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Research Article

Risk Transmission of the Regions in the Yangtze River Economic Belt

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This study mainly uses the method of effective transfer entropy (ETE) to study the risk transmission in each year among the 11 provinces and municipalities in the Yangtze River Economic Belt during the last five years. From the results of the risk transmission network, centralities of the regions, and maximum spanning trees, it can be seen that, in the years of 2015 and 2016, the risk transmission in the Yangtze River Economic Belt is relatively large, and in 2015, Shanghai is the main risk exporter. This may be mainly due to the violent turbulence in the Chinese stock market, and in 2016, although Chinese stock market is in a stable position, the whole risk transmission is still high, but the difference from 2015 is that the input and output risk of each province and municipality are more uniform and are no longer like Shanghai as the main exporter of risk in 2015. From the perspective of risk spillover, the overall trend is from the western region of China to the central region, and finally to the eastern region. Specifically, from the results of the maximum spanning tree, except the stock market crash period in 2015, Chongqing, Guizhou, and Yunnan (the western region) are the main exporters of risk, while Jiangsu, Zhejiang, and Shanghai (the eastern region) are often at the edge at this time, and from the results of the centrality of the region indexes, Hubei, Jiangxi, and Anhui (the central region) are in the hub position of risk transmission.

1. Introduction

China's economy development has changed from high-speed stage to high-quality stage, and the pursuit of high-quality development is bound to become the theme of China's economic construction at present and even in the future. The Yangtze River Economic Belt plays an important role in China's economy, and the Chinese government also wants the Yangtze River Economic Belt to become a new force to lead the high-quality development of the whole China's economy. Therefore, taking the Yangtze River Economic Belt as the research object, analyzing the industrial structure, the financial scale, and the quality of economic development of these regions, and studying the differences are of great theoretical and practical significance.

In recent centuries, the relationship between countries and regions has been strengthened day by day. Especially, after the Second World War, economic globalization and trade liberalization have brought more rapid development to all countries and regions in the world and also brought more convenient life to the people. Integration and globalization have become the trend of world development. Among the countries and regions that are connected to each other, interlocking economic systems share the natural resources and reallocate labour and capital at a very low cost [1].

Urban agglomeration is also one of the productions of the rapid integration and globalization, and urbanization and spatial reconstruction have gradually become a new form of spatial governance and a driving force behind economic growth in recent years [2]. In September 2014, the development of the Yangtze River Economic Belt was officially established as a national strategy. Since then, to promote the integrated development of the Yangtze River Economic Belt and to create a new economic growth point in China become among the most important affairs. The Yangtze River Economic Belt covers 11 provinces and municipalities, including Anhui, Guizhou, Hubei, Hunan, Jiangsu, Jiangxi, Shanghai, Sichuan, Yunnan, Zhejiang, and Chongqing, spanning the eastern, central, and western regions of China.

With the rapid development of the urban integration and agglomeration, many researches have focused on the synergetic development of different regions, such as the economic cooperation and the industrial cluster, and it has been confirmed that the spatial layout and coordination of industries and enterprises make a big boost to the regional development and prosperity [3]. Besides, some scholars measured the degree of the synergetic development of the regions by using the DEA method, the deviation-coefficient method, the distance collaborative model, the analytic-hierarchy process, or other methods [4–6]. In the process of studying the interdependence and interrelation of urban integration and agglomeration, many factors have been fully considered, such as the capital, information, products, infrastructure, and enterprise organizations [7–12]. In addition, the urban integration and agglomeration has attracted extensive other researches about its definition [13], spatial structures [14, 15], development mechanisms [7, 16, 17], and other aspects [18–21], and the spatial econometrics model and the financial regional network are built to describe the interdependence or the information flow of region integration and agglomeration [22–25]. A little few studies focus on the regional risk transmission among the provinces and municipalities in the Yangtze River Economic Belt of China.

There are many methods now to calculate the information transmission or the information flow; one of the most widely accepted methods is transfer entropy, abbreviated as TE. As we all know, the time series, especially the financial time series, always exhibit the nonlinear characteristics. Besides when calculating the information transmission, it is always based on some specific model hypotheses, such as the Copula model or the multivariate GARCH model. These may lead to a big error in the final estimation results. However, TE could overcome the shortcomings above; it could be not only used in the linear environment, but also used in the nonlinear environment. Most importantly, it is model-free and data-driven [26]. No specific model hypotheses need to be made before. In the actual application of transfer entropy, although the sample data is stationary, the amount of data is always not enough and therefore, the noise exists in the series. The effective transfer entropy, abbreviated as ETE, is a solution to reduce the impact of noise greatly, which combines a random shuffling procedure with transfer entropy [27], and ETE is also suitable for the situation, which was not clear before [28]. To infer the distribution of financial time series reasonably is the foundation of empirical research, and kernel density estimation, abbreviated as KDE, could infer the probability density function of data sample very well [29, 30]. Therefore, KDE is used to calculate ETE. The main experimental process is to construct the risk transmission network of 11 region indexes from 2015 to 2019 and analyze their node strength and betweenness centrality. In order to clearly see the risk transmission path, the directed maximum spanning trees, abbreviated as MST, are used [31, 32]. The rest of this paper is organized as follows. Section 2 mainly introduces the methods of transfer entropy and KDE. Section 3 describes the regional indexes and the formula of the regional index risk. Sections 4 and 5 are the results, discussions, and the conclusions.

2. Methods

2.1. Transfer Entropy. Shannon entropy is the basis of transfer entropy, describing the uncertainty of some variable, and it can be defined as formula (1), in which R^m is an m-dimensional space and $\mathbf{A} \in R^m$ [33].

$$H(\mathbf{A}) = -\int_{R^m} p(\mathbf{A}) \log p(\mathbf{A}) \mathrm{d}\mathbf{A}, \tag{1}$$

where $p(\mathbf{A})$ is the probability density function of the occurrence of $\mathbf{A}$ state.

As for the other variable $\mathbf{B} \in R^n$, the conditional Shannon entropy $H(\mathbf{A}|B)$ could be used to describe the uncertainty of $\mathbf{A}$ state given that the occurrence of $\mathbf{B}$ state, $H(\mathbf{A}|B)$, could be defined as formula [34]:

$$H(\mathbf{A}|B) = -\int_{R^{m+n}} p(\mathbf{A}, \mathbf{B}) \log p(\mathbf{A}|B) \mathrm{d}\mathbf{A}\, \mathrm{d}\mathbf{B}, \tag{2}$$

where $p(\mathbf{A}, \mathbf{B})$ and $p(\mathbf{A}|B)$ are the joint and conditional probability density functions.

Given two stationary time series $X \in R^1$ and $Y \in R^1$, the transfer entropy from X to Y can be defined as [35]

$$\begin{aligned}\mathrm{TE}_{X\longrightarrow Y} &= H\left(y_{t+1}|ty_t^{(k)}\right) - H\left(y_{t+1}|ty_t^{(k)}n, qx_t^{(l)}\right)\\ &= \int_{R^{k+l+1}} p\left(y_{t+1}, y_t^{(k)}, x_t^{(l)}\right) \log\left(\frac{p\left(y_{t+1}|ty_t^{(k)}n, qx_t^{(l)}\right)}{p\left(y_{t+1}|ty_t^{(k)}\right)}\right) \mathrm{d}y_{t+1} y_{t+1} \mathrm{d}y_t^{(k)} \mathrm{d}x_t^{(l)},\end{aligned} \tag{3}$$

where $y_t^{(k)} = (y_t, y_{t-1}, \ldots, y_{t-k+1})$, $x_t^{(l)} = (x_t, x_{t-1}, \ldots, x_{t-l+1})$ are the past states; $p(y_{t+1}, y_t^{(k)}, x_t^{(l)})$, $p(y_{t+1}|ty_t^{(k)}n, qx_t^{(l)})$, $p(y_{t+1}|ty_t^{(k)})$ are the joint and conditional probability density functions. $\mathrm{TE}_{X\longrightarrow Y}$ measures the uncertainty reduction or predictability improvement of y_{t+1}, which gains from $x_t^{(l)}$ that is not contained in $y_t^{(k)}$ itself

[36]. This formula could quantify the predictive information transfer between variables [36, 37]. Using the transformation, Formula (3) can be rewritten as follows [34, 38]:

$$\mathrm{TE}_{X\longrightarrow Y} = H\left(y_t^{(k)}, x_t^{(l)}\right) + H\left(y_{t+1}, y_t^{(k)}\right) - H\left(y_{t+1}, y_t^{(k)}, x_t^{(l)}\right) - H\left(y_t^{(k)}\right). \quad (4)$$

2.2. Effective Transfer Entropy. As mentioned above, to reduce the noise of the time series, effective transfer entropy combining a random shuffling procedure with transfer entropy could be better used in the practical applications, and it could be defined as

$$\mathrm{ETE}_{X\longrightarrow Y} = \mathrm{TE}_{X\longrightarrow Y} - \frac{1}{M}\sum \mathrm{TE}_{X\mathrm{shuffed}\longrightarrow Y}, \quad (5)$$

where X_{shuffed} is the random shuffled series of X. M is the number of shuffles [27, 38].

2.3. Kernel Density Estimation. Because KDE can infer the distribution of financial time series reasonably, in this paper, it is used to calculate ETE.

Let $\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_N$ be a sample of $\mathbf{U} \in R^d$, and the probability density function value $\hat{p}(\mathbf{u}_j)$ could be estimated by KDE with a kernel function $K(\cdot)$ as

$$\hat{p}\left(\mathbf{u}_j\right) = \frac{1}{Nh^d}\sum_{i=1}^{n} K\left(\frac{\mathbf{u}_j - \mathbf{u}_i}{h}\right), \quad (6)$$

where h is the bandwidth [29]. In this study, the Gaussian kernel is a better choice, which has been commonly used in the practice, and thus formula (6) could be rewritten as

$$\hat{p}\left(\mathbf{u}_j\right) = \frac{1}{Nh^d}\sum_{i=1}^{n} \frac{1}{\sqrt{(2\pi)^d \det(S)}} \exp\left(-\frac{\left(\mathbf{u}_j - \mathbf{u}_i\right)^T S^{-1}\left(\mathbf{u}_j - \mathbf{u}_i\right)}{2h^2}\right), \quad (7)$$

where S is defined as the covariance matrix of the data, and $\det(S)$ is the determinant of S [29, 39]. The bandwidth could be calculated by [29, 39]

$$h = \left(\frac{4}{d+2}\right)^{1/(d+4)} N^{-(1/(d+4))}. \quad (8)$$

After the estimated value of $\hat{p}(\mathbf{u}_i)$ is obtained, the Shannon entropy could be computed by

$$H(\mathbf{U}) = -\frac{1}{N}\sum_{t=1}^{N} \log \hat{p}\left(\mathbf{u}_t\right), \quad (9)$$

where N is defined as the length of the time series [40, 41].

At last, the transfer entropy could be estimated by

$$\mathrm{TE}_{X\longrightarrow Y} = -\frac{1}{N}\left(\sum_{t=1}^{N} \log \hat{p}\left(y_t^{(k)}, x_t^{(l)}\right) + \sum_{t=1}^{N} \log \hat{p}\left(y_{t+1}, y_t^{(k)}\right) - \sum_{t=1}^{N} \log \hat{p}\left(y_{t+1}, y_t^{(k)}, x_t^{(l)}\right) - \sum_{t=1}^{N} \log \hat{p}\left(y_t^{(k)}\right)\right). \quad (10)$$

3. Data

In this study, the daily transaction data of China regional index is used, which is issued by Shenzhen Securities Information Company Ltd. The numbers and index names are listed in Table 1. All data used in this paper are downloaded from the WIND database, which is the leading Chinese financial information provider.

The time range of the data in this study is all from 5 January 2015 to 31 December 2019. As mentioned before, in September 2014, the development of the Yangtze River Economic Belt was officially established as a national strategy. This paper mainly focuses on the risk transmission among provinces and municipalities after the implementation of the Yangtze River Economic Belt strategy in the recent five years.

Figure 1 shows the overall trend of China's stock market from 2015 to 2019. As shown in the figure, the violent volatility occurs in 2015, while the trend of the stock market is relatively stable in the rest of the four years.

In this paper, we apply formula (11) to calculate the daily volatility rate of the 11 regional indexes as the risk [42, 43]:

$$V_t = 0.511 * \left(H_t - L_t\right)^2 - 0.019 * \left[\left(C_t - O_t\right)\left(H_t + L_t - 2 * O_t\right) - 2 * \left(H_t - O_t\right) * \left(L_t - O_t\right)\right] - 0.383 * \left(C_t - O_t\right)^2, \quad (11)$$

where V_t stands for the volatility rate on day t, H_t denotes the highest price on day t, L_t denotes the lowest price on day t, O_t denotes the opening price on day t, and C_t denotes the closing price on day t, respectively.

Since the calculating of transfer entropy needs the time series to be stationary, in this paper, we apply augmented Dickey-Fuller (ADF) test to examine the stationarity of the 11 regional indexes series. Besides, the Jarque-Bera test is also used to examine whether the indexes series obey Gaussian distribution, and the results are shown in Table 2. It could be seen that all of the 11 volatility rate series are stationary, and all of them do not obey Gaussian distribution.

4. Results and Discussion

4.1. ETE among the Regional Indexes. In this paper, the provinces and municipalities could be considered as the

Table 1: The numbers, names, and the codes of the 11 regional indexes.

No.	Index name	Code
1	Anhui index	CN6001
2	Guizhou index	CN6007
3	Hubei index	CN6012
4	Hunan index	CN6013
5	Jiangsu index	CN6015
6	Jiangxi index	CN6016
7	Shanghai index	CN6024
8	Sichuan index	CN6025
9	Yunnan index	CN6029
10	Zhejiang index	CN6030
11	Chongqing index	CN6031

Figure 1: Shanghai stock exchange composite index (SSECI).

Table 2: Results of the ADF test and Jarque-Bera tests for the whole volatility rate series of the 11 regional indexes.

No.	ADF statistic	Jarque-Bera statistic
1	−3.6740***	90110.0***
2	−8.1173***	225502.4***
3	−4.1886***	130301.4***
4	−3.6768***	103319.7***
5	−3.4437***	112999.3***
6	−3.5923***	118935.8***
7	−7.1535***	96189.7***
8	−3.4715***	221385.0***
9	−9.3385***	82982.5***
10	−3.5244***	82373.7***
11	−8.0298***	218325.8***

***means statistical significance at the 1% level.

nodes in the network. The ETE of the 11 regional indexes' volatility rate are calculated in the five years, respectively, and the colormap networks are used to show the results clearly. If the value of ETE from region i to region j is nonzero, there exists a directed edge with the weight of the value of ETE. Calculate all of the ETE values of the 11 provinces and municipalities, and the network can be constructed. As shown in Figure 2, all of the colorbars are adjusted to the same range, from 0 to 0.18, because the max value in the five years is 0.1739 in the year of 2015, and the numbers on the axes are the serial number of the regional indexes in Table 1, and the direction of the ETE in the five colormaps is from the vertical axis to the horizontal axis. Table 3 shows the mean ETE of each year. From the results displayed in Figure 2 and Table 3 it can be observed that the risk transmission exists, but in different years, the strength and direction are not all the same. In the years of 2015 and 2016, the risk transmission among the 11 provinces and municipalities is at the high level, and the value of the average ETE is 0.1061 and 0.1067, respectively. This implies the strongest risk transmission in these two years. It can also be observed that, in 2015, Shanghai index (No. 7) transmitted much more risk to the other 10 parts. One of the possible reasons is that a big crash in China's stock market started in the year of 2015, and Shanghai is the economic and financial center of China. As the economic vane of China, almost all the companies in the other 10 provinces and municipalities focus on the companies in Shanghai. Naturally, risks also pass from Shanghai to the other provinces and municipalities. In 2016, the whole risk transmission among the 11 parts reached the maximum, exceeding the value in 2015, and in this year, Shanghai did not play the role of the main risk transmitter any longer. One of the possible reasons is that although the stock crash ended in February 2016 [44–46], and the rest time in 2016 the trend of stock market was relatively stable, the information transfer was still strong in the post-crash period [46]. In the years from 2017 to 2019, the value of average ETE is nearly the half of that in 2015 and 2016, which means that the risk transmission among the 11 provinces and municipalities is largely reduced.

4.2. Centrality of the Regional Indexes. In the directed network in Figure 2, it can be divided into Out Node Strength NS_{out} and In Node Strength NS_{in}. Out Node Strength means the influence of a node giving to the others, while In Node Strength means the influence of a node receiving from the others [47]. Tables 4 and 5 are the results of Out and In Node Strengths of the 11 regional indexes.

$$\begin{aligned} NS_{out}^{i} &= \sum_{j} ETE_{ij}; \\ NS_{in}^{i} &= \sum_{k} ETE_{ki}. \end{aligned} \tag{12}$$

The largest values in each year are displayed in bold. In 2015, due to the violent volatility of the China stock market, the out node strength of the Shanghai index is the largest, and the value is much higher than the risk out node strength of the other provinces and municipalities. This is consistent with the conclusion in the heat map Figure 2, and it reveals the impact of the China stock market crash in 2015 on the risk transmission among provinces and municipalities in the Yangtze River Economic Belt.

In 2016, the risk out and in node strength among provinces and municipalities are slightly higher than those in 2015 and reach the highest in five years, which is consistent with the results listed in Table 3. It is worth noting that, at this time, the values of risk out and in node strength among the different provinces and municipalities are relatively close, and the standard deviations of the risk out and in node strength are 0.0988 and 0.0729, the lowest value in each

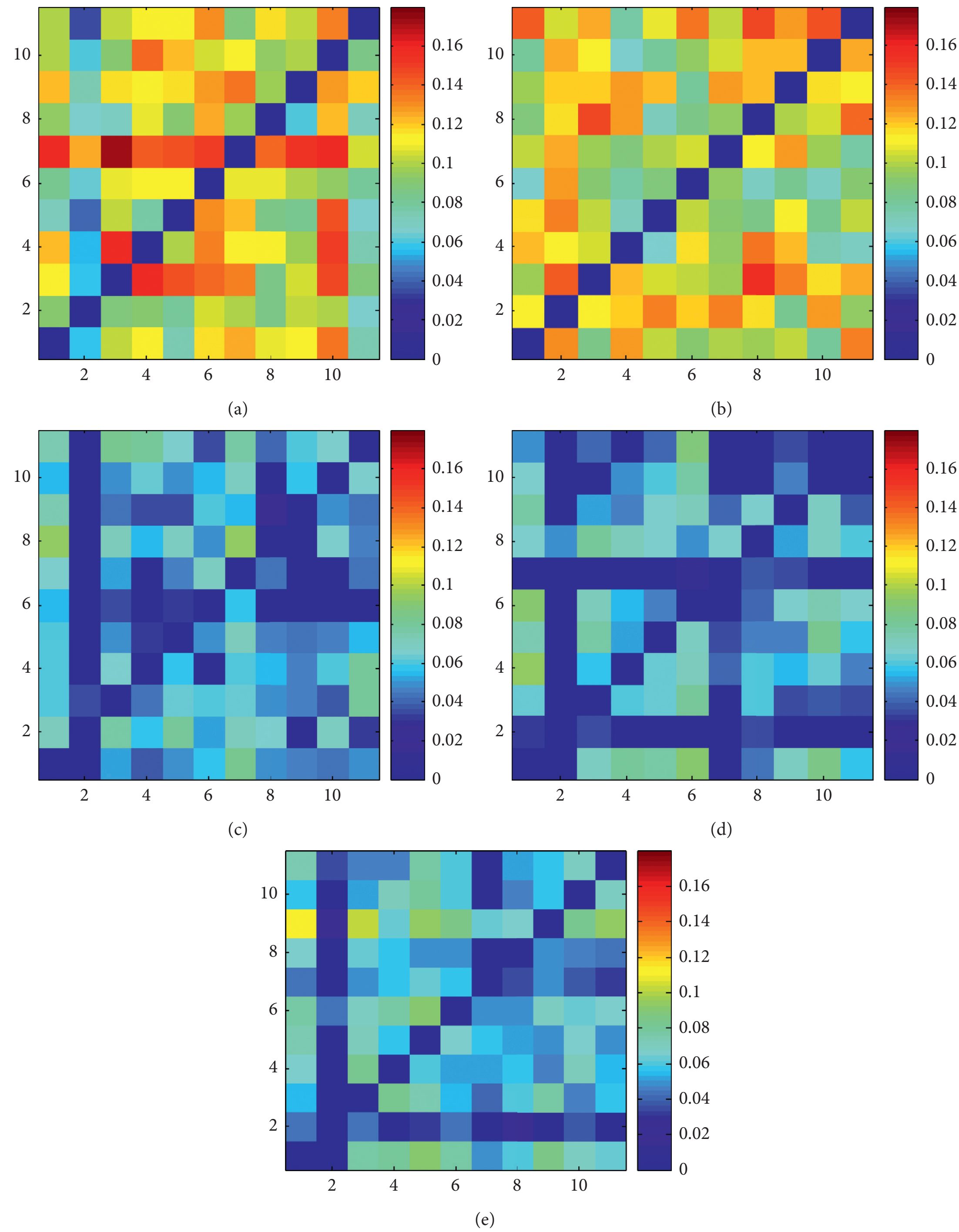

Figure 2: Colormaps of the ETEs among the 11 provinces and municipalities during the five years. (a) 2015. (b) 2016. (c) 2017. (d) 2018. (e) 2019.

year. This shows, that after the violent volatility of the stock market in 2015, although the 11 provinces and municipalities have maintained the high risk transmission to each other, no one is in an absolute risk output position.

From 2017 to 2019, the market performance is relatively stable. The risk out and in node strength of each province and municipality have been greatly reduced compared with those of the previous two years, and the average of the value is half of that in 2015 and 2016. This shows that, in these periods, when the market is relatively stable, the level of risk transmission among the 11 provinces and municipalities is much lower than that of the 2015 stock market disaster period and the 2016 recovery period.

An interesting finding can be obtained by comparison, in the five years, Shanghai, Chongqing, Sichuan, and Yunnan have the largest out node strength. Among them, Chongqing

Table 3: Average ETE among the 11 provinces and municipalities in the five years, respectively.

	2015	2016	2017	2018	2019
Average ETE	0.1061	0.1067	0.0459	0.0412	0.0530

Table 4: Out node strengths of the 11 provinces and municipalities in the five years, respectively.

No.	Index name	2015	2016	2017	2018	2019
1	Anhui index	1.0186	1.0434	0.4700	0.5730	0.6564
2	Guizhou index	0.9073	1.1464	0.5769	0.1033	0.2280
3	Hubei index	1.1693	1.1922	0.5404	0.4394	0.5504
4	Hunan index	1.1201	1.0023	0.4865	0.5503	0.5430
5	Jiangsu index	0.9242	1.0220	0.4488	0.5451	0.5464
6	Jiangxi index	0.9670	0.8478	0.1790	0.5134	0.6555
7	Shanghai index	**1.4532**	1.0259	0.3224	0.1028	0.4240
8	Sichuan index	0.9105	1.0778	0.5424	**0.6230**	0.4216
9	Yunnan index	1.1542	1.1278	0.4260	0.5303	**0.7944**
10	Zhejiang index	1.0080	1.0284	0.4646	0.2981	0.4941
11	Chongqing index	1.0366	**1.2209**	**0.5890**	0.2548	0.5173
	Mean	1.0608	1.0668	0.4587	0.4121	0.5301
	Standard deviation	0.1528	0.0988	0.1142	0.1811	0.1408

Table 5: In node strengths of the 11 provinces and municipalities in the five years, respectively.

No.	Index name	2015	2016	2017	2018	2019
1	Anhui index	1.0520	1.0052	0.6714	0.6156	0.6697
2	Guizhou index	0.6353	**1.2397**	0.0350	0.0482	0.1067
3	Hubei index	1.1177	1.0868	0.5793	0.4799	0.6549
4	Hunan index	1.1702	1.0195	0.4055	0.4117	0.5923
5	Jiangsu index	1.0968	0.9787	0.5500	0.4856	**0.7089**
6	Jiangxi index	1.2668	1.0252	0.4848	**0.6293**	0.6098
7	Shanghai index	1.1340	1.0346	**0.7017**	0.1847	0.3098
8	Sichuan index	1.0360	1.1515	0.3809	0.3947	0.5097
9	Yunnan index	1.0149	1.1137	0.3030	0.4382	0.5433
10	Zhejiang index	**1.3180**	1.0202	0.4418	0.4859	0.5927
11	Chongqing index	0.8275	1.0599	0.4926	0.3597	0.5334
	Mean	1.0608	1.0668	0.4587	0.4121	0.5301
	Standard deviation	0.1831	0.0729	0.1763	0.1629	0.1678

is the largest one two times, respectively, in 2016 and 2017. Except the year of 2015, in which, due to the stock market crash in China, Shanghai has the largest Out Node Strength, in the remaining four years, the provinces and municipalities in western regions of China, where the development of economy and society is unbalanced and there is a big gap with the central and eastern regions of China, have the largest out node strength. On the other hand, Zhejiang, Guizhou, Shanghai, Jiangxi, and Jiangsu have the largest In Node Strength, and Jiangsu, Zhejiang, and Shanghai are all the developed eastern provinces and municipalities of China. Therefore, in the process of preventing risk transmission among provinces and municipalities in Yangtze River Economic Belt, more attention should be paid to the underdeveloped western regions, efforts to prevent risks of the western regions transmitting to other provinces and municipalities should also been made, and the developed eastern regions should mainly focus on the risk prevention.

Betweenness is an effective method to measure the centrality. It could quantify the node's underlying ability to control the information flow in the whole network [48]. Its definition is based on the number of shortest paths between nodes. For a weighted directed network, the shortest path d_{ij}^{w} between node i and j could be defined as

$$d_{ij}^{w} = \min\left(\frac{1}{w_{ih_0}} + \frac{1}{w_{h_0h_1}} + \cdots + \frac{1}{w_{h_kj}}\right), \quad (13)$$

where $w_{ih_0}, w_{h_0h_1}, \ldots, w_{h_kj}$ are the intermediary nodes on the path, and the shortest path can be derived by the Dijkstra's algorithm, and the weighted betweenness centrality, abbreviated as WBC, could be defined as

$$\mathrm{WBC}(i) = \sum_{i\neq s, i\neq t, s\neq t} \frac{g_{st}^{w}(i)}{g_{st}^{w}}, \quad (14)$$

where g_{st}^{w} is the number of shortest paths from node v_s to v_t. $g_{st}^{w}(i)$ is the number of shortest paths from v_s to v_t, and those pass through v_i [48].

The results of WBCs of the 11 provinces and municipalities in the five years are shown in Figure 3 respectively. In 2015, Shanghai has the biggest WBC. This means that Shanghai is not only the largest risk output node, but also the direct risk transmitter to the other provinces and municipalities. In the remaining four years, Sichuan, Hubei, and Jiangxi are the main risk transmission hub nodes, of which Sichuan is the main hub node both in 2016 and 2018. It is worth noting that although Sichuan is the main hub node in 2016, the value of WBC is only 1, indicating that the risk transmission is direct relatively, and the main hub node is not obvious, while, in 2017 and 2019, Hubei and Jiangxi are the main hub nodes, which are in the central region of China, and they are the transitional zone from the eastern coastal area to the western inland. Based on the results of Tables 4, 5 and Figure 3, we can see that the risk transmission among provinces and municipalities in the Yangtze River Economic Belt has a path from the western region to the central region, and finally to the eastern region.

4.3. Directed Maximum Spanning Tree. Maximum Spanning Tree is an effective method to get the key structures of the network [49], and as the risk transmission network is a directed one, in this paper, the Chu-Liu-Edmond algorithm is adopted to build the directed MST [31, 32].

The results directed Maximum Spanning Trees in the five years are shown in Figure 4. It can be seen that, in 2015, Shanghai (No. 7) is the center of risk transmission, and the maximum spanning tree is in a network-shaped, which means that the risk is more directly transmitted from Shanghai to the other provinces and municipalities, while the maximum spanning trees in the rest four years are mostly tree-shaped and echo the result of 4.2, where the result implies that Chongqing, Guizhou, and Yunnan, the western provinces and municipalities, are the main sources

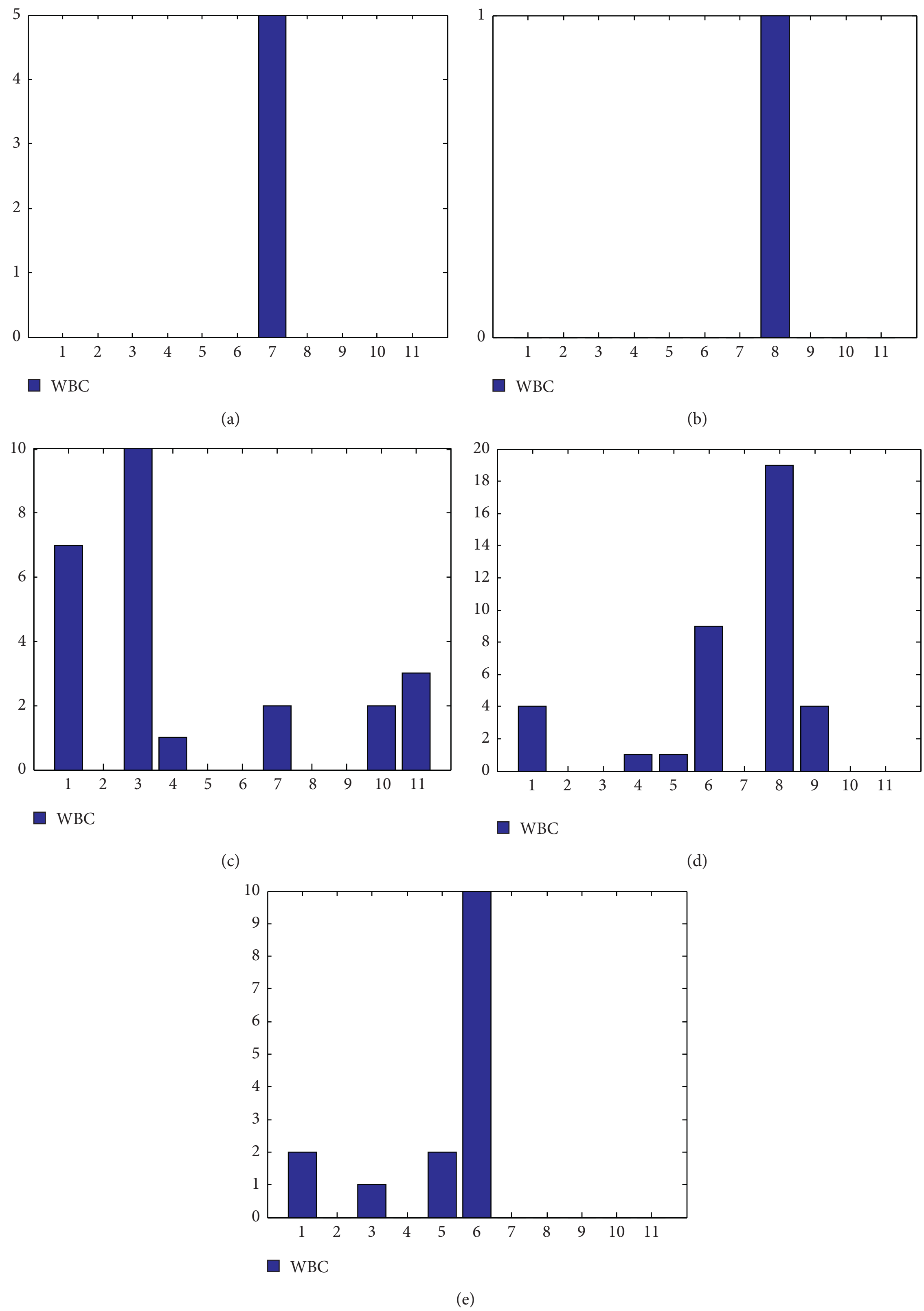

Figure 3: Weighted betweenness centrality (WBC) for the 11 provinces and municipalities. The horizontal axis is the number of the regional indexes. (a) 2015. (b) 2016. (c) 2017. (d) 2018. (e) 2019.

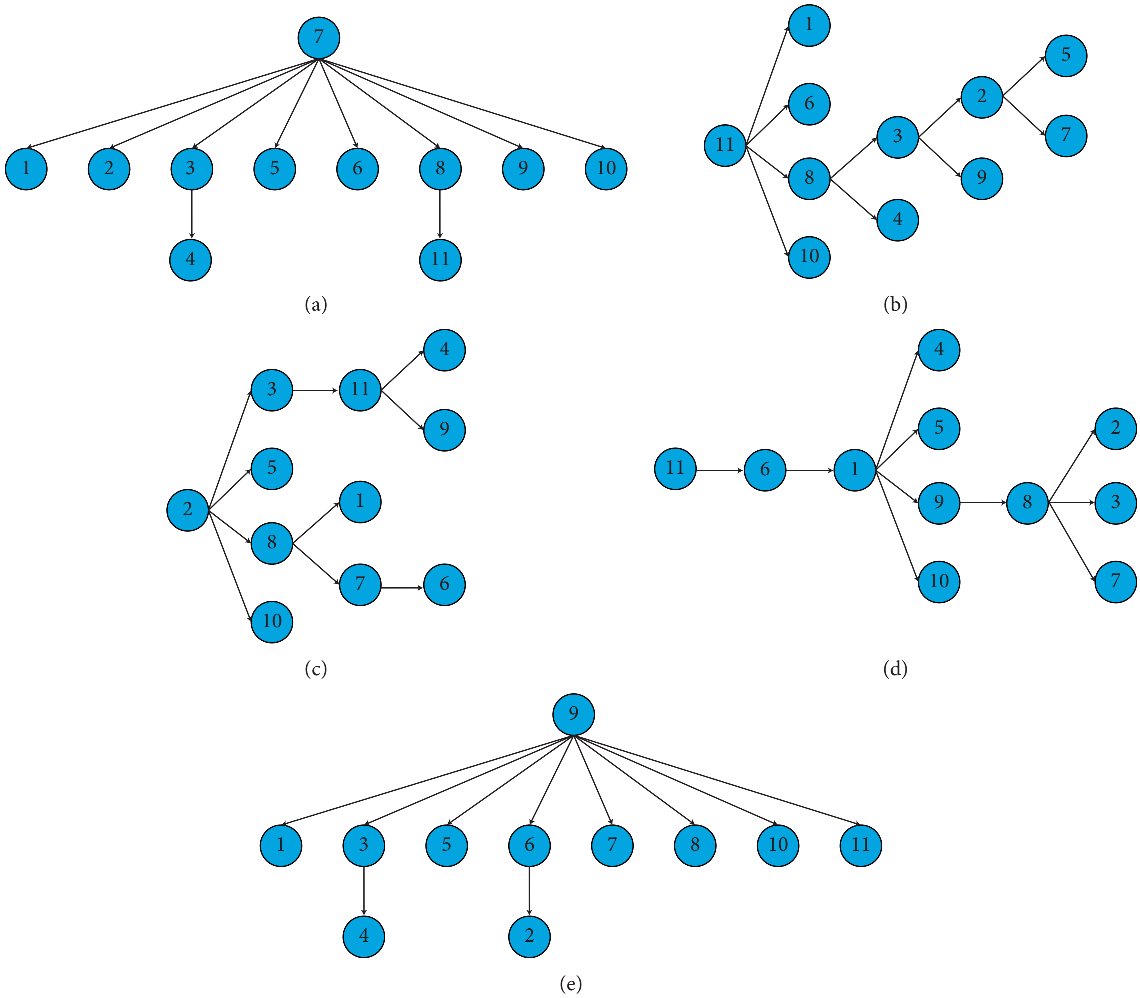

Figure 4: Directed maximum spanning trees (MSTs) of the 11 provinces and municipalities. (a) 2015. (b) 2016. (c) 2017. (d) 2018. (e) 2019.

of risk, while the central and western provinces such as Sichuan, Hubei, and Jiangxi are the main hub nodes, and the eastern regions, such as Shanghai, Jiangsu, and Zhejiang, are almost all risk receivers and in the marginal position of the maximum spanning tree.

5. Conclusions

This paper focuses on the topic of the risk transmission among the regions of Yangtze River Economic Belt by calculating ETE of the 11 provinces and municipalities from 2015 to 2019, and the risk transmission network is constructed based on the value of ETE, which is calculated by the KDE method. Besides, the centrality and the directed MST are used to display the results. The results of this paper display that, in the years of 2015 and 2016, the risk transmission among provinces and municipalities in the Yangtze River Economic Belt is relatively large, and in 2015, Shanghai is the main risk exporter. This may be mainly due to the violent turbulence in the China stock market in 2015, and Shanghai is the economy and finance center of China. In 2016, although the Chinese stock market was in a stable position, the risk transmission among provinces and municipalities was still very high, and the difference from 2015 is that the input and output of risk are close between the 11 provinces and municipalities, no longer like Shanghai in 2015 as the main exporter of risk. This is in line with the characteristics of the post-crisis market, in which period the market still maintains a high correlation.

The 11 provinces and municipalities in the Yangtze River Economic Belt can be distributed into three regions of the east, middle, and west of mainland China, and the development level of different regions varies greatly. From the perspective of risk spillover, the overall trend is from western regions to central regions, and finally to the eastern regions. Specifically, from the results of the maximum spanning tree, except the stock market crash period in 2015, Chongqing, Guizhou, and Yunnan are the main exporters of risk, while Jiangsu, Zhejiang, and Shanghai are often at the edge at this time, and from the results of the centrality of the index, Hubei, Jiangxi, and Anhui are in the hub position of risk transmission. The results of this study are useful for us to grasp the main structure of the risk transmission network and the risk transmission flow among provinces and municipalities in Yangtze River Economic Belt.

Data Availability

All data used in this paper are downloaded from the WIND database, which is the leading Chinese financial information provider. The details are shown in Table 1.

Conflicts of Interest

The authors declare no conflicts of interest.

Authors' Contributions

Xianbo Wu and Xiaofeng Hui proposed the research framework together. Xianbo Wu collected the data, finished the computation, and wrote the paper. Xiaofeng Hui provided some important guidance and advices during the process of this research.

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