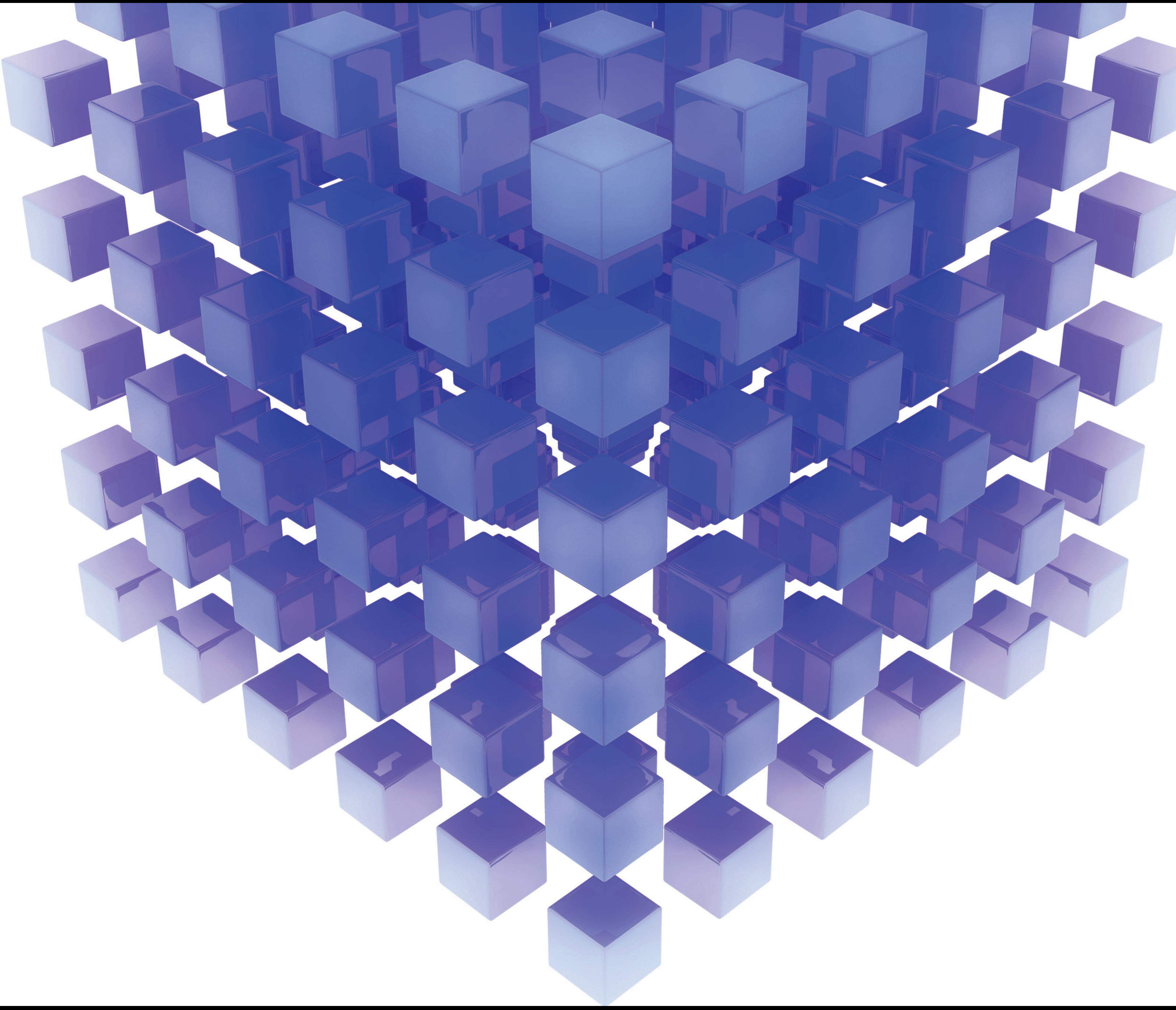
Mathematical Problems in Engineering

Climate-Financial Engineering: A Bridge to Carbon Neutrality

Lead Guest Editor: Xiaohang Ren
Guest Editors: Qiang Ji, Jinyu Chen, and Yukun Shi



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Research Article

Network Effects and Characteristics of Cross-Industrial Tail Risk Spillover in China

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In recent years, the Chinese capital market has suffered several violent shocks, and the characteristics of systemic risk contagion across industries and markets have become increasingly important. It brings great potential danger to the stability of financial markets. Therefore, exploring the risk spillover among the real sectors has gradually attracted the attention of scholars. This paper examines the cross-industrial tail risk spillover network in the Chinese financial market. The characteristics and the dynamic contribution of each industry in the tail risk transmission chains are explored. We use the ΔCoES-ENGDFM-LVDN model based on monthly data from 2006 to 2020 to measure the tail risk of 28 industries in China and form a cross-industrial tail risk spillover network. The results show that different industries have different levels of spillover and importance in the network. Tail risk mainly spills over from the nonfinancial sector to the financial sector. The nonbank financial industry is the main recipient of tail risk spillover and is becoming progressively more important in the risk network. In addition, with the promotion of industrial structure, emerging industries such as communications, computers, and health care have begun to play more important roles in the tail risk spillover network in China. This paper not only enriches the research in the areas of tail risk spillover and systemic risk, but also has implications for regulators to maintain financial stability and prevent financial risks.

1. Introduction

One of the important tasks of China's financial stability goal is to control risk spillover between the nonfinancial sector and financial sector and prevent cross-industrial or cross-market risk contagion. When the business performance of companies is poor, its negative impact may spread rapidly through the industry connection to the whole market. The deterioration of market fundamentals will trigger the increasing linkage between financial market return and risk. The tail risk spillover among industries will also amplify economic volatility. The linkages among industries have significantly exacerbated risk spillover effects and increased the impact of the nonfinancial sector on the financial system, giving rise to new challenges for preventing systemic risks. The industry-level systemic risk indicators include systemic risk contribution and systemic risk exposure. The former refers to the impact of an individual industry under extreme circumstances (e.g., the industry suffers severe losses) on the economic system, while the latter refers to the impact of the economy under extreme circumstances (e.g., the economy falls into a severe recession) on an individual industry. We consider the former. At the same time, since economic and financial variables are usually characterized by "sharp peaks and thick tails," the measurement of systemic risk should focus on the tail risks of industries and economies in extreme situations.

Tail risk is used not only in characterizing the extreme risks, but also to reflect the accumulation of risk spillover levels in extreme cases. Therefore, what is each industry contributing to the systemic risk in the tail risk network? Does the financial sector play a crucial role in risk spillover? How do the intensity, transmission direction, and path of tail risk spillover among industries vary with business cycles? This paper aims to answer these questions.

In recent years, research on the risk spillover among industries in the real sector has gradually attracted academic attention. Networks constructed with the mean and variance tend to underestimate the risk contagion level by ignoring tail risks in extreme cases. The drawbacks of failing to measure the incremental change in risk spillovers from normal to extreme states violate the purpose of Adrian and Brunnermeier [1] on improving the risk spillover measure. In addition, most of the networks constructed by existing studies, either based on causality detection or based on variance decomposition, are information or volatility spillover networks instead of risk spillover networks [2–6]. In addition, most of the existing studies [7, 8] focus on measuring the intensity scale of risk spillover, that is, the level of network association. Scare attention is given to the direction and path of risk transmission and other association structures [9–11]. There are very few studies [12, 13] that consider both the level and structure of association and assess the contribution of risk in the tail risk network.

Academic research has agreed on the level of correlation in China's economic and financial system with obvious cyclical characteristics. The probability of risk spillover in specific industries increases significantly, and the intensity of spillover varies with cyclical characteristics, showing obvious asymmetry in different cycles. Most of the existing studies often ignore the difference in tail risk spillover between the risk accumulation and the release stage [14–16]. To overcome these drawbacks, this paper studies the level and structure of the tail risk spillover network among industries in China, as well as the systemic contribution characteristics of each industry in the risk transmission network. We also aim to identify the core industries in the risk network and make forward-looking suggestions for regulation. Moreover, we identify the differences in the above characteristics in the risk accumulation or release stages.

We introduce a periodic perspective to measure cross-industrial upside and downside tail risks and construct a tail risk spillover network with cyclical properties among China's industries using ΔCoES-ENGDFM-LVDN models, which may be more effective in measuring the cross-industrial tail risk spillover network effects. Specifically, we analyse the key industries in the contagion chain during tail risk spillover and examine the intensity, direction, path, and center of tail risk spillover according to the risk network. Then, from a dynamic perspective, we further consider the trend of tail risk spillover in each industry. We compare the spillover effects both in the risk accumulation stage and release stage and analyze the spillover levels from normal to extreme states. From the time dimension, we longitudinally examine the evolutionary relationship of tail risk spillover among industries in the full sample and each subsample, comparing the differences in spillover effects within different sample periods for the same risk phase (upside risk accumulation or downside risk mitigation).

First, we begin our test by constructing a risk network and analyzing cross-industrial risk spillover effects directly for tail risk. Compared to the networks constructed from the returns and variance [1, 17, 18], tail risk could reflect the incremental change in the level of risk spillover from normal to extreme states. It is possible to avoid the underestimation of the level of risk contagion caused by return and volatility [19, 20].

Second, we use ΔCoES instead of ΔCoVaR, which contains both left-tailed and right-tailed information and is based on a long-term stress scenario. However, ΔCoES does not measure network effects, resulting in tail risk spillover being underestimated [21]. The General Dynamic Factor Model (GDFM) proves the consistency of the estimators when both the sample and time series dimensions are infinite, but it is calculated only for the fluctuation spillover relation. Elastic Net (EN) combines the advantages of LASSO regression and ridge regression. Therefore, this paper introduces ΔCoES into the GDFM with EN to construct and estimate the tail risk spillover network with periodicity among China's industries, which can overcome the limitations of the abovementioned methods. It could also demonstrate the tail risk spillover across industries in the risk accumulation stage and release stage. The results indicate that there are an overall persistent nonlinear spillover effect and significant periodicity effect among industry tail risks in China. Cross-industrial tail risk spillover is more pronounced in the risk release stage. However, the total degree of spillover in the risk accumulation stage gradually grows and has exceeded the total degree in the release stage. This suggests that while the scope of cross-industrial tail risk spillover in China is gradually expanding, the downside risk has not been released sharply.

Third, this paper considers the level of industry tail risk association, structure, and network contribution for both the full sample and the dynamic evolution of each stage. We explore the pattern of risk spillover from normal to extreme and test the tail risk spillover in key industries. It forms a useful complement to previous studies on cross-industrial risk spillover.

This paper contributes to the following streams of literature:

First, identification and measurement of tail risk. Traditional methods are divided into three categories based on real operating business data, directly generated based on complex network theory, and based on financial market data such as stock prices. Linear or nonlinear Granger causality detection [22, 23], generalized variance decomposition [2], LASSO regression [21, 24], and TENET networks [25] were mainly used. In recent years, the construction of correlation networks based on financial market data has gained the attention and recognition of scholars. The network constructed through high-frequency financial market data is not limited to a particular form, which can overcome the untimely assessment of cross-industrial risk spillover caused by the lag of low-frequency data and measure the global and integrated channel effects formed by cross-industrial tail risk spillover [2, 26, 27]. Barigozzi and Hallin [28] use the EN approach to deal with the high-dimensional time series estimation problem involved in the GDFM model and further test the volatility spillover effect among industries in the SP100 index jointly with the LVDN, providing a reference for the study.

The second is the risk spillover characteristics among industries. Most of the existing studies focus on risk contagion within the financial sector, few papers analyze the tail risk diffusion relationship among nonfinancial sectors, and the empirical findings remain controversial [29, 30]. On the one hand, some studies focus on volatility spillover rather than tail risk spillover; on the other hand, the related literature focuses on tail risk to the downside and ignores the upside [31–33]. It neither captures the differences presented by tail risk spillover in the process of upside risk accumulation and downside risk mitigation nor the process of incremental changes in the level of risk spillover.

Finally, the impact of periodic factors on tail risk spillover is examined. The degree of risk spillover among China's financial institutions was at a relatively high level during the subprime mortgage crisis and the implementation of the new round of easing monetary policy in the United States. Some studies suggest that the level of systemic correlation of financial institutions in China has a distinctly periodic character. Some Chinese scholars measure the downside risks of 11 industries in China. The results clearly demonstrate that when the economic downwards pressure increases, facing greater policy uncertainty or implementing expansionary credit policies, there will be more significant risk contagion among industries. At the same time, the nonfinancial sector has strong explanatory power for systemic risk. However, the current research focusing on the impact of cyclical factors on tail risk spillover among industries in the nonfinancial sector still needs to be supplemented.

The rest of this paper is organized as follows: Section 2 presents the methodology, introduces the data, and gives the measurement results of relevant variables. Section 3 reports empirical results and further analysis. Section 4 provides recommendations for improving cross-industrial risk spillover regulation in China.

2. Methodology and Data

2.1. ΔCoES Method to Calculate Upside and Downside Tail Risk. Using ES as a risk metric and replacing conditional events with $X^i \leq VaR_p^i$, Adrian and Brunnermeier [1] present estimates for CoES that measure the tail effect of individual risk contribution. We improved on these and learned the method from Brownlees and Engle [34] to estimate CoES. As a result, we can capture not only the institutions' systemic risk exposure and the institutions' contribution to systemic risk at the same time, but also the long-term stress profiles. It can also use the risk-taking behavior and risk accumulation of institutions during the upside to predict risk mitigation in the downside, thus addressing the procyclicality of the contemporaneous risk metric. Empirical tests show that the upside ΔCoES (as in equation (1)) is appropriate as a forward-looking measure of tail risk, while the downside ΔCoES (as in equation (2)) can lead CoVaR and CoES.

This paper extends the application of the ΔCoES model, which is no longer limited to the financial sector. Using the overall industry-wide market as a benchmark, measure the upside and downside ΔCoES values of tail risk for each industry. The specific calculation steps are as follows: the BEKK-MGARCH model is used to estimate the variance equation of log returns for each industry. The distribution of future one-month returns is simulated by the residual bootstrap method, where the forecast period $h = 22$ denotes the actual number of trading days in a month, and S denotes the number of simulations. The larger the value of S is, the better the simulation effect is, so we take $S = 105$. Based on the information for period T and conditional on the arithmetic rate of return R for the next month ($h = 22$), the $\Delta\text{CoES}^{i|N}$ values for each industry are obtained separately.

$$\begin{aligned}\text{upside}\Delta\text{CoES}_T^{i|N} &= E_T\left(R_{i,T+1:\,T+h} | R_{N,T+1:\,T+h} \leq VaR_{95}^N\right) \\ &\quad - E_T\left(R_{i,T+1:\,T+h} | R_{N,T+1:\,T+h} \leq \text{VaR}_{50}^N\right),\end{aligned} \tag{1}$$

$$\begin{aligned}\text{downside}\Delta\text{CoES}_T^{i|N} &= E_T\left(R_{i,T+1:\,T+h} | R_{N,T+1:\,T+h} \leq \text{VaR}_{50}^N\right) \\ &\quad - E_T\left(R_{i,T+1:\,T+h} | R_{N,T+1:\,T+h} \leq \text{VaR}_{5}^N\right),\end{aligned} \tag{2}$$

where N denotes the number of industries; $R_{T+1}: T + h \geq \text{VaR95}$ denotes the extreme state of the upside risk accumulation phase, and $R_{T+1}: T + h \geq \text{VaR50}$ denotes the normal state of the upside accumulation phase; $R_{T+1}: T + h \leq \text{VaR5}$ denotes the extreme state of the downside risk mitigation, and $R_{T+1}: T + h \leq \text{VaR50}$ denotes the normal state of the downside risk mitigation.

2.2. Cross-Industrial Tail Risk Spillover Network. The available dataset is usually panel data of industry returns with high-dimensional properties when studying interdependencies among industries. We construct the long-term variance decomposition network ΔCoES-ENGDFM-LVDN that can solve the problem of high-dimensional data incidentally well. Second, this approach can study the correlation between financial and real sectors from the perspective of tail risk spillover, addressing the problem that methods such as correlation coefficients of returns and principal component analysis do not measure the contribution or exposure of individual institutions to systemic risk. The drawback that ΔCoVaR, MES, and other methods cannot capture the network effect of tail risk spillover is avoided. In addition, the method effectively bridges the previous deficiency of demonstrating risk only from the network of financial institutions. It should be noted that the results in this paper are mainly based on the heterogeneity part of $\Delta\text{CoES}^{i|N}$, and we argue about its rationality in 3.2. The specific process is as follows: extending the study of Barigozzi and Hallin [28], a two-step dynamic factorial procedure was used. First, the GDFM was applied to extract the common and idiosyncratic components from the tail risk data. Then, the EN model and the LVDN model are applied to identify the size and structure of tail risk spillover among industries.

Denote the two-factor process formed by N industries with tail risk data $\Delta\text{CoES}^{i|N}$ (including upside and downside) as

$$\Delta\text{CoES} = \left\{\Delta\text{CoES}_t^{i|N}: i \in N, t \in T\right\} = \chi_{it} + \xi_{it}, \quad i \in N,\, t \in T, \tag{3}$$

where ΔCoES satisfies second-order stationary, zero mean, and finite variance. ΔCoES is absolutely continuous with respect to the Lebesgue measure on $[-\pi, \pi]$. The qth eigenvector in the spectral density matrix diverges, and the qth+1st eigenvector is bounded. Hallin and Liška [35] prove that the horizontal market shock when the actual data are applied to the GDFM is unique, i.e., $q = 1$. Thus, there are autoregressive processes $A_i(L)\chi_{it} = \eta_{it} = (\eta_{1t}, \ldots, \eta_{Nt})^{'}, t \in T$ and $F_i(L)\xi_{it} = \nu_{it} = (\nu_{1t}, \ldots, \nu_{Nt})', t \in T$, where η_{it} and $\nu_{it}$are n-dimensional white noise processes, and $F_i(L)$ is a one-sided stable VAR filter. Barigozzi and Hallin [28] extracted the idiosyncratic components ξ_{it} of ΔCoES in $F_i(L)$ and used EN for sparse processing ξ_{it}, always admitting a Wold decomposition, which, after adequate transformation, yields the vector moving average (VMA) representation $\xi_{it} = D_i(L)e_{it}$. Comparing the above equations, we can obtain

$$D_i(L) = \left(F_i(L)\right)^{-1} R_i, \tag{4}$$

where the full-rank matrix R_i makes shocks $R_n^{-1}\nu_n = e_n$ orthonormal. R_i follows from a Cholesky decomposition of the covariance C_n^{-1} of the shocks [36], namely, $C_n^{-1} = R_n R_n'$. The residual centrality of the partial correlation network (PCN) based on C_n is ranked, so that the most correlated nodes are hit first. Decomposing R_i based on (4) yields the LVDN on the industry tail risk spillover. $w_{ij}^h = 100\,(\sum_{k=0}^{h-1} d_{k,ij}^2 / \sum_{l=1}^{n} \sum_{k=0}^{h-1} d_{k,il}^2), i, j = 1, \ldots, n$ means the dependence from contemporaneous to lagged h periods in the LVDN network. Taking the tail risk of each industry as node V, the industry tail risk spillover network $G(V, W)$ can be mapped.

2.3. Network-Associated Metrics. Network correlation indicators from Billio et al. [22] and Wanget al. [37] are borrowed to analyze the level and structure of the correlation of tail risk spillover across industries.

2.3.1. Degree of Association. The degree of association includes the degree of exit (δ_i^{To}) and the degree of entry (δ_i^{From}), which measures the external spillover effect of an industry in the network as well as its own spillover shock and is calculated as follows:

$$\begin{aligned} \delta_i^{\text{To}} &= \sum_{i=1, j\neq i}^{N} w_{ij}^h, \\ \delta_i^{\text{From}} &= \sum_{j=1, j\neq i}^{N} w_{ij}^h, \\ & j = 1, 2, \ldots, n. \end{aligned} \tag{5}$$

The out-degree portrays the sum of tail risk spillover caused by the tail risk spillover of an industry as a source. A higher degree of exit indicates that the industry is an active sender of tail risk spillover and the greater the tail risk spillover effect of the industry. The in-degree portrays the sum of tail risk spillover shocks to an industry as a recipient of tail risk spillover from other industries. A higher degree of entry means that the industry is more vulnerable to tail risk spillover from other industries. The total degree of association can be obtained by summing the out-degree and the in-degree, i.e., $\delta^{\text{Tot}} = 1/N \sum_{i=1}^{N} \delta_i^{\text{From}} = 1/N \sum_{i=1}^{N} \delta_i^{\text{To}}$.

2.3.2. Network Density and Closeness. The network density (ND) of N industries reflects the degree of connection between nodes in the network; the greater the density is, the closer the relationship between the nodes is. The ND indicator is expressed as

$$\text{ND} = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j\neq i} E_{i\longrightarrow j}. \tag{6}$$

Closeness (C) measures the average of the shortest distance between an industry node and all other reachable industry nodes in the network; the smaller the C value is, the shorter the distance between the industry and the reachable nodes is. It also means that the connection to the whole network is closer.

$$C(j) = \frac{1}{N-1} \sum_{i\neq j} d_{j\longrightarrow i}. \tag{7}$$

2.3.3. Relative Influence. Relative influence (RI) measures the relative size of the net external spillover of tail risk in an industry. The value of RI ranges from [−1, 1], and the machine formula is

$$\text{RI}(i) = \frac{\delta_i^{\text{To}}(i) - \delta_i^{\text{From}}(i)}{\delta_i^{\text{To}}(i) + \delta_i^{\text{From}}(i)}. \tag{8}$$

If the RI of an industry is positive (or negative), it means that its impact on other industries is greater (or less) than the impact of other industries on it; that is, the intensity of tail risk spillover from that industry to other industries is greater (or less) than the intensity of spillover from other industries to it. The greater the RI is, the greater the external spillover effect of tail risk in that industry is.

2.4. Sample Selection and Data Description. In the selection of industry indicators, we select 28 primary industry1 indices as the sample. The CSI 300 Index is a comprehensive stock price index that reflects the performance of China's stock market as a whole. Therefore, this paper calculates the $\Delta\text{CoES}^{i|N}$ of each industry index to the CSI 300 index to characterize the industry tail risk. The total sample range is December 2006–December 2020, the data frequency is monthly, and all data are from the Wind database. Considering the information available at each point in time and the calculation volume of the bootstrap method, this paper selects the last trading day data of each month and uses the sliding window algorithm to calculate the upside and downside $\Delta\text{CoES}^{i|N}$. The rolling window is set to 12 months. In addition, real-time monitoring of the intensity scale and path direction of tail risk spillover can measure the dynamics of the industry tail risk spillover relationship. We, therefore, combine the characteristics of China's financial market and use the structural breakpoint identification technique to exclude the impact of abnormal stock market fluctuations in 2015. Using a rolling analysis method, we select two subintervals of the total sample range, October 2008–March 2015 and July 2016–December 2020, to construct a phased risk network.

3. Results and Discussion

3.1. ΔCoES Measurement Results for Tail Risk. In this paper, we use ΔCoES to measure the level of tail risk spillover in each industry in China. Figure 1 gives the trend in the level of tail risk. There are two points that can be derived from the figure as follows. One is that the level of spillover during the accumulation of risk determines the level of spillover when the risk is mitigated. The upside ΔCoES is greater than the downside ΔCoES in most periods for each industry in the full sample interval. The reason is that the tail risk accumulates in the economic upward period and releases continuously in the economic downward period. Taking figure (a) as an example, the level of risk spillover from the mining industries increased more significantly during the adjustment period after the international financial crisis in 2008, the stock market volatility in 2015, and the intensification of international trade frictions and geopolitical conflicts in 2018 and 2019. Comparing Figures (a)-(f), we find that the level of tail spillover in each industry shows cyclical variation. The synergy of tail risks among industries suggests that the real sector, represented by mining and transportation, will also be hit as hard as the financial sector when a crisis occurs. However, it should be noted that the level of tail risk spillover also varies among industries. For example, the overall level of tail risk in the transportation sector began to increase significantly in October 2013, and the utilities upside tail risk had several significant increases in August 2009 and 2015 to 2016. Compared with other industries, the overall tail risk level of the financial sector is relatively stable, mainly concentrated in the range of 0.05–0.15.

3.2. Sparsity Testing. In the spectral domain, partial spectral coherence (PSC) is strictly related to the coefficients of a VAR representation [38]. In line with the long-run spirit of the LVDN definition, and since volatilities have strong persistence, we first consider the PSCs at frequency $\theta = 0$, thus looking at long-run conditional dependencies. Selected percentiles of the distributions of the absolute value of the PSC entries for upside $\Delta\mathrm{CoES}_T^{i|N}$ and idiosyncratic components ξ_{it} and the distribution of the absolute value of their differences are shown in Table 1. Both PSCs have many small (in absolute value) entries, which is consistent with our sparsity assumptions. Figures 2(a)-2(c) show the distributions of the absolute value of the PSC entries for upside $\Delta\mathrm{CoES}_T^{i|N}$ and ξ_{it} and the distribution of the absolute value of their differences in turn. Similarly, Table 2 shows the distributions of the absolute value of the PSC entries for downside $\Delta\mathrm{CoES}_T^{i|N}$ and idiosyncratic components ξ_{it} and the distribution of the absolute value of their differences. The two PSCs are shown in Figures 2(d) and 2(e). The above results suggest that the stochastic component also contains important dependencies after removing market-wide shocks. After ENGDFM processing, the form of factor plus sparse VAR can reveal the network internal dependencies. Therefore, we justify the application of ΔCoES-ENGDFM-LVDN to study the tail risk spillover among industries in terms of model treatment.

Left and middle panels: weights in absolute values below the 90th percentile in gray, weights above the 90th percentile in red, and weights below the 10th percentile in blue. Right panel: weights below the 90th percentile in gray, between the 90th and 95th percentiles in blue, and above the 95th percentile in red.

3.3. Association Level and Structure of Cross-Industrial Tail Risk Spillover in the Full Sample. Using China's 28 primary industries as network nodes, the cross-industrial tail risk spillover network is formed based on the estimated results of ΔCoES-ENGDFM-LVDN (as shown in Figure 3). Figures a and b represent the tail risk spillover relationships for each industry between the upside risk accumulation and downside risk release, respectively. We predict the outbreak of financial crisis and the realization of systemic risk release in the downside cycle through the risk-taking behavior and systemic risk accumulation process in various industries in the upside cycle. In theory, the upside risk spillover and right tail dependence are forward warning indicators of the downside and left tail dependence, where the size of the node indicates the size of the tail risk spillover shock to the industry, and the direction of the arrow between the nodes indicates the risk spillover path. The network indicators defined in the previous section are used to analyze the tail risk spillover among industries.

In the process of upside risk accumulation and downside risk mitigation, the network density index (ND) is 0.2248677 and 0.1891534, respectively. The total correlations are 36.17 and 49.41, respectively. This indicates that there is an overall persistent nonlinear spillover effect among industry tail risks in China with periodic variation characteristics. The total correlation of the upside risk accumulation process is smaller than that of the downside risk mitigation process, indicating that when the financial cycle is in the downside, the tail risks of the industry are more likely to hit other sectors along the risk network, showing more significant risk spillover effects. The reason for this is that when economic growth slows and investment and consumption are weak, the relative vulnerability of the industries tends to amplify the shock. A continued deterioration in economic conditions will also affect market stability and investor expectations, so risk contagion effects may differ significantly between economic ups and downs.

Based on the out-degree and in-degree indicators, we can calculate the spillover effect of industry tail risk in period h and analyze its role in the contagion chain. Table 3 collates the out-degree, in-degree, and RI indicators of tail risk spillover relationships for 28 primary industries, with

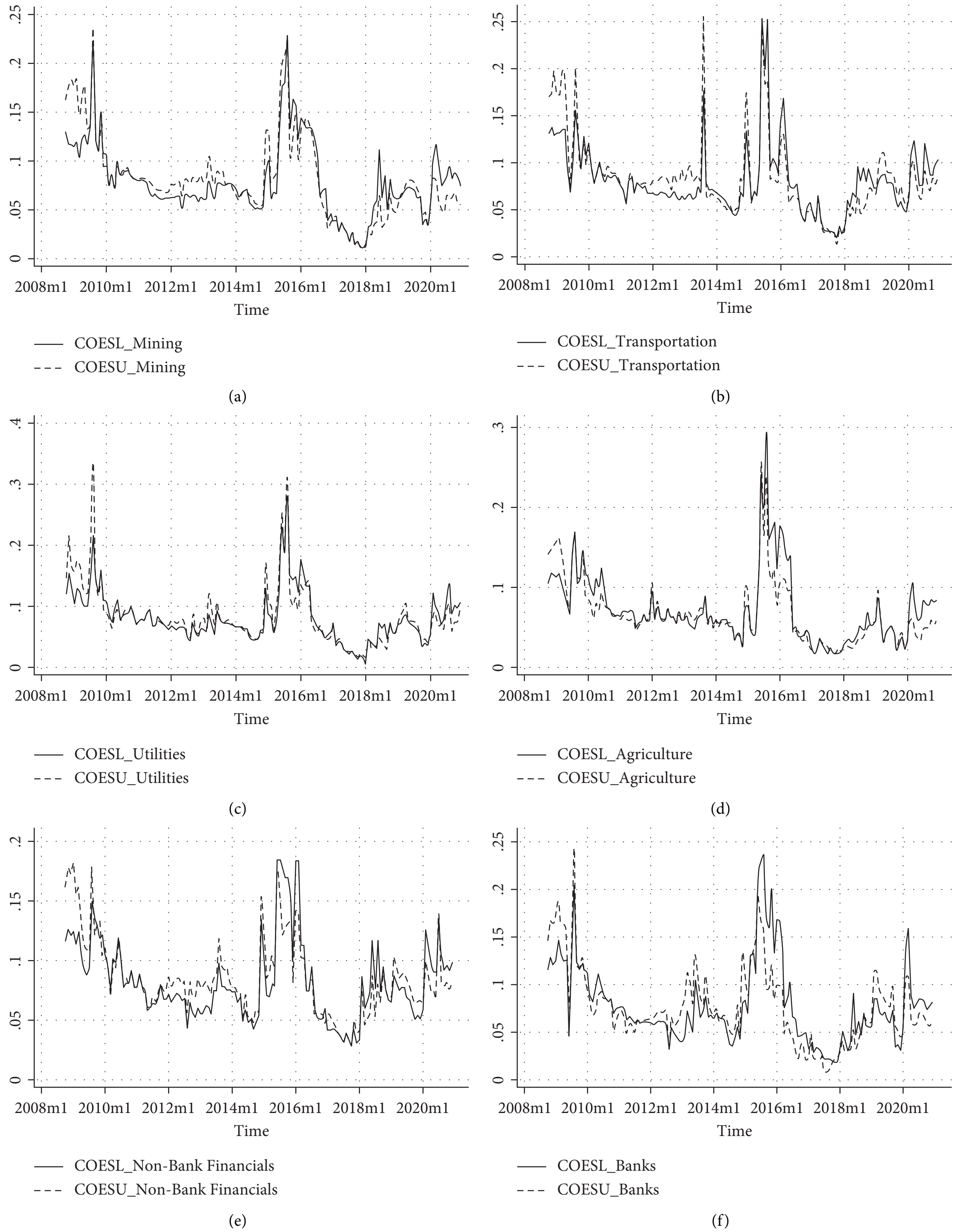


Figure 1: Temporal variation characteristics of the ΔCoES.

columns (2)-(4) indicating the upside risk accumulation phase and columns (5)-(7) indicating the downside risk mitigation phase. In the upside risk accumulation process, the top 10 industry tail risks in descending order of out-degree are Textile and Apparel, Mining, Media, Agriculture, Food and Beverage, Utilities, Chemicals, Conglomerate, Transportation, and Leisure Services. They are active senders of risk spillover, and the spillover effect is

Table 1: The distributions of the absolute value of PSC for risk accumulation.

	Quartiles					
The absolute value of the PSC	50%	90%	95%	97.50%	99%	Maximum
$\lvert PSC_{\Delta CoES}(\theta = 0)\rvert$	0.124362	0.291909	0.323202	0.376626	0.428884	0.566802
$\lvert PSC_{\xi_n}(\theta = 0)\rvert$	0.117153	0.289620	0.328238	0.380161	0.468751	0.643701
$\lvert PSC_{\Delta CoES}(\theta = 0) - PSC_{\xi_n}(\theta = 0)\rvert$	0.043272	0.144979	0.170733	0.199930	0.228674	0.287758

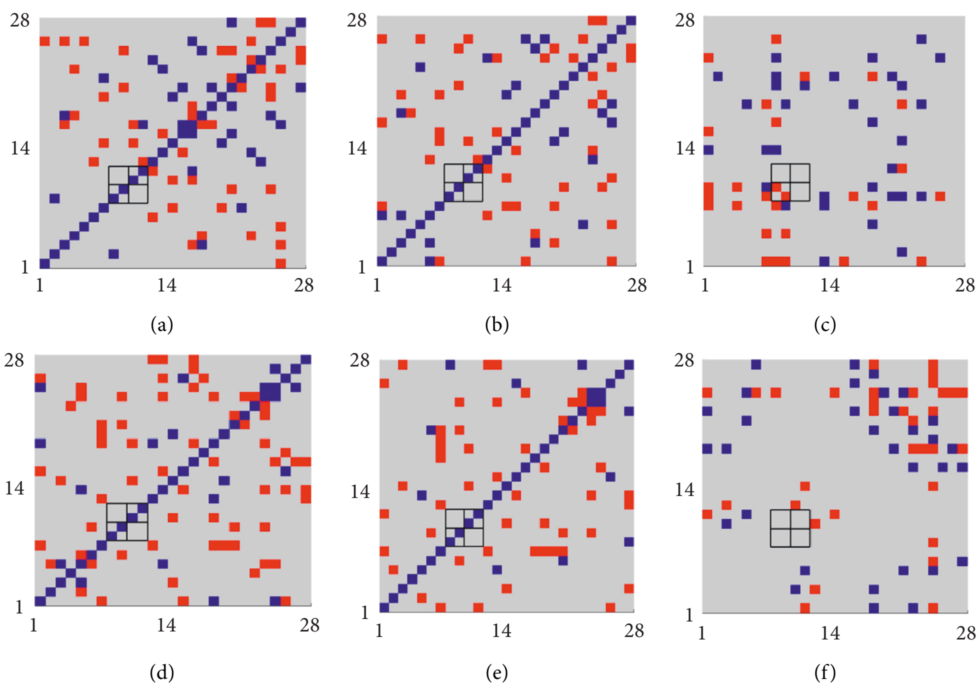
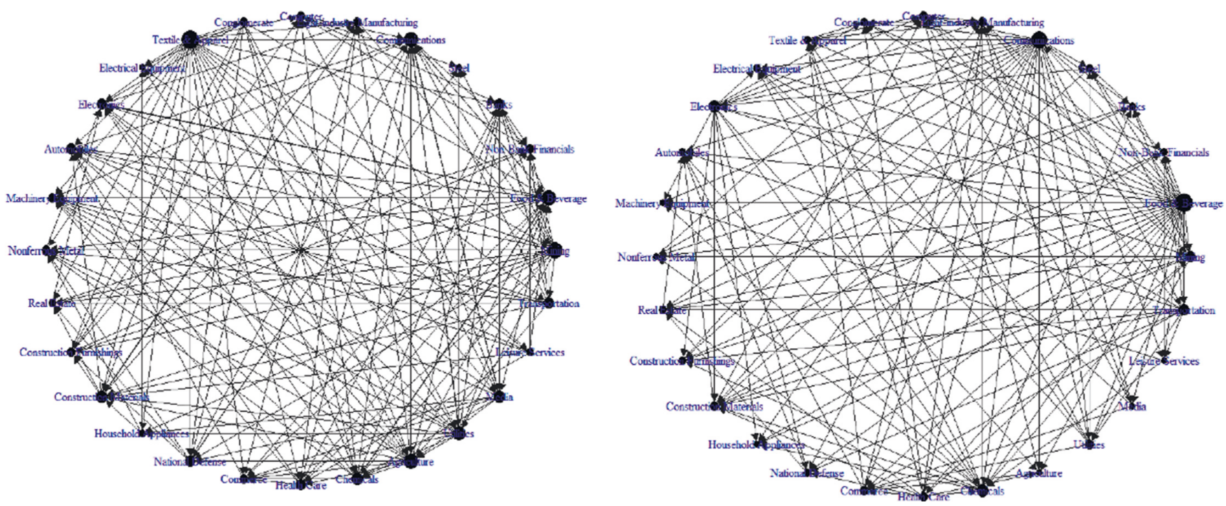


Figure 2: PSC in the process of risk accumulation and risk mitigation. (a) PSC of upside $\Delta CoES_T^{i|N}$. (b) PSC of upside ξ_{it}. (c) Absolute value of upside difference. (d) PSC of downside $\Delta CoES_T^{i|N}$. (e) PSC of upside ξ_{it}. (f) Absolute value of downside difference.

Table 2: The distributions of the absolute value of the PSC for risk mitigation.

	Quartiles					
The absolute value of the PSC	50%	90%	95%	97.50%	99%	Maximum
$\lvert PSC_{\Delta CoES}(\theta = 0)\rvert$	0.125615	0.313493	0.365495	0.435755	0.500213	0.592619
$\lvert PSC_{\xi_n}(\theta = 0)\rvert$	0.118030	0.293803	0.376495	0.436253	0.503897	0.626567
$\lvert PSC_{\Delta CoES}(\theta = 0) - PSC_{\xi_n}(\theta = 0)\rvert$	0.042004	0.109430	0.143421	0.177084	0.230884	0.324330

relatively strong. The top 10 industry tail risks of in-degree are Electronics, Machinery Equipment, Communications, Banks, Commerce, Automobiles, Construction Materials, Nonferrous Metal, nonbank finance, and Electrical Equipment. They are the primary recipients of the infection and are relatively vulnerable to spillover. In the downside risk mitigation process, the top 10 industry tail risks of out degree in order are Food & Beverage, Communications, Transportation, Electronics, Mining, Health Care, Chemicals, Utilities, Textile & Apparel, and Media. The top 10 industry tail risks of in-degree are construction materials, conglomerate, machinery equipment, chemicals, household appliances, nonbank finance, steel, light-industry manufacturing, commerce, and health care. From the above analysis, it can be seen that the nonbank financial industry is reflected in the in-degree ranking, indicating that whether in the upside risk accumulation or downside risk mitigation process, it has played the role of the recipient of tail risk spillover. Thus, it also indicates that the tail risk spillover from China's industry is reflected in the associated directions from the nonfinancial sector to the financial sector. Especially in the process of downside risk mitigation, more attention should be given to the ability of the nonbank financial sector to withstand tail risk spillover. We also found that the real estate industry ranked relatively low in both out-degree and in-degree values throughout the sample period, indicating that the process of analyzing tail risk spillover among industries cannot be prevented and resolved simply by the inherent impression of the industry.



(a) (b)

Figure 3: Full sample of China's cross-industrial tail risk spillover networks. (a) Upside risk accumulation process. (b) Downside risk mitigation process.

Table 3: Out-degree, in-degree, and RI indicator of cross-industrial.

Industry (1)	Upside risk accumulation phase			Downside risk mitigation phase		
	Out-degree (2)	In-degree (3)	RI (4)	Out-degree (5)	In-degree (6)	RI (7)
Mining	114.0545	17.4530	0.734570272	61.6501	32.8652	0.304552808
Transportation	38.4021	7.3969	0.676984214	66.7230	18.1311	0.572652353
Leisure services	26.1311	9.8383	0.452962796	12.8147	31.8501	−0.426183482
Media	86.6538	10.5619	0.782712052	17.7331	39.2600	−0.377710635
Utilities	54.2077	26.2984	0.346673109	29.1218	47.6602	−0.241442005
Agriculture	82.3181	36.6710	0.383624214	8.2766	52.5921	−0.728050706
Chemicals	53.5963	37.6067	0.175318794	37.6897	63.0075	−0.251425064
Health care	25.1435	23.4528	0.034790715	44.5775	55.4160	−0.108392045
Commerce	4.8575	52.3779	−0.83026239	10.1877	57.2267	−0.697758936
National defense	22.4761	33.6635	−0.199278228	9.3160	53.7339	−0.704488032
Household appliances	11.7469	28.1271	−0.410799017	0.0000	62.5923	−1
Construction materials	17.8422	48.3596	−0.460975381	16.5888	68.1793	−0.608607483
Construction furnishings	15.1180	23.3335	−0.213658765	15.7876	32.0357	−0.339752798
Real estate	5.4934	35.4223	−0.731477159	5.6138	52.0842	−0.805407466
Nonferrous metal	4.1867	47.8813	−0.839183376	2.2286	53.2019	−0.919589396
Machinery equipment	0.0000	60.7620	−1	0.0000	63.0327	−1
Automobiles	2.8404	48.3764	−0.88908327	0.0000	51.7961	−1
Electronics	16.9323	62.2757	−0.572459853	66.6504	44.8751	0.195249517
Electrical equipment	0.0000	43.5438	−1	0.0000	54.4843	−1
Textile and apparel	232.4349	0.0000	1	22.4120	46.8030	−0.352394712
Conglomerate	47.9072	33.7010	0.174078095	3.4964	64.7932	−0.897600806
Computer	11.7495	43.3565	−0.573567307	3.1802	51.7017	−0.884107511
Light-industry manufacturing	19.2448	37.9764	−0.327354197	7.2998	60.7444	−0.785439464
Communications	24.0707	60.1110	−0.428125115	239.5348	49.7838	0.655854826
Steel	7.0208	42.3321	−0.715485817	8.9733	62.0339	−0.747256616
Banks	3.8193	54.7705	−0.869625771	8.8933	51.3620	−0.704812689
Nonbank finance	4.5618	43.9214	−0.811819352	2.3020	62.3088	−0.928742563
Food and beverage	80.0580	43.2967	0.298012966	682.5041	0.0000	1
Total degree	36.1738			49.4127		

Columns (4) and (7) of Table 3 present the relative impact indicators for each industry, which measure the magnitude of the net spillover of tail risk in a given industry. During the upside risk accumulation process, the RI indicators of the top ten industries in terms of out-degree are all greater than zero, implying that they all have a positive net tail risk spillover. This can indicate that risks accumulate in several sectors during the upside and start to be mitigated during the downside. Taking into account the ranking by out-degree and the net spillover from the tail risk of the industry represented by RI, there are ten industries, Textile and Apparel, Media, Mining, Transportation, Leisure Services, Agriculture, Utilities, Food and Beverage, Chemicals, and Conglomerate, which become important sources of risk spillover in the process of risk accumulation during the sample period. In the downside risk mitigation process, combining out-degree values and the RI indicator reveals that Food and Beverage, Communications, Transportation, Mining, and Electronics are the main sources of net tail risk spillover. In addition, the number of net spillover industries has decreased during downside risk mitigation. The reason is that the abovementioned industries are important net spillover nodes and sources of risk, and their spillover is gradually mitigated in the process of downside risk mitigation.

A smaller tightness (C) indicates that the node is more closely connected to the whole network. During the accumulation of upside risk, the top 10 industries in order of C from smallest to largest are Machinery Equipment, Communications, Electrical Equipment, nonbank finance, Food and Beverage, Banks, Computer, Automobiles, Electronics, and Nonferrous Metal. During the downside risk mitigation process, the top 10 industries in ascending order of size C are Automobiles, Light-industry Manufacturing, Computer, Household Appliances, Banks, Electrical Equipment, Nonferrous Metal, Mining, nonbank finance, and Machinery Equipment. As shown in the columns of Table 4(2)-(3), certain industries, which are important sources of spillover, do not have high network tightness. In contrast, some risk sources that are not at the center of the risk network may have a stronger tail risk network propagation. It is worth noting that the industries with the same top rankings for closeness, out degree, in degree, and RI in the full sample interval are Machinery Equipment, Communications, Electrical Equipment, nonbank finance, Food and Beverage, Banks, Automobiles, and Nonferrous Metal. The eight industries mentioned above are at the center of the spillover association in the overall tail risk spillover network.

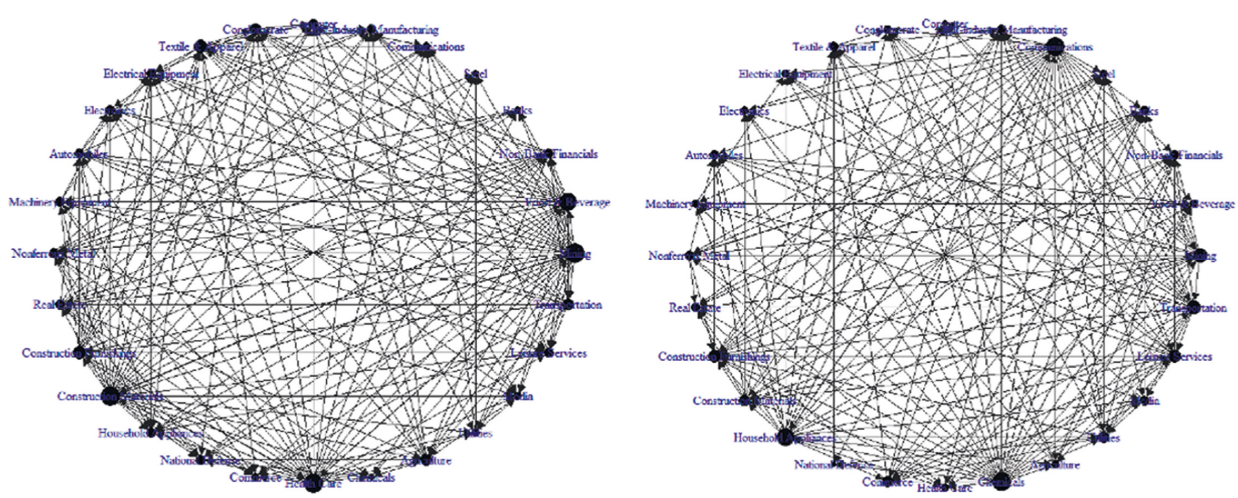
3.4. Dynamics of Cross-Industrial Tail Risk Spillover Correlation. The magnitude and direction of the association of cross-industrial tail risk spillover can change over time. The above examines the spillover of tail risk across industries in the network based on the full sample results but may miss important information changes, and regulators need to grasp the dynamic characteristics of the magnitude and path direction of correlation intensity across industries. This paper divides the sample interval into 2 different periods based on the characteristics of China's economic and financial market operations, combined with structural breakpoint2 identification. The two periods are October 2008–March 2015 (interval I) and July 2016–December 2020 (interval II), excluding the effect of the abnormal stock market volatility phase in 2015. Figure 4 gives the dynamic characteristics of the network correlation structure for the above two intervals.

In the process of risk accumulation in the interval of period I, the top 10 industry tail risks in order of out-degree are mining, food and beverage, health care, construction materials, construction furnishings, textile and apparel, transportation, agriculture, real estate, and nonferrous metals. The top 10 in-degree are communications, steel, automobiles, electrical equipment, chemicals, commerce, leisure services, national defense, electronics, and light-industry manufacturing. Columns 2–4 of Table 5 show the RI values, and the top ten industries, from largest to smallest, are mining, health care, food and beverage, construction materials, transportation, construction furnishings, textile and apparel agriculture, real estate, and nonbank finance. Closeness (C) ranking in order: communications, media, household appliances, light-industry manufacturing, national defense, electrical equipment, commerce, steel, electronics, and computer (as in column 4 of Table 4). In the process of risk mitigation, the top 10 industries ranked by tail risk out-degree ranking in order: chemicals, communications, transportation, household appliances, mining, leisure services, utilities, nonferrous metals, construction materials, and construction furnishings. The top 10 in-degree are steel, automobiles, computer, conglomerate, nonbank finance, electrical equipment, light-industry manufacturing, machinery equipment, food and beverage, and electronics. The RI ranking in order is chemicals, transportation, communications, mining, household appliances, leisure services, utilities, nonferrous metals, agriculture, and construction furnishings (as listed in columns 5–7 in Table 5). C is listed in ascending order as follows: light-industry Manufacturing, Food and Beverage, conglomerate, textile and apparel, nonbank finance, electrical equipment, electronics, automobiles, computer, and banks (as in column 5 of Table 4).

In the process of risk accumulation during the interval II period, the top 10 out-degree rankings of industry tail risk are mining, national defense, agriculture, chemicals, construction materials, electrical equipment, health care, construction furnishings, banks, and electronics. The top 10 in-degree rankings are machinery equipment, media, transportation, food and beverage, nonbank finance, light-industry manufacturing, household appliances, communication, leisure services, and automobiles. Columns 8–10 of Table 5 show the magnitude of RI, with the top ten in descending order: mining, agriculture, national defense, construction materials, chemicals, health care, electrical equipment, construction furnishings, banks, and commerce. C ranking in order: automobiles, machinery equipment, nonferrous metals, light-industry manufacturing, leisure services, household appliances, food and beverages, transportation, steel, and media (as in column 6 of Table 4). In the process of risk mitigation, the top 10 industry tail risks in order of out-degree are machinery equipment, transportation, chemicals, mining, conglomerate, media, utilities, agriculture, health care, and commerce. The top 10 in order of in-degree are nonbank finance, food and beverage, light-industry manufacturing, banks, computers, steel, communications, construction materials, national defense, and nonferrous metals. The RI ranking in order is machinery equipment, transportation, mining, chemicals, media, conglomerate, agriculture, utilities, health care, and commerce (as listed in Table 5, columns 11–13). The C ranking in order is nonbank finance, food and beverage, computer,

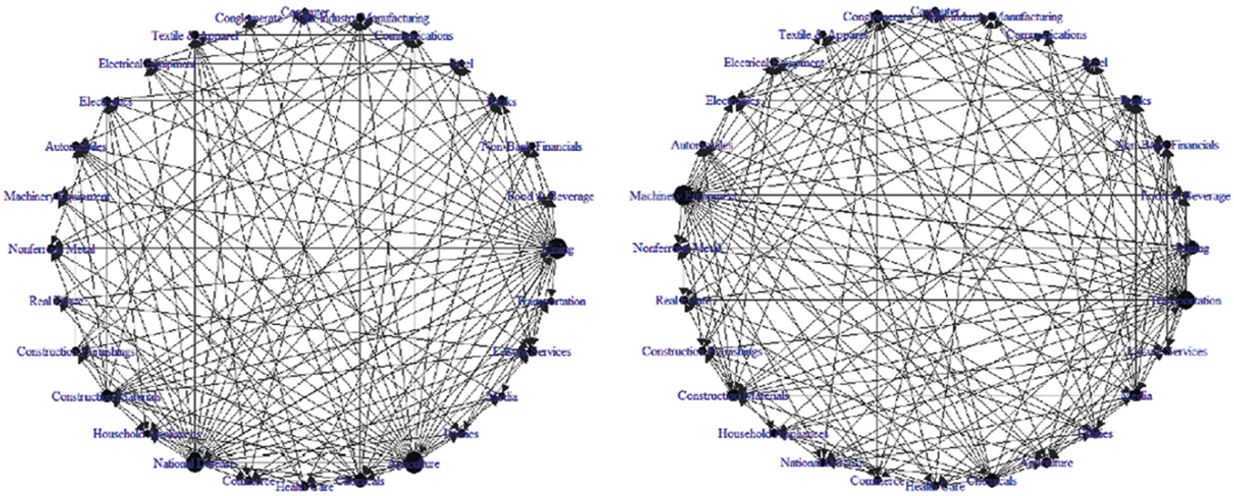
Table 4: Closeness values of China's industry.

Sample interval	Full sample interval		Interval 1		Interval 2	
Industry	Upside (2)	Downside (3)	Upside (4)	Downside (5)	Upside (6)	Downside (7)
Food and beverage	103	756	624	260	289	189
Communications	97	729	278	702	305	219
Transportation	145	702	625	387	291	258
Mining	124	171	625	378	702	260
Electronics	108	702	409	327	311	240
Health care	110	702	623	363	323	254
Utilities	113	186	464	375	319	257
Chemicals	116	182	464	756	312	261
Construction furnishings	118	197	622	358	334	235
Textile and apparel	756	187	541	298	315	226
Media	112	702	278	371	296	251
Leisure services	729	675	435	393	281	255
Construction materials	113	174	624	379	325	235
Commerce	111	193	383	372	308	255
National defense	115	621	381	361	702	247
Banks	104	166	569	357	308	227
Agriculture	115	648	541	371	703	250
Steel	114	182	390	360	293	239
Light-industry manufacturing	109	154	356	229	273	217
Real estate	110	176	595	358	323	239
Computer	107	156	409	341	336	211
Conglomerate	729	175	486	265	300	258
Nonferrous metal	108	168	516	369	264	237
Nonbank finance	101	173	567	308	299	182
Automobiles	107	143	567	335	216	211
Household appliances	123	158	303	702	284	248
Electrical equipment	100	167	381	326	675	234
Machinery equipment	79	173	541	366	254	243



(a) (b)

Figure 4: Continued.



(c) (d)

Figure 4: Cross-industrial tail risk spillover networks in China. (a) Upside risk accumulation process in interval I. (b) Downside risk mitigation process in interval I. (c) Upside risk accumulation process in interval II. (d) Downside risk mitigation process in interval II.

Table 5: Tail risk spillover network indicators among subsamples.

	Interval I						Interval II					
	Upside risks accumulate			Downside risks mitigated			Upside risks accumulate			Downside risks mitigated		
Industry (1)	Out-deg (2)	In-deg (3)	RI (4)	Out-deg (5)	In-deg (6)	RI (7)	Out-deg (8)	In-deg (9)	RI (10)	Out-deg (11)	In-deg (12)	RI (13)
Mining	350.61	13.23	0.9273	102.72	48.18	0.3614	1503.03	4.43	0.994	91.93	37.60	0.419
Transportation	67.29	20.95	0.5252	134.88	12.85	0.8261	0.0000	90.95	−1	162.33	55.24	0.492
Leisure services	7.81	81.43	−0.8249	65.19	56.08	0.0751	2.41	85.09	−0.945	9.83	59.43	−0.716
Media	0.0000	70.37	−1	14.94	63.59	−0.6195	2.11	92.19	−0.955	56.49	65.41	−0.073
Utilities	24.18	69.45	−0.4835	36.50	66.63	−0.2922	8.68	79.91	−0.804	35.38	68.41	−0.318
Agriculture	48.88	61.31	−0.1128	25.56	49.71	−0.3209	160.91	25.46	0.727	29.37	54.61	−0.301
Chemicals	3.63	81.78	−0.9150	1026.23	0.0000	1	48.41	83.70	−0.267	111.81	56.62	0.328
Health care	329.52	16.76	0.9032	16.53	63.15	−0.5851	21.41	49.21	−0.394	26.15	54.26	−0.35
Commerce	0.0000	81.43	−1	18.44	68.55	−0.5760	12.66	78.91	−0.723	22.90	57.74	−0.432
National defense	0.0000	80.79	−1	3.15	67.64	−0.9111	209.03	43.79	0.654	6.46	78.32	−0.848
Household appliances	0.0000	72.04	−1	126.73	67.12	0.3075	0.0000	85.76	−1	13.28	61.10	−0.643
Construction materials	294.46	51.61	0.7017	34.51	71.76	−0.3505	42.41	72.63	−0.263	22.68	80.22	−0.559
Construction furnishing	99.81	42.28	0.4049	28.36	56.16	−0.3289	19.00	83.91	−0.631	6.98	77.86	−0.836
Real estate	40.85	63.78	−0.2191	3.85	72.92	−0.8997	4.54	72.21	−0.882	2.61	75.06	−0.933
Nonferrous metal	29.45	78.37	−0.4537	35.41	66.59	−0.3056	0.0000	84.44	−1	10.76	77.92	−0.757
Machinery equipment	16.54	71.38	−0.6237	10.54	77.06	−0.7593	0.0000	95.88	−1	1225.46	7.21	0.988
Automobiles	24.88	84.78	−0.5463	2.62	86.32	−0.9411	0.0000	84.76	−1	0.0000	71.23	−1
Electronics	7.54	80.62	−0.8290	2.30	73.74	−0.9394	12.98	83.63	−0.731	13.38	71.42	−0.684
Electrical equipment	3.68	83.79	−0.9159	0.0000	79.23	−1	26.77	75.16	−0.475	8.23	65.99	−0.778
Textile and apparel	70.25	46.04	0.2082	6.60	70.73	−0.8292	9.17	77.62	−0.789	0.0000	71.22	−1
Conglomerate	25.88	77.18	−0.4977	0.0000	83.89	−1	0.0000	75.02	−1	60.02	70.03	−0.077
Computer	7.91	72.02	−0.8020	0.0000	85.70	−1	2.21	81.01	−0.947	5.46	86.55	−0.881
Light-industry manufacturing	0.0000	79.79	−1	0.0000	77.53	−1	10.82	89.12	−0.784	2.84	87.95	−0.937
Communications	0.0000	86.83	−1	141.45	64.11	0.3762	7.35	85.62	−0.842	0.0000	83.65	−1
Steel	0.0000	84.83	−1	2.30	88.86	−0.9495	0.0000	81.39	−1	2.68	84.51	−0.939
Banks	6.084	63.12	−0.8242	6.14	70.94	−0.8407	14.13	83.39	−0.71	2.28	87.56	−0.949
Nonbank financials	26.57	65.29	−0.4215	0.0000	81.18	−1	2.44	89.83	−0.947	0.0000	93.56	−1
Food and beverage	333.82	38.41	0.7936	0.0000	74.75	−1	4.53	89.97	−0.904	0.0000	88.61	−1
Total degree	64.99			65.89			75.89			68.90		

Table 6: Subsample index ranking.

	Interval 1 Upside	Interval 2 Upside
In-degree	Communications, steel, automobiles, electrical equipment, chemicals	Machinery equipment, media, transportation, food and beverage, nonbank financials
Out-degree	Mining, food and beverage, health care, construction materials, construction furnishings	Mining, national defense, agriculture, chemicals, construction materials
RI	Mining, health care, food and beverage, construction materials, transportation	Mining, agriculture, national defense, construction materials, chemicals
Closeness	Communications, media, household appliances, light-industry manufacturing, national defense	Automobiles, machinery equipment, nonferrous metal, light-industry manufacturing, leisure services
	Interval 1 downside	Interval 2 downside
In-degree	Steel, automobiles, computer, conglomerate, nonbank financials	Nonbank financials, food & beverage, light-industry manufacturing, banks, computer
Out-degree	Chemicals, communications, transportation, household appliances, mining	Machinery equipment, transportation, chemicals, mining, conglomerate
RI	Chemicals, transportation, communications, Mining, household appliances	Machinery equipment, transportation, mining, chemicals, media
Closeness	Light-industry manufacturing, food and beverage, conglomerate, textile & apparel, nonbank financials	Nonbank financials, food and beverage, computer, automobiles, light-industry manufacturing

automobiles, light-industry manufacturing, communications, textile and apparel, banks, electrical equipment, and construction furnishings (as in column 7 of Table 4).

To facilitate the analysis, we briefly present the above results in Table 6. They show that the level of risk spillover in different industries differs from the average cross-industrial risk spillover in the overall market in different intervals. The cross-sectional dimension allows us to compare the differences in spillover effects between the upside risk accumulation and downside risk mitigation phases within the same sample interval and analyze the accumulation of risk spillover levels from normal to extreme states. The time dimension allows for a longitudinal analysis of the evolution of the industry tail risk spillover relationship across the intervals. It is possible to compare the evolution of risk spillover within the same risk phase (upside risk accumulation or downside risk mitigation) across sample intervals.

First, the differences in tail risk spillover effects among industries are compared. In interval I, the senders of risk spillover during the upside risk accumulation process include the tail risk of the real estate industry, and the receivers of risk spillover do not have banks or nonbank financial industries. Nonbank finance appears in the in-degree ranking as the receivers of tail risk spillover during the downside risk mitigation process. There are no estimates of tail risk in the real estate industry in either the full sample interval or the sample interval II out-degree ranking, indicating that the impact of tail risk in the real estate industry is large in the earlier period. The impact of tail risk accumulation within the real estate industry in China has gradually decreased in recent years with the regulation of this industry. The risk spillover senders and receivers in Interval II are more likely to reflect the tail risks of industries involving emerging sectors of strategic importance, such as communications, computers, and health care, indicating that the impact of strategic emerging industries on the economic and financial system is of increasing concern in the process of structural transformation and upgrading of China's industries. In Interval II, in terms of closeness, tail risks in the nonbank financial industry are not at the center of the network during the upside risk accumulation phase but evolve into an important network center during the downside risk mitigation phase, playing an important role in the risk spillover contagion chain.

Second, the evolution of the cross-industrial tail risk spillover is compared across different intervals. In the process of upside risk accumulation and downside risk mitigation, the network density indicators ND in sample intervals I and II are 0.2592593 and 0.2301587 and 0.1931217 and 0.207672, respectively. The total correlations are 64.99 and 65.89 and 75.89 and 68.90, respectively; thus, the nonlinear effects and cyclical changes of tail risk spillover among industries still exist. Regardless of the upside risk accumulation or downside risk mitigation process, the total correlation in interval II is greater than that in interval I. This indicates that the impact of tail risk spillover in China has been gradually expanding in the cross-industrial range in recent years from the vertical time dimension. In the interval I time period, the total correlation of the upside risk accumulation process is smaller than the total correlation of the downside risk mitigation process, while in the interval II time period, the result is the exact opposite. The total correlation of the upside risk accumulation process shifts to be larger than the total correlation of the downside risk mitigation process, indicating that the downside risk is not fully mitigated in the process of expanding the impact of tail risk spillover in recent years. In addition, in the downside and upside risk phases of the two sample subregions, the tail risks of industries such as mining, transportation, utilities, and agriculture in the nonfinancial sector are among the stable risk spillover senders. They provide basic services and production materials supply for other sectors while generating more obvious risk shocks to other industries. The tail risks of the communications, health care, computer, and other industries are gradually rising in the network. This conclusion forms a synthesis of established studies related to cross-industrial risk spillover and an extended validation of them. It is worth noting that although the nonbank financial industry is not in the ranking of risk spillover senders, the in-degree ranking of the industry has improved more significantly in recent years. During the downside risk mitigation phase of Interval II, it is not only the top-ranked tail risk spillover recipient, but also in the center of the network in terms of closeness, which again confirms the characteristics of tail risk spillover from the nonfinancial sector to the financial sector. Based on the fact that China's nonbank financial industry is not the sender but the receiver of tail risk spillover, it is more important to pay attention to the increase in risk exposure of the nonbank financial sector and strengthen its ability to bear tail risk spillover. At the same time, it is also necessary to pay attention to the risk-sending effect presented by the Bank sector during the upside risk accumulation phase and the role it played in promoting risk accumulation.

Finally, the evolution of risk spillover within the same risk stage in different sample intervals is compared. Based on the estimation results, it is found that the total correlation within interval II during the accumulation of upside risk is significantly larger than the total correlation in interval I. This indicates that the upside risks have accumulated faster in recent years, but thanks to effective regulation, the downside risk mitigation is gradually resolved and does not show an accelerating trend of mitigation. That being said, there is still a need to focus on the impact of upside risks.

4. Conclusion

This paper applies the ΔCoES-ENGDFM-LVDN method to construct a tail risk spillover network with periodic properties among China's industries and investigates the level and structure of association of the tail risk spillover network, as well as the role of each industry in the risk contagion chain. We identify the characteristics and the dynamic contribution of each industry in the tail risk transmission chains. On the one hand, this paper analyzes tail risk in-degree, out-degree, RI, and closeness indicators based on cross-sectional dimensions for the full sample period and finds that there is variability in the level of tail risk spillover among industries. For example, the real estate industry, an important source of risk inherently perceived, has ranked relatively poorly in recent years in terms of out and in indicators. The risk spillover indicators in both sample subintervals show that the mining, transportation, utilities, and agriculture sectors in the nonfinancial sector are stable sources of risk. The nonbank financial industry is the recipient of tail risk spillover and gradually evolves into an important network center in the downside risk mitigation phase. This indicates that the tail risk spillover in China's industries is reflected in the direction of correlation from the nonfinancial sector to the financial sector. On the other hand, the in-degree ranking of the nonbank financial industry has improved significantly in recent years. It becomes the most central industry in the tail risk network and is very closely linked to other industries. The reason for this is likely due to the rapid growth of China's nonbank financial business, whose regulatory avoidance, high leverage, and maturity mismatch characteristics have led to increased vulnerability of the nonbank finance. In addition, the real estate industry had a large tail risk impact in the early period (interval I), but the output effect of tail risk in the real estate industry is gradually weakening as national regulations are gradually taking effect (interval II). At the same time, emerging industries in China, such as communications, health care, and computers, have been more represented among the senders and receivers of tail risk since 2016. This also indicates that emerging industries in China are increasingly worthy of attention.

The network density and the total degree of correlation indicators show that there are a continuous nonlinear spillover effect and an obvious cyclical characteristic among China's industry tail risk as a whole. The spillover effect of industry tail risk during the downside risk mitigation process is more pronounced, but the gradual growth of the total degree of the upside risk accumulation process has exceeded the total degree of the downside. This suggests that although the impact of cross-industrial tail risk spillover in China has gradually expanded, due to effective regulation, it has not been released sharply.

Based on the above findings, this paper puts forward the following policy recommendations. First, the regulator should expand the scope of concern, not only focusing on the financial sector, but also paying attention to the tail risk spillover effect of the nonfinancial sector. Focus more on stable risk spillover sectors represented by mining, transportation, utilities, and agriculture. At the same time, it is important to avoid falling into the rigidity of thinking and not simply focusing on risk prevention in traditional high-risk spillover industries, such as the real estate industry. Depending on the role and status of different industries in the tail risk spillover process, different regulatory policies should be selected in a targeted manner. When establishing a risk warning system related to each industry in China, the different systematic contributions of each industry in the risk transmission chain should be taken into account comprehensively. A dynamic adjustment mechanism should be introduced to lay the foundation for a more reasonable prevention of tail risk spillover. Second, as the nonbank finance has long been in the position of the recipient of tail risk spillover, improving the ability of the nonbank finance to resist risks, reducing the vulnerability of the industry, and regulating its operation are the focus of risk prevention. Third, with the improvement of capital structure and industrial restructuring, the importance of emerging industries in the risk spillover network is gradually increasing, and more attention should be given to the risk contagion of such industry fluctuations for the overall industries and preventing tail risk transmission from the nonfinancial sector to the financial sector. [39].

Data Availability

Data are available upon request to corresponding author.

Additional Points

(1) Tail risk spillover in China's industries has both periodicity and variability characteristics. (2) Cross-industrial tail risks spillover from the nonfinancial sector to the

financial sector in China. (3) The impact of the tail risk of emerging industries on the whole economic and financial system is gradually increasing in China. (4) The impact scope of cross-industrial tail risk spillover in China has gradually expanded, but the downside risk has not been released sharply. Network effects and characteristics of cross-industrial tail risk spillover in China.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Evaluation of Interest Balance of Low-carbon Collaborative Innovation Subjects

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The most important subsystem of regional low-carbon innovation capability is low-carbon technology innovation system. It is necessary to objectively evaluate the balance of interest among low-carbon technology innovation subjects. This paper constructs the theoretical framework model of benefit balance evaluation of low-carbon collaborative innovation (LCCI). It also explores the main content and index system of evaluation and makes a specific evaluation with TOPSIS method. Our study shows the follow conclusions: ① The interest balance of the subjects of LCCI includes not only the interest balance among subjects, but also the balance of interests within the subject. ② Subjects have different motivations for cooperation. ③ The benefit distribution of LCCI includes the distribution of all tangible and intangible benefits. ④ The equilibrium state is dynamic. When it is unbalanced, it can be adjusted according to the evaluation results to achieve equilibrium. Finally, according to the research conclusions, three suggestions are put forward for LCCI management practice.

1. Introduction

Globalization has an uncertain impact on carbon emissions, which will affect climate change [1]. And climate change caused by carbon emissions has received great attention from countries around the world [2, 3]. Many countries and regions around the world have taken positive measures to reduce carbon emissions, among which regional low-carbon innovation capability is one of the important indicators [1, 4]. The most important subsystem of regional low-carbon innovation capability is low-carbon technology innovation system. The subject of low-carbon technological innovation refers to the social organization or role that participates in the whole process of low-carbon technological innovation activities, occupies a leading position, and plays a leading role in technological innovation activities. It mainly includes enterprises, universities, and research institutions [5].

The Low-carbon Collaborative Innovation (LCCI) is to transform the industry in the direction of social, environmental, and economic sustainable development [6, 7]. This kind of cooperation is based on the different resource advantages and interest needs of different subjects [8]. Among them, the advantage of research institutions (including universities and research institutes) is their rich R & D resources, equipment, and talent. At the same time, the advantages of firms are capital and market demand [9]. In Yong [10]'s research on LCCI, it shows that the most significant benefit realized by firms is an increased access to new university research and discoveries, and the most significant benefit by faculty members is complementing their own academic research by securing funds for graduate students and lab equipment, and by seeking insights into their own research. This cooperative innovation mode based on complementary advantages can not only increase the innovation level of firms [11, 12] and the competitive advantage of enterprises [13], but also promote the national regional innovation ability [14] and the reform of national innovation system [15]. As a result, it has been rapidly popularized since its emergence.

According to the Bulletin of China's National Economic and Social Statistics, the turnover of granted patents and technology contracts in China increased by 31.9 and 35.32 times, respectively, in the 20 years from 2001 to 2020 (China). Thus, the LCCI has become one of the mainstream modes of modern innovation [16].

LCCI can create more benefits. However, it involves different subjects, and it will involve the issue of interest distribution. Surely, different subjects participate in cooperation with different purposes and invest different resources [17–19]. If the subject is not satisfied with their interest distribution, he will withdraw from the cooperation, or even no longer participate in such a cooperation [20]. This will not be conducive to the development of LCCI. Therefore, ensuring the rationality of interest distribution is the basis of LCCI.

If we do not know the real attitude of the main body to the distribution of interests, we will not be able to judge its willingness to participate in such projects. This will inevitably affect the sustainable development of low-carbon collaborative innovation, regional low-carbon innovation capacity [21], and even strategic objectives such as "carbon peak" and "carbon neutralization" [22].

Therefore, this paper is a study on the evaluation of the balance of interest distribution of LCCI subjects, which is instructive for the rational participation of LCCI project subjects in cooperation and the rational distribution of cooperation interests. Make an objective evaluation of the specific situation of the main interest. The evaluation results are fed back to the corresponding subjects to help them cooperate more stably in the next step. We first build the theoretical framework model of evaluation, and then use specific cases for research. The arrangement of the rest of this paper is as follows. Literature review is given in Section 2. Theoretical basis and research design in Section 3. Case application and analysis are described in Section 4. Discussion is conducted in Section 5. Conclusions and future work are presented in Section 6.

This study can guide the evaluation of low-carbon collaborative innovation projects and the balance of subject interest distribution.

2. Literature Review

2.1. Research on Low-Carbon Collaborative Innovation (LCCI). There are many studies related to low-carbon collaborative innovation. In summary, they are mainly reflected in the following aspects:

2.1.1. The Research on the Cooperation Motivation of the Main Body. McKelvey et al. [23] finds that the cooperation effect between universities and enterprises is better than that between enterprises, and better than that between universities. Fernández López et al. [24] studies 375 companies in Spain, Portugal, and France through semi structured interviews. It shows that more innovative enterprises tend to cooperate with universities. However, the motivation of cooperation between high-tech enterprises and non-high-tech enterprises is different.

Beath et al. [25] believes that the basic goal of the university is to carry out basic research, followed by applied research. However, the research of Banal-Estañol et al. [26] indicates that cooperation to a certain extent will help the research subjects obtain more research innovation and funding sources. However, excessive cooperation will seriously hinder the research and innovation output by reducing a large amount of research time. Freitas and Verspagen [27] study the relevant data of the Netherlands and show that the different motives of the main body have an impact on the organizational structure design of the project. Moreover, the specific organizational structure and technical objectives do not always have advantages, but only have advantages under specific institutions [28].

Clearly, different subjects have different motives to participate in LCCI.

2.1.2. The Research on the Influencing Factors of Cooperation. Kazuyuki [15] find that the scale of cooperative enterprises will affect the performance. Generally, small-scale companies have stronger investment and better performance in cooperation. Bodas Freitas et al. [29] studies that the cooperation performance of enterprises in different industry stages will be different. And the coordination of the relationship between members is also crucial to performance. Hemmert [30] studies the close interaction among various subjects in collaborative innovation projects, which has an impact on the effect of subject participation in cooperation.

Fischer et al. [31] and others study that the level and quality of school enterprise cooperation have an impact on cooperation performance. Williams and Allard [32] shows that a well-educated and skilled labor force contributes to the promotion of industry university research and collaborative innovation projects. Maietta [33] uses multivariate probity model to study the driving factors of a collaborative innovation projects.

There are also researches on the influence of collaborative innovation atmosphere [34], resource dependence among subjects [35], incentive mechanism [36] on low-carbon collaborative innovation.

Therefore, the influencing factors of low-carbon collaborative innovation involve many aspects and perspectives.

2.1.3. The Research on the Stability of Cooperation. Lee et al. [37] takes the school enterprise cooperation in Tokyo as an example and shows that culture and organization are the biggest obstacles to the stability of cooperation. Hemmer et al. [38] shows that deep-rooted cultural differences lead to the instability of cooperation by influencing the mutual trust between subjects. Musio and Vallanti [39] studies 197 collaborative innovation projects in Italy, which show that perceived barriers from the main body will cause instability of cooperation. Guzzini and Iacobucci [9] show that the larger the scale, the worse the stability of cooperation. At the same time, the stability of collaborative innovation cooperation is also worse for enterprises with innovative nature.

Jasmina et al. [40] show that normative contracts and effective and reasonable policies can better deal with intellectual property rights, conflicts of interest, copyright, and other issues, which is an important guarantee for stable cooperation. The research of Estrada et al. [41] shows that the specific cooperation mode should be adjusted with the progress of cooperation, otherwise it will lead to the instability of cooperation. Liu [42] shows that an effective way of interest distribution will increase the stability of cooperation and the willingness of re-cooperation among subjects, while an unbalanced way of interest distribution will lead to the rupture of cooperation.

From the above literature, there are many perspectives to explore the low-carbon collaborative innovation.

However, there are few studies on the evaluation of the balance of interest distribution in low-carbon collaborative innovation.

2.2. Research on Benefit Distribution of Low-Carbon Collaborative Innovation. The benefit is the key for the university-industry collaborative innovation to keep a long-term stable relationship [42]. While benefit distribution is beneficial to the performance of collaborative innovation, and can improve the efficiency by influencing the incentive mechanism [42] in the same time, the most critical factors for benefits "realization are: "strategic", "inter-relational" and "cultural" [43].

Freitas and Verspagen [27] rely on in-depth data on 30 university-industry collaborations in the Netherlands, and provide preliminary evidence that the effective cooperation between UIC is to create different institutional incentives by targeting different individual motivations.

Sivadas et al. [44] point out that the complexity of the interest relations, the differences of each organization unit goal, and the lack of constraint mechanism inevitably lead to the interest conflict between different organizations, which causes the instability of cooperation and the failure of the innovation cooperation. Establishing an appropriate and clear benefit distribution mechanisms is the guarantee of successful collaborative innovation.

Therefore, Jasmina et al. [40] point out that effectively coordinating the distribution interests of innovation cooperation is the key to achieve "win-win" before launching innovation cooperation activities. Li et al. [45] show that according to the different needs of alliance members, the profit distribution model can fully encourage alliance members to participate in collaborative innovation and improve the performance of collaborative innovation.

Reasonable distribution of interests can not only meet the reasonable needs of individuals, but also optimize the overall interests [46]. It can also improve the willingness to innovate, which has a positive role in promoting environmental and economic development [47].

2.3. Research on Evaluation Methods. There are a lot of research on different evaluation methods and their applications, which are summarized as follows:

2.3.1. Data Envelopment Analysis (DEA). After Charnes and Cooper (1980) introduced DEA into accounting related evaluation, Tomkins et al. [48] apply it to the efficiency evaluation of university departments.

Subsequently, Sherman and Gold [49] and Chen and Yeh [50] use DEA to evaluate the operation efficiency of banks. The evaluation results are divided into two categories: low efficiency and high efficiency. And put forward the path from low efficiency optimization to high efficiency. Boles et al. [51] evaluate the performance of sales staff with DEA. Donthu and Yoo [52] evaluate the production efficiency of retail industry.

However, any random error can be calculated as the efficiency difference by DEA, which will lead to lower average efficiency. This is the deficiency of DEA for evaluation [53].

2.3.2. Key Performance Indicators (KPI). KPI is the basic element of an organization's ability to monitor its strategic health, which helps to ensure the realization of the organization's strategic objectives [54]. Pan and Wei [55] add KPI evaluation index system to the optimization of enterprise business process framework, which accelerates the dynamic structure of the process to quickly adapt to market changes. Trompet et al. [56] compare the performance differences between urban bus operators in maintaining the regularity of high frequency line service with KPI. Chan and Chan [57] use KPI to measure and evaluate the success of construction projects, put forward the views of stakeholders in emerging countries, and evaluate the performance of intermediaries in a specific ITT project [58].

However, the evaluation and improvement of key performance indicators is often a temporary and consultant-driven process, rather than a process using scientific principles [59] .

2.3.3. Balanced Scorecard (BSC). BSC is not only a measurement system, but also a management system, which can achieve long-term strategic goals [60]. Krylov [61]uses BSC in the long-term, medium-term, and short-term management decision-making of distribution activities. Cooper et al. [62] make further research on the extended application of BSC, which is based on the actor network theory (ANT). Akkermans and Oorschot [63] shows that BSC only focuses managers' attention on a few indicators for performance evaluation, which is not conducive to the quality of evaluation.

2.3.4. Segmentation Evaluation. Zhang [64] shows that this kind of evaluation method usually divides the evaluation objects into three groups: analysis group, experience superiority group, and experience difference group for comparative evaluation, and then makes strategies according to the evaluation ability level. Prabha and Kumar [65] makes a comparative study of segmentation evaluation from both objective and subjective aspects and believed that objective evaluation would be more scientific. Wang et al. [66]

evaluate the quality of grouping evaluation methods from two perspectives: unsupervised and supervised.

2.3.5. Multi Criteria Decision Making Method (MCDMM). TOPSIS is a multicriteria evaluation method. It identifies solutions from a limited set of alternatives based on simultaneously minimizing the distance from the ideal point and maximizing the distance from the lowest point [67]. TOPSIS can be used for ranking evaluation [68] and is widely used in supply chain management and logistics [69], human resource management, energy management, water resource management and other fields [70].

Indeed, the general idea of the evaluation method is to compare the efficiency of input and output with the reference or standards. There are many methods for evaluation, and each has its own advantages and disadvantages and adaptability. From the review of the above literature, we can see that there are many research perspectives on low-carbon collaborative innovation. There are also many research papers on evaluation methods. The authors of these papers have contributed a lot to the theoretical development in the field. However, the shortage is that the literature of evaluating the balance of interest distribution of LCCI subjects is relatively scarce.

Therefore, this manuscript focuses on how to evaluate the interest balance of low-carbon collaborative innovation subjects and to make up for the lack of existing theoretical research. In this way, it can fill the shortage of existing evaluation research on the benefit distribution of low-carbon project subjects, and the rational distribution research of project subjects.

We use literature research method [71] and case analysis method [72] to carry out the research. Firstly, we build a theoretical framework model to evaluate the interest balance of the main body, based on the existing literature research and the practice of low-carbon collaborative innovation. Then it is used in specific cases to verify the feasibility of the theoretical model.

3. Theoretical Basis and Research Design

3.1. definition of Related Concepts and Principles

3.1.1. Defining Low-Carbon Collaborative Innovation. The carrier of LCCI is the project, which is the Low-carbon Collaborative Innovation (LCCI). LCCI is a kind of project that firms cooperate with universities, research institutes, and other enterprises to develop new technologies and new processes [73]. In addition to the most important forms of University-Industry Collaborative Innovation, there are also different forms of cooperation between universities and colleges, universities and research institutes, enterprises, and enterprises. Like this, Wu et al. [74] describe the Cooperative innovation Projects(CIP): specific projects in which companies and public research institutions or other companies cooperate to create new technologies, products, materials, systems, or manufacturing processes.

3.1.2. Defining the Subject of LCCI. LCCI is a multiparty cooperation project, including universities (including scientific research institutions), enterprises, governments, and other multibody, which are carried out for scientific and technological innovation or transformation of scientific and technological innovation achievements.

Each participant has different knowledge, culture, resources, technology, and other backgrounds. They have a different understanding of the value of technology and market expectations. Then the subject includes two levels: the subject between subjects and the subject within subjects.

The subject subjects refer to the cooperative members composed of universities, enterprises, and governments. The subject within the subjects refers to the internal members of the university and the internal members of a firm. The main body of the internal universities refers to University Core R & D personnel and general participants. The main body of the internal enterprises refers to firm, key technical personnel, and general participants.

3.1.3. Defining the Interest Balance among the Subjects of LCCI. Referring to the idea of literature [75], the balance of interest distribution among subjects refers to the balance of all interests including all kinds of tangible and intangible interests.

It is only after a comprehensive economic calculation that the payment is equal to the harvest that it can be regarded as achieving equilibrium. Therefore, the balance of interest among the subjects refers to the balance of distribution among all subjects participating in the project cooperation. Therefore, the key point of interest distribution equilibrium is that the interest requirements of each subject can be met.

From the definition of the subject of LCCI, we can see that the interest balance among the subjects of LCCI should include two levels: the balance between subjects and the balance within subjects. Therefore, only when the balance can be achieved between subjects and within the subjects, it means that the profit distribution of LCCI is balanced.

3.2. Determining the Content of Evaluation. If we want to evaluate the effect of interest balance among the subjects of LCCI, we should consider the balance of all participants [76]. This is obvious from the above definition. It includes not only the balance of interest distribution among subjects, but also the balance within subjects. The balance within subjects includes the internal balance of universities and enterprises.

Therefore, according to the above analysis, we determine the evaluation content of interest balance of low-carbon collaborative innovation subjects as shown in Figure 1.

3.3. Construct an Evaluation Index System. The index system is determined according to the evaluation content. Then, the index system to evaluate the benefit balance of LCCI should be divided into three levels.

It includes the interest balance index between subjects and the interest balance index of the internal subjects, which

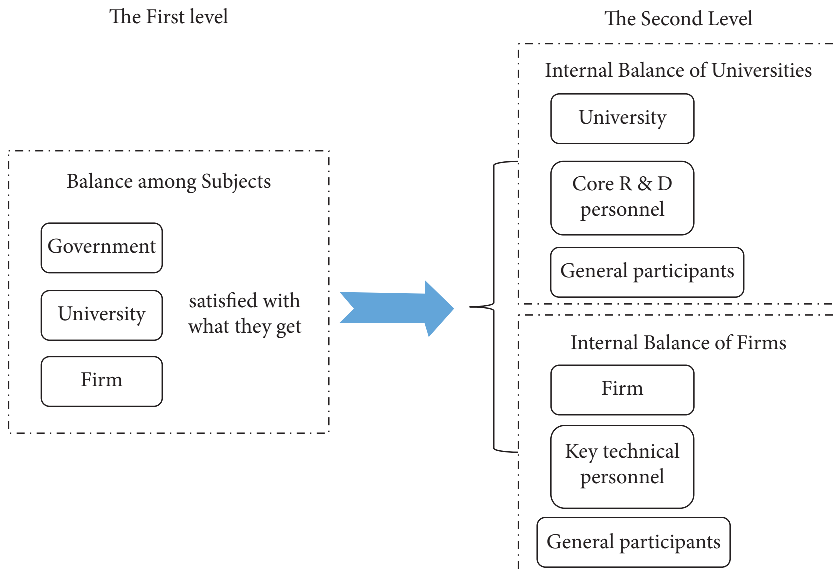

Figure 1: The content of evaluating the balance of benefit distribution of LCCI.

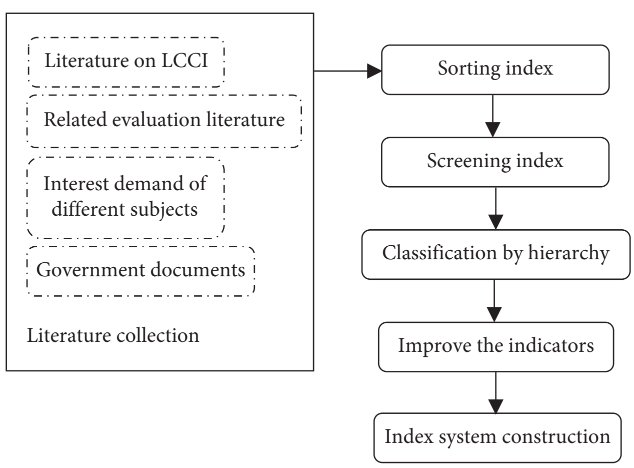

Figure 2: Construction of the benefit balance evaluation index system of LCCI.

includes the internal interest balance index of the university subject and the internal interest balance index of the enterprise subject.

Design the evaluation index according to the following steps. The first is the combination of literature research methods, collecting relevant literature, sorting out the literature, and specific analysis and extraction [77]. The second is based on the project practice survey. Finally, sorting, screening, and determine the final index system.

The specific index system construction process is shown in Figure 2.

Based on the process of Figure 2, the index system for evaluating the interest balance of LCCI is finally constructed as shown in Table 1.

3.4. Determination of Evaluation Method. The evaluation object of this paper is the balance of interest distribution of collaborative innovation project subjects. It includes the balance of interest distribution between subjects and the balance of interest distribution within subjects.

The primary purpose of LCCI is to pursue the maximum of total income, which is the premise to seek the maximum of individual income. This is the principle of balanced distribution [20]. This determines that the evaluation of the main interest's balance is a moderate qualitative description. Therefore, the evaluation method can deal with qualitative analysis more accurately.

Because the index weight of the evaluation index system constructed in the previous paper is unknown. Therefore, the evaluation method is needed to deal with the problem of multiindex and uncertain weight information.

Compared with the evaluation method described above, it is not difficult to determine that TOPSIS evaluation method is more suitable. Therefore, TOPSIS is selected as the specific evaluation method of this paper.

Olson [90] makes a comparative study of different methods for determining weights in TOPSIS and finds that their accuracies for TOPSIS are very close. This shows that the weight determination method in TOPSIS is flexible.

In addition, TOPSIS has the following advantages:

(1) It can ensure the diversity of evaluation data forms and help to build a reasonable evaluation model [91].

(2) There are no strict restrictions on the data distribution and the number of indicators. It has a good effect on processing small sample data and multi-index data. It can also be used for longitudinal and transverse comparison [92].

Therefore, this paper selects TOPSIS for a specific evaluation calculation and then expands the evaluation results in the adjustment link.

Firstly, we construct the mathematical model. And then calculate the weight coefficient and the degree of closeness to

Table 1: Index System of interest balance of LCCI.

Target	First level indicators	Secondary indicators	Assessment element	Evaluation criteria	References
Benefit balance effect among subjects in LCCI	Balance of interests among subjects A	Enhancing regional innovation capability A1	Enhancing regional influence to promote regional development	Satisfaction of improving regional innovation capability	[78]
		Universities get funding A2	The foundation for supporting more theoretical innovation	The satisfaction degree of university funds income	[79]
		The opportunity of training talents in universities A3	Cultivating talents with the combination of theory and practice	Satisfaction with training talents	[31]
		Transformation of knowledge achievements in universities A4	Transforming theory into practice and sublimating theory	Satisfaction with university scientific research achievements	[11]
		Universities enhance their influence A5	Enhance the reputation of the university	Satisfaction with the construction of university reputation	[80]
		Enterprises get technical support A6	Overcome technical problems	Satisfaction with enterprise development	[81]
		Enterprises enhance innovation ability A7	Upgrade the existing core technology and process	Satisfaction with the improvement of enterprise innovation	[82]
		Enterprises are expected to gain more market opportunities A8	Successful cooperation can enter the market earlier	On the satisfaction degree of improving the competitiveness of enterprises	[14]
		Enterprise strategy implementation, competitiveness promotion A9	Enhance the core competitiveness	Satisfaction with the implementation of enterprise strategy	[83]
	The internal interest balance of universities B	Project and funding of the team B1	Project funding income	On the success of team building	[84]
		Improvement of core R & D personnel B1	The increase of core R & D personnel's ability	Satisfaction with ability improvement	[36]
		Commission B3	Increase of funds for core R & D personnel	Satisfaction with the use of funds	[33]
		Get more intellectual property or monograph B4	Number and level of published papers	Satisfaction with scientific research output	[85]
		Accumulation of experience B5	General participants accumulate experience	Satisfaction with experience accumulation	[86]
	The internal interest balance of enterprise C	Increase contacts C1	Value added of network through the project	Satisfaction with resource accumulation	[36]
		Improve management ability C2	Management ability and team building ability improvement	Construction of organizational atmosphere	[87]
		Improving skills is conducive to career development C3	The promotion of the comprehensive ability of the core technical personnel	Improve satisfaction with growth	[88, 89]
		Complete the project and get the reward C4	Project success and reward	Fairness of material reward	[85]
		Complete the assessment task arranged by the organization C5	Complete the task	Salary satisfaction	[33]

complete the evaluation of the collaborative innovation benefit balance.

Based on this evaluation, the variance of closeness degree is calculated, and the variances are sorted. By sorting the variances, we can determine the overall satisfaction of the allocation scheme under different criteria and determine the objects to be adjusted to realize the scheme optimization.

3.5. Optimized TOPSIS Evaluation Idea

3.5.1. Determination of Criteria. According to the designed index system, combined with specific cases, ask experienced experts to make a preliminary score. The design of expert scoring is based on the research idea of right triangle fuzzy function scale proposed in literature [93]. Expert scoring

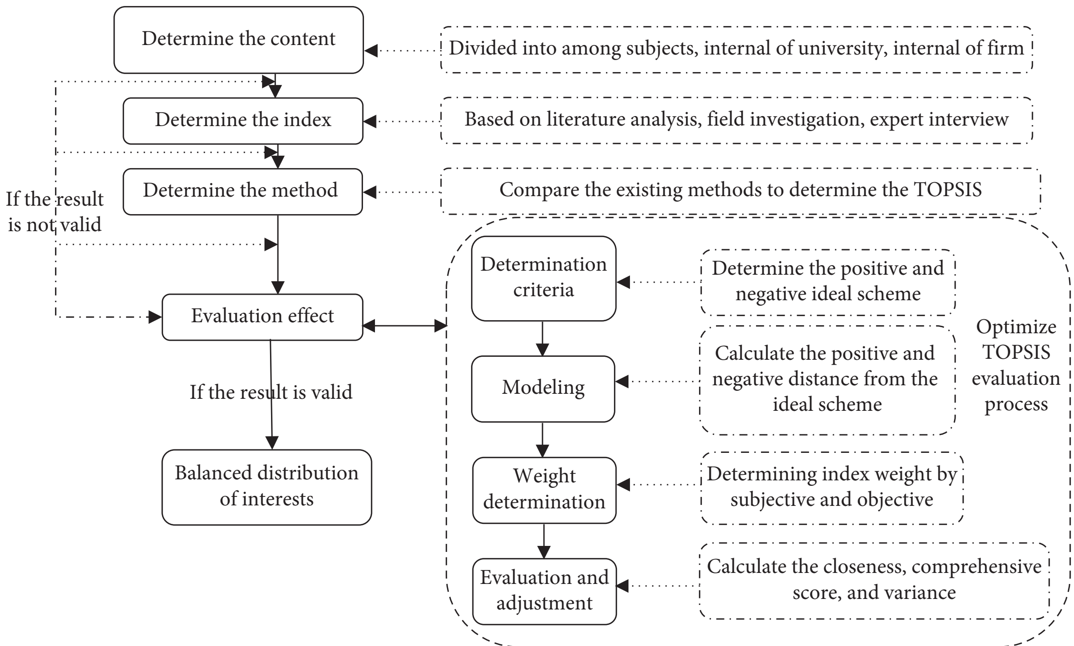

Figure 3: Research theoretical framework for evaluating the balance of main interests of LCCI.

includes lower limits, approximate values, upper limits, membership degree, and nonmember ship degrees.

Then we deal with the expert's score and calculate the ideal scheme and negative ideal scheme. The ideal scheme G^+ refers to the minimum uncertainty and higher degree of excellence under this criterion. The negative ideal scheme G^- refers to the maximum uncertainty and lower degree of excellence under this criterion [94]. The calculation formula is as follows:

$$G = \begin{cases} G^+ = (G_1^+, G_2^+, \ldots, G_n^+), \\ G^- = (G_1^-, G_2^-, \ldots, G_n^-), \end{cases} \tag{1}$$

where

$$\begin{cases} G_j^+ = \left[\left(\max\limits_{1\le i\le m} a_{ij}^U, \max\limits_{1\le i\le m} a_{ij}^V, \max\limits_{1\le i\le m} a_{ij}^L\right); 1, 0\right], j = 1, 2 \ldots, n, \\ G_j^- = \left[\left(\min\limits_{1\le i\le m} a_{ij}^U, \min\limits_{1\le i\le m} a_{ij}^V, \min\limits_{1\le i\le m} a_{ij}^L\right); 0, 1\right], j = 1, 2 \ldots, n. \end{cases} \tag{2}$$

3.5.2. Building Model. Gap D refers to the distance between the evaluation object A_i and the ideal scheme G^+ and the negative ideal scheme G^- [67, 94]. It is given by

$$D = \left\{ D^+ = D_i^+ = \sum_{j=1}^{n} \omega_j D\left(A_{ij}, G_j^+\right), i = 1, 2, \ldots m, D^- \right. = D_i^- = \sum_{j=1}^{n} \omega_j D\left(A_{ij}, G_j^-\right), i = 1, 2, \ldots m. \tag{3}$$

It is not difficult to know from the definition principle that the smaller D_i^+, the better the evaluation effect, and the larger the D_i^-, the better the evaluation effect.

The specific calculation formula of D is based on the formula in reference [95]:

$$\begin{aligned} DA\ , B = \frac{1}{6}\Big\{&\left[(1 + v_a - w_a)u_a^U - (1 + v_B - w_B)u_b^U\right] \\ &+ \left[(1 + v_a - w_a)u_a^V - (1 + v_B - w_B)u_b^V\right] \\ &+ \left[(1 + v_a - w_a)u_a^L - (1 + v_B - w_B)u_b^L\right]\Big\}. \end{aligned} \tag{4}$$

for

$$\begin{aligned} A &= \left[u_a^U, u_a^V, u_a^L, v_a, w_a\right], \\ B &= \left[u_b^U, u_b^V, u_b^L, v_b, w_b\right]. \end{aligned} \tag{5}$$

Using the idea of the integration of subjective and objective weighting method [96] for reference, the index is weighted as follows. The weight coefficient of the optimal criterion is calculated according to the integrated weight principle of the maximum comprehensive evaluation target value. The weight calculation formula is given by

$$\begin{aligned} \omega_j &= \frac{\sum_{i=1}^{m} A_{ij}}{\sum_{j=1}^{n}\sum_{i=1}^{m} A_{ij}}, \\ \sum_{j=1}^{m} \omega_j &= 1, \quad 0 \le \omega_j \le 1. \end{aligned} \tag{6}$$

3.5.3. Discussion of Results. Total considerate closeness d_i[97] and comprehensive score γ_i are calculated by

$$d_i = \frac{D_i^+}{D_i^+ + D_i^-}, \tag{7}$$

$$\gamma_i = d_i * \omega_j. \tag{8}$$

Table 2: Decision matrix transpose matrix of Expert 1.

Index hierarchy	Assessment element	Subject 1 (Government)	Subject 2 (University)	Subject 3 (Enterprise)
Balance of interests among subjects	Enhancing regional influence to promote regional development	[(10,9,7),0.65,0.35]	[(7,5,3),0.74,0.26]	[(6,4,2),0.74,0.26]
	The foundation for supporting more theoretical innovation	[(10,9,7),0.65,0.35]	[(7,5,3),0.74,0.26]	[(6,4,2),0.74,0.26]
	Cultivating talents with the combination of theory and practice	[(10,8,6),0.67,0.33]	[(7,5,3),0.74,0.26]	[(6,4,2),0.74,0.26]
	Transforming theory into practice and sublimating theory	[(10,8,6),0.67,0.33]	[(7,5,3),0.74,0.26]	[(6,4,2),0.74,0.26]
	Overcome technical problems	[(10,9,7),0.65,0.35]	[(7,5,3),0.74,0.26]	[(6,4,2),0.74,0.26]
	Upgrade the existing core technology and process	[(10,9,7),0.65,0.35]	[(7,5,3),0.74,0.26]	[(6,4,2),0.74,0.26]
	Enhance the core competitiveness	[(10,9,7),0.65,0.35]	[(7,5,3),0.74,0.26]	[(6,4,2),0.74,0.26]
		Subject 1 (university)	Subject 2 (main R & D personnel)	Subject 3 (general participants)
The internal interest balance of universities	Project funding income	[(10,9,7),0.65,0.35]	[(8,6,4),0.71,0.29]	[(3,1,1),0.82,0.18]
	The increase of core R & D personnel's ability	[(10,8,6),0.67,0.33]	[(7,5,3),0.74,0.26]	[(4,2,0),0.79,0.21]
	Increase of funds for core R & D personnel	[(9,7,5),0.70,0.30]	[(6,4,2),0.76,0.24]	[(5,3,1),0.77,0.23]
	Number and level of published papers	[(9,7,5),0.70,0.30]	[(7,5,3),0.74,0.26]	[(3,1,1),0.82,0.18]
		Subject 1 (enterprise)	Subject 2 (main technical personnel)	Subject 3 (general participants)
The internal interest balance of enterprise	Value added of network through the project	[(10,8,6),0.67,0.33]	[(10,8,6),0.66,0.34]	[(3,1,1),0.82,0.18]
	Management ability and team building ability improvement	[(8.5,6.5,4.5),0.71,0.29]	[(7.5,5.5,3.5),0.73,0.27]	[(3,1,1),0.82,0.18]
	The promotion of the comprehensive ability of the core technical personnel	[(9,7,5),0.70,0.30]	[(8,6,4),0.71,0.29]	[(4,2,0),0.79,0.21]
	Project success and reward	[(7.5,5.5,3.5),0.73,0.27]	[(6.5,4.5,2.5),0.75,0.25]	[(3,1,1),0.82,0.18]

The comprehensive score value γ_i is ranked from small to large, and the specific value indicates the comprehensive performance of the evaluation object. The smaller the value of d_i, the better the performance of the scheme. After ranking the scores of each subject in different indicators, we can get the satisfaction of different subjects in different indicators. This is the subject's satisfaction with the distribution of interests.

One of the purposes of this paper is to evaluate the balance of interests of the subjects of LCCI. Another one is to put forward the adjustment scheme for the imbalance index of the evaluation results. Therefore, we further study how to determine the adjustment scheme after the completion of the comprehensive score and ranking.

According to the value of d_i, we can judge the satisfaction degree of the relevant subjects to the allocation scheme under the corresponding criteria. However, we cannot judge the overall satisfaction of the allocation schemes under this criterion. We can make a horizontal comparison on the satisfaction of subjects under the same criteria, but we cannot make a vertical comparison between different criteria.

Therefore, according to the idea of variance in specific references [98], the variance of allocation scheme based on population closeness under each criterion is calculated. In this way, the stability of the scheme can be judged. At the same time, the schemes under different criteria are sorted and compared. This is also a longitudinal comparison between different criteria.

The variance s_i^2 is calculated by

$$\overline{d_{ij}} = \frac{\sum_{j=1}^{n} d_{ij}}{n}, \tag{9}$$

$$s_i^2 = \frac{1}{n}\sum_{j=1}^{n}\left(d_{ij} - \overline{d_{ij}}\right)^2. \tag{10}$$

The smaller the variance s_i^2 is, the more stable the interest equilibrium state is under the corresponding criteria. On the contrary, the larger the scale, the more adjustable the space of the interest equilibrium state under the corresponding criteria.

3.6. Research Theoretical Framework. Based on the above analysis, the theoretical framework model for evaluating the benefit balance of LCCI is constructed in Figure 3.

4. Case Study and Analysis

4.1. Background. Taking the LCCI of "development and industrialization of new peach varieties" as the specific case

Table 3: Decision matrix transpose matrix of Expert 2.

Index hierarchy	Assessment element	Subject 1 (Government)	Subject 2 (University)	Subject 3 (Enterprise)
Balance of interests among subjects	Enhancing regional influence to promote regional development	[(9,7,5),0.73,0.27]	[(9,7,5),0.69,0.31]	[(9,7,5),0.69,0.31]
	The foundation for supporting more theoretical innovation	[(8,6,4),0.75,0.25]	[(8,6,4),0.71,0.29]	[(10,8,6),0.66,0.34]
	Cultivating talents with the combination of theory and practice	[(7,5,3),0.77,0.23]	[(10,8,6),0.66,0.34]	[(10,8,6),0.66,0.34]
	Transforming theory into practice and sublimating theory	[(9,7,5),0.73,0.27]	[(9,7,5),0.69,0.31]	[(9,7,5),0.69,0.31]
	Overcome technical problems	[(7,5,3),0.77,0.23]	[(8,6,4),0.71,0.29]	[(10,8,6),0.66,0.34]
	Upgrade the existing core technology and process	[(7,5,3),0.77,0.23]	[(8,6,4),0.71,0.29]	[(10,8,6),0.66,0.34]
	Enhance the core competitiveness	[(8,6,4),0.75,0.25]	[(9,7,5),0.69,0.31]	[(9,7,5),0.69,0.31]
		Subject 1 (university)	Subject 2 (main R & D personnel)	Subject 3 (general participants)
The internal interest balance of universities	Project funding income	[(9,7,5),0.73,0.27]	[(10,8,6),0.66,0.34]	[(8,6,4),0.71,0.29]
	The increase of core R & D personnel's ability	[(9,7,5),0.73,0.27]	[(10,8,6),0.66,0.34]	[(8,6,4),0.71,0.29]
	Increase of funds for core R & D personnel	[(10,8,6),0.70,0.30]	[(10,8,6),0.66,0.34]	[(8,6,4),0.71,0.29]
	Number and level of published papers	[(9,7,5),0.73,0.27]	[(9,7,5),0.69,0.31]	[(8,6,4),0.71,0.29]
		Subject 1 (enterprise)	Subject 2 (main technical personnel)	Subject 3 (general participants)
The internal interest balance of enterprise	Value added of network through the project	[(10,8,6),0.70,0.30]	[(9,7,5),0.69,0.31]	[(7,5,3),0.74,0.26]
	Management ability and team building ability improvement	[(10,8,6),0.70,0.30]	[(9,7,5),0.69,0.31]	[(7,5,3),0.74,0.26]
	The promotion of the comprehensive ability of the core technical personnel	[(9,7,5),0.73,0.27]	[(9,7,5),0.69,0.31]	[(8,6,4),0.71,0.29]
	Project success and reward	[(10,8,6),0.70,0.30]	[(10,8,6),0.66,0.34]	[(8,6,4),0.71,0.29]

of this paper. It is used to verify the feasibility of the theoretical framework model.

Professor A of Z University and his research team rented the experimental base of Z University to cultivate and improve a new peach variety.

The development funds come from the government funded projects applied by Professor A. They initially mastered the cultivation technology of this new peach variety.

After the completion of the laboratory research stage, Professor A and the township garden cooperatives (B small enterprises) carried out the research on expanding the yield of new peach varieties. The purpose is to make the new varieties stable in quality and quantity for a long time.

Enterprise B has ¥800,000 of Industrial Science and technology poverty alleviation fund provided by the government, which is used to develop the local planting industry. It is in S County, Hunan Province, China, which is a poor county.

The initial cooperation agreement is as follows.

(1) Professor A will cooperate with enterprise B on behalf of University Z. The cooperation is divided into three stages.

(2) The trial period is two years, and the land area is 5 mu. Enterprise B paid ¥80000 for research and development. Employ one farmer to plant at the price of 100 yuan per day.

(3) The pilot phase lasted for 3 years, with more than 100 mu of land. The cooperative paid ¥200,000 and employed 10 farmers to grow it.

(4) The stage of large-scale production lasts for 10 years and covers an area of 2,000 mu. Enterprise B pays 1 million yuan (estimated) for research and development, including ¥300,000 in advance for start-up. The number of employed farmers is to be determined(The government gives enterprise B a start-up capital of ¥300,000, and the rest of the capital is bank loans at this stage).

(5) If the new variety cultivation technology is completely successful, the new technology and the expected income generated will be converted into shares, with Z university accounting for 30% and B enterprise accounting for 70%.

Other relevant information in the pilot and pilot stages is as follows:

Table 4: Decision matrix transpose matrix of Expert 3.

Index hierarchy	Assessment element	Subject 1 (Government)	Subject 2 (University)	Subject 3 (Enterprise)
Balance of interests among subjects	Enhancing regional influence to promote regional development	[(10,9,7),0.70,0.30]	[(10,9,7),0.68,0.32]	[(10,8,6),0.74,0.26]
	The foundation for supporting more theoretical innovation	[(10,10,8),0.68,0.32]	[(10,8,6),0.71,0.29]	[(10,9,7),0.71,0.29]
	Cultivating talents with the combination of theory and practice	[(10,10,8),0.68,0.32]	[(10,9,7),0.68,0.32]	[(10,8,6),0.74,0.26]
	Transforming theory into practice and sublimating theory	[(10,9,7),0.70,0.30]	[(10,9,7),0.68,0.32]	[(10,9,7),0.71,0.29]
	Overcome technical problems	[(10,9,7),0.70,0.30]	[(10,9,7),0.68,0.32]	[(10,9,7),0.71,0.29]
	Upgrade the existing core technology and process	[(10,9,7),0.70,0.30]	[(10,9,7),0.68,0.32]	[(10,9,7),0.71,0.29]
	Enhance the core competitiveness	[(10,9,7),0.70,0.30]	[(10,9,7),0.68,0.32]	[(10,9,7),0.71,0.29]
		Subject 1 (university)	Subject 2 (main R & D personnel)	Subject 3 (general participants)
The internal interest balance of universities	Project funding income	[(10,8,6),0.72,0.28]	[(10,8,6),0.71,0.29]	[(8,6,4),0.79,0.21]
	The increase of core R & D personnel's ability	[(10,9,7),0.70,0.30]	[(10,8,6),0.71,0.29]	[(8,6,4),0.79,0.21]
	Increase of funds for core R & D personnel	[(10,9,7),0.70,0.30]	[(10,9,7),0.68,0.32]	[(8,6,4),0.79,0.21]
	Number and level of published papers	[(10,9,7),0.70,0.30]	[(10,8,6),0.71,0.29]	[(8,6,4),0.79,0.21]
		Subject 1 (enterprise)	Subject 2 (main technical personnel)	Subject 3 (general participants)
The internal interest balance of enterprise	Value added of network through the project	[(10,9,7),0.70,0.30]	[(10,8,6),0.71,0.29]	[(10,9,7),0.71,0.29]
	Management ability and team building ability improvement	[(10,9,7),0.70,0.30]	[(10,8,6),0.71,0.29]	[(10,9,7),0.71,0.29]
	The promotion of the comprehensive ability of the core technical personnel	[(10,9,7),0.70,0.30]	[(10,9,7),0.68,0.32]	[(10,9,7),0.71,0.29]
	Project success and reward	[(10,9,7),0.70,0.30]	[(10,9,7),0.68,0.32]	[(10,9,7),0.71,0.29]

(1) 15% of the project management fee. The students who participated in the project received a total of ¥30000 labor allowance.

(2) If the project is successful, the managers of enterprise B will get a bonus of ¥80,000, and the planters will get 30,000 yuan in addition to their daily salary.

We only consider the balance of interest in the pilot and pilot stages because the large-scale production stage is not over.

4.2. Specific Evaluation Process

4.2.1. Establish the Standard of Interest Distribution Balance in LCCI. Drawing on the idea of the literature [93], we invited five experts to set up a panel. They give specific comments on the above evaluation indicators, combined with the actual interests of the main requirements. Then the decision matrix and its transpose matrix are constructed (see Appendix A (Tables 2-6)). We calculate the arithmetic mean decision transpose matrix of five experts (see Appendix B (Table 7)).

According to formulas (1) and (2), the criteria for calculating the equilibrium of interest distribution (i.e., ideal solution and negative ideal solution) in LCCI are shown in Table 8.

4.2.2. Calculate the Distance, Closeness d_i, And the Optimal Weight Coefficient ω_j of Each Index. The total considerate closeness d_i and comprehensive score γ_i were calculated.

According to the distance formula (3), G^+, G^- under each criterion index are calculated. The results are shown in Table 9.

The weight ω_j is calculated according to formula (4). According to formula (5), we calculate the closeness degree d_i. The results are shown in Table 10.

4.2.3. Determine and Rank the Comprehensive Score γ_i. According to formula (8), calculate the comprehensive scores γ_i of each index, and sort them out. The results are shown in Table 11.

It can be seen from Table 11 that the relative closeness degree of the ideal state of income and interest balance of different subjects in LCCI is $\gamma_3 < \gamma_2 < \gamma_1$. This shows that:

(1) In the interest distribution among the subjects, the government has the highest degree of interest realization, followed by universities, and finally enterprises.

(2) In the internal benefit distribution of university, the degree of benefit realization of university is the highest, followed by the core R & D personnel, and finally the general participants.

Table 5: Decision matrix transpose matrix of Expert 4.

Index hierarchy	Assessment element	Subject 1 (Government)	Subject 2 (University)	Subject 3 (Enterprise)
Balance of interests among subjects	Enhancing regional influence to promote regional development	[(10,8,6),0.77,0.23]	[(10,9,7),0.72,0.28]	[(10,8,7),0.74,0.26]
	The foundation for supporting more theoretical innovation	[(10,8,6),0.77,0.23]	[(8,6,4),0.80,0.20]	[(10,9,8),0.71,0.29]
	Cultivating talents with the combination of theory and practice	[(10,8,6),0.77,0.23]	[(8,6,4),0.80,0.20]	[(10,8,6),0.74,0.26]
	Transforming theory into practice and sublimating theory	[(10,9,7),0.75,0.25]	[(8,6,4),0.80,0.20]	[(10,9,7),0.71,0.29]
	Overcome technical problems	[(10,9,7),0.75,0.25]	[(10,9,7),0.72,0.28]	[(7,5,7),0.82,0.18]
	Upgrade the existing core technology and process	[(10,9,7),0.75,0.25]	[(10,9,7),0.72,0.28]	[(7,5,7),0.82,0.18]
	Enhance the core competitiveness	[(10,9,7),0.75,0.25]	[(10,9,7),0.72,0.28]	[(7,5,8),0.82,0.18]
		Subject 1 (university)	Subject 2 (main R & D personnel)	Subject 3 (general participants)
The internal interest balance of universities	Project funding income	[(10,8,6),0.77,0.23]	[(10,8,6),0.75,0.25]	[(6,4,6),0.85,0.15]
	The increase of core R & D personnel's ability	[(10,9,7),0.75,0.25]	[(10,8,6),0.75,0.25]	[(6,4,8),0.85,0.15]
	Increase of funds for core R & D personnel	[(10,9,7),0.75,0.25]	[(10,9,7),0.72,0.28]	[(4,2,6),0.90,0.10]
	Number and level of published papers	[(10,9,7),0.75,0.25]	[(10,8,6),0.75,0.25]	[(3,1,5),0.93,0.07]
		Subject 1 (enterprise)	Subject 2 (main technical personnel)	Subject 3 (general participants)
The internal interest balance of enterprise	Value added of network through the project	[(10,9,7),0.75,0.25]	[(10,8,6),0.75,0.25]	[(7,5,7),0.82,0.18]
	Management ability and team building ability improvement	[(10,9,7),0.75,0.25]	[(10,8,6),0.75,0.25]	[(6,4,7),0.85,0.15]
	The promotion of the comprehensive ability of the core technical personnel	[(10,9,7),0.75,0.25]	[(10,9,7),0.72,0.28]	[(4,2,7),0.90,0.10]
	Project success and reward	[(10,9,7),0.75,0.25]	[(10,9,7),0.72,0.28]	[(5,3,7),0.88,0.12]

(3) In the internal interest distribution of enterprises, the realization degree of the enterprise's interest is the highest, followed by the core technical personnel, and finally the general participants.

5. Discussions

According to the ranking results of the above cases, the total considerate progress of the interest distribution of different levels of subjects and their ideal interest balance state is $\gamma_3 < \gamma_2 < \gamma_1$ in this LCCI.

The specific analysis shows that although the realization degree of interest balance of some subjects is higher than that of other subjects, there is still a gap with the ideal state.

Then, the gap between the ideal state and other subjects with weak realization degree of interest balance is larger. This means that there is a certain degree of imbalance in the distribution of interests in the LCCI.

The imbalance of interest distribution will inevitably lead to the instability of cooperation [99]. The subject who is not satisfied with the distribution of their own interests, can put forward adjustment requirements. Then we need to adjust the plan according to the evaluation results. Thus how to adjust the plan according to the evaluation results? The comparison can be made according to the closeness D in Table 11.

In addition, according to formulas (9) and (10), the variance s_i^2 of each criterion distribution scheme is calculated. And they are sorted by variance. The results are shown in Table 12.

The following conclusions can be drawn from Table 12:

(1) The balance of interest distribution among subjects is the best, followed by the balance within enterprises, and finally the balance within colleges and universities.

(2) Specifically, the three indicators of the optimal distribution equilibrium state are the satisfaction of the main body to cultivate talent, the satisfaction of enterprise strategy implementation, and the satisfaction of enterprise development. The three worst indicators of distribution equilibrium are the satisfaction of the research output, the success of team building, and the satisfaction of the use of funds.

(3) In this case, the key object to be adjusted is the internal distribution of colleges and universities.

After determining the adjustment object, the specific adjustment scheme is determined as follows:

(1) The analysis results are objectively reflected to the corresponding subjects.

(2) Relevant subjects measure the specific distribution scheme and take the corresponding specific adjustment measures.

Table 6: Decision matrix transpose matrix of Expert 5.

Index hierarchy	Assessment element	Subject 1 (Government)	Subject 2 (University)	Subject 3 (Enterprise)
Balance of interests among subjects	Enhancing regional influence to promote regional development	[(10,10,5),0.73,0.27]	[(10,8,3),0.75,0.25]	[(10,9,2),0.66,0.34]
	The foundation for supporting more theoretical innovation	[(8,6,4),0.82,0.18]	[(10,8,3),0.75,0.25]	[(6,4,2),0.80,0.20]
	Cultivating talents with the combination of theory and practice	[(9,7,3),0.80,0.20]	[(10,9,3),0.72,0.28]	[(10,8,2),0.69,0.31]
	Transforming theory into practice and sublimating theory	[(10,9,5),0.75,0.25]	[(10,10,3),0.70,0.30]	[(10,9,2),0.66,0.34]
	Overcome technical problems	[(10,8,3),0.77,0.23]	[(9,7,3),0.78,0.22]	[(10,9,2),0.66,0.34]
	Upgrade the existing core technology and process	[(10,8,3),0.77,0.23]	[(8,6,3),0.80,0.20]	[(10,9,2),0.66,0.34]
	Enhance the core competitiveness	[(7,5,3),0.84,0.16]	[(7,5,3),0.83,0.17]	[(10,10,2),0.63,0.37]
		Subject 1 (university)	Subject 2 (main R & D personnel)	Subject 3 (general participants)
The internal interest balance of universities	Project funding income	[(10,10,5),0.73,0.27]	[(10,10,4),0.70,0.30]	[(10,8,0),0.69,0.31]
	The increase of core R & D personnel's ability	[(10,8,5),0.77,0.23]	[(10,9,3),0.72,0.28]	[(10,10,0),0.63,0.37]
	Increase of funds for core R & D personnel	[(8,6,5),0.82,0.18]	[(10,8,2),0.75,0.25]	[(10,8,0),0.69,0.31]
	Number and level of published papers	[(10,8,3),0.77,0.23]	[(10,9,3),0.72,0.28]	[(9,7,0),0.72,0.28]
		Subject 1 (enterprise)	Subject 2 (main technical personnel)	Subject 3 (general participants)
The internal interest balance of enterprise	Value added of network through the project	[(10,9,6),0.75,0.25]	[(10,8,5),0.75,0.25]	[(9,7,0),0.72,0.28]
	Management ability and team building ability improvement	[(10,9,4.5),0.75,0.25]	[(9,7,3),0.78,0.22]	[(10,8,0),0.69,0.31]
	The promotion of the comprehensive ability of the core technical personnel	[(10,10,5),0.73,0.27]	[(9,7,3),0.78,0.22]	[(10,8,0),0.69,0.31]
	Project success and reward	[(9,7,3.5),0.80,0.20]	[(10,9,2.5),0.72,0.28]	[(8,6,0),0.74,0.26]

(3) Then invite the same experts to reevaluate the adjusted scheme according to the above procedures. Such a cycle, until the adjustment is balanced.

6. Conclusions, Contributions, And Suggestions

6.1. Conclusions and Theoretical Contributions. Based on the characteristics of literature research and practice, this paper first constructs a theoretical framework model to evaluate the interest balance of LCCI. Then, specific cases are selected for application analysis to verify the feasibility of the evaluation model.

Specifically, the innovations of this paper are as follows:

(1) In the evaluation content, besides the interest balance among subjects, the interest balance within subjects is also considered.

(2) TOPSIS is used to evaluate the LCCI. We not only use the closeness degree d_i to compare the equilibrium satisfaction of different subjects under the same criterion horizontally, but also design each criterion based on the variance s_i^2 of closeness degree to compare the satisfaction of the overall allocation scheme under different criteria vertically. Based on the horizontal comparison, we can judge the satisfaction of different subjects to the scheme under the same criteria. Based on the vertical comparison, we can judge the concentration degree of all subjects' satisfaction with the scheme under different criteria. This means that we can judge the difference between the main body and the scheme under the criterion.

This is beneficial to the LCCI, the evaluation of its interest balance, and the application of TOPSIS evaluation method.

Specifically, this paper has the following conclusions and theoretical contributions:

(1) The equilibrium of the benefit of LCCI includes not only the distribution equilibrium among subjects, but also the internal interest balance of the subjects.

Interest balance is not the state of one subject's interest maximization, but the realization of each subject's interest under the whole interest maximization.

This conclusion is consistent with the research conclusions of Ankrah et al. [20] and Patra [46], However, the difference is that this paper not only evaluates the interest balance among subjects, but also evaluates the interest balance within the subjects.

Table 7: Transpose matrix table of expert arithmetic average decision matrix.

Index hierarchy	Assessment element	Subject 1 (Government)	Subject 2 (University)	Subject 3 (Enterprise)
Balance of interests among subjects	Enhancing regional influence to promote regional development	[(9.8,8.6,6),0.72,0.28]	[(9.2,7.6,5),0.72,0.28]	[(9,7.2,4.4),0.71,0.29]
	The foundation for supporting more theoretical innovation	[(9.2,7.8,5.8),0.73,0.27]	[(8.6,6.6,4),0.74,0.26]	[(8.4,6.8,5),0.72,0.28]
	Cultivating talents with the combination of theory and practice	[(9.2,7.6,5.2),0.74,0.26]	[(9,7.4,4.6),0.72,0.28]	[(9.2,7.2,4.4),0.71,0.29]
	Transforming theory into practice and sublimating theory	[(9.8,8.4,6),0.72,0.28]	[(8.8,7.4,4.4),0.72,0.28]	[(9,7.6,4.6),0.70,0.30]
	Overcome technical problems	[(9.4,8,5.4),0.73,0.27]	[(8.8,7.2,4.8),0.73,0.27]	[(8.6,7,4.8),0.72,0.28]
	Upgrade the existing core technology and process	[(9.4,8,5.4),0.73,0.27]	[(8.6,7,4.8),0.73,0.27]	[(8.6,7,4.8),0.72,0.28]
	Enhance the core competitiveness	[(9,7.6,5.6),0.74,0.26]	[(8.6,7,5),0.73,0.27]	[(8.4,7,4.8),0.72,0.28]
		Subject 1 (university)	Subject 2 (main R & D personnel)	Subject 3 (general participants)
The internal interest balance of universities	Project funding income	[(9.8,8.4,5.8),0.72,0.28]	[(9.6,8,5.2),0.71,0.29]	[(7,5,3),0.77,0.23]
	The increase of core R & D personnel's ability	[(9.8,8.2,6),0.73,0.27]	[(9.4,7.6,4.8),0.72,0.28]	[(7.2,5.6,3.2),0.76,0.24]
	Increase of funds for core R & D personnel	[(9.4,7.8,6),0.73,0.27]	[(9.2,7.6,4.8),0.72,0.28]	[(7,5,3),0.77,0.23]
	Number and level of published papers	[(9.6,8,5.8),0.73,0.27]	[(9.2,7.4,4.6),0.72,0.28]	[(6.2,4.2,2.8),0.80,0.20]
		Subject 1 (enterprise)	Subject 2 (main technical personnel)	Subject 3 (general participants)
The internal interest balance of enterprise	Value added of network through the project	[(10,8.6,6.4),0.72,0.28]	[(9.8,7.8,5.6),0.71,0.29]	[(7.2,5.4,3.6),0.76,0.24]
	Management ability and team building ability improvement	[(9.7,8.3,5.8),0.72,0.28]	[(9.1,7.1,4.7),0.73,0.27]	[(7.2,5.4,3.6),0.76,0.24]
	The promotion of the comprehensive ability of the core technical personnel	[(9.6,8.4,5.8),0.72,0.28]	[(9.2,7.6,5.2),0.72,0.28]	[(7.2,5.4,3.6),0.76,0.24]
	Project success and reward	[(9.3,7.7,5.4),0.74,0.26]	[(9.3,7.9,5),0.71,0.29]	[(6.8,5,3.8),0.77,0.23]

The results we obtained further extend the previous literature and show that in the evaluation of the interest balance of LCCI, while evaluating the interest balance among subjects, the interest balance within the subjects should also be evaluated.

Because the internal individual satisfaction of the main body will affect the stability of the cooperation among the main body by affecting the internal stability of the main body. This shows that the evaluation content should be determined comprehensively and hierarchically to carry out the benefit balance evaluation of LCCI.

(2) The interest balance among subjects and within subjects will have different satisfaction with different indicators. It means that the d_i value of different subjects and different indicators is different.

This shows that different subjects have different interests or different motives to participate in LCCI. This is consistent with the conclusions of Beath et al. [25], Freitas and Verspagen [27] and Freitas and Verspagen [27]. However, the difference is that these papers show that not only the motives of the participants are not the same, but also the motives of the internal individuals are not the same. This is an extension of previous studies.

This shows that the research on the subject motivation and interest balance of LCCI should not only consider the motivation among the subjects, but also consider the individual motivation within the subject, as well as the emphasis of the indicators involved.

(3) The distribution of benefits in LCCI includes both tangible benefits that can be measured by money and intangible benefits that are lagging and lack of fixed measurement standards.

Defining the category of interests is one of the bases for the balanced distribution of interests in LCCI. A comprehensive definition of interest is the guarantee for the rational formulation of distribution strategies and the realization of interest balance. This is consistent with the conclusion of Liu [42], Jasmina et al. [40]. However, the difference is that this paper considers the interest, needs, and realization of the government participating in such projects. However, previous studies only considered the conventional interests of universities and enterprises.

Table 8: Positive and negative ideal solutions under each criterion.

Index hierarchy	Assessment element	G^{+}	G^{-}
Balance of interests among subjects	Enhancing regional influence to promote regional development	[(10,10,5),1,0]	[(6,4,2),0,1]
	The foundation for supporting more theoretical innovation	[(10,10,4),1,0]	[(6,4,2),0,1]
	Cultivating talents with the combination of theory and practice	[(10,10,3),1,0]	[(6,4,2),0,1]
	Transforming theory into practice and sublimating theory	[(10,10,5),1,0]	[(6,4,2),0,1]
	Overcome technical problems	[(10,9,3),1,0]	[(6,4,2),0,1]
	Upgrade the existing core technology and process	[(10,9,3),1,0]	[(6,4,2),0,1]
	Enhance the core competitiveness	[(10,10,3),1,0]	[(6,4,2),0,1]
The internal interest balance of universities	Project funding income	[(10,10,5),1,0]	[(3,1,0),0,1]
	The increase of core R & D personnel's ability	[(10,10,5),1,0]	[(4,2,0),0,1]
	Increase of funds for core R & D personnel	[(10,9,5),1,0]	[(5,2,0),0,1]
	Number and level of published papers	[(10,9,5),1,0]	[(3,1,0),0,1]
The internal interest balance of enterprise	Value added of network through the project	[(10,9,6),1,0]	[(3,1,0),0,1]
	Management ability and team building ability improvement	[(10,9,4.5),1,0]	[(3,1,0),0,1]
	The promotion of the comprehensive ability of the core technical personnel	[(10,10,5),1,0]	[(4,2,0),0,1]
	Project success and reward	[(10,9,3.5),1,0]	[(3,1,0),0,1]

For example, the government needs to help the poor and promote regional development in the case of this study. By supporting and promoting the project, the purpose of solving part of the employment problem has been achieved to a certain extent. It can also help enterprises develop, expand, and enhance their influence, to achieve the goal of regional poverty alleviation and regional development.

This shows that the interests of LCCI should be considered completely. We should not only examine the common tangible and intangible interests, but also examine the uncommon, tangible and intangible interests according to the actual situation.

(4) The interest balance of LCCI is a dynamic process and an ideal state. In practice, it is difficult for the subjects to be balanced all time, and most of the time they are unbalanced.

Therefore, scientific and reasonable evaluation is necessary. This can help the subject know the current situation in real time and adjust it. In this way, measures can be taken to reduce the instability of cooperation before the crisis. The degree of satisfaction among the subjects of this study can be calculated by the degree of closeness d_i.

This is consistent with the research conclusions of Lai et al. [67], Liang et al. [97].

However, the difference is that this study also calculates the variance s_i^2 of each criterion based on the closeness degree d_i. The variance is used to rank the distribution schemes under different criteria. To judge and select the criteria with great differences in the subject's attitude towards the scheme and adjust them. This can further optimize the equilibrium state and increase the stability of cooperation.

6.2. Practical Contribution. Combined with the above research conclusions, we can know that the evaluation of the interest balance of LCCI aims to provide an indication for the current interest state of each subject. And the balance of interests is a dynamic and ideal state. The long-term imbalance of interest balance will affect the stability of cooperation and even lead to project failure. Through the evaluation, an appropriate intervention can be carried out to prevent this situation.

Therefore, the following suggestions are put forward for the practice management of LCCI.

(1) Establish a comprehensive and systematic cognitive concept and establish a standard distribution plan and inspection process.

The interest balance of LCCI includes not only the interest balance among subjects, but also within subjects. At the same time, the definition of interest includes not only the common, tangible, and intangible interests, but also the uncommon but practical interests that cannot be ignored.

Therefore, in the management practice, we should establish a comprehensive and systematic cognition and establish a set of standardized inspection process to facilitate different subjects to inspect their own situation and take reasonable actions. To reduce the risk of cooperation failure, we should alleviate contradictions and avoid blind action.

(2) Pay attention to targeted management adjustment, strengthen the protection of vulnerable groups.

Participants have different motivations and interests. And the subjects are in different positions in the project, so the discourse power of subjects will be different.

Therefore, in the practice of LCCI management, we should pay attention to targeted management according to the different interests of different subjects. At the same time, it is easy to be ignored because of the relatively low position of the general participants and technicians in the organizational structure.

Therefore, we should strengthen the protection mechanism of the interests of vulnerable groups, avoid the cooperation in trouble, and ensure the balance of interests.

Table 9: Calculated distances.

Index hierarchy	Assessment element	Subject 1 D_i^+	Subject 1 D_i^-	Subject 2 D_i^+	Subject 2 D_i^-	Subject 3 D_i^+	Subject 3 D_i^-
Balance of interests among subjects	Enhancing regional influence to promote regional development	2.51	5.82	3.13	5.20	3.44	4.89
	The foundation for supporting more theoretical innovation	2.42	5.58	3.25	4.75	3.13	4.87
	Cultivating talents with the combination of theory and practice	2.25	5.42	2.62	5.05	2.73	4.94
	Transforming theory into practice and sublimating theory	2.52	5.81	3.38	4.95	3.38	4.95
	Overcome technical problems	1.79	5.55	2.30	5.04	2.45	4.88
	Upgrade the existing core technology and process	1.79	5.55	2.36	4.98	2.45	4.88
	Enhance the core competitiveness	2.20	5.47	2.64	5.02	2.84	4.83
The internal interest balance of universities	Project funding income	2.57	5.77	2.97	5.36	4.47	3.87
	The increase of core R & D personnel's ability	2.53	5.80	3.13	5.20	4.30	4.03
	Increase of funds for core R & D personnel	2.32	5.68	2.84	5.16	4.13	3.87
	Number and level of published papers	2.31	5.69	2.90	5.10	4.50	3.50
The internal interest balance of enterprise	Value added of network through the project	2.37	5.97	2.84	5.50	4.22	4.11
	Management ability and team building ability improvement	2.10	5.74	2.75	5.08	3.72	4.11
	The promotion of the comprehensive ability of the core technical personnel	2.62	5.72	3.08	5.25	4.22	4.11
	Project success and reward	2.00	5.50	2.26	5.24	3.48	4.02

Table 10: Calculation of d_i and ω_j.

Index hierarchy	Assessment element	d_i Subject 1	d_i Subject 2	d_i Subject 3	ω_j Subject 1	ω_j Subject 2	ω_j Subject 3
Balance of interests among subjects	Enhancing regional influence to promote regional development	0.301	0.376	0.413	0.071	0.068	0.079
	The foundation for supporting more theoretical innovation	0.302	0.406	0.391	0.064	0.059	0.075
	Cultivating talents with the combination of theory and practice	0.293	0.341	0.356	0.063	0.067	0.079
	Transforming theory into practice and sublimating theory	0.302	0.406	0.406	0.069	0.067	0.084
	Overcome technical problems	0.244	0.313	0.335	0.066	0.065	0.077
	Upgrade the existing core technology and process	0.244	0.321	0.335	0.066	0.063	0.077
	Enhance the core competitiveness	0.286	0.345	0.370	0.063	0.063	0.077
The internal interest balance of universities	Project funding income	0.308	0.357	0.536	0.069	0.072	0.055
	The increase of core R & D personnel's ability	0.304	0.376	0.516	0.068	0.068	0.062
	Increase of funds for core R & D personnel	0.290	0.356	0.517	0.064	0.068	0.055
	Number and level of published papers	0.288	0.363	0.563	0.066	0.067	0.046
The internal interest balance of enterprise	Value added of network through the project	0.284	0.340	0.506	0.071	0.070	0.059
	Management ability and team building ability improvement	0.268	0.352	0.475	0.068	0.064	0.059
	The promotion of the comprehensive ability of the core technical personnel	0.314	0.370	0.506	0.069	0.068	0.059
	Project success and reward	0.266	0.301	0.464	0.063	0.071	0.055

(3) Implement flexible management measures and set up a special regulation department.

Interest balance is a dynamic process, so it is necessary to monitor the state of interest distribution in real time, deal with the imbalance crisis in time, and make appropriate adjustments.

Therefore, in the practice of management, we should pay attention to the flexibility of management and set up a special regulatory agency. Timely inspect the realization of the interests of all parties. And feedback to senior management to implement intervention to eliminate the crisis and take precautions.

6.3. Research Prospects. In theory, this paper is based on related research. And the conclusion will contribute to the research of LCCI, benefit distribution, index design, and benefit balance evaluation, which can enrich the theoretical literature in the corresponding fields.

Table 11: Comprehensive sorting results.

Index hierarchy	Assessment element	Subject 1	Subject 2	Subject 3	sort
Balance of interests among subjects	Enhancing regional influence to promote regional development	0.021	0.026	0.033	$\gamma_3 < \gamma_2 < \gamma_1$
	The foundation for supporting more theoretical innovation	0.019	0.024	0.029	$\gamma_3 < \gamma_2 < \gamma_1$
	Cultivating talents with the combination of theory and practice	0.018	0.023	0.028	$\gamma_3 < \gamma_2 < \gamma_1$
	Transforming theory into practice and sublimating theory	0.021	0.027	0.034	$\gamma_3 < \gamma_2 < \gamma_1$
	Overcome technical problems	0.016	0.020	0.026	$\gamma_3 < \gamma_2 < \gamma_1$
	Upgrade the existing core technology and process	0.016	0.020	0.026	$\gamma_3 < \gamma_2 < \gamma_1$
	Enhance the core competitiveness	0.018	0.022	0.029	$\gamma_3 < \gamma_2 < \gamma_1$
The internal interest balance of universities	Project funding income	0.021	0.026	0.030	$\gamma_3 < \gamma_2 < \gamma_1$
	The increase of core R & D personnel's ability	0.021	0.026	0.032	$\gamma_3 < \gamma_2 < \gamma_1$
	Increase of funds for core R & D personnel	0.019	0.024	0.028	$\gamma_3 < \gamma_2 < \gamma_1$
	Number and level of published papers	0.019	0.024	0.026	$\gamma_3 < \gamma_2 < \gamma_1$
The internal interest balance of enterprise	Value added of network through the project	0.020	0.024	0.030	$\gamma_3 < \gamma_2 < \gamma_1$
	Management ability and team building ability improvement	0.018	0.022	0.028	$\gamma_3 < \gamma_2 < \gamma_1$
	The promotion of the comprehensive ability of the core technical personnel	0.022	0.025	0.030	$\gamma_3 < \gamma_2 < \gamma_1$
	Project success and reward	0.017	0.021	0.026	$\gamma_3 < \gamma_2 < \gamma_1$

Table 12: Calculation and ranking of variance of each criterion.

Index hierarchy	Assessment element	$\overline{d_{ij}}$	s_i^2	sort
Balance of interests among subjects	Enhancing regional influence to promote regional development	0.363	0.22%	6
	The foundation for supporting more theoretical innovation	0.367	0.21%	5
	Cultivating talents with the combination of theory and practice	0.330	0.07%	1
	Transforming theory into practice and sublimating theory	0.371	0.24%	7
	Overcome technical problems	0.297	0.15%	3
	Upgrade the existing core technology and process	0.300	0.16%	4
	Enhance the core competitiveness	0.334	0.12%	2
The internal interest balance of universities	Project funding income	0.400	0.96%	14
	The increase of core R & D personnel's ability	0.398	0.78%	11
	Increase of funds for core R & D personnel	0.387	0.91%	13
	Number and level of published papers	0.405	1.34%	15
The internal interest balance of enterprise	Value added of network through the project	0.377	0.89%	12
	Management ability and team building ability improvement	0.365	0.72%	9
	The promotion of the comprehensive ability of the core technical personnel	0.397	0.65%	8
	Project success and reward	0.344	0.74%	10

In practice, this paper selects an actual case to do the evaluation analysis. We carry out the empirical analysis based on a certain number of LCCI. The management suggestions based on the conclusions can boost the management needs of LCCI.

At the same time, the paper also has some limitations and prospects.

(1) The evaluation index of this paper is designed according to the general practice needs of LCCI and related literature.

However, LCCI in practice will have different interests due to different fields.

Therefore, in practice, evaluation evaluators should consider not only the general interest evaluation indexes, but also more special indexes with practical significance.

(2) The case of this paper is a LCCI of agricultural product R & D, in which the subjects are relatively simple.

Among the subjects, there are only government, single university, and single enterprise. In the internal distribution of the subject, only the main managers, core technical personnel, and general participants.

In the actual LCCI, many cooperation subjects are more complex.

For example, the main body of a university may include multiple universities and research institutions. The main body representing an enterprise may include the cooperation of multiple enterprises, and these enterprises may also have different sizes. The size of the enterprise will also have a certain impact on the cooperation [100]. Therefore, in the follow-up research, we can choose LCCI with complex subjects as a case to evaluate the interest balance.

Appendix

A. Decision Matrix of Five Experts

Decision matrix transpose matrixes of Experts 1, 2, 3, 4, and 5 are shown in Tables 2–6, respectively.

B. Expert Arithmetic Means Decision Matrix

Transpose matrix table of expert arithmetic average decision matrix is shown in Table 7.

Data Availability

Data generated or analyzed during the study are available from the corresponding author on request.

Conflicts of Interest

The authors declare no conflict of interests.

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Research Article

The Spatial Spillover Effect of Environmental Regulation and Technological Innovation on Industrial Carbon Productivity in China: A Two-Dimensional Structural Heterogeneity Analysis

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Environmental regulation and technological innovation are two crucial factors for improving industrial carbon productivity. However, prior research ignored the spatial spillover effects of these factors, and heterogeneity caused by industrialization level and resource dependence did not acquire attention either. Thus, we use the STIRPAT model and spatial panel Durbin model to study the spatial spillover effects of two independent variables. Then, a two-dimensional structural heterogeneity analysis is conducted according to the industrialization level and resource dependence. The results are as follows: improving environmental regulation and technological innovation is good for industrial carbon productivity. Simultaneously, there are obvious regional differences under two-dimensional structural heterogeneity. From the perspective of space, industrial carbon productivity has high spatial autocorrelation, and it can be enhanced through local environmental legislation, as well as technological innovation. Environmental regulation's spatial spillover impact inhibits the improvement of industrial carbon productivity in surrounding provinces, resulting in a pollution haven effect. However, there is no evident regional spillover effect of technological innovation. Therefore, we provided new perspectives from spatial spillover and structural heterogeneity to optimize low-carbon policies.

1. Introduction

As a large amount of greenhouse gas emissions has been produced, global warming has caused frequent occurrences of extreme weather. Therefore, alleviating global climate change and reducing greenhouse gas emissions have become urgent issues. To mitigate climate change, China regarded carbon neutrality as an important part of ecological progress and promised to reach carbon neutrality by 2060. However, according to data released by the International Energy Agency [1], nearly 60 percent of global emissions were from China in 2016, and the industrial sector is the main source, consuming 67.9 percent of China's energy and emitting 83.1 percent of carbon dioxide [2]. Thus, reducing industrial carbon emissions is crucial to achieving China's commitment, and a big challenge for China is how to reduce industrial carbon dioxide emissions while achieving sustainable economic development. Exactly, industrial carbon productivity is the embodiment of CO_2 reduction and economic growth. Improving carbon productivity reflects an important effort to achieve China's commitment to carbon reduction and global climate change strategy.

Carbon productivity, the ratio of GDP output to carbon dioxide, was put forward by Kaya and Yokobori [3]. Considering the high pollution attribute of industrial industry, it is extended as the output level of industrial added value per unit of industrial carbon dioxide, which refers to industrial carbon productivity [4]. To improve industrial carbon productivity, it is necessary to explore its influencing factors. Porter's hypothesis, a classical theory, exactly gave us an appropriate framework to analyze such an issue. Porter's hypothesis describes the relationship between environmental regulation, technological innovation, and enterprises' productivity [4]. It is considered that environmental regulation gives a driving force to technological innovation and finally improves the productivity of enterprises. However, due to the existence of industrial pollutants, such as CO_2, how to improve green total factor productivity (GTTP) of enterprises has been a new topic under Porter's hypothesis framework. Many researches have discussed the effect of environmental regulation on GTTP [5, 6]. The result shows that, in the long run, environmental regulation would achieve the win-win goal for enterprise competitiveness and environmental protection. And technological innovation is also regarded as a driven factor of GTTP in some regions [7–9]. Therefore, we bring environmental regulation, technological innovation, and industrial carbon productivity into a framework, studying its impact mechanism to reduce industrial carbon emissions and promote high-quality industrial development. In addition, due to the imbalances of industrialization level and resource endowment, environmental regulation and technological innovation might generate different effects in different regions [10, 11]. With the continuous propulsion of industrialization, there is an obvious phenomenon that industrial development in some provinces mainly relies on natural resources. This may induce industry structure change and economic agglomeration [12, 13], and the economic agglomeration will accelerate carbon emissions in turn [14]. Therefore, we further explored two-dimensional structural heterogeneity caused by industrialization level and resource dependence when studying the driving factors. Meanwhile, the influence of two independent variables on industrial carbon productivity may spill over to the surrounding areas. Based on such consideration, we dug into the spatial agglomeration characteristics and spatial spillover effects of them.

The contributions of this study are as follows. First, according to Porter's hypothesis, this paper integrated environmental regulation, technological innovation, and industrial carbon productivity into a framework to analyze their relationship. And when analyzing spatial spillover effects, we adopted an improved STIRPAT model and Spatial Durbin model to carry through. Secondly, three different spatial matrices are creatively used to ensure robustness when discussing spatial spillover effects. Finally, to investigate the heterogeneity, 30 provinces in China are divided into four quadrants based on the two-dimensional structural heterogeneity analysis of industrialization level and resource dependence.

The rest of the sections are as follows: literature about industrial carbon productivity, environmental regulation, and technological innovation is reviewed in Section 2. Section 3 states the econometric model, index of variables, and data source. Section 4 presents the empirical analysis and related discussions. Section 5 gives a conclusion for the paper and offers some suggestions.

2. Literature Review

We mainly review the literature from the following three aspects. Firstly, as for the relationship between environmental regulation and industrial carbon productivity, we summarized three conclusions: (1) environmental regulation stimulates carbon productivity, which was the innovation compensation effect. Environmental regulation with appropriate intensity can induce the driving force of technological innovation, cover the compliance cost caused by environmental regulation, and finally realize the double dividend of economy and environment. For example, Wu et al. [15] believed that environmental regulation effectively restricted and controlled the growth of carbon emissions in central and eastern China. Li et al. [16] found that the disclosure of pollution information transparency index (PITI) has significantly improved the environmental quality of Chinese cities. Yang et al. [17] discussed that carbon trading policies can effectively reduce carbon emissions at a provincial level in China. (2) Environmental regulation decreased carbon productivity, namely, compliance cost effect. For example, Jensen et al. [18] found that declaring climate policy would stimulate energy demand and accelerate carbon emission. Zhang et al. [19] confirmed that because of local fiscal decentralization, environmental regulation policies did not work to reduce carbon emission. (3) There is not only a linear relationship between them. Many factors will change the effect of environmental regulation, and carbon productivity will give a different response to it [20]. For instance, Munasinghe [21] pointed out that appropriate environmental regulation would reduce the radius of the inverted U-shaped curve and even reach the peak earlier. Yin et al. [22] also found that if conducting stricter environmental regulations, the inflection point of carbon emissions might be achieved forward. They all believed that enhancing environmental regulation was helpful to reach the peak of carbon emission in advance. But the impact of environmental regulations on industrial carbon productivity did not receive much attention.

Secondly, there are the following views about technological innovation and industrial carbon productivity: (1) To improve carbon productivity, technological innovation might be the key. Li et al. [23] believe that technology gradually plays a dominant role in the growth of total factor industrial carbon productivity. Long et al. [24] verified that technological progress significantly improved industrial carbon productivity. Cheng et al. [25] showed that technological innovation can effectively reduce carbon emissions with significant heterogeneity and asymmetry. (2) Technological innovation may reduce carbon productivity. The rebound effect of energy explains that technological innovation may not reduce carbon emissions. The reason is that technological innovation will increase productivity. To replace labor and capital investment in production activities, increased productivity may lead to more energy consumption and carbon emissions [26]. Mizobuchi [27] extended the research of Brännlund et al. [28] and calculated the rebound effect with Japanese household data, concluding that the rebound range was about 27%. Lin and Du [29] confirmed that, in China, the rebound effect of energy was between 30% and 40%. Most researches about the rebound effect take carbon emission as the main object, while little attention is paid to industrial carbon productivity.

Thirdly, we notice the effect of resource dependence and industrialization level on industrial carbon productivity. Auty and Mikesell [30] first proposed the concept of resource curse when they studied economic development in countries with more mines. Compared with countries owning a few resources, the countries with abundant natural resources tended to develop slowly. Many scholars verified and confirmed the existence of the resource curse [31]. Some studies even pointed out that abundant natural resources (especially oil) harmed manufacturing and limited its prospect of economic growth [32, 33]. In China, different provinces have diverse resource endowments. Some provinces have formed an economic model relying on the comparative advantages of mineral resources. As a result of economies of scale, learning effect, coordination effect, adaptive effect, and vested interests, resource-based provinces have formed path dependence [34]. Such provinces constantly insist on the inherent development mode and maintain the high-carbon development path with high energy consumption. Thus, regions with high resource dependence have significantly different impacts on carbon productivity compared with other regions. Government departments will formulate policies to regulate the economic activities of mining enterprises and adopt stricter environmental regulations in mining areas with rich resources to protect the ecological environment, maintain ecological balance, and improve industrial carbon productivity. Additionally, different conditions of economic development will cause different driving forces on the industrialization level in each region. The improvement of the industrialization level will increase air pollutants [35]. Therefore, the level of industrialization has an impact on the formulation of regional environmental regulations and the evolution of technological innovation. Obviously, the eastern part of China has a higher level of industrialization, more flexible environmental regulation policies, and more active technological innovation. Therefore, regional differences in industrialization level may affect the development level of environmental regulation and technological innovation, leading to differences in industrial carbon productivity. In a word, the degree of resource dependence and industrialization in different regions produces heterogeneity for environmental regulation and technological innovation. And they may further cause a heterogeneous impact on industrial carbon productivity.

To sum up, many scholars have conducted fruitful studies on environmental regulation, technological innovation, and carbon emissions. However, there are still some shortcomings. Firstly, many works of literature only pay attention to a single target of environmental regulation, without considering economic and carbon reduction targets simultaneously. Most of them only verify the impact of environmental regulation on carbon intensity or total factor productivity, rather than industrial carbon productivity. Secondly, existing literature mostly adopts the geographical administrative division method to consider regional heterogeneity. Few studies consider the heterogeneous effects of industrialization levels and resource dependence on industrial carbon productivity in different regions. Finally, to estimate the spatial spillover effect, most studies choose a geographic adjacency matrix, instead of geographical distance matrices based on the inverse of the highway mileage or its squared. And fewer papers verify the robustness of the results through multiple spatial weight matrices.

3. Methodology and Data

3.1. STIRPAT Model. To sum up, many scholars have conducted fruitful studies on environmental regulation, technological innovation, and carbon emissions. However, there are still some shortcomings. Firstly, many works of York et al. [36] proposed the STIRPAT model, and this paper introduced environmental regulation into it so that we can explore environmental regulation, technological innovation, and industrial carbon productivity [37]. The improved STIRPAT model is formula (1).

$$\ln \mathrm{ICP}_{it} = \alpha_0 + \beta_1 \ln \mathrm{ERI}_{it} + \beta_2 \ln T_{it} + \gamma \mathrm{Contr}_{it} + \eta_i + \lambda_t + \varepsilon_{it}. \tag{1}$$

As shown in model (1), the dependent variable lnICP is industrial carbon productivity. lnERI stands for environmental regulation and lnT stands for technological innovation. Subscript i refers to provinces, and t represents year. β_1 and β_2 are the coefficients of environmental regulation and technological innovation, respectively. Contr refers to control variables, which specifically are foreign direct investment level (FDI), the structure of energy consumption (ECS), and population size (lnPS). ε denotes error term, η represents individual effects, and λ denotes time effects.

3.2. Spatial Durbin Model. To explore the spatial spillover effect, we add spatial weight matrices based on model (1) to construct a spatial panel Durbin model as shown in model (2).

$$\begin{aligned} \ln \mathrm{ICP}_{it} &= \alpha_0 + \rho \sum_{j=1}^{n} W_{ij} \ln \mathrm{ICP}_{it} + \gamma_1 \sum_{j=1}^{n} W_{ij} \ln \mathrm{ERI}_{it} + \gamma_2 \sum_{j=1}^{n} W_{ij} \ln T_{it} \\ &\quad + \beta_1 \ln \mathrm{ERI}_{it} + \beta_2 \ln T_{it} + \gamma_3 \sum_{j=1}^{n} W_{ij} \mathrm{Contr} + \gamma \mathrm{Contr}_{it} + \eta_i + \lambda_t + \varepsilon_{it}, \end{aligned} \tag{2}$$

where ρ is the spatial autoregressive coefficient of ln ICP. γ_1 and γ_2 are the spatial lag coefficients of independent variables, respectively. W_{ij} represents the spatial weight matrix which is constructed in three ways. A binary contiguity matrix is built following the principle of the geographic adjacent relation (W_1). Another method of establishing spatial weight matrix is based on geographical distance according to the reciprocal of highway mileage between provincial capitals (W_2). Moreover, we further build the inverse squared distance matrix using highway mileage (W_3) for robustness. The specific forms of the three matrices are as follows, where d_{ij} is the highway mileage between provincial capitals i and j:

$$W_1 = \begin{cases} 0, & \text{if } i \text{ and } j \text{ are adjacent}, \\ 1, & \text{if } i \text{ and } j \text{ are not adjacent}, \end{cases} \tag{3}$$

$$W_2 = \begin{cases} \dfrac{1}{d_{ij}}, & i \neq j, \\ 0, & i = j, \end{cases} \tag{4}$$

$$W_3 = \begin{cases} \dfrac{1}{d_{ij}^2}, & i \neq j, \\ 0, & i = j. \end{cases} \tag{5}$$

It should be noted that a spatial regression model based on point estimation will generate bias [38]. Due to spatial correlation, coefficient estimates of explanatory variables do not represent true spillover effects. But we can use the partial derivative method to obtain its direct effect and indirect effect. Therefore, the SDM model can be converted into formula (6), and the partial differential equation matrix of explanatory variables is shown as formula (7) [39].

$$Y_t = (1 - \rho W)^{-1} (\beta X_t + \phi W X)^{-1} + (1 - \rho W)^{-1} \varepsilon_t, \tag{6}$$

$$\frac{\partial Y}{\partial X_{it}} \cdots \frac{\partial Y}{\partial X_{Nt}} = (1 - \rho W)^{-1} \begin{bmatrix} \beta_k & W_{12}\lambda_k & \cdots & W_{1N}\lambda_k \\ W_{21}\lambda_k & \beta_k & \cdots & W_{2N}\lambda_k \\ \cdots & \cdots & \ddots & \vdots \\ W_{N1}\lambda_k & W_{N2}\lambda_k & \cdots & \beta_k \end{bmatrix}. \tag{7}$$

3.3. Index of Variables. Industrial carbon productivity (ICP): we measured it through the ratio of industrial added value to industrial carbon dioxide emissions. However, China's central government does not currently publish direct data on carbon dioxide emissions. Thus, it needs to be calculated through the physical consumption of the energy mix. The calculation method is formula (8), which contains nine energy sources such as raw coal, kerosene, crude oil, gasoline, diesel, fuel oil, coke, natural gas, and electricity.

$$\mathrm{CE}_{i,t} = \sum_{r=1}^{9} En_{i,r,t} \times S_r \times F_r \times \frac{44}{12}, \tag{8}$$

where $CE_{i,t}$ indicates the industrial CO_2 emissions of province i in year t. $En_{i,r,t}$ denotes the energy consumption and the energy type is r. S_r stands for the reference coefficient of all energy standard coals provided in China Energy Statistical Yearbook [40] (Table 1). F_r is the carbon emission coefficient of China published by the Chinese Academy of Sciences (Table 2) [41]. Finally, the regional industrial CO_2 emissions are calculated in units of 10,000 tons.

Environmental regulation intensity (ERI): currently, there is no uniform standard to measure environmental regulation. It is more common to regard the expenditure of pollution treatment and control for unit output, policy quantities, pollutant emissions, and per capita income as indicators of environmental regulation [42]. Dasgupta et al. [43] proposed that the national income level was highly correlated with environmental regulation. Through the correlation coefficient, Xu [44] tested that the severity of environmental regulations is endogenously determined by income level. Thus, in this study, we choose per capita disposable income to measure environmental regulation.

Technological innovation (TE): as a key to achieving carbon peak and carbon neutrality in China, technological innovation is important for high-quality economic development. Existing studies usually adopt the number of patents as an indicator to stand for technical level and technological innovation ability [45]. Considering the availability of data, effective invention patents of industrial enterprises above designated size are used to measure technological innovation.

Foreign direct investment (FDI): using the ratio of actual utilization of foreign direct investment to GDP, foreign direct investment in each province was measured. The actual utilization of foreign direct investment is converted from dollars to RMB according to the exchange rate.

Population size (PS): the population size is considered to be constant in a short time. Thus, the population size is taken as the control variable, and the number of populations in each province is regarded as its indicator. Meanwhile, to avoid the heteroscedasticity problem, the population is processed in a logarithm.

Energy consumption structure (ECS): it is measured by the proportion of coal consumption in total energy consumption. It directly reflects carbon content in each energy. Calculating formulas are as follows:

$$\mathrm{CC} = En_{1,i,t} \times S_1, \tag{9}$$

$$\mathrm{EC} = \sum_{r=1}^{9} En_{r,i,t} \times S_r, \tag{10}$$

where CC is coal consumption, EC is the total energy consumption, and the sign of various energy consumption of each province is $En_{i,r,t}$. S_r is the standard coal conversion coefficient of each kind of energy source. $r = 1$ means that the energy variety is raw coal. According to equations (9) and

Table 1: The standard coal conversion coefficient of energy mix.

Energy mix	Convert units	The standard coal conversion coefficient
Raw coal	ton	0.7143
Gasoline	ton	1.4714
Fuel oil	ton	1.4286
Coke	ton	0.9714
Kerosene	ton	1.4714
Natural gas	104 m^3	13.3
Crude oil	ton	1.4286
Diesel	ton	1.4571
Electricity	104 kw·h	1.229

Table 2: Carbon emission coefficient of energy mix.

Energy mix	Convert units	Carbon emission coefficient
Raw coal	ton	0.7476
Coke	ton	0.1128
Crude oil	ton	0.5854
Gasoline	ton	0.5532
Kerosene	ton	0.3416
Diesel	ton	0.5913
Fuel oil	ton	0.6176
Natural gas	10^4 m^3	0.4479
Electricity	10^4 kw·h	2.2132

(10), a calculation formula of the energy consumption structure could be derived as shown in the following:

$$\mathrm{ECS} = \frac{En_{1,i,t} \times S_1}{\sum_{r=1}^{9} En_{r,i,t} \times S_r}. \tag{11}$$

3.4. Data Source. In this paper, data of 30 provinces and autonomous regions in 2004–2016 are all collected from yearbooks and databases. But because of the availability of data, Taiwan, Hong Kong, Macao, and Tibet are excluded from our sample. Per capita disposable income of residents, industrial added value, GDP in each province, and the population size are collected in the China Statistical Yearbook (2005–2017) [46]. Energy consumption structure and the CO_2 emission are calculated according to 9 kinds of energy in China Energy Statistical Yearbook (2005–2017) [47]. Effective invention patents of industrial enterprises are in the Science and Technology Statistical Yearbook of China (2005–2017) [48]. Actual utilization of foreign direct investment is taken from Wind Database.

4. Empirical Result

4.1. The Trend of Industrial Carbon Productivity Change. Figure 1 depicts the developing trend of GDP and industrial carbon productivity in China. Obviously, from 2004 to 2016, industrial carbon productivity generally shows a steady rising trend. And it increased from 67,716 yuan/ton to 142,271 yuan/ton with an increased rate of 110%. However, the trend of industrial carbon productivity is flat from 2008 to 2009. And after that, there is a sharp increase. We inferred that it may be accounted for by the global crisis. From 2014 to 2016, China's economic growth is stable, but the growing trend of industrial carbon productivity slows down. Beijing, Tianjin, Shanghai, Guangdong, and other economically developed provinces show a significant increasing trend, while Heilongjiang, Yunnan, Ningxia, and Xinjiang provinces decrease. It is noteworthy that the industrial carbon productivity in 2016 is higher than in 2004 in Shanxi, Inner Mongolia, Liaoning, Hainan, Gansu, and Qinghai provinces. But in recent years, it has been decreasing obviously. The decline of industrial carbon productivity in these provinces is probably influenced by resource dependence and industrialization levels.

4.2. Results of the Nonspace Panel Model. Variance Inflation Factor (VIF) analysis, one index to exampling multicollinearity between variables, is required before estimating regression coefficients (Table 3). Table 3 shows that VIF values of all variables range from 1.1 to 5.58, with an average of 2.95. All the VIF values of each variable are smaller than 10, which indicates that there is no multicollinearity between variables.

Based on the econometric model (5), we conduct empirical tests using different methods. As shown in Table 4, the outcome of the Hausman test shows that we need to reject the null hypothesis, which means that, in our study, a fixed-effects model is more appropriate. According to the Bayesian Information Criterion (BIC), we find that the value of BIC in column (2) is smaller. It means that the explanatory power of column (2) is fitting better. Besides, the core explanatory variables of column (2) are significant at a 1% significance level. Therefore, we select the individual fixed effect model to analyze and explain the results.

When only considering the effect of two independent variables, environmental regulation and technological innovation are both significantly positive. It can be concluded that environmental regulation positively relates to industrial carbon productivity, which is similar to technological innovation. The results show that environmental regulation and technological innovation have strong positive effects on industrial carbon productivity. After adding control variables one by one, we can get the same conclusion. But the influence of environmental regulation is greater than technological innovation by comparing the coefficient of two variables. Specifically, for every 1% increase in environmental regulation intensity, the dependent variable will increase by 0.512%. While if technological innovation increases by 1%, industrial carbon productivity will only increase by 0.0795%. This implies that the current level of technological innovation does not have an effective promotion effect on industrial carbon productivity. Hence, stringent environmental regulation contributes more to the improvement of industrial carbon productivity than other means. But as an important way for sustainable development, technological innovation cannot be ignored. For control variables, FDI is significantly positive at the 1% significance level, while ECS is significantly negative. This means that we should expand foreign direct investment to improve industrial carbon productivity and get off overreliance on coal consumption as soon as possible.

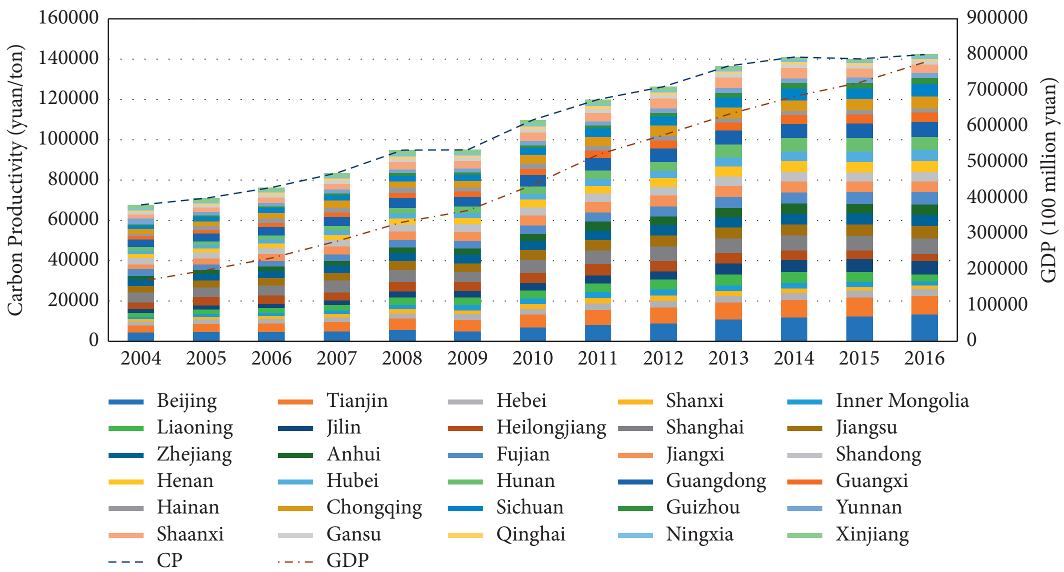

Figure 1: The trend of industrial carbon productivity and GDP in China.

Table 3: Variance inflation factor analysis of the variables.

Variable	LnTE	LnERI	LnPS	ECS	FDI	Mean VIF
VIF	5.58	3.98	2.67	1.42	1.10	2.95

4.3. Two-Dimensional Structural Heterogeneity Analysis. The term resource-based industry has been focused on and used widely in recent years, but there is not a uniform definition for it. At present, the resource-based industry in a narrow sense refers to the mining of minerals and the primary processing of minerals [5]. Considering the availability of data, we determined 11 resource-based industries according to the narrow concept mentioned above as shown in Table 5. Based on the existing research, we measure each province's resource dependence through the proportion of resource-based industrial employees in all industrial employees. If the proportion is more than 40%, the province will be defined as a province with high resource dependence. Figure 2 shows the proportion of resource-based industrial employees in all industrial employees in 2015 in each province. And Hebei, Shanxi, Heilongjiang, Guizhou, Gansu, Yunnan, Ningxia, Shaanxi, Inner Mongolia, Qinghai, and Xinjiang provinces can be assigned to provinces with high resource dependence.

Besides, per capita GDP, industrialization rate (the ratio of industrial added value to GDP), industrial structure, employment structure, and urbanization rate are international indicators for measuring the industrialization level. In this paper, we adopt the ratio of industry sector value added in GDP to measure the industrialization level according to Xu and Lin [49]. 30 provinces and autonomous regions in China are divided into two parts by the average annual ratio of industrialization rate from 2004 to 2016.

Finally, from the two-dimensional structure of industrialization level and resource dependence, 30 provinces and autonomous regions in China are divided into 4 quadrants. As shown in Figure 3, Region I represents the provinces with high industrialization levels and high resource dependence. Region II includes the provinces with high industrialization levels and low resource dependence. Region III shows the provinces with low industrialization levels and low resource dependence. Region IV represents the provinces with low industrialization levels and high resource dependence. According to the division, we test this study by subgroups.

4.3.1. Results of Heterogeneity Analysis. Based on the regional division above, this section further considers regional heterogeneity. And the estimated results of subgroups are shown in Table 6. The results of column (1) show the regression outcome of provinces in Region I. We can find that resource dependence and industrialization level change effects of independent variables. In these provinces, environmental regulation is significantly positive, while technological innovation is not significant. That is probably because the economic development in such provinces is highly dependent on coal and other fossil resources. The inherent path dependence will easily lead to the neglect of cultivating technology innovation ability, and then it will hinder the breakthrough in the core technology of carbon emission reduction. As a result, to combat climate change, the government will formulate the economic activities of industrial enterprises through environmental regulations rather than technological innovation. To enhance industrial carbon productivity, strengthening environmental regulation will be the dominant way in such provinces.

Column (2) indicates Region II with low resource dependence and high industrialization level, and column (3) indicates Region III with low resource dependence and low industrialization level. The results of these two columns both show the significant impact of environmental regulation at 1% level. Enhancing environmental regulation intensity can restrain the extensive carbon emission effectively. But provinces in Region II are mostly located in eastern China,

Table 4: Regression results of the nonspace panel model.

	(1) OLS	(2) Individual fixed effect	(3) Time fixed effect	(4) Double fixed effect	(5) Random effect
LnERI	0.625*** (7.89)	0.512*** (8.84)	0.740*** (6.82)	0.208 (1.40)	0.467*** (8.32)
LnTE	0.0725*** (3.42)	0.0795*** (5.31)	0.0515 (1.89)	0.0286 (1.13)	0.0774*** (5.13)
FDI	0.0912*** (10.42)	0.0386*** (3.62)	0.0904*** (8.54)	0.0379*** (3.66)	0.0513*** (5.13)
ECS	−0.00202 (−1.42)	−0.00937*** (−6.68)	−0.00107 (−0.71)	−0.00824*** (−5.10)	−0.00832*** (−6.05)
LnPS	0.230*** (6.64)	−0.656** (−2.69)	0.248*** (6.23)	−0.653** (−2.70)	0.198** (2.85)
_cons	−0.576 (−0.71)	8.034*** (4.57)	−1.686 (−1.60)	11.27*** (5.63)	1.534* (2.02)
Obs	390	390	390	390	390
R^2	0.719	0.916	0.728	0.924	
F/Wald	196.0	113.2	58.55	90.64	786.15
BIC	234.5	−62.04	292.8	−31.50	.
Hausman test		29.32 [0.0000]			

Note: the value in the parenthesis is the t-statistic or z-statistic; *, **, and *** denote 10%, 5%, and 1% significance level, respectively.

Table 5: The list of resource-intensive industries.

Type	Resource-intensive industries
Mining	Oil and gas exploitation industry Ferrous metal mining and dressing industry Nonferrous metal mining and dressing industry Coal mining and washing industry Nonmetallic mining and dressing industry
Primary processing industry	Nonmetallic mineral products industry Petroleum processing, coking, and nuclear fuel processing Ferrous metal smelting and rolling processing industry Metal products industry Nonferrous metal smelting and rolling processing industry Electricity and heat production and supply

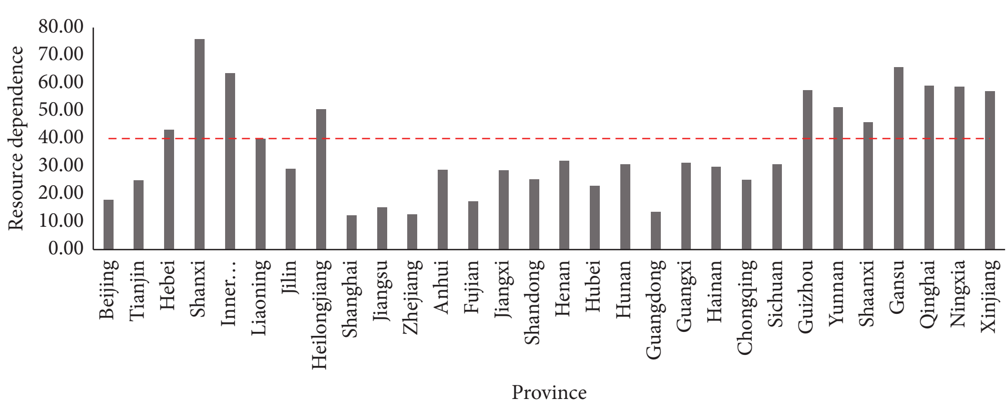

Figure 2: The proportion of resource-intensive industrial employees in all industrial employees.

and they are all in the late stage of industrialization. They finished the transfer of heavy industry with high emissions and their technological innovation capabilities were stronger than the central and western provinces. As a consequence, in Region II, technological innovation could offer a significant impact. However, for the provinces in Region III, its impact is not significant. This is because the provinces with low resource dependence and low industrialization levels are all in central and western China except Beijing and Shanghai. In these provinces, the holistic capacity of innovation is

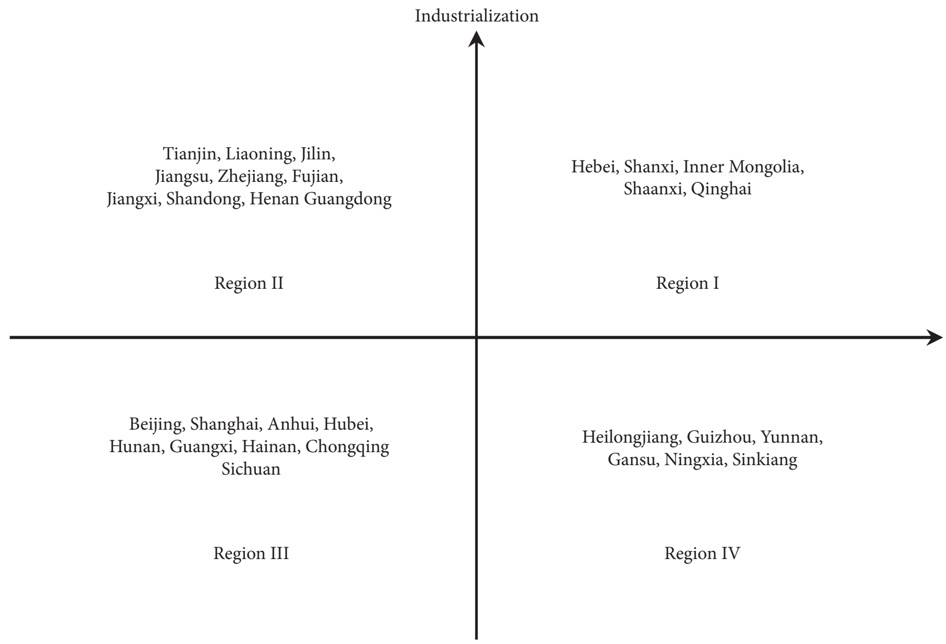

Figure 3: Regional division based on the two-dimensional structure.

Table 6: Results of heterogeneity analysis.

	(1) Model I	(2) Model II	(3) Model III	(4) Model IV
LnERI	0.752***	0.450***	0.779***	0.0889
	(7.81)	(5.83)	(8.56)	(0.68)
LnTE	0.00872	0.122***	0.0242	0.182***
	(0.33)	(5.42)	(1.22)	(4.48)
FDI	0.0146	0.0394***	0.0774***	−0.00607
	(0.65)	(4.22)	(3.61)	(−0.09)
ECS	−0.00519*	−0.00368*	−0.0206***	−0.00878*
	(−2.58)	(−2.38)	(−8.87)	(−2.22)
LnPS	−1.406	−0.105	−0.635	−5.467***
	(−1.35)	(−0.41)	(−1.84)	(−6.63)
_cons	13.30	3.834*	5.846*	51.62***
	(1.50)	(2.17)	(2.47)	(7.59)
Obs	65	130	117	78
R2	0.950	0.893	0.928	0.892
F	116.2	68.35	102.0	55.25

Note: the value in the parenthesis is the *t*-statistic; *, **, and *** denote 10%, 5%, and 1% significance level, respectively.

laggard, and the productivity of green products is weak. There are few valid industrial patents so that technological innovation does not work. Comparing column (2) with column (3), it can be found that the effect of technological innovation is changed by the industrialization level. The heterogeneity is verified.

The regression results of column (4) represent the provinces in Region IV. This kind of province has superiority in natural endowment, but the level of industrialization is low. It means that primary or tertiary industry may be the dominant industry in Region IV. Pollution caused by industry is not obvious. Thus, the effect of environmental regulation is not significant anymore. As economic development in such provinces is not strongly dependent on industry, technological innovation has shown its advantages. Besides, FDI has a positive effect in Region II and Region III (columns 2 and 3), but it is not significant in Region I and Region IV (columns 1 and 4). This means that, with high resource dependence, the way of economic development is stubborn, opening to the world and introducing foreign capital is insufficient. The influence of energy consumption structure on industrial carbon productivity is significantly negative in all provinces, indicating that China's energy consumption structure is still in a high-carbon mode.

4.4. Endogeneity Test and Robustness Test. The estimation results of the model may be biased due to the endogenous problems of environmental regulation and technological innovation. Thus, we use the instrumental variables to estimate. In this paper, the lagged terms of environmental regulation and technological innovation are used as instrumental variables. For environmental regulation, we introduced the first-order and second-order lagged terms of it. For technological innovation, we introduced the third-order and fourth-order lagged terms of it. Estimated results using OLS, 2SLS, and GMM are all displayed in Table 7. The result of instrument variables shows that there are no overidentification problem, underidentification problem, and weak instrumental variables. The selection of instrumental variables is reasonable. Comparing 2SLS with OLS, the coefficients of environmental regulation and technological innovation are all improved after considering endogenous variables. That is to say, the influence of environmental regulation and technological innovation was underestimated through OLS estimation. On this basis, to eliminate the heteroscedasticity of the error term, we further adopt the GMM Model to estimate. Using GMM, the coefficient of

Table 7: Results of endogeneity test and robustness test.

	(1) OLS	(2) 2SLS	(3) GMM		(4) OLS
LnERI	0.512^{***} (8.84)	0.567^{***} (3.64)	0.536^{***} (3.75)	LnERI_1	0.454^{***} (18.54)
LnTE	0.0795^{***} (5.31)	0.112^{**} (2.93)	0.112^{***} (3.39)	TE_1	0.147^{**} (3.15)
Control variables	Yes	Yes	Yes	Control variables	Yes
_cons	8.034^{***} (4.57)	−0.0789 (−0.05)	0.237 (0.16)	_cons	5.424^{**} (3.29)
N	390	270	270	N	390
R^2	0.916	0.696	0.696	R^2	0.929
Sargan_p		0.1156			
Kleibergen-Paap rk LM		74.855^{***}			
Kleibergen-Paap rk Wald F		43.770 > 9.93			

Note: the value in the parenthesis is the t-statistic; ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

environmental regulation is in the middle compared with OLS and 2SLS. The coefficient of technological innovation with GMM is consistent with the estimated result of 2SLS. Environmental regulation and technological innovation still significantly enhance industrial carbon productivity.

To avoid the estimation bias caused by the selection of proxy indicators, the logarithms of the national per capita GDP (LnERI_1) [42] and the R&D input intensity (TE_1) are selected as substitute indicators for environmental regulation and technological innovation, respectively. TE_1 is the ratio of internal expenditure on R&D to the GDP of each province. It reflects the situation of technological innovation directly [50]. Estimated results are illustrated in column (4) of Table 7. We can find that there is a significantly positive impact of environmental regulation at 1%, and technological innovation is 5%. The conclusion of this paper is robust.

4.5. Analysis of Spatial Spillover Effect

4.5.1. Analysis of Spatial Autocorrelation. This part mainly talks about the spatial autocorrelation characteristics of industrial carbon productivity. Considering the reliability of the classic method, we adopted Global Moran's I index to investigate the spatial autocorrelation. Global Moran's I index is calculated as equation (12):

$$\text{Global Moran's I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(Y_i-\overline{Y}\right)\left(Y_j-\overline{Y}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}},$$

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i-\overline{Y}\right)^2, \tag{12}$$

$$\overline{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i,$$

where Y_i and Y_j represent different space units. The subscripts i and j mean the unit number, and the total number is n. The values of Moran's I represent a level of agglomeration, ranging from −1 to 1. Value 1 means a clustering trend, while value −1 means a discrete trend in the spatial distribution [51]. Figure 4 shows the results under matrices W1, W2, and W3 from 2004 to 2016, where Global Moran's index is significantly positive in each year. We can find that there is a spatial agglomeration characteristic of industrial carbon productivity. The value of Global Moran's I in Figure 4 increased gradually, which indicated that the spatial autocorrelation of industrial carbon productivity is gradually enhancing, and the agglomeration effects are more obvious. Besides, local spatial autocorrelation in this section is verified by Local Moran scatterplot with the W1 matrix (Figure 5), and the results in 2004, 2008, 2012, and 2016 are displayed as representatives. The Local Moran's index is calculated as follows:

$$\text{Local Moran's I}_i = \frac{\left(Y_i-\overline{Y}\right)\sum_{j=1}^{n} W_{ij}\left(Y_j-\overline{Y}\right)}{S^2}, \quad i \neq j,$$

$$S^2 = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i-\overline{Y}\right)^2,$$

$$\overline{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i. \tag{13}$$

According to Figure 5, each year, the trend lines of industrial carbon productivity are all located in quadrants one and three, which indicate H-H agglomeration and L-L agglomeration, respectively. In 2016, only eight provinces were in the second quadrant and the fourth quadrant, which exhibits discrete trends in spatial distribution. The rest of the provinces all present the characteristics of agglomeration. Meanwhile, the provinces with H-H agglomeration characteristics increase year by year and most of them are with low resource dependence. The provinces with L-L agglomeration characteristics are

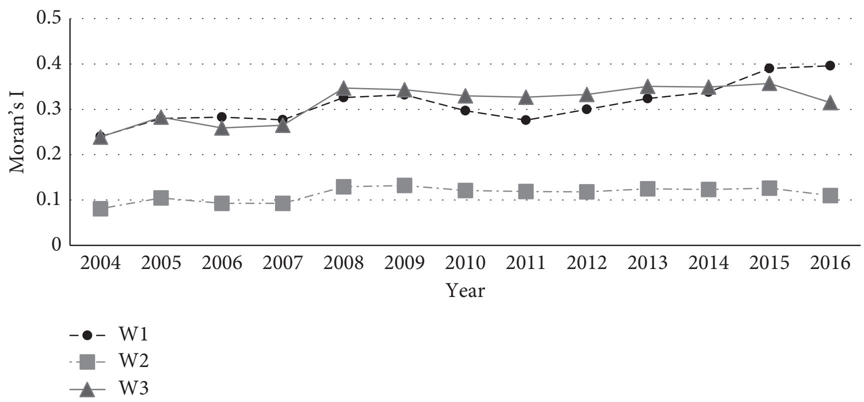

Figure 4: The trend of Global Moran's I index under different spatial weights.

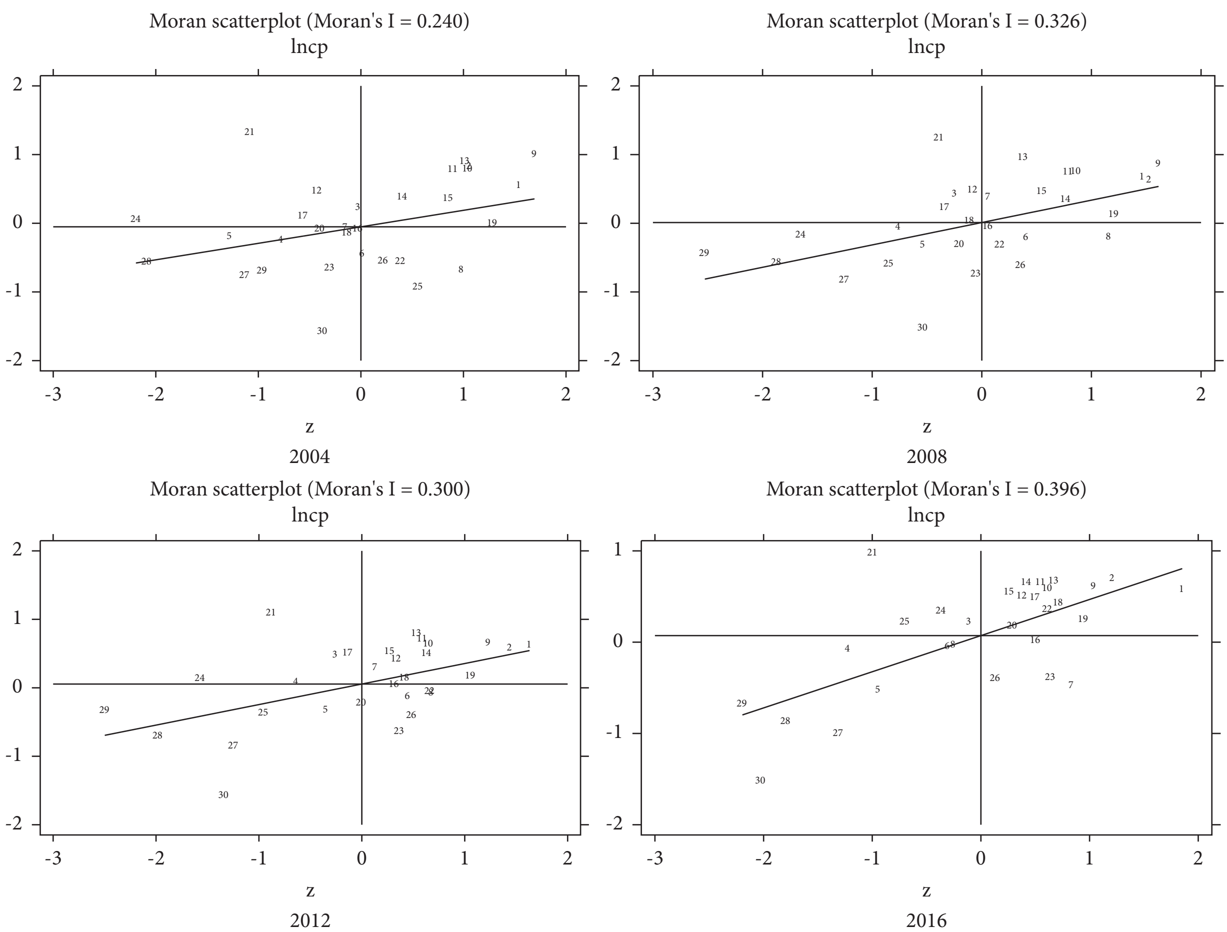

Figure 5: Local Moran's I index scatterplot.

mainly located in northwestern China and most of them are with high resource dependence.

4.5.2. Spatial Durbin Model Estimation. As mentioned in the methodology and data, we use the Durbin model to discover spatial spillover effects with three spatial weight matrices. The results are shown in Table 8. According to models (1)–(4) based on the W1 matrix, the spatial lag coefficients (rho) of the dependent variable are notably positive. It indicates that industrial carbon productivity has a significantly spatial autocorrelation and shows H-H aggregation and L-L aggregation characteristics. Industrial carbon productivity in surrounding provinces will influence the local, promoting or decreasing together. For the *W2* matrix and *W3* matrix, model (5) and model (9) show that using spatial individual fixed effect model, the values of rho are 0.2440 and 0.1429, respectively. They are

Table 8: Results of spatial panel Durbin model estimation.

	W_1				W_2				W_3			
	(1) Individual fixed effect	(2) Time fixed effect	(3) Double fixed effect	(4) Random effect	(5) Individual fixed effect	(6) Time fixed effect	(7) Double fixed effect	(8) Random effect	(9) Individual fixed effect	(10) Time fixed effect	(11) Double fixed effect	(12) Random effect
$LnERI_1$	0.8311*** (7.86)	0.2976*** (5.25)	0.8763*** (8.13)	0.7049*** (7.83)	0.9756*** (8.91)	0.2739*** (4.81)	1.0232*** (9.61)	0.7689*** (8.58)	0.9201*** (8.46)	0.2715*** (4.86)	0.9707*** (9.02)	0.8214*** (8.51)
TE_1	0.2353*** (4.44)	0.1660*** (8.96)	0.2202*** (4.16)	0.1298*** (3.50)	0.2150*** (4.18)	0.1688*** (8.63)	0.1789*** (3.57)	0.1222*** (3.42)	0.1762*** (3.32)	0.1568*** (7.64)	0.1794*** (3.50)	0.1159*** (3.03)
FDI	0.0386*** (4.25)	0.0643*** (5.66)	0.0365*** (3.99)	0.0345*** (3.84)	0.0287*** (3.14)	0.0796*** (6.88)	0.0236** (2.55)	0.0290*** (3.14)	0.0290*** (3.24)	0.0721*** (6.44)	0.0222** (2.49)	0.0326*** (3.67)
ECS	−0.0040*** (−3.03)	−0.0019 (−1.36)	−0.0049*** (−3.51)	−0.0050*** (−3.83)	−0.0050*** (−3.57)	−0.0019 (−1.31)	−0.0040*** (−2.78)	−0.0053*** (−3.77)	−0.0044*** (−3.15)	−0.0022 (−1.51)	−0.0037*** (−2.65)	−0.0048*** (−3.51)
LnPS	−0.4548 (−1.55)	0.2762*** (11.70)	−0.4222 (−1.44)	0.2939*** (4.66)	−0.0381 (−0.14)	0.3089*** (13.16)	−0.1143 (−0.43)	0.3339*** (4.98)	−0.5581* (−1.80)	0.3033*** (13.77)	−0.6134** (−2.02)	0.3133*** (4.35)
_cons				−0.9187 (−0.84)				−4.6858 (−1.59)				−0.7051 (−0.61)
$W * LnERI_1$	−0.5735*** (−5.08)	0.1119 (1.18)	−0.1899 (−0.80)	−0.4174*** (−4.17)	−0.7902*** (−4.98)	−0.7390** (−2.20)	−0.0659 (−0.11)	−0.4909*** (−3.33)	−0.6306*** (−5.11)	−0.2188* (−1.71)	0.0351 (0.14)	−0.4922*** (−4.22)
$W * TE_1$	−0.1736** (−2.11)	−0.0200 (−0.46)	−0.0625 (−0.69)	−0.0341 (−0.52)	−0.1852 (−1.11)	0.1924 (1.54)	0.4550** (1.97)	−0.0383 (−0.29)	−0.0110 (−0.12)	0.0520 (1.23)	0.1435 (1.50)	0.0526 (0.79)
W * FDI	0.0165 (0.83)	0.0392 (1.56)	0.0082 (0.38)	0.0141 (0.76)	−0.0338 (−0.64)	0.2280*** (2.76)	−0.0998 (−1.55)	−0.0495 (−0.98)	−0.0231 (−1.05)	0.0734** (2.48)	−0.0461** (−2.02)	−0.0189 (−0.90)
W * ECS	0.0009 (0.49)	0.0114*** (3.69)	−0.0033 (−1.18)	0.0020 (1.01)	0.0051* (1.81)	0.0015 (0.12)	0.0029 (0.27)	0.0045 (1.54)	0.0035 (1.45)	0.0024 (0.61)	0.0011 (0.27)	0.0040 (1.63)
W * LnPS	1.6805*** (2.82)	−0.0025 (−0.04)	2.0712*** (3.20)	0.1158 (0.89)	2.8014** (2.53)	0.3567** (2.07)	4.9832*** (3.11)	0.6680* (1.74)	1.4126*** (2.87)	0.0765 (1.33)	2.4207*** (4.18)	0.1882 (1.22)
rho	0.3468*** (5.18)	0.0263 (0.32)	0.2443*** (3.30)	0.3113*** (4.53)	0.2440* (1.73)	−0.2316 (−1.12)	−0.2402 (−1.19)	0.2044 (1.40)	0.1429* (1.68)	0.0787 (0.86)	0.0589 (0.67)	0.1295 (1.50)
R^2	0.298	0.775	0.355	0.748	0.530	0.328	0.478	0.744	0.192	0.663	0.296	0.725

all positive at the significance level of 10%. But in models (6)–(8) and models (10)–(12), the spatial lag coefficients of industrial carbon productivity (rho) are not significant. Therefore, interpreting the spatial spillover effect according to the spatial individual fixed effect model is the best choice. According to the results of models (1), (5), and (9), the coefficients of environmental regulation are all positive and significant (*W1*: 0.8311, *W2*: 0.9756, and *W3*: 0.9201). And technological innovation is similar (*W1*: 0.2353, *W2*: 0.2150, and *W3*: 0.1762). It demonstrates the robustness of conclusions that strict environmental regulation and technological innovation are conducive to boosting local industrial carbon productivity. And then, we will discuss further to see the direct effects and indirect effects of each explanatory variable under *W1*, *W2*, and *W3* (Table 9) [52].

Table 9 extensively shows the outcomes of direct effect, indirect effect, and total effect. And results of the spatial individual fixed effect model based on *W1*, *W2*, and *W3* are displayed, respectively. The direct effects of environmental regulations under all spatial weight matrices are significantly positive at the significance level of 1% (*W1*: 0.8089, *W2*: 0.9707, and *W3*: 0.9110), which means that the enhancement of local environmental regulations is beneficial to local industrial carbon productivity. However, the spillover effects of environmental regulation intensity are −0.4136, −0.7320, and −0.5726, which means that local environmental regulation has a negative relationship with industrial carbon productivity in surrounding provinces. The reason may be that strengthening local environmental regulations will lead to pollution shelter effect. Companies with heavy pollution will migrate to neighboring provinces where environmental regulation is not strict. Thus, the migration of companies with heavy pollution increases carbon emissions and reduces industrial carbon productivity in the neighboring provinces. As for technological innovation, the direct effects are all significantly positive under each spatial weight matrix (*W1*: 0.2254, *W2*: 0.2116, and *W3*: 0.1751), but the indirect effects of the technological innovation are not significant. It shows that the local technological innovation can increase local industrial carbon productivity but does not contribute to neighboring provinces. The reason is complex. On the one hand, technological innovation has a time lag and a dissemination effect. The dissemination effect could improve the level of technology in neighboring provinces and then push their industrial carbon productivity. But because of the existence of time lag, the impact of technological innovation in neighboring provinces does not always manifest itself promptly. On the other hand, the influence of innovation agglomeration will have both positive and bad consequences. Innovation agglomeration possibly leads to the flow of innovation elements between provinces and generates uncertain influence for the industrial carbon productivity in neighboring provinces finally. In conclusion, the spillover effect of technological innovation is neither specific.

Table 9: Results of the direct effects and indirect effects.

Variables	Effect	(1) W_1	(2) W_2	(3) W_3
$LnERI_1$	Direct	0.8089*** (7.89)	0.9707*** (8.74)	0.9110*** (8.32)
	Indirect	−0.4136*** (−4.05)	−0.7320*** (−4.69)	−0.5726*** (−5.01)
	Total	0.3953*** (9.04)	0.23873** (2.15)	0.3384*** (7.40)
TE_1	Direct	0.2254*** (4.51)	0.2116*** (4.32)	0.1751*** (3.48)
	Indirect	−0.1326 (−1.24)	−0.1688 (−0.76)	0.0179 (0.18)
	Total	0.0928 (0.82)	0.0428 (0.20)	0.19300** (2.04)
FDI	Direct	0.0423*** (4.62)	0.0291*** (3.20)	0.0293*** (3.36)
	Indirect	0.0423 (1.50)	−0.0376 (−0.52)	-0.0224 (-0.89)
	Total	0.0846 *** (2.59)	−0.0086 (−0.11)	0.0070 (0.24)
ECS	Direct	−0.0041*** (−3.18)	−0.0050*** (−3.70)	−0.0043*** (−3.26)
	Indirect	-0.0004 (−0.17)	0.0054 (1.51)	0.0036 (1.36)
	Total	−0.0045 (−1.55)	0.0004 (0.12)	−0.0007 (−0.28)
LnPS	Direct	−0.3045 (−1.15)	0.0227 (0.09)	−0.5080* (−1.68)
	Indirect	2.2142*** (2.84)	3.7180** (2.43)	1.5216*** (2.80)
	Total	1.9097*** (2.65)	3.7406** (2.55)	1.0136** (2.39)

Note: the value in the parenthesis is the *t*-statistic; ***, **, and * indicate 1%, 5%, and 10% significance level, respectively.

5. Conclusion and Policy Implication

This paper examines the impact of environmental regulation and technological innovation on industrial carbon productivity using data from 30 Chinese provinces and autonomous areas from 2004 to 2016. The modified STIRPAT model and Durbin model are adopted as the main instrument for exploring spatial spillover effects. After that, we construct the two-dimensional structural heterogeneity analysis according to industrialization level and resource dependence to detect their moderating effect.

This paper reveals the following: (1) for industrial carbon productivity, environmental regulation serves as a driving force to it, similar to technological innovation. The enhancement of environmental regulation intensity can limit the carbon emission behavior of industrial enterprises so that CO_2 reduces and industrial carbon productivity improves. Technological innovation will also play the same role through the revolution of low-carbon technology and raising production efficiency. (2) There is an obvious heterogeneity caused by resource dependence and industrialization level. Specifically, environmental regulation has a positive effect in provinces with high resource dependence and high industrialization levels (Region I) and provinces with low resource dependence and low industrialization levels (Region III), but technological innovation has no effect. In provinces with high resource dependence and low industrialization level (Region IV), while environmental regulation has no substantial impact on industrial carbon productivity, technological innovation does. In provinces with low resource dependence and high industrialization levels (Region II), environmental regulation and technological innovation are all significant. This implies that, to realize effective carbon reductions, diverse policies should be adopted in different regions with nonuniform industrialization levels and resource endowment. (3) Foreign direct investment is positively correlated with industrial carbon productivity. This is probably because the growth of the economy stimulated by foreign direct investment overpasses the growth of carbon emissions so that increasing foreign direct investment plays a positive role. However, the structure of energy is inversely related to industrial carbon productivity. The greater the share of coal consumption, the more adverse to the realization of carbon emission reduction targets, which is reasonable. It shows that the current energy consumption structure dominated by fossil fuels is unreasonable and needs to be adjusted urgently. (4) Industrial carbon productivity exhibits spatial autocorrelation from the perspective of spatial agglomeration. The characteristics of H-H and L-L agglomeration are obvious. Local environmental regulation and technological innovation are advantageous to local industrial carbon productivity, but the spillover effect of environmental regulation is not beneficial to neighboring provinces' industrial carbon productivity. This is because the enhancement of local environmental regulation may dislodge the polluting enterprise to the adjacent provinces and cause more CO_2 there. The industrial carbon productivity in adjacent provinces will decrease inevitably. Furthermore, because of the dual effects of diffusion effect and time lag, the spillover effect of technological innovation is insignificant. Technology cooperation in adjacent provinces is weak. And the linkage effect of technological innovation is not obvious so that the flow of innovation elements between different provinces is unplanned. This may exacerbate the ambiguity around technological innovation's impact on industrial productivity.

Based on the preceding conclusions, policy recommendations are made to provide advice to decision makers in order to improve industrial carbon productivity.

First, in general, the government needs to strengthen the rigor of environmental regulation and vigorously promote technological innovation. Environmental regulation policy plays a favorable role in China's emission reduction and high-quality industrial development. Technological innovation should be encouraged towards cleaner production, energy conservation, and emissions reduction, achieving green development and low-carbon transition finally.

Second, the government should make appropriate policies to promote industrial carbon productivity in different provinces respectively, taking two-dimensional structural heterogeneity of resource dependence and industrialization level into consideration. In provinces with high resource dependence and high industrialization level (Region I) and provinces with low resource dependence and low industrialization level (Region III), environmental regulations have a greater impact on industrial carbon productivity. Environmental regulation should be regarded as the main tool to improve industrial carbon productivity in such provinces. However, in provinces with high resource dependence and low industrialization levels (Region IV), technological innovation is more effective in improving industrial carbon productivity. Hence, it needs to continuously improve technological innovation capacity and cooperation with neighboring provinces, to promote industrial carbon productivity in neighboring provinces. As for the provinces with low resource dependence and high industrialization levels (Region II), environmental regulation and technological progress both have a positive impact. Improving industrial carbon productivity in these provinces can be accomplished by tightening regulations and stimulating technological innovation.

Third, the government should pay attention to spatial linkage and regional cooperation when making industrial emission reduction policies. Environmental regulation may have a negative spillover impact, causing polluting businesses to relocate. Polluting firms want to settle in areas where environmental restrictions are slack. This may promote regional environmental polarization and enhance the difficulty of carbon reduction. Thus, the government should reinforce the collaborative governance between adjacent provinces. Additionally, the spillover effect of technological innovation is not significant. It is necessary to heighten the technical collaboration and increase the number of joint patents to realize the linkage mechanism of technological innovation among provinces. In addition, the government should focus on the flow of innovation factors, as well as the spread of technological innovation and reducing the time-lag effect of technological transformation.

This paper has some limitations which can be studied in the future. First, the conclusion of this study was inferred by provincial data. It might be more interesting to explore whether we can get the same or other meaningful outcomes using the city's data. Second, the heterogeneity caused by industrialization level and resource dependence is confirmed in this paper. But it is not clear whether they change the effects of independent variables. Future researches could pay more attention to the moderating effects of industrialization level and resource dependence, observing the difference they generate on environmental regulation and technological innovation.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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