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Research Article

The Role of Technology in the Impact of Non-Renewable Energy Consumption on Ecological Resilience: Application of Threshold Structural Vector Autoregression (TSVAR) Model

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Abstract
New technologies play an increasingly vital role in managing energy resources and enhancing environmental sustainability. Given the significant challenges posed by the use of non-renewable energy sources, it is essential to examine how technology can mitigate their consumption and promote ecological resilience. This study investigates the asymmetric effects of non-renewable energy consumption on ecological resilience through technological influence in Iran over the period 1990–2022, using the Threshold Structural Vector Autoregression (TSVAR) model. The results reveal a threshold of 0.171% for the growth rate of non-renewable energy consumption, beyond which the impact on ecological resilience differs substantially. The study finds that the ecological response varies depending on whether energy consumption is above or below this threshold. These findings underscore the importance of integrating advanced technologies and digital solutions into the energy sector. Policy implications include prioritizing technological innovation and smart energy systems to improve efficiency, reduce reliance on fossil fuels, and ultimately strengthen ecological resilience across multiple dimensions.

Keywords Energy consumption . Ecological resilience . Information and communications technology . TSVAR model

Introduction

Environmental issues have become one of the most significant global concerns in recent decades. A comparative search of terms such as “environment,” “inflation,” “unemployment,” and “economic growth” in major search engines highlights the increasing prominence of environmental topics in public discourse. Despite the absence of a universally accepted definition, the environment is generally described as the sum of all living and non-living

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components that support life on Earth. By early 2023, the global population surpassed eight billion, exerting unprecedented pressure on the planet's capacity to sustain human life. Key threats include rapid population growth, climate change, deforestation, and pollution—defined as the introduction of harmful substances or energies beyond the environment's natural capacity to absorb them, disrupting ecological balance. The exponential growth in human population, combined with industrialization and urbanization throughout the 20th century, has led to severe environmental degradation. Climate change and biodiversity loss have historically been the two most pressing global environmental issues. The 1987 Brundtland Report marked a turning point in environmental governance by introducing the concept of sustainable development, emphasizing that natural resources cannot be exploited without regard for future generations. Sustainable development integrates three interconnected dimensions: economic, ecological, and social (Pacheco-Vega, 2017). The concept of resilience, derived from the Latin word "resilio," meaning "to leap back," was introduced by Holling (1973) in an ecological context. Resilience refers to a system's ability to anticipate, absorb, adapt to, or recover from disruptive events. Ecological literature distinguishes between two definitions: one focusing on system stability near equilibrium, and the other—ecological resilience—emphasizing a system's ability to reorganize following large perturbations, potentially settling into a new equilibrium state (Dakos & Kéfi, 2022). In today's world, environmental resilience faces critical challenges, notably the continued dependence on non-renewable energy sources. Despite the environmental degradation associated with fossil fuel consumption, transitioning to renewable energy remains economically and technologically challenging for many nations. Existing industrial infrastructures are heavily reliant on non-renewable energy, and altering them incurs significant costs. Consequently, energy consumption habits and production technologies, both of which change slowly over time, remain major determinants of environmental resilience. While renewable energies are typically more cost-efficient and environmentally friendly, the transition process is hampered by entrenched consumption patterns and technological lock-ins. Moreover, advancements in information and communication technology (ICT) present a dual-edged sword. On the one hand, ICT can enhance energy efficiency and enable cleaner production processes. On the other hand, ICT infrastructure itself consumes significant energy, particularly as digitalization, cloud computing, and data centers proliferate globally. The theoretical relationship between ICT and environmental degradation has been explored through multiple frameworks. Ecological modernization theory posits that technological innovations improve energy efficiency and reduce environmental harm. In contrast, Jevons' paradox suggests that increased efficiency lowers energy service costs, potentially stimulating greater energy consumption and offsetting efficiency gains (Atsu et al., 2021; Reiger, 2021). Another theoretical strand identifies both linear and non-linear effects of ICT on carbon dioxide emissions. The linear effect suggests that ICT adoption reduces emissions, while the non-linear effect implies an inverted U-shaped relationship. ICT's environmental impact occurs through three channels: the first-order (direct) effects of ICT production and distribution, the second-order (indirect) effects through process improvements, and the third-order (rebound) effects that align with Jevons' paradox (Charfeddine & Umiai, 2023).

Empirical studies provide nuanced insights into these theoretical perspectives. Salahuddin & Alam (2015) found that internet usage increased electricity consumption in Australia, though green technologies could mitigate adverse environmental effects. An Higón et al. (2017) identified an inverted U-shaped relationship between ICT and carbon emissions across 142 economies. LU (2018) demonstrated that in 12 Asian countries, ICT usage reduced carbon dioxide emissions despite rising energy consumption. Akande et al. (2019) highlighted that smart cities are not necessarily sustainable, emphasizing the role of greenhouse gas emissions and ICT infrastructure disparities among European cities. Further studies in the BRICS countries (Haseeb et al., 2019; Chien et al., 2021; Tekin, 2024) confirmed long-term equilibrium relationships between ICT, energy consumption, and environmental quality, with varying effects depending on the development level and energy policies. Khan et al. (2020) and Appiah-Otoo et al. (2023) extended these findings globally, illustrating that ICT reduces emissions in technologically advanced nations but may exacerbate environmental degradation in low-technology contexts. Tekin & Dirir (2024) showed that LPG consumption negatively correlates with CO_2 emissions, underscoring the complexity of energy-environment dynamics. Collectively, these studies underscore the intricate interplay between ICT development, energy consumption, and ecological resilience. While ICT holds potential to mitigate environmental degradation, its positive impact depends on complementary factors such as renewable energy adoption, efficient energy usage, and supportive policy frameworks.

In the context of the impact of energy consumption on ecological resilience, considerable studies have been conducted, most of which have not aimed to test the type of effect but rather its magnitude. This is because it is generally expected that increasing energy consumption has a negative and diminishing effect on ecological resilience. However, in this study, the importance of information and communication technology (ICT) in determining the extent of the impact of non-renewable energy consumption on ecological resilience will be assessed. This point can reveal the extent to which technology can mitigate the environmental consequences of non-renewable energy consumption, and in fact, it is this aspect that distinguishes the present study from similar research in which the role of energy consumption on ecological resilience has been evaluated. Against this backdrop, the present study addresses a crucial research gap: the lack of understanding regarding how the level of non-renewable energy consumption alters the effect of technology on ecological resilience. The core research question is whether technology can buffer or amplify the ecological consequences of non-renewable energy use—and if so, under what conditions. The novelty of this research lies in three main contributions: first, the adoption of a Threshold Structural Vector Autoregression (TSVAR) approach, which allows for the identification of regime-dependent effects and nonlinear dynamics; second, the estimation of a specific consumption threshold above which the environmental role of technology shifts significantly; and third, the integration of ecological resilience into the energy-ICT-environment nexus, which has received limited empirical attention. By leveraging the TSVAR model, this study examines how energy-related shocks propagate through the ecological system in different consumption regimes and explores the role of technological capacity in shaping these effects. This approach provides a dynamic and policy-relevant framework to evaluate the ecological sustainability of energy transitions in the digital age.

Research Hypotheses

H1: Technological advancement moderates the negative effects of non-renewable energy consumption on ecological resilience below the identified threshold.
H2: At higher levels of non-renewable energy consumption, the impact of technology on enhancing ecological resilience becomes stronger due to increased environmental fluctuations.

Material and Methods

Hamilton investigated non-linear and threshold models in economic analysis for the first time in 1994 (Lange & Rahbek, 2009). The Threshold Structural Vector Autoregression (TSVAR) model is a non-linear model that obtains structural failure under the threshold limits in a relationship. The effect of some variables may be different in the states above and below the threshold limit, and in such a situation, the use of non-linear models that allow the separation of positive and negative impulses and the analysis of their effects in values above and below the threshold, have advantages over other patterns. Therefore, in this research, the TSVAR model was used to investigate the role of information and communication technology in the impact of non-renewable energy consumption on ecological resilience from 1990 to 2022. The TSVAR model can be specified as Equation 1.

$$Y_t = C_1 + A_1 Y_t + B_1(L) Y_{t-1} + (C_2 + A_2 Y_t + B_2(L) Y_{t-1}) I[Z_{t-d} > \gamma] + U_t \quad (1)$$

In this relation, Z_t represents the threshold variable, d is the interval, $I[Z_{t-d}>\gamma]$ represents an index function, and γ is the threshold value. $A_1(L)$ and $A_2(L)$ are simultaneous matrices ($K\times K$) because the simultaneous effects may be different in regimes. $B_1(L)$ and $B_2(L)$ are polynomial matrices ($K\times K$) with discontinuity. U_t is the sequential and uncorrelated structural disturbance vector. Yt is a vector of endogenous variables ($K\times 1$), which includes the growth of non-renewable energy consumption (GENERGY), the growth of ecological resilience (GECORES), and the multiplicative variable of the growth of information and communication technology in non-renewable energy consumption (GENTEC). Information and communication technology (ICT) is considered a proxy for the level of technological advancement, as higher levels of ICT development can reduce the amount of energy consumed per unit of output. In practice, a significant portion of economic activities that are costly and time-consuming in the real world are transferred to the virtual domain through ICT, and the volume of such activities depends largely on the level of ICT penetration.

To measure ICT, the number of internet users has been used, with data obtained from the International Telecommunication Union (ITU). Non-renewable energy consumption is measured using annual fossil fuel consumption data, and ecological resilience is proxied by CO_2 emissions from fossil fuel combustion. The data on CO_2 emissions from all fossil fuels are sourced from *Our World in Data*. Accordingly, the vector of endogenous variables is specified as $Y_t = [GENERGY, GENTEC, GECORES]$

If Z_{t-d} is smaller than the threshold value (γ), it takes zero; otherwise, it takes 1. Therefore, the threshold vector autoregression model can be written as Equation 2:

$$\begin{array}{ll} C_1 + A_1 Y_t + B_1(L) Y_{t-1} + U_t & if\ I = 0 \\ (C_1 + C_2) + (A_1 + A_2) Y_t + [B_1(L) + B_2(L)] Y_{t-1} + U_t & if\ I = 1 \end{array} \quad (2)$$

After being divided into two different regimes, the non-linear structural vector autoregression approach can now be used to analyze the response of ecological resilience to different impulses. A vector autoregression pattern of order (P) can be expressed as Equation 3.

$$Y_t = \mu + A_1 Y_{t-1} + \cdots + A_p Y_{1-p} + \varepsilon_t \qquad A(L) Y_t = \mu + \varepsilon_t \quad (3)$$

In the above relation, $A(L)$ is a polynomial matrix with an interval of order P and $\varepsilon_t \sim N(0, \Omega)$. According to Weld theory, a fixed process can represent a discontinuous distribution of uncorrelated disturbance components under weak rule conditions. Therefore, Equation 3 can be written as Equation 4.

$$Y_t = A^{-1}\ (L)\varepsilon_t\ and\ Y_t = B(L)\varepsilon_t \quad B_0 = 1\ and\ Y_t = B(L)\varepsilon_t \quad B_0 = 1 \quad (4)$$

The elements of ε_t are simultaneously correlated. Therefore, these elements cannot be shown as structural shocks. Elements of ε_t are orthogonal by applying constraints. Therefore, equation 4 can be rewritten as Equation 5.

$$Y_t = C(L) e_t \quad (5)$$

If β_0 is the unit matrix, Equations 6 and 7 could be presented.

$$\varepsilon_t = C_0 e_t \qquad \beta_j C_0 = C_j \tag{6}$$

$$B(L)C_0 = C(L) \tag{7}$$

In this case, the matrix C_0 contains nine components, and the three available internal variables are used in the system. By normalizing VAR (et), Equation 8 has presented.

$$\Omega = C_0 C'_0 \tag{8}$$

Based on this, the specification of the research model is in the form of Equation 9.

$$\begin{pmatrix} GENERGY \\ GENTEC \\ GECORES \end{pmatrix} = \begin{bmatrix} C_{11} & 0 & 0 \\ C_{21} & C_{22} & 0 \\ C_{31} & C_{32} & C_{33} \end{bmatrix} * \begin{bmatrix} e_t^{GENERGY} \\ e_t^{GENTEC} \\ e_t^{GECORES} \end{bmatrix} \tag{9}$$

ε_t is the adjusted error related to three variables: energy growth, ecological resilience growth, and energy technology growth. It was assumed that the relationship between ε_t and structural disorders is recursive. The TSVAR model estimates the model by testing the existence of a threshold effect structure. Hence, the hypothesis $C_2 = A_2 = B_2(L) = 0$ is tested first. However, the threshold value is undetected under the null hypothesis (there is no threshold effect). Also, the distribution of traditional statistical tests becomes non-standard due to the disturbing parameters. This problem is solved by following the three steps proposed by Balke (2000). First, the least-squares threshold model is estimated for all possible threshold values. Second, the Wald test statistic determines the difference between regimes for each threshold value. Third, three test statistics (i.e., Sup-Wald, Avg-Wald, and Exp Wald) are considered and used together. The Sup-Wald statistic is the maximum Wald statistic at all possible threshold values. The Avg-Wald statistic is the average of the Wald statistic over all possible threshold values. The Exp-Wald statistic is a function of the sum of the Wald exponential statistics. The empirical distribution of three statistics under the null hypothesis is obtained through the simulation method provided by Hansen (1996). If the statistic is significant, the null hypothesis of linear structure is rejected, and the threshold model is used to perform the analysis. Finally, the estimated threshold value is used to minimize the log determinant of the residual covariance matrix.

Results and Discussion

The results of the Phillips-Perron test are presented in Table 1. According to the results of Table 1, all the research variables are significant at the level of error of 5%. The results of the threshold significance test in the SVAR model based on Equation 9 are as follows in Tables 2 and 3.

Table 1. Philips-Perron unit root test

Variable	Include in test equation	PP t-static	Probability	Result
GENERGY	Intercept	-6.941	0.000	S
	Intercept and Trend	-8.517	0.000	S
GICT-GENERGY	Intercept	-4.070	0.003	S
	Intercept and Trend	-4.679	0.003	S
GECORES	Intercept	-5.134	0.000	S
	Intercept and Trend	-10.345	0.000	S

According to the results of Table 1, all the research variables are significant at the level of error of 5%. The results of the threshold significance test in the SVAR model based on Equation 9 are as follows in Tables 2 and 3.

Table 2. Threshold test

	Test Statistics		Result
Wald Test	Value	P-Value	
Sup-Wald	50.80	0.000	
Avg-Wald	37.25	0.000	0.171433
Exp-Wald	23.32	0.000	

The results of the non-linear test in Table 2 show that the parent statistic rejects the null hypothesis and, therefore, the model has threshold effects. Avg-Wald, Sup-Wald, and Exp-Wald test statistics are significant for the obtained threshold value. This shows that the TSVAR model has a threshold value and divides the period into two regimes. Following the confirmation of a statistically significant threshold and the division of the sample into two regimes, there is no further need for additional robustness or stability tests. This is because the statistical framework employed in this study is, by construction, embedded with valid inferential properties. In threshold models, the breakpoint (i.e., the threshold value) is not identified under the null hypothesis. However, by applying the Sup-Wald test in conjunction with a grid bootstrap procedure, threshold uncertainty is uniformly accounted for, and valid confidence sets for both the threshold and other model parameters can be obtained. As shown by Hansen (2000), this method ensures proper test size and desirable asymptotic power, thereby eliminating the need for further investigation into the stability of the threshold or the distribution of the test statistic. In addition, the structural identification in this model is based on long-run zero restrictions, which remain valid across both regimes. As Lütkepohl (2005) demonstrates, as long as these long-run restrictions hold, structural identification remains robust to small perturbations in lag length or sample specification. Furthermore, simulation-based evidence in the literature confirms that the finite-sample performance of threshold models remains reliable even with samples of approximately 100–200 observations—provided the model design (including lag selection, threshold variable, and trimming percentage) conforms to established setups (Chan, 1993; Hansen, 1996). Hence, there is no compelling need for auxiliary robustness experiments under alternative specifications. From a diagnostic perspective, the use of AIC/BIC for lag selection, and the passing of standard residual tests—namely, the Ljung–Box test for serial independence and the ARCH–LM test for homoskedasticity—together indicate that the classical moment conditions of VAR models are satisfied. Accordingly, as noted by Hamilton (1994) and Karlsson (2013), when these diagnostic criteria are met, there is little inferential gain from switching to alternative covariance estimators or identification schemes. Moreover, the use of a bootstrap approach in the estimation and testing stages relaxes any distributional assumptions on the residuals, thus mitigating the need to assume normality in the structural innovations (Cavaliere & Taylor, 2009). An additional important feature of the model design is the lagged specification of the threshold variable. Introducing the threshold variable with lags serves to implicitly address potential endogeneity concerns. Since the lagged threshold variable is orthogonal to the current structural shocks, its inclusion eliminates contemporaneous correlation and ensures exogeneity. Combined with the nonparametric nature of the bootstrap inference, this design reinforces the statistical integrity of the model and further guards against endogeneity bias. Therefore, if the growth of ecological resilience is lower than the threshold value, the growth of ecological resilience is in the first regime, and if the growth of ecological resilience is higher than the threshold value, the growth of ecological resilience is in the second regime. After confirming the existing threshold effect and dividing the period into two regimes, the non-linear impulse response function was used to analyze the dynamic effects of technology growth on the development of ecological resilience. In Figure 1, the response of the growth of ecological resilience in the country to the growth of information and communication technology at high threshold values, and in Figure 2, the response of the growth of ecological resilience in the country to the growth of information and communication technology at low threshold values are presented

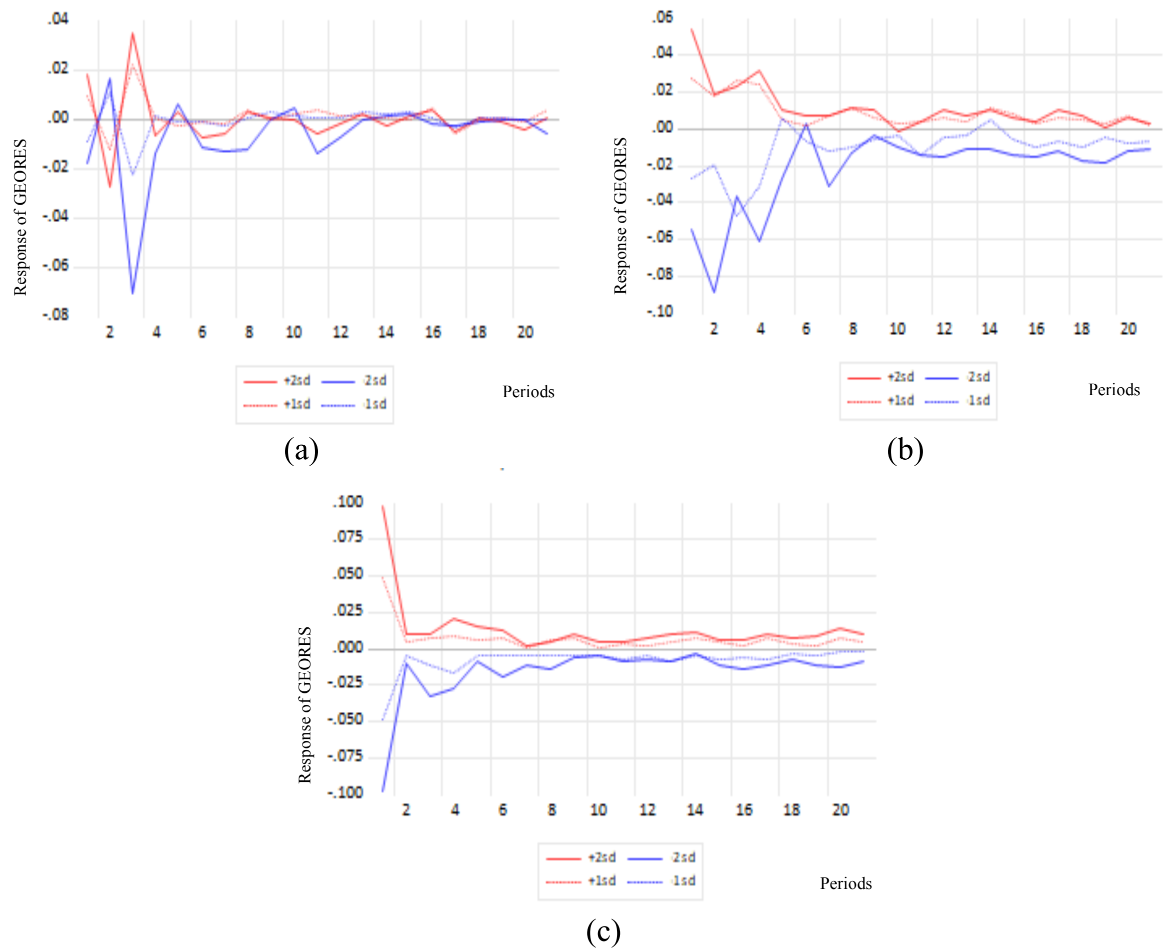

Figure 1. The reaction of the growth of ecological resilience in values higher than the threshold of non-renewable energy consumption; (a)Response curve of ecological resilience growth to positive and negative shocks in non-renewable energy consumption growth; (b)Response curve of ecological resilience growth to positive and negative shocks in non-renewable energy consumption technology growth; (c) Response curve of ecological resilience growth to positive and negative shocks in ecological resilience growth

As can be seen from Figure 1, in values higher than the growth threshold of non-renewable energy consumption, fluctuations are more intense than impulses, especially in the early periods. With a positive impulse, the system reacts immediately, and a sudden leap occurs in the growth of ecological resilience. After the initial shock, the system undergoes continuous fluctuations, and finally, it slowly returns to its initial state and goes towards damping with continuous fluctuations. On the other hand, when a negative impulse occurs, the system undergoes significant fluctuations, and a sharp decrease in ecological resilience is observed. Fluctuations of negative impulses are usually stronger and longer than those of positive impulses.

In general, at the upper limit of the non-renewable energy consumption threshold, technology's impact is greater, and this result is determined by more severe fluctuations and stronger reactions of the system to shocks. In this case, technologies that consume more energy significantly affect ecological resilience. In fact, ecological resilience increases with the increase of technology. This finding confirms the first hypothesis, which posited that the impact of technology on ecological resilience increases above the threshold level of non-renewable energy consumption.

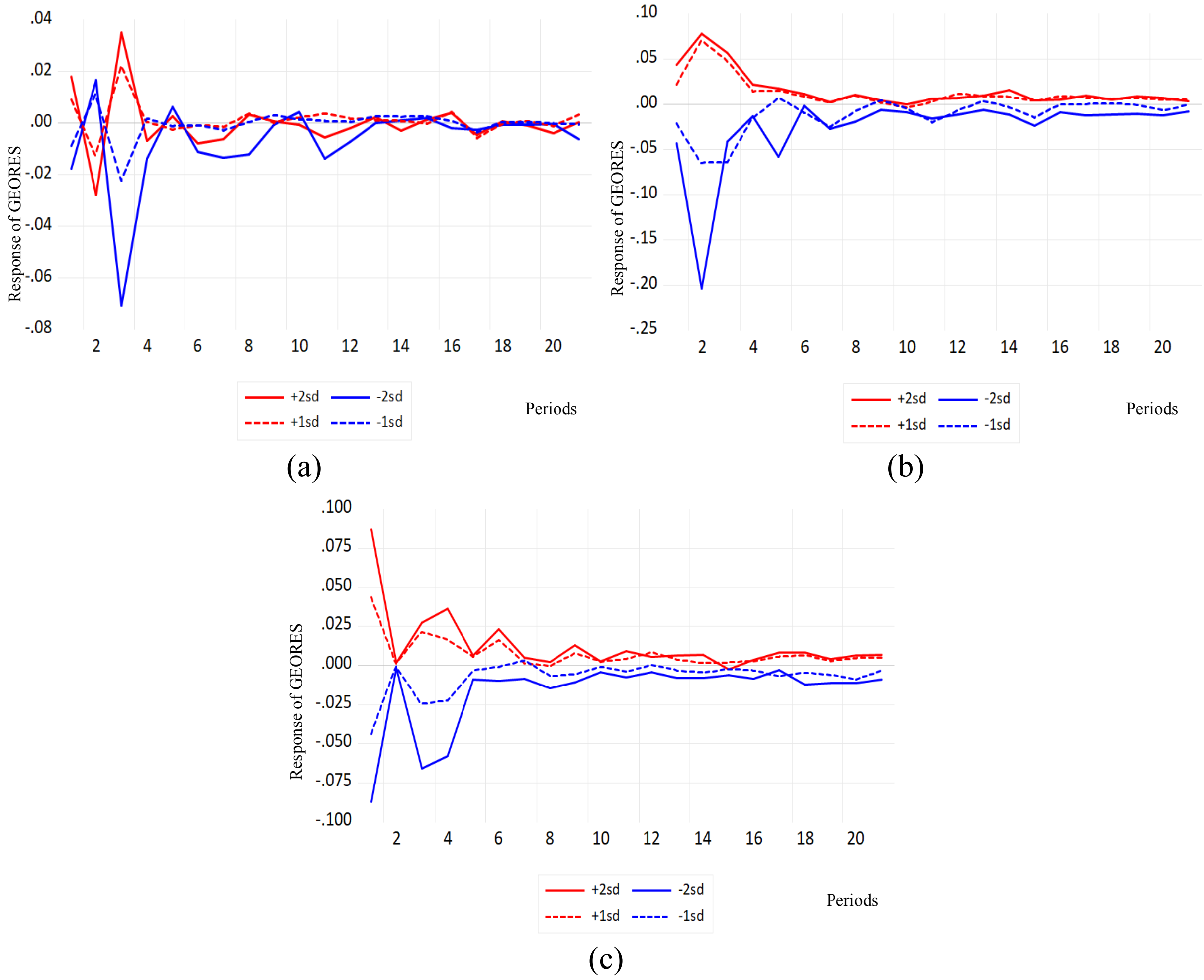

Figure 2. The reaction of the growth of ecological resilience in values lower than the threshold of non-renewable energy consumption; (a) Response curve of ecological resilience growth to positive and negative shocks in non-renewable energy consumption growth; (b) Response curve of ecological resilience growth to positive and negative shocks in non-renewable energy consumption technology growth; (c) Response curve of ecological resilience growth to positive and negative shocks in ecological resilience growth

Figure 2 shows that ecological resilience has shown a less and gentler reaction to both positive and negative impulses in the short term, which indicates that ecological resilience is less sensitive to impulses in this range of non-renewable energy consumption. In the long term, fluctuations are minimized, and the effects of impulses are almost eliminated.

In general, in Figure 2 compared to Figure 1, ecological resilience has shown a milder response to shocks, which indicates that these fluctuations are less and return to the initial state faster. This indicates that the impact of technology in the state lower than the threshold of non-renewable energy consumption is more limited. Accordingly, the second hypothesis is supported, as the influence of technology appears less significant when non-renewable energy consumption remains below the threshold.

Conclusion

The increasing trend, along with the fluctuation of the price of renewable energy carriers in the last half century, the significant increase in global production, and the spread of ecological crises has made the use of non-renewable energy sources an inevitable necessity for policymakers and economic planners. In this regard, the role that technology can play in the impact of economic growth on ecological resilience is of particular importance. Considering the effects of environmental impulses on the ecological system, the importance of using advanced technologies to predict, identify, and deal with these impulses increases. Advanced technologies can optimize the consumption of non-renewable energy, prevent extreme instabilities and fluctuations in the system, and reduce their negative effects on the ecological system. This research investigated the role of technology and the threshold effects of non-renewable energy consumption. The results showed that the growth threshold of non-renewable energy consumption in influencing ecological resilience through technology was 0.171%. At the upper limit of the non-renewable energy consumption threshold, the impact of technology is greater, and this result is determined by the long-term and more intense fluctuations of ecological resilience to shocks. In fact, ecological resilience increases with increasing technology. In general, depending on the mechanism of transfer of momentum effects in the Threshold Structural Vector Autoregression (TSVAR) model, the impact of non-renewable energy consumption momentum on technological ecological resilience is different in various regimes. This issue indicates that the effect of non-renewable energy consumption on ecological resilience depends on the level and amount of non-renewable energy consumption, and the change in the amount of non-renewable energy consumption under any condition has not increased ecological resilience.

Based on the findings of this study, policymakers in the energy and environmental sectors are advised to adopt a more strategic approach toward the ecological consequences of economic growth. In this context, it is essential to design and implement operational plans aimed at developing and deploying modern technologies in the energy sector—including smart energy management systems, optimization of power transmission infrastructure, and the digitalization of energy production and consumption processes. Such measures can significantly enhance energy efficiency, reduce dependence on non-renewable resources, and ultimately strengthen ecological resilience. It is worth noting that any delay in pursuing this technological transition may result in intensified pressure on the country's biocapacity, increased environmental instability, and a decline in socio-economic sustainability.

Declarations

Ethics Approval This article does not contain any studies with human participants or animals performed by any of the authors. Therefore, ethics approval was not required.

Availability of Data and Material The data used in this research were obtained from publicly available databases. These datasets are available upon reasonable request from the corresponding author.

Conflicts of Interest / Competing Interests 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.

Authors' Contributions All authors contributed to the study conception and design. All authors read and approved the final manuscript.

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