

Research Article

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Regional Environment Risk Assessment Over Space and Time: A Case of China

<https://doi.org/10.1515/econ-2022-0049>
received December 03, 2022; accepted October 08, 2023

Abstract: Faced with increasingly serious environmental risks, it is necessary to conduct a comprehensive evaluation of the regional environment to provide a solid foundation for environmental policies and actions in the future. This article builds a composite environment risk index that considers spatiotemporal factors and uses annual socio-economic and environmental data of China's 31 provincial administrative regions from 2004 to 2019 to quantitatively analyze environmental risks. Furthermore, the article employs a panel data model to empirically test the key factors that lead to environmental risks. Moreover, this article employs SVAR models to analyze the dynamics of regional environmental systems in China. The study finds that, at least at this stage, the environmental risks in provincial regions in China are still relatively high, and the key factors of the risks are economic growth, urbanization development, secondary industry growth, and green policy. Therefore, China must adopt more stringent environmental protection policies and actions in the future.

Keywords: environment risks, composite environment risk index, socio-economic factors, environmental factors, provincial regions in China

1 Introduction

To implement the Paris Agreement reached by the 193 member states of the United Nations in 2015 and achieve the Sustainable Development Goals (SDGs) by 2030, China has been actively taking comprehensive environmental protection actions to improve the environment at national

and regional levels (United Nations, 2015a,b). However, due to differences in environmental resources and development conditions, different ecological and environmental situations may occur even if each region practices stricter environmental protection. This requires a scientific assessment of environmental risks. The spatial-temporal factor analysis of regional environment status can help every region recognize the existing problem, so as to further implement corresponding policies and measures toward the goal of the SDGs (Liu et al., 2021; United Nations, 2021).

The environmental quality of a region is determined by many factors, such as natural resources (especially water resources), natural disasters, waste discharge, and pollution treatment (Afridi et al., 2021; Bryan et al., 2018; Xu et al., 2020). In a certain period of time, if they change significantly or drastically, it indicates that the environment is at greater risk. In order to extract effective information from multi-dimensional environment indicators, it is necessary to construct a composite environment risk index to quantify environmental risks.

However, the construction of a composite environmental risk index faces two thorny issues. The first is that the indicators have different units and quantity levels, which can lead to heterogeneity and incompatibility of the indicators. This requires standardizing the raw data of the indicators through the scientific method. Another is the determination of the weight of each indicator in the total composite index, as it needs to consider the dual effects of time and space.

At present, multi-level and multi-indicator evaluation methods have been widely used, and some composite indexes, such as the Bertelsmann Index (Lafortune et al., 2018; Miola & Schiltz, 2019; Sachs et al., 2018, 2021) and the Distance Measure Index (OECD, 2017), have been constructed. The SDG Index used for sustainability evaluation is another famous composite index. It was constructed through multi-dimensional indicators, which have achieved good results in actual evaluation (Halkos & Argyropoulou, 2022).

However, due to the need to address the issue of the different units of indicator data and the objective determination of weights for each indicator in the application of multi-indicator synthesis methods, further improvement

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and refinement is necessary. Especially, the existing methods do not solve the heterogeneity of the indicators of variables, because they only perform general non-dimensionalization (such as range standardization and non-dimensionalization) of the variable's indicators (Li, 2021; Liu et al., 2019; Streimikiene et al., 2021). Moreover, when synthesizing different index of variables, the weight of each index needs to be determined first, but the usual method (e.g., simple average method, subjective scoring method, and fuzzy decision method) has greater subjectivity, which affects the reliability of the measurement (Dhiman & Deb, 2020; Ervural et al., 2018; Palczewski & Salabun, 2019).

In order to improve the reliability of the measurement, this article makes an improvement from three aspects. First, the relative distance between individuals and their mean is used to define the risks. The mean here contains the dual information of a specific indicator at different times and different spaces. This method can not only realize the dimensionlessness of the index of the variable but also enhance the comparability of the results over time and space.

Second, the article unitizes the risk variables defined above to ensure that the calculated values of each relative risk index are within the range of 0 and 1. This method can not only realize the homogeneity, comparability, and synthesizing of data but also reduce the problem of possible divergence and instability (Dou, 2022).

Finally, the article uses the unitized index data to calculate the weights. Because of the homogeneity of the unitized data, it may realize the scientific determination of the weights in the calculation of the composite index when they are used to determine the weight. It solves the uncertainty of weight determination in traditional multi-standard decision analysis such as simple average method, subjective scoring method, and fuzzy decision method.

The research shows that the composite risk index proposed here is suitable for the evaluation of complex system objects such as natural ecological and environmental systems. Moreover, it can also be applied to more complex cases and more broad fields such as society, economy, finance, management, technology, and so on.

This article attempts to addresses three problems using our own method and model. First of all, what is the actual situation of the environment (risks) in each region. Second, what is the dynamic evolution process and trend of the environment (risks) in each region over time. Third, the article empirically analyses the key factors that lead to the environmental risks in various regions.

The study finds that the environment quality of each province-level region is unstable during the selected sample period, and most of the regions are in a risk or high-risk

state in recent years. The empirical results indicate that the key factors leading to environmental risks are economic growth, urbanization development, secondary industry growth, and green policies (e.g., environmental governance, environmental protection investment, energy safety, technologies and innovations, environmental education, and environmental sensitivity). Generally, economic growth, secondary industry growth, and green policies are conducive to reducing environmental risks, while urbanization will exacerbate environmental risks.

The remainder of the article is structured as follows. The second section elaborates on environmental risk measurement and evaluation. The third section is an empirical analysis of the determinants of regional environmental risks. Section 4 is a dynamic test of the regional environment system. In Section 5, we discuss the results. The last is the conclusion.

2 Measurement and Evaluation of Regional Environment Risks

2.1 Method and Model

We first consider the case of a general two-level indicator system here. We use $CI_t^{(i)}$ to represent the composite index of specific individual i ($i = 1, 2, \dots, I$), $I_{j-t}^{(i)}$ ($j = 1, 2, \dots, J$) to represent the first-level index, and $I_{jk-t}^{(i)}$ ($k = 1, 1, \dots, K$) to represent the second-level index (the lowest-level index). Suppose that each second-level indicator ($I_{jk-t}^{(i)}$) contains sample data $X_{jk-t}^{(i)}$ ($j = 1, 2, \dots, J$; $k = 1, 2, \dots, K$; $t = 1, 2, \dots, T$). Thus, we can get $CI_t^{(i)} = (I_{1-t}^{(i)} \ I_{2-t}^{(i)} \ \dots \ I_{j-t}^{(i)} \ \dots \ I_{J-t}^{(i)})'$, $I_{j-t}^{(i)} = (I_{j1-t}^{(i)} \ I_{j2-t}^{(i)} \ \dots \ I_{jk-t}^{(i)} \ \dots \ I_{jK-t}^{(i)})'$, and $I_{jk-t}^{(i)} = (X_{j1-t}^{(i)} \ X_{j2-t}^{(i)} \ \dots \ X_{jk-t}^{(i)} \ \dots \ X_{jK-t}^{(i)})$.

Our goal is to perform a weighted average of the variable values ($X_{jk-t}^{(i)}$) of different second-level indicators in each period to obtain the composite index value of their corresponding upper-level indicators (indicators of level 1) ($I_{j-t}^{(i)}$). The formula is as follows:

$$I_{j-t}^{(i)} = \sum_{k=1}^K w_{jk-t}^{(i)} I_{jk-t}^{(i)} = \sum_{k=1}^K w_{jk-t}^{(i)} X_{jk-t}^{(i)}, \quad (1)$$

where $w_{jk-t}^{(i)}$ represents the weight corresponding to $X_{jk-t}^{(i)}$.

Similarly, the calculated first-level comprehensive indicators ($I_{j-t}^{(i)}$) are averaged with the corresponding weights to obtain the environmental risk index ($CI_t^{(i)}$) of individual i in period t . Thus, the formula is as follows:

$$CI_{i,t}^{(i)} = \sum_{j=1}^J w_{j,t}^{(i)} I_{j,t}^{(i)}, \quad (2)$$

where $w_{j,t}^{(i)}$ represents the weight corresponding to $I_{j,t}^{(i)}$.

In order to achieve comparability over time and space, different individuals and times of the same index (including primary and secondary indicators) use the same weight. That is:

$$w_{jk,t}^{(i)} = w_{jk}, \quad (3)$$

$$w_{j,t}^{(i)} = w_j. \quad (4)$$

The above is a general solution idea. In order to measure the environmental risk, let us redefine the value of the variable X . For the sake of simplicity, we here use the absolute value of the relative deviation to measure the risk, and it is calculated as follows:

$$x_{jk,t}^{(i)} = d(X_{jk,t}^{(i)}, \bar{X}_{jk}^{(i)}) = ||X_{jk,t}^{(i)} - \bar{X}_{jk}^{(i)}|/\bar{X}_{jk}^{(i)}|, \quad (5)$$

where $\bar{X}_{jk}^{(i)} = \sum_{t=1}^T X_{jk,t}^{(i)}/T$, and it is the mean of the variables of sub-indicator k in the second layer (the last layer) of individual i for period t .

However, due to the different orders of magnitude of different indicators including the first and second levels, the difference in the risk values is often large and lacks comparability, which brings difficulties to the determination of the weights. It has puzzled academia in the construction of the composite index of multidimensional indicators for a long time.

Traditional methods of weight determination are often subjective, which reduces the credibility of research results. In order to solve this problem, we will unitize (process through logistic function conversion) the risk value ($x_{jk,t}^{(i)}$) calculated by formula (5) (Kramer, 1991) as follows:

$$U_{jk,t}^{(i)} = 1/(1 + \exp(-x_{jk,t}^{(i)})), \quad (6)$$

where $U_{jk,t}^{(i)}$ represents the risk value after unitization processing.

For the variable value ($U_{jk,t}^{(i)}$) of the sub-indicator k of the index j of the specific object i (sub-index k in the last layer), we first obtain their time mean ($\bar{U}_{jk}^{(i)}$). Then, we averaged the time averages ($\bar{U}_{jk}^{(i)}$) of sub-indicator k of different individual i between different individuals again. Therefore, we will perform the following operations:

$$\bar{U}_{jk} = \frac{1}{I} \frac{1}{T} \sum_{i=1}^I \sum_{t=1}^T U_{jk,t}^{(i)}, \quad (7)$$

where \bar{U}_{jk} means the average of the unitized risk value ($U_{jk,t}^{(i)}$) at different times and in different individuals.

The weight of the corresponding second-level index ($I_{jk,t}^{(i)}$) can be calculated from equation (7) as follows:

$$w_{jk,t}^{(i)} = w_{jk} = \bar{U}_{jk} / \sum_{k=1}^K \bar{U}_{jk}, \quad (8)$$

where $w_{jk,t}^{(i)}$ represents the weight of sub-indicator k in the second-level index ($I_{jk,t}^{(i)}$) of the index j ($I_{j,t}^{(i)}$) of the individual i the period t . For the same secondary index, because the differences between individuals and between times are not considered here, the same weights (w_{jk}) are used for the risk values ($U_{jk,t}^{(i)}$) of the same period and all individuals. Therefore, we can get $w_{jk,t}^{(i)} = w_{jk}$.

The unit risk composite index ($CU_{j,t}^{(i)}$) of the corresponding first-level index ($I_{j,t}^{(i)}$) of each individual i can be calculated in different periods from formula (6) and formula (8) as follows:

$$CU_{j,t}^{(i)} = \sum_{k=1}^K w_{jk} U_{jk,t}^{(i)}. \quad (9)$$

Similarly, we can calculate the weight ($w_{j,t}^{(i)}$) of the index j of the first layer ($I_{j,t}^{(i)}$) using the result calculated by formula (9) as follows:

$$\bar{CU}_j = \frac{1}{M} \frac{1}{T} \sum_{i=1}^I \sum_{t=1}^T CU_{j,t}^{(i)}, \quad (10)$$

$$w_{j,t}^{(i)} = W_j = \bar{CU}_j / \sum_{j=1}^J \bar{CU}_j, \quad (11)$$

where \bar{CU}_j represents the average of the first-level index composite index ($CU_{j,t}^{(i)}$), and $w_{j,t}^{(i)}$ represents the weight of the index j in the first-level index system of individual i in period t . For the same first-level indicator, because the differences over space and time are not considered here, the same weights (w_j) are used for the risk values ($CU_{j,t}^{(i)}$) of all individuals and the same period. Therefore, we can get $w_{j,t}^{(i)} = w_j$.

We can calculate the final unit risk index (UERI) of each individual i in different periods from formulas (9) and (11) as follows:

$$UERI_t^{(i)} = \sum_{j=1}^J w_j CU_{j,t}^{(i)}. \quad (12)$$

The unit risk index (UERI) is de-unitized and multiplied by 100 to obtain the composite risk index (ERI) for different periods as follows:

$$ERI_t^{(i)} = \ln \left(\frac{1}{UERI_t^{(i)}} - 1 \right)^{-1} \times 100. \quad (13)$$

2.2 Indicator and Data

Generally, the broad sense of space should include three aspects: geographical space, international space, and China's regional space (Streimikiene et al., 2020, 2021; Streimikiene & Kyriakopoulos, 2023). However, this article focuses on the study of China's provincial administrative region (space). Due to the vast territory of China and the distinct characteristics of each region, the use of provincial-level regional sample data in China has good display performance. As for the time dimension, theoretically, the longer the time, the better the display. However, in practice, too long a time span can lead to data incompatibility, as early China did not pay attention to environmental issues until the beginning of this century when they gradually became more important. In addition, there is also an issue of early data loss. Therefore, the sample period selected in this article is from 2004 to 2019.

Considering the availability of data, the conciseness of research, and the comparability of results, this article selects indicators from four dimensions such as water resources, natural disasters, waste discharge, and environmental governance investment, as their changes can directly lead to fluctuations and risks in the environmental system.

Furthermore, the indicator of the water resources has three sub-indicators of surface water, groundwater, and other water resources (unit: 100 million cubic meters). The indicators of natural disaster have four sub-

indicators, including flood, drought, wind, and hail disaster and freezing disaster (unit: thousand hectares). The indicators of waste discharge has three sub-indicators of wastewater, waste gas, and garbage (unit: 10,000 tons). The indicators of environmental governance investment include six sub-indicators such as waste water, waste gas, solid waste, noise, other governance, and forestry project investment (unit: ten thousand yuan) (Dou, 2015, 2016; González-González et al., 2021; Noori et al., 2021; Shi & Moser, 2021).

This article uses annual data of 31 provincial administrative regions in China from 2004 to 2019. The raw data come from China's National Bureau of Statistic (2021). In order to improve the reliability of the measurement results, we have performed statistical processing on individual missing or abnormal data.

2.3 Results and Evaluation

2.3.1 Descriptive Statistical Analysis

Figure 1 shows the descriptive statistics of the environment risks of 31 provincial administrative regions in China. Obviously, almost all the provincial regions show a skewed distribution. However, Shanxi, Liaoning, Jiangxi, Shandong, Hubei and Shaanxi show significant left-skewed distributions, while other regions show right-skewed

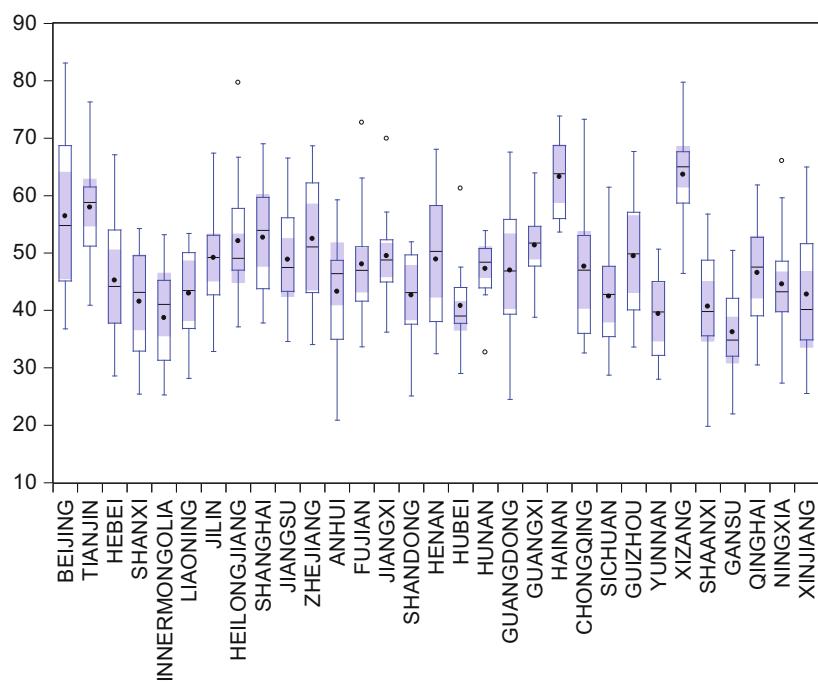


Figure 1: Box plot of the ecological risk index of each provincial region.

distributions. This indicates that the environment risks in most areas are high.

In terms of maximum value, Beijing has the highest maximum value, and Xizang is in second place. Moreover, the maximum value of Tianjin, Hainan, and Chongqing is significantly higher than other regions.

In terms of minimum value, Shaanxi and Anhui have the same and the lowest minimum, and Gansu has the second minimum. In addition, Shandong, Guangdong, Inner Mongolia, and Shaanxi have minimum values that are relatively close and slightly higher than Gansu.

As for the mean value, Xizang has the largest mean value, Hainan's mean value is second and closer to Xizang, and Gansu's mean value is the smallest. This result is closely related to the special natural and socio-economic conditions of each region.

2.3.2 Change in Environment Risks

The research indicates that, the environment of 31 provincial regions in mainland China shows an unstable state during the sample period. Moreover, most of the provincial-level regions have large fluctuations.

We find that, first of all, the time trend of environment changes in most areas is not significant, and it does not show significantly and relatively stable phase characteristics. Second, the environment in most regions shows divergent changes. Finally, although the environmental protection policies

and measures of the national and various regions have become increasingly strict in recent years, the phenomenon of tail-lifting is prominent (Figure 2).

2.3.3 Analysis of Environmental Risk Dashboard Graph

For the sake of intuitive analysis, we divide the environmental risk index from 0 to 100 into five levels: (0, 20), (20, 40), (40, 60), (60, 80), and (80, 100). They represent no-risk, low-risk, risk, high-risk, and extreme risk, respectively. Correspondingly, we use dark green, light green, yellow, blue, and red squares to represent them, respectively. Then, we draw a Dashboard graph according to the various provincial regions in different years (Schmidt-Traub et al., 2017).

Figure 3 shows that most of the province-level regions in China have high environmental risks, and they have been in a risky or high-risk state in recent years. The environmental risks in Beijing are relatively high in the early stage, which has improved slightly after governance, but become serious in the later stage. This shows that the environmental pressure on Beijing, the capital of China, is increasing. Tianjin, Shanghai, and Zhejiang have similar situations to Beijing, but to a lesser degree.

Among the 31 provincial-level regions, Xizang has the most prominent environmental problems with 12 blue and 4 yellow in the sample period, which is significantly at risk and high risk. Followed by Hainan, there are 10 blue and 6

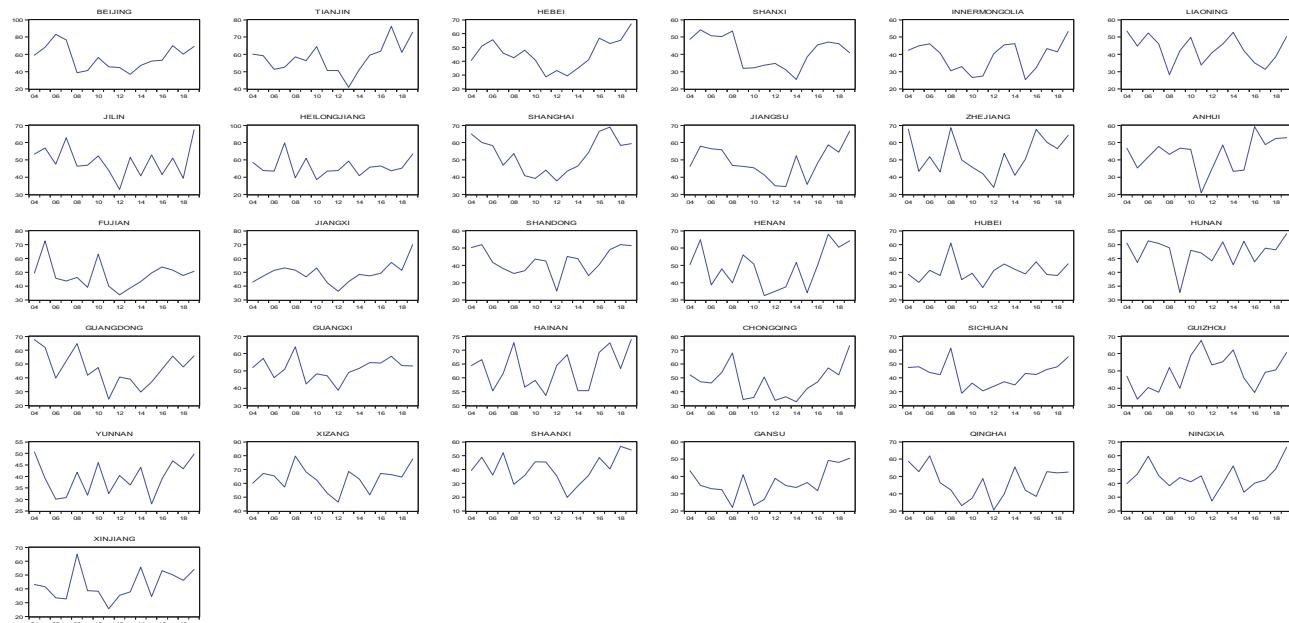


Figure 2: Changes in environmental risks in provincial regions.

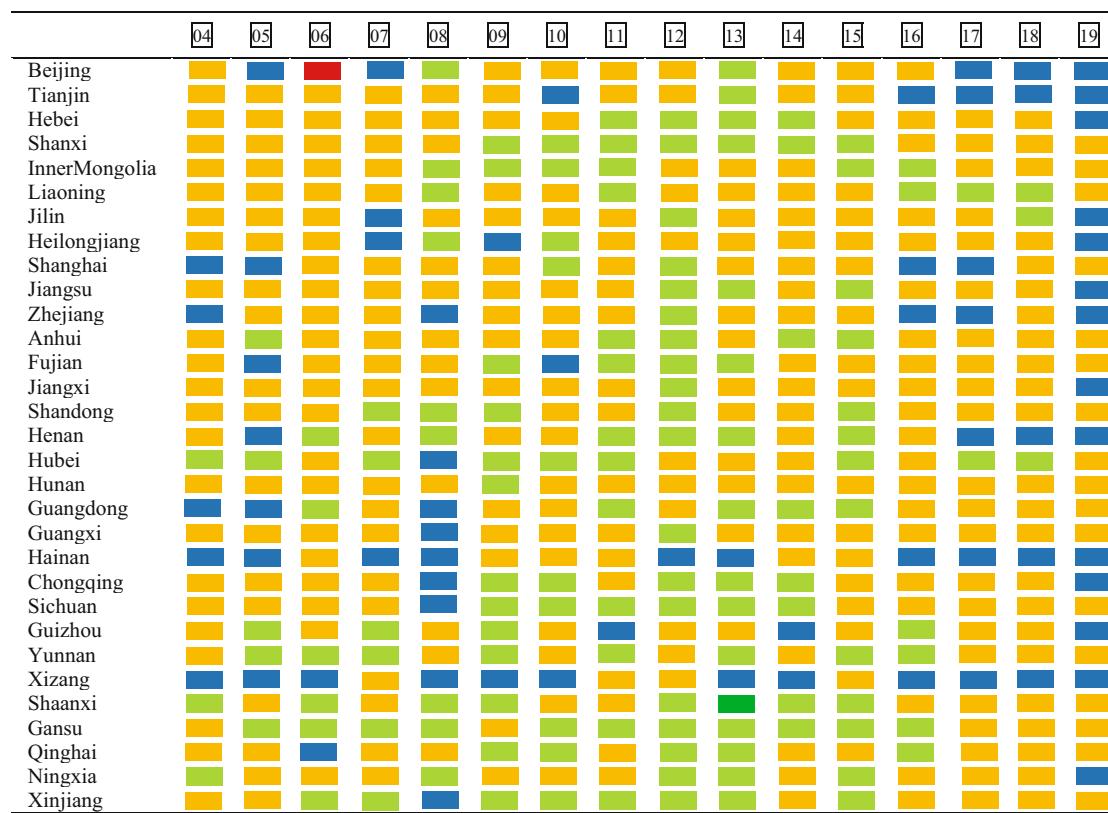


Figure 3: SDG Dashboards 2004–2019. Note: We divide the environment risk index from 0 to 100 into five levels: [0, 20], [20, 40], [40, 60], [60, 80], and [80, 100]. They respectively indicate no risk, low risk, risk, high risk, and extreme risk. Correspondingly, we use dark green (■), light green (■), yellow (■), blue (■), and red (■) squares to represent them, respectively.

yellow in the sample period, which is also at risk and high risk. This may be closely related to the special conditions of the two provincial regions.

2.4 Regional Comparative Analysis

In order to better examine the particularities of each region, we used systematic cluster analysis to classify the environmental risks of China's 31 provincial administrative regions (Figure 4). According to Figure 4 and our research purpose, we divide them into seven types.

Among the seven types, Beijing (Type I), Heilongjiang (Type II), and Guizhou (Type VII) become a separate category, which shows that they are quite different from other regions, and have their own environment and socio-economic characteristics. Beijing, as the capital of China, despite its huge investment in environmental protection, the excessive accumulation of population and economic resources has led to greater risks to the environment. Heilongjiang is located in the northernmost part of China, and is one of the three northeastern provinces that are

lagging behind in development at this stage. Although its ecological conditions are relatively good, its socio-economic conditions are relatively weak. Guizhou is one of the most underdeveloped regions in China and has a relatively special natural environment as well as a relatively backward social economy.

Type III includes three regions of Tianjin, Hainan, and Xizang. Tianjin is one of the most developed regions in China, but water resources are scarce and the natural environment is highly volatile. Hainan is an independent island with rich tropical biological resources, but the environmental and socio-economic conditions have changed significantly due to large-scale development in recent years. Xizang is an area with rich ecological resources but the most fragile natural ecosystem in China, so it is greatly affected by climate change. The high environmental risks of Hainan Province and Xizang Autonomous Region are inseparable from their own special environment and climatic conditions. Natural disasters occur frequently in Hainan Province, while the ecological environment of the Xizang Autonomous Region is fragile and natural disasters occur frequently. Therefore, the environment management in these special areas is difficult.

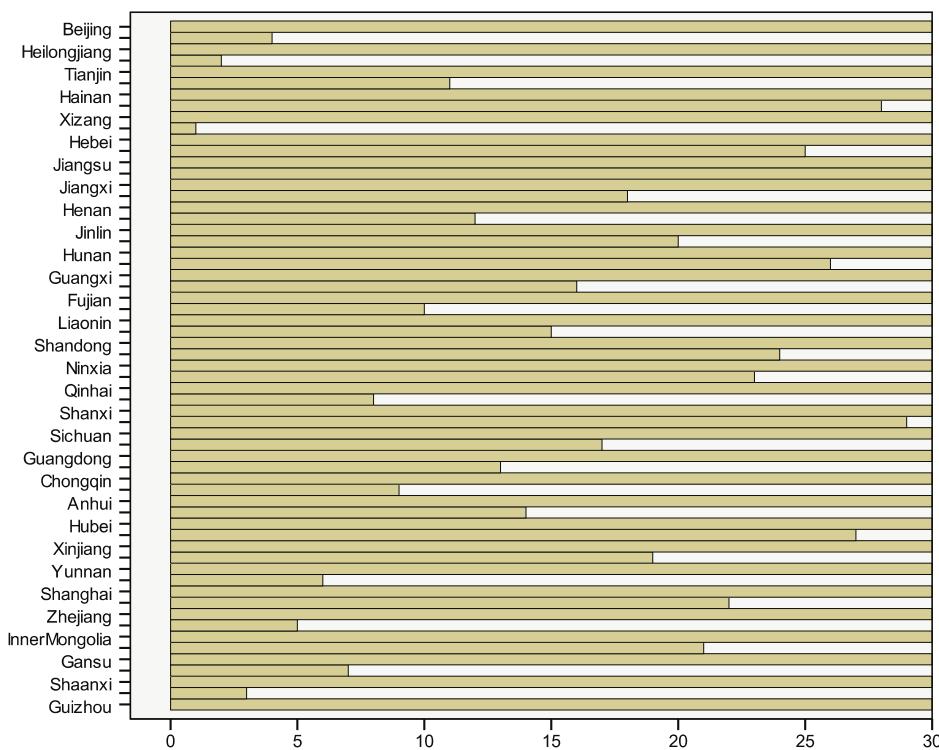


Figure 4: The ice chart of hierarchical cluster analysis.

Shanghai and Zhejiang are Type V regions. They are all developed areas in China and geographically adjacent, but the area of jurisdiction is relatively small. Because of their excessive concentration of population and economic resources, they have similar ecological and environmental risks.

InnerMongolia, Gansu, and Shaanxi in Type VI are located in the northwestern region of China, and their environment has similarities. InnerMongolia is one of the most developed areas of animal husbandry in China, but the environment is at a relatively high risk due to pasture degradation and extreme climate change. Both Gansu and Shaanxi have a serious water shortage and drought problem, which has led to serious soil desertification and soil erosion. Therefore, their environmental risks are prominent.

Except for the above six types of regions, the rest of the regions belong to Type IV, which covers 20 provincial administrative regions. For example, Hebei, Shanxi, Liaoning, Jilin, Jiangsu, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Chongqing, Sichuan, Yunnan, Qinghai, Ningxia, and Xinjiang. They can be geographically divided into the eastern coastal region (Fujian, Guangdong, Jiangsu, and Shandong), the northwest region (Qinghai, Ningxia, and Xinjiang), the southwest region (Guangxi, Sichuan, and Yunnan), and the central inland region (the rest). The environmental risks in these areas are either caused by the environmental governance lagging

behind the socio-economic development or caused by the shortage of water resources and climate change or caused by the combination of the two.

3 Determinants of Regional Environmental Risks

3.1 Model and Data

The environmental risk of a region is determined by many factors. However, for China at this stage, the effects of several key socio-economic factors are important. The first is the impact of economic growth on the environment. On the one hand, economic growth has a negative impact on the environment; on the other hand, economic growth has increased the fiscal revenue of regional governments, and it will help the government to increase investment in environmental governance, which is conducive to the improvement of the environment (Li et al., 2021; Shi et al., 2020).

The growth of the secondary industry has both favorable and unfavorable effects. At this stage, as the secondary industry occupies a large proportion of GDP, its development can significantly promote economic growth. At the

same time, since the secondary industry has the characteristics of high inputs, high energy consumption, high outputs, and high emissions, it has an adverse impact on the environment. The final result depends on the strength of the both (Chen et al., 2020; Zhang & Liu, 2021).

In recent years, China's urbanization has developed rapidly, but the impact of urbanization on the environment is significant. First of all, the development of urbanization (especially the development of small cities) directly erodes the environmental resources such as land resources, forest resources, and water resources, and this impact is irreversible. Second, although urbanization has a resource agglomeration effect, the city itself needs to consume a lot of resources and produce a lot of waste, which has a significant adverse impact on the environment (Ahmed et al., 2020; Yao et al., 2021).

Green policies play an important role in improving the environment. China has not only adopted strict environmental protection policies but has also continuously increased its investment in environmental governance. In terms of industrial policies, the state has been investing large amounts of financial funds in recent years to transform traditional high-energy-consumption and high-pollution industries, and actively support the development of green and low-carbon industries. At present, the government has formulated and implemented a complete set of green policies, which has fundamentally improved the environment (Cao et al., 2021; Qin et al., 2021; Yang et al., 2021).

According to the above theoretical analysis and considering the reality of China's economic development and environmental changes at this stage, this article selects the key factors of economic growth, secondary industry growth, urbanization development, and green policy for empirical analysis. The equation is set as follows:

$$\begin{aligned} \text{LnERI}_{it} = & \beta_0 + \beta_1 \text{LnED}_{it} + \beta_2 \text{LnGP}_{it} + \beta_3 \text{LnIR}_{it} \\ & + \beta_4 \text{LnUR}_{it} + \varepsilon_{it}, \end{aligned} \quad (14)$$

where ERI stands for environment risk, ED stands for economic growth, GP stands for green policy, IR stands for secondary industry growth, UR stands for urbanization development, i represents cross-sectional individual, t means time, and ε is white noise series.

Because the socioeconomic development and the natural environment of the regions are different, the environmental risks of the regions in China are different. In order to clarify the real situation of the environment in various regions, this article takes 31 provincial administrative regions in mainland China as the research object, and the sample period is from 2004 to 2019. All data come from the yearbook of the National Bureau of Statistics (2021).

3.2 Baseline Model Estimation

Table 1 reports the estimation results of equation (14). It can be seen that economic growth (ED), urbanization development (UR), secondary industry growth (IR), and green policies (GP) have all a significant impact on the environment. The empirical results show that the faster the economic growth of a region, the smaller the environmental risk in the region. This is because the government has attached great importance to environmental protection in recent years, which has forced the government to increase financial investment in environmental governance as much as possible, while economic growth has laid the financial foundation for the government to increase financial investment. In addition, strict ecological and environmental protection policies have reduced the impact of social and economic development on the environment.

In theory, the development of the secondary industry can make an adverse impact on the environment. However, the empirical results here show that it is beneficial to reduce environmental risks (Table 1). One possible explanation is that the key secondary industries in all regions are concentrated in cities, and the government has implemented strict environmental protection policies for industrial enterprises with high energy consumption, high emissions, and high pollution, which has prompted enterprises to improve efficiency (Chen et al., 2020), thereby minimizing the adverse effects of the development of the secondary industry on the environment. Moreover, since the secondary industry accounts for a large proportion of GDP at this stage, the better the development of the secondary industry in a region, the faster the economic growth, which is conducive to improving the environment.

The implementation of the green policy is important to the improvement of the environment, as it helps to significantly reduce the environmental risks. The role of the green policy is that it not only increases the financial investment of the central government and the regional governments in the governance of the environment but also strictly restricts the economic behavior of economic agents that may deteriorate the environment. In recent

Table 1: The estimation result of the equation (14)

Variable	Coefficient	Std. Error	T-Statistic	Prob.
LnED	-0.0570	0.0273	2.0917	0.0370
LnGP	-0.0721	0.0293	2.4591	0.0143
LnIR	-0.4544	0.0681	6.6748	0.0000
LnUR	0.1986	0.0912	2.1789	0.0298
C	5.4115	0.3724	14.5300	0.0000

years, the breadth and depth of the implementation of green policies in all regions has been continuously increasing, effectively reversing the continuous deterioration of the environment in the early stages of reform and opening up (Kahn et al., 2022).

The empirical results show that the development of urbanization will exacerbate the environmental risks. China's urbanization is characterized by extensive and rapid progress. The first is that all regions have been making great efforts to promote urbanization, which not only encroaches on a large amount of land, forests, and other ecological resources, but also the excessive expansion of the city in the short term, resulting in a large population agglomeration and industrial development, has caused the growth of urban wastes to make great pressure on the environment. Second, the development of some small- and medium-sized cities lacks scientific planning and strict governance, resulting in a comprehensive and irreversible impact on the local environment.

Shanxi, Heilongjiang, Fujian, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Guizhou, Qinghai and Ningxia, are between 5.4 and 5.5. Five areas, including Tianjin, Jiangsu, Zhejiang, Jiangxi, and Henan, are between 5.5 and 5.6. Only Xizang is above 5.6.

The individual differences of different provincial administrative regions are caused by the differences in the endowment of environmental resources, the level of social and economic development, and the degree of environmental protection and governance in each region, and the environment of a region is jointly determined by these key factors. However, due to the large differences in these factors and conditions in different provincial administrative regions in China at this stage, the emergence of individual differences is inevitable. This shows that the environmental protection and governance of the regions in China must adopt corresponding policies in accordance with their own actual situation in the future.

3.3 Analysis of Individual Differences

Figure 5 reports the differences of the individuals. We can find that the environmental risks of provincial administrative regions in China are different. From the perspective of individual differences, the environmental risk level of Beijing, Inner Mongolia, Yunnan, and Gansu is below 5.3. Nine areas, including Liaoning, Jilin, and Jilin, Shanghai, Anhui, Shandong, Hubei, Sichuan, Shaanxi, and Xinjiang, are between 5.3 and 5.4. Twelve areas, such as Hebei,

3.4 Robustness Test

In order to test the reliability of the estimation results of the equation, we reduce the scope of the sample to re-estimate equation (14). Table 2 reports the estimation results. It shows that the influence of all explanatory variables is still statistically significant, the sign of each coefficient has not changed, and the value of the coefficient only has a small change compared with Table 1. This demonstrates that the estimation results of equation (14) are reliable.

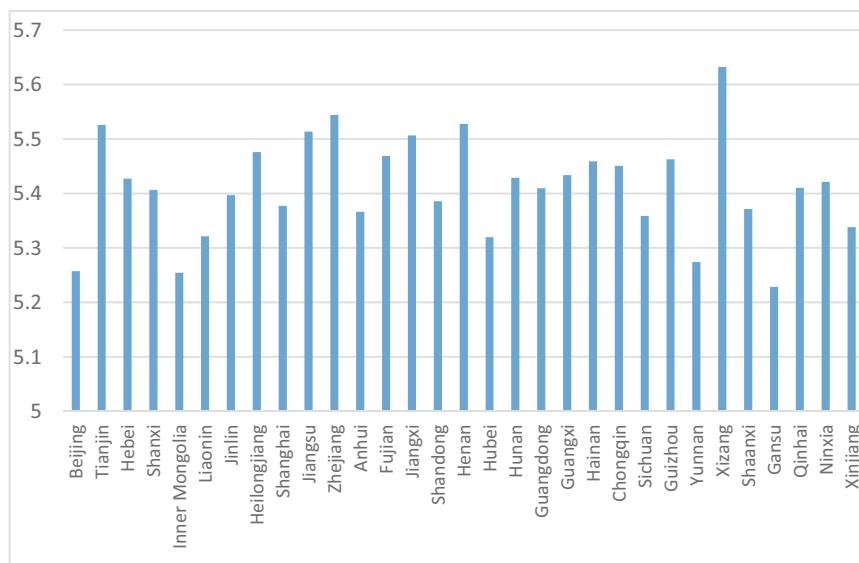


Figure 5: The differences of individuals.

Table 2: The results of robustness test

Variable	Coefficient	Std. Error	T-Statistic	Prob.
LnED	-0.0835	0.3730	3.0358	0.0025
LnGP	-0.0945	0.0302	3.1339	0.0018
LnIR	-0.4032	0.0696	5.7932	0.0000
LnUR	0.1829	0.0907	2.0163	0.0443
C	5.5632	0.3727	14.9268	0.0000

4 Dynamic Test of Regional Environment System

This study applies the SVAR model to investigate how several factors affect the dynamic changes of the ecological environment system. We specify the model as follows:

$$B_0 y_t = \Gamma_0 + \Gamma_1 y_{t-1} + \Gamma_2 y_{t-2} + \Gamma_3 y_{t-3} + \Gamma_p y_{t-p} + u_t, \quad (15)$$

where B_0 represents the coefficient matrix of the current period, Γ_0 represents the constant term, Γ_i ($i = 1, 2, \dots, p$) represents the coefficient matrix of the lag period, y represents the variable matrix in the system and $y = (\text{ERI}, \text{ED}, \text{GP}, \text{IR}, \text{UR})'$, u is white noise series, and t is the time ($t = 1, 2, \dots, n$).

The SVAR model can not only describe the current relationship between the variables in the system but also describe the structural relationship of each period compared with the

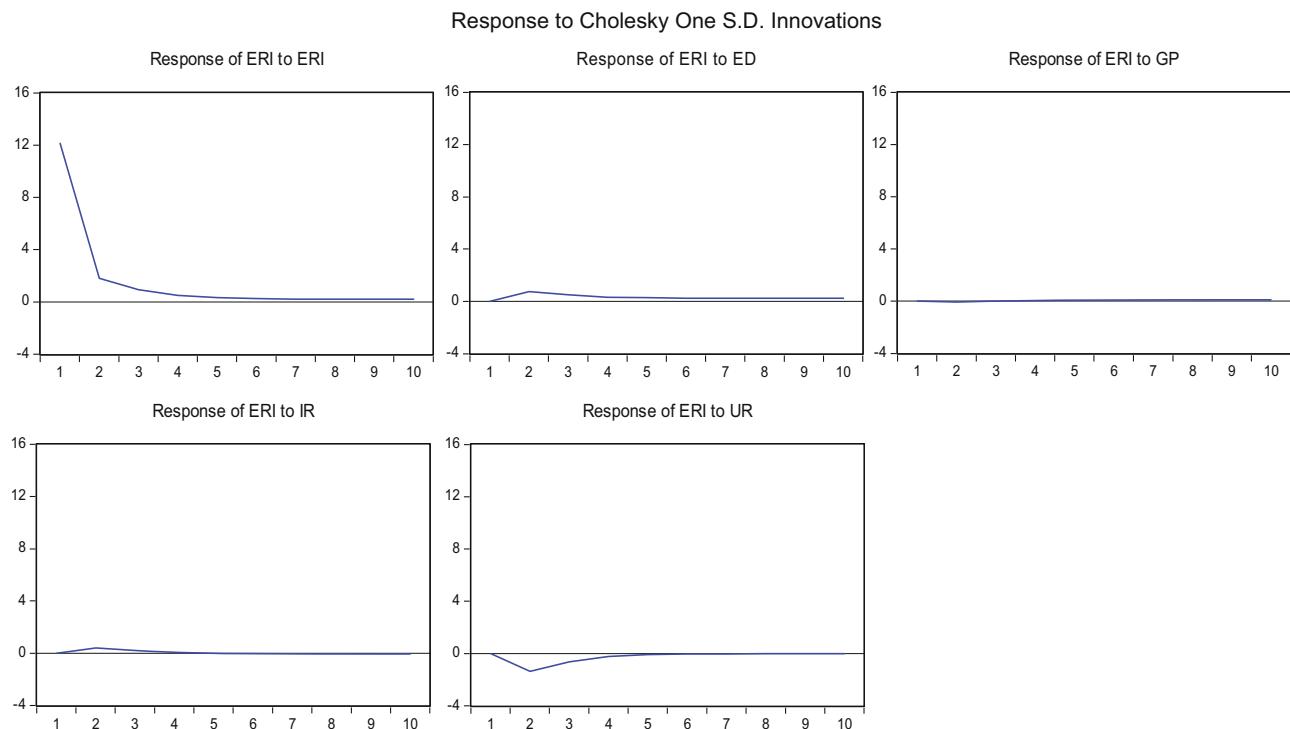
VAR model. Therefore, it can better characterize the dynamic influence of the variables in the system.

4.1 Dynamics of Type I Areas

Figure 6 reports the dynamics of ecosystems in Type I regions. The self-shock impact caused by changes in ecological risk (ERI) has the characteristics of significant convergence and periodic changes. It decreases sharply in the second period, rapidly in the third to sixth period, but stabilizes and converges to the mean value after the sixth period. This shows that although the ecological risk variable (ERI) has a certain degree of self-perturbation, it tends to be gradually stable over time.

The change in economic growth (ED) has a certain positive impact on the ecological environment (ERI), but the impact is relatively small. The disturbance caused by it is relatively large from the first period to the fifth period, but it is in a relatively stable state of change after the sixth period. However, the disturbance it causes does not converge to the mean.

The change in green policy (GP) has relatively little disruption to the ecosystem. From the first period to the fourth period, it has almost no effect. It produces a certain disturbance after the fifth period, but the impact is small

**Figure 6:** Impulsive response of ERI to other variables in type I.

(almost converges to the mean value) and shows a stable state.

The development of the secondary industry (IR) has a certain impact on the ecological environment (ERI) as a whole, and there is a phenomenon of alternating positive and negative impacts. It has a positive effect in periods 1–4, but little effect in periods 4–7. However, it has a negative effect after the 7th period, but this effect is small and shows a stable trend.

Urbanization development (UR) has a disturbing effect on the ecological environment (ERI). It leads to a significant negative change in the ecological environment (ERI) during the first to the fifth period, while the change caused by it is significantly smaller and shows a stable state from the fifth to the eighth period. However, it converges to its mean value after period 8 (Figure 6).

4.2 Dynamics of Type II Areas

In Type II areas, the self-shock effects caused by changes in ecological risk (ERI) are complex. During periods 1–2, the

effect it caused drops sharply and goes from positive to negative. The negative volatility it causes becomes smaller after period 2, but it has a small positive volatility and converges to its mean in period 3. After period 6, it has another slight negative swing, but the swing is smaller (Figure 7).

The disturbing effects of changes in economic growth (ED) on the ecosystem (ERI) are complex. From the first period to the fourth period, it has a significant negative disturbance, and the disturbance effect gradually becomes larger from the first period to the second period, but becomes smaller from the third period. After the fourth period, its perturbation converges to the mean and continues until the seventh period. After period 7, it produces positive disturbances, but the fluctuations are small and relatively stable (Figure 7).

Figure 7 shows that change in green policy (GP) has less perturbation effect on the ecosystem (ERI). It converges to its mean value in all other periods except for a slight positive perturbation in periods 2–4. Therefore, green policies are conducive to improving the ecological environment.

For Type II regions, the disturbance of the secondary industry development (IR) on the ecological environment

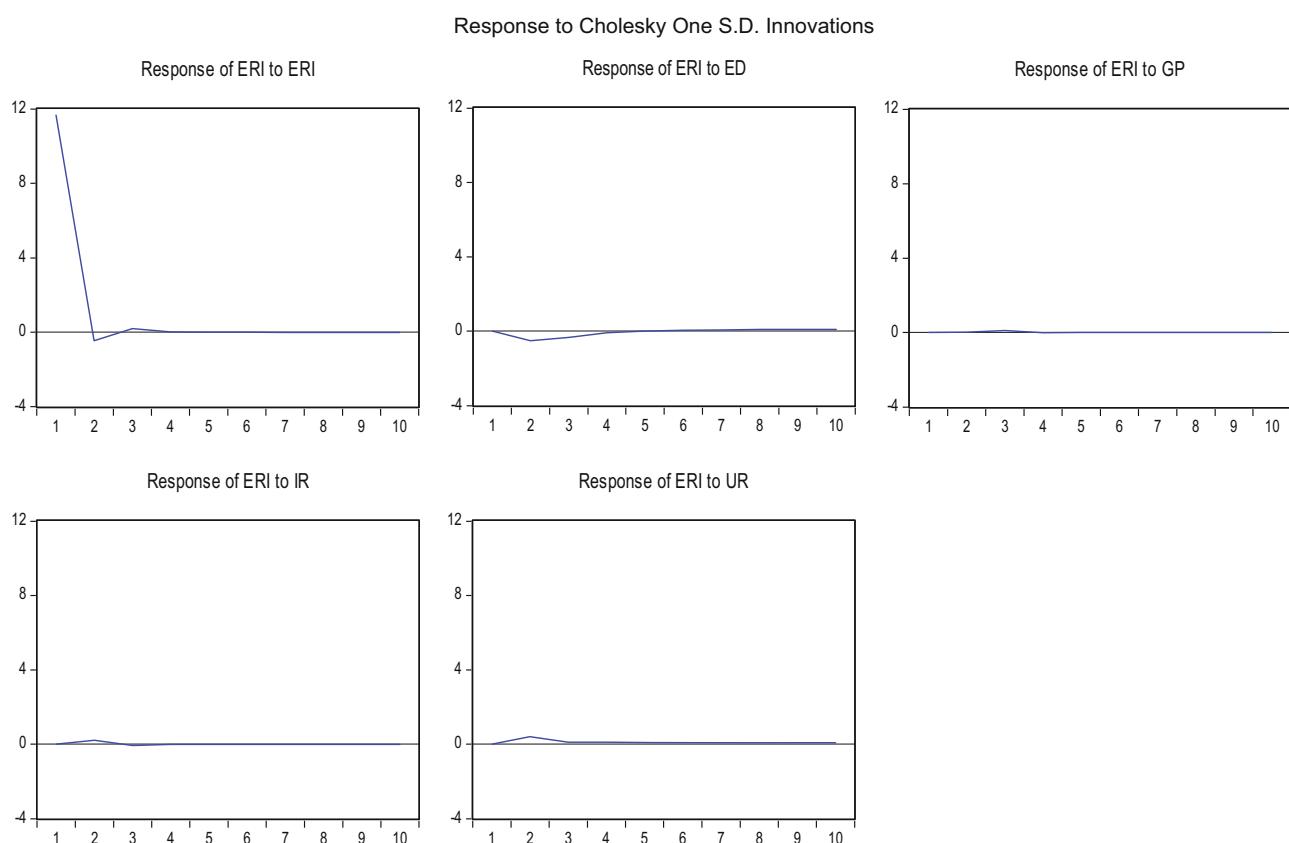


Figure 7: Impulsive response of ERI to other variables in type II.

(ERI) is small. Except for a slight positive perturbation in periods 1–3, it converges to the mean in all other periods (Figure 7).

Urbanization development (UR) has always a positive disturbance effect on the ecological environment (ERI). In the first to third period, the positive change caused by it is significant. But after the third period, the change it caused is significantly smaller and shows a stable state (Figure 7).

4.3 Dynamics of Type III Areas

In Type III regions, the self-shock impacts of change in ecological risk (ERI) are complex. During periods 1–2, it results in a positive effect with a sharp decline. After period 2, its positive volatility gradually becomes smaller. It converges to its mean during periods 3–4. After period 4, it has a slight negative swing and has been trending steadily (Figure 8).

The disturbing effects of change in economic growth (ED) on the ecosystem (ERI) are complex. It has a significant negative perturbation effect from the first period to the fourth period, and its perturbation effect gradually becomes larger during the first period to the second period, but it becomes smaller after the third period. After the fourth period, it produces a positive disturbance effect, and its disturbance effect becomes slightly larger and shows a relatively stable state from the fifth period (Figure 8).

The disturbances caused by changes in green policy (GP) to the ecosystem (ERI) have always shown negative changes. It produces a significant negative perturbation effect during the periods 1–4. However, its negative perturbation effect begins to become smaller and shows a relatively stable state after the fourth period (Figure 8).

Figure 8 shows that the development of the secondary industry (IR) has always a negative disturbing effect on the ecological environment system (ERI). The negative disturbance generated by it is relatively large from the first period to the fourth period, but then becomes smaller and shows a relatively stable state.

Urbanization development (UR) has always a positive disturbance effect on the ecological environment (ERI). However, the positive change caused by it is relatively significant during periods 1–4, but then becomes smaller and relatively stable (Figure 8).

4.4 Dynamics of Type IV Areas

Figure 9 reports the dynamics of the ecological environment (ERI) system in the Type IV areas. The self-shock impacts caused by the change in ecological risk (ERI) have the characteristics of stages. It shows a positive effect and declines sharply during periods 1–2. However, its positive volatility gradually becomes smaller from period 2 to

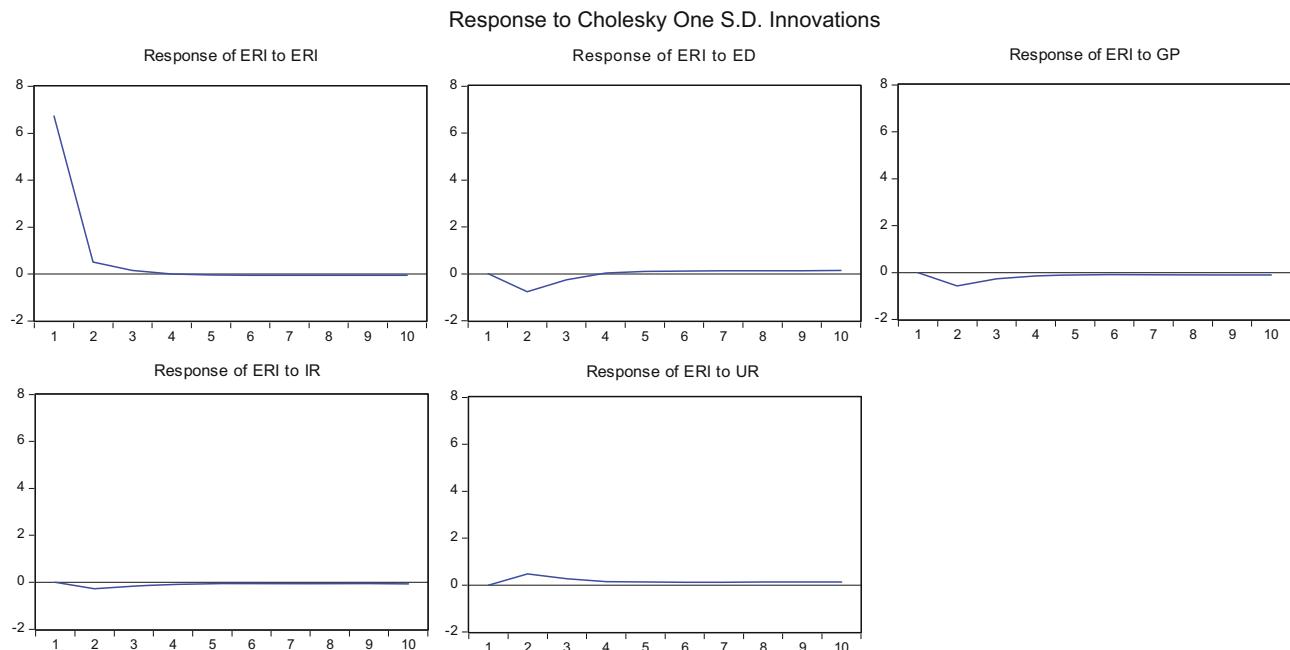


Figure 8: Impulsive response of ERI to other variables in type III.

period 4. Further, it converges to its mean during periods 4–6, but has a slight negative fluctuation and has been showing a stable trend after the sixth period (Figure 9).

The disturbing effects of changes in economic growth (ED) on the ecosystem (ERI) are complex. It has a significant negative perturbation effect from the first to the fourth periods, and its perturbation effect gradually becomes larger during the first to the second period, but it becomes smaller from the third period. Furthermore, it converges to its mean during periods 4–6, and it produces relatively small positive disturbance and shows a relatively stable state after the sixth period (Figure 9).

The disturbance caused by a change in green policy (GP) to the ecosystem (ERI) is not particularly significant, but its disturbance presents three changes: negative, convergent, and positive. It produces a negative perturbation effect from period 1 to period 4, but the fluctuation range is relatively small. Further, it converges to its mean during periods 4–5. However, it produces a relatively small positive disturbance and shows a relatively stable state after the fifth period (Figure 9).

Figure 9 shows that the development of the secondary industry (IR) has a negative disturbing effect on the ecological environment system (ERI) from the first period to the fifth period. Among them, the negative disturbance effect caused by it shows a trend of increasing from the first period to the second period, and the negative disturbance effect gradually becomes smaller from the second period to

the fifth period. Then, its effect is insignificant and has been converging to its mean after period 5.

The disturbance effect of urbanization development (UR) on the ecological environment (ERI) presents a state of negative and positive change, but the magnitude of change is relatively small. It shows a small change from negative to positive during the first to fourth periods, but has been showing a relatively small and stable positive change after period 4 (Figure 9).

4.5 Dynamics of Type V Areas

The self-shock impact caused by a change in ecological risk (ERI) presents the characteristics of positive change. It shows a positive impact but decreases sharply from periods 1–2, but its positive volatility gradually decreases from period 2 to period 4. Then, it has a small positive fluctuation and has been showing a stable trend after the fourth period (Figure 10).

The disturbance effect of change in economic growth (ED) on the ecosystem (ERI) shows a positive divergent trend. It has a smaller positive perturbation effect in the first to third period, but its perturbation effect becomes larger during the third to the seventh period and becomes larger after the seventh period. Although it produces a relatively small positive disturbance and presents a relatively stable state in stages, it exhibits divergence (Figure 10).

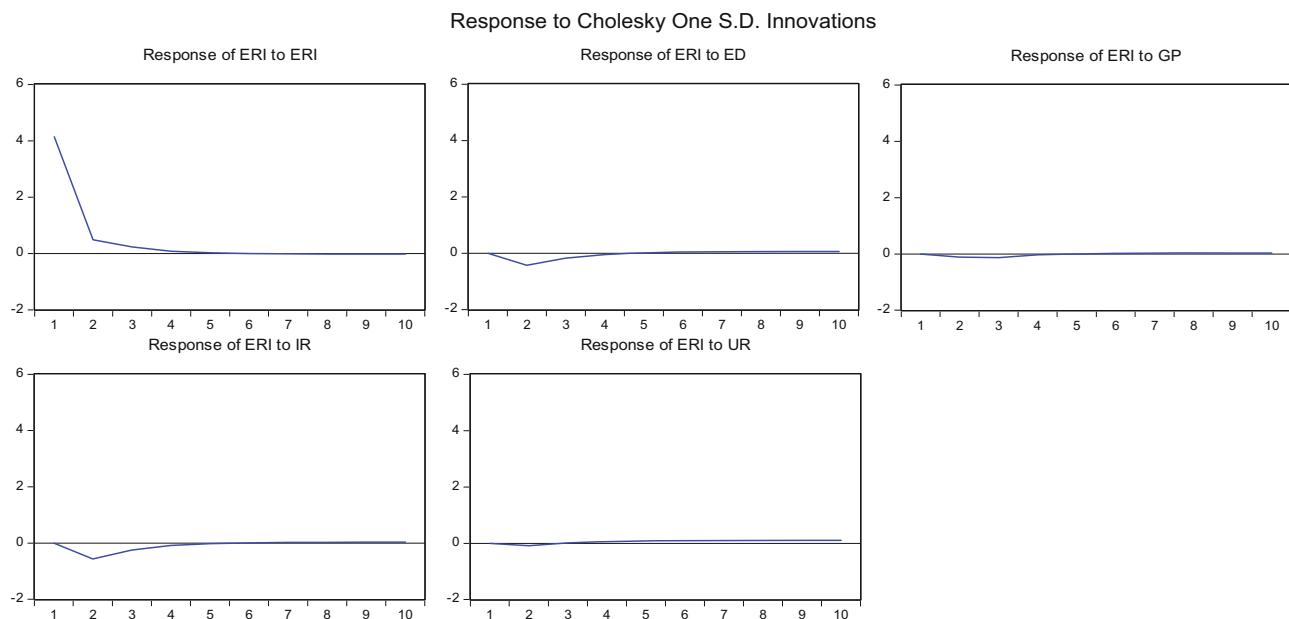


Figure 9: Impulsive response of ERI to other variables in type IV.

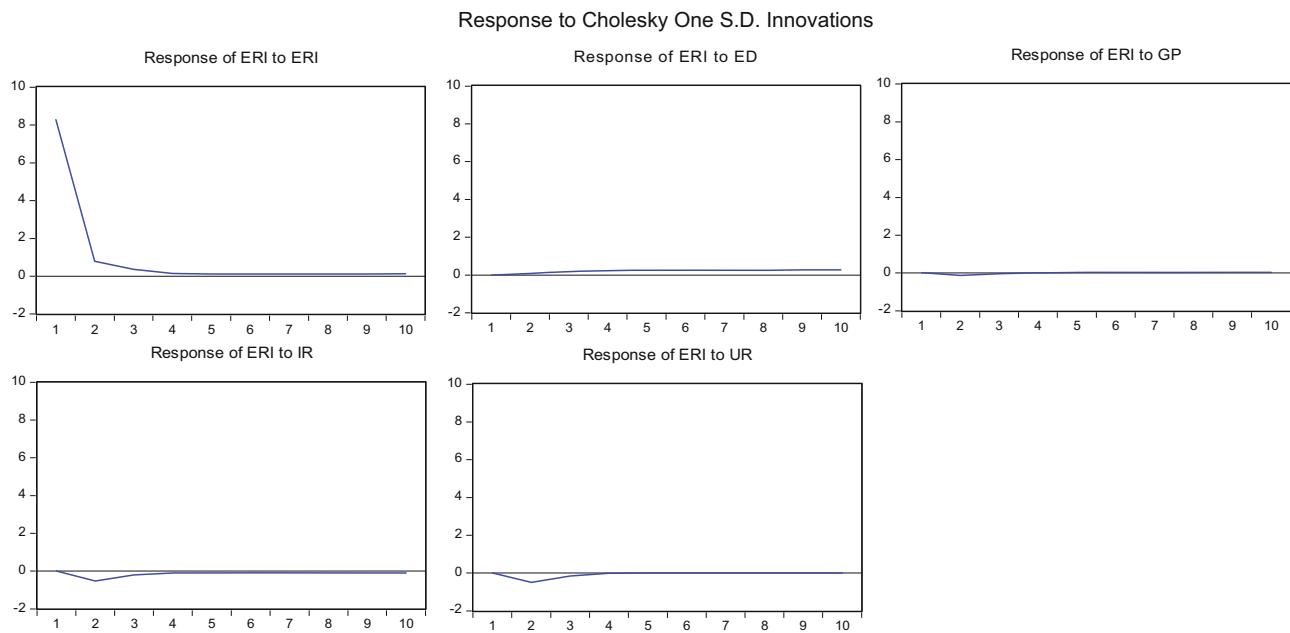


Figure 10: Impulsive response of ERI to other variables in type V.

Ecosystem (ERI) disturbances caused by green policy (GP) change are not significant. It produces a slight negative perturbation effect from period 1 to period 4 and always converges to its mean starting from period 4 (Figure 10).

The development of the secondary industry (IR) has always a negative disturbing effect on the ecological environment system (ERI). Its negative perturbation effect tends to increase from the first to the second period, while the negative perturbation effect gradually becomes smaller in the second to the fourth period. Further, its negative perturbation effect is small after the fifth period, and it has been showing a stable trend (Figure 10).

The disturbance effect of urbanization development (UR) on the ecological environment (ERI) shows a gradually increasing negative change from the first to the second period, but its negative change gradually becomes smaller after the second period. But since period 3, it has been converging to its mean (Figure 10).

4, but the magnitude of negative fluctuation is smaller and has been showing a stable trend (Figure 11).

The disturbance effect of economic growth (ED) change on the ecosystem (ERI) presents alternately negative and positive features. It shows a gradually increasing trend of negative perturbation in the first to second period, but its negative perturbation effect gradually becomes smaller in the second to fourth period. Then, the disturbance effect changes from negative to positive from the fourth period, and has a gradually increasing trend. However, its positive perturbation effect appears to be relatively stable after the sixth period (Figure 11).

For Type VI regions, the disturbance to the ecosystem (ERI) caused by green policy (GP) changes is complex. It produces a progressively larger positive disturbance during periods 1–2, but the positive disturbance begins to decrease from periods 2–4. Then, its perturbation effect changes from positive to negative starting from period 4 and shows a divergent trend (Figure 11).

The disturbance effect of the development of the secondary industry (IR) on the ecological environment system (ERI) presents a state of negative and positive change. It produces a gradually increasing negative perturbation effect during the period 1 to 2, but its negative perturbation effect gradually becomes smaller in the periods 2 to 4. However, its perturbation effect changes from negative to positive after the fourth period and has been showing a stable trend after the fifth period (Figure 11).

The disturbance effect of urbanization development (UR) on the ecological environment (ERI) is always in a

4.6 Dynamics of Type VI Areas

In the Type VI areas, the self-shock impact caused by a change in ecological risk (ERI) presents the characteristics of positive and negative change. It shows a positive effect and decreases sharply from periods 1 to 2, but the positive fluctuation gradually decreases from period 2 to period 4. It starts to fluctuate from positive to negative after period

positive state. Its positive fluctuation range is not significant from the first period to the second period, but its positive change is more significant after the second period and shows a relatively stable trend (Figure 11).

4.7 Dynamics of Type VII Areas

In the Type VII areas, the self-shock impact caused by a change in ecological risk (ERI) presents a positive disturbance. Its positive fluctuation decreases sharply in periods 1–2, but gradually decreases in periods 2 to 3. However, its positive perturbation amplitude becomes small after the third period and has been showing a stable trend (Figure 12).

Change in economic growth (ED) has a positive disturbing effect on the ecosystem (ERI). Its positive perturbation effect is relatively large in the first to second period, but its positive perturbation effect is not significant during the second to third period. From the third period onwards, the positive perturbation effect slightly increases and shows a relatively stable state (Figure 12).

The disturbances caused by green policy (GP) change to the ecosystem (ERI) alternate negatively and positively. It produces a small negative perturbation effect from period 1 to period 2, but produces an insignificant positive perturbation effect from period 2 and almost converges to its mean (Figure 12).

The disturbance of the secondary industry development (IR) to the ecological environment system (ERI) is relatively small. It produces a relatively significant negative perturbation effect from period 1 to period 2, but the negative perturbation effect is small from period 2 and almost converges to its mean (Figure 12). This can be related to the industrial backwardness of the region.

The disturbance effect of urbanization development (UR) on the ecological environment (ERI) is in a positive state. Its positive fluctuation range is relatively large from period 1 to period 2, but its positive change is not significant after period 2 and almost converges to its mean value (Figure 12).

5 Discussion

The composite environmental risk index model constructed here is based on the mixed data of a specific combination of time and space effect. If it is only a single individual, we can assume that the spatial factor effect is zero (Dou, 2022). In addition, this article uses the absolute deviation of individuals from their mean to measure risk. In fact, we can also define other Loss functions to measure risk according to different research objects and purposes.

Our research object is China's provincial administrative regions. Although China's provincial administrative

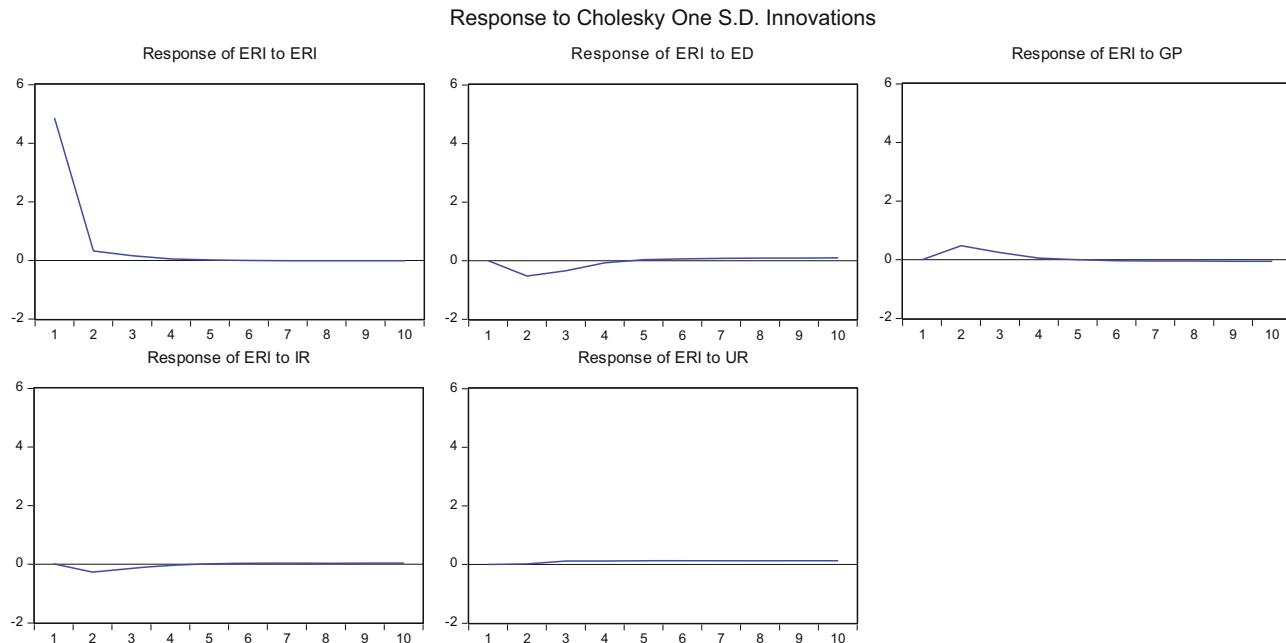


Figure 11: Impulsive response of ERI to other variables in type VI.

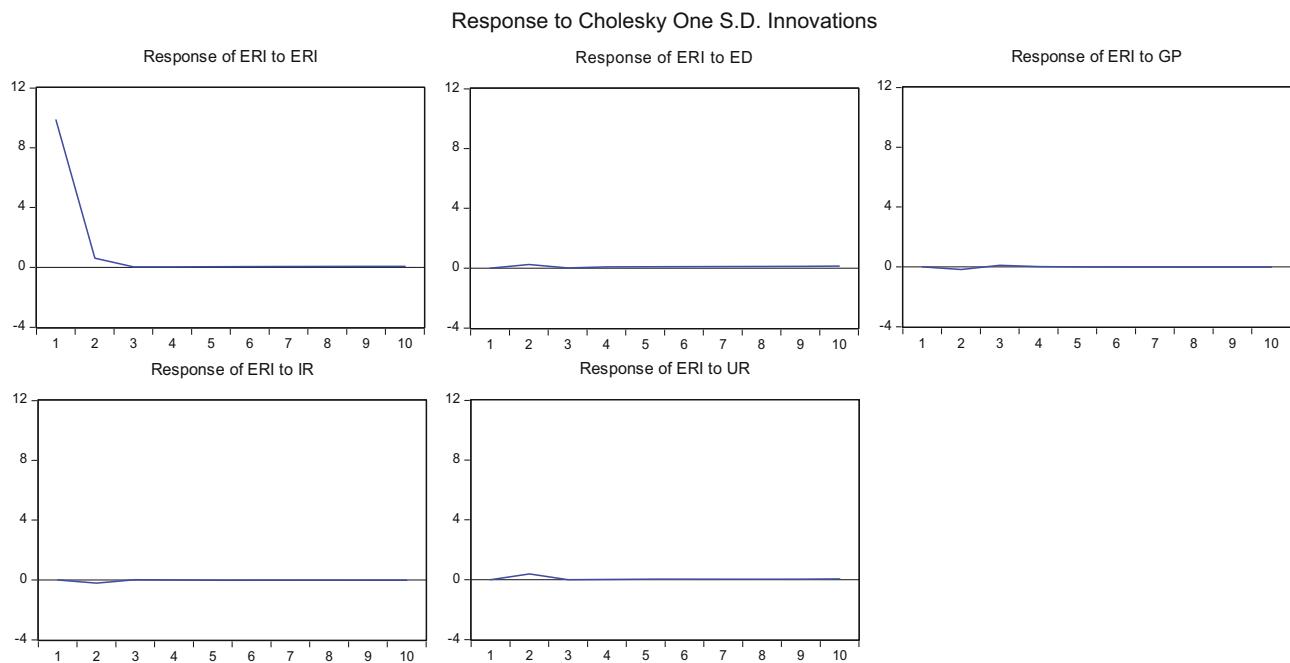


Figure 12: Impulsive response of ERI to other variables in type VII.

regions are independent regions, they are all in a unified market system. Therefore, there may be spatial spillover effects between different regions (Bai et al., 2023). However, as far as the composite environmental risk index model is concerned, it is fully applicable to research objects with countries as regions, as we use statistical means of sample cross-sections when calculating spatial factors for comparison and analysis. Generally, we do not need to consider the heterogeneity of sample individuals (spaces), as their weights are calculated using the same method. That is to say, the effects of organizational constraints and the spatial limits are not significant.

Our model measures the changes in the ecological environment (environmental risks). Therefore, we are considering environmental indicators such as water resources, natural disasters, waste discharge, and environmental governance investment. Of course, we can also quantify environmental changes (environmental risks) from the perspective of ecological environmental behavior, selecting indicators such as environmental concerns, social economic sequences, and environmental governance for quantitative analysis (Xu & Bao, 2023). However, it may be more suitable to choose environmental display indicators for measurement and evaluation for large distributed areas such as provincial-level regions in China.

There are many factors that lead to environmental risks. This article focuses on the role of economic growth, secondary industry, urbanization, and green policies. In fact, they can be further decomposed into more specific

factors. Especially, green policies include many related policies (Li et al., 2023). In addition, different regions adopt different green policies. Due to the complexity of these issues, this article only provides a general analysis.

The results of the dynamic analysis of the regional environment system indicate that the effectiveness of China's environmental protection policies is significant. From the empirical results of at least seven types of regions we have divided, we can find that due to the implementation of strict environmental protection policies, the ecological environment conditions in each region are gradually stabilizing, but this does not mean that the environmental conditions in all regions of China have been completely improved. Due to the large area of China's provincial-level regions, there are significant differences in the ecological environment conditions of different sub-regions within each provincial-level region. This may lead to differences in the conclusions compared to the intuitive perception of specific regions. To this end, regions can be divided into smaller areas for measurement and evaluation based on different research objectives and tasks.

6 Conclusion

The goal of this article is to construct an composite environment risk index to measure and evaluate the environmental risks of the regions in mainland China. The study

finds that the risk index of each region shows significant and unstable changes during the 2004–2019 sample period, which indicates that the environment of these regions is at a greater risk. Further, we find that the environment of each province-level region in China has the following characteristics of changes. First of all, the environmental changes in most regions do not show significant and relatively stable phased characteristics. Second, the environment of most regions shows divergent changes. Finally, although the environmental protection policies and measures of the national and all regions have become stricter in recent years, the environmental risks have not been significantly improved.

This article empirically tests the impact of four key economic variables of economic growth, urbanization development, secondary industry growth, and green policy on the environment on the basis of environment risk measurement and evaluation. The study finds that economic growth, secondary industry growth, and green policies have a negative correlation with the environment risk index, while there is a positive correlation between urbanization development and the environment risk, which is in line with the actual situation in China. Although economic growth and the growth of the secondary industry have certain adverse effects on the environment, China has been implementing strict environmental protection policies in recent years and at the same time continuously increasing investment in environmental governance, thereby reducing the negative impact on the environment. Because the goal of green policies is to improve the environment, it has a positive impact on the environment. On the other hand, because China's urbanization development is large-scale, rapid, and extensive, it has a direct negative impact on the environment.

The research results of this article show that although China's regional environmental risks are still relatively large at this stage, China's regional environmental risks will be controlled within a reasonable range with China's social and economic development and the continuous implementation of environmental protection policies. The future regional environment governance should focus on the following aspects on the premise of solving social and economic problems and regional imbalances.

- 1) Full implementation of green policies. Because green policies have direct and significant effects on improving the environment, China must implement more stringent green policies in all areas of consumption, product and energy production, circulation, and urban infrastructure construction in the future (Yang et al., 2022).
- 2) Significantly increase capital investment in water resources and watershed management, biodiversity protection, and environment infrastructure (Crist et al., 2017; Moffette et al., 2021). The first is to increase financial

investment in environmental governance. Because the environment has the attributes of public goods, the central and local governments must bear the corresponding governance and protection responsibilities. The second is to encourage social capital to participate in the governance and protection of the environment through financial and fiscal policies to make up for the lack of fiscal funds. With the increasing environmental awareness of the public and enterprises, the potential of social capital is huge.

- 3) Comprehensively to promote the development of high-quality urbanization. At this stage, China's urbanization has achieved a large-scale quantitative expansion and has been in a stage of transition from a quantitative development to a qualitative development. Therefore, China must promote the high-quality development of cities in a timely manner. This is not only a requirement for the management and protection of the environment, but also an inevitable requirement for improving the efficiency of urban development.

The research provides a multi-index and comprehensive environment risk assessment method. The advantage of this method is that it can not only perform multi-index and multi-scale evaluation but also extract the spatial and temporal effects of the objects evaluated. Therefore, the results measured by such a method are conducive to objective evaluation from the vertical and horizontal dimensions. In addition, this method provides a methodological basis for risk measurement and evaluation of more complex systems, subsystems, and larger index systems.

Acknowledgments: The authors thank anonymous reviewers and editors for valuable comments and revision suggestions.

Funding information: The authors state no funding involved.

Conflict of interest: The authors state no conflict of interest.

Article note: As part of the open assessment, reviews and the original submission are available as supplementary files on our website.

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