Urban Public Safety Risk Assessment Based on Dynamic Factor Analysis

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Keywords: Urban public safety; Dynamic factor analysis; Risk assessment; Vulnerability

Abstract: Scientific prevention and control of urban public safety risks are essential to improve people's well-being and promote the improvement and innovation of public safety institutional mechanisms. In order to analyse the key factors affecting the level of urban public safety, an assessment model is constructed based on three levels of indicators: exposure and sensitivity, vulnerability and risk response capacity. Also, the urban public safety risks of 31 provinces, municipalities and autonomous regions in China from 2015 to 2019 are comprehensively evaluated with the help of dynamic factor analysis to explore the changes, advantages and disadvantages of urban public safety development in different regions. This paper finds that the 6 key influencing factors of urban public safety risk in China are economic and social security development, medical and urban construction investment, fire and traffic accidents, environmental regulation, climate disasters, and urban congestion. Horizontally, the distribution of urban public safety risks shows a gradual increase from east to west, with relatively less risk in the eastern coastal areas. Vertically, the pattern of risk changes varies from place to place, with relatively stable changes in low-risk and high-risk areas, and greater volatility in medium-low and medium-high risk areas.

1. Introduction

The city-cantered mode of social and economic organization and operation is an important symbol of a modernized country. Data shows that by 2021, China's population urbanization rate has reached 64.72%, with the scale of cities expanding and the status of cities rising. Along with the rapid economic and social development, the complexity and instability of cities are gradually increasing and insecurity factors are increasing, which bring great challenges and difficulties to the city management. Among these outstanding problems, urban public safety is a key element that must be strongly concerned and urgently needs to be improved as a prerequisite for the sustainable development of urbanization [1]. Since the SARS outbreak in 2003, China has established a comprehensive emergency management system that can response to "all kinds of disasters, during the whole process with multiple subjects in the structure" and has incorporated public safety as an important element in the national strategic plan for the first time. At the same time, a series of laws and standards have been enacted in recent years in terms of legislation and urban planning, providing a guarantee for urban public safety governance. In the 2018, China established the Ministry of Emergency Management, which has promoted innovation and practical capabilities in terms of organization, management mechanism, and program planning [2]. The outbreak of the Covid-19 in 2020 has brought great threats to people's lives and properties around the world and once again puts the issue of public safety in the hot spot. In China, the emergency management bears the mission of protecting people and society, and public safety should be elevated to the level of modernization of the national governance system and governance capacity to plan and deploy. So, the strategy for high-quality development of China's emergency cause should be developed to contain the budding of risks at the source and to continuously improve the prevention phase of emergency management [3].

Risk assessment can reveal latent risk factors in urban public safety, provide a good early warning effect, and take targeted measures to improve safety in all aspects in response to the variability of each region and subject [4]. For the assessment of various urban emergencies and risks, scholars mostly consider from specific events or regional characteristics, Daniela [5] assesses the risk of natural disasters in intellectual cities in terms of disaster exposure, vulnerability and municipal income, and local development dimensions. Shuidentifies the spatial factors of urban flooding risk based on grayscale coevolution matrix and uses artificial neural network algorithm to construct a multi-geographic unit convolutional neural network model for assessment [6]. Ma et.al combines various methods such as whole process analysis of urban heavy rainfall and flooding disasters and three types of hazard source analysis to measure risk in terms of regional vulnerability, adaptability and recoverability [7]. Sun et.al combines population characteristics as a separate examination with resilience and vulnerability to measure mega-city public safety risk, and conducts an example analysis of Shanghai [8]. Zhao et.al builds a comprehensive multi-hazard risk assessment model for urban clusters from the aspects of socio-economic foundation, historical disaster conditions, disaster chain effects, disaster prevention and mitigation, and inter-city collaborative relief [9]. Yang and Qu construct a single-hazard risk assessment system based on (PSR) model and calculate the assessment results of each hazard through coupled incentive model to serve disaster risk management in urban high-risk areas [10]. By combing the relevant studies of scholars, this paper introduces dynamic factor analysis method, which overcomes the shortcomings of traditional factor analysis on panel data analysis and can better explain the horizontal and vertical changes of urban public safety risk status in different regions in practical application.

2. Indicators, Data and Methods

2.1 Indicator system construction

Risk factors affecting urban public safety are diverse and uncertain, and public safety events in modern cities involve not only natural safety, but also ecological and environmental safety, water safety, energy safety, and information system safety. Various events not only damage the safety of people's lives and properties, but also bring unpredictable social impacts [11, 12]. The study of vulnerability is a fundamental paradigm in the current interdisciplinary study of disasters [13]. The introduction of the concept of vulnerability for the evaluation of this particular system of cities satisfies the need for long-term sustainability of cities and follows the general rule of urban risk research. Su et.al argues that vulnerability measures the human sensitivity to hazards and the ability to respond and recover from their impacts [14]. Wang et.al clarifies the concept of urban vulnerability and constructs an urban public safety vulnerability evaluation system consisting of structural and coercive factors [15]. Ioanna et.al focuses on urban centers in the EMME region, proposes a conceptual framework of urban vulnerability under specific conditions of climate change (including five aspects: environmental, human, urban habitat, technical economy and socio-economy) and points out that methods of assessment by quantifying exposure and endurance [16]. In addition, with the multidimensional extension of the vulnerability concept, the "capability" assessment framework has gradually diverged from it and formed a more comprehensive public safety assessment system with the "vulnerability" assessment framework. For example, Hao et al use a combination of particle swarm optimization algorithm, entropy power method and kernel density estimation to construct a resilience assessment method for urban clusters, which is convenient for analyzing the dynamic evolution and spatial characteristics of urban cluster resilience [17]. Based on the above literature study, this paper constructs an urban public safety risk assessment system from three levels: urban exposure and sensitivity, urban vulnerability and risk response capacity. Among them, population factor is the main factor causing unreasonable urban structure and scale so population density is selected to measure urban exposure and sensitivity; urban vulnerability indicators refer to common urban disaster categories; risk coping capacity indicators measure the capacity of 5 aspects: urban economic development, social defense, medical resources, infrastructure construction, and ecological protection. The specific indicators are shown in Table 1.

Table 1 Urban public safety risk assessment indicator system

Level I indicator	Level II indicator
Exposure and Sensitivity	Population density
Disaster vulnerability	Geological and climatic disasters Fire and traffic accident Production safety accident Health and environmental events
Risk response ability	Economic development Social defines Medical resources Infrastructure construction Ecological protection

2.2 Data sources

This paper collects and organizes data on 20 indicators from 2015-2019 from 31 provinces, municipalities and autonomous regions across China, with relevant data from the China City Statistical Yearbook, Financial Statistical Yearbook, China Social Statistical Yearbook, provincial and municipal statistical bulletins, water resources bulletins, etc. for each year.

2.3 Introduction to the research methodology

The quantitative research methods of scholars on urban public safety risk assessment generally show a variety of methods and disciplines. Among them, probabilistic statistical methods such as principal component analysis, factor analysis, cluster analysis and comprehensive assessment methods based on fuzzy theory and grey theory are widely used. Meanwhile, with the support of computer systems, big data analysis methods such as Bayesian mixture models, Gaussian mixture models and maximum expectation algorithms are favoured by more and more scholars. This paper adopts Dynamic Factor Analysis (DFA). DFA is a multivariate statistical analysis method that combines traditional factor analysis with linear regression models and integrates the results of static cross-sectional analysis and dynamic time series analysis. The method was first designed and proposed by Coppi and Zannella in 1978, and later scholars such as Chow S and Zu[18] provided references for the technical implementation of the method on statistical software. The dynamic factor analysis method integrates the static structure of the assessment objects, the average dynamic structure of the indicators and the differences of each object over time, thus enabling the simultaneous horizontal level comparison and vertical dynamic development change analysis of the urban public safety risk situation. The calculation is followed by the following seven steps:

Step I: Data standardization to eliminate dimensional gaps. This paper adopts the "Min-Max standardization method" to standardize the panel data of 20 indicators in the national provinces from 2015 to 2019.

Step II: Solve the average covariance matrix S_T based on the covariance matrix $S(t)$ of each year:

$$S_T = \frac{1}{T}\sum\nolimits_{t=1}^{T} S(t) \tag{1}$$

Step III: solve eigenvalue and eigenvector of S_T and variance contribution rate of each common factor. See Table 2 for correlation results;

Step IV: extract the common factor and establish the original factor load matrix. See Table 3 for the results;

Step V: solve the required static score matrix:

$$C_{\mathrm{ih}} = \left(\overline{Z}_i - \overline{Z}_.\right)' a_h \tag{2}$$

Where, $\overline{Z_{\mathrm{t}}} = \frac{1}{I}\sum_{\mathrm{i}=1}^{I} Z_{it}$ is the average vector of a single object and $\overline{Z_{\mathrm{t}}} = \frac{1}{I}\sum_{\mathrm{i}=1}^{I} Z_{it}$ is the overall average vector, $i = 1, 2, \cdots, I$, $t = 1, 2, \cdots, T$;

Step VI: Solve the required dynamic score matrix:

$$C_{iht} = \left(Z_{it} - \overline{Z_t}\right)' a_h,\ h = 1,\cdots,k,\ t = 1,\cdots,T \tag{3}$$

Where, $\overline{Z_t} = \frac{1}{I}\sum_{i=1}^{I} Z_{it}$ the matrix $\overline{Z_t}$ is the average value of each index in t^{th} year;

Step VII: Calculate the average score *E*,

$$E = \frac{1}{T}\sum C_{iht} \tag{4}$$

Where, C_{iht} is the dynamic score of each evaluation object in t^{th} year.

3. Empirical results and analysis

3.1 Common factor extraction

Firstly, the eigenvalues and variance contribution rates are obtained according to steps 1-3 (Table 2), and the common factors are extracted with reference to the principle of eigenvalues greater than 1 and cumulative contribution rates of 80%-85%. The cumulative variance contribution rate of the 6 common factors extracted in this paper is 81.78%, which basically reflects most of the evaluation information of the index. Secondly, in order to clearly reflect the situation of the common factors, the maximum variance orthogonal rotation is used to obtain the rotated factor loading array (Table 3).

Table 2 Common factor eigenvalue and variance contribution rate

Common factor	Eigenvalue	Variance contribution rate	Cumulative variance contribution rate
F1	4.6465	0.2323	0.2323
F2	4.4292	0.2215	0.4538
F3	1.9410	0.0971	0.5508
F4	1.8666	0.0933	0.6442
F5	1.7552	0.0878	0.7319
F6	1.7180	0.0859	0.8178

Table 3 Common factor load matrix

Indicator	Factor					
	F1	F2	F3	F4	F5	F6
Population density	0.1965	-0.0036	-0.1574	-0.1691	-0.1940	0.7667
Precipitation anomaly degree	-0.1826	0.0652	0.0677	0.0113	-0.9277	0.0075
Geological hazard index	0.3619	-0.1440	-0.0047	0.4821	0.4073	0.2366
Fire traffic accidents per million casualties	0.0829	0.2316	0.8494	0.1965	0.0523	-0.1236
Per capita direct economic loss of fire and traffic accident	-0.2544	0.2337	0.7510	-0.1034	-0.2766	-0.0489
Deaths due to production safety accidents in GDP of RMB 100 million	0.2599	0.6795	0.3998	0.0634	0.1326	-0.0485
Incidence of infectious diseases	0.2469	0.5659	0.0431	0.4279	-0.4475	-0.1023
Number of sudden environmental events	-0.1028	-0.5404	-0.0238	0.5104	0.2075	0.1480
GDP per capita	0.8662	0.1979	-0.1344	0.0376	0.2394	0.1008
Per capita fiscal expenditure	0.9139	-0.3179	0.0753	-0.0616	0.0954	-0.0206
Insurance density	0.9374	0.2451	0.0417	0.0825	0.0476	-0.0283
Minimum standard of living security	0.8990	-0.0300	-0.0699	0.0216	-0.0490	-0.0430
Unemployment insurance coverage rate	0.7581	0.2264	-0.1154	0.0625	0.0475	-0.0987
Number of beds per 10,000 people in the hospital	-0.1568	0.9191	0.2209	0.0444	-0.0779	-0.0481
Number of doctors per 10,000	-0.0121	0.9350	0.1694	0.0437	-0.0473	0.0463

Per capita road area	-0.4947	0.1808	-0.1323	0.1712	0.2114	0.7200
Daily domestic water consumption per capita	0.1434	-0.7876	-0.1227	-0.0003	0.1520	0.1954
Investment amount of urban construction	0.2858	0.8396	-0.0541	-0.2235	-0.0398	0.1593
Proportion of investment in environmental pollution control in GDP	0.0326	-0.0470	0.3114	-0.5824	0.0839	0.5477
Comprehensive utilization rate of industrial solid waste	0.1155	0.1281	-0.4587	0.5578	0.4391	-0.3352

As can be seen from Table 3, the F1 factor focuses on the level of socio-economic development and the insurance and social security situation, in which the loadings of per capita financial expenditure and insurance density exceed 0.9. And F1 is named as the economic and social security development factor; F2 factor loadings on the number of hospital beds per 10,000 people, the number of doctors per 10,000 people, urban construction investment loadings exceed 0.8. And F2 factor is named as medical security and urban construction investment factor; F3 factor mainly reflects the fire and traffic accident situation, and it is named as fire and traffic accident factor; F4 factor mainly reflects the role of environmental events and environmental construction, and it is named as environmental regulation factor; F5 factor is named as climate disaster factor because the absolute value of the load of precipitation anomaly exceeds 0.9; F6 factor is named as congestion factor because the load of population density and road area per capita is high, which reflects the distribution of population and roads in the city. In general, the sum of the contributions of F1, F2 and F4 factors reaches 0.5416, and these three factors reflect the public safety risk response capability, indicating that the risk response capability has a greater impact on the level of urban public safety; F3, F5 and F6 summarize the main disasters and causes that pose threats to urban public safety.

3.2 Analysis of risk assessment results

The static composite score and the dynamic average composite score of public safety risks of cities in each province nationwide are calculated from steps 5-7 (Table 4). The higher the score, the greater the risk to public safety in the city. On the contrary, the lower the score, the higher the level of public safety. Among them, those with scores less than zero are higher than the national average, and those with scores greater than zero are lower than the national average.

Table 4 Comprehensive evaluation results of 2015-2019

Province	2015	2016	2017	2018	2019	Average comprehensive score	Static factor score	Ranking	Class
Beijing	-1.139	-1.044	-1.129	-0.991	-1.374	-1.136	-0.975	1	Low risk
Shandong	-0.759	-0.753	-0.747	-0.838	-0.608	-0.741	-0.834	2	
Jiangsu	-0.679	-0.658	-0.905	-0.714	-0.649	-0.721	-0.923	3	
Shanghai	-0.262	-0.552	-0.722	-0.863	-0.814	-0.642	-0.912	4	
Inner Mongolia	-0.754	-0.323	-0.135	-0.138	-0.276	-0.325	-0.227	5	Medium to low risk
Hebei	-0.336	-0.270	-0.266	-0.337	-0.299	-0.302	-0.312	6	
Zhejiang	0.053	-0.262	-0.324	-0.446	-0.362	-0.268	-0.345	7	
Liaoning	-0.306	-0.220	-0.060	-0.214	-0.264	-0.213	-0.174	8	
Henan	0.020	-0.166	-0.265	-0.243	-0.124	-0.156	-0.259	9	
Guangdong	-0.035	-0.085	-0.156	-0.278	-0.213	-0.153	-0.278	10	
Sichuan	0.008	-0.144	-0.173	-0.103	-0.135	-0.109	-0.022	11	
Anhui	0.051	0.032	-0.051	0.005	0.054	0.018	-0.103	12	Medium and high risk
Hubei	-0.244	0.052	-0.025	0.150	0.202	0.027	0.061	13	
Jilin	0.043	0.017	0.079	0.036	0.033	0.041	0.159	14	
Ningxia	-0.072	0.033	0.183	0.005	0.106	0.051	0.062	15	
Hunan	0.070	0.128	0.077	0.033	-0.020	0.058	0.094	16	

Tianjin	0.086	-0.226	0.031	0.150	0.326	0.073	0.219	17	
Chongqing	0.110	0.054	0.134	0.145	0.029	0.094	0.198	18	
Heilongjiang	0.257	0.006	0.031	0.034	0.178	0.101	0.069	19	
Shanxi	-0.013	0.119	0.156	0.180	0.104	0.109	0.128	20	
Fujian	0.235	0.299	0.057	0.012	0.126	0.146	0.002	21	
Shaanxi	0.289	0.113	0.251	0.140	0.149	0.189	0.208	22	
Tibet	0.180	0.261	0.110	0.538	0.021	0.222	0.502	23	
Jiangxi	0.387	0.288	0.243	0.243	0.307	0.294	0.246	24	
Yunnan	0.490	0.181	0.221	0.404	0.362	0.332	0.601	25	
Gansu	0.342	0.235	0.316	0.467	0.401	0.352	0.481	26	
Guangxi	0.213	0.110	0.187	0.734	0.824	0.413	0.415	27	
Guizhou	0.070	0.396	0.699	0.556	0.539	0.452	0.724	28	
Xinjiang	0.246	0.871	0.692	0.371	0.182	0.473	0.134	29	
Hainan	0.688	0.784	0.657	0.276	0.364	0.554	0.425	30	High risk
Qinghai	0.758	0.722	0.837	0.688	0.831	0.767	0.638	31	

3.2.1. Cross-sectional regional comparative analysis Section Titles

The provinces are ranked based on the average composite score, and the national urban public safety risk level is divided into four levels based on the ranking, namely low risk (score <-0.5), medium-low risk (-0.5 < score <0), medium-high risk (0 < score <0.5), and high risk (score >0.5). The regional distribution of the national urban safety risk situation is drawn according to the divided risk levels (Figure 1). From Table 4 and Figure 1, it can be seen that 1) Beijing, Shandong, Jiangsu and Shanghai are low-risk areas of public safety. Beijing has the lowest risk for five consecutive years; Shanghai has gradually reduced the risk in recent years, and it has catched up with Shandong and Jiangsu on urban public safety after 2018; 2) Except for Sichuan, which is located in the western region, the areas classified as low and medium risk levels are basically from the central and eastern regions of China. Among them, Inner Mongolia ranks second only to Shandong in 2015, and Sichuan and Zhejiang score lower than the national average in 2015 and public safety risks has seen decline; 3) The most provinces and municipalities are classified as medium-high risk level, with a relatively large share of geographical distribution located in the central and western regions, in addition to Heilongjiang and Jilin in the northeast and Tianjin, Fujian and Guangxi in the eastern region. 4) Hainan and Qinghai are both classified as high risk level. It can be clearly seen from Figure 1 that the distribution of public safety risks in China's cities, including Beijing, Shanghai and Guangzhou, shows a gradual increase from east to west, with the eastern coastal region having a relatively high level of public safety.

Figure 1 Distribution of urban public safety risks in China.

3.3.2. Trend analysis of vertical dynamics Subsection Titles

To present more clearly the vertical changes of public safety risks in cities of 31 provinces, municipalities and autonomous regions, a summary chart of dynamic changes of public safety risks in cities nationwide from 2015 to 2019 is drawn based on the evaluation results of each year in Table 4 (Figure 2).

As can be seen from Figure 2, there are six main characteristics of vertical changes in urban public safety risks in the country during 2015-2019: V-type, inverted V-type, N-type, inverted N-type, W-type, and M-type, which portray the different change trends of urban public safety risks. Among them, V-type, N-type and W-type indicate an upward trend of recent risks, while inverted V-type, inverted N-type and M-type indicate a downward trend of recent risks, and W-type and M-type features have stronger volatility. The V-shaped characteristics are: Tianjin, Shanghai, Zhejiang, Anhui, Jiangxi, Henan, Guangdong, a total of seven regions; inverted V-shaped characteristics are: Shanxi, Inner Mongolia, Liaoning, Hunan, Guizhou, Xinjiang, a total of six regions; N-shaped characteristics are: Hebei, Jiangsu, Fujian, Shandong, Hubei, Hunan, Ningxia, a total of seven regions; inverted N-shaped characteristics are: Jilin, Guangxi, Chongqing, Sichuan, Yunnan, Gansu, a total of six regions; the W-shaped features are: Heilongjiang, Shaanxi, Qinghai, a total of three regions; M-shaped changes are: Beijing and Tibet, a total of two regions.

From the above 4 risk level classifications, among the low-risk regions, Beijing, Shandong and Jiangsu have experienced relatively stable changes, and Shanghai's urban public safety risk has significantly decreased in recent years; among the medium-low and medium-high risk regions, the declining changes in urban public safety risk in Inner Mongolia, Liaoning, Jilin, Hunan, Guizhou and Xinjiang have been maintained for two years or more, while other provinces and municipalities have recently shown varying degrees of elevation and short-term decline in risk; and within the high-risk region, urban public safety in Hainan has improved during 2016-2018, and the risk changes in Qinghai fluctuate little, with public safety always at a low level. The dynamic trends of urban public safety risks in the above provinces and municipalities are caused by multi-level and multi-faceted reasons. The following section will analyse the key factors affecting the level of public safety in cities by analysing the static scores of each public factor.

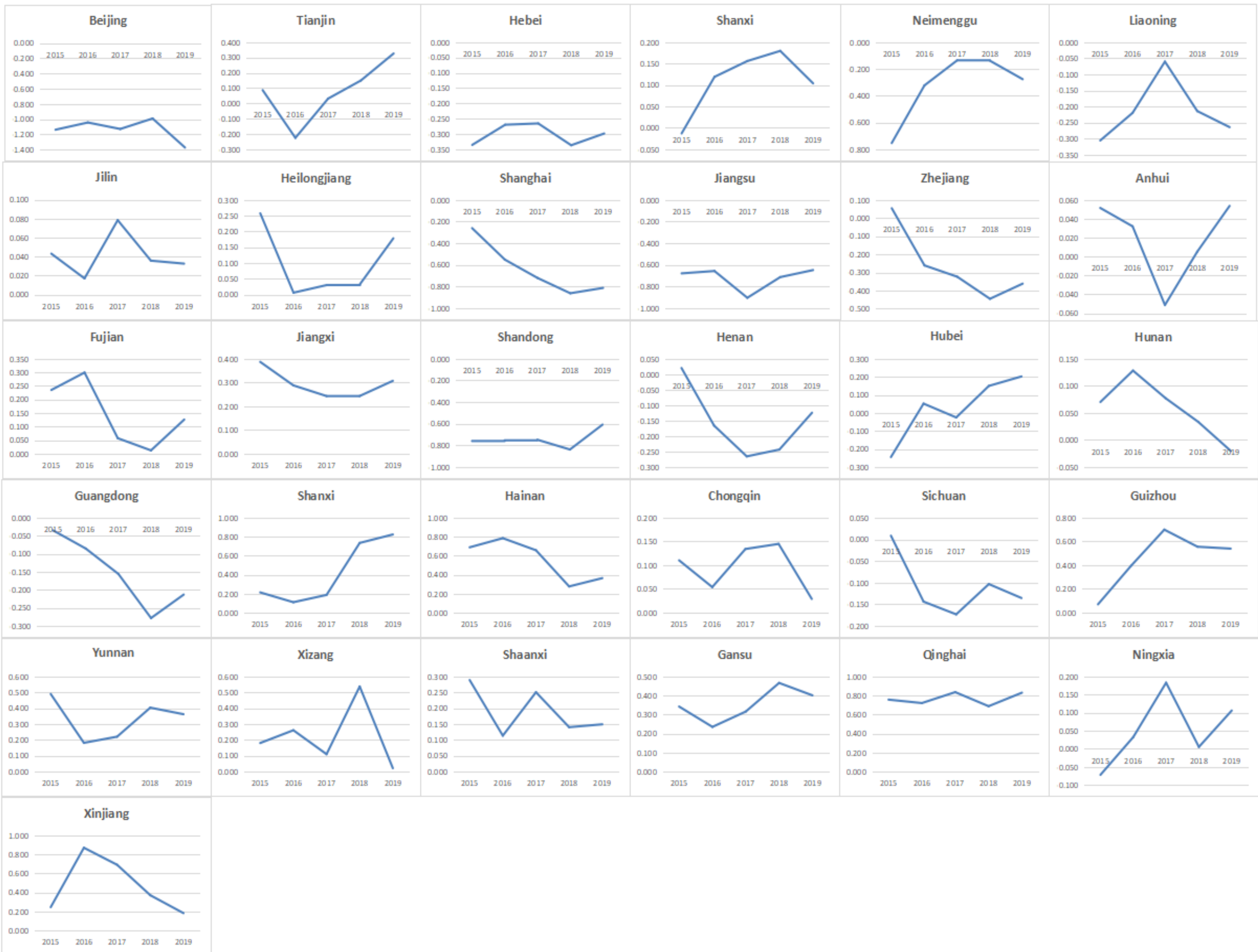

Figure 2 Dynamic change trend of urban public security risk in China.

3.3.3. Static factor structure analysis

In order to visualize the determinants of public safety risk in each region, a scatter plot of the static score structure is drawn for further analysis, as shown in Figure 3, where the zero value line represents the domestic average of the factor.

Firstly, the factors related to risk coping capacity are analyzed. 1) The regions with strengths in all three factors, F1, F2 and F4, are Liaoning and Jiangsu, indicating that these two regions have a relatively balanced development at the level of risk coping capacity, with no obvious shortcomings. 2) From the perspective of the F1 factor, Beijing and Shanghai score significantly better on this factor, indicating their economic and social security capacity is relatively strong. This is also the reason for their higher static factor rankings. In the case of Beijing, the environmental regulation factor does not reach the national average, while Shanghai is weaker in the medical security and urban construction investment factors, which points to the direction of the overall development of their future risk coping capacity. 3) From the perspective of the F2 factor, the five regions of Shandong, Guangdong, Zhejiang, Sichuan, and Henan score significantly better, indicating that their per capita medical resources are relatively adequate. Combined with the the raw data, this paper finds that the government's investment in urban infrastructure construction in these five regions also exceeds the national average. In addition, according to the results of scores, it can be seen that the deficiencies of Shandong and Henan are reflected in the economic and social security development factor, the deficiencies of Zhejiang and Guangdong are reflected in the environmental regulation factor, and Sichuan needs to improve in both factors. 4) From the perspective of the F4 factor, the six regions, namely Tianjin, Heilongjiang, Shandong, Jilin, Hebei, and Inner Mongolia have obvious advantages. According to the indicators, it is found that the comprehensive utilization rate of solid waste is significantly higher in the eastern and northeaster regions than in other regions, which is closely related to the major local industrial categories and the degree of industrial technology development. Among them, Hebei's deficiency is reflected in the economic and social security development factors; Tianjin and Inner Mongolia's deficiency is reflected in the medical security and urban construction investment factors, and Jilin and Heilongjiang have capacity deficiencies in both factors. 5) The regions that do not reach the national average in all three factors are Hainan, Chongqing, Guizhou, Qinghai and Xinjiang, and the average composite score and static factor score of these regions are also at a low level. Therefore, it can be concluded that the lack of risk response capability is the main reason for the high risk of urban public safety in these regions.

Secondly, the factors related to various types of disasters are analyzed, and the higher the factor score, the greater the impact of that disaster on urban public safety. 1) The F3 factor reflects the degree of risk of fire and traffic accidents, as can be seen from Figure 3, Tianjin, Hainan, Guizhou and Zhejiang have higher scores on this factor, indicating that these regions have great risk potential in fire and traffic accidents; on the contrary, Shanghai, Henan and Tibet perform well on this factor. 2) The F5 factor mainly reflects the impact of climate disasters. From the overall situation of the country, 18 regions have scored more than 0 on this factor, indicating that more than half of the provinces in China are affected by more serious climate disasters and have shortcomings in climate disaster prevention and control. Beijing, Guizhou and Yunnan perform poorly on this factor, while Shanghai and Xinjiang perform better. 3) The F6 factor covers the two indicators of population density and road area per capita, on which Tibet, Inner Mongolia, Ningxia, Shandong and Jiangsu have obvious advantages, while Shanghai, Heilongjiang, Shaanxi, Henan and Tianjin have obvious shortcomings. From the above comparison, it can be found that the imbalance between transportation supply and demand is a key issue that needs to be urgently addressed in response to the risk of population congestion naturally carried by urbanization development. Nationwide, 17 regions score below the national average on this factor, indicating that urban congestion is also a key factor contributing to the increased risk of urban public safety.

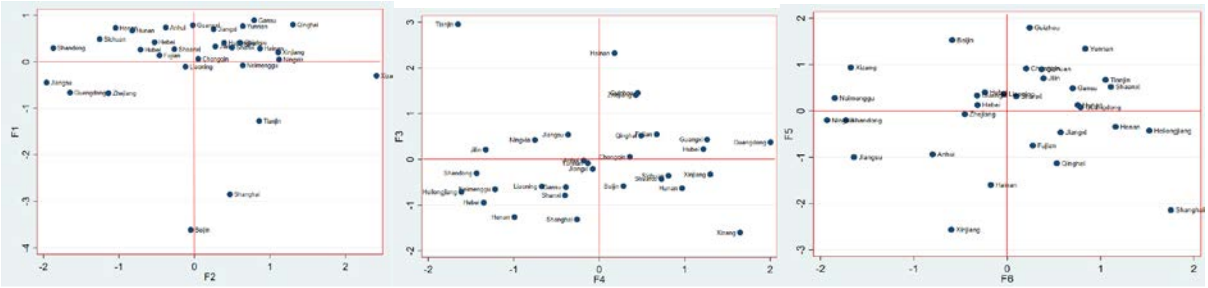

Figure 3 Static structure diagram of common Factor.

4. Conclusions and Recommendations

This paper uses dynamic factor analysis to conduct a comprehensive assessment of urban public safety risks in 31 provinces, municipalities and autonomous regions nationwide from 2015-2019, and obtains the regional distribution of urban public safety risks nationwide and the characteristics of dynamic changes in risks in each region. Also the strengths and weaknesses of urban public safety development in each region have been analyzed through factor structure analysis. The assessment results show that: 1) China's urban public safety risks are classified into four levels: low risk, medium-low risk, medium-high risk, and high risk based on the average composite score, with the largest proportion of areas classified as medium-high risk. Overall, the distribution of urban public safety risks across the country shows a gradual increase from east to west, with the eastern coastal region being relatively less at risk. 2) The pattern of risk change varies, with relatively stable changes in low-risk and high-risk areas, and greater volatility in medium-low and medium-high risk areas. The urban public safety conditions in Shanghai, Inner Mongolia, Liaoning, Jilin, Hunan, Guizhou and Xinjiang have continued to improve in recent years.

Through the classification of the 6 public factors and further analysis, it is found that the strengths and weaknesses of each region are obvious. Since the risk response capacity factor has a large impact, the risk response capacity should be enhanced to reduce urban public safety risks. This paper suggests that efforts need to make for improvement in the following 3 aspects:

(1) Consolidate the economic foundation of the city and play the function of social insurance defines. As can be seen from Figure 2, in terms of economic and social insurance development factors, 22 regions in the country have not reached the average level, and the gap is large compared with the advantageous regions. The current risk prevention and control and emergency management work is continuously developing towards intelligence and automation, and the solid economic foundation provides the necessary financial support for the stockpiling of emergency materials, the dynamic rehearsal of plans, and the construction of public opinion networks. It has also and further guaranteed the construction of various rescue bases and emergency shelters. At the same time, when the government coordinates the financial budget of public safety and emergency management projects, it can introduce social capital appropriately to broaden the financing channels. The insurance mechanism is an important tool for the society to prevent and resolve risks, and it can also strengthen the function of risk assessment while realizing the budgeting of disaster relief funds and forming a benign interaction with public safety risk management funds.

(2) Rationalize the layout of urban medical resources and services and improve residents' awareness of health safety. The above analysis reveals significant disparities in medical resources and services among provinces and municipalities in China, which makes many regions lack emergency response and rescue capabilities in the face of major health events. For each province, it is necessary to strengthen the unified deployment capacity of the cities in the province, optimize the spatial layout of hospitals and health centres, improve the cooperation mechanism among various health institutions, and encourage the transfer of high-quality medical resources to poor areas. For the whole country, the government should strengthen the training and introduction of medical talents to weak areas and adjust the training system to make the structure of urban medical talents match the local health service demand. In addition, the improvement of health safety awareness

among urban citizens helps residents to judge the risks in health services which facilitate the effective dissemination of information and smooth communication.

(3) Strengthen the capacity of environmental regulation and build a firm ecological security barrier. From the environmental regulation factor scores, it is found that nearly half of the regions in China have insufficient capacity. Therefore, in practice, the government should place more emphasis on the leading role of enterprises and industries in addition to using the existing administrative control policies and market stimulation [19]. Meanwhile, the government should bring into play the innovative capacity of enterprises in industrial technology and form a cooperative multi-entity control structure so as to improve the efficiency of responding to various environmental pollution events.

Secondly, effective handling of various disaster events and precise prevention and control of risk factors are crucial. For the main disasters and causes explored in this paper, the following two suggestions are made:

(1) Disaster prevention and mitigation should be planned based on a resilience perspective. Traditional disaster prevention and mitigation planning focuses on defense, but in the face of increasingly frequent extreme natural disasters and technological innovations, risk prediction needs to be more dynamic and targeted to adapt to the new regular urban safety norm.[20, 21] First, cities should pay attention to the collection, organize and analysis of disaster information, build a real-time monitoring and early warning information platform for multi-hazard risks, and coordinate government and social forces to make accurate judgments on potential safety hazards. Second, cities should improve the construction of disaster prevention and mitigation infrastructure projects such as transportation, energy, communication, water supply and drainage facilities, build a city safety assurance network, and form a resilient city spatial layout to disperse and transfer risks and reduce the destructiveness of disasters.

(2) The urban population layout should be continuously optimized to promote the coordinated development of population and resources. Natural endowments, differences in productivity levels and transportation factors are the key reasons for the unbalanced population distribution, and natural factors are usually difficult to control. The central cities' pressure caused by socio-economic factors is generally applied industrial restructuring as a fundamental measure. For example, the establishment of the "Xiong'an New Area" has explored a new mode of optimizing the densely populated and economic areas, and has adjusted the spatial layout structure of Beijing-Tianjin-Hebei regions. Specific regions should reposition themselves and identify their potential competitive advantages. The government should implement more open preferential policies and encourage the innovation of industrial models to promote the adaptation and balance of demographic structure and social resources in the region.

Acknowledgements

The research described in this paper was substantially supported by Grant (No. 19BGL235) from the National Social Science Fund of China.

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