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Economic Diversification, Oil Revenue and Energy Transition in Oil Dependent Countries: A Wavelet Decomposition and Panel Data Approach

Salem Hathroubi[1]*, Chaker Aloui[2], Hela Ben Hamida[1]

[1]Imam Mohammad IBN Saud Islamic University, Saudi Arabia, [2]Prince Sultan University, Saudi Arabia.
*Email: sahathroubi@imamu.edu.sa

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ABSTRACT

In oil-dependent countries, the energy transition process is ongoing and it appeals substantial and necessary adjustments in terms of diversification. We attempt to provide a systematic analysis of the connectedness between energy transition, oil revenue and economic diversification using novel econometric approach, wavelet decomposition and panel data estimation. Our attention will be focused on the dynamics and causal relationships between energy transition process and economic diversification by checking the role of oil revenue. We use second generation unit roots, and a particular attention is given to cross-sectional dependence of the series. Results show that correlations between wavelet components are absent in the short term, weak in the medium term, and moderate in the long-run. Causality tests support a bidirectional causality between economic diversification and energy transition and between economic diversification and net oil revenue, in the medium and long-run scale levels. Our results would have several prominent implications for policy makers, in oil-dependent countries, when designing energy transitions and economic diversifications strategies, and gives and insightful look about the future of these countries.

Keywords: Energy Transition, Oil Revenue, Economic Diversification, Wavelet Decomposition, Panel Data
JEL Classifications: C23, C33, Q32, Q48

1. INTRODUCTION

The process of development adopted by developed countries based on the reconstruction from agricultural to energy-intensive industrialized output can't be, nowadays, followed by developing countries because of new challenges the world is facing, notably a climate emergency. Developing countries cannot, therefore, stake their futures on fossil fuels. These new circumstances are particularly important for oil-dependent countries (ODCs), where net oil revenue represents a considerable percentage of their GDP. ODCs are facing numerous challenges and vulnerabilities. These include macroeconomic instability, delayed industrialization, and volatility of export revenue caused by oil price fluctuations. Their high dependence on oil revenues has shown their vulnerability to external shocks. The recent coronavirus pandemic and the war in Ukraine have highlighted many difficulties. The sudden drop in oil global demand led to an oil price collapse which increased pressure on public finance. Oil-dependent countries are then obliged to observe the enhancing role of diversification in a context of energy transition.

It's established in the literature (see for example, Van der Ploeg, 2011) that one of the main challenges, oil-dependent countries are facing to manage their wealth is the Dutch disease phenomenon according to which a resource boom leads to negative economic consequences. These consequences can include real exchange rate appreciation and reduced competitiveness in non-oil and tradable sectors. Other specific challenges of oil-dependent countries have been developed in the analytical framework of resource curse (Atkison and Hamilton, 2003; Auty, 2007; Ross, 2015), including revenue volatility, weak institutions and governance, and limited transferability of skills. Although this literature has not reached a consensus, oil-dependent countries are expected to face new challenges related to climate change and the global energy transition. Indeed, the global roadmap to reduce the use of hydrocarbons calls for a structural shift and transition to low-carbon and sustainable models of economic development.

In fact, the global energy transition has deep implications for oil-dependent countries, which face an array of new and multi-dimensional imperatives, challenges and opportunities. In such context, economic diversification and investment in renewable energy are ones of the main options for sheltering the economy of oil-dependent countries from oil shocks and oil-price volatility. Economic and export diversification is perceived as a key to reducing commodity dependence and increasing the economic resilience of this group of countries. Diversification not only minimizes the risks associated with economic concentration but also generates faster economic growth by expanding productive capacities and shifting resources from low to high-productivity sectors, and promoting economic structural transformation. Successful cases of diversification often combine various pathways, for example, by adding value to primary commodities or producing a larger number of products within or outside the commodity sector. A country may also diversify by investing its financial resources into a broad set of assets to minimize risk.

Diversification can be horizontal or vertical. Horizontal diversification typically broadens the range of production and exports, while vertical diversification involves greater variety in a sector's value chain, such as refining crude oil to produce gasoline or petrochemicals. Oil dependent countries can also diversify their markets – by increasing the range of countries to which they export. By diversifying their economies, ODCs can avoid the overconcentration of exports which can affect public revenue and the potential for investing in sustainable development. Without adequate fiscal policy frameworks, this can lead to volatile and unsustainable spending and fluctuations in output. One way to address this is by saving a portion of oil revenues for future use through sovereign wealth funds. Such funds can also make countries more resilient by transforming wealth based on natural resources into other types of assets and investing in new sectors like tourism and renewable energy.

In ODCs, the stability of state revenues is a sine quoi-non condition for the success of energy transition. In these countries, state revenues are usually instable, and this instability is mainly due to oil price volatility. To protect themselves against revenue volatility and mitigate carbon risk they should diversify their economies. However, we observe that some oil-dependent countries have managed to diversify their exportations whereas others have not. Karanfil and Omgba (2023) hypothesized that differences in the level of diversification may be associated with differences in their structural characteristics.

The present study delves into this topic and offers new insights into the economic complexity-energy transition-oil revenue nexus and extends our understanding of how and to which extent energy transition and economic diversification are linked. It fills the gap in the literature and contributes to the existing body of research in several ways. First, as far as we know, the combined effect of oil revenue and energy transition on the process of economic diversification has never been understandably tackled. Second, by focusing our study on the ten main oil dependent countries, policy-makers and planners can design the future energy system configurations that help the transition to a sustainable clean energy system. Third, this paper is the first to combine wavelet decomposition with scale-by-scale panel data estimation. This exercise is important because, contrary to Fourier transform which assumes that the signal is homogenous over time, wavelets provide a unique tool for the analysis of economic relationships over different time frames.

The paper is structured as follows. In the first section, we review the literature. The second section presents the methodology. The third section will be devoted to present data and their wavelet decomposition. Section four analysis the results, and section five concludes the paper and suggests some policy recommendations.

2. LITERATURE REVIEW

Numerous empirical studies have been interested to the relationship between energy price volatilities and economic diversification using various empirical methodologies to account for the non-linearity and asymmetry in such relationship. Nonetheless, few works have been interested to the link between diversification and energy transition in oil-dependent countries. Al Naimi (2021) analyzed the economic diversification trends in the GCC region with a special focus on Saudi Arabia. She stated that one of the main pillars to achieve the transformation of Saudi economy is the establishment of a knowledge-based economy and that the process of economic diversification is likely to suffer from setbacks along the way.

Fattouh and Sen (2021) address three key questions and tried to answer in the context of Arab oil countries. How are diversification efforts in key oil exporters linked to the ongoing global energy transition? Will the hydrocarbon sector play any role during the energy transition? And will the emergence of renewables as competitive energy source impact economic diversification strategies in these countries? They argument that, first, the speed of the energy transition is highly uncertain and heavily driven by government policies. Second, the diversification strategy adopted by oil-exporting countries will be conditioned by the speed of the energy transition, during which the oil sector will continue to play a key role in these economies, including in their diversification efforts. Third, there is a co-dependence between the success of diversification efforts in oil exporters and the global energy transition.

Karanfil and Omgba (2023) and Djimeu and Omgba (2019) investigated the impact of oil price volatility (particularly oil booms) on economic diversification for a large country sample of 134 countries over the period 1965-2010. They uncovered that oil booms harm countries with low initial diversification levels and have no impact on those that are initially diversified. Moreover, oil booms affect countries with very weak manufacturing sectors. Charfeddine and Barkat (2020) investigated the short-long run lead-lag interactions between oil and gas revenues on the level of economic complexity in Qatar using a nonlinear ARDL model. Their results show that oil volatility shocks exhibit an asymmetrical impact on economic sophistication levels and their effect is more pronounced over the long run. The authors documented the high resilience of Qatar's economy to negative shocks and positive shocks tend to upgrade economic complexity. Alfaki and El Anshasy (2022) explored the non-linear dependence structure between oil price volatility and the nonoil economy in the United Arab Emirates using a copula framework. The authors uncovered that the service sector is the most resilient to oil negative shocks. Matallah (2022) explores the relationship between economic diversification for 11 oil-dependent countries and governance for the period 1996-2018 using the GMM method. She shows that higher governance results in more diversification while higher oil revenues lead to poor diversification and lower governance in MENA oil-exporting countries.

The aforementioned literature presents two main lacks, the study of the simultaneous effect of energy transition and oil revenue fluctuations on economic diversification and the use of novel econometric technics. Our paper looks to fill these gaps.

3. EMPIRICAL METHODOLOGY

Traditional econometric methods based on Fourier transform, such as spectral method, do not take into account time resolution and suffer from many drawbacks. In the Fourier transform, the timing of shocks is not taken into account and assumes the homogeneity of the signal for all frequencies over the entire length of the series. Accordingly, Fourier transform is usefulness only when frequencies are stationary and their composition is fixed. This assumption is too restrictive for economic and financial series which are usually characterized by non-stationarity and other proprieties such as seasonality, trends, cycles, volatility, and regime shifts. These reasons among others have led to a rapid expansion of the use of wavelet in economics and finance. Sincar (2002), Gencay et al. (2002), Crowley (2007), and Ramsey (2008) were among others to propose the application of wavelet in economics. Wavelet approach has the advantage to deal with stationary and non-stationary series and allows their decomposition in the time-frequency domain. In the literature, two types of wavelets exist, continuous and discrete, and the latter are more used in economics. Based on translations (scaling s) and dilations (time position u) of a function, called mother function ($\psi_{u,s}(t)$), wavelet transform allows to decompose a time series into different frequency components. Following Grinsted et al. (2004), and Kiviaho et al. (2012), the mother wavelet can be written:

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \quad (1)$$

u gives the exact position of the wavelet. and s specifies how the wavelet is stretched. When the discrete wavelet transform (DWT) is considered, $u = 2^{-j}$ and $s = k2^{-j}$, $(j,k) \in Z^2$.

It's worth noting that the application of wavelets in economics has been always concerned by purely time series domain. Recently, Hong and Kao (2004) and Li and Andersson (2021) have adapted discrete wavelet transform to panel data. They argue that traditional panel methods such as system GMM and Arenello and Bond (1991) are only valid as long as the model errors are serially uncorrelated. Li and Andersson (2021) consider, while testing for serially correlated errors is crucial for panel models and econometric modeling, most of the tests, Breusch and Pagan (1980), Bera et al. (2001), are established for no serially correlation against the alternative of serial correlation of some known form. The assumption of known form of serial correlation in panel data was relaxed by Lee and Hong (2001), and Hong and Kao (2004). They construct a class of tests using the wavelet spectrum, which can be applied to a wide range of panel data models, including static and dynamic models, and fixed-effect and random-effect models.

3.1. Wavelet Method for Panel Data

Following Gallegati et al. (2015) and Saldivia et al. (2020), we propose a scale-by-sale panel data approach to study the short-medium- and long-term connectedness and causality inter-relationships between economic diversification, energy transition, and net oil revenue in oil-dependent countries. Hong and Kao (2004) were the first to use wavelet transform to test for serial correlation with unknown form in panel data extending the wavelet spectrum-based serial correlation test in single series proposed by Lee and Hong (2001). Given two series Y_{it} and X_{it} which can be static or dynamic (integrating lags of Y_{it}), the panel data model in Hong and Kao (2004) is given by:

$$Y_{it} = \alpha + X'_{it}\beta + \mu_i + \lambda_t + \varepsilon_{it} \qquad t = 1,\ldots\ldots,T_i; i = 1,\ldots\ldots n \quad (2)$$

μ_i is an individual effect which is mutually independent for the individual, and λ_t is a common time effect. To test for serial correlation:

$$H_0 : cov(\varepsilon_{it}, \varepsilon_{it-|h|}) = 0 \; for\, all\, h \neq 0 \, and \, i = 1,\ldots,n$$

$$H_1 : cov(\varepsilon_{it}, \varepsilon_{it-|h|}) \neq 0 \; for\, some\, h \neq 0 \, and \;\, some\, i$$

Hong and Kao use the demeaned estimated errors
$\hat{\xi}_{it} = \hat{\varepsilon}_{it} - \bar{\varepsilon}_{i.} - \bar{\varepsilon}_{.t} - \bar{\varepsilon}$

With $\hat{\varepsilon}_{it} = Y_{it} - X'_{it}\beta, \bar{\varepsilon}_{i.} = \frac{1}{T}\sum_{t=1}^{T_i}\hat{\varepsilon}_{it}, \bar{\varepsilon}_{.t} = \frac{1}{n}\sum_{i=1}^{n}\hat{\varepsilon}_{it},$

$$\bar{\varepsilon} = \frac{1}{nT}\sum_{i=1}^{n}\sum_{t=1}^{T_i}\hat{\varepsilon}_{it}$$

In addition, instead of using the lag h autocovariance function on the demeaned estimated residuals, $R_i(h) = E(\xi_{it}\xi_{it-|h|})$, Hong and Kao use the power spectrum

$f_i(w) = \frac{1}{2\pi}\sum_{h=-\infty}^{+\infty} R_i(h)e^{-ihw}, w \in [-\pi, \pi]$ because it can contain the information on all serial correlation at all lags.

Moreover, Hong and Kao construct a wavelet-based spectral density $\Psi_{jk}(w)$ which can capture the local peaks and spikes in spectral density by shifting the time effect index k as:

$$\psi_{jk}(w) = \frac{1}{\sqrt{2\pi}} \sum_{m=-\infty}^{\infty} \psi_{jk}\left(\frac{w}{2\pi} + m\right), w \in [-\pi, \pi]$$

Where $\psi_{jk}(t) = 2^{j/2}\psi(2^j t - k)$ is the basic mother wavelet, where k is the location index and j is the scale index. Then, Hong and Kao propose the heteroscedasticity test:

$$\tilde{W}_1 = \frac{\sum_{i=1}^{n}\left[2\pi T_i \sum_{j=0}^{J_i} \sum_{k=1}^{2^j} \hat{\alpha}_{ijk} - \hat{R}_i^2(0)(2^{J_i+1} - 1)\right]}{2\left[\sum_{i=1}^{n} \hat{R}_i^4(0)(2^{J_i+1} - 1)\right]^{1/2}}$$

And its corrected form:

$$\tilde{W}_2 = \frac{1}{\sqrt{n}} \frac{\sum_{i=1}^{n}\left[2\pi T_i \sum_{j=0}^{J_i} \sum_{k=1}^{2^j} \hat{\alpha}_{ijk} - (2^{J_i+1} - 1)\right]}{2(2^{J_i+1} - 1)^{1/2}}$$ which follow $N(0,1)$. J_i is the resolution level in wavelet decomposition and $\hat{\alpha}_{ijk} = \frac{1}{\sqrt{2\pi}} \sum_h R_i(h) \Psi_{jk}{}^*(w)$ are empirical wavelet coefficients and $\Psi_{jk}{}^*(w)$ is the complex conjugate of spectral density. $\tilde{W}_1$ and $\tilde{W}_2$ are spectral density-based tests and require no specification of the alternative form, thus they are applicable to a wide range of serial correlations (Li and Andersson 2021). Nevertheless, according to Li and Andersson (2021), the tests of Hong and Kao present many disadvantages, among others, they have slow convergence rates and because they are based on DWT, the data set should be a multiple of power 2. These critics lead Li and Andersson (2021) to extend the time series test of unknown form of Gencay (2010) to panel data using Fisher type test combining the p-values from individual serial correlation tests. They propose to estimate errors in equation (2) for each individual i, and transform the estimated errors to the wavelet domain using the Haar filter-based MODWT. They obtain two sets of transform coefficients, W_i and V_i, which represents respectively, the higher half part and lower half part of frequency component in the errors on the frequency band [0,1/2]. Gencay (2010) shows that the test statistic $S_i = \sqrt{4T}\left(\frac{1}{2} - G_i\right)$ follows an $N(0,1)$ distribution under H_0 and can be used to test for an unknown order of serial correlation in time series, where $G_i = \frac{\sum_{t=1}^{T_i} W_{it}^2}{\sum_{t=1}^{T_i} W_{it}^2 + \sum_{t=1}^{T_i} V_{it}^2}$. In order to combine the individual wavelet-ratio test with the Fisher type of the test based on p-values of individual tests defined in Choi (2001), Li and Andersson (2021) choose the inverse normal test statistic $Z = \frac{1}{\sqrt{n}} \sum_{i=1}^{n} \phi^{-1}(p_i)$, where ϕ is the cumulative density functions for normal distribution and $p_i = 1 - \Gamma(S_i^2)$, Γ is the cumulative density function for Chi-square distribution. Li and Andersson use S_i^2 which follows χ^2 (1) distribution instead of S_i to obtain the P-values in the panel framework because it's a one-sided test and can be used to test the heterogeneous alternatives, and because it performs better to small-sample.

3.2. Wavelet Panel Series Decomposition

Because of the practical limitations of DWT, in this paper, we perform MODWT to decompose panel data in their time-scale components. This decomposition will allow to analyze separately the short, -medium and long-term relationships between economic diversification and energy transition with panel data framework taking into account net oil revenue movements. The proposed approach is based upon the multiresolution decomposition proprieties of the wavelet transform that provides a time-scale representation of a given signal by describing its evolution on a scale-by scale basis. Specifically, after decomposing all variables into their time-scale components through the MODWT, we gather data for each time scale component into separate panel data sets and estimate the relationship between the degree of diversification, energy transition and net oil revenue on a scale-by-scale basis using panel data regression analysis. To decompose the series, we use the Daubehies (1993) least asymmetric wavelet filter of length 8, LA (8), since it provides the most precise time alignment between wavelet coefficients on several scales and the original time series[1]. For annual data, we usually choose a level of decomposition J=3 (Gallegati et al. 2015, Saldivia et al., 2020) and we obtain one vector of scaling coefficients (S3) which describes the smoothed behavior of the data and three vectors of detailed coefficients (D1, D2, D3) representing deviations from the smooth behavior. For each variable, D1 captures the movements of the series in the short-run (2-4 years), D2 in the medium-run (4-8 years), D3 in the long-run (8-16 years), while S3 captures oscillations in periods longer than 16 years, corresponding to the low-frequency components of a signal.

In addition, we explore the causality relationships between economic diversification, energy transition and net oil revenue using panel data approach taking into account possible cross-sectionally dependence and heterogeneity between countries. According to Bhattacharya et al. (2016), the non-treatment of cross-sectional dependence can lead to substantial biases and distortions in the econometric estimates.

3.3. Panel Cross-Section Unit Root Test

First generation tests for the presence of unit roots in panel data (Levin et al., [2002]; Im et al., [2003]), assumed that individual time series in the panel are cross-sectionally independently distributed. This restrictive assumption has consequences in terms of biased and inconsistent results (see among others Choi and Chue [2007]; Bai and Ng [2004]). Recognizing these deficiencies, a second generation of panel unit root tests have been proposed in the literature to deal with the problem of cross-section dependence (see Breitung and Pesaran [2007]; Choi [2006]; for a survey).

In this paper we use two second generation tests of cross-sectionally dependence, namely, the cross-sectionally augmented *IPS* test

1 See Percival and Walden (2000) for a detailed discussion of how to choose an appropriate wavelet filter.

(CIPS) developed by Pesaran (2007), and the panel analysis of non-stationarity in idiosyncratic and common components test (PANIC) developed by Bai and Ng (2004).

For panel data of N individual and T periods, the CIPS test can be written:

$$CIPS\left(N,T\right)=\frac{1}{N}\sum_{i=1}^{N}t_i(N,T) \tag{3}$$

Where t_i (N,T) is the cross-sectionally augmented Dickey-Fuller statistic of the pth cross-section order given by the t-ratio of the OLS estimate of b_i in the following regression:

$$\Delta y_{it}=a_i+b_i y_{i,t-1}+c_i\bar{y}_{t-1}+\sum\nolimits_{j=0}^{p}d_{ij}\Delta\bar{y}_{t-j}+\sum\nolimits_{j=1}^{p}\delta_{ij}\Delta\bar{y}_{i,t-j}+\varepsilon_{it} \tag{4}$$

The critical values of CIPS statistic and its truncated version are tabulated in Pesaran (2007) for the three main specifications, namely the case without intercept or trend, model with intercept only, and model with intercept and trend.

The PANIC test developed by Bai and Ng (2004) is based on a factor model in which non-stationarity can arise from common factors, idiosyncratic components, or both. The PANIC test is based on the following equation:

$$Y_{it}=D_{it}+\lambda_i^{'}F_t+\xi_{it} \tag{5}$$

$$\xi_{it}=\rho\xi_{it-1}+v_{it}$$

Where Y_{it} is the observed data, D_{it} are the model deterministic dynamics, F_t is a vector of common factors, λ_t is a vector of parameters (factor loadings), and ξ_{it} are the individual specific (idiosyncratic) errors. The series Y_{it} is said to be non-stationary if one component of F_t is not stationary, and/or the idiosyncratic term is not stationary. Then, a crucial feature of the method of Bai and Ng (2004) is that the unobserved components of the model, F_t and ξ_{it}, can each be, I(0) or I(1). And this allows a wide spectrum of possible outcomes for the proprieties of the observed data Y_{it}. Practically, in order to implement the PANIC test, Bai and Ng suppose that V_{it} is a mean zero, stationary, and invertible MA process, and N/T⟶0. The test is based on ADF regression, and supposed that tests on common factors are independent of tests on idiosyncratic components.

3.4. Panel Granger Causality

Macro-panel data with large number of individuals (N) and many time periods (T) are becoming available. This has led to the extension of time series econometrics such as stationarity and causality to panel data. One of the main contributions in this field is the procedure developed by Dumitrescu and Hurlin (DH) (2012). They provide an extension of the methodology developed by Granger (1969) to detect causality in panel data.

To depict such causality relationships between economic diversification and energy transition, and between economic complexity and net oil revenue, we perform the panel Granger causality test developed by Dumitrescu and Hurlin (2012). The underlying regression of the test is:

$$y_{it}=\alpha_i+\sum\nolimits_{k=1}^{K}\gamma_{ik}\,y_{i,t-k}+\sum\nolimits_{k=1}^{K}\beta_{ik}\,x_{i,t-k}+\varepsilon_{it} \tag{6}$$

with i=1,…, N and t=1,…,T

Where $x_{i,t}$ and $y_{i,t}$ are the observations of two stationary variables for individual i and period t. Dumitrescu and Hurlin assume that, coefficients are allowed to differ across individuals but are time invariant. The parameters α_i denote the individual-specific effects, γ_{ik} denote the heterogeneous autoregressive coefficients, and β_{ik} are the heterogeneous feedback coefficients, or Granger-causality parameters. The lag order K, which should be selected based on an information criterion (AIC/BIC/HQIC), is identical for all individuals, and the panel must be balanced. The test of DH assumes that there can be causality for some individuals but not necessarily for all. The null hypothesis of the absence of causality for all individuals of the panel is:

H_0: β_{ik}=0 *for all i and k*

And the alternative is:

H_1: β_{ik}≠0 *for some i and k*

According to DH, the standardized statistic $\bar{Z}$ when T and N are large follows a standard normal distribution.

$$\bar{Z}=\sqrt{\frac{N}{2K}}\times(\bar{W}-K) \tag{7}$$

Where $\bar{W}$ is the average of the individual Wald statistics of Granger non-causality. For a fixed T>5+3K, DH propose the standardized approximation statistic $\tilde{Z}$ which follows a standard normal distribution.

$$\tilde{Z}=\sqrt{\frac{N}{2K}\times\frac{T-3K-5}{T-2K-3}}\times\left(\frac{T-3K-3}{T-3K-1}\times\bar{W}-K\right) \tag{8}$$

Using Monte Carlo simulations DH have shown that the test exhibits good finite sample proprieties, even when T and N are small. In sum, according to Granger causality test of DH, rejecting the null hypothesis indicates the existence of causality between some entities of the variables, but not for all entities. According to Xiao et al. (2023), the method of DH (2012) can suffer from substantial size distortions because their test statistic is theoretically justified only for sequences where N/T^2⟶0.

As mentioned earlier, one of the main issues to consider in panel data is cross-sectional dependence. DH (2012) proposed a block bootstrap procedure in 8 steps, detailed in subsection 6.2 (p.1458) of their paper. They take into account cross-sectional dependence by using bootstrapped critical values for $\bar{Z}$ and $\tilde{Z}$ instead of asymptotic critical values when performing Granger non-causality tests. The results of the procedure for different N and T are reported in Table 1 (p. 1458).

Table 1: PANIC unit root test statistics by time scale

Variable	Test statistics for common factors				Pooled statistics for idiosyncratic elements			
	S3	D3	D2	D1	S3	D3	D2	D1
ECI	−6.27	−5.12	−6.04	−9.45	3.63	4.67	3.45	3.32
ET	−4.48	−6.03	−6.64	−8.00	3.59	4.04	2.70	3.40
NOR	−6.40	−7.12	−7.03	−3.61	2.99	4.06	2.98	3.84

Source: Authors' calculation. PANIC: Panel analysis of non-stationarity in idiosyncratic and common components test, ECI: Economic complexity index, ET: Energy transition, NOR: Net oil revenue

4. DATA DESCRIPTION AND STATISTICAL PROPRIETIES

The proposed methodology is applied to annual balanced panel of the 10-major oil-dependent countries in terms of oil-net revenue as a percentage of GDP (Libya, Iraq, Angola, Saudi Arabia, Oman, Kazakhstan, Iran, UAE, Qatar, Algeria) over the period (1998-2022)[2].

These countries are responsible of about 6.17% of global emission and have adopted COP27 climate change goals which aim to reach carbon neutrality by 2050 and keep global warming below +1.5°C.

We use the percentage of renewable energy in total final energy consumption as a measure of energy transition. The series is from the World Bank. To measure economic diversification, we use the economic complexity index (ECI) from the Observatory of Economic Complexity (Harvard University). This index measures the number of products made by an economy and controls for the likelihood that the same product is also made by others. Countries that produce goods or services that are not made elsewhere receive higher complexity scores than countries whose products are widely manufactured. The oil-net revenue (NOR) is the revenue minus production cost of oil. We take the percentage to GDP and is from the GlobalEconomy.com data base. Table 2 presents descriptive statistics of the variables. We can observe that the ET exhibits the highest volatility measured by SD, whereas the ECI has the lowest SD. The ET and NOR time series are skewed to the right, while the ECI is slightly skewed to the left. The Kurtosis reveals the ET manifests the greatest Platikurtic. The Jarque-Bera test is significant for the three variables showing a substantial departure from the normal distribution. Figures 1 and 2 the dynamics of ET and NOR relatively to ECI.

4.1. Cross-Sectional Correlation and Cross-Sectional Dependence Test Results

First, we perform co-movement analysis across countries using wavelet correlation coefficients for different leads and lags in the short-, medium-, and long-term. Following Kozak (2009), a strong correlation is established if the coefficient is bigger than 0.6, moderate if it is between 0.4 and 0.6, weak if it is between 0.2 and 0.4, and if the coefficient is <0.2 there is absence of correlation. Average wavelet cross-correlation coefficients presented in Table 3 show that there is absence of correlation in the short and medium term and relatively moderate positive correlations in the long term. In addition, signs of correlation coefficients can be interpreted in terms of pro-cyclicity and counter-cyclicity between cyclical component of the series. In the short and medium term (D1 and D2) correlation coefficients are negative indicating a countercyclical movement between economic

2 We consider the World Bank classification in 2022. The choice of the sample period and countries is constrained by the availability of all data series for all the countries. To obtain a balanced panel, we moved away R. of Congo classified 3rd, Guyana classified 7th, Azerbaijan classified 8th, and Chad classified 10th and replaced them by UAE classified 11th, Qatar classified 13th, Kazakhstan 15th, and Algeria 16th for which data are available on the study period.

Table 2: Descriptive statistics of the variables

Statistics	ECI	ET	NOR
Mean	−0.601	6.617	28.483
Maximum	0.899	76.110	65.157
Minimum	−2.848	0.000	2.252
SD	0.704	17.876	13.651
Skewness	−0.398	2.780	0.652
Kurtosis	2.961	9.049	2.747
Jarque-Bera	6.372	56.26	17.676
P	0.041	0.000	0.000
Observations	240	240	240

SD: Standard deviation, ECI: Economic complexity index, ET: Energy transition, NOR: Net oil revenue

Figure 1: Economic complexity index and energy transition measure

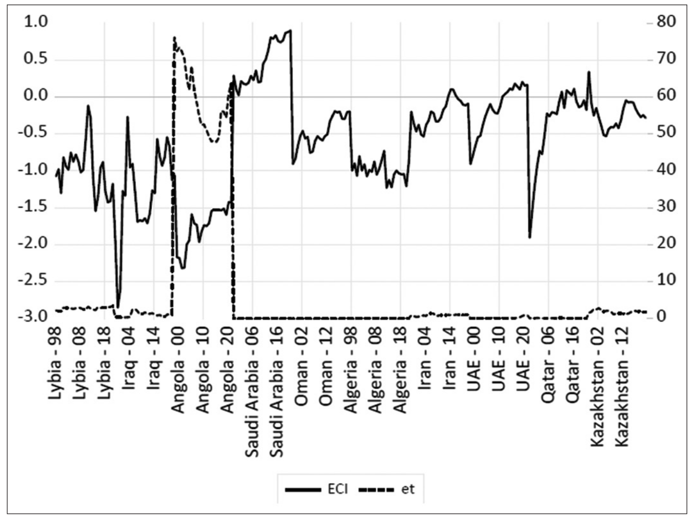

Figure 2: Economic complexity index and net oil revenue

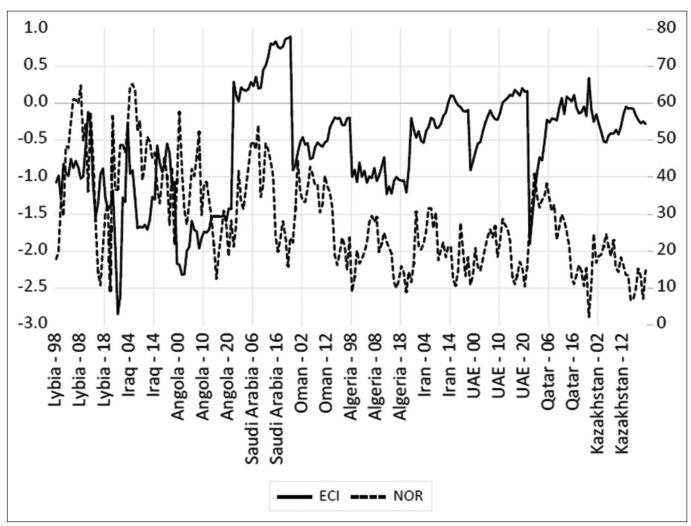

Table 3: Full simple average wavelet cross correlation coefficients in different time scale

Time scale	j=−5	j=−4	j=−3	j=−2	j=−1	j=0	j=1	j=2	j=3	j=4	j=5
Between ECI and ET											
D1	0.03	−0.03	−0.01	0.08	−0.07	−0.12	0.02	−0.01	−0.01	0.03	0.02
D2	0.06	0.06	0.03	−0.03	−0.16	−0.26	−0.11	0.07	0.13	0.04	−0.04
D3	0.53	0.45	0.33	0.18	0.09	0.08	0.10	0.19	0.27	0.39	0.44
S3	0.62	0.48	0.51	0.21	0.12	0.08	0.17	0.33	0.37	0.51	0.48
Between ECI and NOR											
D1	0.01	−0.04	0.03	−0.12	−0.06	−0.08	0.01	0.01	−0.00	−0.00	0.01
D2	−0.10	−0.04	−0.11	−0.15	−0.05	−0.11	−0.12	0.02	0.11	0.02	−0.08
D3	0.56	0.56	0.45	0.34	0.15	−0.06	0.40	0.36	0.52	0.49	0.55
S3	0.52	0.47	0.36	0.25	−0.07	−0.09	0.07	0.17	0.44	0.51	0.58

Source: Authors' calculation. ECI: Economic complexity index, ET: Energy transition, NOR: Net oil revenue

complexity and energy transition, and between economic complexity and net oil revenue. Nonetheless, we observe no feedback between variables, the lead-lag relationships are not observed. In the long-run, the coefficients of the (D3) scale and of the smooth component (S3) are positive indicating pro-cyclicity between variables. In addition, we observe that the intensity of the feedback increases as the horizon scale increases. These results could be specific to oil dependent countries. In these countries, the process of diversification is in its first phase with differentiated levels between countries**.** During this stage, more energy resources are needed for the production process using energy intensive technologies. In addition, because of subsidized low fuel costs in all dependent countries, the process of energy transition toward a cleaner energy system is slowed down.

In order to test for cross-sectional dependence between countries we use the CD test of Pesaran (2007).

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{i,j}\right) \tag{9}$$

Where $\hat{\rho}_{i,j}$ is the pair-wise correlation coefficient from the residuals of the ADF regression (4). Results of Table 4 indicate the rejection of the null hypothesis of cross-sectional independency. We deduce that there are sufficient grounds for cross-section correlation in the error terms among the variables in the panel. Thus, cross-sectional dependency was taken into account in the econometric estimations.

4.2. Unit Root Tests Results

In economic and econometric analysis, the knowledge of the level of stationarity of series is important. First generation tests for unit roots in panel data assume cross-section independence between individuals. This assumption may be not reasonable if data support co-movement between variables. These reasons and others lead us to conduct second generation tests. Results of CIPS and PANIC tests taking into account cross-sectional dependencies for the variables (ECI, ET, NOR) and their wavelet decomposition (S3, D1, D2, D3) are presented in Tables 1 and 5. CIPS test indicates that the null hypothesis of panel unit root at the D1, D2, D3, and S3 scales for all variables is accepted[3]. Thus, we can conclude that all these components are stationary.

3 The ADF test statistics (CADF) that are used in the computation of the CIPS statistic are not presented but are available upon request.

Table 4: Pesaran's cross-sectional dependence test statistics for ECI, ET, and NOR by time scale

Variable	CD-test			
	S3	D3	D2	D1
ECI	3.13 (0.000)	16.24 (0.000)	45.22 (0.000)	30.41 (0.000)
ET	4.92 (0.000)	18.02 (0.000)	33.55 (0.000)	17.48 (0.000)
NOR	4.73 (0.000)	16.07 (0.000)	22.05 (0.000)	23.53 (0.000)

Source: Authors' calculation. Parenthesis are *P* value. ECI: Economic complexity index, ET: Energy transition, NOR: Net oil revenue

Table 5: CIPS unit root test statistics by time scale

Variable	CIPS			
	S3	D3	D2	D1
ECI	−10.13	−6.31	−66.15	−4.48
ET	−49.92	−14.16	−3.61	−3.26
NOR	−10.73	−12.00	−2.85	−11.53
Critical value	1%=−2.59 5%=−2.34 10%=−2.21			

Source: Authors' calculation. ECI: Economic complexity index, ET: Energy transition, NOR: Net oil revenue

Results of PANIC test for common factors that influence the panel, using the Schwert (1989) rule, and the pooled version of the individual ADF test statistics for the idiosyncratic elements associated with each cross-section[4] indicate that the selected number of common factors, based on the average of the Bai and Ng (2004) test statistics, is 6. Pooled ADF test statistics indicate that we cannot reject the null hypothesis that all of the cross-sections are simultaneously co-integrated for all variables. Individual ADF-t statistics show that wavelet components are stationarity for all variables and countries, confirming results of CIPS test results.

5. SCALE-BY-SCALE PANEL DATA ESTIMATION

The decomposition of the series using MODWT described in the precedent section allows to obtain one smooth and three details components for each variable and each country. We then constitute 4 panel data sets composed by 10 cross-section units (10 countries) with 24 observations each (1998-2022), where any

4 Details results of these tests are available upon request.

Table 6: "Scale-by-scale" panel data regression

Coefficient	Aggregate	S_3	D_3	D_2	D_1
β_J	−0.0858 (−1.089)	**0.0199** (6.087)	**0.0251** (8.444)	**−0.0129** (−3.553)	−0.0026 (−0.800)
δ_J	**−0.0543** (−2.337)	**0.0708** (3.285)	0.0803 (1.831)	**−0.0676** (−2.473)	−0.0181 (−0.790)
Adjusted R^2	0.762	0.861	0.259	0.051	0.014

Fixed individual effects estimation of the economic diversification-energy transition-net oil revenue for the ten-major oil-dependent countries. T-statistics in parenthesis. 5% significance in bold

Table 7: Scale by scale Demitrescu-Hurlin panel Zbar-satatistic test

Causality direction	Aggregate	S3	D3	D2	D1
ECI → ET	1.171 (0.241)	19.18 (0.000)	18.296 (0.000)	7.049 (0.000)	1.009 (0.342)
ET → ECI	0.891 (0.372)	11.10 (0.000)	27.418 (0.000)	6.039 (0.000)	7.573 (0.000)
ECI → NOR	4.147 (0.000)	8.232 (0.000)	34.912 (0.000)	15.123 (0.000)	0.064 (0.948)
NOR → ECI	1.193 (0.232)	18.39 (0.000)	12.169 (0.000)	13.385 (0.000)	5.296 (0.000)

P-value in parenthesis. ECI: Economic complexity index, ET: Energy transition, NOR: Net oil revenue

single panel includes components corresponding to a specific frequency band. We use Hausman (1978) test to choose between fixed effects model and random effects model. Under the null hypothesis, the individual effects are not correlated. In our case the $\overline{\chi^2_{(2)}}$ test is 3.435 rejecting the null hypothesis at 5%. Then, we propose to estimate for each panel data set a fixed effect model with individual-specific effects.

$$ECI[S_J]_{it} = \alpha_{J,i}+\beta_J ET[S_J]_{it},+\delta_J NOR[S_J]_{it}+\varepsilon_{J,it} \quad (10)$$

And

$$ECI[D_J]_{it} = \alpha_{J,i}+\beta_J ET[D_J]_{it},+\delta_J NOR[D_J]_{it}+\varepsilon_{J,it} \quad (11)$$

Where $ECI[S_J]_{it}$, $ET[S_J]_{it}$, and $NOR[S_J]_{it}$ represent the smooth component of economic complexity index (economic diversification),energy transition measure, and net oil revenue respectively for country i at time t, and $ECI[D_j]_{it}$, $ET[D_j]_{it}$, and $NOR[D_J]_{it}$ represent the detail components of the three variables at each j scale, j=1,2,…J, for the country i at time t, and α_i are individual effects with i=1,2,…N. Table 6 presents the results of panel regression estimates at different scale levels using the fixed effect estimator. We also report, in the first column, the results with aggregate data to serve as benchmark.

Panel data estimate of the relationship between economic complexity index, as a measure of economic diversification, energy transition, and net oil revenue using aggregate data provides negative relationship between variables. Particularly, we observe a non-significant one between ECI and ET while there is a significant relationship between ECI and net oil revenue. Nonetheless, when the same relationship is examined at different frequency bands the comparison among regressions at different scale levels indicates that the effects of energy transition and net oil revenue on economic diversification differ in terms of estimated sign, size effects, and significance. We observe a clear evidence of sign reversal and significance. While at the aggregate level, energy transition has no effect on economic diversification, the smooth component S3 which captures oscillations with a period longer than 16 years, and the scale level D3 (8-16 years) corresponding to long- term cycles become positive and significant. At scale D2 (4-8 years) corresponding to medium-term, and scale D1, corresponding to high frequency band, the effect of energy transition on economic diversification remains negative and non-significant for D1 but significant for D2.

The relationship between economic diversification and net oil revenue (NOR) presents different pattern. At the aggregate level, the relationship is negative and significant, while at the disaggregate level, only the smooth component and medium-term scale level (D2) are significant, with a more ample size effect and sign reversal. The negative relationship displayed at medium-run D2 scale becomes positive in the long-run.

The analysis of the direction of causality using DH methodology in Table 7 shows that at the aggregate level, there is absence of causality between economic complexity and energy transition, while we observe a bidirectional one in the medium D2 scale and in the long-run (D3 and S3) scale. Nevertheless, the non-causality hypothesis in the D1 scale can't be rejected. Concerning, the relationship between economic complexity and net oil revenue, at the aggregate level, the causality runs only from economic complexity to net oil revenue. At the disaggregate level, there is a bidirectional causality in the long-run (D3 and S3) scale and in the medium D2 scale. In the short-run D1 scale, only net oil revenue causes economic complexity.

6. CONCLUSION AND POLICY RECOMMENDATIONS

The transition away from fossil fuels to clean energy system will imply structural transformation of worldwide economic system with differentiated effects on individual economies. For oil-dependent countries this implies a considerable cut of their main resource funds. Without international support and suitable diversification strategy, these countries will face disastrous consequences on workers and government plans. Oil dependent countries are then constrained to diversify their economy in a context of energy transition. If these countries fail in their diversification efforts, this could result in output disruptions and more volatile oil prices. In contrast, if they succeed in their diversification objectives, they will increase the resilience of their economies and influence the speed of energy transition. It is then of main importance to study the nature and amplitude of linkages between economic complexity and energy transition in the context of oil dependent countries**.** In this vein, this paper has adopted wavelet method to decompose series in different frequency bands and scale-by-scale panel data techniques to estimate correlations and causality relationships between economic diversification and energy transition taking into account net oil revenue. In a first step, we apply MODWT to decompose series and isolate cyclical components in order to distinguish the relationship in different time horizons. In a second step, we conduct co-movement analysis, scale by sale panel data estimations, and causality tests to determine and understand the different relationships between the variables retained by the study. In addition, in order to obtain accurate econometric estimations, our analysis consider data proprieties such as heterogeneity and cross-section dependence. Our results show that, while at the aggregate level and in the short term D1 scale, there is no effect of energy transition on economic diversification, the relationship becomes significant with positive coefficients for D3 and S3 scale indicating that energy transition matters for economic diversification in the long-run for oil dependent countries. Moreover, while at the aggregate level and medium-term D2 scale there is a significant negative effect of net oil revenue on economic diversification, there is a positive interaction between the long-run smooth components (S3) of the two variables. DH causality test results indicate that at the aggregate level there is absence of causality between ECI and ET and a unidirectional one from ECI to NOR. The analysis at different time scale components show that bidirectional causality relationships prevail in the medium D2 scale and long-run D3 and S3 scales for both ECI-ET and ECI-NOR relationships. In the short term D1 scale, ECI causes neither ET nor NOR, while both cause ECI.

The findings of this paper suggest that it is more informative to consider the distinction of time horizons to better understand interactions between the cyclical components of the series. The adopted approach has allowed better understanding the complex relationships between economic diversification and energy transition. In the context of energy transition, oil dependent countries have to diversify their economies in order to make them more resilient. The rational use of net oil revenue could help these countries to plan both objective of diversification and energy transition. Oil dependent countries is an heterogenous group, with diverse size, demography, wealth and economic structure. It is then appropriate to tailor reforms to country circumstances and capacities. Among these reforms, oil dependent countries should ensure that the use of oil funds is governed by clear and transparent rules. They have to support horizontal diversification by enhancing allocation of oil revenues in a manner that reduces production costs in new sectors and raises their efficiency. They also have to enhance vertical diversification in existing sectors by moving into higher value-added products. Because of the energy transition toward a cleaner energy system, oil revenues will eventually dwindle and Governments' resources will diminish. This can impair the capacity of oil dependent countries to support sustainable economic growth. In this context, oil dependent countries need a new policy toward fossil fuel subsidies and the development of strong private investment sector which become the impetus for economic development when public investment can no longer be maintained.

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