Spatiotemporal Evolution of the Coupling Coordination Degree Between Financial Agglomeration and Green Technology Innovation in China

Jingmin Chai[1,2*], M. H. Yahya[1], Saidatunur Fauzi Saidin[1]

[1]School of Business and Economics, University Putra Malaysia, Selangor 43400, Malaysia

[2]College of Economics and Management, Yuncheng University, Yuncheng, Shanxi 044000, China

[*]Corresponding Author

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ABSTRACT

With China's transition toward high-quality development, financial agglomeration (FA) and green technology innovation (GTI) have become key drivers of green transition and sustainable development. Existing studies mainly focus on the relationship between FA and general technological innovation, while the coordinated development of FA and GTI has received limited attention. Theoretically, FA promotes GTI through capital agglomeration, optimised resource allocation, knowledge spillover, and specialised labour division. GTI enhances FA by generating new financing demands and improving capital allocation efficiency. Through these mechanisms, FA and GTI form a mutually reinforcing and coordinated development relationship. This study investigates their coordinated development from the perspective of coupling coordination. Using panel data of 30 Chinese provinces from 2007 to 2022, the assessment index systems for FA and GTI are constructed, and the coupling coordination degree (CCD) model, data visualisation techniques, Moran's I index and spatial visualisation methods are employed to explore the spatiotemporal evolution characteristics of the CCD between FA and GTI. The results indicate that the CCD steadily increased during the period of this study, while the coordination level remained relatively low. Significant regional disparities exist, where Eastern China performs better than the other three regions. In the analysis of development types of the CCD, GTI is found to play a more important role as the restrictive factor than FA. In the spatial autocorrelation analysis, the CCD exhibits significant positive spatial autocorrelation, with High–High mainly in Eastern China and Low–Low mainly in Western and Northeastern China. This study extends the literature by shifting the focus from general technological innovation to GTI and examining its coordinated development with FA from a coupling coordination perspective, thereby enriching the theoretical understanding of finance–innovation coordination under the sustainability transition and providing policy implications for integrating financial and innovation resources to promote balanced regional development and high-quality economic growth.

Keywords: Financial Agglomeration; Green Technology Innovation; Coupling Coordination Degree; Spatiotemporal Evolution.

INTRODUCTION

At present, China's economy has developed from an era of rapid development into an era of high-quality development. With the increasing resource and environment constraints and the ongoing progress of dual carbon objectives, how to integrate economic growth and ecological protection well becomes an important problem to promote high-quality development. Financial development and technological innovation are the two major engines of economic growth and can play a pivotal role in improving the allocation of resources, upgrading industrial structures, and developing greenly.

On the one hand, financial resources have been increasingly inclined to concentrate in particular geographic locations in recent years, and hence, financial agglomeration (FA) becomes a more and more important phenomenon affecting the development of regional economy. On the other hand, green technology innovation (GTI), which is one of the most important paths of green transformation and plays a vital role in realizing low-carbon economy, directly impacts the sustainable development ability of a region. Theoretically, FA may promote GTI by means of capital supply, knowledge spillover effects, and talent agglomeration, etc., and in turn, the progress of GTI creates new demand for finance and improves the efficiency of financial resource allocation.

Prior studies have mainly concentrated on the linkages among financial development and technology innovation, financial development and economic growth, and GTI and economic development. In comparison, the literature on coordinated development between FA and GTI is still relatively limited. GTI has the characteristics of both innovation-driven development and sustainable development. Its financing needs, resource allocation, and financial support differ from those of general technological innovation. The relationship between FA and GTI therefore requires further study. Most studies examine the relationship between FA and GTI from the perspective of one-way effects or underlying mechanisms. Existing studies rarely treat them as two interacting systems. Few studies examine their coordinated development from the perspective of coupling coordination. China also shows large regional differences in financial resources, innovation capacity, and green development. These differences may lead to regional heterogeneity and spatial clustering in the coordinated development of FA and green technology innovation. Systematic research on these issues is still limited.

To address these gaps, this study investigates the spatiotemporal evolution of the coupling coordination degree (CCD) between FA and GTI in China, with particular attention to its temporal evolution, development types, and spatial distribution characteristics.

LITERATURE REVIEW

Connotation and Measurement of Financial Agglomeration

When financial development reaches a certain level, the characteristics of the financial industry itself will drive all kinds of financial resources to tend to cluster in a certain area, thus forming the phenomenon of FA. Regarding the connotation of FA, there are mainly two different ways to define it. One is to define the connotation of FA from the dynamic or process level. FA is the formation process or development dynamic of the cluster that financial activities or financial institutions create and maintain through some kind of circular logic (Krugman, 1991; Pandit et al.,2001). The other is to define the connotation of FA from the static or result level. FA is a special industrial structure in which interconnected financial institutions, including financial regulatory authorities, financial enterprises and financial intermediaries, are geographically concentrated in a specific region and have close links with other industries (Kindleberger, 1978; Porter, 1998; Buera et al., 2008).

Regarding the measurement of FA, existing studies primarily employ two approaches: single-indicator methods and comprehensive indicator systems. Single-indicator methods mainly include metrics such as the Herfindahl index (Herfindahl, 1997), spatial Gini coefficient (Krugman, 1991), and location entropy (Haggett, 1965; Zhang et al., 2019), which assess FA from perspectives including industrial concentration, spatial distribution, and specialization. Nevertheless, there is a limit to single indicators' ability to reflect the multifaceted essence of FA. To address the problem, scholars have increasingly turned to comprehensive indicator systems for the construction of FA evaluation framework according to factors including the scale of finance, the efficiency of finance, financial markets, and financial environment. In the course of measuring the level of FA, these FA evaluation frameworks have applied approaches such as principal component analysis (Ding et al., 2009), factor analysis (Li & Bai, 2014), and entropy approach (Wen et al., 2023). In comparison with single indicators, comprehensive indicators better reflect the development of regional FA.

Connotation and Measurement of Green Technology Innovation

GTI is a kind of innovative activities in which the targets of resource saving and environment protection are integrated into the conventional technological innovation. It was introduced in the 1990s due to the prevalence of green development concept. For the first time, the idea of green technology was put forward by Braun and Wield (1994), and they claimed that green technology is a kind of technological innovation activities which not only satisfy the requirement of economic development but also consider the requirements of environment protection. According to Beise and Rennings (2005) and Horbach et al. (2012), GTI involves innovative products, process, organization, and marketing modes which can help reduce environmental pollution and resource consumption. From China's "Guidelines for Building a Market-Oriented Green Technological Innovation System" (2019), we learn that GTI is an innovative activity which focuses on energy conservation, emission reduction, pollution control and ecological improvement, and it plays an important role in pushing economy toward green transformation and high-quality development.

In terms of measuring GTI, the current researches mainly use two kinds of methods, which are single indicator method and comprehensive index system method. The single indicator method typically selects indicators such as the number of green patent applications (Zheng et al., 2026), the number of green patent authorizations (Faber & Frenken, 2009), and R&D investment (Hall & Helmers, 2013) to measure the level of GTI. However, GTI has dual attributes of economic benefits and environmental benefits, and a single indicator is unable to comprehensively reflect its development status. Therefore, more and more scholars have adopted comprehensive index system methods, constructing evaluation systems from dimensions such as innovation foundation, innovation input, and innovation output, and using methods such as principal component analysis (Xu & Wang, 2017) and entropy method (Miao et al., 2021) to calculate the level of GTI. Compared with the single indicator method, the comprehensive evaluation method can more comprehensively reflect the development level of regional GTI and has become the mainstream choice in current research.

Relationship between Financial Agglomeration and Green Technology Innovation

In the evolution of research on the relationship between FA and GTI, early studies primarily focused on the effects of financial development on technological innovation (Schumpeter, 1934; Levine, 1997), the influence of technological innovation on financial development (Berger, 2003), and their bidirectional interactions (Yu, 2013). In addition, some scholars specifically examined the relationship between financial development and GTI (Ye & Cheng, 2019). Since then, more research has been conducted to evaluate the influence of FA on technology innovation (Li & Hu, 2017), the impact of technology innovation on FA (Luo, 2012), and the spillover effects between them (Wen et al., 2023).

According to a literature review, there are relatively few studies that examine the association between FA and GTI, and those that do, report mixed findings. According to Lu (2021), FA has a substantial positive effect on regional green innovation efficiency. Zhang and Wang (2021) reported that FA has no significant impact on GTI efficiency at the technology commercialisation stage, but significantly enhances GTI efficiency during the research and development stage. Feng (2022) suggested that FA influences green economic efficiency through the mediating role of GTI.

Some studies have emphasised the mediating role of FA in facilitating GTI. In the context of the digital economy promoting GTI (Jiang & Chen, 2023) and big data driving innovation processes (Jin et al., 2021), FA has been shown to play a significant mediating role. FA enhances GTI capacity through synergistic interactions with environmental regulations and exhibits significant spatial spillover effects. This enhancement effect varies across cities with differing levels of economic development and regional characteristics (Yao & Wang, 2022).

Summary and Research Gaps

Existing studies provide an important basis for understanding the relationship between FA and green technology innovation. Several research gaps remain. GTIhas the characteristics of both innovation-driven development and sustainable development. Its resource allocation needs, risk characteristics, and financial support differ from those of general technological innovation. The coordination between FA and GTIcannot be fully explained by traditional theories on the relationship between finance and technological innovation. More research is needed in the context of sustainable development. Existing studies mainly focus on the relationship between FA and general technological innovation or regional innovation capacity. Less attention has been paid to the coordinated development of FA and green technology innovation. Most studies examine the one-way effect of FA on GTIor its underlying mechanisms. Few studies treat FA and GTIas two interacting systems. Few studies examine their coordinated development from the perspective of coupling coordination. Some studies consider regional heterogeneity and spatial spillover effects. Systematic research on the spatiotemporal evolution and spatial differences in the CCD between FA and GTIis still limited.

This study adopts a coupling coordination perspective. It examines the coordinated development between FA and GTI and their spatiotemporal evolution. It enriches research on the coordinated development of finance and green innovation in the context of sustainable development. It provides a reference for regional green transformation and high-quality development.

Theoretical Mechanisms and Research Hypotheses

Coupling Coordination Theory

Coupling coordination theory is a systems-based theoretical framework that emphasises the interdependence and interactive mechanisms among multiple subsystems, examining how individual elements, through synergistic effects, contribute to the orderly and stable development of the system during dynamic evolution (Lin et al., 2024). The concepts underlying coupling coordination theory have been applied across various fields, including economics, the social sciences, and the natural sciences, thereby establishing it as an interdisciplinary analytical approach (Wang et al., 2021).

The concept of "coupling" originated from physics and is used to describe the phenomenon where two or more systems form an interrelated relationship through mutual connection and interaction. This refers to the interaction process in which a system transforms from an unorganized condition to an organized one (Glassman, 1973). “Coordination” mainly emphasizes the situation in which different subsystems can have mutual promotion, interaction, and coordination during their development process, showing the orderliness and stability in the development of the entire system.

The coupling degree only can be used in reflecting the degree of interdependence and the extent of interaction between systems; meanwhile, it cannot reflect the coordinated development degree of these systems. To address such a problem, the notion of coupling coordination degree (CCD) was proposed. The higher the CCD value is, the more coordinated development can take place in these subsystems in terms of resource sharing, functional complementarity and coordinated development; conversely, the lower the CCD value is, the development imbalance and mutual constraint exist among systems, which will make it hard to create synergic effects.

Based on the coupling coordination theory, FA and GTI can be regarded as two interrelated subsystems. The development of both is not only dependent on their own development levels but also influenced by their interactive relationship. Therefore, using the CCD model to examine the coordinated development level of FA and GTI can more comprehensively reveal the characteristics of their coordinated evolution and regional differences, providing a theoretical basis for promoting high-quality regional development.

Theoretical Mechanism Analysis

The close interconnection between FA and GTIconstitutes a crucial driver of high-quality regional economic development. These two subsystems are deeply interdependent: GTIrequires substantial capital investment, while the financial sector depends on technological advancement to enhance competitiveness and expand its scope of operations. This reciprocal dependence intensifies with the deepening of global integration, thereby fostering greater integration and synergy between the financial and technological systems.

FA fuels GTIby concentrating talent, capital, and knowledge, thereby generating economies of scale and powerful spillover effects. It provides essential funding and reduces financing costs for innovation activities, which is particularly critical during the early and high-risk stages of technology commercialisation. Furthermore, well-developed financial centres offer robust risk management, transaction support, and strategic guidance. Such FA fosters efficient financial markets that reduce transaction costs and mitigate information asymmetries, thereby providing technology-oriented enterprises with diversified financing channels and enhancing regional innovation capacity.

Conversely, GTIactively promotes FA. Regional technological advancement attracts financial and material resources, thereby stimulating market development and laying the foundation for the formation of a financial hub. It also drives the demand for highly skilled labour, contributes to improvements in regional educational attainment, and fosters the optimisation of the social credit environment, thereby creating a favourable financial ecosystem that enables the industry to thrive. Technologically advanced systems also compel the financial sector to modernise its services, develop innovative financial products, and integrate real-time information flows from the innovation sector, thereby further promoting FA.

This bidirectional relationship can be conceptualised as an interactive coupling mechanism. The sustainable development of the entire regional system depends on this synergistic interaction. If any subsystem lags behind in development, benign coupling cannot be achieved. An underdeveloped financial system may be unable to provide adequate funding or risk-sharing mechanisms for green technology innovation, thereby constraining its growth and weakening investment returns. Similarly, a lagging innovation subsystem may undermine regional economic sustainability and long-term development quality, thereby holding the entire system back.

Research Hypotheses

Existing studies have examined the coupling coordination relationship between FA and regional innovation capacity across different regions. The findings indicate that the CCD between FA and regional innovation capacity has been continuously improving while exhibiting significant regional disparities (Wang and Liu, 2020; Chen, 2022; Pang et al., 2022). Building on these findings, this study focuses on green technology innovation.

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Based on the theoretical analysis of coupling coordination mechanisms among FA and GTI, and considering existing studies and the realities of China's economic and social development, this research proposes the following hypotheses.

Research Hypothesis 1: Over time, the CCD between FA and GTIin China exhibits an increasing trend.

Research Hypothesis 2: The CCD between FA and GTIexhibits spatial heterogeneity across China.

RESEARCH METHODOLOGY

For the systematic exploration of the CCD between FA and GTI and their evolution characteristics in terms of space-time dimensions, this paper builds a research framework and carries out this research from three aspects: development level measurement, temporal evolution study, and spatial differentiation study. The research framework of the whole study is presented in Figure 1.

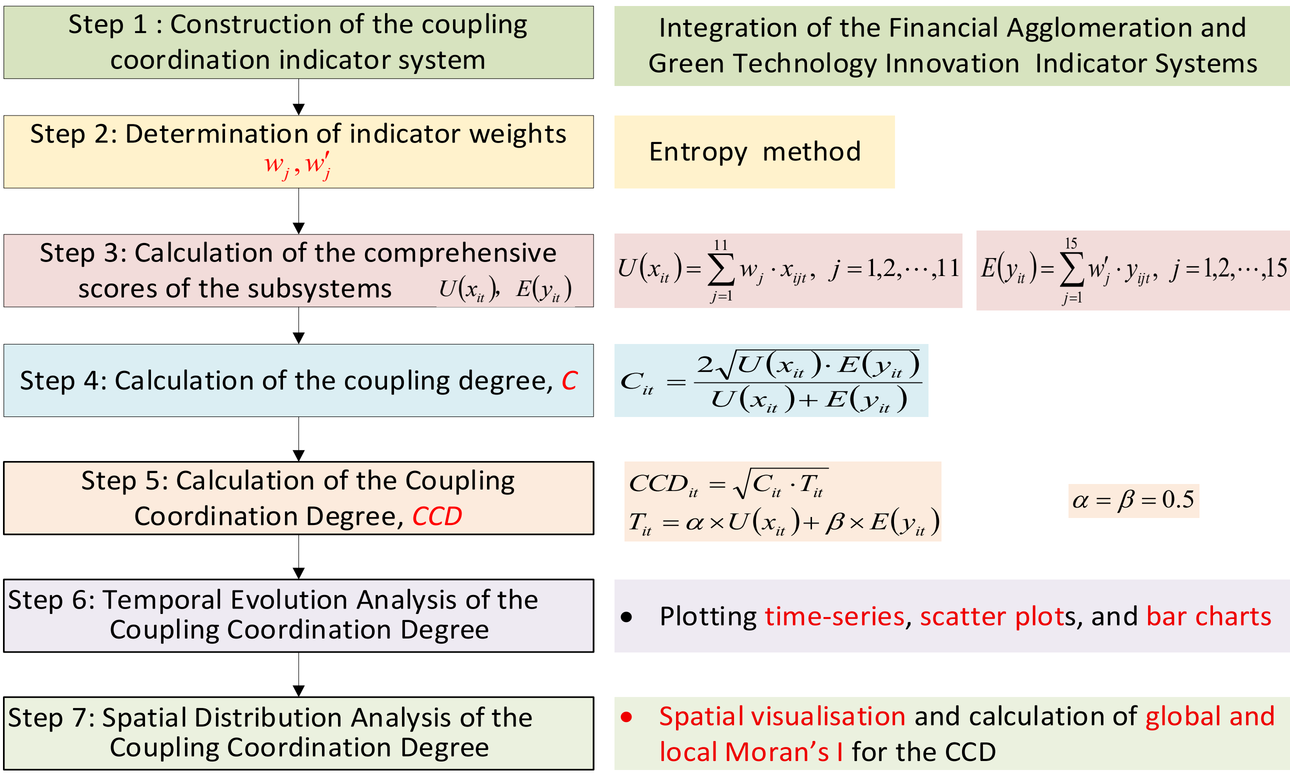

Figure 1: Research Framework

Data Source

The sample of this research includes 30 provincial-level administrative regions in China (excluding Tibet, Hong Kong, Macao, and Taiwan), with the use of panel data for the period between 2007 and 2022. The information is mainly collected from such sources as China Statistical Yearbook, China Statistical Yearbook on Science and Technology, China Energy Statistical Yearbook, China Labour Statistical Yearbook, Almanac of China's Finance and Banking, various provincial statistical yearbooks, as well as the databases of National Bureau of Statistics of China and China National Intellectual Property Administration. Some indexes have been additionally calculated on the basis of the initial data.

In order to better analyse regional disparities, the research is conducted according to the classification criteria

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that were adopted by the National Bureau of Statistics of China in June 2011 and identifies four main economic regions among 30 provincial-level administrative regions in China: eastern, central, western, and northeastern regions.

Construction of the Coupling Coordination Indicator System for Financial Agglomeration and Green Technology Innovation

The coupling coordination model is a tool used to analyse the interaction intensity and level of coordinated development among multiple subsystems. To comprehensively, systematically, and quantitatively reflect the status of each subsystem and their interactions intensity, and to scientifically assess their degree of coordinated development, it is essential to construct a coupling coordination indicator system.

Indicator System for FA

The location quotient is one of the most widely used single indicators for measuring FA (Zhang et al., 2019). To provide a more comprehensive representation of the FA subsystem, this study uses the location quotient as the core indicator, and further incorporates several indicators reflecting both the scale and efficiency of the financial sector. The FA indicator system is shown in Table 1.

The location quotient (LQ), also referred to as the specialisation index, is an indicator used to measure the concentration of a specific industry within a region relative to the national level or a broader regional level. It reflects the degree of specialisation and comparative advantage for a given industry within a region and can also be used to assess the spatial distribution of production factors. A highly agglomerated industry generally indicates a high level of specialisation. Drawing on the studies of Quan and Quan (2023) and Lei et al. (2023), this research constructs a FA index based on the location quotient. Specifically, it is defined as the ratio of (1) the share of financial sector value added in regional GDP during a given period to (2) the corresponding share of national financial sector value added in national GDP during the same period. The calculation formula is presented as follows:

$$LQ_{it} = \frac{fva_{it} / grp_{it}}{FVA_t / GDP_t} \tag{1}$$

Where LQ_{it} represents the location quotient (LQ) of the financial sector in region i in year t; fva_{it} represents the value added of the financial sector in region i in year t, and grp_{it} denotes the regional GDP of region i in year t. FVA_t represents the national value added of the financial sector in China in year t, while GDP_t denotes the national GDP of China in year t.

The FA location quotient reflects the difference between a region's financial sector structure and the national average. If $FA_{it} > 1$, the FA level of region i exceeds the national average, indicating a comparative scale advantage. If $FA_{it} < 1$, the FA level of region i is lower than the national average, indicating that the financial sector does not exhibit agglomeration characteristics. If $FA_{it} = 1$, the FA level of region i is equal to the national average, indicating no significant FA characteristics. The larger the value of FA_{it}, the higher the level of FA.

During the process of FA, the continuous concentration of financial institutions, capital, and financial professionals in a specific region leads to the expansion of financial scale. Financial scale reflects the overall level of financial development in a region by measuring the aggregate size of its financial activities. To capture the overall financial scale, this research selects three indicators: the location quotient of the financial sector (X1), value added of the financial sector (X2), and the number of employees in the financial sector (X3). Furthermore,

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from a sectoral perspective, four additional indicators are selected to represent the scale of the banking, securities, and insurance sectors: deposit balance of financial institutions (X4), loan balance of financial institutions (X5), trading value in the securities market (X6), and primary insurance premiums (X7）.

Financial efficiency primarily measures the input-output relationship within the financial sector. When FA reaches a certain level, economies of scale and information spillover effects emerge, enhancing the capacity of financial resources to generate effective output for the economy and thereby improving financial efficiency. This research selects four indicators to measure financial efficiency: financial interrelations ratio (FIR) (X8), deposit-to-loan ratio of financial institutions (X9), insurance penetration (X10), and insurance density (X11).

The financial interrelations ratio (FIR) reflects the degree of economic monetisation (Goldsmith, 1969). In this research, the FIR is calculated as follows:

$$FIR = \frac{Total\ deposits\ and\ loans\ of\ financial\ institutions\ at\ year-end}{Gross\ Regional\ Product}$$

The deposit-to-loan ratio reflects the ability of financial institutions to convert deposits into loans, indicating their efficiency in resource allocation. In this study, it is regarded as a negative indicator, as an excessively high value suggests that financial resources are not being effectively utilised. The calculation formula is as follows:

$$Deposit-to-Loan\ Ratio = \frac{Deposit\ balance\ of\ financial\ institutions\ at\ year-end}{Loan\ balance\ of\ financial\ institutions\ at\ year-end}$$

Insurance penetration refers to the ratio of annual insurance premium income to regional GDP. It reflects the importance of the insurance sector in the overall economy.

Insurance density refers to the per capita insurance premium calculated based on the local population. It reflects the level of insurance coverage and the development of the insurance market in a country or region.

Table 1: Indicator System for FA

Dimension	Indicator	Unit	Data Source or Calculation Method	Attribute	Weight
Financial Scale	X1	N/A	$FA_{it} = \frac{fva_{it} / grp_{it}}{FVA_t / GDP_t}$	+	0.045
	X2	100 million yuan	China Statistical Yearbook	+	0.122
	X3	persons	China labour Statistical Yearbook	+	0.057
	X4	100 million yuan	Almanac of China's Finance and Banking	+	0.109
	X5	100 million yuan	Almanac of China's Finance and Banking	+	0.104
	X6	10 billion yuan	=Trading Value on the Shenzhen Stock Exchange+ Trading Value on the Shanghai Stock Exchange	+	0.296
	X7	100 million yuan	Almanac of China's Finance and Banking	+	0.099
Financial	X8	N/A	=（Deposit Balance of Financial Institutions	+	0.040

Efficiency			at Year-end + Loan Balance of Financial Institutions at Year-end) / Gross Regional Product		
	X9	N/A	= Deposit Balance of Financial Institutions at Year-end / Loan Balance of Financial Institutions at Year-end	-	0.011
	X10	%	Almanac of China's Finance and Banking	+	0.035
	X11	yuan per person	Almanac of China's Finance and Banking	+	0.081

(Source: Adapted from He et al. (2015), Bai et al. (2014), Luo et al. (2013), and Zhou et al. (2015))
Note: Attribute = "+" indicates a positive indicator, Attribute = "–" indicates a negative indicator, "N/A" indicates that the indicator is dimensionless (i.e., it has no unit).

Indicator System for GTI

In constructing an indicator system for GTI, a key issue is how to incorporate environmental pollution and energy consumption into the traditional technology innovation indicator system. There is broad consensus on the treatment of energy inputs, whereby capital, labour, and energy are regarded as input factors. However, two main approaches exist for incorporating environmental pollution into the evaluation indicator system. The first approach incorporates environmental pollution as an input factor in the evaluation model (Ramanathan, 2005), while the second treats environmental pollution as an undesirable output factor in the evaluation system of GTI(Chung et al., 1997). This research draws on the studies of Hu et al. (2023) and Chen (2022), among others. Based on these approaches, an indicator system is constructed from three dimensions: (a) innovation input, (b) innovation output, and (c) innovation environment. In addition, the classification standards for positive and negative indicators proposed in these studies are also adopted. Table 2 presents the definitions of the variables included in the GTI indicator system.

In selecting indicators for GTIinput, this research considers four aspects: energy input (Y1, total electricity consumption), capital input (Y2, actual R&D capital stock), R&D funding input (Y3, intramural R&D expenditure), and human capital input (Y4, full-time equivalent of R&D personnel).

Innovation output indicators are divided into two sub-dimensions: desirable outputs and undesirable outputs. Desirable outputs are evaluated based on three aspects: product output (Y5, sales revenues of new products of industrial enterprises above designated size), innovation activity output (Y6, total turnover in the technology market), and green patent granted (Y7, number of granted green invention patents; Y8, number of granted green utility model patents). Undesirable outputs are measured in terms of pollutant emissions. The research follows the approach adopted by most scholars, using the industrial "three wastes"[1] as negative indicators to assess the environmental performance of innovation outputs. Industrial wastewater pollution is measured using chemical oxygen demand (COD)[2] emissions (Y9). Higher COD values indicate more severe water pollution. Industrial waste gas pollution is measured using sulphur dioxide (SO_2) emissions (Y10). As a representative air pollutant generated by industrial activities, SO_2 emission levels reflect enterprises' technological capabilities in waste gas treatment and cleaner production. Industrial solid waste is measured by the generation of common industrial solid waste (Y11), reflecting the amount of non-recyclable or temporarily unused solid waste generated during industrial processes and indirectly indicates resource utilisation efficiency and pollution control capabilities.

Regarding innovation environment indicators, the research evaluates four dimensions: the educational

[1] The industrial "three wastes" refer to industrial wastewater discharge, industrial waste gas emissions, and industrial solid waste discharge.
[2] Chemical oxygen demand (COD) refers to the total amount of oxygen required for oxidation-reduction reactions in a water body and is widely used as an indicator of water pollution severity.

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environment (Y12, the number of students enrolled in higher education per 100,000 people), cultural environment (Y13, total collection of public libraries), infrastructure (Y14, highway density), and government financial support for scientific and technological innovation (Y15, science and technology expenditure by local governments).

Table 2: Indicator System for GTI

Dimension	Primary Indicator	Secondary Indicator	Unit	Data Source or Calculation Method	Attribute	Weight
Innovation Input	Energy Input	Y1	100 million kWh	China Electric Power Statistical Yearbook	-	0.006
	Capital Input	Y2	10,000 yuan	Perpetual Inventory Method (base year: 2000)	+	0.102
	R&D Funding Input	Y3	10,000 yuan	China Statistical Yearbook on Science and Technology	+	0.098
	Human Capital Input	Y4	Person-year	China Statistical Yearbook on Science and Technology	+	0.082
Innovation Output	Product Output	Y5	10,000 yuan	China Statistical Yearbook on Science and Technology	+	0.116
	Innovation Activity	Y6	100 million yuan	Website of the National Bureau of Statistics of China	+	0.173
	Green Patent Granted	Y7	Item	Chinese Research Data Services Platform (CNRDS)	+	0.141
		Y8	Item	Chinese Research Data Services Platform (CNRDS)	+	0.129
	Pollutant Emission	Y9	Ton	China Statistical Yearbook on Environment	—	0.003
		Y10	Ton	China Statistical Yearbook on Environment	-	0.009
		Y11	10,000 tonnes	China Statistical Yearbook on Environment	-	0.005
Innovation Environment	Educational Environment	Y12	Person	China Statistical Yearbook	+	0.021
	Cultural Environment	Y13	10,000 volumes	China Statistical Yearbook & 2007 China Library Yearbook	+	0.047
	Infrastructure	Y14	Km/100 km²	= Highway Mileage / Land Area	+	0.030
	Government Financial Support	Y15	100 million Yuan	China Statistical Yearbook	+	0.037

(Sources: Adapted from Chen (2022), Pang et al. (2020), Wang and Yang (2015), Li and Zhang (2017), and Song (2014).)
Note: Attribute = "+" indicates a positive indicator. Attribute = "–" indicates a negative indicator.

Determination of Indicator Weights

The weights of the indicators will be found using the entropy method. This decision was made considering the need to exclude any kind of subjectivity and to make sure that the significance of each indicator matches the contribution that the indicator makes to the dataset in terms of information. Entropy is an objective method of assigning weights to indicators depending on how much information each indicator contains. The higher the entropy indicator, the more evenly distributed the data are and the greater the uncertainty; thus, the indicator contains less valuable information and needs to have a lower weight assigned to it. Conversely, a lower entropy value indicates stronger discriminating power and more useful information, and thus warrants a higher weight. Drawing on Lin (1991), the calculation procedure of the entropy method is illustrated in Figure 2.

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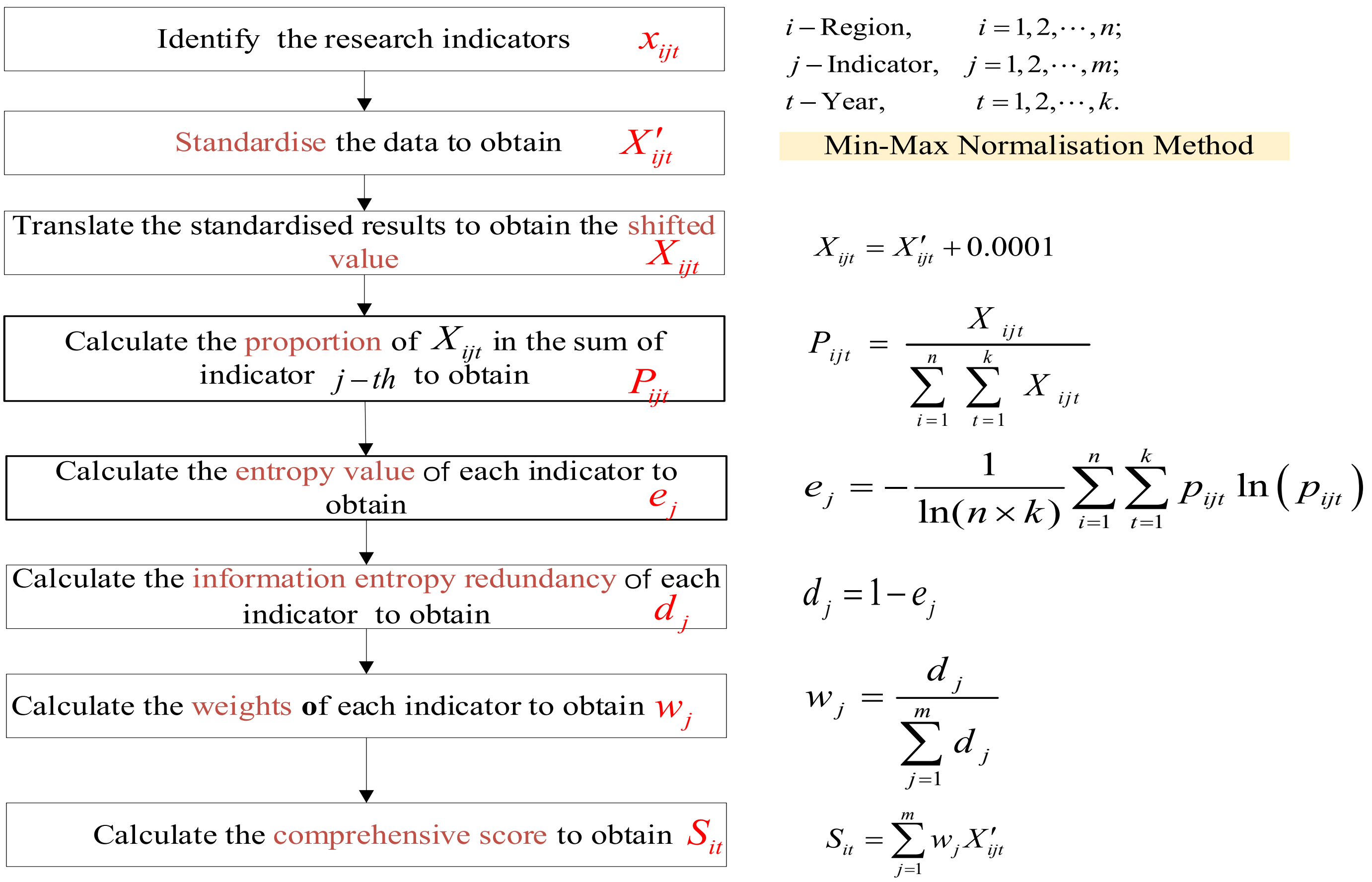

Figure 2: Calculation Procedure of Entropy Method

In Figure 2, i, j, and t denote the region, indicator, and year, respectively; n=30, m, and k=16 represent the number of regions, indicators, and years, respectively, where m=11 for the FA subsystem and m=15 for the GTI subsystem. x_{ijt} denotes the original value of indicator j for region i in year t; X'_{ijt} denotes the standardised value; X_{ijt} denotes the shifted value, obtained by adding 0.0001 to the standardised value to avoid zero values in the subsequent logarithmic calculation; P_{ijt} represents the proportion of X_{ijt} in the total value of indicator j across all regions and all years; e_j denotes the entropy value of indicator j; d_j represents the information entropy redundancy of indicator j; w_j denotes the weight of indicator j; and S_j represents the comprehensive score of region i in year t. The formulas for the min-max normalisation method are given as follows:

For a positive indicator,

$$X'_{ijt} = \frac{x_{ijt} - \min\{x_{1j1}, \cdots, x_{1jk}; x_{2j1}, \cdots, x_{2jk}; \cdots; x_{nj1}, \cdots, x_{njk}\}}{\max\{x_{1j1}, \cdots, x_{1jk}; x_{2j1}, \cdots, x_{2jk}; \cdots; x_{nj1}, \cdots, x_{njk}\} - \min\{x_{1j1}, \cdots, x_{1jk}; x_{2j1}, \cdots, x_{2jk}; \cdots; x_{nj1}, \cdots, x_{njk}\}} \quad (2)$$

For a negative indicator,

$$X'_{ijt} = \frac{\max\{x_{1j1}, \cdots, x_{1jk}; x_{2j1}, \cdots, x_{2jk}; \cdots; x_{nj1}, \cdots, x_{njk}\} - x_{ijt}}{\max\{x_{1j1}, \cdots, x_{1jk}; x_{2j1}, \cdots, x_{2jk}; \cdots; x_{nj1}, \cdots, x_{njk}\} - \min\{x_{1j1}, \cdots, x_{1jk}; x_{2j1}, \cdots, x_{2jk}; \cdots; x_{nj1}, \cdots, x_{njk}\}} \quad (3)$$

The indicator weights obtained using the entropy method are presented in the final column of Tables 1 and 2.

Measurement of the Financial Agglomeration and Green Technology Innovation Subsystems

Based on the indicator weights, the comprehensive scores of the FA subsystem, denoted as ***U(x)***, and the GTI subsystem, denoted as ***E(y)***, are calculated using the weighted summation method. These scores reflect the development levels of regional FA and GTI, respectively. Higher scores indicate higher levels of subsystem development. These scores provide the basis for the subsequent coupling coordination analysis.

Calculation of Coupling Degree

The coupling degree (C) is used to measure the strength of interaction and the degree of interdependence between the FA and GTI subsystems. Drawing on the studies of Fang et al. (2021) and Lin et al. (2024), the coupling degree model for the FA–GTI system is specified as follows:

$$C_{it} = \left[\frac{U(x_{it}) \cdot E(y_{it})}{\left(\frac{U(x_{it}) + E(y_{it})}{2} \right)^2} \right]^{\frac{1}{2}} = \frac{2\sqrt{U(x_{it}) \cdot E(y_{it})}}{U(x_{it}) + E(y_{it})} \tag{4}$$

Where C_{it} denotes the coupling degree between FA and GTI for region i in year t; $U(x_{it})$ and $E(y_{it})$ denote the comprehensive score of the FA and GTI subsystems, respectively. The coupling degree ranges from 0 to 1, with higher values indicating stronger interactions between the two subsystems.

Calculation of Coupling Coordination Degree

Although the coupling degree reflects the strength of interaction and interdependence between the FA and GTI subsystems, it cannot capture their development levels or coordination status, nor can it distinguish between benign and maladaptive coupling relationships. For example, two subsystems at relatively low development levels may still exhibit a high coupling degree if they evolve synchronously. Therefore, a high coupling degree does not necessarily imply a high level of coordinated development. To comprehensively evaluate both the interaction intensity and development quality of the two subsystems, the CCD model is further introduced. Following Cheng et al. (2017) and Song et al. (2018), the CCD model for the FA–GTI system is specified as follows:

$$\begin{aligned} CCD_{it} &= \sqrt{C_{it} \times T_{it}} \\ T_{it} &= \alpha \times U(x_{it}) + \beta \times E(y_{it}) \end{aligned} \quad .(5)$$

Where CCD_{it} denotes the CCD of region i in year t; C_{it} denotes the coupling degree; T_{it} represents the comprehensive development index of the FA–GTI coupled system; $U(x_{it})$ and $E(y_{it})$ denote the comprehensive scores of the FA and GTI subsystems, respectively. α and β represent the weights assigned to the two subsystems. Considering the equally important roles of FA and GTI in regional green transformation and high-quality development, and following Lin et al. (2024), this study sets $\alpha = \beta = 0.5$. The CCD ranges from 0 to 1, with higher values indicating a higher level of coordinated development between the two subsystems.

To facilitate the analysis of coordination stages, the CCD is classified into ten levels according to the criteria proposed by Liao (1999) and Wang and Ma (2011), as shown in Table 3.

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Table 3: Classification Criteria for the CCD of FA and GTI

Level	Value Range	Stage	Level	Value Range	Stage
1	$0.0 \le CCD < 0.1$	Extreme Uncoordination	6	$0.5 \le CCD < 0.6$	Barely Coordination
2	$0.1 \le CCD < 0.2$	Severe Uncoordination	7	$0.6 \le CCD < 0.7$	Primary Coordination
3	$0.2 \le CCD < 0.3$	Moderate Uncoordination	8	$0.7 \le CCD < 0.8$	Moderate Coordination
4	$0.3 \le CCD < 0.4$	Mild Uncoordination	9	$0.8 \le CCD < 0.9$	Good Coordination
5	$0.4 \le CCD < 0.5$	Marginal Uncoordination	10	$0.9 \le CCD \le 1.0$	High-Quality Coordination

Furthermore, the coupling coordination development type can be identified according to the ratio of $U(x_{it})$ to $E(y_{it})$. Specifically, when $U(x_{it})/E(y_{it}) < 0.8$, the system is classified as the FA lagging type; when $0.8 \le U(x_{it})/E(y_{it}) \le 1.0$, it is classified as the synchronised development type; and when $U(x_{it})/E(y_{it}) > 1.0$, it is classified as the GTI lagging type.

Temporal Evolution Analysis of the Coupling Coordination Degree

To examine the temporal evolution of the CCD between FA and GTI, this study conducts a dynamic analysis at the national, regional, and provincial levels. Time-series analysis is employed to identify the overall development trend of CCD, while compound annual growth rate (CAGR) analysis is used to compare the growth dynamics of coordinated development across regions. Scatter plots are developed in order to expose the inequalities between provinces, while classification analysis is done for CCD in order to detect the change in coordination stage levels. Moreover, analysis of CCD types in the context of coupling is carried out in the light of the relative development status of the FA and GTI sub-systems.

Spatial Distribution Analysis of the Coupling Coordination Degree

In order to look into the spatial distribution of the CCD between FA and GTI, this study applies both spatial visualisation and spatial autocorrelation methods. ArcGIS 10.8 is employed to visualise the spatial distribution of CCD classification levels and their evolution over time. Global Moran's I and Local Moran's I are used to examine global and local spatial autocorrelation, respectively. Spatial autocorrelation reflects the degree of similarity among observations across neighbouring spatial units (Moran, 1948). To ensure robustness, three alternative spatial weight matrices are adopted, and the results of the Local Moran's I analysis are visualised using Local Indicators of Spatial Association (LISA) cluster maps.

Spatial Weight Matrices

This study constructs three spatial weight matrices: the geographic distance matrix (W_{d^2}), the economic distance matrix (W_{eco}), and the spatial contiguity matrix (W_{01}). All spatial weight matrices are row-standardised prior to analysis.

Following Paas and Schlitte (2008), the geographic distance matrix is constructed using the inverse squared spherical distance between the provincial capitals. as follows:

$$w_{ij,d^2} = \begin{cases} \dfrac{1}{d_{ij}^2}, & i \ne j \\ 0, & i = j \end{cases} \tag{6}$$

Where w_{ij,d^2} denotes the spatial weight between regions *i* and *j*; d_{ij} represents the spherical distance, which is calculated based on the latitude and longitude of the capital cities of regions i and j.

The economic distance matrix is constructed using the inverse of the absolute difference in average GDP per capita between regions (Wan et al., 2025):

$$w_{ij,eco} = \begin{cases} \dfrac{1}{\left|\overline{PGDP_i} - \overline{PGDP_j}\right|}, & i \neq j \\ 0, & i = j \end{cases} \tag{7}$$

Where $w_{ij,eco}$ denotes the spatial weight between regions *i* and *j*; $\overline{PGDP_i}$ and $\overline{PGDP_i}$ represent the sample-period average GDP per capita for regions *i* and *j*, respectively.

The spatial contiguity matrix is defined based on geographical adjacency between regions (Anselin, 2003), where regions sharing a common boundary or vertex are assigned a value of 1 and 0 otherwise:

$$w_{ij,01} = \begin{cases} 1, & i \neq j, \textit{ region i and region j are contiguous,} \\ 0, & i \neq j, \textit{ region i and region j are not contiguous,} \\ 0, & i = j \end{cases} \tag{8}$$

Where $w_{ij,01}$ denotes the spatial weight between regions *i* and *j*.

Global Moran's I index

Following Das and Ghosh (2016), the Global Moran's I index is employed to examine the overall spatial autocorrelation of CCD. The index is calculated as follows:

$$I_t = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_{it} - \overline{x}_t\right)\left(x_{jt} - \overline{x}_t\right)}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)\sum_{i=1}^{n}\left(x_{it} - \overline{x}_t\right)^2} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_{it} - \overline{x}_t\right)\left(x_{jt} - \overline{x}_t\right)}{S_t^{\,2}\left(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\right)} \tag{9}$$

Where *n* denotes the number of regions; w_{ij} represents the spatial weight between regions *i* and *j*; x_{it} and x_{jt} denote the observed values of CCD in region *i* and *j* in year t, respectively; $\overline{x_t}$ denotes the mean value of CCD across all regions in year t, $\overline{x_t} = \frac{1}{n}\sum_{i=1}^{n} x_{it}$; S_t^2 is the variance of CCD in year t, $S_t^{\,2} = \frac{1}{n}\sum_{j=1}^{n}\left(x_{jt} - \overline{x}_t\right)^2$.

A positive Global Moran's I indicates that regions with similar CCD levels tend to be spatially clustered, whereas a negative Global Moran's I indicates that regions with dissimilar CCD levels tend to be spatially adjacent. A value close to zero suggests a random spatial distribution.

Local Moran's I Index

The Local Moran's I index is employed to identify local spatial clustering patterns of CCD and is calculated as follows:

$$I_{it} = \frac{\left(x_{it} - \overline{x_t}\right)}{S_t^2} \sum_{j=1}^{n} w_{ij} \left(x_{jt} - \overline{x}_t\right) \tag{10}$$

Where I_{it} denotes the *Local Moran's* I index for region i in year t. The definitions of the remaining variables are the same as those in Equation (9).

A positive Local Moran's I indicates positive local spatial autocorrelation, suggesting that a region tends to be surrounded by neighbouring regions with similar CCD levels. Conversely, a negative Local Moran's I indicates negative local spatial autocorrelation, suggesting that a region tends to be surrounded by neighbouring regions with dissimilar CCD levels.

RESULTS AND DISCUSSION

Development Levels of Financial Agglomeration and Green Technology Innovation

Figures 3 and 4 illustrate the trends in the comprehensive scores of FA and GTI, respectively, at both the national level and across the four major economic regions from 2007 to 2022.

The results indicate that the comprehensive scores of both FA and GTI generally exhibited an upward trend during the study period, suggesting continuous improvements in financial development and green innovation capacity in China. Regional differences are clearly observed: the highest level of CCD always appeared in Eastern China, while the lowest one was observed in Western China. The difference between the central region and the northeastern region increased continuously, while the difference between the northeastern region and the western region narrowed down step by step. Overall, the development trend of FA and GTI exhibits a certain degree of convergence.

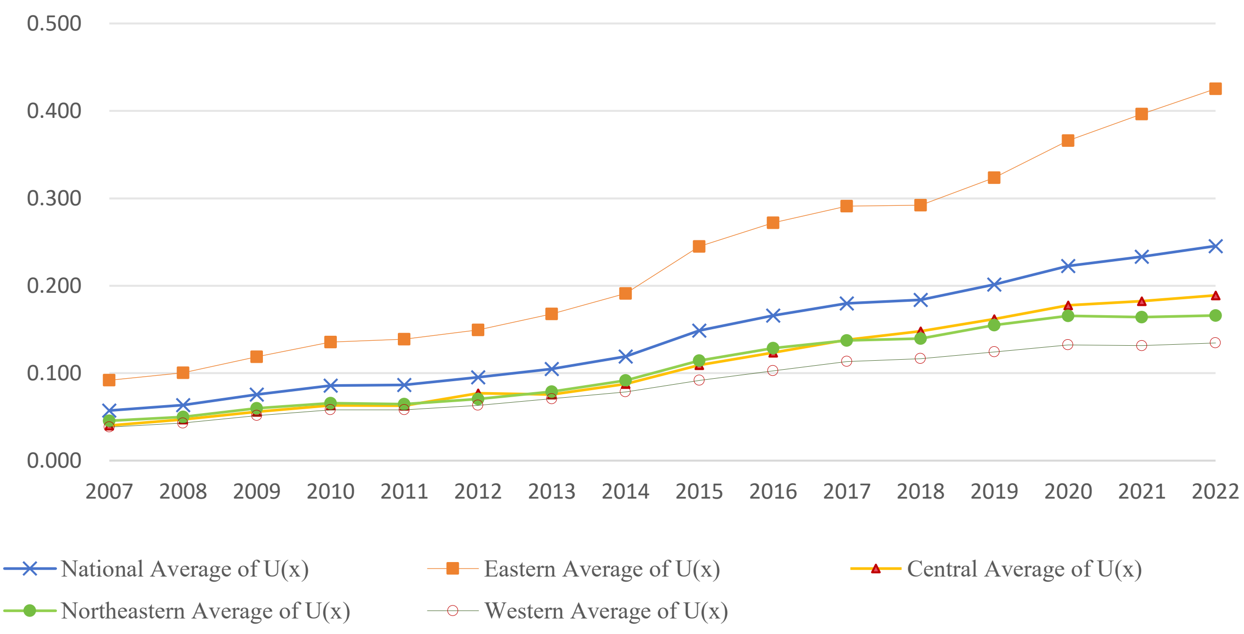

Figure 3: Annual Average Comprehensive Scores of FA for China and Its Four Major Economic Regions, 2007–2022

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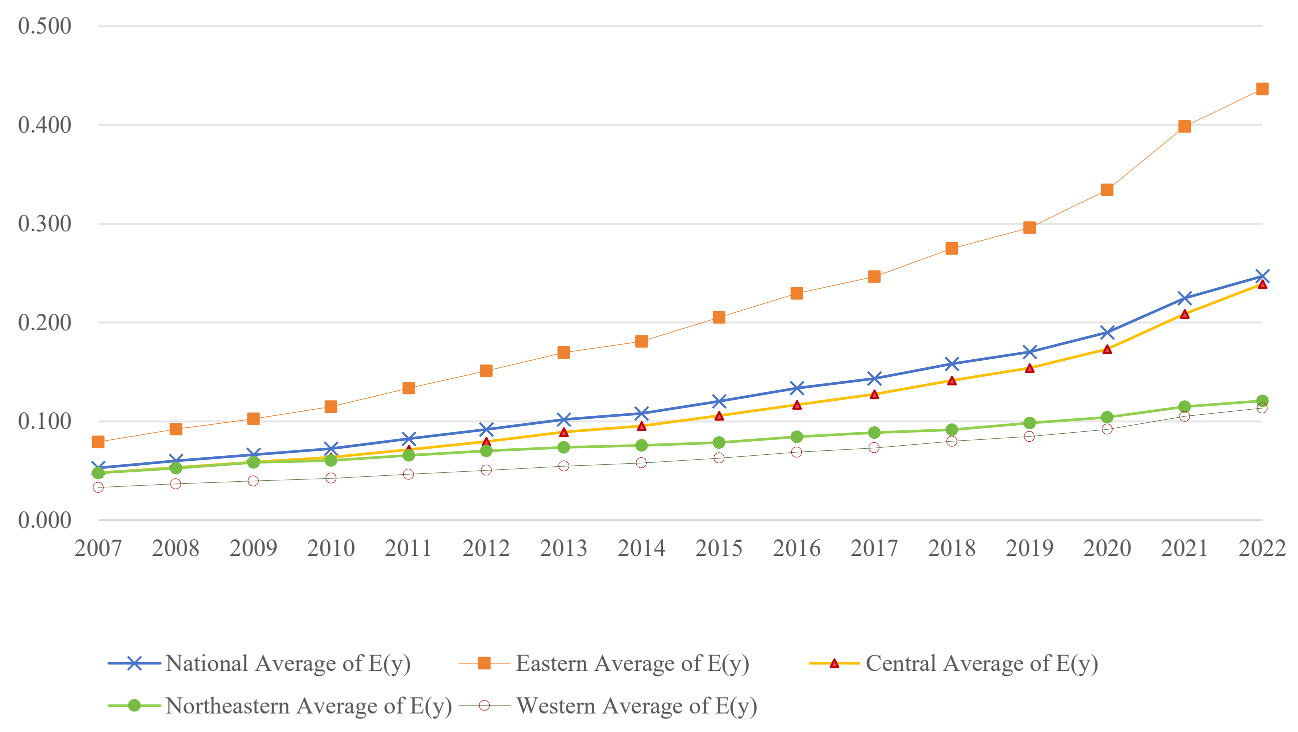

Figure 4: Annual Average Comprehensive Scores of GTI for China and Its Four Major Economic Regions, 2007–2022

Coupling Degree between Financial Agglomeration and Green Technology Innovation

Table 4 presents the average annual coupling degree between FA and GTI from 2007 to 2022. The results are reported for both the national level and the four economic regions. Overall, the coupling degree remained at a relatively high level during the sample period. This suggests a close connection between FA and GTI. Although the coupling degree exhibited a slight downward trend with minor fluctuations, all values remained above 0.95. Among the four regions, Northeast China recorded the largest decline, reflecting a weakening interaction between FA and GTI in that area. Overall, the results indicate that FA and GTI maintained a close coupling relationship during the study period.

However, the coupling degree only reflects the strength of interaction between FA and GTI, it fails to capture the extent of coordinated development between the two subsystems. For example, in 2012, the comprehensive scores of FA and GTI in Hainan were 0.043 and 0.040, respectively, while those in Tianjin were both 0.102. Despite the significant differences in subsystem development levels between these two regions, their coupling degrees were both equal to 1 in 2012. This suggests that a high coupling degree can occur even when the development levels of the subsystems are low. Therefore, to more accurately assess the quality of interaction and the degree of coordinated development between the two subsystems, this study introduces the CCD model for further analysis.

Table4: Annual Average Coupling Degree between FA and GTI in China and Its Four Major Economic Regions, 2007–2022

Year	National	Eastern	Central	Northeastern	Western
2007	0.993	0.993	0.989	0.996	0.993
2008	0.994	0.995	0.993	0.998	0.994

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2009	0.992	0.993	0.995	1.000	0.987
2010	0.990	0.992	0.995	0.999	0.982
2011	0.991	0.995	0.992	1.000	0.986
2012	0.990	0.995	0.990	1.000	0.984
2013	0.988	0.994	0.990	0.999	0.979
2014	0.986	0.992	0.992	0.995	0.974
2015	0.979	0.987	0.990	0.982	0.967
2016	0.977	0.985	0.988	0.977	0.964
2017	0.975	0.985	0.990	0.975	0.958
2018	0.978	0.990	0.991	0.974	0.962
2019	0.977	0.990	0.990	0.969	0.961
2020	0.978	0.989	0.991	0.967	0.963
2021	0.984	0.991	0.990	0.977	0.975
2022	0.986	0.991	0.986	0.982	0.981

Coupling Coordination Degree between Financial Agglomeration and Green Technology Innovation

Using the CCD model, the coordinated development level between FA and GTI was estimated for China, the four major economic regions, and 30 provincial-level administrative regions over the period 2007–2022. The results are reported in Table 5. As shown in Table 5, the CCD between FA and GTI generally exhibited an upward trend during the study period, indicating a gradual improvement in the coordinated development of the two subsystems. However, the coordination level was still low. Regional differences remained evident.

Table 5. CCD between FA and GTI, 2007–2022

Region	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
National	0.226	0.240	0.256	0.270	0.278	0.293	0.307	0.321	0.346	0.365	0.379	0.390	0.406	0.426	0.446	0.461
Eastern Region	0.283	0.301	0.322	0.342	0.357	0.375	0.397	0.417	0.455	0.479	0.496	0.511	0.533	0.565	0.600	0.623
Beijing	0.398	0.411	0.433	0.459	0.470	0.495	0.521	0.550	0.600	0.629	0.645	0.651	0.679	0.709	0.765	0.794
Tianjin	0.263	0.267	0.280	0.293	0.304	0.319	0.334	0.346	0.367	0.384	0.385	0.391	0.403	0.417	0.429	0.434
Hebei	0.210	0.227	0.247	0.258	0.262	0.276	0.292	0.308	0.334	0.355	0.375	0.392	0.411	0.433	0.452	0.468
Shanghai	0.359	0.382	0.407	0.425	0.437	0.444	0.463	0.488	0.539	0.571	0.584	0.590	0.613	0.642	0.695	0.735
Jiangsu	0.307	0.332	0.363	0.392	0.420	0.450	0.483	0.510	0.555	0.588	0.617	0.640	0.672	0.723	0.771	0.800
Zhejiang	0.303	0.331	0.353	0.375	0.396	0.415	0.438	0.454	0.501	0.515	0.535	0.563	0.593	0.637	0.677	0.707
Fujian	0.221	0.234	0.247	0.263	0.275	0.291	0.308	0.322	0.350	0.366	0.376	0.389	0.407	0.433	0.451	0.468
Shandong	0.271	0.294	0.319	0.345	0.362	0.380	0.407	0.426	0.462	0.487	0.508	0.521	0.539	0.580	0.619	0.653
Guangdong	0.339	0.362	0.393	0.424	0.453	0.479	0.514	0.541	0.618	0.665	0.696	0.725	0.764	0.820	0.881	0.915
Hainan	0.159	0.167	0.180	0.191	0.195	0.204	0.212	0.218	0.228	0.236	0.243	0.249	0.254	0.259	0.257	0.259
Central Region	0.208	0.223	0.238	0.251	0.257	0.276	0.284	0.300	0.325	0.343	0.361	0.377	0.394	0.415	0.437	0.455
Shanxi	0.205	0.216	0.231	0.237	0.236	0.246	0.258	0.267	0.285	0.298	0.305	0.312	0.322	0.332	0.341	0.347
Anhui	0.209	0.225	0.240	0.250	0.260	0.276	0.294	0.309	0.335	0.357	0.377	0.396	0.409	0.435	0.466	0.491
Jiangxi	0.180	0.191	0.205	0.217	0.221	0.229	0.244	0.262	0.284	0.304	0.313	0.331	0.352	0.373	0.392	0.406
Henan	0.221	0.239	0.255	0.273	0.285	0.293	0.311	0.327	0.350	0.372	0.395	0.415	0.429	0.449	0.465	0.479
Hubei	0.228	0.241	0.259	0.274	0.280	0.341	0.313	0.336	0.366	0.386	0.409	0.427	0.449	0.478	0.507	0.530
Hunan	0.206	0.224	0.238	0.252	0.260	0.271	0.285	0.301	0.329	0.344	0.368	0.381	0.401	0.422	0.450	0.479
Northeastern Region	0.215	0.225	0.242	0.250	0.254	0.264	0.274	0.286	0.306	0.321	0.330	0.333	0.349	0.360	0.368	0.374
Liaoning	0.246	0.259	0.274	0.288	0.291	0.306	0.320	0.334	0.354	0.372	0.383	0.387	0.401	0.413	0.423	0.431
Jilin	0.207	0.213	0.229	0.229	0.232	0.240	0.247	0.256	0.274	0.292	0.300	0.302	0.323	0.331	0.337	0.342
Heilongjiang	0.191	0.205	0.223	0.232	0.238	0.245	0.255	0.269	0.289	0.298	0.306	0.312	0.323	0.335	0.344	0.348
Western Region	0.187	0.197	0.210	0.220	0.225	0.234	0.245	0.255	0.270	0.284	0.295	0.303	0.312	0.323	0.332	0.340
Inner Mongolia	0.156	0.167	0.181	0.191	0.198	0.209	0.215	0.223	0.236	0.252	0.264	0.270	0.277	0.284	0.283	0.292
Guangxi	0.171	0.183	0.199	0.207	0.217	0.229	0.242	0.252	0.267	0.282	0.291	0.300	0.308	0.320	0.347	0.342
Chongqing	0.224	0.241	0.254	0.270	0.278	0.285	0.293	0.305	0.322	0.337	0.347	0.360	0.373	0.391	0.405	0.418
Sichuan	0.229	0.252	0.271	0.284	0.294	0.310	0.331	0.344	0.372	0.401	0.422	0.439	0.453	0.477	0.501	0.521
Guizhou	0.181	0.186	0.199	0.209	0.214	0.220	0.228	0.237	0.247	0.260	0.272	0.284	0.297	0.303	0.307	0.316
Yunnan	0.191	0.207	0.219	0.225	0.226	0.234	0.244	0.253	0.268	0.280	0.290	0.298	0.305	0.312	0.319	0.329
Shaanxi	0.216	0.226	0.241	0.254	0.259	0.270	0.291	0.306	0.327	0.341	0.355	0.369	0.387	0.406	0.425	0.443

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Gansu	0.172	0.181	0.195	0.202	0.206	0.217	0.228	0.240	0.256	0.269	0.278	0.282	0.290	0.300	0.304	0.307
Qinghai	0.153	0.155	0.167	0.179	0.177	0.185	0.189	0.195	0.207	0.210	0.221	0.220	0.219	0.221	0.221	0.220
Ningxia	0.184	0.185	0.192	0.198	0.198	0.205	0.212	0.219	0.227	0.236	0.244	0.249	0.253	0.257	0.259	0.261
Xinjiang	0.178	0.181	0.194	0.201	0.203	0.212	0.221	0.230	0.241	0.252	0.261	0.264	0.271	0.280	0.282	0.290

Temporal Evolution Characteristics of the Coupling Coordination Degree

Overall Evolution Trends

Figure 5 presents the annual average CCD values for China and the four major economic regions from 2007 to 2022. CCD increased over time at both the national and regional levels. This implies that the coordinated relationship between FA and GTI has gotten better during the study period. This improvement in CCD was supported by the continued implementation of green finance and ecological civilisation policies. Financial resources also provided sustained support for green innovation.

Between 2007 and 2009, CCD was highest in Eastern China, then Northeastern, Central and Western China. However, from 2010 onwards, Central China surpassed Northeastern China in terms of ranking and became the second-best performing region. On the other hand, Eastern China continued to outperform the national average, while Western China stayed below it. Since 2011, Central China's CCD has moved closer to the national level. The gap between Northeastern and Western China also narrowed. Although CCD improved in all regions, regional differences were still apparent.

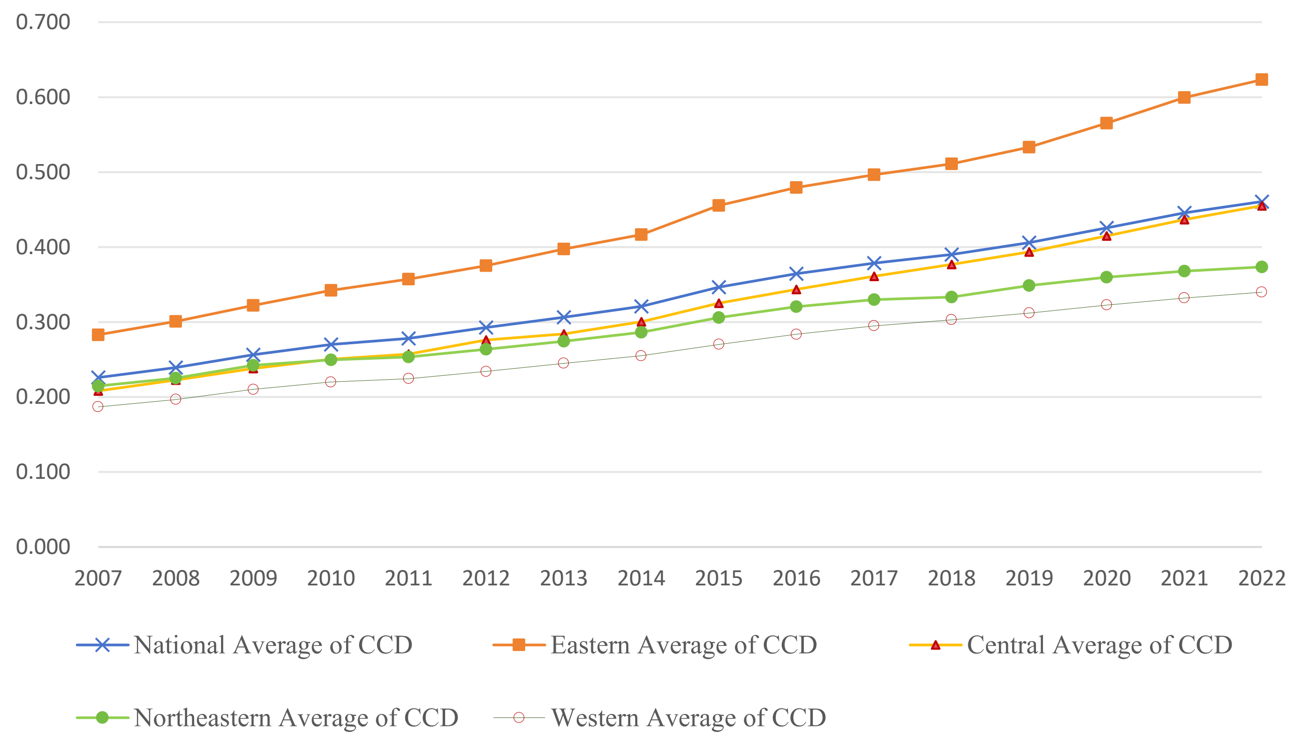

Figure 5: Annual Average CCD for China and Its Four Major Economic Regions, 2007–2022

Growth Dynamics of CCD

Figure 6 shows the Compound Annual Growth Rate (CAGR) of CCD. The CAGR of the CCD at the national level was 4.863%. Regional differences in CCD growth were evident. Eastern China recorded a CAGR of 5.401%, slightly higher than that of Central China (5.353%). Western China and Northeastern China grew at a slower pace, with rates of 4.068% and 3.759%, respectively. Across provinces, Guangdong showed the strongest growth (6.839%), whereas Ningxia experienced the weakest growth (2.375%).

The CCD between FA and GTI keeps getting better during the sample period. The Eastern and Central regions enjoy sound economic conditions, so their coordination degree rises at a higher speed. The western and northeastern regions advance at a much lower rate. In view of such regional differentiation, it is urgent to strengthen the integration of financial industry and green innovation in backward region

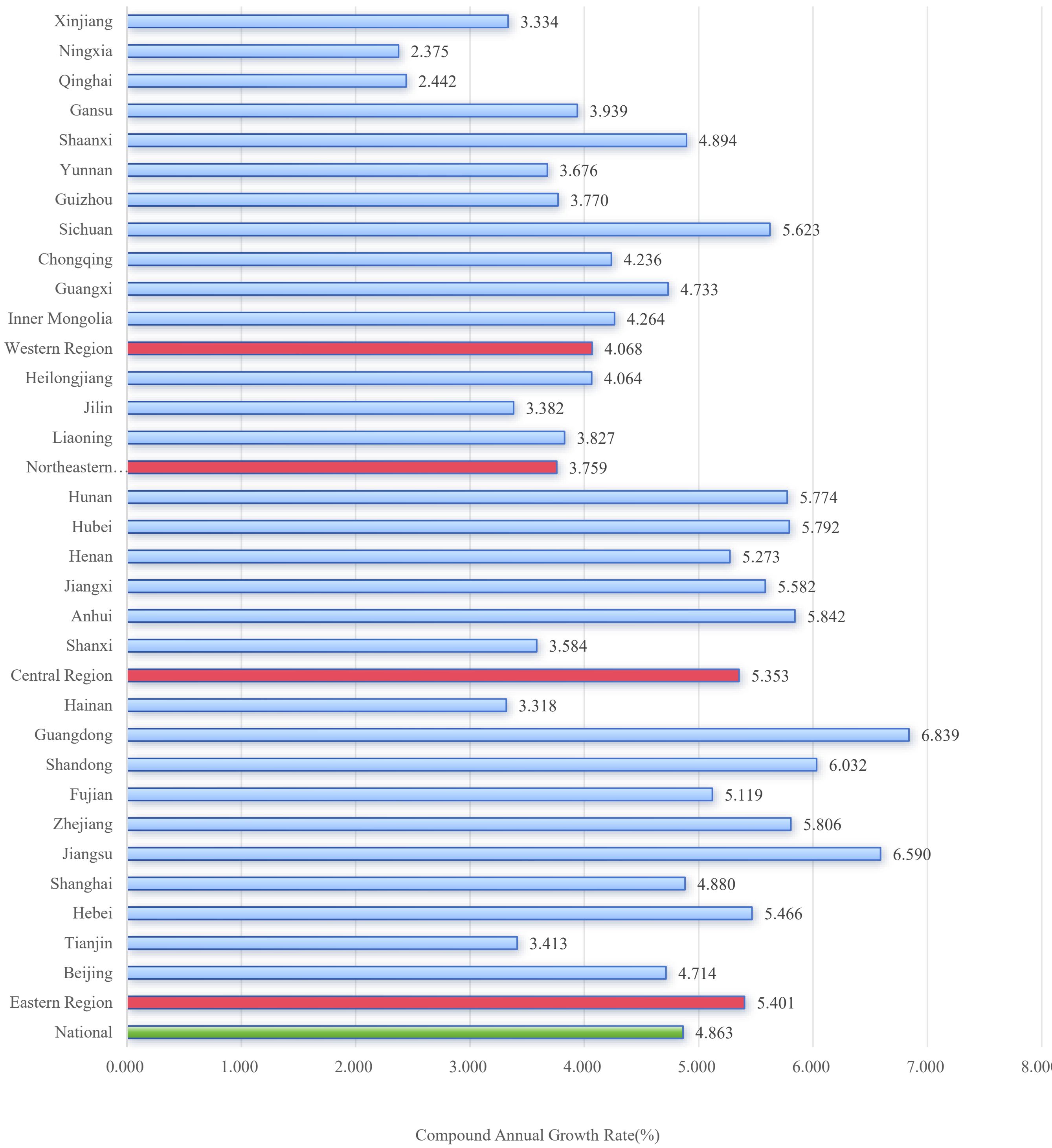

Figure 6: Compound Annual Growth Rate of the CCD for China, Its Four Major Economic Regions, and 30 Provincial-Level Administrative Regions, 2007–2022

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Provincial Disparities in CCD

Figure 7 tracks the annual changes in the CCD between FA and GTI across 30 provinces. The majority of provinces saw steady growth in this CCD throughout the sample period, which reflects widespread progress in the coordinated development of FA and GTI. Minor short-term drops only emerged in individual years for a small number of regions: Shanxi in 2011, Hubei in 2012, Inner Mongolia and Hainan in 2021, Guangxi in 2022, and Qinghai in 2011, 2018, 2019 and 2022.

The fluctuations were largely driven by imbalances between FA and GTI. In Shanxi, Inner Mongolia, Guangxi, and Hainan are primarily due to decreases in FA levels compared with the previous year, despite an increase in GTI levels during the same period. In Hubei (2012), the FA comprehensive score increased by 0.066, whereas the GTI comprehensive score increased by only 0.010. The significant disparity in the growth of the two subsystems resulted in a decline in the CCD level. In Qinghai, neither FA nor GTI showed a sustained upward trend; instead, both exhibited substantial fluctuations, resulting in pronounced volatility in the CCD over multiple years. Despite such differences, CCD in most cases grew up. Regional differences, however, were still present.

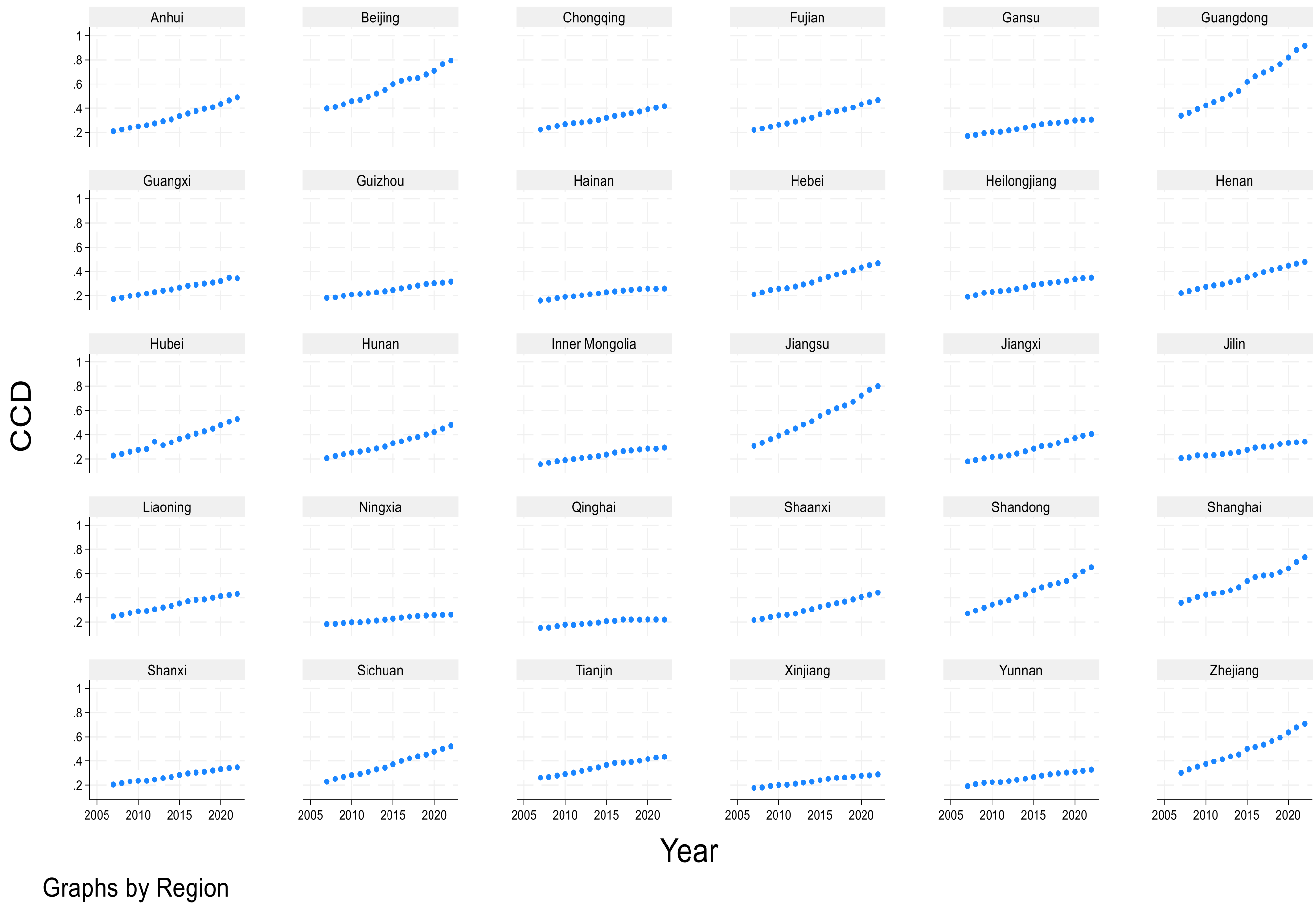

Figure 7: Scatter Plot of CCD for 30 Provincial-Level Administrative Regions in China, 2007–2022

Evolution of CCD Classification Levels

Figure 8 displays the CCD classification level changes from 2007 to 2022. The country level classification has evolved from Moderate Uncoordination to Marginal Uncoordination. This means that there has been a gradual improvement of the CCD between FA and GTI over the period. Nevertheless, there has not yet been any coordination in the CCD by 2022. There is room for further improvements.

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There have been different patterns for different regions. For instance, Eastern China was able to make the greatest achievement since its classification improved by four levels from Moderate Uncoordination to Primary Coordination. Central and Western China experienced two-level advancement, and Northeastern China made one-level improvement. Even though all regions were able to make improvements, there was still regional disparity.

In Eastern China, with the exception of Hainan (Moderate Uncoordination) and Tianjin, Hebei, and Fujian (Marginal Uncoordination), all other provinces had entered the coordination stage. Among them, Guangdong achieved the highest level, reaching High-Quality Coordination, followed by Beijing, Shanghai, Jiangsu, and Zhejiang at Moderate Coordination, and Shandong at Primary Coordination. In Central China, only Hubei had reached Barely Coordination, while Anhui, Jiangxi, Henan, and Hunan were at Marginal Uncoordination, and Shanxi remained at Mild Uncoordination. In Northeastern China, all three provinces were still at the uncoordinated stage: Jilin and Heilongjiang were at Mild Uncoordination, while Liaoning was at Marginal Uncoordination. In Western China, only Sichuan had reached Barely Coordination, while the remaining provinces were still at varying degrees of uncoordination: Chongqing and Shaanxi were at Marginal Uncoordination; Guangxi, Guizhou, Yunnan, and Gansu were at Mild Uncoordination; and Inner Mongolia, Qinghai, Ningxia, and Xinjiang remained at Moderate Uncoordination.

These patterns point to an uneven spatial distribution of CCD, with Eastern China continuing to outperform the other regions. Eastern China showed the fastest improvement in coordination. This is likely associated with its higher level of economic development, a more developed financial system, and stronger green innovation capacity. Central China also improved steadily. Regional development strategies and industrial transfer contributed to this progress. Coordination developed more slowly in Northeastern and Western China. Industrial structure, financial resources, and innovation capacity limited their development. Overall, the coordinated development of FA and GTI still showed a clear regional gradient across China.

Hubei and Sichuan were the only provinces to reach the coordinated development stage in Central China and Western China, respectively. This pattern is consistent with the development level of regional financial centres. According to the 39th Global Financial Centres Index (GFCI), only three cities in Central and Western China were included in the ranking: Wuhan (the capital of Hubei), Chengdu (the capital of Sichuan), and Xi'an (the capital of Shaanxi). Wuhan was the only global financial centre in Central China. It has national carbon finance infrastructure, including the China Emissions Allowances Registration System, and the green innovation cluster in the Donghu High-tech Development Zone. These advantages strengthen the allocation of green financial resources and support regional green technology innovation. Chengdu and Xi'an were the two ranked cities in Western China, but their development levels differed greatly. Chengdu ranked 37th globally. It has the Tianfu New Area Green Finance Reform and Innovation Pilot Zone, the Sichuan United Environment Exchange, and the Green Rongtong regional green investment and financing platform. It also has a well-developed clean energy industry, including lithium battery and photovoltaic industries. These conditions create a strong foundation for green finance to support innovation. Xi'an ranked 79th globally. Its financial centre was less competitive. It had fewer supporting resources for green finance and low-carbon technological innovation. Its ability to attract and allocate green innovation resources was weaker than Chengdu's. Shaanxi ranked second in coupling coordination within Western China. It remained in the disorder stage. The other provinces in Central and Western China have not developed high-level financial centres with strong resource concentration. Their green industries and innovation capacity remain relatively weak. They also lack specialised green financial services. FA provides limited support for green technology innovation. Most provinces remain at different stages of disorder.

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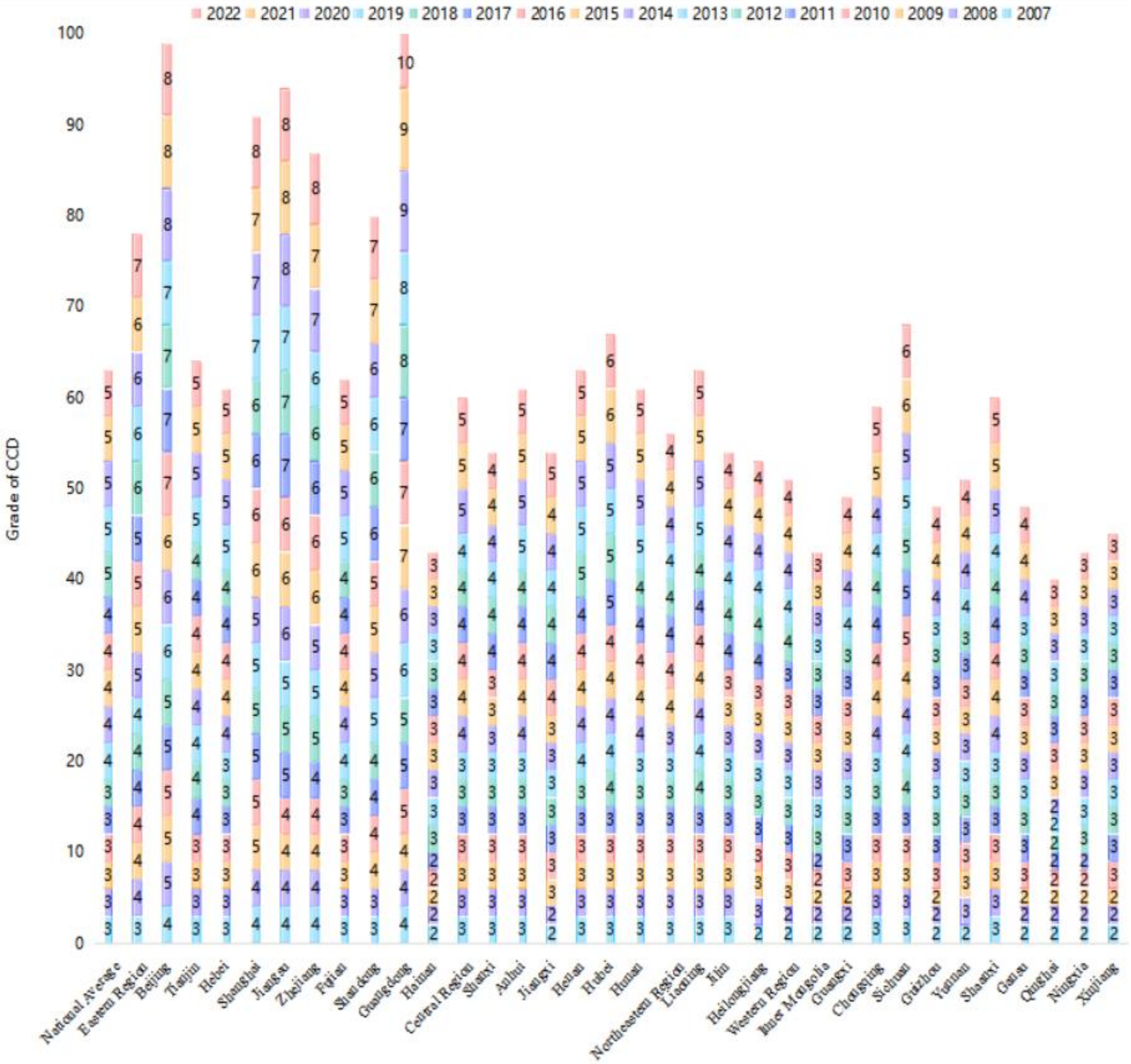

Figure 8: CCD Classification Levels for China, Its Four Major Economic Regions, and 30 Provincial-Level Administrative Regions, 2007–2022

Note: The numerical codes in the figure correspond to the CCD classification levels defined in Table 3.

Evolution of CCD Types

Figure 9 presents changes in CCD types. From 2007 to 2022, 15 provinces consistently are the GTI-lagging type. In these provinces, the growth of GTI did not keep pace with the expansion of FA. The provinces can be grouped into several categories according to their development patterns. (1) High-financial-agglomeration regions. Beijing and Shanghai are China's leading financial and innovation centres. Both cities exhibit high levels of FA. However, GTI has grown more slowly than FA, resulting in a GTI-lagging pattern. (2) Traditional industrial bases. Hebei and Liaoning are heavily reliant on resource-intensive industries, and their GTI foundations are fragile. Trapped by resource path dependence and arduous industrial upgrading tasks, local GTI cannot achieve rapid expansion. (3) Resource-based economies. Shanxi, Inner Mongolia, Guizhou, Qinghai, Ningxia, and Xinjiang are representative resource-based regions. Their economic growth depends on coal, minerals and other natural resources. They have energy-consuming industries which comprise a significant part of the economy. Such situation hinders the development of GTI. (4) Ecological resources abundant regions with poor innovation

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conversion. Guangxi, Chongqing, Sichuan and Yunnan have many resources such as hydroelectric power and forest ecological resources but they cannot convert ecological advantages into GTI output. (5) Traditional industry-based region. Fujian province has a traditional industrial sector which includes textile production, food processing and construction materials production. There is low level of technology in these industries and they do not have enough incentives for GTI investment.

The rest of 15 provinces had transitions among three types of CCD during the period from 2007 to 2022. These transitions show that the relationship between FA and GTI was not static. (1) The transition of Tianjin, Jilin and Gansu was between the synchronous type and GTI-lagging type. In the recent years the GTI-lagging type became more typical. FA level was quite stable in these provinces while GTI was changing. (2) The transition of Zhejiang and Guangdong was between the GTI-lagging type and the synchronous type. The latter became more typical in the later years. (3) In case of Henan Province the transition was from the synchronous type to the GTI-lagging type and then to the synchronous type again. (4) Jiangsu, Shandong, Hubei, Anhui and Hunan provinces had transition between the synchronous type and FA-lagging type. Sometimes FA development was slower than GTI development. (5) In Hainan, Jiangxi, Heilongjiang and Shaanxi provinces there were transitions between all three types of CCD. Periodic mismatch between FA and GTI happened in these regions.

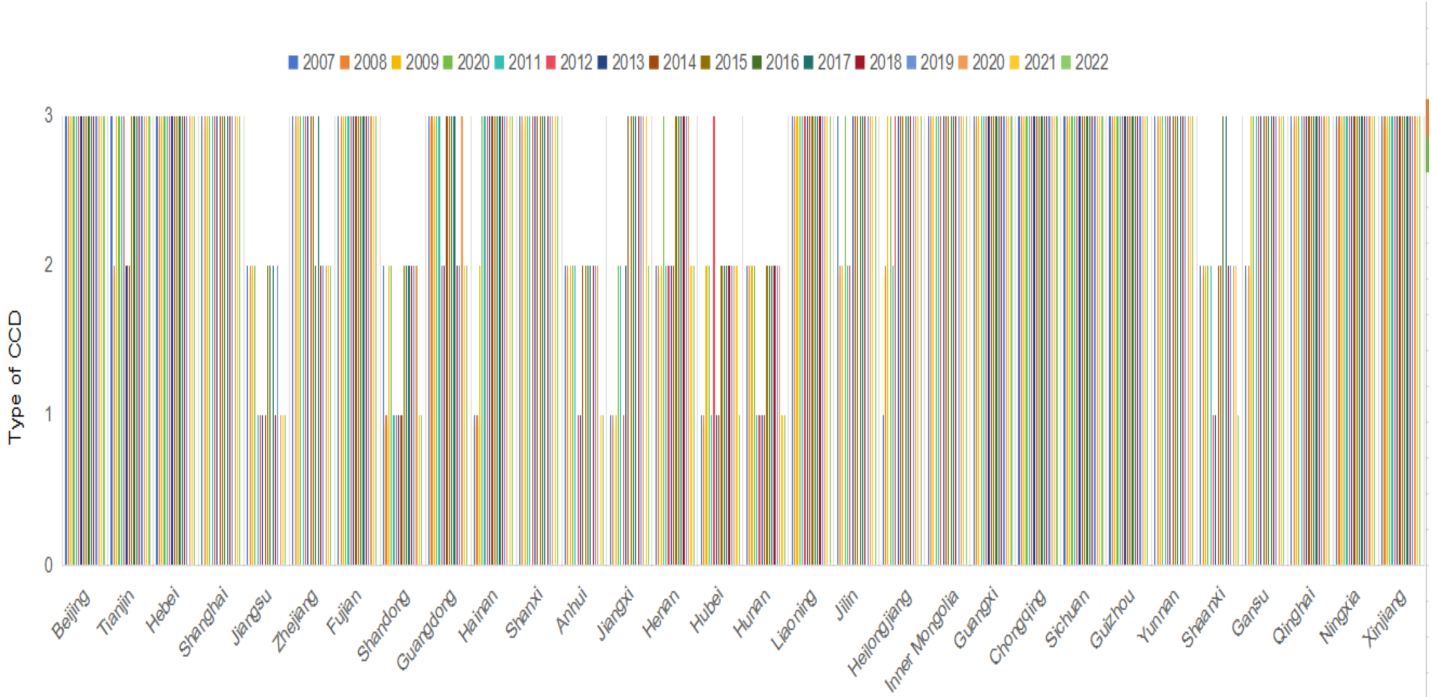

Figure 9: CCD Types for 30 Provincial-Level Administrative Regions in China, 2007–2022

Note: Types are defined as follows: 1 = FA Lagging Type, 2 = Synchronous Type, 3 = GTI Lagging Type.

Spatial Distribution Characteristics of the Coupling Coordination Degree

Spatial Distribution Patterns

Figure 10 showed the spatial distribution of the CCD in 2007, 2012, 2017, and 2022. Differences could be easily seen across the provinces. All the provinces witnessed an increase in the value of the CCD, even if to different degrees. This reflects greater coordination between the FA and GTI.

There were differences in the spatial distribution of the CCD. Provinces in Eastern China saw higher CCD levels compared to other regions. Among the provinces in Central and Western China, Hubei and Sichuan showed good results. Only Guangdong Province attained the High-Quality Coordination in 2022. Despite improvements in the CCD, differences existed in the regional context. The East-Central-Northeastern-West trend prevailed, and few provinces managed to reach the coordination development stage.

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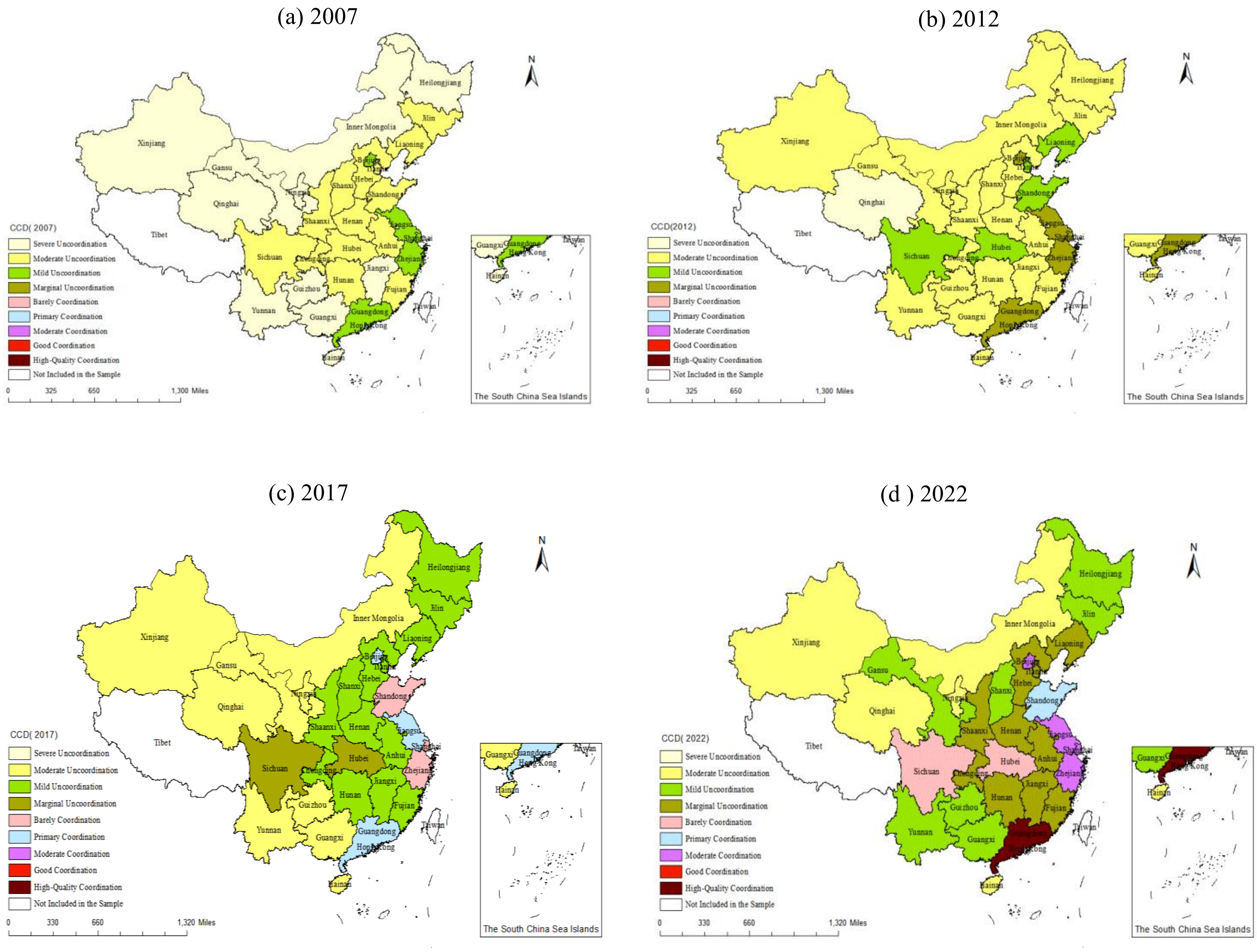

Figure 10: Spatial Distribution of CCD in China, 2007, 2012, 2017, and 2022

Global Spatial Autocorrelation Analysis

The Global Moran's I index assesses whether CCD exhibits significant spatial autocorrelation at the national level. Table 6 reports the results of the Global Moran's I test. Under all three spatial weight matrices, Moran's I values are positive and significant at the 10% level or better. This points to the presence of positive spatial dependence in CCD across provinces. Provinces with similar CCD levels are more likely to be located near each other. As a result, High-High and Low-Low clusters can be observed. Different spatial weight matrices produce consistent results.

Moran's I followed different patterns under the three spatial weight matrices. Moran's I values were generally highest under the economic distance matrix. Economic proximity played a stronger role in the spatial clustering of CCD than geographical proximity. Under the geographic distance and economic distance matrices, the Moran's I values showed an overall downward trend. This trend indicates a gradual weakening of spatial dependence. Under the spatial contiguity matrix, the values changed only slightly and remained relatively stable. Overall, positive spatial clustering remained significant throughout the study period despite some variation in its strength.

Table 6: Global Moran's I of CCD, 2007–2022

Year	Geographic Distance Matrix (W_{d^2})			Economic Distance Matrix (W_{eco})			Spatial Contiguity Matrix (W_{01})		
	Moran's I	Z-Score	P-Value	Moran's I	Z-Score	P-Value	Moran's I	Z-Score	P-Value
2007	0.232	2.956	0.003	0.312	3.672	0.000	0.217	2.095	0.036
2008	0.231	2.910	0.004	0.296	3.469	0.001	0.227	2.163	0.031
2009	0.222	2.805	0.005	0.286	3.353	0.001	0.227	2.153	0.031
2010	0.213	2.707	0.007	0.282	3.309	0.001	0.231	2.180	0.029
2011	0.221	2.785	0.005	0.279	3.266	0.001	0.242	2.263	0.024
2012	0.211	2.665	0.008	0.276	3.231	0.001	0.227	2.135	0.033
2013	0.212	2.683	0.007	0.262	3.091	0.002	0.237	2.224	0.026
2014	0.206	2.624	0.009	0.260	3.069	0.002	0.235	2.212	0.027
2015	0.197	2.524	0.012	0.254	3.015	0.003	0.220	2.088	0.037
2016	0.188	2.434	0.015	0.247	2.944	0.003	0.205	1.972	0.049
2017	0.177	2.318	0.021	0.230	2.765	0.006	0.193	1.874	0.061
2018	0.184	2.385	0.017	0.216	2.615	0.009	0.202	1.948	0.052
2019	0.183	2.382	0.017	0.215	2.606	0.009	0.201	1.937	0.053
2020	0.187	2.425	0.015	0.207	2.529	0.011	0.210	2.014	0.044
2021	0.190	2.450	0.014	0.204	2.495	0.013	0.218	2.076	0.038
2022	0.198	2.530	0.011	0.204	2.490	0.013	0.225	2.130	0.033

Local Spatial Autocorrelation Analysis

Local Moran's I was used to examine spatial autocorrelation at the provincial level under the geographic distance, economic distance, and spatial contiguity matrices. Figures 11-13 present the LISA cluster maps of the CCD under three types of spatial weight matrices in 2007 and 2022.

High–High clusters were observed mainly in Eastern China. Low–Low clusters were more common in Western China. This pattern points to clear spatial clustering in the coordinated development of FA and GTI.

Under the economic distance matrix, Hainan belonged to the Low–Low cluster in 2022. Although located in Eastern China, Hainan's economic structure differs from that of the more developed coastal provinces and is closer to that of less-developed regions. Both tourism and real estate sectors have continued to play an important part in the economy, although the performance of FA and GTI is still weak. Based on the spatial contiguity matrix, Hainan has been identified as an Low–High pattern. There is only one adjoining province for Hainan, which is Guangdong, whose CCD level is much higher than Hainan's.

Guangdong belongs to the High-Low pattern based on both the geographic distance and spatial contiguity matrices. Its CCD level is much higher than those of other adjoining provinces. There seems to be no significant spatial spillover effect from Guangdong to other provinces.

More provinces had statistically significant Local Moran's I values in 2022 compared to 2007. This points to stronger local spatial dependence. The coordinated development of FA and GTI became increasingly interconnected across regions. Spatial spillovers and interregional linkages were more evident than before. These findings highlight the importance of regional cooperation and the cross-regional flow of financial and innovation resources.

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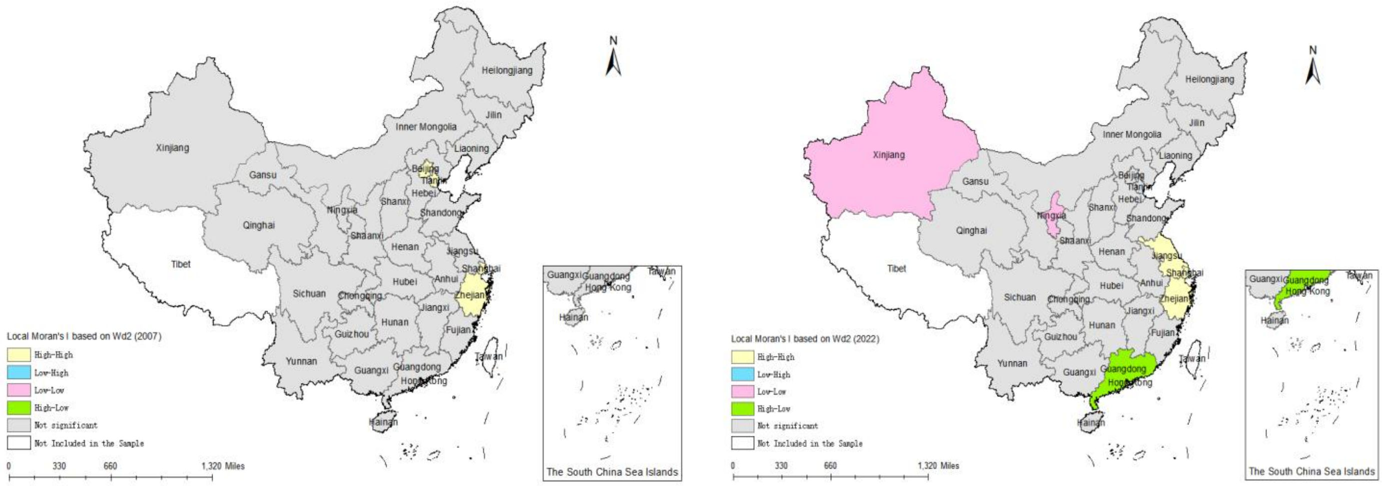

Figure 11: LISA Cluster Maps of the CCD under the Geographic Distance Matrix in 2007 and 2022

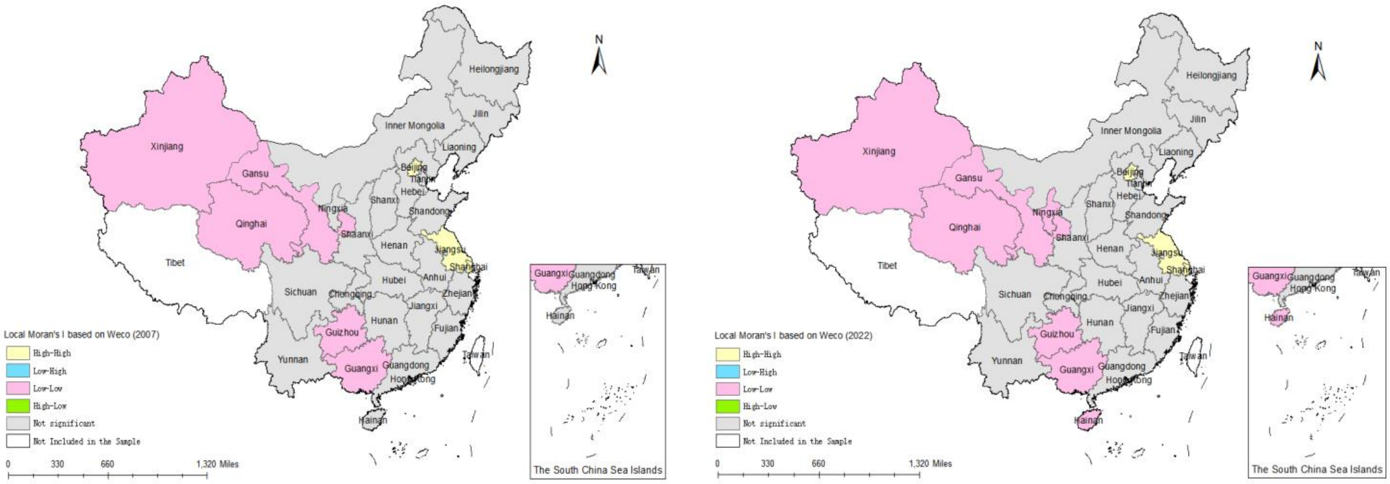

Figure 12: LISA Cluster Maps of the CCD under the Economic Distance Matrix in 2007 and 2022

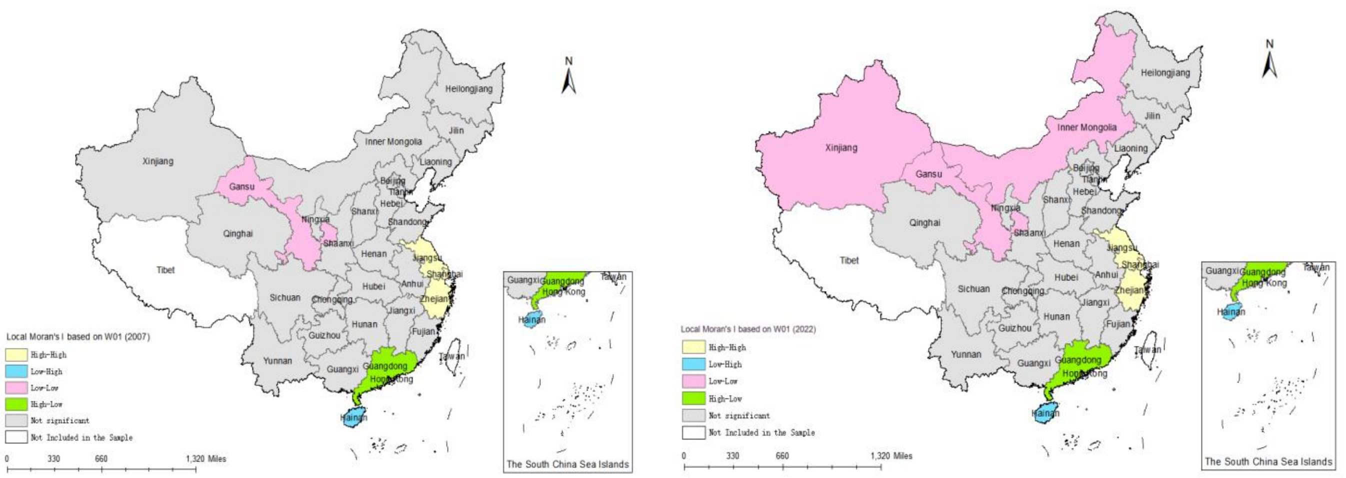

Figure 13: LISA Cluster Maps of the CCD under the Spatial Contiguity Matrix in 2007 and 2022

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CONCLUSION

Main Findings

This study explores the spatiotemporal evolution of the CCD between FA and GTI in China from 2007 to 2022. In summary, the key findings of the study can be summarised as below.

First, the CCD between FA and GTI increased gradually during the entire study period, suggesting an increasing trend in the coordinated development of these two subsystems. However, it is found that the CCD level has been relatively low and did not enter the coordination stage in the national scale. There have been serious gaps in the CCD between regions throughout the entire study period. Eastern China has consistently possessed the highest CCD levels, while Western and Northeastern China have been lower than the other regions.

Second, it can be found that the evolution of the development types of coupling coordination development exhibits obvious heterogeneity among different provinces. Many provinces have possessed the GTI-lagging development type, which means that the development of GTI has lagged behind the concentration of the financial resources. This finding is particularly noticeable in resource-based and traditional industrial regions, reflecting the continuing challenge to transform the advantage in finance into GTI development.

Third, obvious positive spatial autocorrelation is found under geographic distance matrix, economic distance matrix and spatial contiguity matrix. The provinces with similar CCD levels would cluster in space, and High-High clusters are mainly located in Eastern China while Low-Low clusters are mainly located in Western China. The increasing proportion of provinces with significant local spatial autocorrelation means that inter-region interactions are playing an increasingly important role in the process of coordinated development.

In conclusion, it is clear that even though the development of coordination between FA and GTI has made great progress, regional imbalances still persist. The promotion of integrated development of financial development and GTI, cross-region cooperation and diffusing innovation and financial resources among high-coordinated regions is essential for balanced regional development.

Policy Implications

From the above findings, some policy suggestions s can be put forward.

First, greater financial support should be directed towards GTI. GTI remains the main constraint on the coordinated development of FA and GTI. Governments and financial institutions can expand green credit, green bonds, green investment funds, and other green financial instruments to ease financing constraints. Financial institutions should improve the allocation of financial resources. They should support green technology research, the commercialisation of innovation, and strategic emerging industries. These measures will strengthen the coordinated development of FA and GTI.

Second, different policies and strategies should be applied in accordance with the conditions of each region. Eastern China should shift its policy focus from expanding coordination to improving the quality of coordinated development by strengthening frontier green innovation and enhancing the spillover of financial and innovation resources. Central China should continue improving regional financial services and innovation capacity by taking advantage of industrial transfer and regional development strategies. In contrast, Western and Northeastern China should prioritise industrial transformation, optimise financial resource allocation, and strengthen green innovation capacity to narrow regional disparities in coordinated development. Notably, Hubei and Sichuan, as the only provinces in Central and Western China to reach the coordination stage, could further consolidate their advantages by strengthening regional innovation hubs and promoting the diffusion of successful development experiences to neighbouring provinces.

Third, policies should reflect different coupling coordination types.. For high-financial-agglomeration regions, represented by Beijing and Shanghai, policy efforts should focus on increasing investment in green technology R&D, strengthening innovation incentive mechanisms, and improving the transformation of financial advantages into green innovation outcomes. For traditional industrial bases, such as Hebei and Liaoning, priority should be given to accelerating industrial upgrading, strengthening innovation infrastructure, and enhancing enterprises' green innovation capabilities. For resource-dependent regions, including Shanxi, Inner Mongolia, Guizhou, Qinghai, Ningxia, and Xinjiang, governments should promote the development of green industries and the circular economy while encouraging financial institutions to provide diversified green financial products to support industrial transformation. For ecological-resource-rich regions with relatively weak innovation transformation, such as Guangxi, Chongqing, Sichuan, and Yunnan, greater emphasis should be placed on strengthening technology transfer platforms and financial support to facilitate the transformation of ecological advantages into green innovation advantages. For traditional manufacturing regions, represented by Fujian, policies should encourage enterprises to accelerate green technological upgrading and improve the technological sophistication and environmental performance of traditional industries.

Fourth, policies should also respond to changes in CCD. In provinces oscillating between the synchronous and GTI-lagging types, such as Tianjin, Jilin, and Gansu, governments should stabilise green technology R&D investment and establish long-term financial support mechanisms to reduce periodic fluctuations. In provinces such as Zhejiang and Guangdong, where the coordinated relationship has gradually improved, efforts should focus on consolidating the alignment between financial services and green innovation to sustain high-quality coordinated development. For provinces experiencing transitions among all three coupling coordination types, including Hainan, Jiangxi, Heilongjiang, and Shaanxi, adaptive policy frameworks should be developed to identify stage-specific mismatches between FA and GTI and implement flexible coordination strategies according to different development stages.

Finally, interregional cooperation and policy coordination should be strengthened. Given the significant positive spatial autocorrelation identified in this study, governments should promote cross-regional cooperation in financial services, technology transfer, innovation platforms, and talent mobility to facilitate the diffusion of financial resources, knowledge, and green technologies from high-performing regions to less-developed regions. At the same time, stronger coordination among financial, industrial, environmental, and innovation policies should be established to create a supportive institutional environment for the long-term coordinated development of FA and GTI.

Limitations and Future Research

Despite its theoretical and practical contributions, this study has several limitations.

First, although the indicator systems and the entropy method provide a comprehensive measure of FA and GTI, the choice of indicators may still affect the evaluation results. The current indicator system also does not fully capture emerging dimensions such as green finance, digital finance, innovation quality, and energy efficiency. Future research can refine the indicator system and compare different weighting methods to test the robustness of the results.

Second, this study uses provincial-level panel data. These data cannot fully capture differences within provinces, especially in geographically large provinces. Future research can use city-level or county-level data to provide a more detailed analysis of the coordinated development between FA and GTI.

Finally, this study focuses on the temporal evolution and spatial distribution characteristics of the CCD between FA and GTI. It does not examine the determinants and driving mechanisms in depth. Future research can use spatial econometric models and other quantitative methods to identify the factors behind regional differences and examine the mechanisms of coordinated development between FA and GTI.

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