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CHARACTERISTICS OF SPATIAL AND TEMPORAL EVOLUTION OF THE DISTRIBUTION OF HIGH-TECH TEXTILE ENTERPRISES IN CHINA AND ITS INFLUENCING FACTORS

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Annotation. The spatial distribution of high-tech textile firms directly affects the effectiveness of industrial agglomeration, technological diffusion, and competitiveness enhancement. Using provincial panel data (2011–2023), this study adopts centroid migration analysis, Gini coefficient decomposition, and spatial Durbin modeling to systematically explore the spatiotemporal evolution and underlying determinants of China's high-tech textile firms. Reportedly, there is a pronounced two-stage growth trajectory, characterised by rapid expansion from 2012 to 2017 and a marked slowdown after 2018, including negative growth during and following the COVID-19 pandemic. Further econometric evidence from the spatial Durbin model highlights land prices, industrial scale, market potential, human capital, and technological innovation capacity as key factors exerting significant spatial spillover effects. Conversely, wage levels and regional economic development also affect enterprise location decisions but exhibit comparatively weaker spatial spillovers. This study contributes to the interdisciplinary discourse bridging economic geography and business management by clarifying the multifaceted drivers of industrial spatial distribution. Thus, the findings offer actionable insights and policy guidance for optimising textile industry layouts and regional economic coordination under China's dual-circulation development framework, with broader implications for emerging economies.

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Keywords: high-tech textile sector, distribution, migration, spatial Durbin models.

JEL classification: C21, F22, R23, L67, O14.

Introduction

The textile industry plays a key role in the development of China's economy by fostering job placement, export earnings, and livelihood protection (Zhu, Yu, 2015). Since the abolishment of quota restrictions on textile and garment products in 2005, the Chinese textile industry has realised rapid expansion, both locally and globally (Sun, Liang, 2020). In 2023, the proportion of Chinese textile enterprises in industrial enterprises above the scale was nearly 9.15% (*The China Statistical Yearbook*, 2024). As a labour-intensive industry, the competitiveness of China's textile industry in the global arena has been reduced to a certain extent by the rising costs of labour and raw materials. Based on China's "Textile Industry Economic Operation Report 2023", the 2023 Chinese textile exports to Europe, Japan, and the US amounted to 18.2%, 14.2%, and 11.7%, respectively, showing a decline, compared with 2022. Under the new development pattern of the "double cycle", enterprises in the textile industry urgently need to cope with the increasing market competition through product differentiation and production cost control (Xu, Zhou, 2021). Specifically, the high-tech textile industry plays a key role in transforming scientific research into economic benefits (Xinle *et al.,* 2022). Thus, an in-depth study of the development trend of high-tech textile enterprises and their spatial distribution pattern has theoretical and practical value.

Although China's high-tech textile industry has made remarkable progress, there is still much room for improvement in its level of development. From the innovation dimension, the *China Torch Statistical Yearbook* reports that from 2010 to 2022, the total number of high-tech enterprises in China increased from 31,900 to 394,500, while the number of high-tech textile industry enterprises only increased from 1,227 in 2000 to 9,774 in 2022 during the same period.[1] This shows that the growth rate of the development scale of high-tech textile industry enterprises is significantly lower than the growth rate of the overall high-tech enterprises. The "Implementation Plan for Quality Improvement and Upgrading of the Textile Industry 2023–2025" clearly states that the future development of China's textile industry should focus on enhancing independent innovation capabilities and accelerating the cultivation of advanced textile manufacturing enterprises. The phenomenon of path dependence in enterprise location choice has recently received extensive attention (Binz *et al.,* 2016; Martin, 2010), offering a theoretical basis for the scientific formulation of regional industrial policy. High-tech textile enterprises bear the important mission of innovating and upgrading the industry. Under the double background of industry scale expansion and external competitive pressure, the spatial distribution pattern of high-tech textile enterprises directly determines whether China's textile industry can rely on such enterprises to form an effective industrial agglomeration effect, thus realising the diffusion of technological innovation and improving the overall competitiveness of the industry.

The key questions that need to be solved include the following:

RQ1: What kind of evolutionary pattern does the regional distribution of high-tech textile enterprises show?

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[1] The object of this research is textile enterprises, which encompasses the following four industries: textile industry, textile clothing and apparel industry, leather, fur, feather and their products and footwear industry and chemical fiber manufacturing industry. The data was obtained from *www.tianyancha.com*.

RQ2: What are the multi-dimensional driving factors affecting their clustering characteristics at the regional level?

An in-depth investigation of these issues not only grasps the direction of industrial transfer and agglomeration but also offers important theoretical support and practical reference for the structural adjustment and industrial upgrading of the textile industry.

This study focuses on high-tech textile firms, filling a gap in the literature on industry-specific distribution patterns. Industrial location theory is also extended in this study by analysing macroeconomic factors and their spatial interactions. Lastly, this research offers practical implications for industrial upgrading, regional coordination, and policy formulation.

The present study aims to investigate the spatial-temporal evolution characteristics of high-tech textile firms in China (2011–2023) at the provincial and city levels. This paper also intends to estimate the trajectory of enterprise distribution's gravity centre migration and gauge the regional Gini coefficient for high-tech textile firms at the provincial and city levels. In addition, the influencing factors of enterprise distribution are also meant to be explored in this study using a spatial Durbin model.

1. Literature Review

Existing studies primarily focus on the following three dimensions: the spatial and temporal evolution characteristics of the spatial distribution of high-tech firms, the main driving factors affecting the distribution of the firms, and the research on the regional distribution related to textile industry firms. In terms of the spatio-temporal evolution pattern, studies depict that there are significant spatial agglomeration characteristics of high-tech firms (Zhang *et al.,* 2013; Cao *et al.,* 2017), commonly using kernel density estimation (Xia, Shien, 2024), regional centre of gravity migration (Sun *et al.,* 2012), and the inequality indices, such as the Gini coefficient and the Thiel index (Wang, 2022). The agglomeration phenomenon of high-tech firms is notable.

However, the scholars find diverse results due to diverse research methods. For instance, Qin, Gang (2024) found that the overall distribution of Chinese high-tech firms shows the characteristics of "dense in the east and sparse in the west, more in the south and less in the north", gradually spreading to the central and western parts of the country, with the centre of its agglomeration shifting from "three cores" to "three poles and multiple cores". Furthermore, Xiao *et al.* (2018) indicate that China's high-tech firms exhibit a multi-core spatial structure, with the regional centre of gravity showing a small tendency to migrate to the northwest, and the Gini coefficients displaying an expanding trend in the degree of agglomeration.

In terms of the influencing factors, Wheeler, Mody (1992) suggest that new firms tend to be established in areas with numerous production activities, with raw materials, labour supply, and infrastructure acting as noticeable factors affecting the agglomeration of firms. Arauzo-Carod *et al.* (2009) analysed the impact of agglomeration economies on the location choices of emerging firms within metropolitan areas. Fornahl *et al.* (2009) confirmed the positive impact of concentration of industrial activities, revealing the role of dominant German firms on the spatial and geographic agglomeration. Scholars also identify the transportation infrastructure (Ma, 2022), research institutions (Lejpras *et al.,* 2011), and government interventions (Fukugawa, 2006) as factors influencing the firms' distribution. Ding *et al.* (2013) found that the layout of Shanghai's textile firms presents a suburbanisation trend, and the distribution of textile firms is also affected by the distribution of high-tech textile firms. Likewise, at the level of factors influencing the distribution of textile industry firms, limited studies have systematically reviewed the factors influencing the firms' distribution. The availability of infrastructure facilities, such as road network availability and telecommunication services, contributes to the business growth of Kenyan textile firms (Mugo, 2019). Boichenko (2021) confirmed the importance of financial support for the European textile industry. Li (2020) shows that industrial policies, especially ecological policies, can lead to optimised TFP in the textile industry.

2. Research Methodology

2.1 Gini Coefficient Decomposition

Referring to Simarro's (2017) and Gustafsson's (2001) methods, this paper utilises the Gini coefficient to reflect the inequality in the distribution of high-tech textile firms at the level of the four key Chinese regions and provinces. It also categorises the overall Gini coefficient into the contribution of intra-regional disparity and the contribution of inter-regional net value disparity and the contribution of hyper-variance density. Using Dagum's Gini coefficient method to categorise and analyse the disparities between regions and concurrently exploring the reasons for the formation of disparities, the overall and intra-regional Gini coefficients and their decompositions are computed using Eqs. (1) to (6):

$$G = \frac{\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}|y_{ij} - y_{hr}|}{2n^2\mu} \tag{1}$$

The Gini coefficient for region j:

$$G_j = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}|y_{ij} - y_{hr}|}{2n_j^2\mu_j} \tag{2}$$

Regional differences:

$$G_w = \sum_{j=1}^{k} G_j p_j s_j \tag{3}$$

Gini coefficient between regions j and h:

$$G_{jh} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}|y_{ij} - y_{hr}|}{n_j n_h(\mu_j + \mu_h)} \tag{4}$$

Inter-regional net value difference:

$$G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}(p_j s_h + p_h s_j) D_{jh} \tag{5}$$

Supervariable density:

$$G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}(p_j s_h + p_h s_j)(1 - D_{jh}) \tag{6}$$

Where k is the number of dividing regions, n_j or n_h is the number of provinces included in the region j or h, y_{ij} or y_{hr} respectively, the level value of the number of high-tech textile firms in each city in the region of j or h, $\bar{y}$ is the mean value of the number. G_w is the intra-regional variation, whereas G_{nb} is the net inter-regional variation. G_t is the hypervariance density. μ_j or μ_h is the mean value of the number of high-tech textile enterprises in the region j or regions h, $\mathrm{p_j} = \mathrm{n_j}/\mathrm{n}$; $\mathrm{s_j} = \mathrm{n_j}\mu_\mathrm{j}/(\mathrm{n}\mu)$. D_{jh} is the relative impact of the number of high-tech textile enterprises in the region or between regions j or h. It is calculated by employing the formula $\mathrm{D_{jh}} = (\mathrm{d_{jh}} - \mathrm{p_{jh}})/(\mathrm{d_{jh}} + \mathrm{p_{jh}})$, where $\mathrm{d_{jh}} = \int_0^\infty \mathrm{dF_j(y)} \int_0^\mathrm{y} (\mathrm{y} - \mathrm{x})\mathrm{dF_h(x)}$, $\mathrm{p_{jh}} = \int_0^\infty \mathrm{dF_h(y)} \int_0^\mathrm{y} (\mathrm{y} - \mathrm{x})\mathrm{dF_j(y)}$.

2.2 Centre of Gravity Migration Calculation

is paper calculates the centre of gravity migration of the distribution of high-tech textile industry firms (Wang *et al.,* 2023). Since the number of high-tech textile firms in region i is W_i, and the longitude and latitude of regional i is X_i and Y_i, the number of firms in each region weighted the longitude and dimension is used to calculate the centre of gravity of the coordinates (x, y), the method of which is shown in Eqs. 7 and 8.

$$x = \frac{\sum W_i X_i}{\sum W_i} \tag{7}$$

$$y = \frac{\sum W_i Y_i}{\sum W_i} \tag{8}$$

Following the calculation of the centre of gravity for each year, the path of the centre of gravity migration is obtained by connecting them sequentially in the order of years.

2.3 Data Sources

30 provinces or municipalities directly under the Chinese central government, excluding Tibet, were chosen for the timeframe from 2011 to 2023, with a sample observation of 390. The data at the provincial level is obtained from the National Bureau of Statistics and the *China Statistical Yearbook*. The data of textile industry firms is retrieved from Tianyiqiao. Based on the available information on high-tech firms in China's textile industry compiled by Tianyecha, the number of firms in each region in each year is calculated. Due to the firm write-offs in regions during the year, the number of counted firms is the net number of existing firms. GDP is deflated using the CPI to eliminate the effect of price factors. All variables are tailored at the 1% level to eliminate the outliers' effect.

3. Results

3.1 Spatio-Temporal Evolution and Differential Analysis

3.1.1 Temporal Changes in the Number of High-Tech Enterprises in Textile Industry

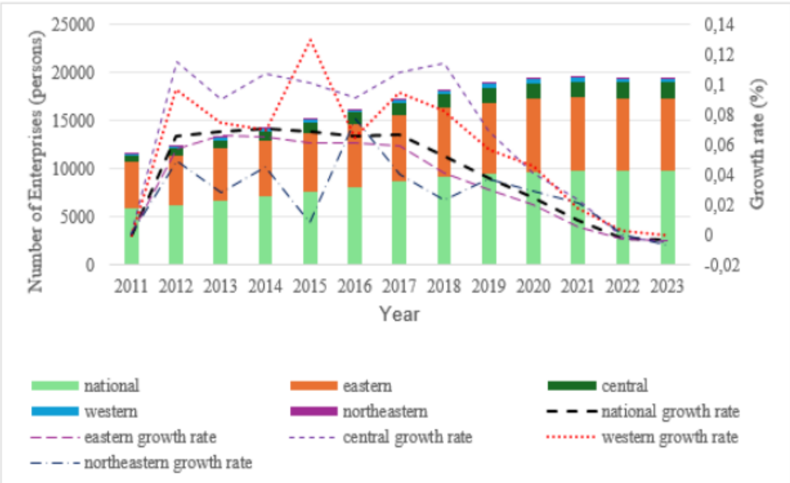
In *Table 1*, the number of high-tech firms in the textile industry in the country and sub-regions in general shows a trend of continuous growth (nearly 60%) from 2011 to 2023, rising from 5,851 in 2011 to 9,740 in 2023, thus reflecting the strong vitality of the high-tech firms in the Chinese textile industry. Based on the region's growth rate changes, the central region's growth rate is the largest. Since the central region's firm base is not large, the textile industry density is also small. Specifically, firms are more economic active in the geographic space, and their border with the eastern region can still possess the spatial spillovers, human capital spillovers, and other externalities. Although the western region grew from 196 to 397, the absolute number is still low, but the growth rate is relatively high and obvious.

Table 1. Number and growth rate of high-tech enterprises in textile industry in China and different regions, 2011 to 2023

Year	Total	Growth rate	Eastern	Growth rate	Central	Growth rate	Western	Growth rate	Northeastern	Growth rate
2011	5,851	-	4,834	-	719	-	196	-	102	-
2012	6,235	6.56%	5,111	5.73%	802	11.54%	215	9.69%	107	4.90%
2013	6,666	6.91%	5,451	6.65%	874	8.98%	231	7.44%	110	2.80%
2014	7,135	7.04%	5,805	6.49%	968	10.76%	247	6.93%	115	4.55%
2015	7,624	6.85%	6,163	6.17%	1,066	10.12%	279	12.96%	116	0.87%
2016	8,125	6.57%	6,540	6.12%	1,163	9.10%	297	6.45%	125	7.76%
2017	8,671	6.72%	6,927	5.92%	1,289	10.83%	325	9.43%	130	4.00%
2018	9,132	5.32%	7,211	4.10%	1,436	11.40%	352	8.31%	133	2.31%
2019	9,477	3.78%	7,431	3.05%	1,536	6.96%	372	5.68%	138	3.76%
2020	9,709	2.45%	7,579	1.99%	1,599	4.10%	389	4.57%	142	2.90%
2021	9,800	0.94%	7,623	0.58%	1,636	2.31%	396	1.80%	145	2.11%
2022	9,774	-0.27%	7,599	-0.31%	1,633	-0.18%	397	0.25%	145	0.00%
2023	9,740	-0.35%	7,573	-0.34%	1,626	-0.43%	397	0.00%	144	-0.69%

Source: created by the authors.

Compared to the central region, the growth rate of enterprises in the western region is slightly smaller (see *Table 1*). However, less competition, abundant materials, and lower enterprise density have inspired the strong growth of enterprises. Northeast growth is relatively lagging, with the number of enterprises increasing only from 102 in 2011 to 144 in 2023, the smallest growth rate among all regions, thus urgently requiring capital investment. The growth trend of firms in each region is largely aligned with the national trend (nearly 80% of the total), with the eastern region consistently dominating the number of enterprises, growing from 4,834 in 2011 to 7,573 in 2023. This remarkable growth is attributed to the eastern region's comprehensive advantages in terms of resource endowment, technology accumulation, and market scale. However, the growth rate in the eastern region is smaller due to the excessive enterprise base, which is weakened by the competitiveness within the industry and geospatial congestion. The number of enterprises in the central region increased significantly from 719 to 1,626, owing to the recent increase in policy support, the gradual infrastructure improvement, and the expansion of domestic demand in the regional economy.



Source: authors' work.

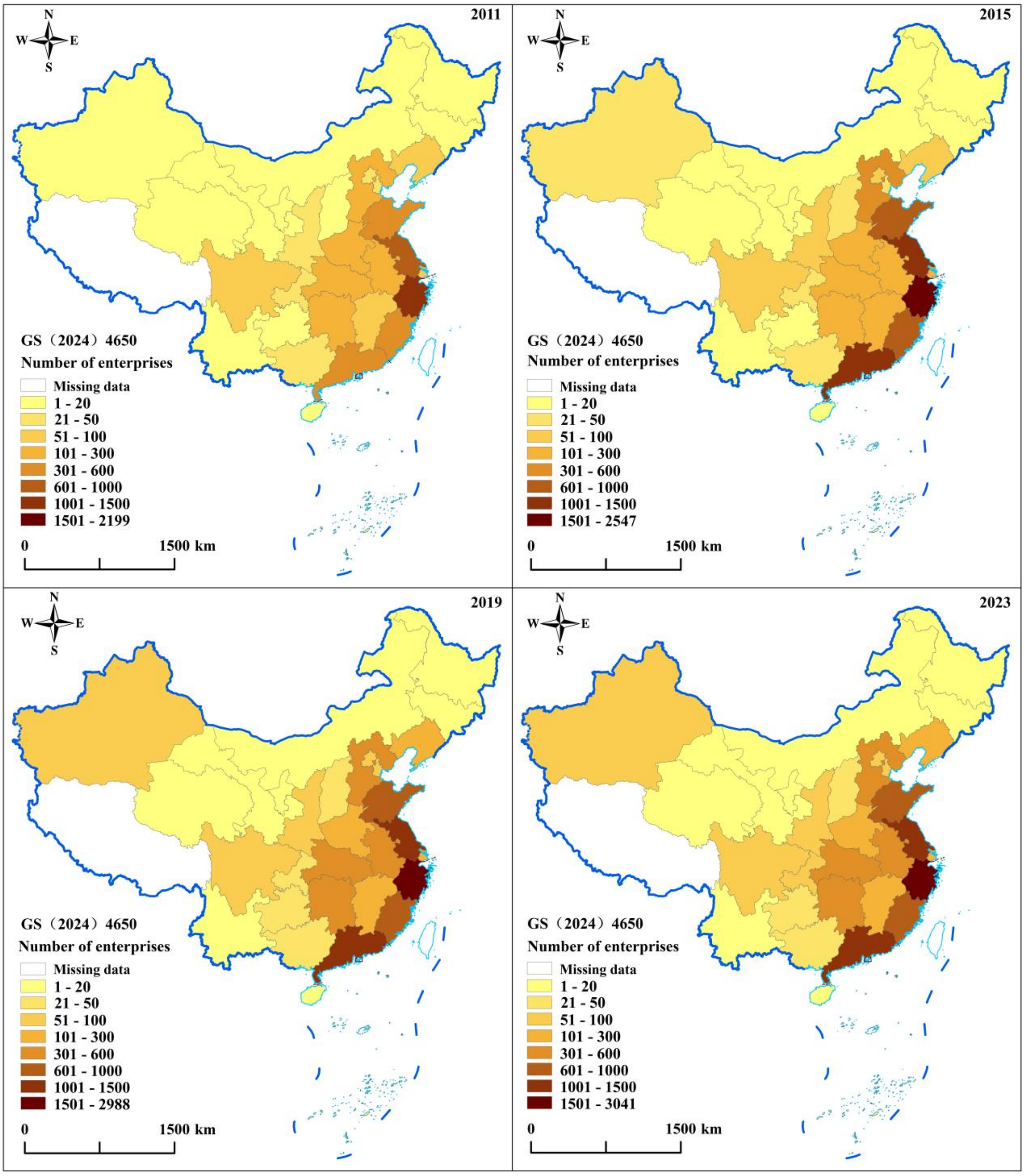
Figure 1. **Time Sequence Chart of the Number and Growth Rate of High-tech Textile Enterprises**

Based on the chronological changes, except for individual years, the number of firms has maintained overall growth, especially between 2012 and 2017 (*Figure 1*). The total number of firms has exceeded 5% growth rate and maintained an increasing trend, given the joint promotion of national policies, technological innovation, and increased market demand. However, this growth only lasted until the end of 2017. From the beginning of 2018, the growth rate began to appear at a significant decline. Meanwhile, the growth rate gradually slowed down, and the number of firms appeared to accelerate the convergence of the trend. The growth rate of the cliff-type declined, especially after 2020. During and after 2022, the growth rate became negative due to emergencies such as the COVID-19 pandemic, making investments insufficient and exposed to higher risks. Overall, the vitality of China's textile industry is notable, but there are large differences in the region's distribution. The central and eastern regions show strong growth potential. Conversely, the western and northeastern regions must optimise business processes and strengthen the R&D to improve their development level.

3.1.2 Temporal and Spatial Evolution of the High-Tech Textile Enterprises' Distribution

The geographical distribution of high-tech textile firms (2011–2023) is illustrated in *Figure 2*. Based on the distribution map of firms in 2023, the number of firms shows a decreasing gradient from east to west, and the coastal area (with good transportation facilities) represents a dense zone of firm distribution, in which the number of firms in the three coastal areas of Zhejiang, Jiangsu, and Guangdong ranks the top three. The textile sector, on the other hand, is a low-skill labour-intensive industry, dependent on the global market to give full play to the price benefit offered by China's cheap labour. Thus, locating in the coastal areas is more conducive to exports. Developed regions such as Beijing, Shanghai, and Tianjin have fewer firms, although their geographical location also belongs to the coastal region. Likewise, the firms' distribution around such regions is higher, representing the characteristics of labour division in urban agglomerations. Moreover, urban agglomerations centred on developed regions do not focus on production in the division of labour but instead play the role of productive services. Such a division of labour enhances regional production efficiency, promotes industrial upgrading, and optimises resource allocation to form economies of scale (Wheeler, 2001).

The number of firms in central China is more moderate, as central China borders with the coastal region, and situating in central China can still relish the spatial spillover effect of industrial technology and human capital (Chang *et al.,* 2016). The plains in central China provide the cultivation of raw materials for the textile industry at competitive prices. Although the number of firms in the western region is small, it is also a notable source of textile raw materials. Therefore, the imperfect transport infrastructure and the low economic development (Shi *et al.,* 2022) may affect the location of high-tech textile firms in the western region. Based on the change in the number of firms' distribution (2011–2023), the distribution of high-tech textile firms has shifted to the East Coast as the agglomeration area, maintaining the "gradient" of the East to the west of the attenuation. Meanwhile, the number of firms in the western region shows smaller growth, while the eastern region exhibits substantial growth. Given the limitations of resource endowment and geographic location, the western region has not realised convergent growth.



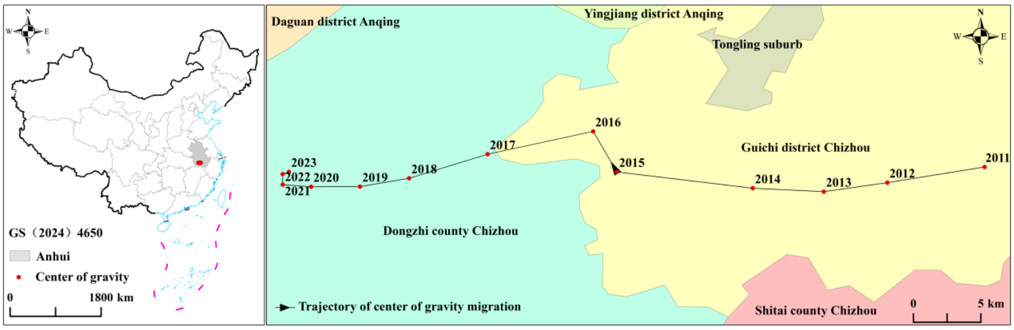
Source: authors' work.

Figure 2. **Distribution of High-tech Textile Enterprises, 2011-2023**

3.1.3 Migration Analysis of the Centre of Gravity of Location Distribution

The migration path of the centre of gravity of high-tech textile firms during 2011–2023 is shown in *Figure 3*. The centre of gravity of distribution during the indicated time period falls within Anhui Province, since the two regions of Jiangsu and Zhejiang are the concentrated areas of firm distribution, while the central and western regions have a smaller number of distributions, which pull the centre of gravity of firms slightly to the West. Based on the migration path, the centre of gravity is migrating to the West on a yearly basis. Thus, the industrial links between the east and the central and western regions are gradually strengthening, which is conducive to the formation of a wider range of industrial synergies.

The migration direction of the path can be divided into five intervals. The first interval is from 2011 to 2015; during this time, the centre of gravity and the direction of change from east to west, slightly tilted to the southwest, shifted to westward migration. In the second interval (2015–2016), there can be observed a more substantial change in the migration directions of the centre of gravity, for the original direction to west changed its direction to the north from the south. In the third interval (2016–2021), the migration direction of the centre of gravity shifted to migration from east to west with a slight tilt to the southwest. In the fourth interval (2021–2022), the migration direction of the centre of gravity changed from south to north, but the change distance is observably smaller. During the fifth interval (2022–2023), the migration direction of the centre of gravity began to shift with a tendency to migrate back to the departure point, but the migration distance was even smaller. In terms of the changes, starting from the change in direction in 2016, there is a clear decreasing trend in migration distance.



Source: authors' work.

Figure 3. **Trajectory of the Centre of Gravity Migration of High-tech Textile Enterprises**

3.1.4 Regional Differences in the Distribution of High-Tech Textile Enterprises

Overall differences. The Gini coefficient is used to analyse the regional differences in high-tech textile enterprises across the country and in the four major regions (see *Table 2*). The enterprise distribution data is used at the provincial level to discuss the differences between and within the East, the Middle East, the West, and the Northeast regions.

Table 2. Gini coefficient decomposition of the high-tech textile enterprises' distribution based on regions

	G	G_{jj}				G_{nb}		G_w		G_t	
	Total	Eastern	Central	Western	Northeastern	Between	Contribution%	Within	Contribution%	Overlap	Contribution%
2011	0.755	0.598	0.302	0.469	0.536	0.543	71.965	0.179	23.692	0.033	4.344
2012	0.751	0.595	0.293	0.472	0.530	0.539	71.764	0.177	23.570	0.035	4.666
2013	0.749	0.591	0.286	0.460	0.533	0.538	71.820	0.175	23.410	0.036	4.771
2014	0.746	0.588	0.285	0.451	0.516	0.536	71.803	0.174	23.286	0.037	4.912
2015	0.743	0.586	0.278	0.435	0.506	0.532	71.599	0.172	23.203	0.039	5.197
2016	0.741	0.588	0.265	0.422	0.480	0.530	71.499	0.172	23.158	0.040	5.343
2017	0.738	0.586	0.257	0.412	0.487	0.526	71.302	0.170	23.052	0.042	5.646
2018	0.734	0.585	0.259	0.411	0.476	0.521	70.908	0.169	22.979	0.045	6.114
2019	0.732	0.585	0.261	0.407	0.464	0.517	70.657	0.168	22.948	0.047	6.395
2020	0.730	0.585	0.258	0.410	0.451	0.515	70.475	0.168	22.939	0.048	6.586
2021	0.729	0.585	0.258	0.410	0.441	0.513	70.385	0.167	22.918	0.049	6.697
2022	0.728	0.585	0.259	0.410	0.437	0.512	70.371	0.167	22.925	0.049	6.704
2023	0.728	0.585	0.261	0.410	0.440	0.512	70.344	0.167	22.945	0.049	6.711

Source: authors' work.

Table 2 shows that the variability in the distribution of high-tech firms in the textile industry has gradually narrowed down in 2011–2023, with the overall Gini coefficient decreasing from 0.755 to 0.728. Regional disparity of high-tech textile firms has gradually narrowed over this time, with an improved overall degree of inequality. The contribution rate of inter-regional differences is the highest. The inter-regional Gini coefficient shows a downward yearly trend, gradually narrowing the inter-regional gap. Concurrently, the contribution of intra-regional disparities has stabilised at between 22.9% and 23.7%, ranking as the second largest source of overall disparities. Although intra-regional disparities still exist, their impact on overall disparities is relatively small. The steady decline in the intraregional Gini coefficient also reflects the gradual reduction of disparities within the region. Besides, the small contribution of hyper variance density further suggests that the impact of sample overlap between regions on the distributional differences of high-tech enterprises in the textile industry is relatively limited.

Intra-regional differences. Even though the intra-regional differences in the eastern region are the largest, the level of its Gini coefficient is lower than that of the overall national Gini coefficient, with the overall level between approx. 0.58 and 0.60, and the change is small (see *Table 2*). The Northeast and West regions have the second and third highest intra-regional differences, respectively, with the Gini coefficient showing a gradual downward trend. The Gini coefficients of the eastern and northeastern regions both exceeded 0.5, indicating large internal differences, while the Gini coefficients of the central and western regions were always at a low level, with relatively balanced internal development. Between 2011 and 2023, the Northeast region’s internal differences converged the fastest (18% decline), with the Gini coefficient dropping from 0.536 to 0.440; the Western and Central regions followed (13% decline), with the Gini coefficient dropping from 0.469 to 0.410, and from 0.302 to 0.261, respectively.

Inter-regional differences. The regional differences in high-tech firms in the textile industry nationwide show a general trend of gradual reduction from 2011 to 2023, but inter-regional differences are still an important factor affecting overall inequality (see *Table 3*). In terms of specific differences between regions, the difference between the Eastern region and other regions, the difference between the Eastern and Central regions is decreasing on yearly basis, from 0.7175 in 2011 to 0.6548 in 2023. The most obvious decrease, the geographic location of the coast, is a notable factor affecting the distribution of high-tech textile enterprises. While the Central region borders the Eastern region, with the extrapolation of time, the Eastern region may have reached saturation in terms of the number of firms, and the Central region has become the second choice area for firms due to its proximity to the coast. Therefore, the gap between the two regions is narrowing, yet the gap between the East and the West is always the most pronounced.

Table 3. Interregional variations

	East-Central	East-West	East-Northeast	Central-West	Central-Northeast	West-Northeast
2011	0.718	0.936	0.894	0.762	0.611	0.611
2012	0.709	0.934	0.895	0.767	0.629	0.600
2013	0.705	0.933	0.898	0.770	0.646	0.595
2014	0.697	0.933	0.899	0.777	0.661	0.575
2015	0.692	0.929	0.904	0.772	0.684	0.550
2016	0.688	0.929	0.903	0.775	0.684	0.531
2017	0.680	0.927	0.905	0.777	0.701	0.530
2018	0.668	0.925	0.906	0.783	0.721	0.513
2019	0.662	0.923	0.906	0.785	0.727	0.500
2020	0.658	0.922	0.905	0.785	0.730	0.491
2021	0.655	0.921	0.904	0.785	0.729	0.486
2022	0.655	0.921	0.903	0.785	0.728	0.482
2023	0.655	0.921	0.904	0.784	0.729	0.484

Source: authors’ work.

Even though the Gini coefficient declines from 0.9355 (2011) to 0.9205 (2023), it is still high, reflecting the East's benefits in terms of resources, technology, and markets (see *Table 3*). This is followed by the inter-regional gap between the Eastern and Northeastern regions, whose Gini coefficient shows a trend of gradual expansion after experiencing phased fluctuations from 0.8938 in 2011. This indicates a tendency for the gap between the Eastern and Northeastern regions in terms of the level of economic development to intensify.

The difference between the Central and the Western region is generally greater than the difference between the Central and the Northeastern region, both of which show an upward trend. The difference between the Western and the Northeastern region is relatively small and shows a downward trend, with the most pronounced decline rate. Based on the trend of changes in the differences, the relative gap between different regions reveals a divergence. The Eastern and other regions have the most serious differences, while the size of differences between the other regions is more similar, and the differences between the East-Northeast, Central-West, and Central-Northeast is the obvious expansion. The inter-group differences imply that the main reason for the level of national differences may be the continuously growing imbalance in the distribution of enterprises between the Central and Eastern regions and the other regions.

Analysis of inter-provincial and intra-provincial disparities. This study recounts the number of enterprises distributed at the city level and discusses the changes in the overall differences between and within provinces using the Gini coefficient decomposition method (see *Table 4*). The overall Gini coefficient calculated using the number of firms at the city level is practically the same as the Gini coefficient calculated using the provinces in the previous section. The coefficient of intergroup difference between provinces is shrinking year by year, from 0.678 in 2011 to 0.630 in 2023. However, the difference between provinces is still the main source of the overall difference, and the contribution to the overall difference reaches more than 80% in every year.

Table 4. The Gini coefficient decomposition of the distribution of high-tech textile industry enterprises based on provinces

Year	G	G_{nb}		G_w		G_t	
	Total	Between	Contribution%	Within	Contribution%	Overlap	Contribution%
2011	0.753	0.678	90.111	0.025	3.287	0.050	6.602
2012	0.755	0.672	88.944	0.025	3.346	0.058	7.710
2013	0.756	0.668	88.423	0.025	3.293	0.063	8.284
2014	0.758	0.664	87.590	0.025	3.310	0.069	9.100
2015	0.759	0.657	86.514	0.025	3.316	0.077	10.170
2016	0.759	0.653	85.953	0.025	3.326	0.081	10.721
2017	0.756	0.646	85.502	0.025	3.352	0.084	11.146
2018	0.753	0.639	84.879	0.025	3.342	0.089	11.780
2019	0.751	0.635	84.528	0.025	3.351	0.091	12.121
2020	0.750	0.632	84.298	0.025	3.390	0.092	12.313
2021	0.748	0.630	84.146	0.025	3.356	0.094	12.499
2022	0.748	0.629	84.145	0.025	3.351	0.094	12.504
2023	0.748	0.630	84.191	0.025	3.368	0.093	12.441

Source: authors' work.

However, the change in the difference within the group is not significant and is more stable every year, with the degree of contribution remaining at approx. 3%. This shows that the overall difference in the distribution of high-tech textile industry enterprises and distribution is still uneven distribution between regions. With the change of time, it is possible to observe that the gap between the provinces is being gradually reduced. This may be due to the fact that the number of enterprises in some areas may have reached a more saturated degree. In order to avoid the greater competition, the enterprise will be located close to the cluster of these enterprises, which are more concentrated in the region, thus reducing the distribution of differences between regions. Within the group, variance changes are not significant and are observed to be more stable each year; the degree of contribution is maintained at approx. 3%.

3.2 Influencing Factors of the Distribution of High-Tech Textile Industry Enterprises

3.2.1 Variable Selection

Explained variables. The number of high-tech textile firms in each province is used to describe its spatial distribution, as each year in each province, these firms may exist in the case of cancellation and revocation of business license. The number of textile firms presents the number of renewed firms in the current year to eliminate the effect of the order of magnitude and reduce the anisotropy, the natural log of the processing.

Influential factors. The descriptive statistics of variables and their characteristics are relatively normal (see *Table 5*). Based on the distribution factor of textile industry firms, this paper considers four levels of the impact factors of the land factor price, clothing consumption capacity, raw material supply, and textile industry scale.

Table 5. Descriptive statistics

Variable	Mean	Std. dev.	Min	Max
$Firm$	4.202	1.768	0.693	7.952
$Landprice$	0.061	0.194	0.006	1.700
$Wage$	10.488	0.351	9.442	11.210
$Size$	0.012	0.016	0.000	0.084
$Clothes$	7.057	0.337	6.059	7.721
$People$	54.886	16.031	22.183	102.884
Sci	9.275	1.575	5.398	12.984
$PGdp$	10.816	0.422	9.883	11.910

Source: authors' work.

The consideration levels of the influential factors are defined as follows. (1) Textile industry land grant price ($Landprice$) refers to the regional textile industry enterprises land grant unit area transaction price of the average of the province at year level. (2) Textile industry wage level ($Wage$) is understood as the average wage of non-private textile enterprises above the regional scale. (3) Regional clothing consumption level ($Clothes$) refers to the regional clothing consumption as a proportion of total consumption. (4) Textile industry scale ($Size$) refers to the total assets of textile enterprises above scale as a proportion of the total assets of industrial enterprises above scale in the region.

Referring to Wang et al. (2023) and Lu and Li (2020), this paper selects additional macro variables that may affect the distribution of high-tech textile enterprises. (5) The level of regional human capital ($People$) is understood as the level of regional attraction of foreign investment, measured using the natural logarithm of total foreign investment. (6) The level of economic development ($PGdp$) is measured by the natural logarithm of regional GDP per capita, which is deflated by the CPI using 2011 as the base year to eliminate the impact of prices. (7) The level of scientific and technological development (Sci) refers to the number of effective invention patents of industrial enterprises above the regional scale.

3.2.2 Construction of the Spatial Measurement Model

Spatial weight matrix. The spatial dependence triggered by the spatial location relationship enhances the predictive accuracy of the model. The geographic inverse distance square matrix is used as a spatial matrix to analyse the influencing elements of the distribution of high-tech textile firms, and the matrix is shown in Eq. (9).

$$C_{ij} = \frac{1}{d_{ij}^2} \tag{9}$$

where i and j are provinces and C_{ij} are elements of the matrix, d_{ij}^2 is the square of the distance from the central point of province i to the central point of province j.

Spatial autocorrelation test. The understudied object is ensured to be spatially dependent and correlated. The global Moran index is used as a test method for the spatial agglomeration characteristics of multinational corporations. The Global Moran's Index (Moran's I) is the value of the spatial correlation coefficient to study the correlation characteristics between regions from a holistic perspective (Eq. 10).

Assuming the existence of a spatial sequence, the Moran's index is:

$$I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{10}$$

where S^2 is the sample variance, $S^2 = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}$, and w_{ij} is the element (i, j) in the spatial weight matrix. The Moran index's magnitude is between -1 and 1. An index greater than 0 is positive, less than 0 is negative spatial autocorrelation, and close to 0 means no spatial autocorrelation; the distribution of $\{x_i\}$ in space is random.

Table 6. Spatial autocorrelation test of the distribution of high-tech textile firms

year	I	Z	P-value
2011	0.340	3.904	0.000
2012	0.343	3.936	0.000
2013	0.346	3.970	0.000
2014	0.339	3.875	0.000
2015	0.336	3.851	0.000
2016	0.340	3.897	0.000
2017	0.344	3.942	0.000
2018	0.338	3.876	0.000
2019	0.329	3.777	0.000
2020	0.327	3.753	0.000
2021	0.327	3.752	0.000
2022	0.327	3.751	0.000
2023	0.327	3.758	0.000

Source: authors' work.

Table 6 shows that the spatial distribution of high-tech Chinese textile firms has significant spatial agglomeration and spatial correlation, i.e., high-tech firms show non-random distribution in geographic space. The development of high-tech firms in the textile industry has a certain dependence on the spatial dimension, which may be subject to the joint effect of geographic proximity and regional economic characteristics.

Selection of spatial measurement models. When analysing the factors affecting the distribution of high-tech textile enterprises, the spatial measurement model is chosen reasonably. The corresponding statistics (Wald test and LR test) indicate that the SDM is not reducible to SAR or SEM. Thus, SDM is the optimal model choice.

Based on the Hausman test, the fixed effects model was chosen. Both time and province fixed effects were controlled in the model to better reflect the spatio-temporal dynamic characteristics of the distribution of high-tech textile firms (see *Table 7*).

Table 7. Optimal spatial model selection results

Test Methods	Testing Indicators	statistical volume
Wald test	Wald test spatial lag	48.78***
	Wald test spatial error	36.96***
LR test	LR test spatial lag	44.99***
	LR test spatial error	35.27***
Hausman test	Random effects are superior to fixed effects	76.86***

Note: *** indicates that the p-value corresponding to the test statistic is less than or equal to 0.01.

Source: authors' work.

The spatial Durbin model shown in Eq. (11) is constructed to analyse the influencing factors of the distribution of high-tech textile industry enterprises:

$$Firm_{it} = \rho \sum_{j=1}^{n} W_{ij}\, Firm_{it} + \boldsymbol{X_{it}\alpha} + \beta \sum_{j=1}^{n} W_{ij} X_{itj} + \mu_i + \varphi_t + \varepsilon_{it} \tag{11}$$

Where i is the province, t is the year, $Firm_{it}$ is the distribution number of high-tech textile enterprises, W_{ij} is the spatial matrix, $\boldsymbol{X_{it}}$ is the influencing factors' data matrix, α is the coefficient vector of these influencing factors, reflecting the degree of effect of local influencing factors on the distribution number of local firms. X_{itj} is the jth influencing factor, β is the effect coefficient of the jth influencing factor of neighbouring regions on the region, reflecting the degree of effect of influencing factors in the surrounding areas on the distribution number of local enterprises, μ_i is the province fixed effect, φ_t is the time fixed effect, and ε_{it} is the error term.

3.2.3 The Estimation Results of the Spatial Durbin Model

The majority of the influencing factors have a notable positive effect on the number of enterprises, and the spatial autocorrelation coefficient is significantly negative (see *Table 8*). The coefficient estimates in the spatial Durbin model do not directly reflect the marginal effects of changes in individual explanatory variables on the number of firms. Thus, the partial differentiation method is used to categorise the effects of the estimated results of the spatial Durbin model. The total effect can be further grouped into direct and indirect effects, capturing more accurately the mechanism of each factor in the context of spatial heterogeneity.

Table 8. Spatial Durbin model regression of the distribution of high-tech textile enterprises

Variable	$Firm$	Variable	$Firm$
$Landprice$	-0.161***	$W \times Landprice$	-0.281***
	(0.040)		(0.064)
$Wage$	-0.131***	$W \times Wage$	-0.163
	(0.042)		(0.105)
$Size$	5.433***	$W \times Size$	10.052***
	(1.457)		(3.717)
$Clothes$	0.136*	$W \times Clothes$	-0.321*
	(0.079)		(0.195)
$People$	0.006***	$W \times People$	0.001
	(0.001)		(0.004)
Sci	0.150***	$W \times Sci$	0.240***
	(0.031)		(0.084)
$PGdp$	0.167**	$W \times PGdp$	-0.177
	(0.071)		(0.142)
Province fixed effects	Yes		
time fixed effect	Yes		
Log-likelihood	346.328	R^2	0.679
N	390	ρ	-0.318*** (0.098)

Note: Standard errors in parentheses, *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Source: authors' work.

Table 9. Results of effect decomposition based on the spatial Durbin model

Variable	Direct effect	Indirect effect	Total effect
$Landprice$	-0.149***	-0.194***	-0.343***
	(0.039)	(0.050)	(0.070)
$Wage$	-0.129***	-0.100	-0.229***
	(0.035)	(0.083)	(0.087)
$Size$	5.098***	6.922**	12.019***
	(1.528)	(3.176)	(3.402)
$Clothes$	0.163*	-0.296*	-0.132
	(0.088)	(0.178)	(0.171)
$People$	0.005***	-0.000	0.005
	(0.002)	(0.003)	(0.004)
Sci	0.142***	0.149**	0.291***
	(0.031)	(0.062)	(0.066)
$PGdp$	0.179**	-0.181	-0.001
	(0.075)	(0.130)	(0.117)

Note: Standard errors in parentheses, *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Source: authors' work.

In *Table 9*, the coefficients of direct, indirect, and total effects of industrial land price (*Landprice*) on the distribution number of high-tech enterprises in the textile industry are significantly negative. The local land price increases inhibit the number of firms distributed. Besides, higher land prices in neighboring areas reduce the number of local firms through spatial spillover effects. Offering low-priced industrial land allows local governments to participate in inter-regional subsidy competition (Xu *et al.,* 2017; Yang *et al.,* 2022). Low land prices also promote industrial agglomeration (Wang *et al.,* 2020). The rise in industrial land prices triggers the crowding-out effect, which increases the upfront investment and operating costs, compresses the profit margins, and pressurises the capital flow. Therefore, the rise in industrial land prices reduces the level of local enterprise distribution. Rising industrial land prices in neighbouring regions also exert a dampening effect on the distribution of firms in the region.

As can be observed, the coefficient of the direct effect of the average wage in the textile industry (*Wage*) is significantly negative. The coefficient of the indirect effect fails to reach significance, and the coefficient of the total effect is significantly negative. A higher local wage reduces the number of firms distributed locally, but there are no spatial spillovers. Based on the least-cost location theory, the location choice of firms mainly depends on cost factors, and textile wages affect the location decision of high-tech textile firms. Higher wages directly lead to a rise in labour costs, reducing profitability and reducing the R&D funds, which is not conducive to product upgrading.

All coefficients of the direct, indirect, and total effects of the textile industry size (*Size*) are significant and positive. This results in the expansion of the local textile industry size will promote the number of local enterprises, and the expansion of the size of the neighbouring regions can also promote the local enterprises to improve the number of their distribution. The scale of regional textile industry enterprises reflects the degree of agglomeration of the textile industry in the region and the level of development of the textile industry. A large-scale textile industry implies the possession of a complete and mature upstream and downstream industrial chain, which increases the convenience for high-tech textile enterprises to obtain high-quality textile raw materials and reduce the procurement cost and risk of out-of-stock (Liu, Jiao, 2023). Conversely, advanced textile technology and management experience make the latest technological innovations more accessible to the high-tech textile enterprises (Bröcker, 2004).

The coefficients of direct and indirect effects of the demand for apparel (*Clothes*) are significant at the 1% level, with a positive coefficient for the direct effect and a negative coefficient for the indirect effect. Market size is a significant factor affecting the geographical distribution of economic practices (Sato *et al.,* 2012). The existence of regions with a high level of apparel consumption point to a high consumer demand for various apparel products, especially for high-tech textile products. In order to be closer to the target market, enterprises place their production and sales departments in areas with high market potential. Conversely, the high market potential of the neighbouring areas exerts a competitive effect on the distribution of firms in this region.

The direct and indirect effects of high-skilled human capital (*People*) are notably positive. The rise in the level of high-skilled human capital in the region enhances the distribution level of local and neighbouring firms through the spatial spillover effect. High-skilled human capital enhances the independent innovation ability and accelerates the technological transformation (Baro, 2001; Kim *et al.,* 2021).

The coefficients of the direct and indirect effects of science and technology level (*Sci*) are both significant and positive. The improvement of regional science and technology level not only significantly promotes the growth of the distribution level of local high-tech textile firms, but also can increase the distribution level of the firms in the neighbouring regions through spatial spillover effects. Given the existence of enterprise linkage, some firms will enter the firm-intensive areas for the purpose of sharing the technological spillover effect, promoting the formation of agglomeration (Liu, Zhang, 2021; Menzel, Fornahl, 2010). From the perspective of firm heterogeneity, firms with lower than industry average TFP face a risk of market elimination (Melitz, 2003), and a lower technology level limits their ability to capture knowledge spillovers.

In this case, the neighbouring regions not only attract those firms that failed to enter the high-tech region due to technological differences, but also further promote the growth of the distribution of high-tech textile industry firms.

The direct effect of the level of economic development (*PGdp*) is significantly positive at the 5% level, but neither the indirect nor the total effect reaches a significant level. Regions with higher economic development have better infrastructure (Calderón, Servén, 2010) and a high consumer market potential (Wennekers *et al.,* 2005).

4. Discussion

Spatial-temporal evolution of high-tech textile enterprises. Between 2012 and 201, the number of high-tech textile Chinese enterprises increased rapidly. However, this growth slowed after 2018, especially during and after COVID-19 pandemic, when negative growth rates were witnessed. Geographically, the eastern coastal regions (Guangdong, Jiangsu, & Zhejiang) retained clusters of high enterprise density, with a gradual decline in distribution moving westward. These patterns reflect international trends witnessed in other key textile-producing economies, including Bangladesh, India, and Vietnam, where coastal regions dominate the production, owing to improved logistic infrastructure and access to international markets (Saxena, Salze-Lozac'h, 2010). Furthermore, the post-pandemic downfall in growth is also aligned with the global rising costs of raw materials, disruptions in the supply chains, and changing consumer tastes, illuminating the shared vulnerabilities of global textile industries.

Regional Gini coefficient analysis. With inter-regional disparities being the primary source of total variation, decomposition results indicate a reduction in regional disparities. The disparities between the East and the West, and the East and the Northeast, were noticeable. Intra-regional disparities were largest in the East and Northeast, followed by the West, with the smallest in the Central region. City-level data show that inter-provincial disparities dominated, accounting for over 80% of the variation. Notably, inequality in industrial distribution is also a global concern. For instance, in order to resolve similar disparities in industrial activity among member states, the EU has implemented regional cohesion policies (McCann, 2015), implying that policies meant to narrow regional development gaps are a common international priority.

Gravity centre migration. The gravity centre of high-tech textile enterprises shifted westward and slightly southward over the researched period. Besides, a notable turning point occurred around 2015, after which the rate of migration slowed down. Recent trends (2022–2023) exhibit a potential reversal, with the gravity centre moving back eastward. Evidently, similar shifts have been reported in countries such as Germany and the US, where production activities have reflected tendencies to move inland due to increasing urban costs, and then return to conventional industrial hubs with improved innovation ecosystems (Kinkel, 2012). As a result, the spatial realignment of China represents wider global dynamics of balancing cost-efficiency with innovation and market access.

Factors influencing enterprise distribution. With spatial spillover effects observed for land prices but not for wages, higher land prices and wages reduced firm numbers. Higher technological innovation capabilities and larger regional textile industry scales positively affected firm distribution, with strong spatial spillover effects for innovation. Human capital quality and regional consumption capacity had positive direct effects, while economic development and external market competition had limited spatial spillover effects. The regional demand, skilled labour, and innovation ecosystems are confirmed as vital drivers of enterprises clustering in Italy, Turkey, and South Korea (Peirone *et al.,* 2024). In addition, labour and land cost constraints affect firm distribution in a similar manner globally, especially in economically saturated areas. Such cross-national parallels confirm that the Chinese case offers useful insights for economies undertaking spatial restructuring of high-tech textile sectors.

The findings of this study resonate with global trends of industrial transformations, particularly in developing countries. Integrating China's case into global relative frameworks not only increases theoretical generalizability but also offers policy implications for other economies navigating technological transformation, regional imbalances, and post-COVID-19 industrial recovery.

Conclusions

The spatial distribution of high-tech textile enterprises has an impact on competitiveness, technological diffusion, and industrial agglomeration. Using the provincial data from the time period of 2011–2023, this paper employs Gini coefficient decomposition, centroid migration analysis, and the spatial Durbin modeling to analyse the underlying determinants and spatio-temporal evolution of Chinese high-tech textile firms. The study findings confirm a prominent two-stage growth trajectory, characterised by rapid expansion (2012–2017) and a noticeable slowdown after 2018, including instances of negative growth during and following the COVID-19 pandemic. The spatial Durbin model reveals human capital, market potential, industrial scale, land prices, and technological innovation capacity as pivotal factors exerting considerable spatial spillover effects. Conversely, the regional economic development and wage levels also have an impact on enterprise location decisions but exhibit relatively weaker spatial spillovers. This study contributes to the interdisciplinary discourse bridging business management and economic geography by elucidating the multifaceted drivers of industrial spatial distribution.

The present study proposes different implications. In the context of industrial strategies, enterprises in Eastern regions should focus on innovation, niche markets, and value-chain upgrading, while those in Western and Central regions should optimise production efficiency, leverage cost advantages, and strengthen collaborations with their Eastern counterparts. In terms of regional development, authorities should support coordinated development by enhancing cross-regional collaboration platforms to facilitate technological transfer and industrial cooperation. Meanwhile, the targeted policies should support the Western, Central, and Northeastern regions. From the perspective of corporate incentives, policymakers should implement innovative subsidies, land price discounts, and human development programmes to attract high-tech textile enterprises. Moreover, market activation strategies, such as organising trade fairs, can also trigger local demand. At large, this paper extends useful insights for researchers, policymakers, and corporations to enhance regional innovation, optimise industrial layouts, and augment sustainable economic development in the high-tech textile industry. Hence, the study findings are expected to play a vital role in the optimization of the textile industry layouts and regional economic coordination under the dual-circulation development framework of China, with broader implications for developing countries.

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ERDVINĖ IR CHRONOLOGINĖ KINIJOS AUKŠTŲJŲ TECHNOLOGIJŲ TEKSTILĖS ĮMONIŲ RAIDA BEI JĄ LEMIANTYS VEIKSNIAI

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Santrauka. Aukštųjų technologijų tekstilės įmonių geografinis pasiskirstymas tiesiogiai veikia pramonės aglomeracijos veiksmingumą, technologijų sklaidą ir konkurencingumą. Siekiant sistemingai ištirti Kinijos aukštųjų technologijų tekstilės įmonių erdvinę ir chronologinę raidą bei pagrindinius veiksnius, pasitelkti paneliniai provincijų duomenys (2011–2023 m.). Tyrime taikyta kompleksinė metodologija, apimanti centroidų migracijos analizę, Gini koeficiento dekompoziciją ir erdvinį Durbino modelį. Analizės rezultatai atskleidė aiškią dviejų etapų augimo trajektoriją: 2012–2017 m. laikotarpiu fiksuotas spartus augimas, o nuo 2018 m. – ryškus sulėtėjimas, peraugęs į neigiamą augimą COVID-19 pandemijos metu ir po jos. Erdvinio Durbino modelio ekonometriniai įverčiai rodo, kad pagrindiniai veiksniai, reikšmingai lemiantys erdvinę plėtrą, yra žemės kainos, pramonės mastas, rinkos potencialas, žmogiškasis kapitalas ir technologinių inovacijų pajėgumas. Darbo užmokestis ir regionų ekonominė plėtra silpniau veikia įmonių vietos pasirinkimą. Šis tyrimas prisideda prie tarpdisciplininio diskurso, jungiančio ekonominę geografiją ir verslo vadybą, ir leidžia išsamiau paaiškinti pramonės erdvinio pasiskirstymo veiksnių įvairovę. Gauti rezultatai suteikia praktinių įžvalgų bei politikos formavimo gairių, padedančių optimizuoti tekstilės pramonės išdėstymą ir stiprinti regioninį ekonominį koordinavimą, atsižvelgiant į Kinijos dvigubos apyvartos plėtros modelį. Platesniame kontekste šios įžvalgos yra aktualios ir kitoms besivystančioms ekonomikoms.

Reikšminiai žodžiai: aukštųjų technologijų tekstilės įmonių sektorius; pasiskirstymas; migracija; erdvinis Durbino modelis.