649	−0.17229	−0.22779		−0.10094	0.017835	−0.03083	0.097268
	0.8	−0.03824	−0.09443	−0.1764	−0.22867		−0.07997	0.055927	−0.00833	0.067637
	0.9	−0.05391	−0.04116	−0.10415	−0.28156		−0.02057	0.074414	−0.08127	0.119458
	0.95	−0.06993	−0.02768	−0.08463	−0.30253		−0.01557	0.085284	−0.10363	0.175093
	0.99	0.002213	−0.02322	−0.1016	−0.35543		−0.03525	0.022711	−0.07202	0.082298
	0.01	−0.01168	−0.02051	0.197136	−0.15896		−0.00687	−0.00714	0.005959	−0.20436
	0.05	0.017956	−0.02599	0.027507	−0.10624		−0.01313	0.006102	0.066433	−0.23823
	0.1	−0.07528	−0.0249	0.060196	−0.06355		−0.00687	−0.04124	0.015179	−0.25859
	0.2	−0.05314	0.000959	0.030813	−0.07224		−0.06177	−0.0542	−0.03922	−0.20558
	0.3	−0.05238	0.009284	0.037821	−0.08447		−0.05594	−0.0545	−0.04329	−0.19974
WTI/ WEI	0.4	−0.04687	0.011155	0.061624	−0.11529	WTI/ EPU	−0.0451	−0.04454	−0.06197	−0.22092
	0.5	−0.04507	−0.00026	0.067758	−0.09446		−0.05073	−0.05296	−0.07732	−0.22774
	0.6	−0.03262	0.000459	0.049128	−0.10451		−0.06749	−0.03558	−0.08151	−0.20518
	0.7	−0.04203	0.024469	0.043968	−0.09833		−0.06742	−0.00303	−0.08662	−0.21865
	0.8	−0.01358	0.042648	0.02246	−0.09893		−0.02319	−0.04284	−0.08724	−0.21601
	0.9	0.003746	0.041724	0.020367	−0.13731		−0.0202	−0.02086	−0.03644	−0.25371
	0.95	0.008395	0.04417	−0.01692	−0.16355		−0.0251	−0.00914	−0.01186	−0.26473
	0.99	−0.00834	−0.07799	0.004168	−0.09263		0.00218	−0.00192	−0.013	−0.36299

(Koenker and Xiao, 2002; Ma and Koenker, 2006). The QQR allows the complete capture of the potential asymmetric response of the target variable through the distributions of the explanatory and explained variables. Moreover, this technique can resist data non-normalities, especially outliers. Ultimately, the QQR method allows for examining the effect of the exogenous variable's quantiles on an endogenous variable's quantiles, anything that improves predictive ability (Sim and Zhou, 2015). Our Quantile-on-Quantile estimations are consistent with previous findings and confirm the demand-side theory. Fig. 9 denominates for when WEI exceeds the median, it signals increased economic activity and aggregate demand, which in turn leads to higher oil prices. Interestingly, regions with low oil prices intersect with regions with low WEI. The impact of EPU on both Brent and WTI oil prices is negative, especially in high EPU quantiles. This confirms that oil prices decline during periods of high uncertainty. BADI has an asymmetric effect on both WTI and Brent oil prices. This finding is aligned with Sun et al. (2014); Choi and Yoon (2020); Pouliasis and Bentsos (2024) findings. BADI can impact oil prices through three channels, first, it relates through shipping companies' transportation costs. Second, it may be because of global economic fluctuations. Finally, it may be due to supply shocks on crude oil transport services. On the other hand, Sun et al. (2018) demonstrate that the cross-market dynamic relationship between the crude oil cost and dry bulk freight rates is a hedging strategy for investors to adjust their portfolio. Our result in Fig. 14 depicts robust results with wavelet quantile correlation and connectedness results.

5.3. Quantile and Frequency Connectedness

In this section, we focus on the shock directions of the interactions among the BADI, WEI, EPU, BRENT, and WTI, focusing on quantile and frequency connectedness spillover dynamics, including left tail, right tail, and median. Our analysis emphasis lies on methodologies pioneered by Diebold and Yilmaz (2012, 2014), in conjunction with the frequency domain coupling approach proposed by Baruník and Křehlík (2018), and the QVAR method introduced by Ando et al. (2018). Please see Chatziantoniou et al. (2022) for details of the combination of frequency and quantile connectedness spillovers.

In Tables 3 to 5, we report the frequency and quantile connectedness spillovers between BADI, WEI, EPU, WTI, and BRENT. The sum of off-diagonal (column) values gives the contribution of one variable to the total effect of other variables on the forecast error variance decomposition (FEVD). Conversely, the sum of off-diagonal (line) values gives the contribution representing the cumulative effect of shocks to other variables on the forecast error variance of a given variable. The individual elements in each column, excluding the main diagonal, measure the effect of the variable on the forecast error variance of other variables, while the elements in each row, excluding the main diagonal, measure the effect of other variables on the FEVD. The net spillover, which describes how a variable affects and benefits from others, is obtained by subtracting the contribution from the contribution to others. Positive net spillovers indicate that a variable is a net transmitter and less sensitive to external shocks, while negative net spillovers indicate that a variable is a net receiver and more sensitive to shocks from other variables. The overall dispersion in the bottom right corner of the dispersion table

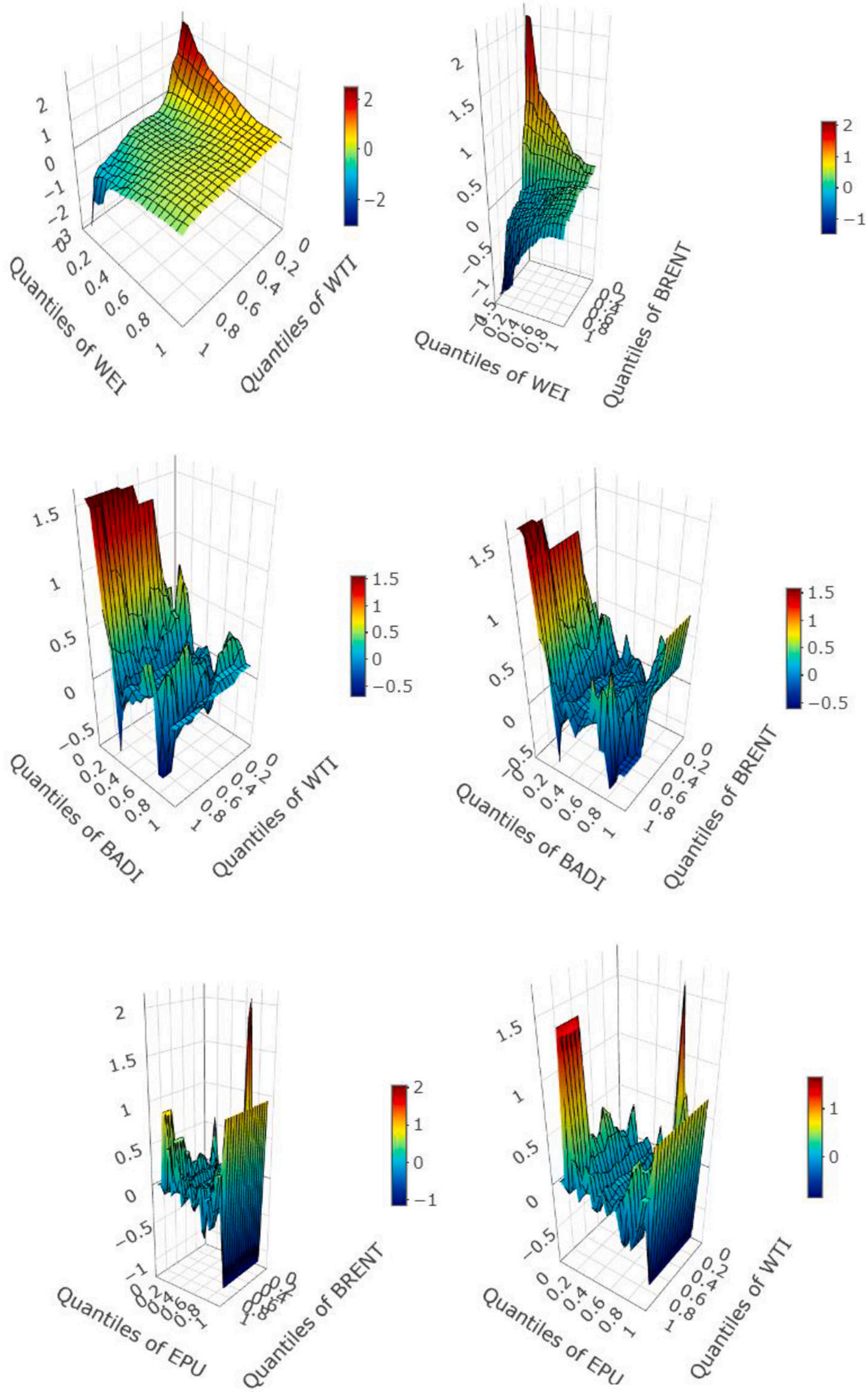

Fig. 9. Quantile-on-quantile technique results.

captures the dispersion of the system by showing the transmission and reception of shocks within the system (Diebold and Yilmaz, 2012).

In Table 3, we report findings in the left tail average dynamic connectedness spillovers among BADI, WEI, EPU, WTI, and BRENT. Our findings point to evidence that left-tail oil price shocks (extreme adverse events) have a significant average impact on economic activity over the observed period and forecast horizon. In particular, "Contributions to Others" WTI (79.51 points) and BRENT (79.74 points) a significant fraction of the total forecast error variance, while taking into account "Contributions from Others" WTI (70.8 points) and BRENT (71.49 points) fewer shocks receivers. Moreover, WTI (8.71 points) and BRENT (8.25 points) are the largest net shock transmitters of the total connectedness spillover. On the other hand, BADI (−3.93 points), WEI (−3.39 points) and EPU (−9.64 points) are net shock receivers. Moreover, short-term and long-term effects show a significant divergence in their frequency distributions, with the short-term spillover (59.61 points) being significantly larger than the long-term spillover (27.83 points). Moreover, the WEI (13.55 points) is the most dominant net shock transmitter in the left tail connectedness spillover system in the short run.

Table 3
Average dynamic connectedness – Left Tail.

	BADI	WEI	EPU	WTI	BRENT	FROM
BADI	31.29 (23.44; 7.85)	17.75 (12.65; 5.09)	15.77 (11.83; 3.95)	17.47 (12.34; 5.13)	17.73 (12.44; 5.28)	68.71 (49.27; 19.45)
WEI	18.57 (9 9.57)	29.22 (13.86; 15.35)	15.31 (7.73; 7.58	18.4 (8.95; 9.45	18.5 (8.91; 9.59)	70.78 (34.6; 36.18)
EPU	16.09 (14.84; 1.25)	17.24 (15.58; 1.66)	31.97 (30.22; 1.75)	17.39 (15.67; 1.72)	17.3 (15.67; 1.63)	68.03 (61.77; 6.26)
WTI	14.86 (9.73; 5.14)	15.96 (9.93; 6.02)	13.77 (9.46; 4.31)	29.2 (19.92; 9.27)	26.21 (17.72; 8.48)	70.8 (46.84; 23.96)
BRENT	15.27 (9.72; 5.54)	16.44 (9.98; 6.46)	13.53 (9.06; 4.47)	26.24 (17.23; 9.02)	28.51 (18.92; 9.59)	71.49 (45.99; 25.49)
TO	64.79 (43.29; 21.5)	67.39 (48.15; 19.24)	58.39 (38.09; 20.31)	79.51 (54.19; 25.32)	79.74 (54.75; 24.98)	**TCI = 87.45 (59.61; 27.83)**
Inc. Own	96.07 (66.72; 29.35)	96.61 (62.01; 34.6)	90.36 (68.3; 22.06)	108.71 (74.12; 34.59)	108.25 (73.67; 34.58)	
Net	−3.93 (−5.98; 2.05)	−3.39 (13.55; −16.94)	−9.64 (−23.68; 14.04)	8.71 (7.35; 1.36)	8.25 (8.76; −0.51)	

Note: This table displays average dynamic connectedness in the left tail, calculated through rolling windows spanning 100 weeks and a 10-step-ahead generalized forecast error variance decomposition. Within each cell, the first two values in parentheses denote short- and long-term frequency connectedness measures, while the initial value represents average total connectedness measures. Each cell corresponds to the transmission of spillovers from the variable identified in the top row to the variable listed in the first column. The "FROM" column captures spillovers from all other variables to the variable listed in the first column, while the "TO" row reflects spillovers from the variable listed in the top row to all other variables. The "NET" row presents the net spillover index, where a positive (negative) value indicates whether a variable functions as a net shock transmitter (receiver).

Table 4
Average dynamic connectedness – Median.

	BADI	WEI	EPU	WTI	BRENT	FROM
BADI	89.65 (70.95; 18.7)	1.94 (1.07; 0.87)	1.47 (1.28; 0.19)	3.3 (2.39; 0.91)	3.63 (2.48; 1.16)	10.35 (7.22; 3.13)
WEI	1.85 (0.67; 1.19)	90.8 (24.52; 66.28)	1.94 (0.53; 1.41)	2.05 (0.5; 1.56)	3.35 (0.63; 2.72)	9.2 (2.33; 6.87)
EPU	1.45 (1.35; 0.09)	1.69 (1.43; 0.25)	92.95 (88.95; 4)	1.64 (1.53; 0.11)	2.28 (2.09; 0.19)	7.05 (6.4; 0.65)
WTI	1.35 (1.17; 0.18)	1.4 (0.78; 0.63)	0.79 (0.72; 0.08)	56.88 (48.66; 8.23)	39.57 (33.99; 5.58)	43.12 (36.66; 6.46)
BRENT	2 (1.65; 0.35)	1.36 (0.82; 0.54)	1.34 (1.21; 0.13)	41.2 (34.16; 7.04)	54.1 (45.55; 8.56)	45.9 (37.84; 8.05)
TO	6.65 (4.84; 1.82)	6.39 (4.11; 2.29)	5.54 (3.74; 1.8)	48.19 (38.57; 9.62)	48.83 (39.19; 9.64)	**TCI = 28.90 (22.61; 6.29)**
Inc. Own	96.3 (75.78; 20.52)	97.19 (28.63; 68.57)	98.49 (92.69; 5.8)	105.07 (87.23; 17.84)	102.94 (84.74; 18.2)	
Net	−3.7 (−2.38; −1.31)	−2.81 (1.78; −4.59)	−1.51 (−2.66; 1.15)	5.07 (1.92; 3.16)	2.94 (1.35; 1.59)	

Note This table displays average dynamic connectedness in the median region, calculated through rolling windows spanning 100 weeks and a 10-step-ahead generalized forecast error variance decomposition. Within each cell, the first two values in parentheses denote short- and long-term frequency connectedness measures, while the initial value represents average total connectedness measures. Each cell corresponds to the transmission of spillovers from the variable identified in the top row to the variable listed in the first column. The "FROM" column captures spillovers from all other variables to the variable listed in the first column, while the "TO" row reflects spillovers from the variable listed in the top row to all other variables. The "NET" row presents the net spillover index, where a positive (negative) value indicates whether a variable functions as a net shock transmitter (receiver).

In Table 4, we report the findings for average dynamic connectedness spillover among BADI, WEI, EPU, WTI, and BRENT in the median region. In terms of total connectedness spillovers, while WTI (5.07 points) and BRENT (2.94 points) emerge as the strongest net shock transmitters, BADI (−3.7 points), WEI (−2.81 points) and EPU (−1.51 points) are the net shock receivers in the system. However, WEI (1.78 points) is a strong shock transmitter in the short run.

Finally, in Table 5 we report the findings average dynamic connectedness spillover among BADI, WEI, EPU, WTI, and BRENT in the right tail. WEI (4.52 points) is the most de dominant net shock transmitter in the system in terms of total connectedness spillovers. Moreover, it is a large shocker with 27.72 % of the shocks in the system in terms of short-term connectedness spillovers.

Our findings from the short-term left-tail, median, and right-tail connectedness spillover analyses support the hypothesis that economic activity dominates the market and emphasizes the demand-driven market mechanism, which is consistent with (Kilian, 2009; Ji, 2012; Güntner, 2014; D'Ecclesia et al., 2014; Juvenal and Petrella, 2015; Baumeister and Kilian, 2016a; Baumeister and Kilian, 2016b). Figs. 10, 12 and 14 show the left tail, median, and right tail "NET" time-varying connectedness spillover, respectively. Figs. 11, 13 and 15 visually illustrate the directional interaction and connectedness spillover potential between BADI, WEI, EPU, WTI, and BRENT through a spanningnetwork.

6. Conclusion

6.1. Summary, weaknesses, and future studies

In this study we investigate the nexus of the spot prices of oil (WTI/BRENT), Economic Policy Uncertainty (EPU), the Baltic Dry Index (BADI), and the weekly fluctuations in US economic activity (WEI). The sample period is weekly covering 842 observations ranging from January 11, 2008, to May 11, 2024. In understanding the one-way direction drivers of oil prices, we employ the rolling window quantile Granger causality test, and for robustness dynamic quantile and frequency connectedness analysis. Furthermore, we estimated the coefficient to drivers of oil price utilizing the recently developed WQC and Quantile on Quantile regression.

In light of the above findings, we provide evidence that the BADI, a key measure of global aggregate demand, significantly affects international oil prices, particularly during periods of tail risk, when market extremes are present. As global economic activity changes, the Baltic Dry Index reflects these changes with increasing sensitivity, increasing its impact on Brent crude oil prices. This dynamic suggests that oil prices are increasingly responsive to fluctuations in global economic activity and policy uncertainties, particularly during extreme market conditions. Therefore, the interaction between the Baltic Dry Index and oil prices highlights the critical importance of global demand and economic stability in shaping oil market behavior during periods of heightened risk. Furthermore, the US weekly economic indicator and EPUs play a critical role in influencing oil prices. During tail risk scenarios, oil prices show increased sensitivity to fluctuations in these indicators, highlighting the impact of global and US economic activity as well as economic policy

Table 5
Average dynamic connectedness – Right Tail.

	BADI	WEI	EPU	WTI	BRENT	FROM
BADI	31.09 (24.66; 6.43)	17.62 (13.86; 3.76)	17.7 (14.3; 3.4)	16.09 (12.68; 3.41)	17.5 (13.88; 3.62)	68.91 (54.71; 14.19)
WEI	16.95 (7.42; 9.53)	37.14 (11.44; 25.7)	15.73 (6.5; 9.23)	14.69 (6.68; 8.02)	15.5 (6.99; 8.51)	62.86 (27.58; 35.29)
EPU	17.38 (15.48; 1.9)	17.35 (14.79; 2.56)	32.62 (30.04; 2.58)	15.98 (14.58; 1.4)	16.67 (15.13; 1.54)	67.38 (59.98; 7.4)
WTI	14.74 (12.2; 2.54)	15.89 (13.31; 2.58)	14.51 (12.28; 2.24)	29.27 (26.07; 3.2)	25.58 (22.72; 2.87)	70.73 (60.51; 10.22)
BRENT	16.2 (13.56; 2.64)	16.52 (13.34; 3.18)	15.59 (13.19; 2.4)	24.04 (21.13; 2.91)	27.65 (24.55; 3.1)	72.35 (61.23; 11.13)
TO	65.27 (48.67; 16.61)	67.38 (55.3; 12.08)	63.53 (46.26; 17.26)	70.8 (55.06; 15.74)	75.25 (58.71; 16.54)	**TCI = 75.03 (58.86; 16.17)**
Inc. Own	96.36 (73.33; 23.04)	104.52 (66.74; 37.78)	96.15 (76.3; 19.84)	100.08 (81.13; 18.94)	102.9 (83.25; 19.64)	
Net	−3.64 (−6.05; 2.41)	4.52 (27.72; −23.21)	−3.85 (−13.71; 9.86)	0.08 (−5.44; 5.52)	2.9 (−2.52; 5.42)	

Note This table displays average dynamic connectedness in the right tail, calculated through rolling windows spanning 100 weeks and a 10-step-ahead generalized forecast error variance decomposition. Within each cell, the first two values in parentheses denote short- and long-term frequency connectedness measures, while the initial value represents average total connectedness measures. Each cell corresponds to the transmission of spillovers from the variable identified in the top row to the variable listed in the first column. The "FROM" column captures spillovers from all other variables to the variable listed in the first column, while the "TO" row reflects spillovers from the variable listed in the top row to all other variables. The "NET" row presents the net spillover index, where a positive (negative) value indicates whether a variable functions as a net shock transmitter (receiver).

uncertainties. This increased sensitivity highlights how oil prices are particularly sensitive to changes in economic activity and EPUs during periods of extreme market stress, and highlights the complex interconnection between aggregate demand, economic stability, and oil price dynamics.

According to RWQGC findings, oil prices have become more sensitive to WEI, BADI, and EPU during the tail risk time horizon. This increased sensitivity of oil prices to the WEI, BADI, and EPU during tail risk periods indicates that in times of elevated market volatility and economic uncertainty, oil prices react more strongly to changes in these economic indicators. The heightened sensitivity reflects the greater impact that macroeconomic conditions and policy uncertainties have on energy markets during turbulent periods, necessitating more nuanced and adaptive strategies for managing and forecasting oil prices.

More broadly our findings uncover significant insights that support the demand-side framework hypothesis, indicating the sensitivity of economic activities to EPUs and the granger causal effect of international oil prices during tail-risk time horizons. These findings resonate with prior research by (Albulescu et al., 2019) bolstering our comprehension of macroeconomic dynamics. Furthermore, the robustness of our RWQGC findings is underscored by the results of the quantile and frequency connectedness estimations. Notably, we discern a nuanced

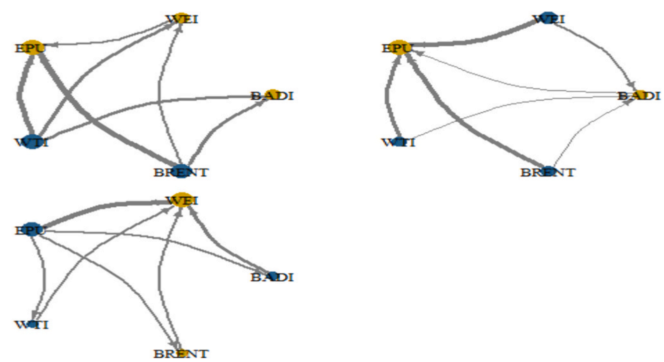

Fig. 11. Depicts the interconnectedness network plot in the Left-Tail spanning the Total (TCI), Short-term (1–5), and Long-term (5-Inf) periods.

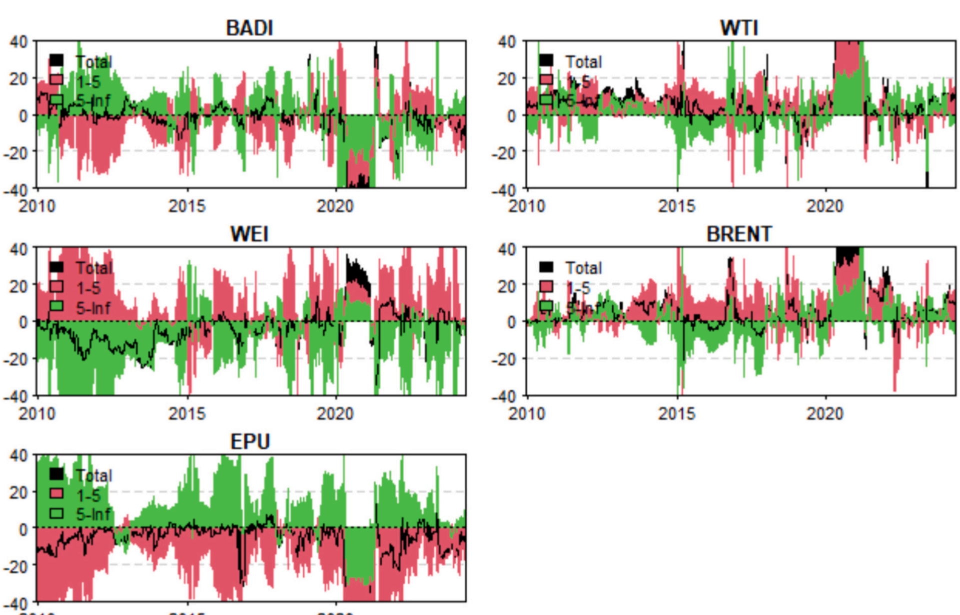

Fig. 10. The visualization presents the left tail findings of net directional spillover for Total (TCI), Short-term (1–5), and Long-term (5-Inf) periods. The black area represents the total dynamic connectedness index (TCI), while the red and green areas indicate the spillover effects for short-term (1–5) and long-term (5-Inf) periods, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

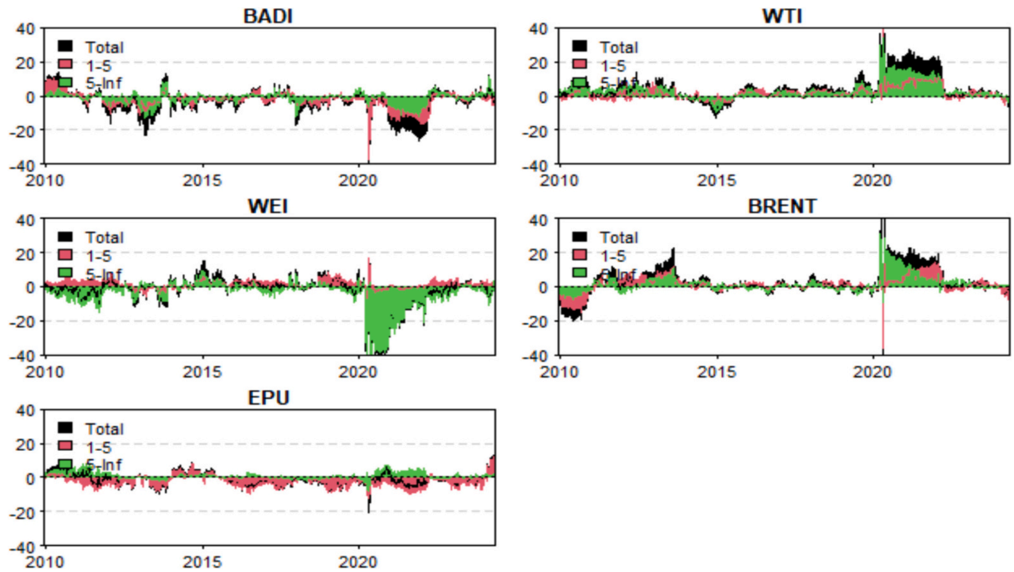

Fig. 12. The visualization presents the Median findings of net directional spillover for Total (TCI), Short-term (1–5), and Long-term (5-Inf) periods. The black area represents the total dynamic connectedness index (TCI), while the red and green areas indicate the spillover effects for short-term (1–5) and long-term (5-Inf) periods, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

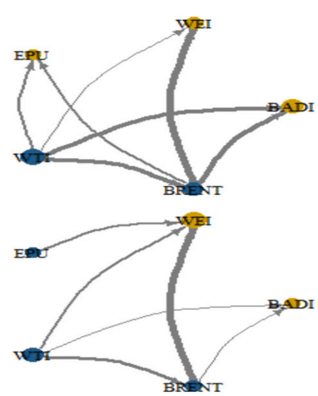

Fig. 13. Depicts the interconnectedness network in the Median spanning the Total (TCI), Short-term (1–5), and Long-term (5-Inf) periods.

relationship between the WEI and WTI across short, medium, and long terms. Initially negative in the short term, this correlation transitions to positive in the long term, revealing the intricate interplay between WEI and WTI dynamics. Similarly, the fluctuating correlation between the BADI and BRENT oil prices, from negative in the short and long terms to positive in the medium term, underscores the complexity of transport price dynamics.

Moreover, the evolving WQC between BADI and WEI, shifting from negative to positive across varying frequency frames, underscores the dynamic impact of the BADI on WEI. Conversely, the consistent negative correlation between BRENT and EPU across all periods highlights the inverse relationship between the series. Furthermore, the positive WQC between WEI and EPU in the medium and long term frequency signifies the intertwined nature of economic activities and policy perceptions. Additionally, our analysis identifies WEI as a significant shock transmitter in the median and right tail, providing a robust confirmation of the hypothesis regarding WEI as drivers of oil prices. Future studies should integrate these external factors into their analyses and explore potential mediating variables to enhance the depth of analysis. In conclusion, while this study offers valuable insights, future research endeavors should delve into the inclusion of mediating variables to achieve a comprehensive understanding of the causal relationships within complex market equilibrium.

6.2. Policy implications

Policy implications of the findings are as follows. Given that the time-varying rolling window granger-causal relationship between WEI and WTI is changing across quantile and time horizons. Therefore, the authorities must ensure that the changing granger-causal relationship does impose a distributed effect on the market equilibrium. Specifically, in the short run, the rise of oil prices corresponds to the fall of the economic activity index, which suggests that the government needs to formulate policy to absorb the negative shock of higher oil prices on the economy such as increasing oil and gas subsidies. However, in the medium run, when the economy has internalized the price shock and the EPU and WTI move harmoniously, the government can reduce the subsidy and incentivize the business sector using other policy instruments. Furthermore, in the long run, when the granger-causal relationship is turning disruptive effect again, the government can impose other policies to incentivize more business activities, such as lowering the lending rate, or reducing tax rate.

With regards to the WQC relationship between BADI and BRENT oil prices, the government should also mitigate the positive correlation given that the rise of oil prices can also increase the rise of transportation prices in the medium run, which affects production costs, increases final good prices, and eventually putting inflationary pressure on the economy. This situation should be responded by an expansionary economic policy that incentivizes firms to increase production despite the rising transportation cost. The policy is expected to prevent economic activities from weakening. This policy is substantial given that the study shows that WEI corresponds to the positive correlation of BADI in the medium and long run. The BRENT and EPU are negatively correlated in the short, medium, and long run. The negative correlation between BRENT and EPU implies the need for policy formulation to diminish the negative impact of oil prices on the economy. Further, the rise of policy uncertainty can be followed by the fall of oil prices, which can reduce oil producer's profitability and reduce economic growth. Moreover, the fall in oil prices can trigger the decline of oil production and subsequently affect the economy adversely. Hence, policy formulation is necessary to offset oil producers' loss and prevent the economy from contracting. On the other side, the fall of oil prices can also boost the domestic economy,

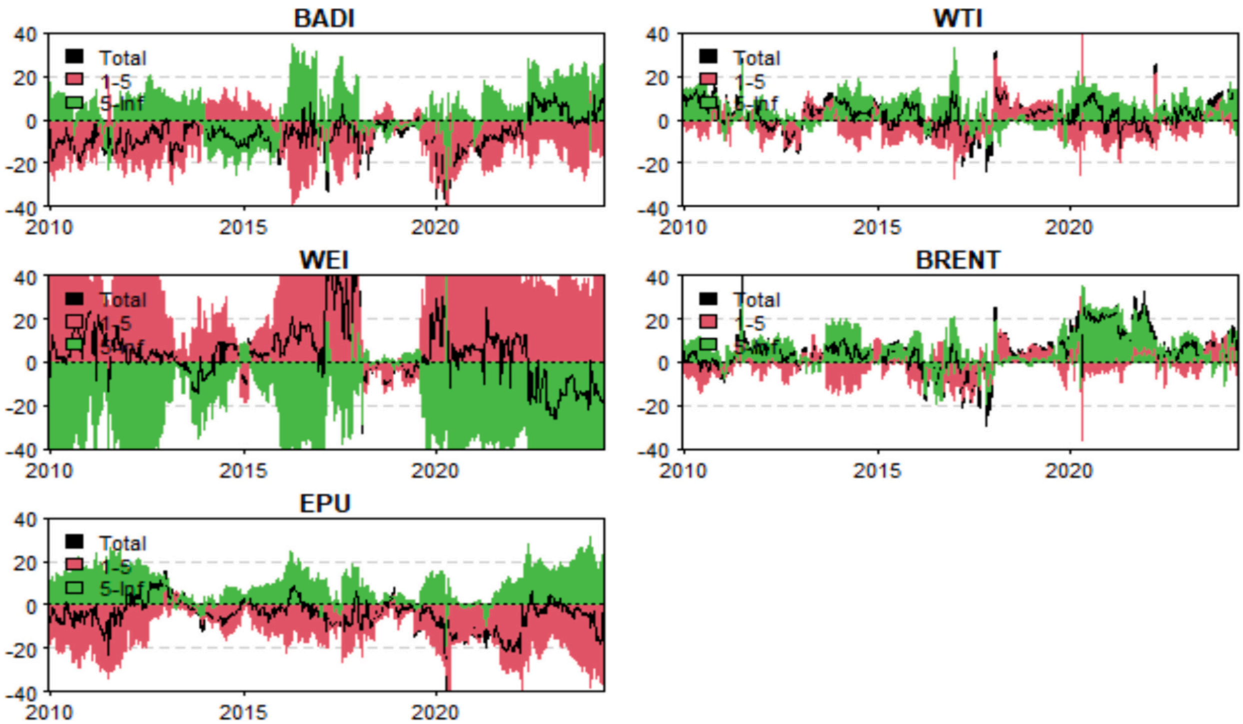

Fig. 14. The visualization presents the Median findings of net directional spillover for Total (TCI), Short-term (1–5), and Long-term (5-Inf) periods. The black area represents the total dynamic connectedness index (TCI), while the red and green areas indicate the spillover effects for short-term (1–5) and long-term (5-Inf) periods, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

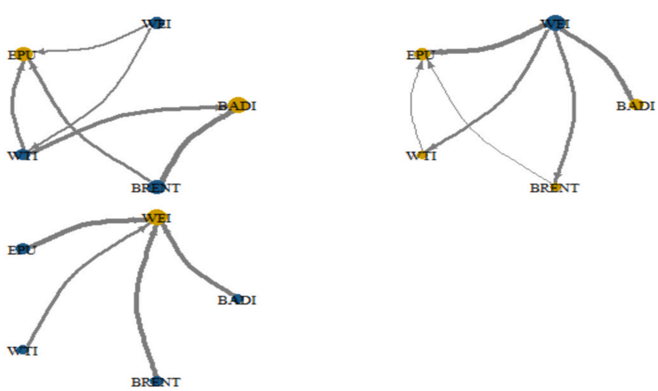

Fig. 15. Depicts the interconnectedness network in the Right-Tail spanning the Total (TCI), Short-term (1–5), and Long-term (5-Inf) periods.

through the channel of higher production, and increase the risk of inflationary pressure.

CRediT authorship contribution statement

Hemachandra Padhan: Writing – original draft, Methodology. **Mustafa Kocoglu:** Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Aviral Kumar Tiwari:** Writing – review & editing, Visualization, Supervision, Project administration, Conceptualization. **Ilham Haouas:** Writing – original draft, Methodology.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2024.107845.

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