IJEEP
INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY
EJ EconJournals
ISSN: 2146-4553

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2024, 14(6), 1-14.

EJ EconJournals

Nexus among Economic Uncertainty, Geopolitical Risk, Oil Price Volatility and Economic Complexity in Saudi Arabia: Fresh Insights from Wavelet Local Multiple Correlations

Chaker Aloui[1]*, Ben Hamida Hela[2], Salem Hathroubi[3]

[1]College of Business Administration, Prince Sultan University, Saudi Arabia, [2]College of Business Administration, Imam Mohammad Ibn Saud Islamic University, Saudi Arabia, [3]College of Business Administration, Imam Mohammad Ibn Saud Islamic University, Saudi Arabia. *Email: caloui@psu.edu.sa

Received: 21 March 2024 **Accepted:** 11 August 2024 **DOI:** https://doi.org/10.32479/ijeep.16274

ABSTRACT

Enhancing future economic growth through higher economic complexity is vital for sustainable growth strategies. Even though most studies are concerned with the key factors governing the economic complexity process, there needs to be more studies about the impact of risk factors on economic sophistication evolvement, particularly for oil-rentier economies. The present paper intends to delve into the dynamic connectedness between some risk factors, such as economic, political, and geopolitical risks and oil price volatility and the progress of economic complexity. We utilized quarterly data (1995Q1-2021Q4) for Saudi Arabia as a heavy oil-rich economy. As the first study to delve into the short-long term connections at various time scales and frequencies within a multivariable setting, we contribute to the literature by offering a spotless picture of economic complexity risk factors. In doing so, we resort to a novel wavelet local multiple correlation method, which can explore the varying patterns of time periods in the interconnections between the variables. Our findings disclose that oil volatility, geopolitical risk, and global uncertainties are positively connected to economic complexity over the long run. In contrast, their short-term effect is weak and mostly insignificant. These results indicate the resiliency of the Saudi economy to external to oil volatility shocks and intensification of global and local uncertainties. These outcomes offer policymakers new insights and prominent policy recommendations when designing economic strategies to achieve higher economic sophistication and sustainable growth.

Keywords: Economic and Policy Uncertainties, Geopolitical Risk, Oil Volatility, Economic Complexity, Wavelet Local Multiple Correlation.
JEL Classifications: D81, O13, Q3

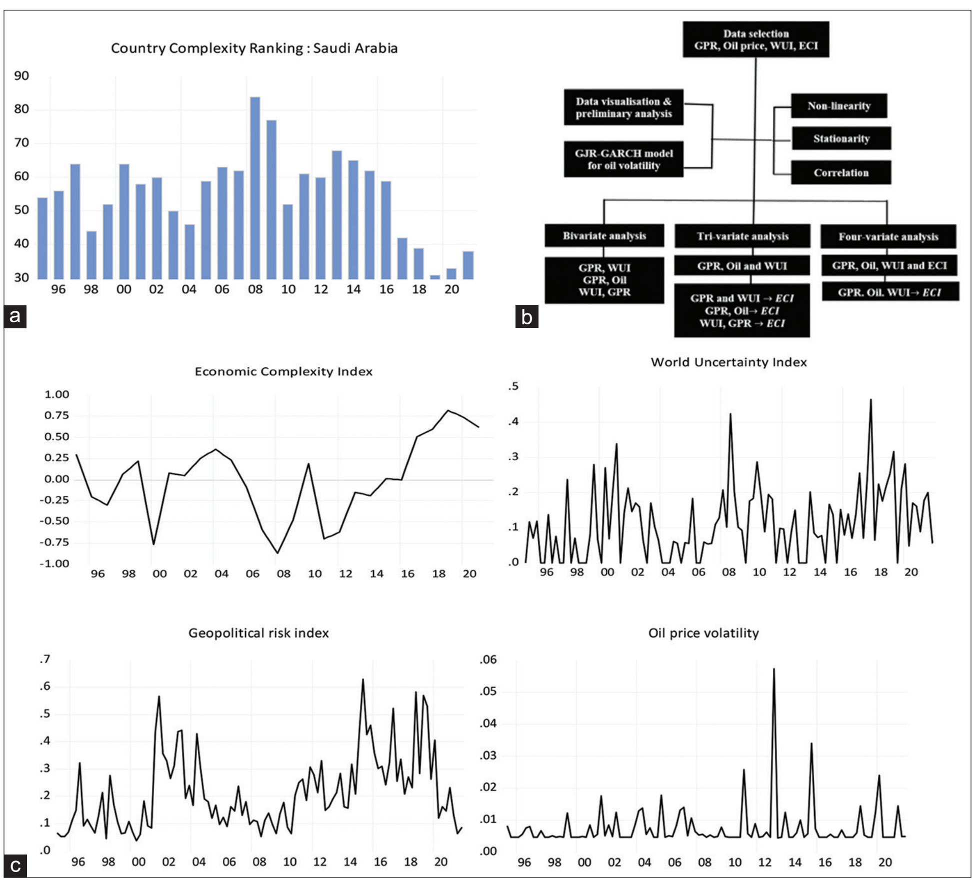
1. INTRODUCTION

Shifting from an oil-exporting economy to a knowledge-based economy is one of the obstacles Saudi Arabia has in its pursuit of economic diversification (Albassam, 2019). To reach their objective, the Saudi authorities were involved in some strategic plans within the 2030 vision to attenuate the high oil dependency by establishing a sound knowledge system that will benefit from foreign direct investments, technology transfers, and industry-based research to increase non-oil exports and diversify the economy. Boosting economic diversification would attenuate uncertainty in the energy markets and ultimately secure sustainable growth (Sweidan and Elbargathi, 2023). Concerning this, Saudi Arabia has drawn an aspirational target to raise the share of non-oil exports in a non-oil GDP from 16% to 50% in 2030. However, oil still dominates the Saudi economy. It will account for 74% of total exports in 2022. Still, it is lower than the average share (84%), and the non-oil share to nominal GDP grew from 52% in 2012 to 56% in 2022, boosted by the private non-oil activities, including real estate, tourism, retail, and whole trade and manufacturing (SAMA: Saudi central bank).

Figure 1, shows the time path of Saudi Arabia's ranking in terms of economic diversification as quantified by the economic complexity index designed by the *Growth Lab* of Harvard University. As we can see, Saudi Arabia has shown sizeable improvements in ECI ranking during the last 5 years. The ECI was selected as a target to gauge the progress of the National Industrial Development Program launched in 2017 as one of the pillars of the 2030 Vision program. Furthermore, the Saudi economy is heavily oil-dependent, so geopolitical risk has become a key risk factor for experts and politicians. Geopolitical risk is "associated with wars, terrorist acts, and tensions between states that affect the normal and peaceful course of international relations" (Caldara and Iacoviello, 2022, p.6). In the Middle East, geopolitics and oil price volatility are closely attached since oil prices are regularly tailed by geopolitical contention, and higher oil prices regularly trail the latter due to its actual and feared trouble in oil supply (El-Gamal and Myers, 2018; Mandal and Datta, 2024). More importantly, oil industries in the Middle East countries such as Saudi Arabia are highly exposed to geopolitical risk. Struggles, tensions, terrorist attacks, military conflicts, and the menace of war intentionally impact the oil supply. For instance, in September 2019, terrorist attacks on Aramco's oil facility caused substantial damage and a spectacular upsurge in oil prices of around 20%. Thus, the adverse impact of geopolitical incidents is greater in firms in more exposed firms, and subsequently, greater firm-level geopolitical risk results in lesser firm-level investment (Caldara and Iacoviello, 2022). Given the significance of this geopolitical uncertainty and its connectedness to oil, the need for Saudi Arabia to boost its economic complexity has become more perilous. Economic diversification is the core of the concept of economic complexity.

According to Hidalgo al. (2009), the degree of knowledge helped by the economy assists research on the knowledge economy. The authors referred to export diversity and ubiquity to assess the knowledge used in the production process. Subsequently, boosting economic complexity involves accumulating and using a greater level of knowledge to serve the production of a larger range of exports made by only a few countries (Hoang et al., 2023). Tracking the progress and the determinants of economic complexity has attracted great attention among policymakers and academia. An extensive body of the existing literature was concerned with the key determinants of the economic complexity: Foreign direct investment (Sadeghi et al., 2020; Antonietti and Franco, 2021; Saqib and Dinca, 2023); institutional governance (Hartmann et al., 2017); human capital accumulation (Shahbaz et al., 2019), income inequality (Hartmann et al., 2017; Lee and Wang, 2021), gender equality found to serve as key drivers of economic complexity. However, less attention has been paid to global risk factors such as geopolitical risk, oil price volatilities, and global economic policy uncertainties as potential determinants of economic complexity. Whether these risk factors impede, slow down, or enhance economic complexity progress still needs to be answered. Oil is arguably one of the key factors driving the

Figure 1: (a) The annual time path of Saudi Arabia's economic complexity ranking (1995-2021), (b) The chart-flow, (c) Time paths of oil price volatility, WUI, GPR, and ECI (Saudi Arabia, 1995:q1-2021:q4)



Source of the data: https://atlas.cid.harvard.edu/rankings economy, and oil price volatility significantly impacts economic growth and the welfare of economies. Although oil impacts economic sophistication in oil-importing countries, little is known about the oil rentiers' economies.

According to Adams et al. (2020) and Hoang et al. (2023), oil-rich countries are more predisposed to wars, tensions, or military conflicts that impede the business environment and innovation process. Moreover, oil-economic complexity may be explained through the "Dutch disease" phenomenon in which higher oil prices can lead to changes in the economic structure in oil-rentier countries, making economic activities more focused on the oil industry, which in turn evict other potential sectors that could eventually boost economic complexity. Consequently, oil sectors will be more concentrated in physical and human capital, which in turn makes oil-rentier countries trapped in low-technology productions and difficult to achieve higher sophistication levels (Sachs and Warner, 1995). For Saudi Arabia, such a "Dutch disease" issue was highlighted by Faudot (2019), who claimed that the structures of its rentier economy are well-established and it is difficult to displace (Faudot, 2019, p. 94). On the other side, uncertainties regarding future government economic policies and political instabilities are unescapable, and their impact on economic activities is profound.

Baker et al. (2016) reported that the rise of economic policy uncertainty has harmed macroeconomic performance. The authors point to considerable effects on stock market volatility, unemployment growth, and investment rates. In the chorus, the ongoing Israeli-Palestinian military conflict, the Russo-Ukrainian war and the subsequent economic sanctions on Russia, the emergence of geopolitics blocs, the Sino-US rivalry, the US-Iranian military escalations, terrorist attacks, and extreme political incidents have substantially raised geopolitical uncertainties worldwide, which may affect not only national securities but the future of multilateral trade developments. According to the recent IMF Report 2023)*,[1]intensifying geopolitical tensions among major economies raised anxieties about global economic and financial fragmentation, which could have potentially significant implications for global financial stability, cross-border allocation of capital, international payment systems, and asset price volatility. For the Bank of England, geopolitical risk and economic policy uncertainty are perceived as an "uncertainty trinity" that could substantially affect the economy (Carney, 2016). Adams et al. (2020) claimed that geopolitical risk is particularly eminent in oil-rich countries prone to conflict, war or war-like tensions, and terror-related conflicts. The 2003 Gulf War escalated the economic uncertainty and geopolitical risk in the Middle Eastern countries and the global economies. The recent COVID-19 constitutes another recent example.

In the economic complexity literature, these downside risks may be perceived differently. They are viewed as factors that slow the economic complexity process since they require continuous research and development investments, innovations, and human capital (for example, Zhu and Li, 2017; Sharma et al., 2023). In opposition to Wang et al. (2014) and Meng and Shi (2017), these risks are perceived as factors exalting economic sophistication as they contribute to research and innovation advancement as options for "self- developments" or "high-risk-high return" opportunities.

Based on the above gaps, our study aims to scrutinize the dynamic interconnections among economic uncertainty, geopolitical risk, oil price volatility, and economic complexity in Saudi Arabia employing Wavelet Multiple Correlation. The following questions are going to be answered. (1) How are geopolitical risk, economic uncertainty, and oil price volatility interconnected in the context of Saudi Arabia? (2) What is the relationship between risk factors and progress economic complexity in Saudi Arabia? (3) What is the long-term influence of oil price volatility, geopolitical risk, and economic uncertainty on economic complexity in Saudi Arabia? (4) Does this interconnectedness display fluctuating forms over different time scales and frequencies?

Given the aforementioned, our study contributes to the literature in the following ways. It aims to extend our understanding regarding the impact of risk factors, namely oil volatility, geopolitical risk, and economic uncertainty, on the progress of economic complexity in Saudi Arabia using the most recent and available datasets. In doing so, we implement the innovative wavelet local multiple correlation (WLMC) suggested by Polanco-Martínez et al., (2020) to investigate the differential impact of these risk factors on economic complexity in the time-periods domain. The use of this method constitutes the main methodological contribution of this study. Three main aspects motivate our choice. First, compared to other wavelet methods, including the cross wavelet transform, the bivariate, the multiple, and the partial wavelets, the WLMC allows us to capture concomitantly the correlation between more than two variables. Thus, this innovative multivariate wavelet designed by Polanco-Martínez et al. (2020) is superior to conventional wavelets. Since we are using quarterly data, the WLMC can detect the variations and the volatility of the used time series and, therefore, provides a new perspective to this convolution by assessing the multivariate interactive relationships between geopolitical risk, economic uncertainty, oil volatility, and economic complexity in Saudi Arabia. More importantly, the WLMC technique allows us to define the "dominant" variable that plays a dominant role across various time horizons. So, using such a method will help better understand the interactions between the used risk indicators and economic complexity. Another benefit of the WLMC is that it describes a single scale-time correlation in the heat map of a single set of multiscale interactions (Zhou et al., 2023). Subsequently, time-varying connectedness within the multivariate setting, which is decisive in our analysis, can offer a clear picture and is simple to apprehend. Due to its key advantages, the WLMC is a suitable and innovative tool to delve into the time-period connectedness between risk factors and economic complexity instead of other conventional wavelets or standard time series models. In addition, the present study uses global oil price volatility as a potential risk factor affecting economic complexity progress. The present study estimates the oil price volatility shocks using a GJR-GARCH time-varying conditional variance rather than using a given oil volatility index. This is the first empirical work using the WLMC to investigate the time-frequency domain

* https://www.imf.org/en/Publications/GFSR/Issues/2023/04/11/global-financial-stability-report-april-2023

connectedness among oil, economic and geopolitical risks, and economic diversification in Saudi Arabia. Our findings will benefit policymakers in introducing relevant and effective policies that will accelerate progress to higher economic sophistication.

The rest of the paper is structured as follows: Section 2 reviews the literature and identifies the research gap. Section 3 elaborates on the empirical methods and the used data. Section 4 relates to and discusses the results. Section 5 conveys the main conclusions, policy implications, and future research avenues.

2. LITERATURE REVIEW

Numerous scholars have studied the complex linkages between economic complexity, geopolitical risk, oil price volatility, and economic uncertainty. Prior studies mostly focus on a single factor in a distinct context. No studies in the existing literature have directly examined the coupled relationship between oil volatility, geopolitical risk, global economic uncertainties, and economic complexity. For this reason, we opted to divide this section into two sub-sections that will approach each relationship separately from theoretical and empirical perspectives.

2.1. Geopolitical Risk, Economic Uncertainty, and Economic Complexity Interplay

The interactions among geopolitical risk, economic uncertainty, and economic complexity have become a central issue for academics, scholars, and policymakers investigations. Studies for instance, Lee and Wang (2021) assessed the impact of country risk on the economic complexity-income inequality for panel data of 43 countries from 1991 to 2016 using the finite-mixture model. The authors uncover that upgrading economic complexity positively correlates to low uncertainty and equal income distribution. Similarly, Ogbuabor et al. (2023) investigated the impact of terrorism and economic uncertainty on economic complexity and the moderating role of institutional governance for a panel of 33 African economies using the GMM method. They documented the negative impact of terrorism and economic uncertainty on economic sophistication levels in these countries. Institutional governance doesn't attenuate such an effect. In their study, Hoang et al. (2023) probed whether geopolitical risk and economic policy uncertainty threaten the economic complexity progress in the context of the abundance of natural resource rents. The authors reached mixed findings using a panel quantile method for two emerging and advanced economies samples. Economic policy uncertainty seems to disrupt the evolution of economic complexity, while geopolitical risk brings some opportunities for boosting economic complexity. Moreover, the effect of these three factors on economic complexity levels seems to vary substantially across quintiles and countries. In line with the study by Hoang et al. (2023), Avom et al. (2022) exhibited that the plethora of natural resources negatively influences economic complexity. They claimed that the resources-complexity nexus is affected by the type of democratic regimes and political ideology. Only one study by Sweidan and Elbarghati (2023) is focused on Saudi Arabia by investigating the differential impact of oil prices, geopolitical risk, and public spending on Saudi economic complexity. Using a standard ARDL model for data from 1970 to 2020 to Saudi data, the authors unveiled that geopolitical risks and oil prices hinder economic complexity over the short run, while their effect is insignificant over the long run. However, government spending is upgrading the economic sophistication levels. Based on these outcomes, Sweidan and Elbarghati (2023) highlighted the ability of the Saudi government to boost economic diversification.

2.2. Oil Volatility-Economic Complexity Nexus

Studies in the present strand of literature have been growing in tandem with the tremendous concern about economic sophistication. Numerous empirical studies concerned the relationship between energy price volatilities and economic complexities. Thus, various empirical methodologies were implemented to account for the non-linearity and asymmetry in the relationship between oil price volatility and the time path of economic complexity. Currently, we narrow our attention to the oil volatility-economic complexity nexus in the context of rich oil-exporting countries. For instance, 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 from 1965 to 2010. They uncovered that oil booms harm countries with low initial diversification levels and do not impact those initially diversified. Moreover, oil booms affect countries with very weak manufacturing sectors. Nusair (2016) used a non-linear distributed lag (NARDL) model to investigate the non-linear short and long-run relationships between real GDP and oil price volatility shocks in the Gulf Cooperation Council (GCC) countries. Their results point out asymmetries. Positive oil shocks exhibit a stronger impact than negative shocks. However, the author has yet to explore the impact of economic diversification. Quite similar conclusions were reached by Jawadi and Ftiti (2019), who explored the impact of oil price volatility on Saudi economic growth using an on/off threshold regression approach. They documented substantial non-linearity and asymmetry in the oil-GDP-diversification interactive relationships and established the contribution of the oil sector to economic growth. These outcomes corroborate those provided by Trabelsi (2017), who showed that Saudi economic sectors' performance responds asymmetrically to oil price volatilities.

Sweidan (2020) utilized the standard Granger causality and panel cointegration tests to investigate the connectedness between oil price volatility and economic diversification in GCC countries from 1989 to 2017. The author pointed out a significant causality between oil price volatility and GCC economic diversification levels. 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 author 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 non-oil economy in the United Arab Emirates using a coupla framework. The authors uncovered that the service sector is the most resilient to oil negative shocks. In a more recent paper, Sweidan and Elbargathi (2023) investigated the impact of geopolitical risk, oil volatility, and government spending on economic diversification for Saudi Arabia using a standard ARDL model and data spanning from 1970 to 2020. The authors uncover that oil and geopolitical uncertainty are hiding economic diversification over the long run while their short-term effects are substantially low.

The aforementioned debate shows that only a few studies were concerned with the impact of geopolitical risk, global uncertainties, and economic complexity dynamics in rich-oil countries and they failed to reach unanimous conclusions. The present study delves into this topic, offers new insights into the oil volatility-uncertainty-economic complexity nexus, and extends our understanding of how and to which extent global risk factors are linked to economic complexity progress in a rich and oil heavily dependent economy. It fills the gap in the literature and contributes to the existing research in several ways. First, as far as we know, the combined effect of oil price volatility and local and global uncertainties on economic complexity has never been understandably tackled. Only two studies by Sweidan and Elbargathi (2023) and Hoang et al. (2023) are pinpointed in the existing literature. Sweidan and Elbargathi (2023) investigated the impact of geopolitical risk, oil prices, and government spending on economic diversification in Saudi Arabia. The present study distinguishes itself from prior studies in various aspects. When comparing our study to Sweidan and Elbargathi (2023), we perceive that this study has yet to consider the joint effect of these three factors on economic sophistication. In addition, the authors used a linear ARDL model, meaning that both asymmetry and non-linearity were not considered. Also, this research did not account for the time-frequency varying pattern of the interrelationships. Furthermore, the authors measure economic diversification using the Herfindhal-Hireschman index. At the same time, the present paper refers to the economic complexity (ECI) index elaborated by Hidalgo and Haussmann (2009) which assesses a country's productive structure that integrates information concerning the sophistication of the export products. In addition, the authors refer to oil spot prices and do not estimate the oil volatility shocks. To answer the question: "How do economic policy uncertainty, geopolitical risk, and oil rents affect economic complexity"? Hoang et al. (2023) employed panel quintile regression to a sample of 19 emerging and advanced economies. Again, the authors did not account for the time-frequencies in the risk factors-economic complexity relationship. In addition, the research is concerned with oil rents and not oil volatility shocks. To fill such gaps in the literature, the present study investigates the dynamic connectedness between some risk factors such as global economic, political, and geopolitical risks and oil volatility shocks and the progress of economic complexity in Saudi Arabia. Doing that, we resort to the novel wavelet local multiple correlation method suggested by Polanco-Martínez et al. (2020). Such a technique allows us to test the combined effect of risk indicators and oil shocks on economic sophistication in the time-frequency domain and therefore to account for asymmetry, non-stationarity, and non-linearity in the various pairwise relationships. In addition, while other studies used oil price time series to investigate the oil impact on economic complexity, the present study estimates the oil price volatility shocks using the time-varying GJR-GARCH model conditional variance. Such volatility metric accounts for the major stylized facts of oil price volatility shocks.

3. METHODS AND DATA ANALYSIS

In this section, we first explore the WLMC correlation suggested by Polanco-Martínez et al. (2020), then present the time series used in the analysis and their stochastic properties.

3.1. The Wavelet Local Multiple Correlation Method

This sub-section exposes the WLMC approach suggested by Polanco-Martínez et al. (2020). The WLMC is implemented using a freely R computer software called *Wavemulcor*. The R codes are offered with all technical instructions to carry out the WLMC analysis. Following Polanco-Martínez et al. (2020), we present the local multiple regression, which serves as the foundation of the WLMC approach, and then we introduce the wavelet local multiple correlation and its estimation.

3.1.1. The local multiple regression

The local multiple regression idea serves as the base of the WLMC. Let's consider X as a (n) multivariate time series dimension observed at time $t = 1,\ldots,T$ According to Fernández-Macho, (2018), $x_i \in X$, a local regression at a fixed s $\in \{t = 1,\ldots,T\}$ can be used to minimize the weighted sum of squared errors as follows:

$$S_s = \sum_t \theta(t-s)\left[f_s\left(X_{-i,t}\right) - x_{i,t}\right]^2 \tag{1}$$

Where $\theta(x)$ refers to a given moving average weight function depending on the time lag between X_t and X_s f_s (X_{-i}) designate a local function of $\{X/x_i\}$ around . If we let *(s)* vary along time, then the local coefficients of determinations will be equal to:

$$R_s^2 = 1 - \frac{RwSS_s}{TwSS_s}, (s) = 1,\ldots T \tag{2}$$

In the above Eq., RwSS_s and TwSS_s in the above Eq. refer to the residual and the total weighted sum of squares, respectively.

3.1.2. The wavelet local multiple correlation

Let's consider that $W_{jt} = (w_{1jt}, w_{2jt}, \ldots, w_{njt})$ are the wavelet coefficients for scale λ_j, with $j = \{1,2,\ldots,J\}$ and J denotes the maximum level of the wavelet transform decomposition using the maximum overlap discrete wavelet transform (MODWT) to each of the used time series $x_i \in X$, $i = \{1,2,\ldots,n\}$. According to Fernández-Macho, (2018), the wavelet local and multiple correlations $(\rho_{X,s}(\lambda_j))$, corresponding to a given scale λ_j can be estimated as the square roots of the regression coefficients of determination (Eq. 2) for that linear combination of variables w_{ij}, $i = \{1,2,\ldots,n\}$. Where such determination maxima coefficients. Subsequently, from Eq. (2) we get:

$$\hat{\rho}_{X;s}\left(\lambda_j\right) = \sqrt{R_{js}^2}\,;\; j = \{1,2,\ldots,J\}\,; s \in \{t = 1,\ldots,T\} \tag{3}$$

On the other hand, the coefficient of determination $R2$ in the regression of zi on the remaining variables of the system is equivalent to the square correlation between the observed and the generated $\hat{z}_i$ from such regression. Fernández-Macho, (2018) stated that a consistent estimator of the WLMC can be expressed as follows:

$$\hat{\rho}_{X;s}\left(\lambda_{\mathrm{j}}\right) = Corr\left(\theta\left(t-s\right)^{\frac{1}{2}} w_{ij}, \theta\left(t-s\right)^{\frac{1}{2}} \hat{w}_{ij}\right), s \in \left\{t = 1, \ldots, T\right\} \tag{4}$$

In Eq. (4), w_{ij} is chosen so that its multiple local regression on the regressors $\{w_{ij}, k \neq j\}$ maximizes the associated determination coefficients and $\hat{w}_{ij}$ designate the associated vector of fitted values of w_{ij} (Polanco Martínez et al., 2020, p. 7)

Methodically, we follow three succeeding steps (see the chart flow in Figure 1b) to carry out the WLMC analysis between geopolitical risk, oil volatility, global economic uncertainty, and economic complexity. First, we resort to the GJR-GARCH model to estimate oil price volatility. We consider the time-varying GJR-GARCH conditional variance as a proxy of oil price volatility over the sample period. Secondly, we proceed to dataset visualization and statistic descriptions regarding stationarity, non-linearity, and normality. Finally, we put the WLMC method into operation. In doing so, bivariate, tri-variate, and four-variate scenarios are explored. For each scenario, the WLMC heat maps are plotted and correspondingly analyzed.

3.2. Data and Preliminary Analysis

3.2.1. Datasets

To perform our analysis of the time-frequency connectedness between economic complexity, geopolitical risk, oil price volatility, and world uncertainty we collect quarterly data for Saudi Arabia covering the period 1995Q1-2021Q4. The time series are gathered from various sources. As for the geopolitical risk (GPR), we refer to the GPR suggested by Caldara and Iacoviello (2018). The GPR index time series were collected from Caldara and Iacoviello's (2018) database (http://matteoiacoviello.com/). Geopolitical events-related news is used as the basis of the GPR index. The index replicates the outcomes extracted from the automated text search of 11 international and U.S. national newspapers' electronic archives chosen by the above authors. The geopolitical risk-related words in each newspaper are counted daily to calculate the daily GPR index. When it comes to economic and political uncertainty, we resort to the World Uncertainty Index (WUI) suggested by the International Monetary Fund (Ahir et al., 2022). The WUI distinguishes itself from other uncertainty indicators such as the Economic Policy uncertainty index (EPU) by the fact that it captures uncertainty related to economic and political developments over the short and long term. The index is built for 143 countries every quarter from 1952 using the Economist Intelligence Unit (EIU) country reports. Similar to the GPR and EPU measures, the WUI index is constructed by compiling EIU reports and counting the number of times the words "uncertain", "uncertainty" and "uncertainties" are mentioned. Then, the raw counts are scaled by the total number of words in each report. Compared to the EPU index and other volatility measures, the WUI is based on a single source following a standard process having a particular topic related to economic and political uncertainties, while the EPU uses quite a similar compilation method but uses various sources (Ahir et al., 2022, p.5). Accordingly, the WUI is found to be significantly and positively correlated to EPU (0.75), stock volatility index (0.43), and bond index (0.53). For Saudi Arabia, the WUI time series was collected from the FRED-St Louis Economic Research database (https://fred.stlouisfed.org/series/). The economic diversification is approximated by the economic complexity index (ECI) designed on a country basis by the *GrowthLab* of Harvard University (https://atlas.cid.harvard.edu/countries/188). The underlying idea of the ECI is that higher diversified economies tend to diversify their exports that on average have low ubiquity, simply because only a few economies can produce these sophisticated goods (Hartmann et al., 2017). Conversely, less sophisticated economies tend to produce few ubiquitous products. Based on inherent changes in export diversities and the ubiquity levels, Hidalgo and Haussmann (2009) created a measure of a country's productive structure that integrates information concerning the sophistication of the export products.

3.2.2. Stochastic properties of the time series

We collect annual data from the Saudi country profile for the period 1995-2021. ECI is an index designed by Hidalgo and Hausmann (2009) to assess the productive structure of a given economy. The index reflects information about the degree of economic diversification and comparative advantages and the uniqueness of a given product (Hidalgo and Hausmann, 2009). A high ECI reflects a highly diversified, sophisticated economy and a lower ubiquity of exports. The ECI index is available within a yearly frequency. It is worth noting that ECI is only available within a yearly frequency. So, the time series was converted into quarterly frequency using the quadratic much sum method (Lahiani, 2018; Shahbaz et al., 2019; Arshian et al., 2020 and Waheed et al., 2020). For the oil prices, we collect monthly average oil prices from the World Bank Price database (https://pubdocs.worldbank.org/). Prices are expressed in nominal US dollars. The common sample period for GRP, Oil, WUI, and ECI period goes from 1995: q1- 2021: q4.

Figure 1c reports the time-movements of the selected variables over the whole sample period. For the oil, price volatility was approximated by the time-varying conditional variance extracted from a GJR-GARCH specification. Estimations' details of the GJR-GARCH modelling are reported in the data preliminary analysis sub-section. As we see, two types of volatility spikes can be identified. Some small spikes occurred in the periods of 1995-2007, whether starting from 2008, and other huge spikes in terms of conditional variances appear to have surged again occurred during the periods 2008-09 (2008-09: global financial crisis); mid-2014-16 (biggest drop in oil price history); 2020-2021 (Covid-19 health crisis) and 2022-23 (Russia-Ukrainian War). When looking at the WUI time path, we observe that the index is extremely volatile and it is to some extent moderately synchronized with the GPR. We can note that the WUI spikes near the 9/11 attack, the Gulf War, the 2008 global financial crisis (GFC), the euro debt crisis, the 2016 US election, and the Covid-19 health crisis. The GPR index shows substantial volatility during the whole sample period with various spikes around extreme events in Saudi Arabia or the Middle East region (Khobar terrorist attacks on June 1996, the Iraq war in 2003, the Arab Spring in 2011, military involvement of Saudi Arabia in Yemen, in March 2015, the terrorist attacks on Saudi oil facilities on march 2022, the diplomatic conflict and geopolitical tensions between Saudi Arabia and Qatar on June 2017, the hostilities between Saudi Arabia and Iran, the Syrian civil war, the covid-19 outbreak, and the ongoing Russia-Ukraine military conflict, the political unrests in Egypt and Libya as well as the recent covid-19 outbreak. The descriptive statistics of the used time series are conveyed in Table 1.

Figure 1b, reports the time-movements of the selected variables over the whole sample period. For the oil, price volatility was approximated by the time-varying conditional variance extracted from a GJR-GARCH specification. Estimations' details of the GJR-GARCH modelling are reported in the data preliminary analysis sub-section. As we see, two types of volatility spikes can be identified. Some small spikes occurred in the periods of 1995-2007, whether starting from 2008, and other huge spikes in terms of conditional variances appear to have surged again occurred during the periods 2008-2009 (2008-2009: global financial crisis); mid-2014-2016 (biggest drop in oil price history); 2020-2021 (Covid-19 health crisis) and 2022-2023 (Russia-Ukrainian War). When looking at the WUI time path, we observe that the index is extremely volatile and it is to some extent moderately synchronized with the GPR. We can note that the WUI spikes near the 9/11 attack, the Gulf War, the 2008 global financial crisis (GFC), the euro debt crisis, the 2016 US election, and the Covid-19 health crisis. The GPR index shows substantial volatility during the whole sample period with various spikes around extreme events in Saudi Arabia or the Middle East region (Khobar terrorist attacks on June 1996, the Iraq war in 2003, the Arab Spring in 2011, military involvement of Saudi Arabia in Yemen, in March 2015, the terrorist attacks on Saudi oil facilities on march 2022, the diplomatic conflict and geopolitical tensions between Saudi Arabia and Qatar on June 2017, the hostilities between Saudi Arabia and Iran, the Syrian civil war, the covid-19 outbreak, and the ongoing Russia-Ukraine military conflict, the political unrests in Egypt and Libya as well as the recent covid-19 outbreak.

The descriptive statistics of the used time series are conveyed in Table 1. From these statistics, we note that the two uncertainty indexes (GPR and WUI) exhibit the highest mean values. Oil price volatility and ECI have very low averages. The ECI is the most volatile with a standard deviation of 0.43 followed by GPR. This latter exhibits higher volatility than WUI. The skewness statistic is positively signed for all the time series indicating that the distributions have tails that are more pronounced to the right (platikurtic). Furthermore, the highest kurtosis value is observed for the oil volatility time series, which means that most conditional variances are located in the tails of the distribution and not around the mean. This is consistent with Figure 1 showing substantial spikes of oil volatility around the period mid-2014-2016 and the covid-19 outbreak. The Jarque Bera test values are statistically significant and strongly reject the assumption of the Gaussian distribution. Figure 2 plots the distribution details of the used time series. In Table 2, we report the pairwise unconditional variances

Table 1: Descriptive statistics

Statistics	ECI	GPR	Oil-volatility	WUI
Mean	0.0063	0.2153	0.0078	0.1108
Maximum	0.8200	0.6300	0.00573	0.4641
Minimum	−0.8700	0.0360	0.00418	0.0000
SD	0.4365	0.1377	0.0082	0.0992
Skewness	0.0032	1.0118	4.4696	0.9117
Kurtosis	2.2534	3.4391	25.3196	3.8339
Jarque-Bera	2.5082***	19.29***	26.01***	18.32***
Probability	0.2800	0.0000	0.0000	0.0000

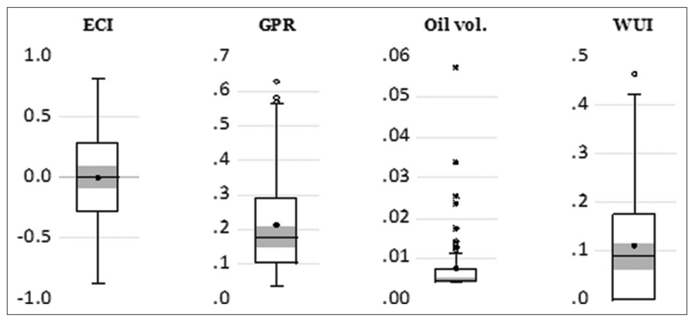
***Designates the significance level of 1%. SD: Standard deviation, ECI: Economic complexity index, GPR: Geopolitical risk, WUI: World uncertainty index

Table 2: Pairwise unconditional correlations

Variables	ECI	GPR	Oil-volatility	WUI
ECI	1			
GPR	0.35***	1		
Oil-volatility	0.229***	0.08	1	
WUI	0.153*	0.143*	0.22***	1

*, ** and ***Designate, respectively, the significance levels of 1%, 5%, and 10%. Oil volatility is approximated by the time-varying conditional variance of the GJR-GARCH (1, 1) model for oil price changes. ECI: Economic complexity index, GPR: Geopolitical risk, WUI: World uncertainty index

Figure 2: The box plot



between the time series. From these correlations, we perceive that the ECI is positively and significantly correlated to the three risk factors: GPR (0.35) and oil. Vol. (0.229) and WUI (0.15). The lowest correlation is observed for the WUI. Furthermore, oil price volatility is moderately and positively correlated to WUI, which could be explained by the fact that oil volatility may be perceived as a major component of world economic and political uncertainty since Saudi Arabia is the world's top oil exporter and a leading member of OPEC+. However, the volatility of oil prices is not significantly correlated with geopolitical risk. The GPR index risk is positively and moderately correlated to WUI.

3.2.3. The oil price volatility shocks

Here, the GJR-GARCH model is employed to estimate oil price volatility. Since the publication of Engle's (1982) seminal paper, the GARCH-class models have been extensively used to model the time-varying behavior of asset volatilities. Numerous GARCH-class specifications are estimated to take into account the main stylized facts of oil price volatility, such as the IGARCH, TGARCH, CO-GARCH, EGARCH, FI-EGARCH, FI-APARCH, and FI-GARCH. In the present study, we use the GJR-GARCH model by Glosten et al. (1993) to model oil price volatility. The main feature of the GJR-GARCH specification is the account for the commonly observed facts of oil price changes in time series, which is the stronger effect of lagged negative shocks on the variance compared to positive shocks known as the *"leverage effect."* The increased risk is assumed to emerge from the increased leverage induced by negative shocks. In the GJR-GARCH model, unlike positive shocks, a huge negative change in negative shocks is followed in the oil price time series.

The following mean equation denotes our model:

$$r_t = \mu + \Psi r_{t-1} + \varepsilon_t \; \varepsilon_t = z_t h_t \tag{5a}$$

$$z_t \sim N(0,1) \tag{5b}$$

r_t implies a vector of the logarithmic return returns. μ is a constant vector with (n) as length. The autoregressive coefficients are represented by vector Ψ, while $\varepsilon_t = [\varepsilon_{i,t}, \ldots \varepsilon_{n,t},]$ indicates the residual errors' vector. Accordingly, the GJR-GARCH (1,1) model's conditional variance, ($h_{i,t}^2$) is written as follows:

$$h_{i,t}^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1} \tag{6}$$

The following model defines a multivariate indicator vector that allows negative and positive volatility shocks to have asymmetric effects (Glosten et al.. 1993), which goes as follows:

$I_{t-1} = (1, if\ \varepsilon_{t-1} < 0, 0 \text{ otherwise})$

The estimated parameter (γ) refers to the leverage effect (i.e., the effect of both negative and positive volatility shocks). A positive value would indicate a greater impact of negative shocks than positive ones. According to Glosten et al. (1993), if the parameters in the above equation guarantee the following constraints: α, β and γ≥0, ω>0, and $\gamma + \frac{\alpha + \beta}{2} < 1$ Then, the conditions of positivity and stationarity in the volatility process are satisfied. Table 3 reports the GJR-GARCH estimations' results. Panel A shows the parameters' estimations, while diagnostic test results are reported in Panel B. From these outcomes, we note that the autoregressive parameter is positively signed and significant in the oil price mean equation. When scrutinizing the GJR-GARCH conditional variance equation, we notice that the ARCH/GARCH estimated parameters are positive and significant indicating the existence of ARCH and ARCH effects in oil price volatility. Furthermore, the sum of these parameters is lower than one, which means that the unconditional variance of the percentage change in oil prices can be defined, and shocks to the conditional variance of the oil price returns will not be persistent. Moreover, the estimated parameter of GJR is found to be positive and statistically significant, which implies that the variables have an asymmetric response to volatility shocks. This supports the goodness fit of the GJR-GARCH specification to model oil price volatility. Finally, the diagnostic tests indicate no autocorrelations of the squared residuals as shown by the Ljung-Box statistic. The LM-ARCH test grants the absence of remaining ARCH effects in the residual time series. Therefore, these outcomes show the appropriateness of the standard GARCH specification to generate the conditional variance which is used as a proxy for volatility oil prices.

3.2.4. The non-linearity BDS test

Here, we implement a non-linearity test to explore the non-linear serial dependence in the time series. Doing that, we refer to the BDS test suggested by Brock et al. (1996). From these test results (Table 4), we reject the null hypothesis that the time series are linearly dependent. The BDS test statistics are strongly significant for all the time series under all the selected dimensions. This outcome corroborates the normality test results and reveals that the time series does not follow a normal distribution. This result supports using the WMLC as a non-linear framework because using a linear approach may result in erratic outcomes, which lead to erroneous policy formulations.

4. EMPIRICAL RESULTS

4.1. The Bivariate Scenario GPR, Oil vol., and WUI

As highlighted earlier, we use the WLMC method to assess the time-frequency co-movements between GPR, WUI, Oil vol., and ECI. Here, we are concerned with the bivariate case. The WLMC is used for the multivariate case (n ≥ 2). Figure 3 reports the WLMC heat maps for all the pair-wises. It is worth noting that the WLMC heat map shows the strength of the correlation and its behavior across time scales and periods (frequencies). To make the WLMC's interpretation straightforward, it is worth noting that the bar color (right side) shows the strength of the correlation, whereas the red color indicates a strong positive correlation, while the blue one refers to a strong and negative correlation. The periods are expressed in quarters and are reported on the left side. In the present study, three periods are considered [2-4], [4-8] and [8-16] quarters. Following Martínez et al. (2020) and Zhou et al. (2023), we presume that periods below [2-4] quarters may reflect short-term behavior, while [4-8] and [8-16] periods reflect mid and long-term behaviors, respectively.

Table 3: GJR-GARCH estimations results

Panel A: GJR-GARCH estimates	
Cst. (m)	0.005 (0.95)
AR (1)	0.233*** (4.79)
Cst.(v)	0.004*** (5.25)
ARCH (1)	0.04*** (3.66)
GARCH (1)	0.66*** (3.11)
GJR (γ)	0.173*** (2.89)
Panel B: Test diagnostics	
Q (20)	10.3 (0.96)
ARCH (10)	0.56 (0.73)

*, **, and ***Refer to significance at the 1%, 5%, and 10% levels. Q (20) shows the Ljung-Box test statistic of the squared residuals at length (20). The calculated t-student statistics are shown in parentheses, while the *P* values are shown between brackets

Table 4: BDS test results

Dimension	Oil-volatility	GPR	WUI	ECI
2	13.78***	6.29***	9.29***	32.19***
3	10.77***	7.54***	9.77***	32.66***
4	10.05***	7.77***	10.41***	33.38***
5	9.10***	8.35***	15.51***	35.19***
6	9.77***	8.73***	15.43***	37.74***

***Refers to significance at a 1% level. ECI: Economic complexity index, GPR: Geopolitical risk, WUI: World uncertainty index

Figure 3: The WLMC heat-maps: bivariate scenarios GPR, Oil vol., and WUI. (a) Oil vol. versus GPR, (b) WUI versus GPR, (c) Oil vol. versus WUI

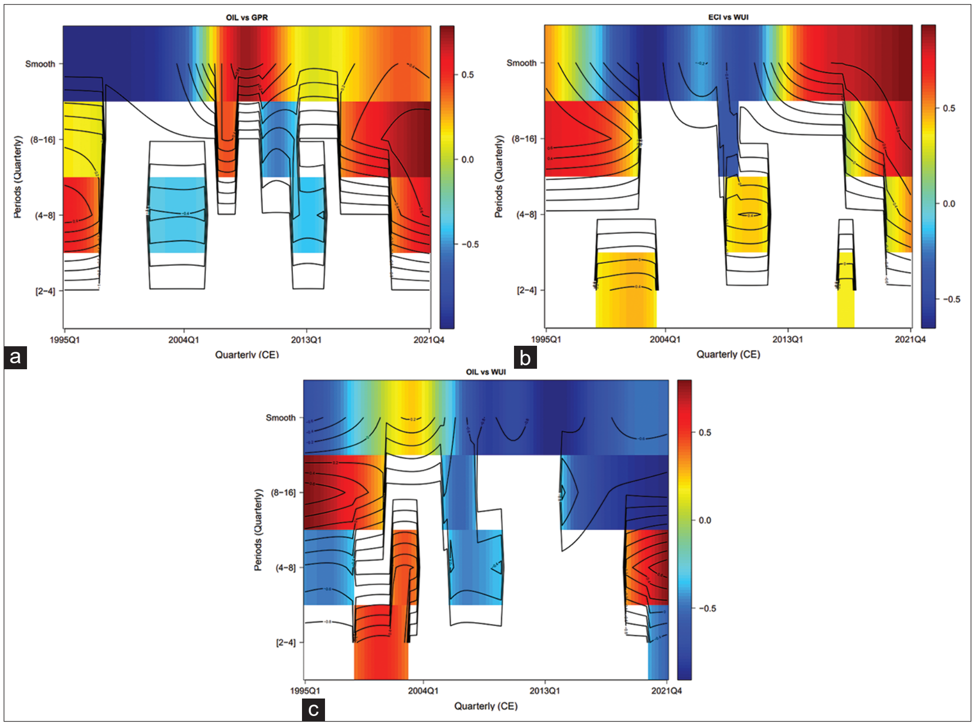


Figure 3 reports the wavelet local multiple heat map (bivariate case) for the three regressors oil vol., GPR, and WUI. The white-colored intervals (periods) indicate that the correlation is not significant at the 5% level. The wavelet filter is set as (wf) = "la8"

Figure 3a reports the WLMC for Oil vol. and GPR. The visual inspection of this heat map reveals that Oil vol. and GPR connectedness substantially vary over time scales and periods (frequencies). For instance, the WLMC shows that oil-GPR correlation is negative (CV*<−0.5) over the 6-10 quarters' periods during the sub-periods 2003Q1 -2004Q2 and 2012Q3 - 2013Q2. In addition, an interval of yellow color emerges during the commencement of the sample period 1995Q1-1998Q3 over the long run ([12-24] quarters' frequency). Two other intervals of red colors (i.e., high positive correlation) are spotted during the sub-periods 1995Q1-1998Q3 over the 6-10 quarters' periods. The second interval is detected during the sub-period 2014Q2-2021Q4 over the mid-and long-run time horizons (6-24 quarters' periods). Taken as a whole, these patterns disclose that the Oil vol.-GPR correlations considerably vary across time scales and periods. These outcomes corroborate the Spearman correlation result in the sense that the Spearman correlation is very weak (CV = 0.08). Still, this apparent weak correlation is a sample average and therefore ignores the time-periods varying pattern of the correlation. Our findings are consistent with Wang et al. (2022) who revealed a sizeable change in the oil-GPR correlations over time scales and frequency bands (investment horizons) using the standard wavelet coherence method for data covering the period 1997-2019. Quite similar findings are found by Ding et al. (2022), who investigated the impact of various sources of uncertainties, including GPR, on oil prices using quintile-quintile- -regression (Q-Q) and wavelets transform techniques. They revealed that both causality directions and correlations change over periods and frequencies.

*	CV: correlation value

The time-periods connections for Oil-WUI are displayed in Figure 3c. As we see, Oil and WUI are strongly and negatively associated over the long run (above [8-16] quarters' frequency). However, their connectedness is generally insignificant over the short and mid-terms. In summary, despite their time-frequency varying correlations, GPR and WUI may be viewed as suitable risk indicators to predict oil price volatility. Similar findings are reached by Liu et al. (2019) and Yao and Liu (2023). When looking at the WLMC plot between WUI and GPR (Figure 3b), we observe that the two risk indicators correlated, but the strength and sign of their correlations substantially vary over time and frequencies. The two risk indicators are positively correlated over the [2-4] and [4-8] quarters' bands, with values ranging between 0.4 and 0.7 for only three sub-periods. For the remaining sub-periods, the periods are pointed in blank, meaning their correlation is insignificant at the 5% level. Over the long run [8-16] quarters' frequencies, the power and the sign of correlations vary over time and frequencies. The correlation is negative (CV < −0.5) during the period 2000Q1-2013Q2 and turns out to be positive (CV > 0.5) for the rest of the sample period. The time-periods connections for Oil-WUI are displayed in Figure 3c. As we see, Oil and WUI are strongly and negatively associated over the long run (above [8-16] quarters' frequency). However, their connectedness is generally insignificant over the short and mid-terms. In summary, despite their time-frequency varying correlations, GPR and WUI may be viewed as suitable risk indicators to predict oil price volatility.

4.2. The Trivariate Scenario for Oil vol., GPR, WUI

Here, we explore the WLMC for the three-variate scenario. The heat map is conveyed in Figure 4. Following Polanco-Martínez

Figure 4: WLMC heat-map for the tri-variate scenario GPR, Oil vol., and WUI

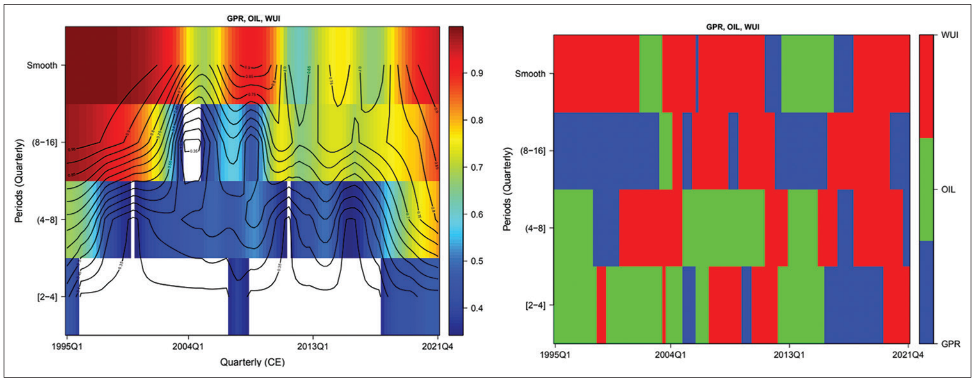


Figure 4 reports the WLMC heat map: three-variate scenario GPR-Oil vol. and WUI. The white-colored intervals (periods) indicate that the correlation is not significant at the 5% level. The wavelet filter is set as (wf) = "la8"

et al. (2020), we let the WMLC select a variable instead of determining on (parameter ymaxr=NULL) which maximizes the multiple correlations for each wavelet scale. The main raison for that is the fact that regardless of the fact it is expected that some of the selected time series will be linked it is however undiscovered how these time series are interrelated to each other across over time scales and periods' bands. WLMC heat map is reported in Figure 4 (left side). The strength of the correlation is considerably varying over time scales and periods. Over the [8-20] quarters' period and throughout the whole sample period, the correlation is strong and positive (CV > 0.7) except for the sub-period 2004Q1-2007Q3 (0.4<CV<06). It is worth noting that the WLMC configuration for a three-variate scenario is not typically similar to the bivariate scenario since the power of the connectedness is noticeably higher over the mid and long run. For the [6-10] quarters' periods, the strength of the WUI-GPR-Oil vol. correlation is lower and ranges from 0.5 to 0.7. However, over the short run, the correlations range from 0.3 to 0.6 with two large sub-periods of insignificant correlation. It is important to highlight that compared to the traditional multiple wavelet coherence methods, which is an *"exclusive"* method, the WMLC suggested by Polanco-Martínez et al. (2020) is an *"inclusive"* multivariate correlation approach which means it doesn't only account for significant correlations between dominant time series but considers all the other remaining significant correlations (Polanco-Martínez et al., 2020, p. 6). In our tri-variate scenario, the *"dominant"* variable that amplifies the multiple correlation and the one that can be used to describe the other variables over time scales and frequencies is pointed out by the WLMC (Figure 4) (right side). For the triplet, WUI, GPR, and oil vol., WUI is the *"dominant"* variable stalked to a slighter degree by Oil vol. This result may be because the construction of the WUI includes information inherent in the news-based GPR indicator.

4.3. The Bivariate Scenario between WUI, GPR, and oil vol. Versus ECI

Figure 5a displays the WLMC heat map between Oil vol. and ECI. The WLMC outcomes are consistent with the Spearman correlation test (Table 2). It shows weak to moderate correlations between the two-time series. The strength of the correlations varies not only over sub-periods but also across periods. Three areas of yellow color (CV < 0.5) of positive and moderate correlation are identified over the periods 1995Q1-1998Q3; 2012Q1-2016Q3 and 2020Q1-2021Q4 over [6-12] and [12-24] quarters' periods. Another area of relatively high and positive correlation (CV > 0.7) is isolated during the period 1995Q1-2004Q4 over the long run ([12-24] quarters' period). Taken as a whole, although the Oil vol.- ECI connection is incontestably varying over time scales and periods, it remains moderate and positive. This means that oil price volatility is positively correlated to economic sophistication in Saudi Arabia. This outcome shows the resiliency of the Saudi economy to oil volatility shocks. To delink the economy from oil volatility shocks, Saudi Arabia has diversified the energy sector through investment in upstream and downstream industries as well as in energy-intensive industries such as petrochemicals, aluminium, and fertilizers, where it has a comparative advantage (Mishrif, 2018). Moreover, while countries heavily reliant on oil, have found it difficult to diversify their economies, Saudi Arabia started implementing the 2030 vision policies to reduce the economic dependence on oil by expanding the non-oil industries that can help to bear up the oil price volatility shocks.

Figure 5b and c report the WLMC heat map for the pair-wises ECI-WUI and ECI-GPR respectively. Here, we explore the dynamic correlation between political, economic, and geopolitical uncertainties and the degree of economic sophistication. When inspecting these heat maps, we perceive that we get typically the same configurations in terms of the strength and dynamics of the correlations over time scales and frequencies (periods). When looking at the WUI-ECI WLMC heat map, we note that over the long run (higher than 16 quarters' period, WUI is strongly and positively correlated to ECI (CV > 0.5), which means that higher world uncertainty may result in higher levels of economic sophistication. Conversely, over the short and mid-term horizons the correlation pattern changes. For instance, the correlation is positive and low (CV < 0.5) during the sub-period 1995Q1-2003Q3, and 2016Q1-2021Q4 over the [6-20] and [6-12] quarters' periods respectively. In addition, a negative correlation is isolated during the end of the sample period (2020Q1-2021Q4 aver short and medium scales ([2-4] and [4-6] quarters' period). Overall, these results show that the ECI-WUI correlation is positive and high over the long term and substantially weak over short and mid-term scales which means that over the long run political and economic uncertainties may generate new opportunities for improving economic diversification. This outcome is consistent with Meng

Figure 5: The WLMC heat-maps: The bivariate scenario GPR, WUI, and Oil vol. versus ECI. (a) Oil versus ECI, (b) GPR versus ECI, (c) WUI versus ECI

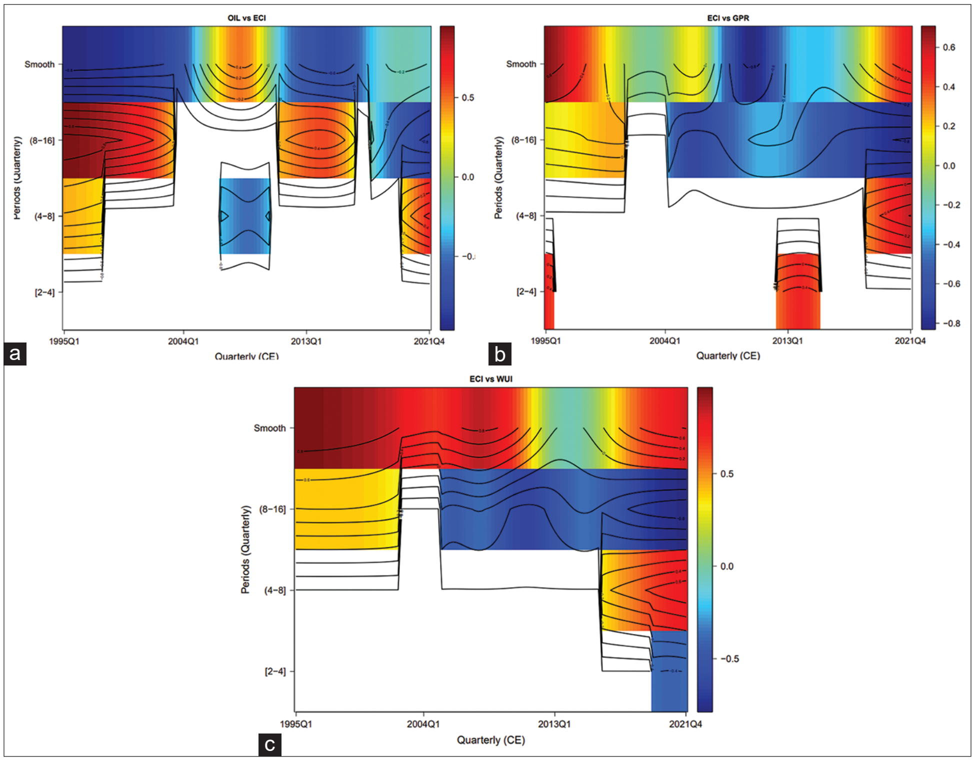


Figure 5 reports the wavelet local multiple heat map (bivariate scenario). The white-colored intervals (periods) indicate that the correlation is not significant at the 5% level. The wavelet filter is set as (wf) = "la8"

and Shi, (2017) and Wang et al. (2014) arguments. Accordingly, higher uncertainty is likely to stimulate research and innovation and develop investment in technology. In this vein, high levels of uncertainties may be viewed as an option for "*self-development*" or "*high risk-high return*" opportunities to upgrade economic sophistication. Conversely, this finding is incongruous with Hoang et al. (2023) empirical results. The authors found that economic uncertainty acts as a risk to the economic complexity progress when assessing the impact of EPU on ECI for a 20 sample of 20 emerging and advanced economies from 1997 to 2019. However, it is worth highlighting that the present study refers to WUI as a global uncertainty indicator, while Hoang et al. (2023) used the EPU index. Other curious outcomes emerge from the ECI-GPR WLMC heat map (Figure 3c). Over the long run (over [8-16] quarters' period), the strength and the sign of the correlation perceptibly vary throughout the entire sample period. Over the mid-and short scales ([2-4] and [4-6] quarters' periods, the correlation turns out to be positive and moderate (0.4<CV<0.7) during the sub-periods 1995Q1-1996Q2; 2012Q1-2014Q4; and 2019Q1-2021Q4.

4.4. The Trivariate Scenario between WUI, GPR, and Oil vol. Versus ECI

The WLMCs plots between the selected time series (WUI, GPR, and Oil vol.) concerning ECI are displayed in Figure 6. In this tri-variate scenario, we choose the ECI as the dependent variable (ymaxr=ECI). We implement the tri-variate wavelet correlation between each pair-wise and ECI. Our main purpose is to analyze further the strength and the dynamics of the joint effect of two selected variables (for example, Oil vol. and WUI) on the ECI in the time-frequency domain. Figure 6a shows the WLMC between Oil vol. and WUI versus ECI. As we see, Oil vol. and WUI are strongly and positively correlated (CV > 0.7) to ECI over the long run (above the 12 quarters), which means that, over the long run, oil price and global economic and political uncertainties have a combined positive effect on the degree of economic complexity in Saudi Arabia. However, their joint effect is considerably lower and sometimes insignificant in the short and mid-run. More precisely, for the [2-4] and [4-8] quarters' periods, the correlations range between 0.3 and 0.6 and turn out to be insignificant for large sub-periods (for example, 2004Q1-2011Q2). A quite similar pattern is observed in Figure 6b showing the wavelet tri-variate scenario between GPR and WUI versus ECI. This outcome discloses that geo, economic, and political uncertainties have no significant effect on economic complexity over the short and mid-run. Their upgrading effect is evidenced only over the long run. Overall, these outcomes reveal that in the face of global uncertainties, Saudi Arabia stands out for its economic diversification efforts that are compelled by the 2030 strategic vision, resulting in an expansion of investments regardless of the prevalent anxieties regarding global geo, economic, and political uncertainties.

4.5. The Fourvariate Scenario for Oil vol., GPR, and WUI Versus ECI

Figure 7 shows the WLMC heat map for the four variate cases. It highlights the joint effect of Oil vol., GPR, and WUI on the dynamics of ECI in the time-periods domain. In this case, the economic complexity index is chosen to be the dependent variable. Several appealing comments emerge from the heat-map

Figure 6: WLMC heat map for the tri-variate scenarios. (a) WLMC: Oil vol., WUI versus ECI, (b) WLMC: GPR, WUI versus ECI

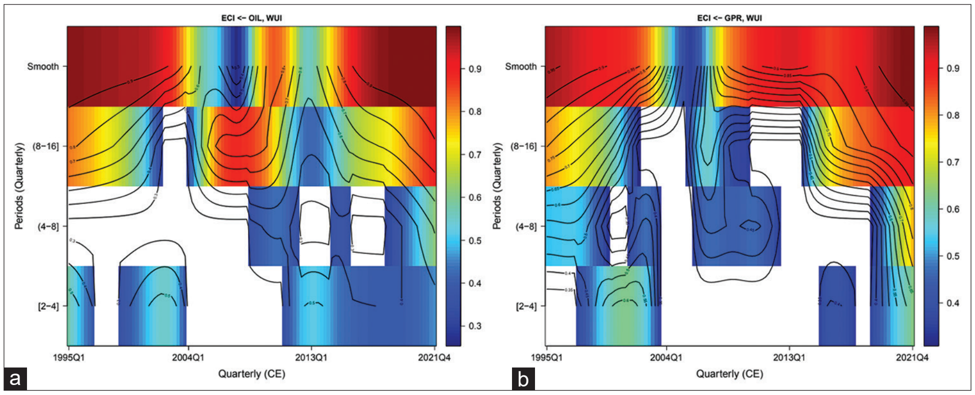


Figure 6 reports the WLMC heat maps for the tri-variate scenario between GPR, Oil, and WUI vs. ECI. The white-colored intervals (periods) indicate that the correlation is not significant at the 5% level. The wavelet filter is set as (wf) = "la8"

Figure 7: The WLMC heat-map for the four-variate case: Oil vol., GPR, WUI versus ECI

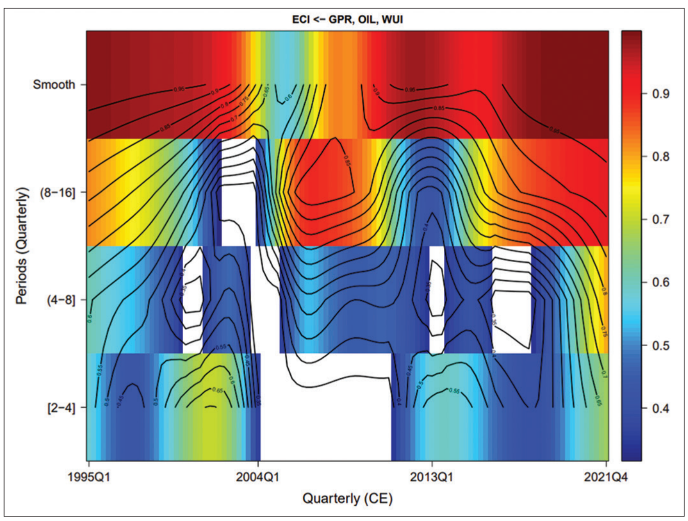


Figure 7 reports the WLMC heat map (four-variate scenario) for Oil vol., GPR, WUI vs. ECI. The white-colored intervals (periods) indicate that the correlation is not significant at the 5% level. The wavelet filter is set as (wf) = "la8"

visual inspection. Firstly, when taken as a whole, oil vol., GPR, and WUI are strongly and positively correlated to ECI over the long run (above [8-16] quarters' period) where the correlation value is higher than 0.8. This positive connection is present nearly the entire sample period. This multivariate outcome is consistent with the bivariate WLCM analysis for the tri-variate scenario (Figure 6a and b). From an economic perspective, this result shows that over the long run, uncertainties inherent to geopolitics, politics, and economics as well as oil price volatilities are considered risk factors upgrading the economic complexity in Saudi Arabia. This finding is to some extent inconsistent with Hoang et al. (2023) conclusions. For these authors, geopolitical risk promotes economic sophistication, while economic policy uncertainty is found to be a threat to the economic complexity process. Furthermore, Hoang et al. (2023) show that the impact of geopolitical risk, economic policy uncertainty as well and natural resources rents on economic complexity for emerging and advanced economies is heterogeneous across countries and quintiles. Secondly, when scrutinizing shorter frequencies (periods), [2-4] to and [8-16] quarters' periods, we record a changing pattern of the correlation dynamics. More precisely, as far as we go for shorter periods, the correlation turns out to be low (0.3 < CV < 0.7) which means that the joint positive impact of GPR, WUI, and Oil vol. tends to decline over the short run. Thirdly, the WLMC heat map uncovers the existence of periods pointed in the blank (2004Q1-2010Q4) indicating that correlations were not significant at the 95% confidence level.

5. CONCLUSION AND POLICY IMPLICATIONS

Improving future economic growth via higher economic complexity is established to be vital for sustainable growth strategies. Even though most studies are concerned with the key factors steering the economic sophistication evolvement, there is scarce knowledge regarding the impact of risk factors on economic complexity progress. In this study, we scrutinized the dynamic interconnections between geopolitical risk, world economic uncertainties, oil price volatility, and economic complexity for Saudi Arabia using quarterly data covering the period 1995 Q1-2022 Q4. The key novelty is that the interrelationships are undertaken with bivariate and multivariate paradigms. In doing that, we resort to the novel WLMC method suggested by Polanco Martínez et al., (2020). Compared to traditional wavelets' methods including wavelet cross-correlation, bivariate, multiple, and partial wavelets, the WMLC assesses a time-varying correlation at various scales within a multivariate time series based on the square root of the regression coefficient of determination in a given linear combination of locally weighted wavelets coefficients (Polanco Martínez et al., 2020). It accounts for non-stationarity and non-linearity when exploring the correlations varying patterns over time scales and frequencies (periods). As far as we know this is the first empirical attempt to implement the WLMC to analyze the time-frequency connectedness between global risk factors and economic sophistication. Broadly speaking, our WLMC bivariate and multivariate analysis reveal that despite the time-frequency varying pattern of their interrelationships, oil price volatility, global geo, economic and political uncertainties, and economic sophistication are significantly and positively associated over the long run. While their short-term correlations are substantially lower and turned out to be insignificant for some episodes. We can conclude that global uncertainties may be perceived as risk factors upgrading the economic sophistication process in Saudi Arabia. Moreover, the WLMC outcomes disclose that the world economic and political uncertainties (WUI) play a *"dominant"* role among the regressors. Lastly, the multivariate wavelet results are to some extent corroborating their counterparts of the bivariate analysis showing that the selected variables are positively associated at high frequencies, although the strength of their correlations is weak at low frequencies.

The WLMC analysis results have several prominent policy implications for Saudi policymakers. We deem these findings useful as a good starting point to assess the efforts undertaken by Saudi authorities to boost economic diversification and attenuate its oil reliance. Results may also be beneficial to design strategic policies in the context of high geopolitical and economic uncertainties and oil volatilities to achieve sustainable growth within the 2030 strategic goals. The key implications, as well as the recommendations, are reported below. Our wavelet local multiple correlation exploration discloses that over the short and mid-terms, geopolitical risk, oil volatility, and economic uncertainty are positively correlated to economic diversification, and the strength of their connectedness largely increases over the long term. This result implies that the increase in geopolitical risk, economic uncertainties, or oil price volatility does not impede the improvements in economic diversification in Saudi Arabia. More importantly, the improvements in economic complexity levels are more distinct over the long run. This shows the resiliency of the Saudi economy over the long run and implies that despite the challenges and the increase of uncertainties in the world's economies and the intensification of the local and regional geopolitical risks, Saudi authorities are pursuing their undertaken efforts to improve economic diversification. Based on that, Saudi policymakers should benefit from this resiliency to promote the non-oil sector and pursue their efforts to develop other sectors showing high comparative advantages. Among these sectors, we Tourism, entertainment, sports, and culture sectors are examples of these sectors. The Saudi policymakers should pursue their efforts to consider these sectors as a priority under the 2030 economic diversification strategy. Increasing domestic household spending and investments in these sectors will transform the country into a major global travel destination in the region. In addition, boosting investments in energy-intensive industries such as petrochemicals, aluminium, and fertilizers, where Saudi Arabia has, a comparative advantage may help to attenuate the effects of oil shocks (Mishrif, 2018).

In keeping with this line of thought, the role of the private sector rises. Strengthening the private sector without relying on government expenditures and public projects and learning from other diversification experiences in similar rentier economies will undeniably help policymakers design and adjust their strategies to boost sustainability through higher economic complexity.

The present study adds to the economic complexity literature and offers some new insightful outcomes regarding the time-frequency connectedness between some risk factors and economic complexity. As with other studies, the present work has some shortcomings and therefore paves the way for future research avenues. First of all, this study offers contextual empirical evidence for Saudi Arabia as an oil-rich country due to Saudi Arabia's distinctiveness in terms of economic size, wealth, and the implementation of a new economic strategy (2030 vision). Thus, our findings cannot be generalized to other countries and it would be useful to conduct a similar approach for other economies of the Gulf Cooperation Council (GCC) region or other top oil exporters since they exhibit high business cycle synchronization (Aloui et al., 2016). Checking the relevance of risk factors as eventual drivers of economic complexity dynamics for large country samples would be very advantageous. Secondly, the present study focused on global risk indicators including geopolitical risk, world economic uncertainty, and oil price volatility as factors affecting economic complexity. Therefore, future investigations should consider other relevant risk factors such as financial stability, foreign direct investment, economic policy uncertainty, other commodity price volatilities, output volatility as well as other institutional and governance (economic transparency, corruption,…) factors as drivers/hinders of the economic sophistication progress. Lastly, matching the WLMC analysis outcomes to other standard wavelets including multiple wavelets, partial wavelets, rolling window wavelet correlations, and wavelet quintile correlation may offer new insightful findings to deliver more informative recommendations to academicians and policymakers.

6. FUNDING

This work was supported and funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (Grant number IMSIU-RG23046).

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