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Measuring the varying relationships between sustainable development and oil booms in different contexts: An empirical study

Yu Qian [a], Zeshui Xu [a], Yong Qin [a], Xunjie Gou [a], Marinko Skare [b,c,*]

[a] Business School, Sichuan University, Chengdu, 610064, China
[b] Juraj Dobrila Univ Pula, Fac Econ & Tourism Dr Mijo Mirkovic, Preradoviceva 1-1, Pula, 52100, Croatia
[c] University of Economics and Human Sciences Warsaw, Poland

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ABSTRACT

Sustainable development, as a global reform that takes into account economic, social and environmental aspects, requires a focus on energy activities, especially those of the oil industry, as they usually have varying degrees of impact on the three aspects mentioned. We, therefore, explore the nexus between sustainable development and oil booms based on data from 38 countries and seven specific countries (China, the USA, Russia, Norway, Brazil, Libya and Kuwait) between 1990 and 2019. First of all, the Bai-Perron tests confirm that structural changes in the oil production growth are more frequent, while the sustainable development index growth is relatively more stable. Then, we examine the performance of this nexus in different subperiods using the panel vector autoregression models and observe significant associations only in the subperiod 2012 to 2019. At last, we find that the Granger causalities and long-run dynamic relationships between sustainable development and oil booms are considerably different across economies in the vector autoregression estimations for each of the seven countries. In a word, the effect of oil production on sustainable development could be positive or negative over time and across economies, and there is no consistent conclusion, and vice versa. Thus, in the sustainable development practice and the green transformation of the oil industry, targeted strategies should be adopted according to the current development stage and the realistic background of specific objects.

1. Introduction

Sustainable development is a global change that is still in its exploratory phase, triggered by a shift in consciousness in human society during the process of pursuing scientific and technological advancement and economic growth. As defined in the Brundtland Report, sustainable development is “development that meets the needs of the present without compromising the ability of future generations to meet their own needs” (WCED, 1987). With a vision of a better future, numerous scholars have carried out rich academic studies on it. Du Pisani (2006) traced the historical roots of this concept while identifying the key elements of sustainable development that require balance and continuous improvement. Le Blanc (2015) and Hák et al. (2016) explored in detail the relevance of the indicators included in the system of Sustainable Development Goals (SDGs) proposed by the United Nations member states. In addition to conceptual reviews and theoretical discussions, there is a large body of sustainable development literature on specific scenarios and approaches, such as the impact of COVID-19 (Wang et al., 2021a), green infrastructure strategies (Ying et al., 2021; Qin et al., 2022), and the application of artificial intelligence (Vinuesa et al., 2020).

Through the existing research, we realize that the rapid rise in material standards following the industrial revolution, but at the cost of reckless resource consumption, has led to an environmental crisis that has caused panic around the world and forced a change in the original assumptions of economic and social development (Du Pisani, 2006). Moreover, we are also aware that the successful integration of “sustainability” and “development” depends on a delicate dynamic balance among three key factors of environment, economy and society (Nguyen and Ngo, 2021; Mentis and Moonsammy, 2022), which varies according to the needs of different economies at specific stages.

Against this backdrop, sustainable development initiatives are relatively more challenging for the energy sector, and at the same time the dynamics associated with energy extraction, production and

* Corresponding author. Juraj Dobrila Univ Pula, Fac Econ & Tourism Dr Mijo Mirkovic, Preradoviceva 1-1, Pula, 52100, Croatia
E-mail addresses: yuqian_echo@163.com (Y. Qian), xuzeshui@263.net (Z. Xu), yongqin_ahsc@163.com (Y. Qin), gou_xunjie@163.com (X. Gou), mskare@unipu.hr (M. Skare).

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consumption would have non-negligible impacts on the sustainable transition. As a typical representative of traditional non-renewable fossil fuels, oil remains a crucial and irreplaceable resource for the production and life of all countries/regions. Activities in the oil industry could not only have direct or indirect shocks to the national economy, but also have short- or long-term impacts on the natural environment.

The oil boom from the 1970s–1980s exerted enormous influence on the Nigerian economy, education, agriculture, commerce and many other aspects (Walker, 2000; Okon, 2018), and the investment decisions made during that period continued to provoke discussion (Marwah, 2014, 2020). The oil boom between 2008 and 2015 provided a stable economy for North Dakota (Archbold et al., 2014). The increased oil production not only created a large number of jobs and led to population growth and a better quality of life (Fernando and Cooley, 2016), but it also brought thorny problems for rail transportation and agricultural development (Bushnell et al., 2022). Apart from the impacts on economic activity and social ecology, it is undeniable that the production of oil would also cause serious environmental pollution, which always brings troubles to the development of other non-oil sectors (Hu et al., 2019; Ike et al., 2020).

From a macro perspective, after a long period of change, both oil prices and oil production rise dramatically compared to the beginning. But apparently, the chain reactions of oil booms are complex and variable, and often intersect with sustainable development concerns. Therefore, it is necessary to closely monitor and measure the impact of oil industry trends on sustainable development and how the oil industry ecology changes as a result of the sustainable development models and goals. Capturing this kind of information would help us to keep abreast of the current state of sustainable development and to explore strategies and approaches to further promote sustainable development from a corresponding perspective. However, there are relatively few studies that directly dissect the relationship between oil booms and sustainable development, so this paper attempts to explore this essential subject through empirical research.

To obtain valid empirical results, it is crucial to select the appropriate indicators that are able to reflect the changes in sustainable development and the oil industry. Oil production and oil price are two highly representative measures of the oil market changes, and countless studies have been carried out around them. Relatively speaking, oil prices are used more frequently than oil production. The common topics involve relationships between oil prices and various issues, including CO_2 emissions (Mukhtarov et al., 2022), economic growth (Ozturk et al., 2021) and stock market volatility (Gao et al., 2021; Wang et al., 2021b). Unlike oil prices, which have a strong economic attribute, oil production is a relatively purer indicator that is able to map the activities in the oil sector. We, therefore, choose to include oil production as one of the variables in the empirical analysis of this study. As for another variable to represent sustainable development, we decide to apply the sustainable development index (SDI) proposed by Hickel (2020). This indicator adds to the human development index (HDI) the consideration of two key indicators of ecological impact, CO_2 emissions and material footprint, and thus it becomes a powerful indicator to measure the nations' performance of sustainable development.

Countries/regions present disparate features in the planning and implementation of sustainable development and positioning in the oil market. Considering the objective circumstance, this paper then attempts to simultaneously apply the panel vector autoregression (PVAR) and vector autoregression (VAR) models to conduct the corresponding empirical analysis from multiple dimensions so as to have both a holistic and specific perspectives. The PVAR methodology allows us to comprehensively observe the relationship between sustainable development and oil booms based on the overall situation of 38 countries from different regions of the world. The VAR methodology enables us to investigate the relationship individually in the context of various economies, including China, the USA, Russia, Norway, Brazil, Libya, and Kuwait. Based on the theory and technique of structural break detection, we also capture the specific time nodes during the sample period when major shocks occurred to offer information for a more precise exploration of the interplay between sustainable development and oil booms.

To be specific, the main contributions of this paper are as follows: (1) Based on the panel data for 38 countries between 1990 and 2019 and the results of structural breaks detection of the series, we shed light on the nexus between sustainable development and oil booms in different subperiods with the help of PVAR estimations. (2) Using Granger causality tests and impulse response functions, different relationships between sustainable development and oil booms are revealed in the context of seven specific countries. (3) We identify multiple structural breaks both in the oil production growth series and SDI growth series by applying the Bai-Perron tests, providing additional information to determine the stability of the relationship between sustainable development and oil booms.

The remaining part of this paper is structured as follows: Section 2 describes the measurement indicator for sustainable development and empirical tools used in this study and reviews the relevant literature. Section 3 explains the methodology employed in this paper and presents the results of the pre-processing of the selected data. In Section 4, the empirical results are displayed and interpreted in turn. Further discussions on the empirical results are given in Section 5. Section 6 summarizes the findings obtained from this study and sets out the corresponding policy implications, the limitations of this study and future research intentions.

2. Theoretical and empirical perspectives

In this section, we focus on reviewing three aspects of the existing literature on the measurement of sustainable development, the connection between sustainable development and oil booms, and the application of the selected econometric techniques in relevant empirical studies.

2.1. Sustainable development measurement

In order to measure the effectiveness and progress of sustainable development, the corresponding indicators set has been expanded or revised with the development of extensive research work. As the triple bottom lines for sustainable development, economy, society and environment are the foundation on which any evaluation system is built. On the one hand, various international organizations have developed plenty of measurement indicators for reference. For example, the 134 comprehensive indicators developed by the United Nations Commission on Sustainable Development (UNCSD) in 1993, which have subsequently been revised several times in response to the change in actual conditions and needs (Ecer et al., 2019; Lassala et al., 2021; Nourani et al., 2021). Besides, researchers have also proposed measurement approaches with different efficacy for specific analysis scenarios. To name a few, Shi et al. (2019) proposed an integrated indicator system and evaluation model for regional sustainable development, which includes four subsystems: economy, society, resource and environment. Liu and Yuan (2023) constructed an assessment system with 11 transport-related indicators, based on the United Nations indicator framework, to measure China's sustainable transport progress. Eustachio et al. (2019) put forward a novel systemic indicator of sustainable development (SISD) framework for measuring and monitoring sustainable development from a systems-thinking and decision-making perspective.

The wide range of indicators and paradigms provides flexible ways to measure sustainable development and a variety of information references, yet it also allows for a greater degree of subjectivity in the selection or construction of indicator combination, quantification of indicators and determination of indicator weight. Moreover, the generality of most measurement approaches across different research scenarios still needs to be enhanced. To overcome these disadvantages, we opt for the SDI proposed by Hickel (2020), which combines the performance of five indicators, i.e., education, life expectancy, income, CO_2 emissions and material footprint. The calculation formula is as follows:

$$\mathrm{SDI} = \frac{\text{Development Index}}{\text{Ecological Impact Index}} \tag{1}$$

where the "Development Index" is calculated as the geometric mean of the education index, the life expectancy index, and the modified income index, and the "Ecological Impact Index" is calculated based on CO_2 emissions and material footprint:

$$\text{Development Index} = \sqrt[3]{\text{Education Index} * \text{Life Expectancy Index} * \text{Income Index}} \tag{2}$$

$$\text{Ecological Impact Index} = 1 + \frac{e^{\mathrm{AO}} - e^{1}}{e^{4} - e^{1}} \tag{3}$$

where the "Education Index" and "Life Expectancy Index" are as in HDI (UNDP, 1990), and $\text{Income Index} = (\ln(\mathrm{GNIpc}) - \ln(100)) / (\ln(20,000) - \ln(100))$ with GNIpc referring to gross national income per capita. If $\mathrm{AO} > 4$, then $\text{Ecological Impact Index} = \mathrm{AO} - 2$. The average overshoot (AO) is calculated as follows:

$$\mathrm{AO} = \sqrt[2]{\left(\frac{\text{Material Footprint}}{\text{boundary}} \geq 1\right) * \left(\frac{\text{CO2 Emissons}}{\text{boundary}} \geq 1\right)} \tag{4}$$

where material footprint and CO_2 emissions values are each divided by their respective per capita planetary boundary (which varies by year depending on population size) to determine the extent of boundary overshoot (or undershoot), which standardizes the units. If the result of either division is less than 1 (undershoot), it is rendered as 1.

It can be seen that SDI fits well with the tenets of sustainable development and conveys the message of pursuing human development under the premise of ensuring ecological efficiency (Menton et al., 2020; Destek et al., 2022). More importantly, the corresponding actual data for most countries in the world can be collected from official sources, both for the five indicators that are components of the calculation and for the SDI itself. This makes our measurement of sustainable development reliable and convenient.

2.2. Literature on sustainable development and oil booms

After carefully reviewing the existing literature on the connections between sustainable development and oil industry dynamics, we find that most of them aim to assess the sustainability of oil countries/regions or oil-related industries, or to discuss the impact of activities in the oil sector on sustainable development. For example, Harris and Khare (2002) discussed issues and strategies related to sustainable development in the context of Alberta's oil industry, and have stressed that only by linking the industry more closely to environmental protection can it achieve long-term sustainable development. Ecer et al. (2019) assessed the sustainability performance of OPEC countries using multi-attribute decision-making techniques. Sarrakh et al. (2022) identified and quantified six key challenges to assess the sustainable transformation of Qatar's oil and gas industry.

Regarding the specific influence of oil developments, Alemzero et al. (2021) found that activities in the oil and gas industry have negative impacts on the selected coastal communities in Ghana, including inadequate infrastructure and services, which are highly detrimental to sustainable economic development. While Abudu et al. (2022) agreed that oil and gas extraction would have adverse effects on the livelihoods of coastal residents, and they have also believed that the industry also contributes to socio-economic benefits such as social welfare and infrastructure. When it comes to the economic and social dimensions, the impact of the oil boom may be open to debate. But at the environmental level, it is undisputed that oil production negatively affects natural resources (Feng and Wang, 2017; Mensah et al., 2018; Hu et al., 2019).

In general, the existing studies usually indirectly or locally reflect the nexus between sustainable development and the oil industry dynamics, which makes it difficult to draw clear conclusions from them. We, therefore, intend to investigate directly the relationship and interaction between oil booms and sustainable development through a series of empirical studies based on quantitative analysis to offer some novel insights. Thus, we formulate the following hypothesis:

H1. The oil boom has a significant effect on sustainable development.

2.3. Application of (P)VAR model and structural break detection

Vector autoregression provides an effective way to model bidirectional relationships and helps capture the dynamic interactions between variables in a system (Eason et al., 2020; Qin et al., 2021). As a classical econometric method, the VAR (Sims, 1980) has been widely researched and applied since its inception, and the related theory and practice are rich and evolving. In studies related to sustainable development, elements such as energy consumption (Chang and Carballo, 2011; Kutlar et al., 2021; Wang and Wang, 2022), CO_2 emissions (Fan et al., 2021) and economic growth (Wada, 2017; Yin et al., 2019) often appear as other variables in VAR models for further causality analysis.

VAR models are suitable for multivariate time series analysis, while the panel VAR approach builds on the strengths of the traditional VAR model with the ability to flexibly test a larger range of panel data. In the research on related topics, PVAR offers a wealth of conclusions from a more macro level. Based on data from 106 countries between 1971 and 2011, Antonakakis et al. (2017) analyzed the dynamic interrelationships among energy consumption, CO_2 emissions and GDP using PVAR and impulse response functions and obtained a series of results. Similarly, using panel data for 30 OECD countries from 1996 to 2017, Wang et al., (2022a) examined the nexus among technological innovation, knowledge economy and sustainability, and have reached the important conclusion that the knowledge economy has a positive impact on sustainable development and technological innovation also positively impact green growth.

When structural changes in the series are not taken into account, the effectiveness of the regression model coefficient estimation would be affected to some extent. Among the many structural change detection methods (Chow, 1960; Quandt, 1960; Aggarwal et al., 1999), the Bai-Perron test (Bai and Perron, 1998) stands out and is widely recognized for its ability to detect multiple unknown structural breakpoints in series simultaneously. For instance, Lin and Zhang (2022) proposed a hybrid forecasting model incorporating the Bai-Perron test to improve the examination and utilization of structural breaks in the existing carbon price prediction models. Kotyza et al. (2021) assessed the structural breaks in the relationship between sugar prices and financial market uncertainty during the financial crisis and the COVID-19 epidemic using the Bai-Perron sequential test. Therefore, this study would also apply the Bai-Perron tests to detect multiple structural breaks in both the time series and panel series, and then attempt to present more abundant empirical results.

3. Methodology

This section aims to introduce the main empirical tools required in this study and to present the sources, pre-processing and basic characteristics of the data used in the analysis. In addition, we outline the complete analytical framework for exploring the relationship between oil booms and sustainable development and visually demonstrate it with the help of the flowchart.

3.1. Empirical strategy

In order to investigate the interplay between oil booms and sustainable development in different dimensions, we adopt the following strategy: Firstly, we identify the shocks of major events in oil production as well as sustainable development by detecting the structural breaks in each series. Based on the results of the Bai-Perron test (Bai and Perron, 1998, 2003a, 2003b), on the one hand, we can confirm the applicability of the selected data to this study, i.e., whether it reflects the relevant significant facts. On the other hand, it would be easier to carry out further exploration in a more targeted manner depending on the location of the breaks. Secondly, a panel series consisting of data from 38 countries are examined based on the PVAR method (Holtz-Eakin et al., 1988), so as to understand the changes in the interrelationship between the two subjects under the global context in a relatively more macro perspective. Meanwhile, the impact of structural breaks is considered to enable a valid assessment in more specific subperiods. Finally, the corresponding data for seven specific countries are analyzed using standard VAR estimation (Sims, 1980), thus creating conditions that allow horizontal comparisons and richer conclusions.

Following Gadea et al. (2016), we form the analytical framework for this paper, as shown in Fig. 1.

3.1.1. Bai and Perron

Bai and Perron (1998, 2003a) proposed a sequential method that can detect multiple unknown structural breaks simultaneously. This method follows the principle of minimizing the sum of squared residuals and considers m potential breaks and $m+1$ regimes in a standard linear regression model defined as:

$$Y_t = X_t^{'}\beta + Z_t^{'}\delta_j + \lambda_t \tag{5}$$

where Y_t is the observed dependent variable, X_t and Z_t are the explanatory variables. β and δ_j are the corresponding vectors of coefficients, and λ_t is the disturbance term.

Under the Bai-Perron methodology, there are three types of tests, which are $supF(k)$ test, $supF(l+1/l)$ test, $UD\,max$ and $WDmax$ tests, respectively.[1] We focus on using the second type of test, $supF(l+1/l)$, to obtain information on the number and exact locations of structural breaks in the series, and then apply the other two types of tests to examine the results to determine the final breakpoints. This strategy ensures the integrity of the analysis process and the reliability of the analysis results.

3.1.2. Vector autoregression

The VAR model is suitable for analyzing the dynamic relationships among multivariate time series variables. Based on Sims (1980), the VAR model takes the following form:

$$V_t = \alpha_0 + \sum_{i=1}^{p} A_i V_{t-i} + \varepsilon_t \tag{6}$$

where V_t is the endogenous variable vector, A_i is the coefficient matrix, α_0 is a vector of constant, and ε_t is a white noise vector.

Based on the estimation of the constructed VAR model, we would further conduct Granger causality tests and impulse response functions (IRFs) analysis. The former helps to reveal causal relationships between variables, while the latter allows us to observe the dynamic impacts that may result from shocks to any variable. The Granger causality test is defined as follows (Granger, 1969):

$$W_t = c_0 + \sum_{j=1}^{m} c_j W_{t-j} + \sum_{k=1}^{n} c_k X_{t-k} + u_t \tag{7}$$

$$X_t = c_0 + \sum_{j=1}^{m} c_j X_{t-j} + \sum_{k=1}^{n} c_k W_{t-k} + v_t \tag{8}$$

where W_t and X_t are the values of the variables W and X respectively, u_t and v_t are the random model elements, and c is the structural model parameters.

3.1.3. Panel vector autoregression

Holtz-Eakin et al. (1988) proposed a VAR model of the panel-data version. In this study, we employ the PVAR model in a generalized method of moments (GMM) framework. Following Abrigo and Love (2016), we illustrate the k-variate homogeneous PVAR of the order p with panel-specific fixed effects as the following equation:

$$U_{it} = U_{it-1}A_1 + U_{it-2}A_2 + \ldots + U_{it-p+1}A_{p-1} + U_{it-p}A_p + Q_{it}B + d_i + e_{it} \tag{9}$$

where i refers to cross-sectional units, t refers to time, U_{it} is a $(1\times k)$ vector of dependent variables, Q_{it} is a $(1\times l)$ vector of exogenous covariates, d_i and e_{it} are $(1\times k)$ vectors of dependent variable-specific panel fixed-effects and idiosyncratic errors, respectively. The $(k\times k)$ matrices $(A_1, A_2, \ldots, A_{p-1}, A_p)$ and the $(l\times k)$ matrix B are parameters to be estimated. And the equations have the following characteristic assumptions: $E(e_{it}) = 0$, $E(e_{it}^{'}e_{it}) = \sum$, $E(e_{it}^{'}e_{is}) = 0$ for all $t > s$.

While ensuring the model meets the stability condition, we would perform Granger causality tests for each equation of the PVAR model and consider further computing the IRFs.

3.2. Data

With the aim of probing into whether and what links between the state of the oil industry and sustainable development, we use oil production data and SDI data of different countries from the last century to recent years as the subjects of this study. The annual data on oil production (thousand barrels daily) for 38 countries are derived from British Petroleum's Statistical Review of World Energy, covering the period 1965 to 2021.[2] The SDI data with an annual frequency for those same countries are taken from the website platform, Sustainable Development Index, covering the period 1990 to 2019.[3]

In different stages of the analysis in this research, we would selectively use the two types of data obtained. For the VAR model, seven representative countries from different regions of the world are selected for separate analysis, including China (Asia Pacific), the USA (North America), Russia (CIS), Norway (Europe), Brazil (South & Central America), Libya (Africa) and Kuwait (Middle East). The data of oil production and SDI from 1990 to 2019 for these countries would form multiple time series for the corresponding modeling and estimation. Similarly, for the PVAR model, we form panel series using oil production and SDI data for 38 different countries only from 1990 to 2019 to ensure consistency in the period of the variables. As for the Bai-Perron tests, we would consider analyzing both time series (different from those in the VAR model) and panel series (same as those in the PVAR model) in different stages. Generally, the oil production from 1965 to 2021 and the SDI from 1990 to 2019 for the seven selected countries would form into multiple time series to be estimated.[4]

For the purpose of improving the applicability of the collected data in

[1] The $supF(k)$ test considers the null hypothesis of no breaks against the alternative of k breaks. The $supF(l+1/l)$ test considers the null hypothesis of l breaks, with $l = 0, 1, \ldots$, against the alternative of $l+1$ breaks. The double maximum tests $UDmax$ and $WDmax$ tests consider the null of the absence of structural breaks against the alternative of an unknown number of breaks.

[2] British Petroleum (2022).

[3] The SDI website platform can be found at: https://www.sustainabledevelopmentindex.org/.

[4] Regarding oil production, Norway only has data from 1971 to 2021, and Russia only has data from 1985 to 2021.

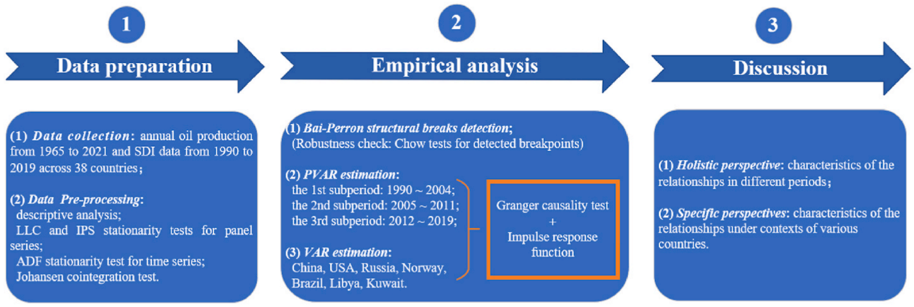


Fig. 1. Analytical framework.

Table 1
Sample descriptive statistics.

Variable		Observation	Mean	Standard Deviation	Min	Max
Panel-38countries	*dSDI*	1102	−0.0018	0.0243	−0.2067	0.2943
	dlnOILP	1102	0.0042	0.1512	−2.0423	1.7269
China	*dSDI*	29	−0.0026	0.0145	−0.0290	0.0130
	dlnOILP	56	0.0511	0.0856	−0.0746	0.3435
USA	*dSDI*	29	−0.0068	0.0148	−0.0440	0.0350
	dlnOILP	56	0.0109	0.0506	−0.0641	0.1559
Russia	*dSDI*	29	−0.0015	0.0010	−0.0350	0.0190
	dlnOILP	36	0.0002	0.0581	−0.1494	0.1037
Norway	*dSDI*	29	−0.0167	0.0255	−0.0940	0.0350
	dlnOILP	50	0.1164	0.3414	−0.0940	1.7047
Brazil	*dSDI*	29	0.0030	0.0049	−0.0050	0.0100
	dlnOILP	56	0.0614	0.0771	−0.0547	0.3334
Libya	*dSDI*	29	−0.0006	0.0151	−0.0610	0.0180
	dlnOILP	56	0.0007	0.3645	−1.2488	1.0933
Kuwait	*dSDI*	29	−0.0044	0.0280	−0.1020	0.0600
	dlnOILP	56	0.0026	0.3601	−1.6507	1.7616

Notes: *dSDI* and *dlnOILP* stand for the growth rates of oil production and SDI, respectively.

Table 2
Results of LLC and IPS stationarity tests for panel series.

Variables	LLC test		IPS test	
	Adjusted $t*$	*P*-value	*t*-bar	*P*-value
dSDI	−5.7813	0.0000	−24.0574	0.0000
dlnOILP	−6.7078	0.0000	−15.8642	0.0000

Notes: Adjusted $t*$ and *t*-bar are the statistical values of these two tests, respectively.

a series of analyses, we first uniformly preprocess the variables involved. On the one hand, we take the logarithm of oil production (*lnOILP*) to reduce the absolute differences between data. On the other hand, we apply first-order differences of *SDI* and *lnOILP* to enhance the stationarity of data, which are denoted as *dlnOILP* and *dSDI*. Regardless of the PVAR estimation or the seven VAR estimations for China, USA, Russia, Norway, Brazil, Libya and Kuwait respectively, each regression model involves only the two variables, *dSDI* and *dlnOILP*. Table 1 shows the descriptive statistics of our variables in each model.

4. Empirical results

In this section, we plan to complete a process of empirical analysis that moves from univariate analysis to multivariate analysis as well as from the whole perspective to the specific perspective. So we can progressively measure the possible impacts of oil booms and sustainable development on each other from different angles and dimensions.

It is important to test the stationarity of the series before any formal quantitative analysis. Therefore, we perform LLC and IPS tests on the panel series and ADF test on the time series respectively. The results are shown in Table 2 and Table 3. Clearly, the panel series *dlnOILP* and *dSDI* could reject the null unit root hypothesis at the 1% level of confidence, both the LLC test and IPS test. This implies that they are both stationary series suitable for the PVAR model. The results of the ADF test also suggest that the time series *dlnOILP* and *dSDI* for the USA, Russia, Norway, Brazil, Libya and Kuwait are all stationary. However, though the series *dlnOILP* satisfies the stationarity condition, the *dSDI* series for China is unable to reject the unit root null hypothesis, showing a non-stationary state. In response to this result, different strategies are adopted concerning the Bai-Perron tests and the VAR estimation. Many objects could be analyzed for structural break detection, and the results can provide sufficient information. We, therefore, determine not to perform the Bai-Perron test on the *dSDI* series for China. Regarding the VAR estimation, we choose to further perform the Johansen cointegration test on these two variables for China to finally determine whether they could be put into the VAR model.

As can be seen from the results in Table 4, the null hypothesis of no cointegration relationship is rejected at the 5% level of confidence, indicating that there is a long-term equilibrium relationship between China's oil production growth and SDI growth over the sample period.

Table 3
Results of ADF stationarity test for time series.

Variable		ADF Test Statistic	5% Critical Value	*P*-value
China	*dSDI*	−1.141	−2.992	0.6983
	dlnOILP	−3.574	−2.926	0.0063
USA	*dSDI*	−4.961	−2.992	0.0000
	dlnOILP	−3.609	−2.926	0.0056
Russia	*dSDI*	−5.608	−2.992	0.0000
	dlnOILP	−3.810	−2.992	0.0028
Norway	*dSDI*	−3.395	−2.992	0.0111
	dlnOILP	−8.380	−2.933	0.0000
Brazil	*dSDI*	−3.383	−2.992	0.0115
	dlnOILP	−3.632	−2.926	0.0052
Libya	*dSDI*	−4.275	−2.992	0.0005
	dlnOILP	−9.553	−2.926	0.0000
Kuwait	*dSDI*	−9.908	−2.992	0.0000
	dlnOILP	−8.451	−2.926	0.0000

Notes: The *dlnOILP* data used for the ADF test cover the entire period from 1965 to 2021, while the *dSDI* data cover only the period from 1990 to 2019.[5].

Table 4
Results of Johansen cointegration test on *dlnOILP* and *dSDI* for China.

Hypothesized Number of Cointegration Relationships	Trace Statistic	5% Critical Value	*P*-value
None	14.11410	12.32090	0.0248
At most 1	5.233488	4.129906	0.0263

Table 5
Bai-Perron test results for structural breaks.

	dSDI	*dlnOILP*
China	○	1976
USA	–	1973; 1984; 1992; 2000; 2008
Russia	–	1999; 2004
Norway	Δ	1978; 1989; 1996; 2004; 2013
Brazil	2002	1978; 1986; 1995; 2003; 2013
Libya	Δ	Δ
Kuwait	–	Δ

Notes: ○ denotes that the series is not tested; – denotes that the series has no structural break; Δ denotes that the series is detected with insignificant breaks and is not included in the scope of the investigation. [6].

Hence, it is necessary to explore in more detail the relationship between sustainable development and oil production changes in the context of China through a standard VAR estimation.

4.1. *Structural breaks detection*

Based on the Bai-Perron test, we obtain the results for the structural breaks over the sample period in both the corresponding time series for the seven selected countries and the panel series for the total 38 countries. Table 5 displays the specific date of the breakpoints gained mainly according to the sequential test $supF(l+1/l)$, which also passes the other two tests.

In comparison, the process of sustainable development is relatively stable, only the series for Brazil has a significant structural break in 2002 among the countries examined individually. Given that sustainable development is a fundamental reform that requires gradual progress and is difficult to be seen visible effects in the short term, this result is comprehensible. Yet, the growth in oil production is more fluctuant and complicated due to the shock of related major events. Looking at the dates under the "*dlnOILP*" column, we note that they are concentrated around periods of major oil market volatility such as the petroleum embargo of 1973, the crude oil price crash of 1986, the Persian Gulf War of 1990, the Asian financial crisis of 1997, the Iraq war of 2003, the great recession between 2007 and 2009, the oil price crash of 2014, etc. Thus, the selected data of oil production growth are able to sensitively reflect the oil industry dynamics.

In addition, we also render robustness checks on the existing breaks using the Chow (1960) test, and the corresponding results are summarized in Table 6.[7] We notice that the breakpoint that occurred in 1986 (the *dlnOILP* series for Brazil) is tested to reject the null hypothesis of no structural change at the 10% significance level, while all the other known breakpoints can reject the null hypothesis at the 1% or 5% significance level. In general, the outputs of the Bai-Perron test are confirmed by the Chow test, meaning that the obtained breakpoints could provide a useful reference for further exploration.

Table 6
Chow test results for structural breaks.

Date			*F*-Statistic	*P*-value
China	*dlnOILP*	1976	14.2932	0.0000
USA	*dlnOILP*	1973	6.8981	0.0022
		1984	9.4903	0.0003
		1992	9.8163	0.0002
		2000	9.5228	0.0003
		2008	14.4691	0.0000
Russia	*dlnOILP*	1999	8.0491	0.0015
		2004	4.9619	0.0133
Norway	*dlnOILP*	1978	8.4657	0.0007
		1989	3.7433	0.0312
		1996	4.6166	0.0149
		2004	13.4488	0.0000
		2013	8.9065	0.0005
Brazil	*dlnOILP*	1978	10.1796	0.0002
		1986	2.9620	0.0910
		1995	6.9747	0.0021
		2003	25.2459	0.0000
		2013	9.9205	0.0002
	dSDI	2002	9.8044	0.0043

Table 7
Results of lag order selection for PVAR(1) model.

Lag	CD	J	J *P*-value	MBIC	MAIC	MQIC
1	0.6100	28.0443	0.1084	−106.528*	−11.956	−48.211*
2	0.5985	16.8236	0.3971	−90.834	−15.176*	−44.180
3	0.6010	11.8558	0.4573	−68.888	−12.144	−33.897
4	0.5935	4.0868	0.8492	−49.742	−11.913	−26.415
5	0.1578	3.8992	0.4198	−23.015	−4.101	−11.352

Notes: * denotes the optimal lag order selected according to the MBIC, MAIC and MQIC criteria.

4.2. *Bivariate analysis of panel series*

4.2.1. *PVAR estimation over the entire sample period*

First, we need to decide the optimal lag order of the model. Table 7 shows the lag order selection procedure based on the Consistent Moment and Model Selection Criteria (CMMSC) proposed by Andrews and Lu

[5] We test the *dlnOILP* series used in the VAR model from 1990 to 2019 for its stationarity by the ADF test and obtain the results that the corresponding *dlnOILP* series for each of the six countries are I(0) except for China.

[6] We maintain the default trimming percentage of 0.15 and the default maximum number of 5 breaks. The type of covariance matrix estimator selected for testing time series is SSR (regression sum of squares), while the type selected for testing panel series is HAC (heteroskedasticity and autocorrelation consistent).

[7] The Chow test is a classic method of estimating known breakpoints in time series.

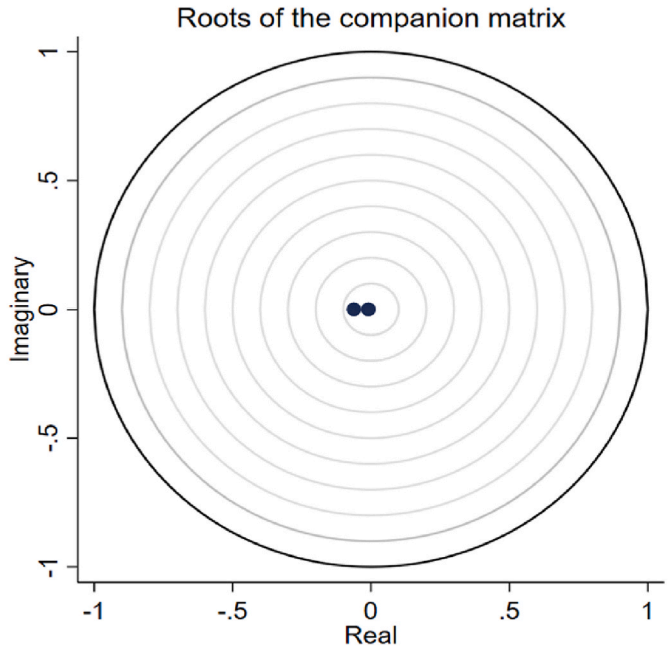


Fig. 2. Stability test on the PVAR model.

Table 8
Results of Granger causality tests between variables.

Equation Variable	Excluded Variable	Lag Order	Chi^2	*P*-value
dSDI	*dlnOILP*	1	0.029	0.864
dlnOILP	*dSDI*	1	0.292	0.589

Notes: Chi^2 is the chi-square Wald statistical value of the test.

Table 9
Robustness check results of Granger causality tests based on different lag orders.

Lag Order	Equation Variable	Excluded Variable	Chi^2	*P*-value
2	*dSDI*	*dlnOILP*	1.964	0.374
2	*dlnOILP*	*dSDI*	3.201	0.202
3	*dSDI*	*dlnOILP*	3.756	0.289
3	*dlnOILP*	*dSDI*	2.056	0.561

Notes: The PVAR model has passed the stability test at both lag orders.

(2001) for the GMM estimation. Accordingly, the optimal lag order for the PVAR model in this study is determined as 1. Then, we carry out the stability test on the established model, and the result is presented in Fig. 2. Clearly, the roots of the characteristic equation corresponding to the PVAR(1) model are both inside the unit circle, indicating that the model we built is stable.

To grasp the relationship between sustainable development and oil production changes, the Granger causality test is conducted on the panel series. It can be seen from Table 8 that the growth of oil production is not the Granger cause of sustainable development. The null hypothesis that the excluded variable does not Granger-cause equation variable cannot be rejected in either direction, i.e., neither oil production growth nor SDI growth has a significant effect on each other. Given that both the oil market and the sustainable development process are influenced to varying degrees by numerous factors over the full period, it is indeed more difficult to directly observe a significant and firm relationship between the two from the whole picture. Therefore, in combination with the structural breakpoint detection technique, we would dig deeper into the association between oil production growth and SDI changes.

In addition to the optimal lag order of 1, we also carry out Granger causality tests for lag orders of 2 and 3 for robustness. Table 9 reports the corresponding results, which confirms that there is no statistical causality between SDI growth and oil production growth.

Table 10
Bai-Perron sequential test results for structural breaks.

Variables	Break Test	F-Statistic	5% Critical Value	Break Date
dSDI	0 vs. 1	9.23	8.58	2012
	1 vs. 2	4.04	10.13	
dlnOILP	0 vs. 1	12.69	8.58	2005
	1 vs. 2	2.14	10.13	

Notes: The 5% critical values are given in Bai and Perron (1998).

Table 11
Robustness check results of Bai-Perron sequential test results based on quarterly data.

Variables	Break Test	F-Statistic	5% Critical Value	Break Date
dSDI	0 vs. 1	9.77	8.58	2012q3
	1 vs. 2	4.43	10.13	
dlnOILP	0 vs. 1	9.34	8.58	2005q4
	1 vs. 2	3.77	10.13	

Notes: The results of the LLC and IPS tests show that the series based on quarterly data are unit root-free stationary. The sequential test results are confirmed by the other two Bai-Perron tests.

Table 12
Results of Granger causality tests for three subperiods.

Sample Period	Equation Variable	Excluded Variable	Lag Order	Chi^2	*P*-value
1990~2004	*dSDI*	*dlnOILP*	1	0.582	0.446
	dlnOILP	*dSDI*	1	1.935	0.164
2005~2011	*dSDI*	*dlnOILP*	1	0.472	0.492
	dlnOILP	*dSDI*	1	2.505	0.113
2012~2019	*dSDI*	*dlnOILP*	2	17.213	0.000
	dlnOILP	*dSDI*	2	1.8388	0.399

Notes: Three PVAR models have passed the stability tests and the selections of optimal lag orders are all based on CMMSC.

4.2.2. *Structural breaks detection in panel series*

Similar to the previous univariate analysis, we respectively conduct the Bai-Perron test for the panel series *dSDI* and *dlnOILP*. In Table 10, we report the results of the corresponding structural breaks in each case.[8] The structural breaks for sustainable development and oil production change between 1990 and 2019 are 2012 and 2005, respectively. Considering the potential impact of the structural changes, we divide the sample into three subperiods based on the two breakpoints to alleviate the bias that such instability may bring to the PVAR estimation. Then, we would further examine the relationship between the oil industry variation and sustainable development by repeatedly performing the PVAR estimation for each of these subperiods.

As a robustness check, we repeat the analysis with quarterly data converted from annual data by using the Chow-Lin interpolation technique (Chow and Lin, 1971).[9] In Table 11, the detected break dates are located in the third quarter of 2012 and the fourth quarter of 2005, respectively. They are consistent with the previous findings.

4.2.3. *PVAR re-estimation for subsample periods*

We establish three PVAR models based on samples from 1990 to 2004, 2005 to 2011 and 2012 to 2019, and complete the selection of lag

[8] We have also tested the relationship between *dlnOILP* and *dSDI*, and the results show that there is no breakpoint found, so we do not consider further research based on this result.

[9] The Chow-Lin interpolation technique is able to transform low-frequency data into higher-frequency data, and we select the average version and maximum likelihood method when we use EViews 10 to complete the transformation.

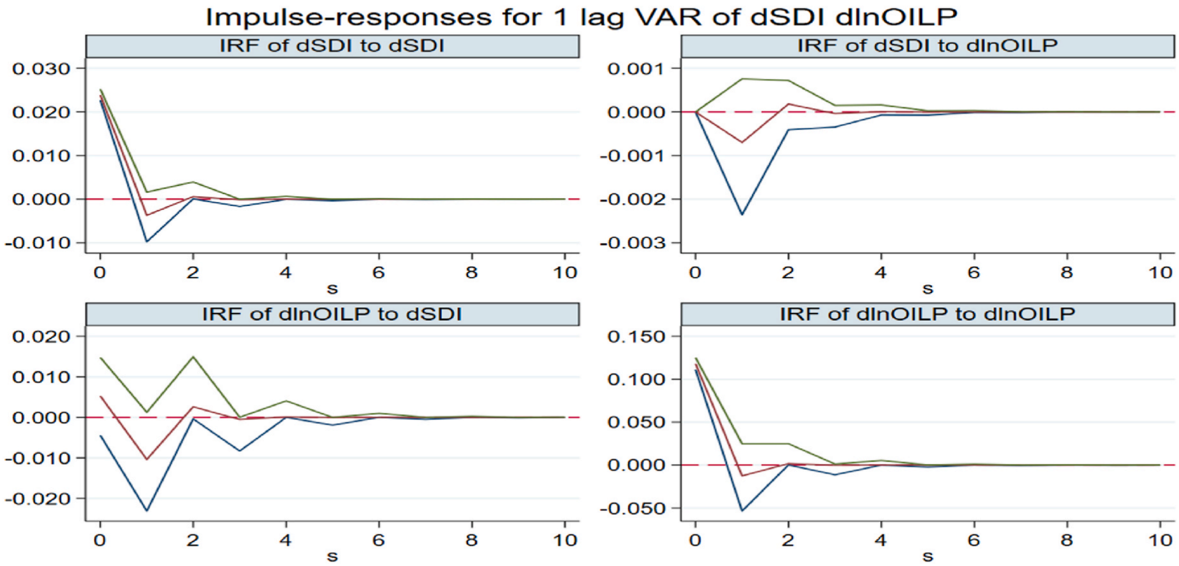


Fig. 3. Impulse-response functions of the PVAR(1) built in the subperiod between 1990 and 2004. [10].

orders, the stability tests and the Granger causality tests in order. From Table 12, we find that only in the third subperiod (2012–2019), the increase in oil production is a unidirectional significant Granger cause of the change in SDI. While in the other subperiods, there is still no significant Granger causality being observed. This result confirms that considering the existence of structural breaks is more conducive to exploring the relationships between variables.

In addition, we apply IRFs to examine the dynamic interrelationships between the variables involved in the PVAR models. Next, we would present and illustrate the distinct results in each subperiod. In Figs. 3–5, the variables' responses to a one-standard deviation shock of *dSDI* or *dlnOILP* for the lag periods (10, 7 and 8 years in each case) are depicted.

(1) The subperiod between 1990 and 2004

It can be seen that the dynamic impacts of both SDI and oil production on each other are statistically insignificant over the whole range of considerations. Specifically, a shock to the SDI growth would have a negative and insignificant effect on oil production, but this lasts for only one period before fading out and converging to zero around the 5th period. The SDI, on the other hand, responds relatively quickly to a shock to oil production growth, but the response in the second half of the first lag period is again negative and tapers off in the second period. The difference is that this negative response would re-emerge in the third period and then take a longer time to disappear, about seven periods.

(2) The subperiod between 2005 and 2011

Similarly, oil production growth responds negatively to an SDI growth shock during the first lag period. Although the degree of response has increased, it is still insignificant. However, we observe that SDI growth responds positively at the start to an oil production growth shock, but it is insignificant as well and quickly disappears.

(3) The subperiod between 2012 and 2019

During this period, IRFs graphs show richer and distinguishing trends. a shock to the SDI growth would have a positive and significant effect on the oil production growth, which presents an expanding trend in the first period and then reaches its maximum in the second period. Thereafter, the response gradually diminishes over time and nearly disappears after seven periods. Regarding the swift positive response of SDI growth to an oil production growth shock, it just monotonically decreases in the first three periods and eventually approaches the zero axis. The response is again insignificant over the most horizon considered.

Collectively, the relationship between oil production growth and SDI changes remains insignificant in the first two subperiods. A shock to SDI growth tends to have a short-lived negative effect on oil production growth, while the positive effect of an oil production growth shock on SDI growth shows a relatively more sustained trend in the second subsample period. The third period is the one we focus on. Fig. 5 reveals the significant positive response of oil production growth to an SDI growth shock, which serves as a reminder to be aware of the progress in sustainable oil development in recent years from policy to practice and to discuss what the sustainable development of energy means specifically.

Because the Cholesky decomposition requires triangulation, resulting that changes in the order of variables would affect the computational results of the IRFs, we re-estimate the IRFs in all three subperiods in the reverse order of variables to test the robustness of the results, as exhibited in Fig. 6 (Please note that here the graphs in the upper right and lower left corner correspond to the initial graphs in the lower left and upper right corner respectively). [11] For the first two subperiods, both the dynamic impacts of oil production growth on SDI growth and SDI growth on oil production growth are consistent in trend with the results in Figs. 3 and 4. For the last subperiod, a shock to SDI growth would still have a significant and positive effect on oil production growth, and the trends in both situations are highly consistent. However, SDI growth responds negatively to oil production growth, which is different from the result in Fig. 5, though the response is also not significant. Overall, the similar IRFs demonstrate that our findings are resistant to different variable orderings, confirming the robustness of the results gained in all three subperiods.

4.3. *VAR estimation of seven specified countries*

In order to capture the interlinkages and impacts between oil productions and sustainable development in more specific contexts, we

[10] Errors are 5% on each side generated by Monte-Carlo with 200 repetitions. So are Figs. 4–6.

[11] The initial order for the VAR model is "*dSDI, dlnOILP*".

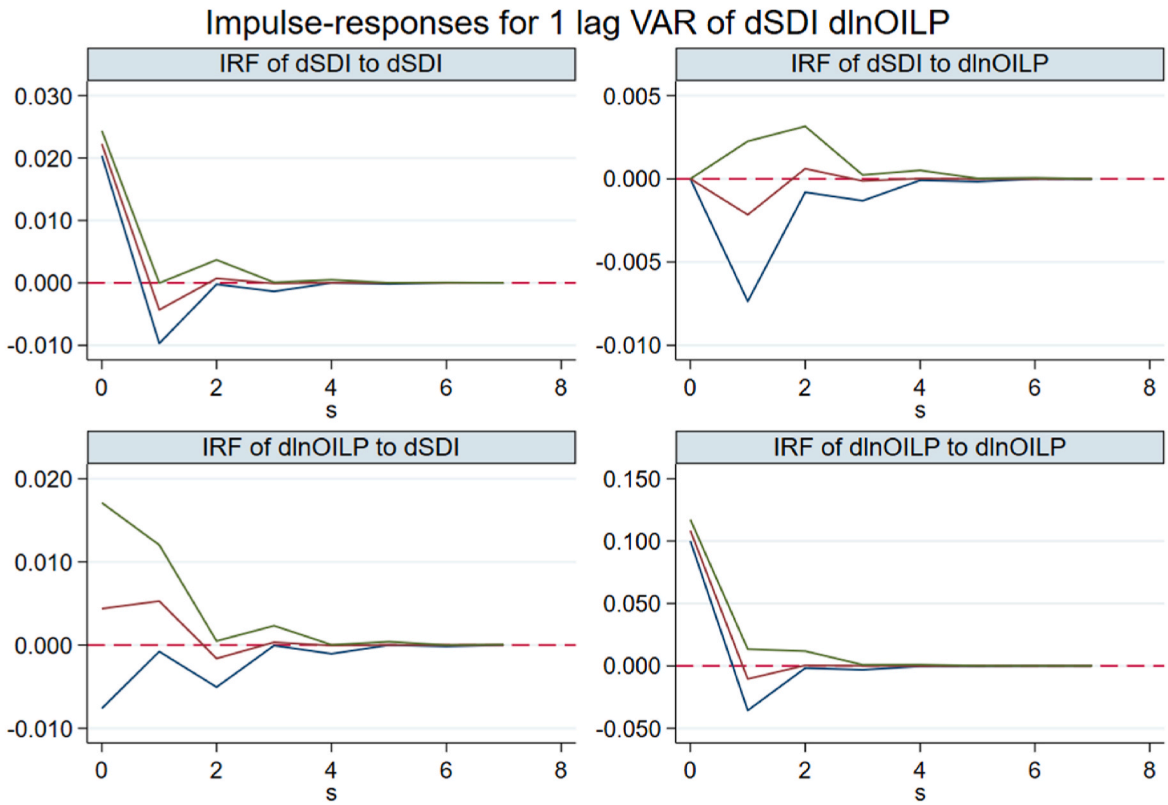


Fig. 4. Impulse-response functions of the PVAR(1) built in the subperiod between 2005 and 2011.

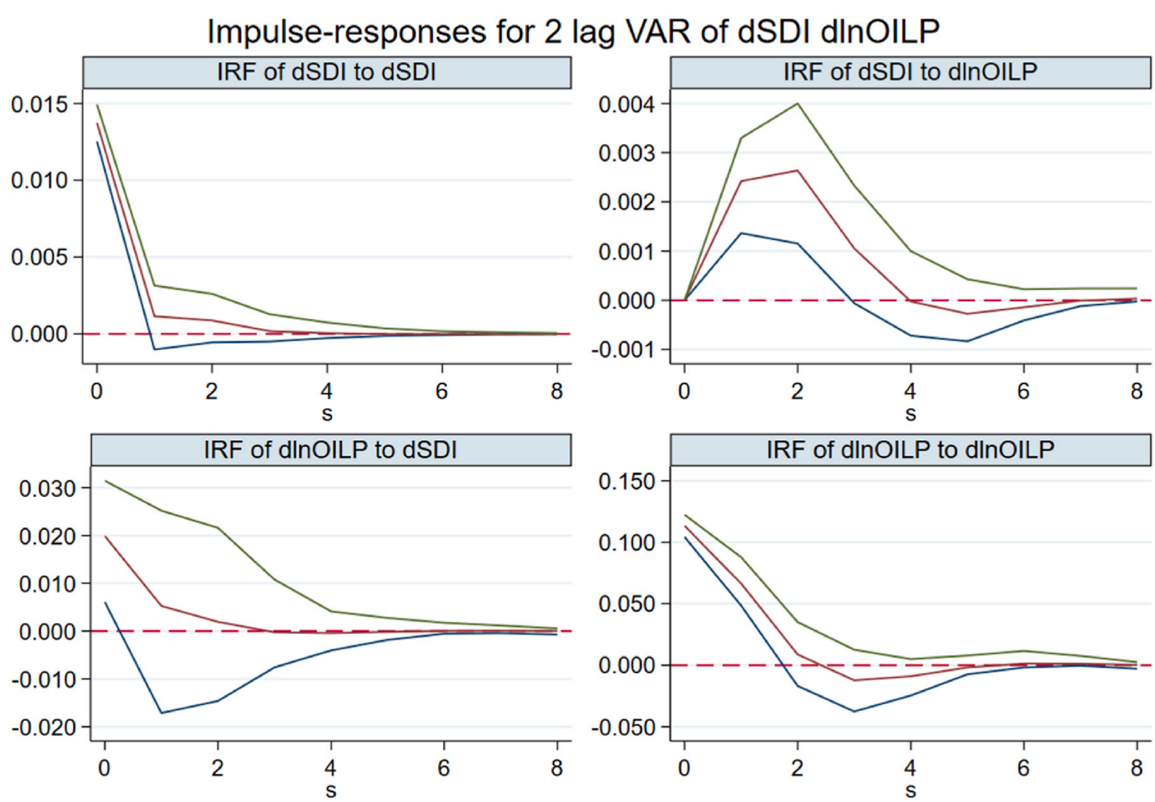
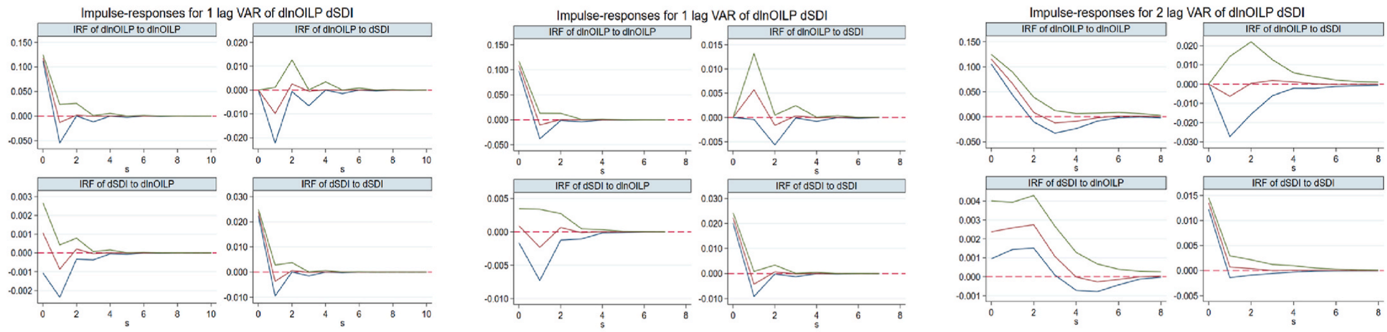


Fig. 5. Impulse-response functions of the PVAR(2) built in the subperiod between 2012 and 2019.

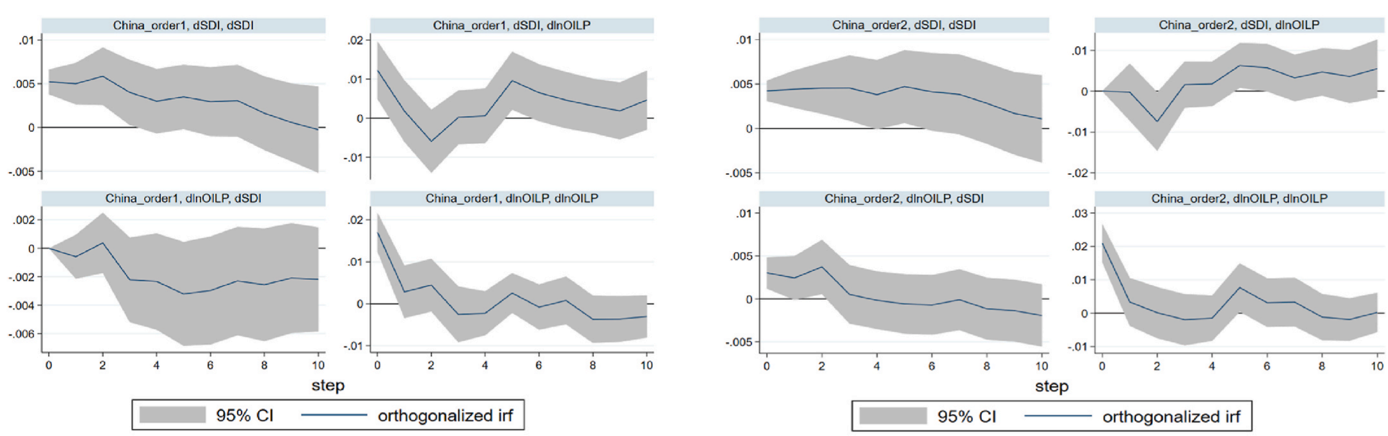


(a) First subperiod. (b) Second period. (c) Third period.

Fig. 6. Robustness check results of impulse-response functions of the system in the inverse order.

Table 13
Results of Granger causality tests for seven countries.

Country	Equation Variable	Excluded Variable	Lag Order	Chi^2	*P*-value
China	*dSDI*	*dlnOILP*	3	11.074	0.011
	dlnOILP	*dSDI*	3	11.528	0.009
USA	*dSDI*	*dlnOILP*	1	0.028	0.599
	dlnOILP	*dSDI*	1	0.175	0.675
Russia	*dSDI*	*dlnOILP*	1	0.308	0.579
	dlnOILP	*dSDI*	1	0.419	0.517
Norway	*dSDI*	*dlnOILP*	3	9.482	0.024
	dlnOILP	*dSDI*	3	8.142	0.043
Brazil	*dSDI*	*dlnOILP*	1	0.072	0.788
	dlnOILP	*dSDI*	1	9.032	0.003
Libya	*dSDI*	*dlnOILP*	3	20.725	0.000
	dlnOILP	*dSDI*	3	1.234	0.745
Kuwait	*dSDI*	*dlnOILP*	1	11.019	0.001
	dlnOILP	*dSDI*	1	4.419	0.036

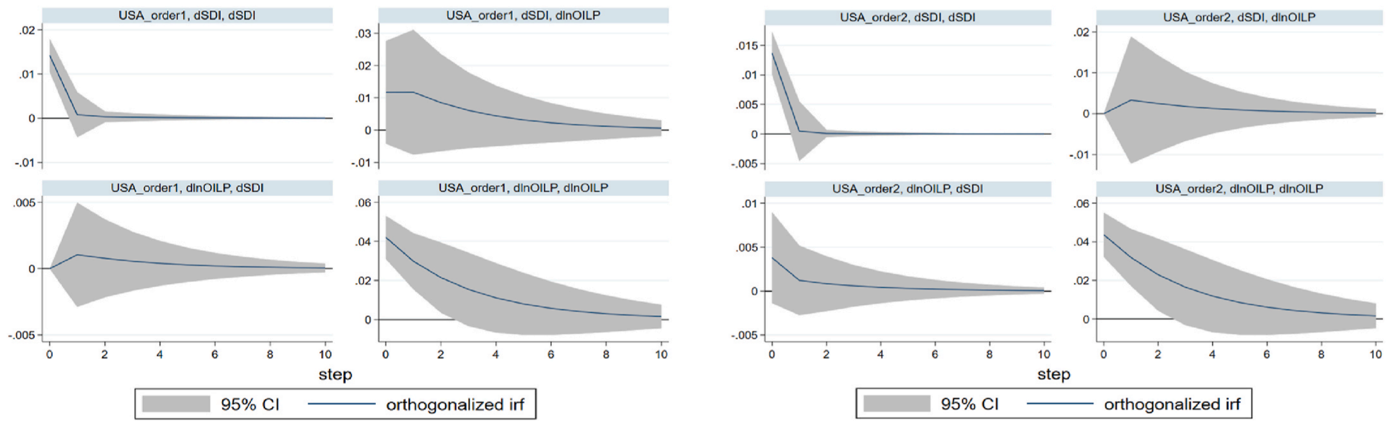


(a) Initial order. (b) Inverse order.

Fig. 7. Impulse-response functions of the VAR(3) built in the context of China.

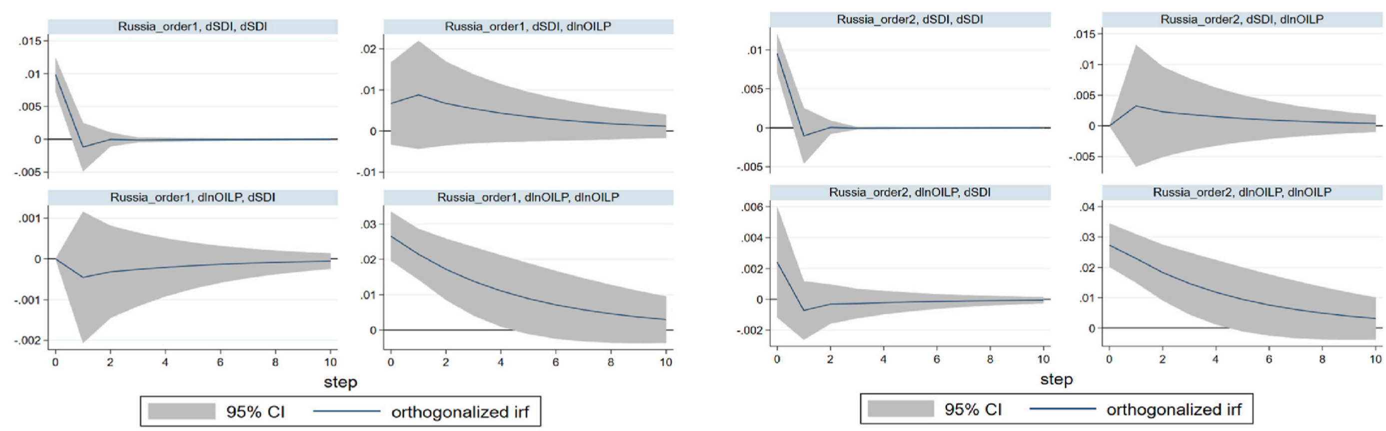
further conduct VAR estimations based on the relevant data for seven countries including China, the USA, Russia, Norway, Brazil, Libya and Kuwait. In line with the process of PVAR estimation, we comprehensively select the appropriate lag period for each VAR model according to multiple information criteria and ensure that each model passes the stability test. After completing the preparatory work, we first examine the causalities between the variables in each model, respectively. Table 13 summarizes the results of the Granger causality tests in the seven models.

On the whole, there are more causality effects between SDI growth and oil production changes. Only models built on the contexts of the USA and Russia cannot be identified with causality in any direction. By contrast, mutual Granger causality between variables can be observed at the 1% or 5% confidence level in the models based on the contexts of China, Norway and Kuwait. Regarding Brazil and Libya, SDI growth is the significant Granger cause of the oil production growth for the former, while oil production growth is the significant Granger cause of SDI growth for the latter.



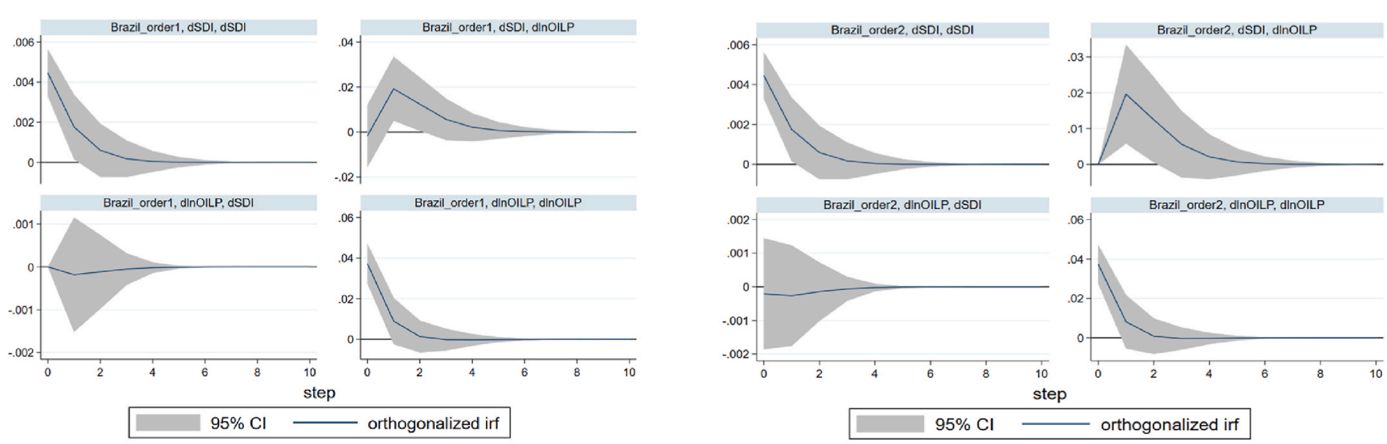
(a) Initial order. (b) Inverse order.

Fig. 8. Impulse-response functions of the VAR(1) built in the context of the USA.



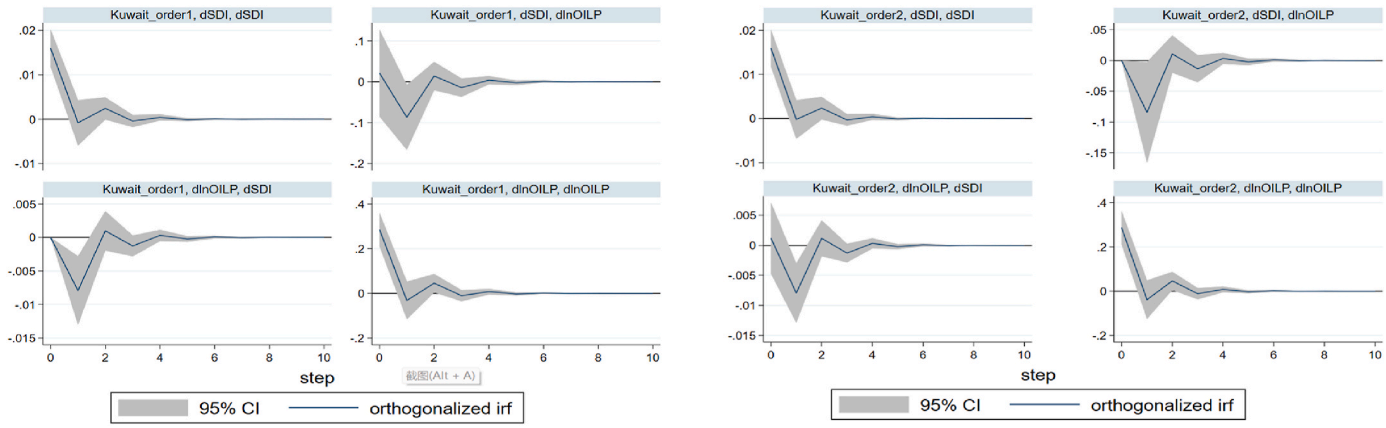
(a) Initial order. (b) Inverse order.

Fig. 9. Impulse-response functions of the VAR(1) built in the context of Russia.



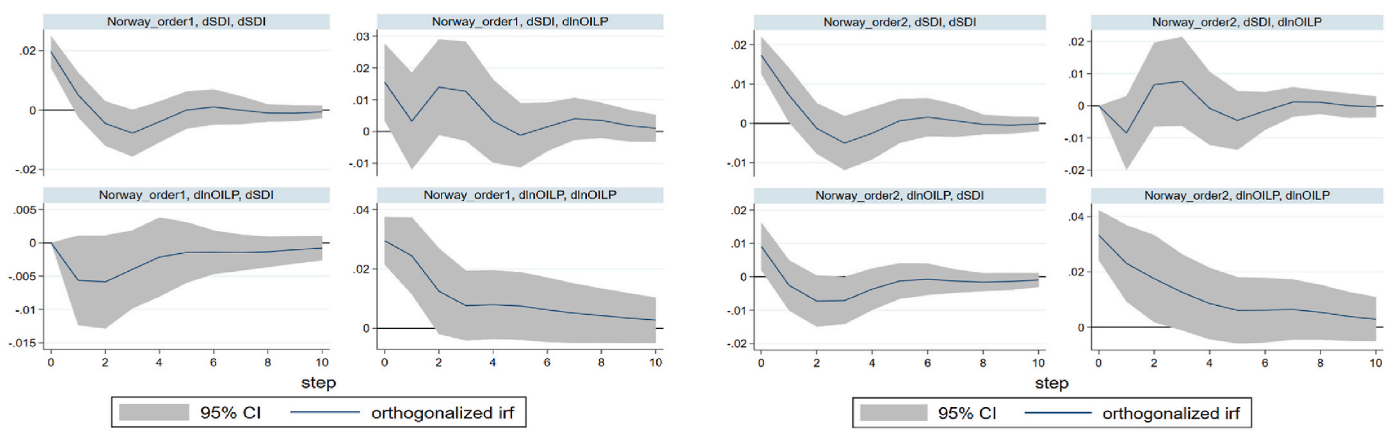
(a) Initial order. (b) Inverse order.

Fig. 10. Impulse-response functions of the VAR(1) built in the context of Brazil.



(a) Initial order. (b) Inverse order.

Fig. 11. Impulse-response functions of the VAR(1) built in the context of Kuwait.



(a) Initial order. (b) Inverse order.

Fig. 12. Impulse-response functions of the VAR(3) built in the context of Norway.

Next, we again employ the IRFs to measure the dynamics occurred in the system when a shock to a certain variable emerges, so as to investigate the similarities and differences in the relationships between sustainable development and oil industry changes in various countries. As the order of the variables would affect the results of the IRFs computations, we simultaneously estimate them in the opposite order in the system to test the robustness of the results obtained.

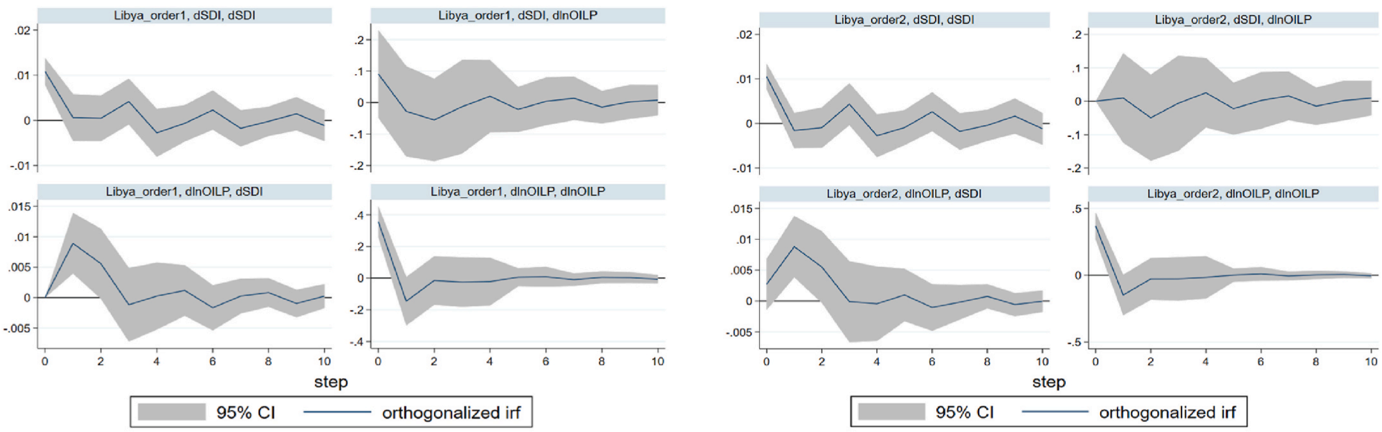
As can be seen from Fig. 7 (a), a shock to SDI growth would have a positive and significant impact on oil production growth. Although the response gradually decreases and even turns insignificant and negative in the second period, it picks up to a significant positive level in the fifth period and does not completely disappear after 10 periods. A shock to oil production growth, however, would have a persistent negative impact on SDI growth without converging to zero even after 10 periods. Though the response correspondingly becomes more and more insignificant as shown in Fig. 8.

Observing the results of the robustness test in Fig. 7(b), the responses of each variable to a shock to each other are similar in the trends. The relatively obvious difference is that the response of SDI growth to an oil production growth shock is positive in the first three periods, especially in the first and second periods when the response is still significant. Generally speaking, the qualitative results we obtained from the analysis of IRFs are robust.

In comparison, the results of IRFs based on the USA and Russian contexts show a more monotonic and insignificant character. For the former, a shock to SDI growth would have an insignificant positive effect on oil production growth and tend to remain at a very low level. For the latter, the response is negative and insignificant, but also maintains at an extremely low level. Besides, for both models, oil production growth responds positively and significantly to an SDI growth shock. Also, the results of the robustness tests confirm the findings well as shown in Fig. 9.

Regarding the VAR models established in the contexts of Brazil and Kuwait, a shock to either variable would only have relatively shorter impacts, which would disappear completely around the fifth period. On the one hand, we observe in Fig. 10 (a) that the response of oil production growth to a shock to SDI growth is significant and positive, but it peaks in the first period and then weakens until it disappears. While a shock to oil production growth would have almost no effect on SDI growth. On the other hand, Fig. 11 (a) displays that both an SDI growth shock and an oil production growth shock would have negative impacts on the other party in the first two periods, and the responses would then approach the zero axis in a similar trend. These results are basically confirmed according to the outputs of the robustness tests in Fig. 10 (b) and Fig. 11 (b).

In Fig. 12 (a), the IRFs graph plotted in the Norway context shows no



(a) Initial order. (b) Inverse order.

Fig. 13. Impulse-response functions of the VAR(3) built in the context of Libya.

significant dynamic impacts in either case. Still, we note that the oil production growth responds positively to an SDI growth shock, and SDI growth responds negatively to an oil production shock, which is roughly confirmed by the robustness test results in Fig. 12 (b).

Finally, we depict the IRFs based on the context of Libya in Fig. 13. A shock to SDI growth would have an insignificant impact that goes back and forth between positive and negative states on oil production growth. While the response of SDI growth to an oil production growth shock presents a similar trend, it starts with a significant and positive effect that needs to be noticed. The results in the graph on the right once again demonstrate robustness.

5. Discussion

Looking at the results of the panel data for 38 countries assessed over the full period from 1990 to 2019, we cannot observe a significant relationship between sustainable development and the oil boom, either in one direction or in both directions. On the one hand, the period of 30 years is not short. Despite the relatively slow advancement of sustainable development, there have been various fluctuations in the oil market during this period (Weiner, 2005; Zavadska et al., 2020; Wang et al., 2022b). In this case, the nexus between the two variables may be unstable accordingly.

On the other hand, the panel data cover a wide range of countries. Whether it is oil production or the implementation of sustainable development, each economy is likely to be in a different state depending on its development stage and the extent to which it holds resources (Güney, 2019; Azam et al., 2021; Endo and Ikeda, 2022). Consequently, the relationship between oil booms and sustainable development varies from country/region to country/region. When the differences are large, it is reasonable that no obvious consistent trend would show up in the PVAR estimation of the panel series. In order to further investigate the nexus between oil booms and sustainable development, we test the causality and dynamic interactions between the two variables by taking different subperiods and countries as research objects, respectively. Next, we would discuss the empirical results both from a longitudinal overall perspective and cross-sectional specific perspectives.

5.1. *A holistic perspective: the characteristics of the relationships in different periods*

Based on the results of the Bai-Perron test, the only structural breakpoint in the SDI growth series is located in 2012, and the only structural breakpoint in the oil production growth series is located in 2005. Looking back at the dynamics of sustainable development and the oil industry, we find the following facts at the corresponding points in time. The United Nations Conference on Sustainable Development (the "Rio+20" Earth Summit), held in 2012, was the third international conference on environmental protection and sustainable development. It aimed to build consensus among governments and all sectors of society on key issues related to the coherent development of the economy and environment to better advance the future synergistic sustainable development agenda (Biermann, 2013). Following the conference, the United Nations released a series of SDGs covering environmental, economic and social aspects to guide how to achieve balanced development between different needs and challenges in the post-2015 (Haines et al., 2017; Higgins-Desbiolles and Wijesinghe, 2018). The existing goals and plans for sustainable development cannot directly provide the final answer, but they do provide the basis for a broad consensus that can lead to a more productive sustainable transition through the process of exploration.

Regarding the fluctuation in the oil industry, Hurricanes Katrina and Rita in the Gulf of Mexico region in 2005 caused a huge impact on the sensitive international oil market (Fratzscher et al., 2014; Ilbeigi and Dilkina, 2018). The hurricanes severely damaged the infrastructure of the oil and gas industry in the affected areas (Cruz and Krausmann, 2008), bringing oil production activities to a virtual standstill and sending oil prices soaring (Batten et al., 2017; Lovcha and Perez-Laborda, 2020). Other natural disasters and emergencies also affected oil supply and demand to varying degrees, such as the Mumbai high north platform fire, the London explosion in July and the Texas City Refinery explosion in March. The occurrence of these frequent and influential shocks may thus have led to structural changes in oil growth trends.

To attenuate the effect of structural breaks on the relationship between oil booms and sustainable development, we divide the sample into three subperiods based on the breakpoint dates and then observe them separately. In the first two subperiods, a shock to either side would mainly have negative effects on the other, except for the positive response of SDI growth to an oil production growth shock in the second subperiod (2005–2011). This output indicates that oil production growth could have a weak and short-term contribution to sustainable development, in a given period. However, we are still unable to find any significant nexus between sustainable development progress and oil production growth in the first two subperiods, either in terms of Granger causality or shock dynamics. Hence, we focus on the interpretation of the phenomena observed in the third subperiod.

In the subperiod from 2012 to 2019, we observe a statistically significant relationship between sustainable development and oil booms. Not only is oil production growth a one-way Granger cause of SDI growth, but also a shock to SDI growth would have a significant and positive effect on oil production growth. These results clearly show that the increase in oil production owns a direct or indirect influence on the advancement of sustainable development, while the sustainable development progress is capable of strongly promoting oil production growth. As is well known, the core of sustainable development lies in achieving balanced economic, environmental and social development (Nguyen and Ngo, 2021; Mentis and Moonsammy, 2022). Although the exploitation and processing of oil are not conducive to carbon emission reduction (Hashemi et al., 2014; Manfroni et al., 2021), it is an important incentive to promote economic growth. In recent years, we have gained a clearer understanding of the pursuit of sustainable development and developed richer implementation paths (Niaz, 2021; Ayilu et al., 2022). The economic and social benefits of planned and rational oil production can, to a certain extent, provide a solid foundation for further sustainable development. When sustainable development is effectively advanced, it also sends a signal that a steady increase in oil production is acceptable.

5.2. Specific perspectives: the characteristics of the relationships under contexts of various countries

By exploring the overall picture across 38 countries at different times, we get a glimpse of the relationship between oil booms and sustainable development. In addition, we select seven countries from different regions of the world in an attempt to understand how this relationship might look in different economies. Based on the empirical results of the corresponding seven VAR models, we confirm that the performance on this theme varies considerably across economies.

The results of the China-based analysis show that oil production growth and SDI growth are mutual Granger causality to each other, and that a shock to SDI growth would have a significant and positive impact on oil production growth in the early and fifth periods. There is a statistically strong correlation between China's sustainable development and oil booms while the former could generally drive the latter. As one of the world's largest energy consumers, China's energy structure has always been dominated by fossil fuels represented by oil and natural gas (Zhu et al., 2022). With the rapid economic development, oil production and consumption in this land are bound to continue to increase for the foreseeable future. Accordingly, the nation's CO_2 emissions and associated material resource consumption will inevitably remain at a high level (Liu et al., 2020). For China, a developing country with a large population, oil is inevitably the choice for its economic and social development at this stage. In order to promote sustainable development in this context, China has launched a series of strategies to balance economic development with a green transition, such as the carbon peaking and carbon neutrality ("double carbon") goals (Zhao et al., 2022). This two-pronged strategy remains a relatively sensible approach until conditions are in place to shift the focus more toward environmental protection.

Similarly, based on the results of the empirical study on Kuwait, we identify a more significant linkage between sustainable development and oil booms. Both the Granger causality and the dynamic long-term relationship between them are bidirectional and significant. It is worth noting that both oil production growth and SDI growth negatively respond to a shock to one another, suggesting a short-term mutually inhibiting relationship between sustainable development and oil booms. Kuwait is very rich in oil reserves and its economic income is highly dependent on oil exports. As a result, Kuwait has long been among the countries with the highest per capita energy consumption and CO_2 emissions in the world (Alsayegh et al., 2018). However, its mono-economic model has made Kuwait highly vulnerable to the dynamics of the oil industry. In the context of sustainable development, the slowdown in oil exploration and production under stricter regulations, coupled with the decline in oil prices in recent years due to the COVID-19 pandemic and other influences, has caused great "trouble" for Kuwait. For the Middle East, the region with the highest concentration of oil-producing countries in the world, overcoming the pain of economic and social structural change in the face of the trend toward sustainable development is a common challenge for the countries concerned (Nematollahi et al., 2016).

For the other countries involved, the corresponding relationships between sustainable development and oil booms are quite different. Besides China or Kuwait-based scenarios already mentioned, a shock to oil production growth would only significantly affect SDI growth in the context of Libya, which is positive. While oil production growth would only respond significantly to an SDI growth shock in the context of Brazil, which is also positive. The empirical result based on Norway shows a reciprocal Granger causality between oil production growth and SDI growth. In addition, the output that oil production growth is a unilateral Granger causality of SDI growth appears only in the Libyan context, while the output that SDI growth is a unilateral Granger causality of oil production growth appears only in the Brazilian context. However, we do not observe any statistically significant nexus in the context of the USA or Russia, neither Granger causality nor the long-term dynamic relationship of the impulse response. Horizontally, the sustainable development and oil industry dynamics of different economies could be widely different, resulting in a greater variation in the relationship between the two subjects.

6. Conclusions and policy implications

Sustainable development is the inevitable path to a better and longer-term future for humanity. This massive global transformation is based on three pillars, economy, society and environment, and is leading to a systematic shift in development thinking and action in countries around the world. For each of the pillars involved, the energy sector, and in particular the oil sector, is a key element with broad and far-reaching implications. With the help of PVAR and VAR models, we have respectively examined the relationship between sustainable development and oil booms in 38 countries and seven specific countries from 1990 to 2019. The results have shown that the relationship takes on a correspondingly differentiated pattern over time and in the context of various economies.

Taken as a whole, there is no statistically significant relationship between sustainable development and oil booms. However, after considering the structural breaks and dividing the series into multiple subperiods accordingly, we have found a significant nexus between the two in the interval from 2012 to 2019. Not only oil production growth is the Granger reason for SDI growth, but also SDI growth has a short-term promoting effect on oil production growth. Horizontally, the relationship between oil booms and sustainable development in the context of different economies is characterized by different features. Among them, the correlation between oil production growth and SDI growth is relatively strongest in the contexts of Kuwait and China. In contrast, the estimation results based on the USA and Russia show no statistically significant relationships between the two. Based on the results of the empirical analysis, we accordingly make the following suggestions:

(1) The formulation and implementation of relevant policies should keep pace with the times and make targeted adjustments to different periods. In line with the three core tenets of sustainable development, the model we are pursuing today is to achieve economic growth and social progress while ensuring environmental and resource sustainability. However, ecological conditions, such as carbon emissions, material footprint and water pollution, as well as the state of economic development, always fluctuate over time. This requires us to consciously shift the priorities of the economic, environmental and social elements when faced with specific situations to effectively guide practical work. At a time of relatively sluggish economic growth, a modest increase in the production and consumption of oil is conducive to

providing an impetus for sustainable development. In contrast, when the economic and social benefits are positive, we should apply more stringent environmental requirements to oil exploration, production and waste disposal.

(2) The sustainable development strategies of various countries around the world should be interlinked and synergistic. Under guiding frameworks such as SDGs developed by the United Nations, each country would then further define its green transition plans appropriate to the social structure, level of development, geographical location and resource holdings. We ought to be aware that it is only feasible to try to achieve overall energy saving and emission reduction before implementing a strong green economy in full swing, rather than fantasizing about applying uniform standards to all economies. Apparently, this requires active consultation and cooperation between governments and all sectors of society around the world on sustainable development agendas and oil industry activities. For instance, developed countries could appropriately shoulder more of the burden of sustainable transition and lead by example to provide practical experience for other countries that still need to primarily drive economic growth at this stage, and where the pace of transition is relatively late. In addition, countries with a single economic model that is highly dependent on oil should also actively seek financial and commercial transformation, reform the oil industry's mode of operation and take the corresponding responsibility for environmental protection and consumption reduction.

(3) The sustainable transformation of the oil industry itself should be a top priority to foster a positive link between sustainable development and oil booms. At present, oil is still used extensively for economic and social development, as well as for people's daily life. It is not enough to rely solely on reforms in other sectors and remedial measures to offset the negative effects of oil production and consumption. Therefore, it is urgent to take steps to realize the low-carbon transformation of the oil industry, such as improving energy productivity and utilization, increasing renewable energy investments, and developing the CCUS (carbon capture, utilization and storage).

CRediT authorship contribution statement

Yu Qian: Conceptualization, Data curation, Formal analysis, Supervision, Visualization, Validation, Writing – original draft, Writing – review & editing. **Zeshui Xu:** Methodology, Validation, Reviewing, Writing – original draft, Writing – review & editing. **Yong Qin:** Data curation, Methodology, Software, Visualization, Writing – review & editing. **Xunjie Gou:** Conceptualization, Data curation, Formal analysis, Supervision, Visualization, Validation, Writing – original draft, Writing – review & editing. **Marinko Skare:** Validation, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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