Interactions Among Energy Consumption per GDP, Technological Innovation Input and Energy Consumption Structure in China During the 14th Five-Year Plan Period

Yan Yi*

Department of Finance and Statistics, Hunan University, Hunan, China

* Corresponding Author Email: yiyan@hnu.edu.cn

Abstract. In the context of China's 14th Five-Year Plan, this paper examines the complex interactions between energy utilization efficiency, technological advancement, and energy-consuming structure. The Vector Autoregressive (VAR) model, impulse response functions, and variance decomposition are used to thoroughly analyze time series data extending from 1999 to 2022 to reveal the dynamic relationships and effect mechanisms among these variables. The results show that the multidimensional adjustment of energy use has been driven in large part by technological innovation. In the short term, the improvement in energy utilization efficiency is predominantly propelled by its inherent inertia, while technological innovation gradually becomes the primary driving force. The positive impact of technological innovation input enhances energy utilization efficiency, while improved energy utilization efficiency stimulates later-stage technological innovation investment. Furthermore, a shift towards reduced GDP energy intensity is essential, focusing on controlling fossil fuel usage while advancing non-fossil energy sources. It underscores the significance of optimizing traditional fossil fuel utilization and gradually transitioning to clean energy sources for sustained and efficient energy-consuming patterns.

Keywords: GDP energy intensity, technological innovation, energy consumption structure, VAR model.

1. Introduction

1.1. Research Background and Relevant Literature Review

1.1.1 Status of Air Pollution in China and Its Energy Consumption Factors

During the 14th Five-Year period (2021-2025), China's air pollution situation reveals improvements as well as challenges. Aiming at deepening China's air pollution prevention and control, many scholars are working on ideas to reduce pollution, especially carbon emissions [1, 2]. Data from the China Environmental Monitoring Terminal shows that in 2022, the average concentrations of six major pollutants in China's atmosphere display the feature of "three decreases, two flats, and one rise". Nonetheless, there is still a significant gap when compared horizontally with other developed and medium-sized developing countries. In 2022, the average concentration of PM2.5 in cities at the prefecture level and above in China was 29 μg/m2, which fell below the 30 mark for the first time, but nearly three times the WHO's recommended safety standard of 10 μg/m2.

While historically, China's air pollution primarily stemmed from coal usage for residential and industrial purposes, in recent years, the escalation in the number of motorized vehicles has also contributed to the increasing proportion of pollution caused by burning petroleum (e.g.CO, SO2, solid particles, and greenhouse gases). Consequently, coal and oil can be the two main fossil energy sources when examining air pollution. There is a need to reduce the relative scale of the two traditional fossil energy consumption, and it could be achieved by two strategies: reducing its losses and developing new energy sources.

1.1.2 China's Economic Development Has a High Dependence on Energy Consumption

GDP is used to measure the total value of final products and services produced in the range of a country or region within a certain period. China's performance appraisal standard is solely GDP for a long, ignoring the huge consumption of energy resources as well as environmental damage. The result

is that energy consumption originating from the development of the national economy far exceeds its growth rate. Under the double constraints of energy and environment, optimizing the structure and efficiency of energy consumption is indispensable for energy conservation and emission reduction [3].

1.1.3 Technological Innovation as an Internal Driver of Multidimensional Adjustment of Energy Consumption

The process of industrial restructuring relies heavily on technological innovation to cut energy use and boost energy effectiveness. The transmission path of technological innovation is not only demonstrated by its capacity to directly increase energy efficiency through new production combinations but also by its ability to indirectly affect energy consumption through the transformation of established industries and the optimization of industrial structure, as well as by exploiting clean alternative energy [4]. Due to technological development, the composition of energy consumption has changed, becoming more diverse and balanced, which will, to some extent, affect energy efficiency.

1.1.4 Energy Consumption Structure and Efficiency Nexus

Optimizing the energy consumption structure enhances energy efficiency by reducing the share of coal in the energy mix through energy source diversification. Using the structure of the system dynamics model, Bi Shenhao et al. discovered that the correlation and interaction of energy consumption structure and energy efficiency form a complex system [5]. There are numerous impacting elements, with economic development being one of the key links [3].

Combining the four aspects mentioned above, this paper summarizes the framework of the energy consumption effect mechanism presented in Figure 1 below and takes it as the starting logic. In the flow chart, Energy consumption includes the absolute amount of energy consumption, the use of its efficiency (unit) and other consumption valuations; energy consumption structure mainly refers to the ratio of non-clean energy to clean energy. At present, there are relatively few studies on the dynamic impact and the extent of the relationship between energy consumption efficiency, technological innovation and energy consumption structure. This is the main point of the paper.

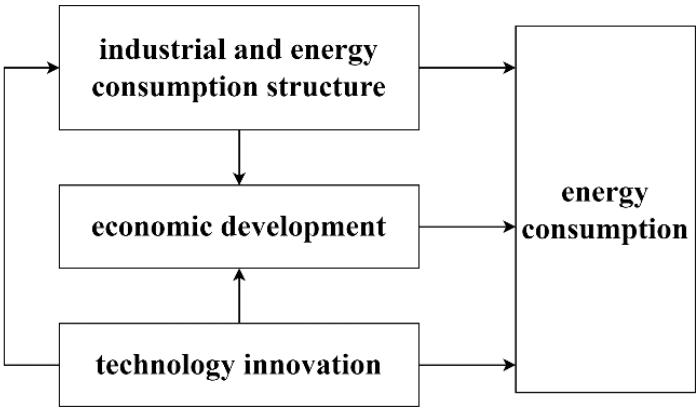


Fig. 1 Energy consumption impact mechanism framework

1.2. Research Theme and Significance

This paper applies the VAR model to multiple time series data from 1999 to 2022 and the 14th Five-Year Plan hotspot to interpret the dynamic interactions between GDP-weighted energy consumption, energy consumption structure, and the contribution of technological innovation. This research estimates the degree of response to its shocks and the length of the response period duration based on the premise that technological breakthroughs are known to result in a cleaner transformation of the energy consumption structure and a reduction in energy consumption per unit of GDP. The relationship between the structure of energy consumption and the amount of energy consumed per unit of GDP is not clearly defined for the following reasons. The reduction in per unit GDP energy

use efficiency may be attributed to higher penetration of new energy sources, but it may also result from optimizing choices of specific varieties of traditional fossil energy sources throughout the process of technology innovations, which does not necessarily account for the decline in the share of fossil energy; similarly, it is unknown if the increase of energy using efficiency will strengthen national management's resolve to implement the energy structural reform considerably.

This paper contrasts the impact response intensity and duration of one individual variable on another individual variable within the three-variable model. It provides initial assessments of the two uncertain transmission paths mentioned above. Furthermore, it extensively analyzes the proportion of contribution to changes in unit GDP energy consumption from intrinsic and external variables. By decomposing the factors affecting unit GDP energy consumption, the focal points of the green energy policy domain are derived.

These days China's energy supply chain strategic security demands persist. The energy production and consumption structure, primarily coal and secondary to oil, cannot be swiftly altered. However, during the 14th Five-Year Plan period, a crucial and opportune phase for achieving a carbon peak, the gravity of ecological and environmental issues continually compelled the establishment of a green and low-carbon energy consumption pattern. This paper centers on three vital indicators concerning energy and presents its perspectives on transformation pathways.

2. Empirical Research Design

2.1. Indicator Selection

Empirical testing of the model requires the identification of specific indicators and data sources for the variables in the model, and the specific three indicators are chosen—Energy utilization efficiency indicator (X), technological innovation indicator (Y), and energy consumption structure indicator (Z). Their interpretations are as follows:

The paper uses energy consumption per unit of GDP to interpret energy utilization efficiency, which refers to the total energy consumed within a specific period for producing one unit of gross domestic product in a country or region. A lower value of this indicator is preferred, indicating reduced reliance on economic development on energy consumption.

As for the technological innovation input indicator, through a review of relevant literature, Lu et al. measured technological innovation input (ln RDINVEST) by logarithmically processing enterprise R&D expenditure [6]. Wu et al. utilized the ratio of research and development expenditure to GDP and the number of patented applications and authorizations as indicators for measuring the input and output of technological innovation [7]. Yu used the R&D expenditure to GDP ratio to gauge the input and output of technological innovation. [8]. Considering data availability and the stationarity of time series data, this paper selects per capita R&D expenditure (logged) as an alternative indicator to measure the level of technological innovation input.

As for the energy consumption structure indicator, according to classifications from the China National Institute of Standardization, coal and oil, due to their non-renewable and polluting attributes, are categorized as high-carbon fossil fuels. Broadly, natural gas belongs to clean energy with relatively clean and low-carbon advantages. Natural gas is one of the key components in China's modern clean energy system and serves as a powerful lever for scaling up new energy development and achieving low-carbon transformation [9, 10]. New clean energy sources are becoming increasingly popular, with hydropower being the most stable and largest generator of electricity. According to China's National Bureau of Statistics, the amount of electricity provided by hydropower in 2022 will be 1202 billion kilowatt-hours (kWh), accounting for 14.33 percent of the total, and is 6.14 percent higher than the share of wind power, which is ranked one place behind. The paper develops a measure of the ratio of primary non-clean energy sources to primary clean energy sources, or the overall consumption of coal and oil compared to the total consumption of hydroelectricity and natural gas, taking data accessibility into account.

All original data were obtained from the China Statistical Yearbook, and the empirical analysis tool was Eviews 10.0. The data are organized in Table 1 below.

Table 1. Time series data for the three major variables from 1999 to 2022.

Year	X: National energy consumption per unit of GDP (equivalent value)	Y: per capita R&D expenditure	Z: Energy consumption structure (consumption of oil and coal/consumption of hydroelectricity and natural gas)
Unit	Tons of standard coal / ten thousand yuan	Ten thousand yuan	-
1999	3.00	8.30	11.66
2000	2.89	9.70	9.53
2001	1.43	10.90	8.26
2002	1.43	12.40	8.52
2003	1.51	14.10	9.31
2004	1.60	17.10	9.10
2005	1.63	18.00	9.20
2006	1.36	20.00	8.90
2007	1.29	21.40	8.52
2008	1.21	23.50	7.47
2009	1.16	24.61	7.33
2010	0.88	27.70	6.46
2011	0.86	30.10	6.69
2012	0.83	31.70	5.90
2013	0.79	33.50	5.45
2014	0.76	35.10	4.92
2015	0.63	37.70	4.62
2016	0.60	40.40	4.24
2017	0.58	43.60	3.88
2018	0.56	44.90	3.52
2019	0.55	46.10	3.29
2020	0.55	46.60	3.12
2021	0.53	48.90	2.92
2022	0.52	49.80	2.82

2.2. Data Preprocessing: Unit Root Test for Smoothness—Augment Dickey-Fuller Test

The Augmented Dickey-Fuller (ADF) test has three models: Model (1) without intercept and time trend terms; Model (2) with only an intercept term; Model (3) with both intercept and time trend terms, as shown below.

$$\Delta X_t = \delta X_{t-1} + \sum_{i=1}^{m} \beta_i \Delta X_{t-1} + \varepsilon_t \quad (1)$$

$$\Delta X_t = \alpha + \delta X_{t-1} + \sum_{i=1}^{m} \beta_i \Delta X_{t-1} + \varepsilon_t \quad (2)$$

$$\Delta X_t = \alpha + \gamma t + \delta X_{t-1} + \sum_{i=1}^{m} \beta_i \Delta X_{t-1} + \varepsilon_t \quad (3)$$

The testing procedure follows (3) – (2) – (1), with the null hypothesis of a unit root presence. In terms of the specific testing approach in this study:

Begin by testing (3). If the null hypothesis is rejected, then examine the significance of its time trend term. If this term is rejected, the trend is stationary; otherwise proceed to test the significance

of the intercept coefficient in (2) — if significant, the series is stationary with an intercept; if not, it is stationary without a time trend and intercept.

Subsequently, if initially not rejecting the null hypothesis in (3) directly test (2). If the null hypothesis is rejected, go back to test the significance of the intercept coefficient in (2) again, investigating whether it is stationary with an intercept; if both (3) and (2) are rejected then test (1) — if (1) is rejected, it is stationary without a time trend and intercept; otherwise, a unit root process is present.

Based on the above procedure, a conclusion can be drawn that all three variables X, lnY, and Z are smooth series, and the test results are as follows in Table 2.

Table 2. Augment Dickey-fuller tests of three variables

Variable name	ADF test value	Critical values for each level of significance			Stationary types
		1%	5%	10%	
X	-3.6291	-4.4163	-3.6220	-3.2486	trend stationary process
lnY	-4.0176	-3.8574	-3.0404	-2.6606	stationary process without intercept term and trend term
Z	-4.7879	-4.4679	-3.6450	-3.2615	trend stationary process

2.3. Model Identification and Setting

The Vector Autoregressive Model (VAR) is suitable when there is no clear economic theory indicating causal relationships and influences among variables. Given the theoretical analysis in the preceding research background and the significance of the study, there exists an interplay and interdependence among unit GDP energy consumption, per capita R&D expenditure, and energy consumption structure, but the specific relationships are not yet clear. To elucidate the strength and trends of the interconnections between these variables, this paper employs the VAR Model for empirical investigation, which has the advantage of not requiring assumptions about endogeneity. It treats all variables as endogenous and estimates the dynamic relationships among all of them. Moreover, it allows the analysis of how random disturbances dynamically impact the system of variables.

Let W_t = {X, lnY, Z}, and W_t is a three-dimensional time series vector including energy utilization efficiency index, technological innovation index and energy consumption structure index. The VAR model is as follows:

$$W_t = \alpha + \sum_{j=1}^{p} A_j W_{t-j} + \mu_t, t = 1,2,\cdots,T \quad (4)$$

Where t is the year; $\alpha$is the intercept term vector; A is the parameter matrix; p is the lag order; $\mu_t$is the random disturbance term.

3. Empirical Research Analyses and Conclusions

3.1. The Lag Order of the VAR Model

The order line with the most significant numbers is chosen by the relevance of each index in the lag length standard, and the ideal lag order is found to be 4. Table 3 below displays the results.

Table 3. Significance of the Lag Length Criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	18.99156	NA	3.73e-05	-1.683322	-1.534201	-1.658085
1	82.46317	100.2183	1.23e-07	-7.417176	-6.820688	-7.316227
2	99.24253	21.19497	5.93e-08	-8.236055	-7.192202	-8.059394
3	119.5397	19.22890*	2.30e-08	-9.425231	-7.934012	-9.172858
4	**144.1072**	**15.51631**	**7.86e-09***	**-11.06392**	**-9.125330***	**-11.00037***
5	156.3396	3.862859	2.27e-08	-11.40417*	-9.018215	-10.73583

3.2. Granger Causality Test

Considering that if the lagged values of certain variables in the VAR model do not significantly affect the dependent variable, there might be doubts about establishing the VAR model. Therefore, the Granger causality test is used for the three variables in this research. The process can be described in this study as follows: If, under the condition of including the past information of X and the other variables (lnY or Z), the coefficients of the lagged terms of the other variables are statistically significant concerning X, then it can be determined that the current X is to a larger extent explained by the past other variables. This implies that the predictive power of the other variables on X is better than the predictive power of only X's past information. The results are presented in Table 4-6.

Table 4. VAR Granger causality test of dependent variable X

Excluded	Chi-sq	Df	Prob.
LNY	20.54933	4	0.0004
Z	25.22758	4	0.0000
All	84.96392	8	0.0000

Table 5. VAR Granger causality test of dependent variable LNY

Excluded	Chi-sq	Df	Prob.
X	12.51043	4	0.0139
Z	6.628570	4	0.1569
All	29.90890	8	0.0002

Table 6. VAR Granger causality test of dependent variable Z

Excluded	Chi-sq	Df	Prob.
X	5.188483	4	0.2685
LNY	14.45957	4	0.0060
All	46.05299	8	0.0000

Table 4 demonstrates the rejection, at the 5% significance level of the hypothesis that the endogenous variables lnY and Z cannot introduce endogeneity into the equation corresponding to endogenous variable X. This indicates that the technological innovation indicator and the energy consumption structure indicator are unidirectional Granger causes for energy utilization efficiency (energy consumption per unit of GDP). The causal relationships, whether individually or with the combined effect of the two preceding variables, are highly significant. For the causal analysis with both lnY and Z as dependent variables in Tables 5 and 6, the overall effects are significant, but each test result has a variable with an accompanying probability greater than 5 % in the explanatory variables. It can only be concluded that technological innovation is the Granger causality of energy consumption structure, and energy efficiency is the Granger causality of technological innovation.

The economic significance of the results is explained as follows: in the time dimension, technological innovation is significantly and causally related to the future cleaner energy consumption structure and the future reduction of energy consumption per unit of GDP, which act as an engine to reduce emissions and consumption. Ensuring the expenditure growth on scientific research and experimentation along with the growth of the economy is essential. Simultaneously, the restructuring of the energy structure will lead to an increase in the efficiency of future energy consumption, which is equivalent to a multiplying effect of technical advancement. Furthermore, the adjustment of the energy structure will lead to future improvements in energy efficiency, which can be considered as the multiplier impact of technical progress. Energy efficiency improvements are expected to provide management authorities and businesses with a favorable externality. (e.g. the cost of production units reduced, the improvement of the level of livability of the city as well as the public's

happiness index, etc.) Therefore, from the macro-micro level, the Chinese government should continue to increase related scientific research and experimental funding.

3.3. Determining Model Stability

Using the graphical method, the unit characteristic roots of the variables all fall in the unit circle as is shown in Figure 2, thus the VAR model is stable.

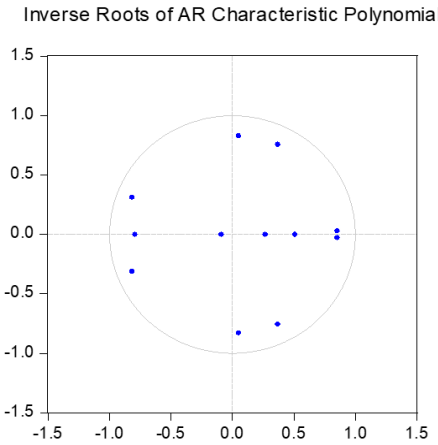


Fig. 2 Result of model stability

3.4. Impulse Response Analysis

The impulse response functions of the VAR model allow us to assess the extent to which a shock in one variable affects the response of other variables while keeping the remaining variables constant. This analysis helps to understand the dynamic interactions among the three variables. It is vital to note that a time of 20 is chosen for both the impulse response and the subsequent variance decomposition due to the necessity of a specific method for structural transformation and the translation of scientific research accomplishments. Figure 3 presents the results. This paper examines the response in terms of positive and negative directions, intensity, and duration.

When technological innovation is hit by one standard deviation of energy use per unit of GDP, it will respond in the opposite direction. As far as China's current situation is concerned, the structural and ingrained pressures on ecological environmental protection have not yet been fundamentally alleviated, especially in key regions and industries, and at the same time, national policymakers have become acutely aware of the importance of pertinent energy-saving and consumption-reduction initiatives in overcoming resource and environmental bottleneck constraints, increasing funding and subsidies for related research and experiments[11]. This is in addition to the dividends brought about by the decline in the usage of energy per GDP. For producers, energy cost reduction can increase profit margins, and may also obtain relevant policy subsidies to encourage enterprises to conduct research in related fields.

Given a one-unit positive shock to the perturbation term of the technological innovation input indicator, the remaining two variables produce a negative response, which is highly consistent with the economic significance. Many scholars have verified that under the background of moderate environmental regulation, the state pushes enterprises to technological innovation can stimulate the innovation compensation effect, improving enterprise productivity and sustainable development performance, and promoting enterprises to form the consciousness of energy saving and emission reduction [12, 13]. By observing the longitudinal axis value, it is found that in the first 10 periods, the impact of technical advancement on lowering the share of non-clean energy is comparable to that on lowering consumption of energy per unit of GDP, but the latter has a more pronounced time lag (almost no change in the first two periods), that is, the process of energy structural adjustment will be slightly slower.

Below is an analysis of how the structure of energy use affects energy consumption as a percentage of GDP. Analyzing their impulse reaction has little significance because the Granger causality test

already demonstrated that energy consumption structure is not a Granger cause for technological innovation. Given that the response of energy efficiency to the impact of energy usage structure swings and alternates between positive and negative, it is uncertain if the optimization of energy-consuming structure has a substantial direct impact on the progress of energy efficiency. Through empirical research, Wang Li et al. found that the mediating effect of energy-consuming patterns can significantly affect the efficiency of energy indirectly, which emphasizes the scientificity of the Chinese government's prioritization of non-fossil energy in energy development [14]. Besides, many scholars also pointed out that in the coal-based resource conditions, China's primary task is to encourage the efficient and green use of traditional fossil fuels, particularly coal. [15]. This paper holds the view that both pathways are important for energy efficiency, and there is no question of who is dominant at present.

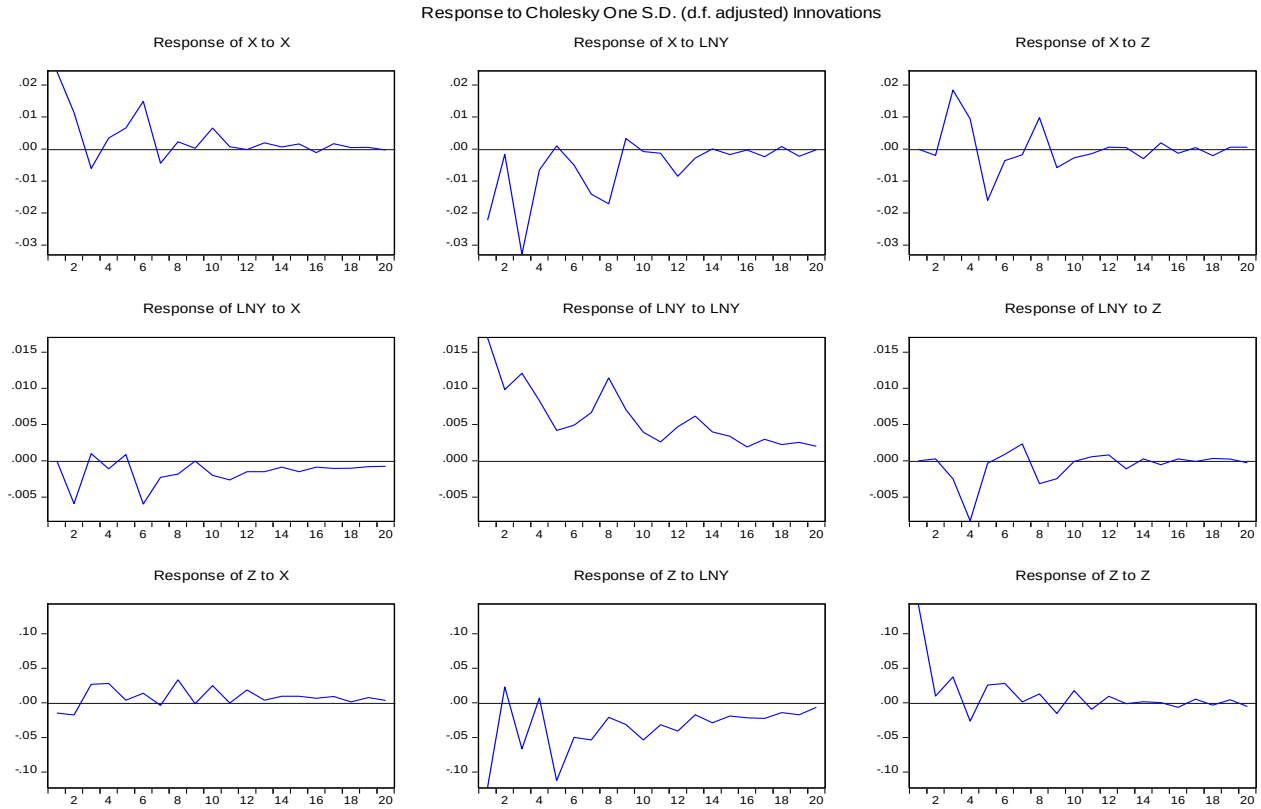


Fig. 3 Results of impulse response analysis

3.5. Variance Decomposition

Variance decomposition allows for a deeper analysis of the interplay among energy utilization efficiency, technological innovation, and energy consumption structure. It examines the proportion of explanatory power that orthogonalized shocks from different variables contribute to the variations in other variables. The results of variance decomposition are illustrated in Figure 4.

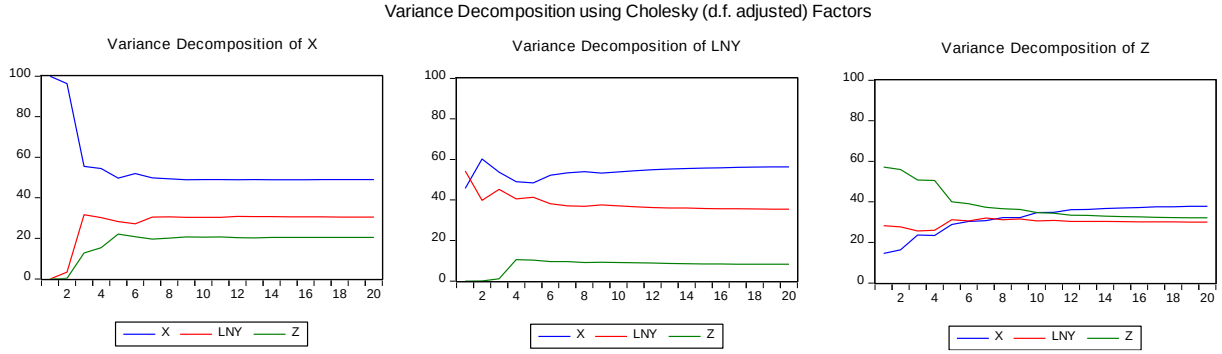


Fig. 4 Results of variance decomposition

Energy utilization efficiency contribution decomposition: In the first two periods, the variance contribution from within energy utilization efficiency is as high as 100% and 95%, sharply declining afterward. This suggests that short-term improvements in energy utilization efficiency rely heavily on its inherent inertia. The contributions of technological innovation and energy consumption structure rose sharply in the latter period, stabilizing at around 20 percent and 30 percent, respectively, with technological innovation, in particular, being a stronger driver.

Technological innovation contribution decomposition: The energy consumption structure contributes less than 10% to technological innovation, showing minimal explanatory power, consistent with the Granger causality results mentioned earlier. Except for the first period, the contribution rate of energy utilization efficiency remains higher than that of technological innovation itself. It corroborates the logic chain of the aforementioned Granger causality and impulse response in the improvement of energy utilization - positive externalities for enterprises, governments, and society - increasing investment in technological innovation.

Energy consumption structure contribution decomposition: From the 6th to the 20th period, the contribution levels of the three factors to energy consumption structure are nearly the same, while the proportion of variance contribution from energy utilization efficiency logarithmically escalates. This signifies that the proportion explaining the clean-up of energy consumption due to decreased energy consumption per unit of GDP is progressively increasing.

4. Conclusions

This paper employs VAR models, impulse response functions, and variance decomposition to study the dynamic interactions and influence mechanisms among energy utilization efficiency, technological innovation, and energy consumption structure. This research provides insights to promote the coordinated development of a cleaner and more sustainable economy in the field of energy usage. Policy analysis and recommendations from several perspectives are offered below.

On the one hand, a cleaner future energy consumption structure and lower future energy consumption per unit of GDP are significantly correlated with technological advancement input, and on the other hand, improved energy utilization efficiency will lead to increased investment in later-stage technological innovation funding. Although energy-saving technology development in China is at a bottleneck stage, the existing low-carbon energy-saving benefits are driving national-level financial support to sustain energy technology innovation, enhance research and dissemination of research outcomes, and prioritize the effectiveness of energy transition.

In the process of reducing GDP energy intensity, it is undoubtedly crucial to focus on controlling fossil fuel consumption and accelerating the development of non-fossil energy sources. The 14th Five-Year Plan outline also emphasizes increasing the proportion of non-fossil energy in total energy consumption to around 20%. Achieving this goal hinges on industrial structural reform. The industrial sector, specially manufacturing, will play a pivotal role in reducing carbon emissions and achieving the "dual carbon" goals. Currently, China's economic structure has a relatively high proportion of secondary industry and energy-intensive industries. The target of decreasing energy consumption per unit of GDP will drive down the proportion of the secondary industry and promote the rise of the tertiary industry. This will accelerate the transformation and upgrading of traditional energy-intensive sectors such as steel, non-ferrous metals, building materials, and chemicals, while also enhancing the share of industries with lower energy consumption, like high-tech manufacturing and equipment manufacturing.

Increasing renewable energy use proportion is not the sole means to promote energy utilization efficiency. Some clean energy sources have higher acquisition costs compared to their social and ecological benefits. So fossil fuels shouldn't be hastily phased out. Optimizing the utilization of traditional fossil fuels like coal and oil is still of great importance. This involves measures such as promoting high-quality smokeless coal, optimizing coal utilization through data management, innovating oil refining processes, implementing refined secondary utilization, and so on. This paper

advocates a balanced approach of increasing clean energy supply (addition) and reducing carbon emissions along the energy industry chain (subtraction).

References

[1] Liu Huajun, Shao Mingji, Guo Lixiang. The road of China's air pollution control in the new era — History review, effectiveness assessment and path outlook. Business Economics and Management, 2023(02): 66-79.

[2] Zhang Yu, Sun Qian, Xue Jinjun, et al. Analysis of the synergistic effect of pollution reduction and carbon reduction and its path investigation. China Population-Resources and Environment, 2022, 32(05): 1-13.

[3] Bi Shenhao, Zhong Xiaohong, Lai Yumin, et al. Study the relationship between energy consumption structure and energy efficiency based on the PVAR model. Industrial Technology and Economics, 2021, 40(07): 65-71.

[4] Liu Fengzhao, Sun Yutao. Empirical analysis of the impact of technological innovation and industrial structure adjustment on energy consumption. China Population-Resources and Environment, 2008(03): 108-113.

[5] Wang Xuejun, Wang Sai. Energy Conservation and Emission Reduction: Optimizing Dual Structures and Improving Energy Efficiency — Analysis of the Relationship between Industrial Structure, Energy Consumption Structure and Energy Efficiency during the 14th Five-Year Plan Period. Price Theory and Practice, 2021(02):140-144+175.

[6] Lv Trangyu, Ma Chunai, Tang Tong, Hao Fuying. Environmental regulation, technological innovation, and energy intensity of industrial enterprises. Statistics and Decision Making, 2023, 39(10): 59-64.

[7] Wu Aidong, Wang Juan. Technological innovation, or structural upgrading efficiency? — analysis of the dominant kinetic energy to promote high-quality development. Science and Technology Management Research, 2019, 39(14): 210-217.

[8] Yu Mingwen. Interaction between technological innovation, service industry structure optimization and residents' consumption upgrading — an empirical analysis based on the VAR model. Research on Business Economy, 2023(09): 48-52.

[9] Hou Jianguo, Yao Huichao, Wang Xiulin, et al. Construction and technology path selection of "natural gas + hydrogen" dual clean and low-carbon energy system. Natural Gas Chemistry-C1 Chemistry and Chemical Industry, 2022, 47(06): 1-5.

[10] Zhu Xingshan, Chen Rui, Pan Jiping. The key supporting role of natural gas in the clean energy system and development suggestions. International Petroleum Economics, 2021, 29(02): 23-29+105.

[11] Liu Yiwen, Zhou Shaocheng. Research on the synergistic effect of formal and informal environmental regulation policies on pollution reduction and carbon reduction. Financial Review Series, 2023(08): 103-112.

[12] Pan Xiongfeng, Ai Bowei, Li Changyu, et al. Dynamic relationship among environmental regulation, technological innovation, and energy efficiency based on large-scale provincial panel data in China. Technological forecasting and social change, 2019, 144: 428-435.

[13] Lin Boqiang, Wang Xizhi, Du Zhili. The impact of environmental regulation on China's industrial energy efficiency. Journal of Xiamen University (Philosophy and Social Sciences), 2021(04): 30-42

[14] Wang Li, Yu Chen, Zhang Yashu. Optimizing energy consumption structure and improving energy efficiency — Analysis of the current situation and influencing factors of energy efficiency in China. Environmental Economics, 2021(12): 50-56.

[15] Zhang Qianqian, Li Baiji. Effect analysis and policy optimization of energy structure influencing factors based on path analysis. Enterprise Economy, 2017, 36 (08): 11-17.