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Trends and Regional Disparities in the High-Quality Development of International Trade: Evidence from China

Xuyun Zheng[a,*], Huilin Lai[b]

Guangdong Polytechnic Normal University, Guangzhou, China
[a]xuyun_zheng@gpnu.edu.cn, [b]lhuil920@163.com
**Corresponding author*

Abstract: *This study examines the spatiotemporal evolution of high-quality development in international trade (HQDIT) in China since its WTO accession. We propose a multidimensional index system to measure the HQDIT index and leverage diverse statistical models to examine its dynamic and spatial patterns. The results demonstrate a fluctuating yet upward trend in China's HQDIT, with the national average index increasing from 0.214 to 0.365. The Eastern region registered the most pronounced improvement, followed by the Central region. Furthermore, the spatial distribution of the HQDIT remains highly uneven. The Eastern region maintains a significant lead, while the Western and Northeastern regions continue to lag, resulting in a dual pattern of "high-quality and high-growth" versus "low-quality and low-growth". The Dagum's Gini decomposition reveals that intra-regional disparities in the Eastern and Western regions first widened and then narrowed, whereas those in the Central and Northeastern regions remained relatively stable. Finally, spatial autocorrelation analysis demonstrates that the HQDIT exhibits significant spatial clustering. The Eastern region forms a high-quality agglomeration area, while the Western region consistently emerges as a low-development depression.*

Keywords: *High-quality development; International trade; Regional disparity; Evolution trend; Spatial distribution*

1. Introduction

The prevailing headwinds of deglobalization, intensifying geopolitical frictions, and the deep restructuring of global value chains are reshaping the rules and governance of international trade (Zhang and Ding, 2024), while the technological revolution driven by digitalization and artificial intelligence is redefining national comparative advantages and undermining the traditional trade pattern long dominated by a pursuit of volume and cost efficiency (Yu and Yao, 2024; Han et al., 2025). In response, scholars and policymakers are increasingly shifting their focus from the mere expansion of trade volumes toward a new paradigm of high-quality development centered on value creation, technological upgrading, and sustainability, a transition conceptualized in this study as high-quality development of international trade (HQDIT). This transition underscores an urgent need for rigorous new frameworks to evaluate international trade development.

Extensive research has been conducted on the methodologies for measuring international trade. The first category of studies focuses on scale indicators such as trade volume (Wang et al., 2024) and growth rates (Constantinescu et al., 2016). The second strand emphasizes trade competitiveness, including the competitiveness index (Bojnec, Š., & Fertő, 2012) and technical sophistication of trade (Liang and Lu, 2024). The third group concentrates on trade dependency ratios (Osakwe et al., 2018) and the import share of different product categories (Kali et al., 2007). However, much of the existing literature focuses on trade volume or structure, with relatively less attention given to the aspects of trade benefits and the underlying foundational drivers behind them. Therefore, this study aims to fill this research gap by evaluating trade development within a comprehensive framework, which collectively considers volume, competitiveness, structure, benefits, and foundations.

China offers a compelling case to identify the high-quality development of international trade. First, as the world's largest merchandise trader, China has held the leading position in global goods trade since 2013, a status underpinned by cost advantages and large-scale production capacity. In recent years, the

Chinese government has reinforced its commitment to greater openness, steadily broadening both the volume and scope of trade. From 2000 to 2022, international trade in China grew from 474.29 billion USD to 6250.94 billion USD, with an average annual growth rate of about 12.45%. This expansion underscores China's growing reliance on the global market and provides us with a wealth of information on changes in international trade. Second, international trade expansion has been accompanied by persistent structural challenges in China, including relatively low industrial value added, weak competitiveness in services trade, and pronounced regional disparities. In response, the Chinese government has made high-quality development a strategic priority of its openness agenda, implementing a broad set of policies aimed at restructuring trade and fostering sustainable growth. These dynamics make China a particularly valuable context for analyzing the transition toward HQDIT.

This article develops a comprehensive framework for assessing HQDIT, encompassing five dimensions: volume, competitiveness, structure, benefit, and foundation. Using provincial panel data from China covering the period from 2002 to 2022, we evaluate the HQDIT and investigate spatial and temporal variations across regions. The findings demonstrate a consistent upward trend for HQDIT in China. Regionally, the Eastern provinces maintain a substantial lead over those in the central, Western, and Northeastern parts of China. Moreover, the development gap between the Eastern and other regions is widening. Intra-regional disparities in the Eastern and Western regions first diverged and then converged, while those in the Central and Northeastern regions remained relatively stable. Spatial autocorrelation analysis demonstrates that the HQDIT exhibits significant spatial clustering. The Eastern region forms a high-quality agglomeration area, while the Western region consistently emerges as a low-development depression.

First, this paper contributes to the growing literature on measuring international trade (Fan et al., 2015; Zou et al., 2025). Previous research has primarily focused on a single dimension, such as volume (Fan et al., 2022; Moridian et al., 2025) or competitiveness (Chen et al., 2020; Mwakalila et al., 2025). However, there is a notable gap in research addressing critical aspects like benefits and foundation, which are essential components of HQDIT. Building on this literature, we extend the measurement by analyzing international trade development across five dimensions and incorporating trade benefits and their underlying foundational drivers. This expansion enhances the literature on international trade and offers new theoretical insights for advancing trade upgrading.

Second, our work contributes to the extensive literature on the patterns of international trade (Li et al., 2024; Yu and Gu, 2025). While the evolving characteristics of international trade (Gharsallah et al., 2024; Muchao et al., 2025) have been extensively examined in prior studies, its regional disparities and spatial patterning have received relatively little attention. We examine the trend evolution of HQDIT and investigate its regional gaps and spatial distribution, capturing differentiated temporal and spatial characteristics previously overlooked. Third, this study contributes to the burgeoning literature on international trade in developing economies (Nguyễn et al., 2025). Given that international trade may vary across regions due to differences in infrastructure, institutions, and culture (Liu et al., 2020; Mao et al., 2024), our research provides a valuable empirical contribution using China as a case study, which is one of the key international trade hubs in developing countries. Our findings hold policy relevance for trade strategy formulation in developing economies.

The rest of the paper is organized as follows: Section 2 describes research methods and data sources. Section 3 presents the findings. Section 4 concludes the paper and discusses policy implications.

2. Research Methods and Data Sources

2.1 The index system

The core features of HQDIT are reflected in a fundamental shift from "quantitative expansion" to "qualitative improvement," as well as a transition from a factor-driven to an innovation-driven pattern (Zhao, 2021). It encompasses not only the development of international trade but also its contribution to economic and social progress and its practical outcomes (He, 2010). Building on existing literature, this paper constructs an evaluation index system comprising five dimensions: trade volume, trade competitiveness, trade structure, trade benefits, and trade foundations. Specific indicators are presented in Table 1.

The trade volume is measured by three indicators: total trade volume, per capita trade volume, and the growth rate of trade volume. The trade competitiveness is composed of three metrics: the trade competitiveness index, international market share, and the export sophistication index. These

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measures reveal comparative advantage, market penetration, and the technological content of exports, respectively. The trade structure seeks to capture the intrinsic composition and market orientation of international trade. It is comprised of three indicators that systematically analyze the product mix (share of high-tech products), the mode of trade (share of general trade), and the geographical diversification (trade structure deviation index). The benefits of trade reflect its efficacy in driving economic and social progress. Its assessment leverages three indicators: the trade contribution to economic growth, the employment contribution of trade, and the foreign direct investment. The trade foundations encompass the foundational infrastructure and institutional capacity that underpin the development of international trade. This dimension is measured by three indicators: economic growth, patents granted, and transportation infrastructure.

Table 1: Evaluation Indicator for High-quality Development of International Trade.

Primary Indicator	Secondary Indicator	Definition	Indicator Weight	Indicator Attribute
Volume	Total Trade Volume	Export + Import	0.075	+
	Per Capita Trade Volume	Total Trade Value / Resident Population	0.072	+
	Growth Rate of Trade Volume	Year-on-year Growth in Trade Value	0.029	+
Competitiveness	Trade Competitiveness	(Export - Import) / (Export + Import)	0.104	+
	International Market Share	China’s Export Value / Global Export Value	0.098	+
	Export Sophistication	Export technical complexity (PRODY) (Hausmann et al.2007)	0.057	+
Structure	Share of High-Tech Products	High-Tech Product Trade Value / Total Trade Value	0.071	+
	Share of General Trade	General Trade Value / Total Trade Value	0.038	+
	Trade Structure Deviation Index	|Regional Trade Dependence - National Trade Dependence|	0.032	-
Benefits	Trade Contribution to Economic Growth	Trade Value Added / GDP growth	0.079	+
	Trade Contribution to Employment	Total Employment × (Export/GDP)	0.081	+
	Foreign Direct Investment	Registered Capital of Foreign-Invested Enterprises	0.094	+
Foundations	Economic Growth	GDP per capita	0.048	+
	Patents Granted	Number of Patents / 10,000 people	0.085	+
	Transportation Infrastructure	Traffic mileage/ Administrative Area	0.037	+

Notes: Export and Import represent the export and import value of all goods and services for China, respectively. The selection range of high-tech products refers to the "Classification of High-Tech Products (Manufacturing Industry) (2017)" issued by the National Bureau of Statistics of China. https://www.stats.gov.cn/sj/tjbz/gjtjbz/202302/t20230213_1902772.html

2.2 Weights determination

Based on the above indicators, we calculate the HQDIT index using the following steps. First, all indicators are normalized to ensure data comparability. For positive secondary indicators, where higher values benefit HQDIT, the normalization formula is $X_{vit}=\frac{x_{vit}-x_{min(v)}}{x_{max(v)}-x_{min(v)}}$, where x_{vit} is the original value of the secondary indicator for province i in year t, and $x_{min(v)}$ and $x_{max(v)}$ are the minimum and maximum values of the indicator across all provinces and time periods, respectively. For negative indicators, the formula is $X_{vit}=\frac{x_{max(v)}-x_{vit}}{x_{max(v)}-x_{min(v)}}$. The second step calculates the weight for each secondary indicator using the formula $W_v=\frac{\alpha+\beta+\gamma}{3}$, where α, β, and γ are the coefficient weights from the Analytic Hierarchy Process, the Equal Weighting Method, and the Entropy Method, respectively. The third step calculates the HQDIT index using the weighted average of the normalized indicators:$H_{it}=\sum_{v=1}^{15} W_v X_{vit}$, where H_{it}denotes the HQDIT for province i in year t.

2.3 Methods for Spatiotemporal Evolution

2.3.1 Kernel Density Estimation

This study employed kernel density estimation to analyze and characterize the dynamic distribution of HQDIT. The specific equation is as follows:

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$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{H_i - \bar{H}}{h}\right). \tag{1}$$

$$K = \frac{1}{\sqrt{2\pi}} e^{-\frac{H_i^2}{2}}. \tag{2}$$

Where *f(x)* denotes the probability density function of the random variable, *n* represents the number of provinces, *K(·)* is the Gaussian kernel function, and $\bar{H}$ indicates the mean of the HQDIT index. *h* denotes the bandwidth, which governs the smoothness of the kernel density curve.

2.3.2 Dagum Gini Coefficient

Dagum (1997) proposed a decomposition method for the Gini coefficient, which can be further decomposed into the within-group Gini coefficient (G_w), the between-group Gini coefficient (G_{nb}), and the transvariation density Gini coefficient (G_t). This approach accounts for the issue of sample overlap, enabling the assessment of the contribution of cross-regional overlap phenomena to overall inequality. The basic expression of the Gini coefficient G is as follows:

$$G = \frac{1}{2n^2\bar{H}}\sum_{i=1}^{n}\sum_{j=1}^{n}\left|H_i - H_j\right| = \frac{1}{2n^2\bar{H}}\sum_{e=1}^{q}\sum_{g=1}^{q}\sum_{i=1}^{n_e}\sum_{j=1}^{n_g}\left|H_{ei} - H_{gj}\right|. \tag{3}$$

Where *n* denotes the total number of provinces, H_i and H_j represent the HQDIT index of provinces i and j, respectively, and $\bar{H}$ indicates the mean value of the HQDIT index across all provinces. q represents the number of regions. n_e and n_g represents the number of provinces in regions e and g. H_{ei} and H_{gj} represent the HQDIT index of the i and j provinces in regions e and g, respectively.

2.3.3 Moran's Index

Moran's index is a statistic used to measure spatial autocorrelation. It quantifies the degree of spatial clustering or dispersion by evaluating the correlation between observed values and their neighboring observations. The formula for Moran's index is given as follows:

$$Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} Z_{ij}(H_i - \bar{H})(H_j - \bar{H})}{\left(\sum_{i=1}^{n}\sum_{j=1}^{n} Z_{ij}\right)\sum_{i=1}^{n}(H_i - \bar{H})^2}. \tag{4}$$

Where *n* denotes the number of provinces. H_i and H_j represent the HQDIT index of province *i* and province j, respectively. $\bar{H}$ indicates the average value of the HQDIT index. $Moran's\ I > 0$ suggests a positive spatial correlation, whereas $Moran's\ I < 0$ implies a negative spatial correlation. Z_{ij} represents the spatial weight matrix. This study employs a geographical inverse-distance squared weighting matrix.

2.4 Data Source

The scope of this study is confined to 30 provinces, autonomous regions, and municipalities directly under the central government in Chinese mainland. Taiwan Province, Tibet Autonomous Region, Macao Special Administrative Region, and Hong Kong Special Administrative Region are excluded from the analysis. The study covers the period from 2002 to 2022. The primary data used in this research are sourced from the Goods Trade Database and the Provincial Economic Database of the Development Research Center (https://www.drcnet.com.cn/). Exchange rate data were obtained from various editions of the China Statistical Yearbook.

3. Results and Analysis

3.1 Measurement Results of High-Quality Development of International Trade

As illustrated in Figure 1, the HQDIT in China showed a fluctuating yet overall upward trend during the sample period. The national average increased from 0.21 to 0.36, representing a growth of 70.5%. Regionally, the Eastern region rose from 0.233 to 0.423, the Central region increased from 0.206 to 0.353, the Western region from 0.196 to 0.302, and the Northeastern region from 0.204 to 0.307. The high-quality development level of trade exhibits a distinct gradient disparity across regions. The Eastern region demonstrates the highest level and the most rapid growth, consistently maintaining a leading position.

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Moreover, the development gap between the Eastern region and other parts of the country shows a tendency to widen. The Central region follows, showing steady improvement over the period. In contrast, although the Western and Northeastern regions have also experienced growth, their overall development level remains relatively low with slower growth rates, leading to a widening divergence compared with the more advanced eastern and central regions.

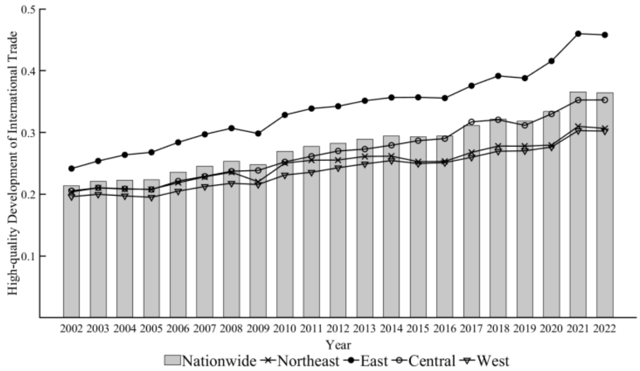
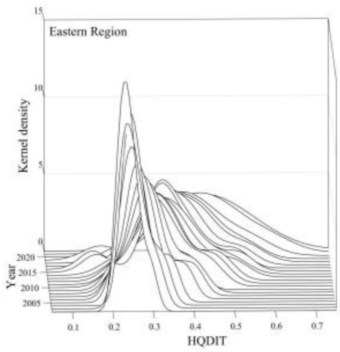
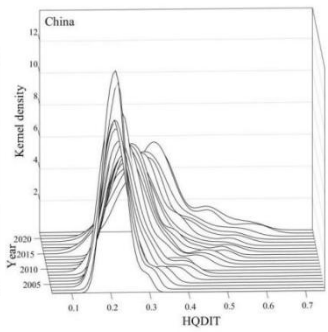


Figure 1: The Evolution of HQDIT in China

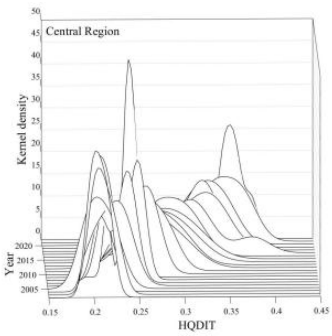
3.2 Analysis of the Characteristics of Temporal Evolution

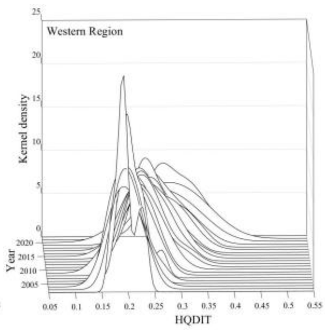
We use kernel density estimation to analyze the distribution dynamics of HQDIT, specifically investigating its location, evolution, dispersion, and polarization. Figure 2 illustrates that between 2002 and 2022, the kernel density curve of HQDIT shifted steadily to the right, with its central value rising from approximately 0.21 to 0.35. This rightward movement signals a sustained improvement in the overall quality of China's international trade. In terms of peak height, the distribution reached its highest point in 2002, followed by a downward trajectory. After a temporary rebound in 2009, the peak gradually declined again and reached a stable plateau after 2018. Taken together, the evolution of the curve suggests that since China's accession to the WTO, the distribution of HQDIT across provinces has followed a "decline-rise-decline-stabilization" trajectory, indicating that regional disparities initially widened but have gradually converged and stabilized in recent years.

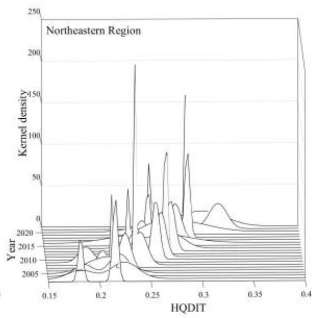




Panel A Nationwide *Panel B Eastern Region*







Panel C Central Region *Panel D Western Region* *Panel E Northeastern Region*

Figure 2: Kernel Density Distribution of HQDIT in China

From the perspective of distributional extensibility, the kernel density curves across all sample

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periods display a pronounced right-skewed tail, which gradually lengthens and rises over time. This pattern indicates that an increasing number of provinces have diverged from the initially low-level, concentrated development model and advanced toward higher levels of development, thereby widening the gap with lower-performing provinces. Nonetheless, the distribution's center of gravity remains on the left side of the curve, suggesting that the HQDIT in China continues to exhibit a "medium-to-low-level agglomeration" pattern, with most provinces still concentrated at relatively low levels of development.

The kernel density curves for all regions have shifted rightward, though to varying degrees. The Eastern and Central regions exhibit more pronounced shifts, while the Western and Northeastern regions display only modest movement. These patterns suggest that international trade in the Eastern and Central provinces has advanced more rapidly, whereas progress in the Western and Northeastern provinces remains comparatively limited. Overall, the evolution of kernel density across regions underscores substantial heterogeneity in the pace of HQDIT.

In the Eastern region, the peak height of the kernel density curve exhibits a clear downward trend, interrupted only by a temporary rebound in 2015–2016 before resuming its decline. This trend indicates a marked decline in the concentration of HQDIT among provinces and a gradual divergence in their performance. The evidence suggests that development paths are diverging: while some provinces have sustained rapid advancement, others are experiencing relative stagnation. This pattern reflects successful innovation and differentiation in development models on one hand, but also underscores persistent shortcomings in regional coordination on the other. These dynamics are further evidenced by the increasingly pronounced right tail of the distribution, which shows that a growing number of provinces in the Eastern region have achieved high levels of development, thereby widening the gap with those that are lagging behind.

The HQDIT trajectory in China's Central region evolved through three phases. Initially (2002-2009), balanced development prevailed, with a peaked distribution curve indicating concentrated trade quality and similar provincial levels. Subsequently (2010-2016), development became discrete, as the peak lowered and spread widened, reflecting growing inter-provincial disparities. Finally (2017-2022), leap-forward development occurred, with the peak rising and shifting upward, marking a transition toward high-level regional equilibrium. This progression—from equilibrium through differentiation to high-level equilibrium—was driven by optimized growth models, enhancing regional coordination.

In the Western region, the peak of the kernel density curve lies mainly between 0.15 and 0.3, with only a modest rightward shift, reflecting both a lag in the advancement of HQDIT and a relatively slow pace of improvement. The peaks in 2002 and 2007 reached the highest levels in the sample period, marking phases of greatest concentration in trade quality across provinces in the region. From 2011 to 2020, the peak height followed a fluctuating downward trajectory, while the curve gradually widened, indicating increasing disparities within the region. After 2020, however, the peak height rose again, pointing to a narrowing of these disparities.

The kernel density estimate for the Northeast region reveals a prominent bimodal shape with a subdued left peak and a robust right peak. This pattern signifies a distinct polarization in development levels, suggesting that most provinces form a developmentally advanced cohort, with a smaller group trailing significantly. From a temporal perspective, the peak height of the distribution curve increased notably in 2007, 2012, and 2019, indicating smaller intra-regional development disparities during these periods. This convergence was likely driven by the deepening of the Northeast revitalization policy and the implementation of high-quality development strategies, which mitigated regional divergence. Conversely, the peak height decreased in other years, signaling expanded development gaps. This pattern suggests that policy dividends prompted a convergence in HQDIT across Northeastern provinces. In contrast, during policy lulls, market forces spontaneously led to greater divergence, revealing the significant interplay of institutional factors and market dynamics in shaping the region's development disparities.

3.3 Analysis of the Characteristics of Spatial Evolution

3.3.1 Spatial Disparities in High-Quality Development of International Trade

This study employs the Dagum Gini coefficient to examine regional disparities in HQDIT and their underlying drivers, with the results reported in Panel A of Figure 3. Over the sample period, the Gini coefficient shows a clear upward trend, rising from 0.071 to 0.125. It increased steadily until 2012 and stabilized after 2016, fluctuating around 0.13. These patterns indicate that, since China's accession to the World Trade Organization, absolute disparities in HQDIT across provinces have generally widened,

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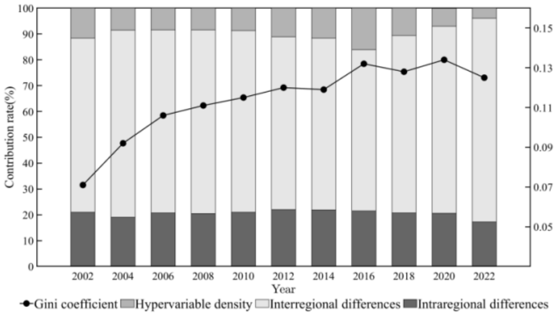
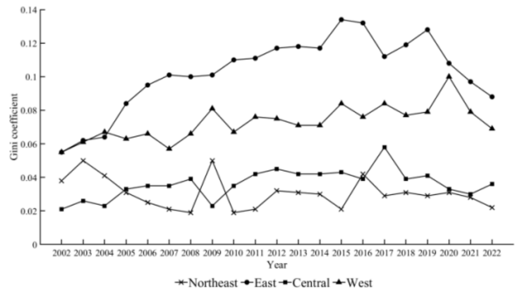
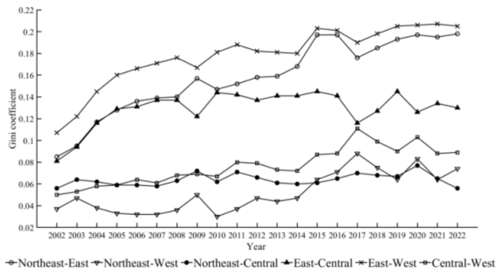
though they began to narrow slightly after 2016. Decomposition of the sources of disparity reveals that inter-group differences are the dominant factor, accounting for roughly 70% of the total and exhibiting an initial contraction followed by subsequent expansion. Intra-group differences are the second largest contributor, representing about 20%, while the contribution from transvariation between groups is relatively minor, at approximately 10%. These results highlight the substantial influence of regional disparities on the overall pattern of HQDIT and point to a pronounced hierarchical differentiation among regions.

Panel B of Figure 3 presents the within-group Gini coefficients for HQDIT across Northeast, East, Central, and West China. In the Eastern region, the Gini coefficient rose sharply from 2002 to 2015, peaking at 0.134, before declining with some fluctuations. This pattern indicates that intra-regional disparities in this region initially widened following China's WTO accession and continued to expand until around 2015, after which they gradually narrowed. The Western region displayed relatively high Gini coefficients overall, signaling substantial internal disparities. These disparities increased until 2020, reaching a peak of 0.10, before beginning to decline, suggesting partial improvement in regional balance. In contrast, intra-regional disparities in the Northeast and Central regions remained comparatively low throughout the period. The Northeast experienced a slight decline, while the Central region saw a moderate increase, indicating relatively stable and balanced development among provinces in these two regions.



Panel A Overall Disparity and Its Sources





Panel B Within-Group Inequality *Panel C Between-Group Inequality*

Figure 3: Gini Coefficient of HQDIT and Decomposition Results

Panel C of Figure 3 reports the between-group Gini coefficients, which highlight that the Eastern region exhibits significantly larger disparities with other regions and an overall fluctuating upward trend. Specifically, the Gini coefficient between the Eastern and Western regions rose from 0.107 to 0.205, that between the Eastern and Northeastern regions increased from 0.085 to 0.195, and that between the Eastern and Central regions grew from 0.081 to 0.130. These trends indicate a substantial development gap between the Eastern and other regions. Specifically, the gaps between the Eastern and Western regions and between the Eastern and Northeastern regions have widened consistently, while the gap between the Eastern and Central regions has remained relatively stable. This pattern suggests that the Eastern region's capacity to drive and diffuse HQDIT to other regions remains limited, and that inter-regional coordination mechanisms need strengthening. By contrast, the relatively small Gini coefficients among the Central, Northeastern, and Western regions reflect smaller disparities. The gap between the Northeast and Western regions changed minimally, whereas disparities between the Northeast and Central regions and between the Central and Western regions exhibited a modest expansion over time.

3.3.2 Spatial Autocorrelation Analysis

Table 2 reports the results of the global Moran's index for HQDIT across 30 Chinese provinces. All Moran's index values are positive, and all p-values are below 0.1, indicating significant positive spatial

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autocorrelation—that is, provincial development levels are spatially clustered rather than randomly distributed. The global Moran's index increased from 0.105 to 0.206 over the study period, reflecting a strengthening of spatial clustering: high-performing regions increasingly cluster together, as do low-performing areas. This trend underscores the importance of regional spillovers and geographic factors in promoting HQDIT, potentially facilitated by enhanced infrastructure connectivity, cross-regional knowledge diffusion, and coordinated policy interventions.

Table 2: Global Moran's Index of HQDIT

year	2002	2005	2008	2011	2014	2017	2020	2022
Moran's I	0.105^{**}	0.140^{**}	0.134^{**}	0.136^{**}	0.103^{**}	0.160^{***}	0.177^{***}	0.206^{***}
P	0.031	0.010	0.012	0.011	0.034	0.005	0.002	0.001

Table 3: Spatial Agglomeration Patterns of HQDIT

Year	High-High aggregation	Low-High aggregation	Low-Low aggregation	High-low aggregation
2002	Anhui, Beijing, Fujian, Hainan, Hebei, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin, Zhejiang	Guangxi, Guizhou, Henan, Heilongjiang, Hubei, Hunan, Jiangxi, Inner Mongolia	Gansu, Ningxia, Qinghai, Shanxi, Xinjiang, Yunnan	Guangdong, Jilin, Shaanxi, Sichuan, Chongqing
2022	Anhui, Beijing, Fujian, Hainan, Hebei, Hubei, Jiangsu, Shandong, Shanghai, Tianjin, Zhejiang	Guangxi, Henan, Hunan, Jiangxi, Liaoning, Inner Mongolia, Shanxi	Gansu, Guizhou, Heilongjiang, Jilin, Ningxia, Qinghai, Shaanxi, Sichuan, Xinjiang, Yunnan	Guangdong, Chongqing

Table 3 reports the spatial aggregation types of HQDIT across provinces. The "High–High" category contains the largest number of provinces with relatively stable membership, reflecting the emergence of core regions that exert strong demonstration effects. In contrast, the number of "Low–Low" provinces has gradually increased, mainly in the Western region, indicating the formation of a development "depression" and highlighting spatial lock-in effects, whereby less developed regions face persistent barriers to upward mobility. Within the "Low–High" category, Hubei province transitioned to the "High–High" group, while Guizhou province shifted to "Low–Low." The upward transition in Hubei province underscores the fact that its own development is strong and the surrounding areas are at a high level of balance, whereas the downward shift in Guizhou province reflects insufficient sustainability in high-quality development and the limited driving capacity of the surrounding areas. These changes suggest that the ability of high-level provinces to radiate development to neighboring areas remains limited and that regional coordination mechanisms require strengthening.

Overall, HQDIT across Chinese provinces exhibits a strong pattern of spatial dependence and clustering. The concentration of "High–High" clusters in the Eastern region and "Low–Low" clusters in the Western region underscores deep-seated regional disparities and spatial lock-in effects, signaling a deeply polarized national development landscape.

4. Conclusion and Policy Implications

4.1 Conclusion

This study develops an evaluation index system for the High-Quality Development of International Trade (HQDIT) along five dimensions: volume, competitiveness, structure, benefits, and foundations. Using a combination of the entropy method, analytic hierarchy process, and equal-weight approach, we construct the HQDIT index for Chinese provinces over the period 2002–2022. Building on this index, kernel density estimation analysis is employed to investigate the dynamic evolution of HQDIT, while the Dagum Gini coefficient and spatial autocorrelation techniques are applied to examine the sources of regional disparities and patterns of spatial agglomeration. The main findings are as follows:

First, HQDIT in China has followed a steady upward trajectory. The index rose from an average of 0.214 in 2002 to 0.365 in 2022, with all regions showing improvement. The Eastern region recorded the fastest growth, followed by the Central region. Second, HQDIT displays marked regional disparities. The Eastern region consistently outperforms other parts of the country, while the Western and Northeastern regions lag behind. Regional gaps—particularly between the Eastern region and the rest of China—are the primary drivers of overall inequality, whereas differences among the Central, Western, and Northeastern regions are relatively modest. This spatial pattern can be summarized as "high-quality and

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high-growth" in the Eastern region versus "low-quality and low-growth" in the Western region. Third, intra-regional disparities in HQDIT reveal notable heterogeneity. Kernel density estimation and Gini decomposition results show that provincial disparities widened steadily up to 2016 but narrowed thereafter. Within-region disparities in the Eastern and Western regions first expanded and then contracted, while those in the Central and Northeastern regions remained comparatively stable. Finally, HQDIT exhibits significant spatial agglomeration and positive spatial autocorrelation. The Eastern provinces form a high-quality cluster, whereas the Western region persistently functions as a low-development area.

4.2 Policy Implication

The findings of this study have several policy implications for countries or regions with economic systems similar to those in China. First, enhance the international trade capacity of lagging regions. This requires strengthened top-level design and coordinated policies to create targeted support systems that improve factor endowments. Key measures include upgrading infrastructure, promoting industrial transformation, and attracting skilled talent. Tax incentives and comprehensive policy packages should be deployed to channel critical resources—such as capital, technology, and human capital—toward these regions.

Second, implement differentiated trade development strategies. Regions with advanced international trade should prioritize high-value-added activities, including high-end manufacturing and digital trade, to reinforce competitiveness. Medium-level regions should enhance their capacity to absorb industrial transfers, pursue smart and green upgrades of traditional industries, and avoid homogeneous competition. Less-developed regions should actively explore new trade growth drivers, improve the business environment, and establish open platforms for international cooperation. Such differentiated strategies can foster a regional economic structure with complementary strengths, thereby enhancing overall competitiveness.

Third, deepen inter-regional collaboration and coordination. Although high-quality trade development exhibits increasing spatial interdependence, coordination mechanisms remain insufficient. Less-developed regions should learn from the experience and innovations of advanced regions, while developed regions should disseminate institutional and managerial best practices to promote wider spillovers. Governments should also strengthen cross-regional infrastructure in transportation, logistics, and information systems to provide a robust foundation for cooperative development.

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