

Economic growth, industrial concentration, and carbon emissions in the textile industry

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ABSTRACT – REZUMAT

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Against the backdrop of global “dual-carbon” goals and China’s economic transformation, the textile industry, as a key high-emission sector, has attracted much attention regarding the dynamic correlations between its carbon emissions, economic growth, and industrial concentration. Based on China’s textile industry data from 2001 to 2020, this paper constructs a Vector Autoregression (VAR) model and systematically explores the interactive relationships among the three through methods such as the Granger causality test, the cointegration test, impulse response, and variance decomposition. The findings are as follows: the Granger causality test shows that only the growth rate of carbon emissions in the textile industry (D_{CO_2}) is a significant Granger cause of changes in industrial concentration (D_{IC}), while there is no significant causal relationship between other variables, indicating that changes in carbon emissions have a one-way driving effect on the adjustment of industrial concentration; the unrestricted cointegration test indicates that there is one long-term cointegration relationship among the three; in the long-term equilibrium, D_{IC} has a significant impact on D_{CO_2} , reflecting that the improvement of industrial concentration can effectively curb carbon emissions; impulse response analysis shows that the response of D_{CO_2} to its own shock is significant in the short term, and the impact of D_{IC} shock on it is transient; D_{IC} shows a positive response to D_{CO_2} shock, while the impact of its own shock is weak; the response of D_{ISV} (growth rate of economic growth) to D_{CO_2} shock lasts longer, and the dynamic interaction among variables is centered on D_{CO_2} ; the variance decomposition results show that the long-term explanatory power of D_{CO_2} to D_{IC} reaches 48.85%, but the explanatory power of D_{IC} to D_{CO_2} is only 11.75%; the impact of D_{IC} on D_{ISV} (11.63%) is stronger than that of D_{CO_2} (7.32%); in the long run, the forecast error variances of the three variables are mainly dominated by their own shocks (about 80% for D_{CO_2} and D_{ISV} , and about 50% for D_{IC}), and the system eventually tends to equilibrium. The study reveals the key role of carbon emissions in the textile industry in adjusting industrial concentration, providing empirical evidence for coordinating industrial concentration and carbon emission governance through policy guidance.

Keywords: economic growth, industrial concentration, carbon emissions in the textile industry, VAR model

Creșterea economică, concentrarea industrială și emisiile de carbon în industria textilă

Pe fondul obiectivelor globale privind „dubla reducere a emisiilor de carbon” și al transformării economice a Chinei, industria textilă, ca sector-cheie cu emisii ridicate, a atras o atenție sporită asupra corelațiilor dinamice dintre emisiile sale de carbon, creșterea economică și concentrarea industrială. Pe baza datelor privind industria textilă din China din perioada 2001–2020, acest articol construiește un model de autoregresie vectorială (VAR) și explorează sistematic relațiile interactive dintre cele trei elemente prin metode precum testul de cauzalitate Granger, testul de cointegrare, răspunsul la impuls și descompunerea varianței. Concluziile sunt următoarele: testul de cauzalitate Granger arată că doar rata de creștere a emisiilor de carbon din industria textilă (D_{CO_2}) este o cauză Granger semnificativă a schimbărilor în concentrarea industrială (D_{IC}), în timp ce nu există o relație cauzală semnificativă între alte variabile, indicând faptul că schimbările legate de emisiile de carbon au un efect de impuls unidirecțional asupra ajustării concentrării industriale; testul de cointegrare fără restricții indică faptul că există o singură relație de cointegrare pe termen lung între cele trei variabile; în echilibrul pe termen lung, D_{IC} are un impact semnificativ asupra D_{CO_2} , reflectând faptul că îmbunătățirea concentrării industriale poate reduce în mod eficient emisiile de carbon; analiza răspunsului la impuls arată că răspunsul D_{CO_2} la propriul șoc este semnificativ pe termen scurt, iar impactul șocului D_{IC} asupra acestuia este tranzitoriu; D_{IC} arată un răspuns pozitiv la șocul D_{CO_2} ; D_{IC} prezintă un răspuns pozitiv la șocul D_{CO_2} , în timp ce impactul propriului său șoc este slab; reacția D_{ISV} (rata de creștere economică) la șocul D_{CO_2} durează mai mult, iar interacțiunea dinamică dintre variabile se concentrează asupra D_{CO_2} ; rezultatele descompunerii varianței arată că puterea explicativă pe termen lung a D_{CO_2} asupra D_{IC} ajunge la 48,85%, dar puterea explicativă a D_{IC} asupra D_{CO_2} este de doar 11,75%; impactul D_{IC} asupra D_{ISV} (11,63%) este mai puternic decât cel al D_{CO_2} (7,32%); pe termen lung, varianțele erorilor de prognoză ale celor trei variabile sunt dominate în principal de propriile șocuri (aproximativ 80% pentru D_{CO_2} și D_{ISV} și aproximativ 50% pentru D_{IC}), iar sistemul tinde în cele din urmă spre echilibru. Studiul relevă rolul cheie al emisiilor de carbon din industria textilă în ajustarea concentrării industriale, oferind dovezi empirice pentru coordonarea concentrării industriale și a guvernancei emisiilor de carbon prin orientări de politică.

Cuvinte-cheie: creștere economică, concentrare industrială, emisii de carbon în industria textilă, model VAR

INTRODUCTION

Against the backdrop of an escalating global climate crisis and China's deepening commitment to its "dual carbon" strategy, the green transformation of traditional manufacturing industries has emerged as a critical breakthrough point for achieving high-quality development [1–3]. As the world's largest producer, consumer, and exporter of textiles, China's textile industry served not only as a vital pillar of the national economy (according to data from the Ministry of Industry and Information Technology, the industrial added value of textile enterprises above designated size increased by 4.4% year-on-year in 2024, with operating revenue reaching 4,953.21 billion yuan, representing a 4.0% year-on-year increase), but also constituted a significant contributor to energy consumption and carbon emissions. It was estimated that the textile and apparel industry accounted for 6% to 8% of global carbon emissions, making it the second-largest consumer and polluter, generating approximately 1.7 billion tonnes of carbon dioxide annually [4]. The textile industry demonstrated a high degree of environmental degradation, with adverse environmental impacts increasing accordingly [5]. The textile industry caused both direct and indirect impacts on environmental degradation, as fossil fuel combustion involved in textile manufacturing processes directly produced greenhouse gases in the atmosphere, whilst indirectly, the textile industry increased toxic emissions generated by higher electricity utilisation rates throughout the entire textile supply chain [6]. Concurrently, China's economy had transitioned from a phase of high-speed growth to one of high-quality development. In 2024, the total GDP exceeded 130 trillion yuan, with per capita GDP surpassing 92,000 yuan, marking a profound transformation in the economic growth model from factor-driven to innovation-driven development, and from scale expansion to quality and efficiency enhancement [7–9].

From a global perspective, climate change has become one of the most severe challenges facing human society. The Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) indicated that if global warming exceeded 1.5°C, the frequency of extreme weather events would increase threefold, with ecosystem collapse risks rising significantly [10, 11]. As a key participant in global climate governance, China had committed to the international community to achieve the "dual carbon" goals of "carbon peaking before 2030 and carbon neutrality before 2060", which represented not merely environmental constraints but strategic guidance for economic transformation [12, 13]. Within this context, the industrial sector, as a primary source of carbon emissions, had its low-carbon transformation listed as a core task in the "14th Five-Year Plan". The textile industry, as an important component of the industrial system, exhibited typical carbon emission characteristics: on one hand, according to the "Feasibility Study Report on Renewable Energy Investment for

Decarbonisation in China's Textile Industry" released by institutions including the China National Textile Information Centre, China's textile fibre processing volume accounted for more than 50% of the global total, with annual carbon emissions from the textile industry comprising approximately 2% of the national total carbon emissions, with industry carbon emissions primarily originating from energy use. The textile industry's energy consumption was dominated by coal and natural gas, and the coal-biased energy structure resulted in carbon emission intensity per unit output being higher than the national industrial average; on the other hand, the textile industry possessed long industrial chains with multiple links (encompassing spinning, weaving, dyeing, and garment production), leading to high end-of-pipe treatment costs and significant technical difficulties [14–16]. Therefore, resolving the textile industry's "high emissions, difficult treatment" dilemma constituted a critical component in implementing the "dual carbon" goals.

Existing research had established a relatively systematic analytical framework for the relationship between economic growth and carbon emissions, with the most representative being the Environmental Kuznets Curve (EKC) hypothesis proposed by Grossman and Krueger (1995), which suggested an "inverted U-shaped" relationship between economic growth and environmental pollution, during the early stages of economic development, accelerated industrialisation processes led to increased pollution emissions; when economic development reached a certain stage, technological progress, industrial structure upgrading, and enhanced environmental awareness would drive emission reductions [17].

Subsequent research further expanded this theory, finding that factors such as energy structure (such as the proportion of fossil energy), technological innovation (such as clean technology research and development), and institutional arrangements (such as environmental regulation) would influence the shape and inflexion point position of the EKC [18]. Research on industrial concentration and carbon emissions primarily focused on two aspects: first, from a market structure perspective, exploring the impact of monopoly or competition levels on corporate environmental behaviour [19]; second, from an industrial organisation perspective, analysing whether increased concentration reduced unit output emissions through economies of scale, scope economies, or technological innovation [20]. For example, some studies argued that leading enterprises in highly concentrated industries possessed greater capacity to undertake environmental protection equipment investments, thereby reducing unit emissions [21]; however, other research indicated that excessive concentration might lead to monopolistic enterprises lacking emission reduction incentives, even evading environmental responsibilities through "pollution transfer". Nevertheless, these studies were predominantly based on general manufacturing or service industry data, with insufficient heterogeneity analysis

targeting specific industries (such as the textile industry). As a typical “multi-link, high-energy-consumption, low-value-added” industry, the textile industry’s industrial concentration effects on carbon emissions might differ significantly from other industries: for instance, concentration in dyeing processes might reduce marginal costs through shared pollution treatment facilities, whilst concentration in spinning processes might improve energy efficiency through equipment upsizing, but these mechanisms have not yet received systematic verification.

Existing research rarely incorporated economic growth, industrial concentration, and carbon emissions into the same analytical framework to explore the dynamic interactive relationships among the three variables. Economic growth might influence industrial concentration through two pathways: first, the “market expansion effect”, economic growth expands market demand, prompting enterprises to scale up and driving concentration increases; second, the “policy guidance effect”, governments actively increase concentration through mergers and acquisitions, elimination of backward capacity, and other policies to promote industrial upgrading. Changes in industrial concentration would, in turn, affect carbon emissions through “technological spillover effects” (demonstration effects of leading enterprises), “economies of scale effects” (unit cost reduction), and “regulatory cost effects” (reduced regulatory difficulty). Therefore, economic growth and industrial concentration might not independently influence carbon emissions but rather jointly affect environmental outcomes through complex interactive mechanisms [22–24]. From a theoretical perspective, this paper’s exploration contributed to deepening the interdisciplinary research between New Structural Economics and Environmental Economics. By treating industrial concentration as a quantitative indicator of industrial structure and exploring its relationships with economic growth (factor endowment upgrading) and carbon emissions (environmental constraints), this study could provide new theoretical explanations for “how industrial structure upgrading coordinates economic growth with environmental objectives”. Additionally, existing research was predominantly based on developed country data, whilst this paper, using China’s textile industry as a sample and combining policy practices under the “dual carbon” strategy background, could enrich the theoretical accumulation of green transformation in traditional industries in developing countries. From a practical perspective, the research conclusions of this paper could provide references for policy formulation. On one hand, it could provide empirical evidence for China’s textile industry’s “clustering and greening” development pathway, for example, how to coordinate industrial concentration enhancement with technological innovation through policy guidance, avoiding “concentration for concentration’s sake” that leads to monopolistic lock-in or innovation inertia; on the other hand, it could provide direction for precise

environmental regulation design, for example, formulating differentiated technical standards and incentive policies for textile enterprises with different concentration levels (such as providing common pollution treatment technology support for small and medium enterprises in low-concentration industries, and strengthening carbon emission information disclosure for leading enterprises in high-concentration industries) [25, 26].

Based on the aforementioned background and issues, this paper proposes to employ a VAR model to systematically investigate the interactive relationships among economic growth, industrial concentration, and textile industry carbon emissions through Granger causality tests, cointegration tests, impulse response, and variance decomposition methods. Under the dual context of “dual carbon” goals and economic transformation, the green and low-carbon development of the textile industry has become a “mandatory question” for China’s industrial transformation and upgrading. This paper focused on the relationships among economic growth, industrial concentration, and textile industry carbon emissions, attempting to answer the core question of “how to achieve carbon emission reduction whilst promoting industrial concentration”. Through theoretical analysis and empirical testing, this paper aimed to provide new perspectives for the green transformation of traditional industries and contribute Chinese experience to global climate governance. The subsequent chapters would systematically verify research hypotheses and propose policy recommendations through theoretical frameworks, data descriptions, model specifications, and results analysis.

LITERATURE REVIEW

The relationship between economic growth and carbon emissions

Carbon dioxide emissions could be categorised into natural emissions and anthropogenic emissions. Natural emissions refer to carbon dioxide released into the atmosphere from ecosystems such as soil, oceans, and forests; anthropogenic emissions refer to carbon dioxide emissions caused by human activities, primarily originating from fossil energy consumption and biomass fuel combustion [27]. The relationship between economic growth and carbon emissions constituted one of the core issues in environmental economics, with its theoretical origins traceable to the Environmental Kuznets Curve (EKC) hypothesis. Grossman and Krueger (1995), through their study of the North American Free Trade Area, first proposed that economic growth and environmental pollution exhibited an “inverted U-shaped” relationship, during the early stages of economic development, accelerated industrialisation processes led to surges in energy consumption and pollutant emissions; when economic development reached a certain stage, technological progress, industrial structure upgrading, and enhanced environmental awareness would drive emissions into a declining

trajectory [17]. This hypothesis provided a classical analytical framework for understanding the contradiction between “development and pollution”, with subsequent research conducting multidimensional expansions around its mechanisms and applicability. Scholars revealed the formation logic of the EKC from perspectives including energy structure [18], technological innovation [28], and institutional arrangements [29]. The high proportion of fossil energy (particularly coal) was considered a key constraining factor for the “inverted U-shaped” inflection point; technological innovation influenced emissions through two pathways: first, the “substitution effect” (clean energy substituting fossil energy), and second, the “efficiency effect” (declining energy consumption per unit output); environmental regulation (such as carbon taxes and emissions trading) promoted corporate innovation through the “Porter hypothesis”, thereby reducing pollution emissions.

Narayan, Saboori, and Soleymani (2016) argued that if current income levels exhibited positive cross-correlation with past CO₂ emission levels, whilst current income levels demonstrated negative cross-correlation with future CO₂ emissions [30], then over time, CO₂ emissions would decline with increasing income, which aligned with the Environmental Kuznets Curve (EKC) hypothesis. Gbadeyan et al. (2024) contended that economic growth was the primary driving factor for global carbon emission increases, and achieving a carbon-balanced environment required the decoupling of these two variables [31]. Hu et al. (2021) investigated the impact of categorised energy consumption, technological innovation, and economic output on carbon dioxide emissions in India. Their empirical analysis results demonstrated that categorised energy consumption and technological innovation had positive effects on economic growth, whilst the utilisation of renewable energy and technological innovation (namely carbon capture and storage technologies) could significantly reduce carbon dioxide emissions [32].

Zhang (2021) selected panel data from the BRICS countries (Brazil, Russia, India, China, and South Africa) for the period 1990–2019 to empirically study the impact of technological innovation and economic growth on carbon emissions [33]. Granger causality test results indicated that unidirectional causal relationships existed both between technological patents and carbon emissions, and between economic growth and carbon emissions (with the former pointing to the latter). Zhang et al. (2024) employed the entropy method and the coupling coordination model to explore the coordination level between economic growth and carbon emissions. Their research results demonstrated that most Chinese cities had room for improvement in the coordination level between carbon emissions and economic growth [34].

Fu et al. (2024) adopted the Thiel index, Tapio decoupling model, and Logarithmic Mean Divisia Index (LMDI) decomposition method to explore the decoupling between economic growth and carbon emissions.

Results indicated that carbon intensity differences primarily originated from disparities between central provinces and underdeveloped western provinces [35]. Hong et al. (2025) analysed the decoupling relationship between carbon emissions and economic growth in China’s textile industry across 30 provinces. Their research results demonstrated that both carbon emissions and GDP growth in China’s textile industry exhibited a “rise-then-decline” pattern, with carbon emissions primarily originating from coal consumption, followed by petrol and natural gas. China’s textile industry achieved strong decoupling between carbon emissions and economic growth, with per capita output value serving as the primary driving factor for carbon emission growth, whilst the energy consumption intensity factor demonstrated the most significant inhibitory effect on carbon emissions [36].

Additionally, some scholars explored the relationship between per capita gross domestic product (GDP) and per capita carbon dioxide emissions, discovering an inverted U-shaped relationship between the two variables. Carbon emissions increased with rising income but at a declining rate, attributed to structural effects and technological effects. When development reached a certain level, namely when structural effects and technological effects offset scale effects, emissions would decrease with increasing income [37].

The relationship between industrial concentration and carbon emissions

Industrial concentration (namely, the market share proportion of leading enterprises within an industry), as a core indicator for measuring market structure, has gradually become a research focus regarding its relationship with carbon emissions in recent years.

Industrial concentration influenced carbon emissions through scale effects and market power. In terms of scale effects, large enterprises in highly concentrated industries might achieve improved energy efficiency through expanded production scales (such as sharing emission reduction technologies and optimising resource allocation), thereby reducing carbon emissions per unit output. For instance, the steel industry could reduce energy waste from redundant construction through capacity integration. However, monopolistic enterprises might delay technological upgrading due to a lack of competitive pressure, leading to increased carbon emissions. Regarding market structure, the concentration measured by the Herfindahl-Hirschman Index (HHI) exhibited a non-linear relationship with environmental efficiency: initial improvements in concentration might reduce emissions through technological diffusion, but exceeding a threshold might suppress innovation due to market monopolisation, forming a “U-shaped” curve. Additionally, spatial agglomeration in highly concentrated industries might generate synergistic emission reduction effects through infrastructure sharing and technological spillovers, but might also

intensify regional environmental pressure due to concentrated pollutant emissions.

Aghion et al. (2005), drawing from Schumpeterian innovation theory, proposed that moderately concentrated market structures (monopolistic competition) were more conducive to enterprise innovation, leading enterprises possessed stronger financial and technological capabilities to undertake environmental research and development costs, thereby reducing emissions per unit output [20]; whilst excessively dispersed market structures (perfect competition) resulted in enterprises struggling to invest in environmental technologies due to minimal profits, leading to a “race to the bottom”. Monopolistic enterprises might evade responsibility through “pollution transfer” (such as relocating high-pollution processes to regions with weak regulation), actually exacerbating carbon emissions at the global level.

However, the aforementioned research was predominantly based on general manufacturing industries (such as automotive and chemical), with insufficient specific analysis targeting the textile industry. The textile industry’s uniqueness lay in: firstly, its long industrial chains (encompassing spinning, weaving, dyeing, and garment production), where dyeing processes accounted for 40% of the industry’s energy consumption and 60% of water consumption, yet dyeing enterprises were typically small-scale and dispersed, resulting in significant industry heterogeneity in concentration; secondly, the textile industry belonged to the “low value-added, high emission” category, where enterprises operated with limited profit margins, and the environmental investment capabilities of leading enterprises differed substantially from small and medium enterprises, potentially altering the traditional direction of industrial concentration’s effect on carbon emissions.

The relationship between economic growth, industrial concentration, and carbon emissions

Within existing research, discussions incorporating economic growth, industrial concentration, and carbon emissions into the same framework were relatively limited, with two primary perspectives existing, as detailed below.

The impact of synergistic effects between economic growth and industrial concentration on carbon emissions

The interactive effects of economic growth and industrial concentration on carbon emissions varied according to economic development stages and industry characteristics. Some studies found that during periods of rapid economic growth, increases in industrial concentration might exacerbate carbon emissions, particularly in energy-intensive industries. For example, in regions with rapid economic growth, high industrial concentration often accompanied higher carbon emission intensity, as large enterprises tended to expand capacity rather than adopt clean technologies. Cole and Elliott (2003) indicated that industrial concentration in developing countries might reinforce “scale effects”, where enterprises pursued

profits through increased output rather than improved energy efficiency [38]. In developed countries, due to stringent environmental regulations and more advanced technology, high industrial concentration might promote green innovation, thereby reducing carbon emissions per unit output [39].

Industrial concentration moderates the carbon intensity effect on economic growth

Industrial concentration might regulate the impact of economic growth on carbon emissions by altering market competition structures. On one hand, large enterprises in highly concentrated industries might possess stronger research and development capabilities, promoting low-carbon technological progress, thereby offsetting carbon emission increases brought by economic growth. Porter and Linde’s (1995) “Porter hypothesis” argued that moderate market concentration could incentivise enterprises to invest in environmental technologies, particularly under policy guidance. Carbon intensity in highly concentrated industries might decline more rapidly with economic growth, as these industries more easily form technological alliances and share emission reduction technologies [29]. On the other hand, if industrial concentration led to monopolies or oligopolies, enterprises might lack emission reduction motivation, even hindering policy implementation. Jaffe et al. (2005) indicated that certain highly concentrated industries (such as fossil energy) might lobby governments to relax environmental regulation, thereby exacerbating the carbon footprint of economic growth [28]. Therefore, the moderating effect of industrial concentration on the relationship between economic growth and carbon emissions depended on whether market structures promoted or suppressed green innovation [40, 41].

Research review

Research on carbon emissions in the textile industry primarily focused on the following three aspects within existing literature: emission characteristic identification, driving factor analysis, and emission reduction pathway exploration. Economic growth and industrial concentration jointly influenced carbon emissions through scale, structural, and technological effects. Although the Environmental Kuznets Curve provided a basic framework, the role of industrial concentration highlighted the necessity for targeted policies to mitigate pollution in concentrated industries.

Existing research still exhibited the following limitations: the role of industrial concentration had not been adequately emphasised, most studies treated industrial concentration as an exogenous variable, failing to thoroughly explore how it influenced carbon emissions through mechanisms such as scale effects and technological diffusion; the interactive mechanisms between economic growth and industrial concentration remained unclear, systematic analysis was lacking regarding “how economic growth promoted industrial concentration increases” and “how concentration increases reacted upon carbon emissions”;

industry-specific analysis was insufficient, the textile industry possessed long industrial chains with strong link heterogeneity (such as significant differences in emission characteristics between dyeing and spinning), yet existing research predominantly treated it as a homogeneous industry, failing to discuss link differences.

Based on the aforementioned academic trajectory and practical demands, this paper's contributions were reflected in the following aspects: expansion of theoretical frameworks, for the first time incorporating economic growth, industrial concentration, and textile industry carbon emissions into a unified analytical framework, systematically revealing the dynamic interactive mechanisms among the three variables.

RESEARCH DESIGN

Variable selection

This study primarily analysed the relationships between economic growth, industrial concentration, and carbon emissions in China's textile industry from 2001 to 2020. The data for economic growth and industrial concentration employed in this study were primarily sourced from successive editions of the China Statistical Yearbook and China Industrial Statistical Yearbook, with missing data supplemented using interpolation methods. Carbon dioxide emission data were obtained from the China Emission Accounts and Datasets (CEADs), utilising textile industry emission data for the period 2001–2020. This database (<https://> derived carbon dioxide emissions from sources including coking products, crude oil, petrol, kerosene, diesel, fuel oil, liquefied petroleum gas, refinery gas, other petroleum products, natural gas, heating, electricity, and other energy sources [42, 43].

Economic growth

This study employed Industrial Sales Value (ISV) to represent economic growth. The core meaning of ISV referred to the monetary representation of the total volume of industrial products sold by industrial enterprises within a specific period, encompassing both the value of products sold from current production and the value of products sold from previous inventory [44, 45].

Industrial concentration

Industrial concentration referred to the degree of dominance that a few enterprises within a particular industry exercised over aspects such as production volume, sales volume, and total assets within that market [46]. It was generally expressed as the percentage that a specific indicator (most commonly the sales revenue indicator) of the several largest enterprises in a market represented of the industry total [47]. Moderately high industrial

concentration could improve efficiency, thereby reducing carbon emissions. This study, referencing the aforementioned definition and combining it with the actual circumstances of the textile industry, employed the proportion of large and medium textile enterprises' annual output value to the total annual sales value of textile enterprises. Textile industry concentration was calculated according to the following formula:

$$IC = LMG_{GDP} / ISV \quad (1)$$

where IC represented textile industry concentration, LMG denoted the annual output value of large and medium enterprises, and ISV represented the annual sales value of the textile industry.

Textile industry carbon emissions.

This study employed a mass balance approach to calculate carbon emissions based on IPCC guidelines (IPCC, 2006), with the formula as follows:

$$CE_i = AD_i \times NCV_i \times CC_i \times O \quad (2)$$

where CE_i denoted CO_2 emissions from i -type fossil fuels, including coal, gas, fuel oil, coke, and others; AD_i represented the combustion amount of i fossil fuel; NCV_i referred to the "net calorific value", namely the heat value per physical unit after combustion of i fossil fuel; CC_i was the "carbon content" of i fossil fuel, which quantified the carbon emissions per unit of net calorific value generated; and referred to "oxidation efficiency", O representing the oxidation ratio during the fossil fuel combustion process.

Process-related emissions referred to CO_2 emissions in industrial production that originated from industrial raw materials rather than fossil fuels [48]. According to IPCC guidelines (IPCC, 2006), process-related emissions could be calculated as follows:

$$CE_t = AD_t \times EF_t \quad (3)$$

where CE_t represented process-related emissions in production; AD_t denoted activity data related to process-related emissions; and EF_t referred to emission factors.

Figure 1 illustrated the temporal trends of three indicators from 2001 to 2020, as follows: Industrial sales value (logarithmic) exhibited an overall pattern of

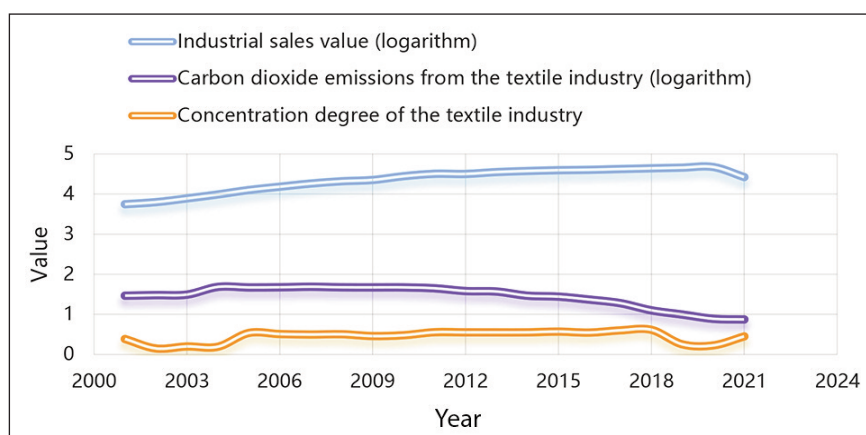


Fig. 1. Trends in economic growth, concentration, and carbon emissions in the textile industry

Table 1

ADF UNIT ROOT TEST					
Variables	Test form	ADF unit root test	ADF unit root test	Test critical value	Conclusion
	(c, t, k)	P value	T statistics	1% level	
CO ₂	(c, t, 0)	0.685	-1.756	-4.532	Non-stationary
IC	(c, t, 0)	0.825	-1.406	-4.533	Non-stationary
ISV	(c, t, 0)	0.841	-1.354	-4.533	Non-stationary
D(CO ₂)	(c, t, 0)	0.004	-5.097	-4.571	Stationary
D(IC)	(c, t, 0)	0.002	-5.425	-4.572	Stationary
D(ISV)	(c, 0, 0)	0.005	-4.249	-3.857	Stationary

Note: c includes the intercept term; t includes the trend term; k is the automatically selected lag order of the difference term. All numbers are rounded to three decimal places.

gradual increase followed by slight stabilisation, indicating that industrial sales scale experienced moderate growth over time. Textile industry concentration demonstrated relatively low values with minimal overall fluctuations, reflecting changes in the degree of market concentration within the textile industry. The small fluctuations indicated that the level of industry concentration remained relatively stable throughout the study period. Textile industry carbon dioxide emissions (logarithmic) displayed minor fluctuations in the early period, followed by a declining trend in the latter period. The later decline reflected the industry's achievements in emission reduction and related initiatives.

Model specification

The VAR model constructed each endogenous variable in the system as a function of lagged values of all endogenous variables in the system, thereby extending the univariate autoregressive model to a "vector" autoregressive model composed of multivariate time series variables [49]. For a k -dimensional time series $Y_t = (y_{1t}, y_{2t}, \dots, y_{kt})'$, the mathematical expression for a p -order VAR model denoted as $VAR(p)$ was:

$$Y_t = \Phi_1 Y_{t-1} + \Phi_2 Y_{t-2} + \dots + \Phi_p Y_{t-p} + \epsilon_t \quad (4)$$

where Y_t represented a $k \times 1$ dimensional endogenous variable vector, Φ_i ($i = 1, 2, \dots, p$) represented $k \times k$ dimensional coefficient matrices, ϵ_t represented a $k \times 1$ dimensional random error vector, also referred to as innovation, with ϵ_t typically assumed to follow a multivariate normal distribution with zero mean and covariance matrix Σ , namely $\epsilon_t \sim N(0, \Sigma)$.

EMPIRICAL TESTING

Unit root testing

During the modelling process of Vector Autoregression (VAR) models, unit root testing constituted a crucial step, with its core purpose being to determine the stationarity of variables, thereby avoiding issues such as "spurious regression" in the model. Following the Augmented Dickey-Fuller (ADF) unit root tests conducted on textile industry economic growth, industrial concentration, and carbon emissions, the results

were presented in table 1. All series achieved stationarity at the first difference, namely $I(1)$.

Stationarity test

The impulse response and variance decomposition require the VAR system to be stable. According to table 2 and figure 2, the reciprocals of the magnitudes of all AR roots are located within the unit circle, so the VAR system can be judged to be stable. No root lies outside the unit circle. VAR satisfies the stability condition.

Table 2

VAR SYSTEM STABILITY CONDITION TEST	
Root	Modulus
-0.750272	0.750272
0.442100 - 0.507967i	0.673411
0.442100 + 0.507967i	0.673411
0.036861 - 0.598203i	0.599338
0.036861 + 0.598203i	0.599338
-0.264461	0.264461

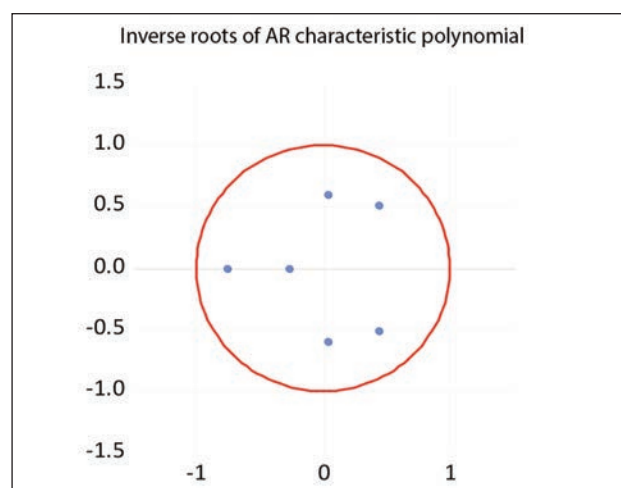


Fig. 2. AR root plot

Granger causality testing

Granger causality testing was employed to determine whether lagged terms of one variable contributed to

Table 3

VAR GRANGER CAUSALITY/BLOCK EXOGENEITY WALT TESTS			
Dependent variable: D_CO ₂			
Excluded	Chi-sq	df	Prob.
D_IC	1.946045	2	0.3779
D_ISV	1.450972	2	0.4841
All	3.866399	4	0.4244
Dependent variable: D_IC			
Excluded	Chi-sq	df	Prob.
D_CO ₂	11.42633	2	0.0033
D_ISV	0.391444	2	0.8222
All	11.73549	4	0.0194
Dependent variable: D_ISV			
Excluded	Chi-sq	df	Prob.
D_CO ₂	1.127565	2	0.5691
D_IC	0.900819	2	0.6374
All	1.638014	4	0.8019

predicting another variable. If lagged terms of variable X could significantly improve the prediction accuracy of variable Y, this was termed "X Granger-causes Y". The results presented in table 3 revealed the following findings:

(1) The lagged terms of both textile industry concentration (D_IC) and industrial sales value (D_ISV) failed to significantly explain variations in CO₂ emissions, indicating that the influence of economic activities (IC and ISV) on carbon emissions was not statistically significant.

(2) The lagged terms of textile industry CO₂ emissions could significantly explain variations in industrial concentration, potentially reflecting the constraining effects of environmental policies (such as carbon reduction initiatives) on industrial production agglomeration. Industrial sales value (D_ISV) demonstrated no significant impact on industrial concentration (D_IC), possibly suggesting a disconnection between industrial production and sales processes (such as inventory accumulation).

(3) Both textile industry carbon emissions (D_CO₂) and industrial concentration (D_IC) failed to significantly explain variations in industrial sales value, potentially indicating that the sales segment was more influenced by external market demand (such as exports and consumption) rather than internal production factors.

Determination of the VAR model lag length

The selection of an optimal lag length ensured that the stochastic disturbance terms of the VAR model

followed vector white noise properties. The calculation results were presented in table 4. All five criteria employed in this study indicated a first-order lag length; therefore, VAR(1) was selected for subsequent analysis.

Cointegration testing

Many economic variables exhibited persistent upward or downward movements, a characteristic that could be generated by stochastic trends in integrated variables. When the same stochastic trends jointly drove a group of integrated variables, this was termed cointegration [50, 51]. Under such circumstances, certain linear combinations of integrated variables remained stationary, and these linear combinations that linked variables with common trend paths were referred to as cointegrating relationships. Cointegrating relationships could be realised through reparameterising VAR models into Vector Error Correction Models (VECM). Cointegration analysis was primarily applied to economic systems where short-term dynamic relationships were easily subject to significant influence from stochastic disturbances, whilst long-term relationships were constrained by equilibrium relationships.

Establishment of the VAR system

Initially, a VAR system was established, with results presented in table 5.

Model validity testing

Firstly, residual autocorrelation was examined. Autocorrelation plots were employed for this examination, which were utilised to demonstrate autocorrelation relationships between different time series data. If the results did not exceed twice the asymptotic standard error of lags, this indicated that the residuals estimated by the VAR model exhibited no cross-correlation. The results reported in figure 3 demonstrated that no cross-correlation existed among the residuals of the variables. The residual series exhibited no significant autocorrelation at various lag orders, satisfying the white noise requirements for VAR model residuals, indicating that the model possessed satisfactory residual characteristics. Secondly, normality testing was conducted. The residuals were tested to determine whether they followed a normal distribution. As demonstrated in table 6, all test p-values were substantially greater than 0.05 (significance level), failing to reject the null hypothesis that "residuals follow a multivariate normal distribution". This indicated that the distributional characteristics of model residuals conformed to the fundamental assumptions of VAR models, ensuring that subsequent residual-based analyses (such as

Table 4

VAR LAG ORDER SELECTION CRITERIA CALCULATION RESULTS						
Lag	LogL	LR	FPE	AIC	SC	HQ
0	-261.4319	NA	2.46e+08	27.83493	27.98406	27.86017
1	-189.6200	113.3871*	337291.7*	21.22316*	21.81965*	21.32411*

Note: *, **, *** denoted significance levels of 10%, 5%, and 1%, respectively.

Table 5

VECTOR AUTOREGRESSION ESTIMATES			
Variable	D_CO ₂	D_IC	D_ISV
D_CO ₂ (-1)	0.222551	0.016860	48.91746
	(0.25211)	(0.00437)	(63.0546)
	[0.88277]	[3.86108]	[0.77580]
D_IC(-1)	5.725383	-0.032026	595.3975
	(10.2250)	(0.17710)	(2557.40)
	[0.55994]	[-0.18083]	[0.23281]
D_ISV(-1)	-0.001323	-2.60E-06	-0.069728
	(0.00107)	(1.9E-05)	(0.26748)
	[-1.23709]	[-0.14017]	[-0.26068]
C	1.978443	0.027990	2494.721
	(2.78291)	(0.04820)	(696.040)
	[0.71093]	[0.58068]	[3.58416]

Table 6

VAR RESIDUAL NORMALITY TESTS				
Component	Skewness	Chi-sq	df	Prob.*
1	-0.044098	0.005834	1	0.9391
2	-0.213355	0.136561	1	0.7117
3	-0.188277	0.106345	1	0.7443
Joint	-	0.24874	3	0.9694
Component	Kurtosis	Chi-sq	df	Prob.
1	4.009822	0.764806	1	0.3818
2	3.319216	0.076424	1	0.7822
3	3.348225	0.090945	1	0.763
Joint	-	0.932176	3	0.8177
Component	Jarque-Bera	df	Prob.	
1	0.77064	2	0.6802	
2	0.212985	2	0.899	
3	0.197291	2	0.9061	
Joint	1.180916	6	0.9778	

Note: * Approximate p-values do not account for the coefficient.

impulse response and variance decomposition) yielded highly reliable results. From the perspective of residual normality, the current VAR model specification was deemed reasonable.

Therefore, following the aforementioned analysis, there existed sufficient grounds to conclude that the

VAR model specification contained no bias and was stable.

Thirdly, the White heteroskedasticity test was conducted. The joint test results, as presented in table 7, demonstrated a p-value of 0.6448 > 0.05 (significance level), failing to reject the null hypothesis. This indicated that from an overall perspective, the VAR model residuals exhibited no significant heteroskedasticity, satisfying the assumption of "constant residual variance".

Table 7

JOINT TEST		
Chi-sq	df	Prob.
66.99416	72	0.6448

The individual components results, as presented in table 8, revealed the following findings: The residual squared terms (res1res1, res2res2, res3res3) exhibited Chi-sq(12) corresponding p-values of 0.1560, 0.7317, and 0.8718, respectively, all substantially greater than 0.05, indicating that individual variable residual squared terms demonstrated no significant heteroskedasticity (namely, each variable's residual variance remained constant). The residual cross-terms (res2res1, res3res1, res3res2) exhibited Chi-sq(12) corresponding p-values of 0.2447, 0.4337, and 0.6797, respectively, all greater than 0.05, indicating that covariances between residuals also demonstrated no significant heteroskedasticity (namely, inter-variable residual correlation fluctuations remained constant). Other auxiliary indicators (R-squared and F-statistics) demonstrated that individual terms' R-squared values were generally low (except for res1*res1), whilst F-statistic p-values were all greater than 0.05, further supporting the conclusion of "no significant heteroskedasticity".

The joint test p-value (0.6448) and all individual component test p-values exceeded 0.05, failing to reject the null hypothesis of "no significant heteroskedasticity in residuals". This indicated that the VAR model residuals exhibited no heteroskedasticity, satisfying the fundamental assumption of "constant variance" for model residuals. From the perspective of heteroskedasticity, the current model's estimation results were reliable, with subsequent analyses (such

Table 8

INDIVIDUAL COMPONENTS					
Dependent	R-squared	F(12,4)	Prob.	Chi-sq(12)	Prob.
res1*res1	0.990185	33.62979	0.002	16.83315	0.156
res2*res2	0.509361	0.346052	0.9311	8.659129	0.7317
res3*res3	0.398821	0.221133	0.9815	6.77996	0.8718
res2*res1	0.878855	2.418189	0.2043	14.94053	0.2447
res3*res1	0.714696	0.835012	0.6386	12.14984	0.4337
res3*res2	0.545278	0.399715	0.902	9.269722	0.6797

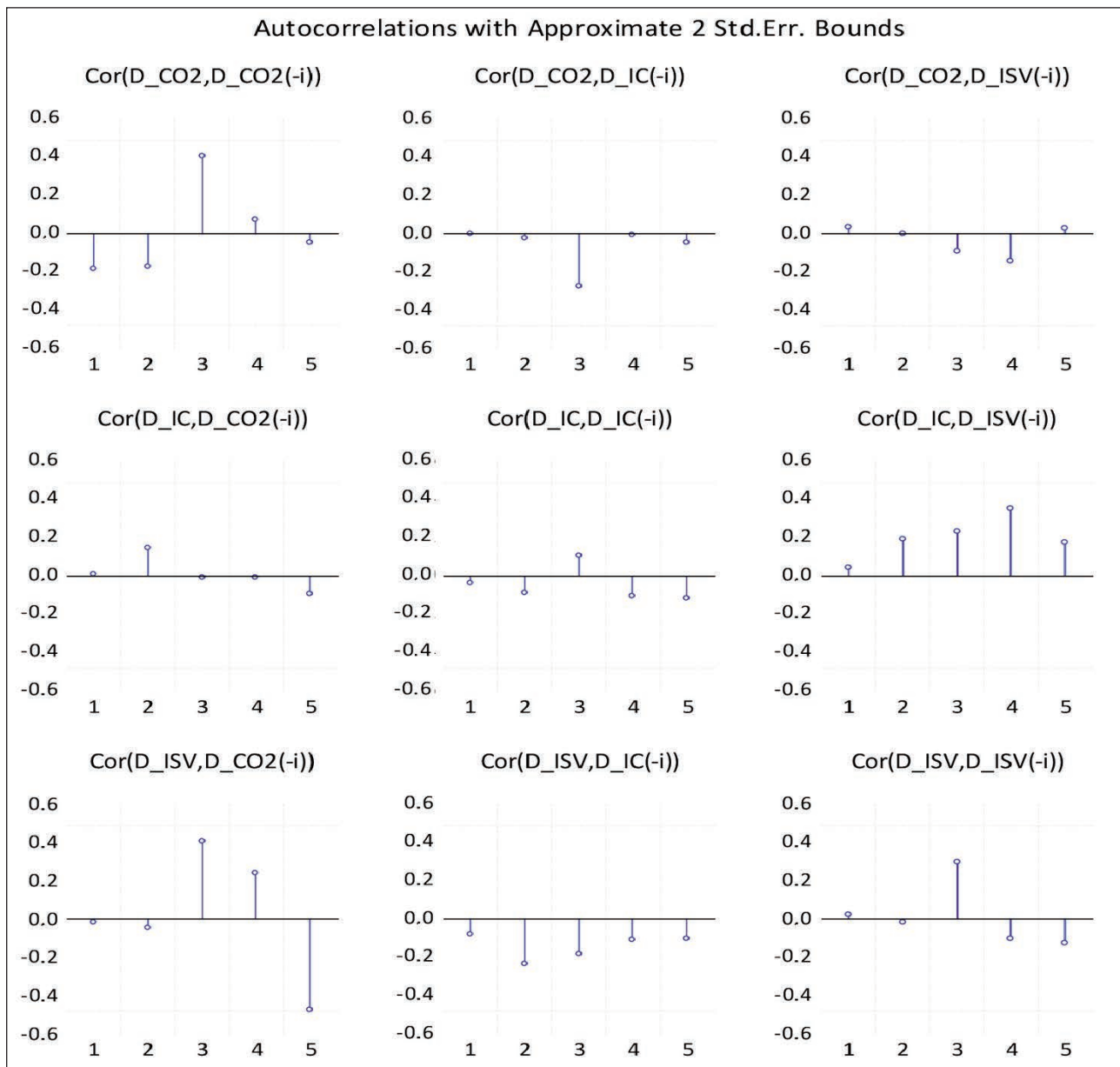


Fig. 3. Autocorrelation plot

as impulse response and variance decomposition) experiencing minimal interference from residual fluctuations [52, 53].

Cointegration analysis

Following the establishment of the VAR system, cointegration testing was subsequently conducted, with test results presented in tables 9 and 10. The results from table 8 demonstrated that at the 0.05 significance level, cointegrating relationships existed between

the textile industry carbon emission change rate (D_CO_2), economic growth change rate (D_ISV), and industrial concentration change rate (D_IC), specifically revealing the existence of one cointegrating relationship. Table 9 presents the standardised cointegrating vectors under the existence of cointegrating relationships. The cointegrating vector could be expressed as:

$$D_CO_2 = -23.61231D_IC + 0.001343D_ISV \quad (5)$$

Table 9

NON-RESTRICTED COINTEGRATION RANK TEST (TRACE)				
Hypothesised No. of CE(s)	Eigenvalues	Trace statistics	0.05 threshold	Prob.**
None *	0.757291	32.06473	29.79707	0.027
At most 1	0.291256	9.410421	15.49471	0.3288
At most 2 *	0.216427	3.902249	3.841465	0.0482

Note: Trace test indicates 1 cointegrating equation(s) at the 0.05 level.

Table 10

NORMALIZED COINTEGRATION COEFFICIENT (STANDARD ERROR IN PARENTHESES)		
D_CO ₂	D_IC	D_ISV
1	23.61231	-0.001343
-	(20.2206)	(0.00133)

From the cointegrating equation, it could be observed that each unit increase in the economic growth change rate resulted in a 0.001343 unit increase in the carbon emission change rate; conversely, each unit increase in the industrial concentration change rate resulted in a 23.61231 unit decrease in the carbon emission change rate.

VAR IMPULSE RESPONSE AND VARIANCE DECOMPOSITION

Impulse response

The impulse response function, based on the VAR model, characterised time-varying causal associations and shock attenuation characteristics between variables through simulating dynamic transmission of structured shocks (orthogonalised innovations identified through Cholesky decomposition). This study focused on a three-variable system (textile industry carbon emission change rate D_CO₂, industrial concentration change rate D_IC, and economic growth change rate D_ISV), employing first-difference series (implying the premise that original series were non-stationary but became stationary after differencing),

to analyse immediate response, persistence, and convergence of shocks, thereby revealing dynamic interactive patterns between variables, as illustrated in figures 4 (1–9).

Figure 4-1 demonstrated that D_CO₂'s response to its own shock exhibited strong short-term inertial dependence following the shock (violent fluctuations in periods 1–3), reflecting the series's own dynamic memory characteristics. After period 4, rapid convergence to zero occurred, conforming to the mean-reverting characteristics of a stationary series and validating the stationarity assumption of the differenced series.

Figure 4-2 illustrates D_CO₂'s response to D_IC shocks. Structured shocks from D_IC triggered short-term negative deviations in D_CO₂ (significantly negative in periods 1–3), followed by asymptotic convergence, indicating that D_IC exerted short-term inhibitory effects on D_CO₂, but demonstrated no long-term cointegrating relationship (long-term response returned to equilibrium).

Figure 4-3 presents D_CO₂'s response to D_ISV shocks. Under D_ISV shocks, D_CO₂ exhibited only weak fluctuations in periods 1–2, rapidly converging to a steady state, indicating that D_ISV's dynamic influence on D_CO₂ was brief and marginal, with low short-term correlation between the two variables.

Figure 4-4 displayed D_IC's response to D_CO₂ shocks. D_CO₂ shocks triggered immediate positive impulses in D_IC (significantly positive in periods 1–2), followed by attenuated oscillations (small fluctuations in periods 3–6), ultimately converging. This

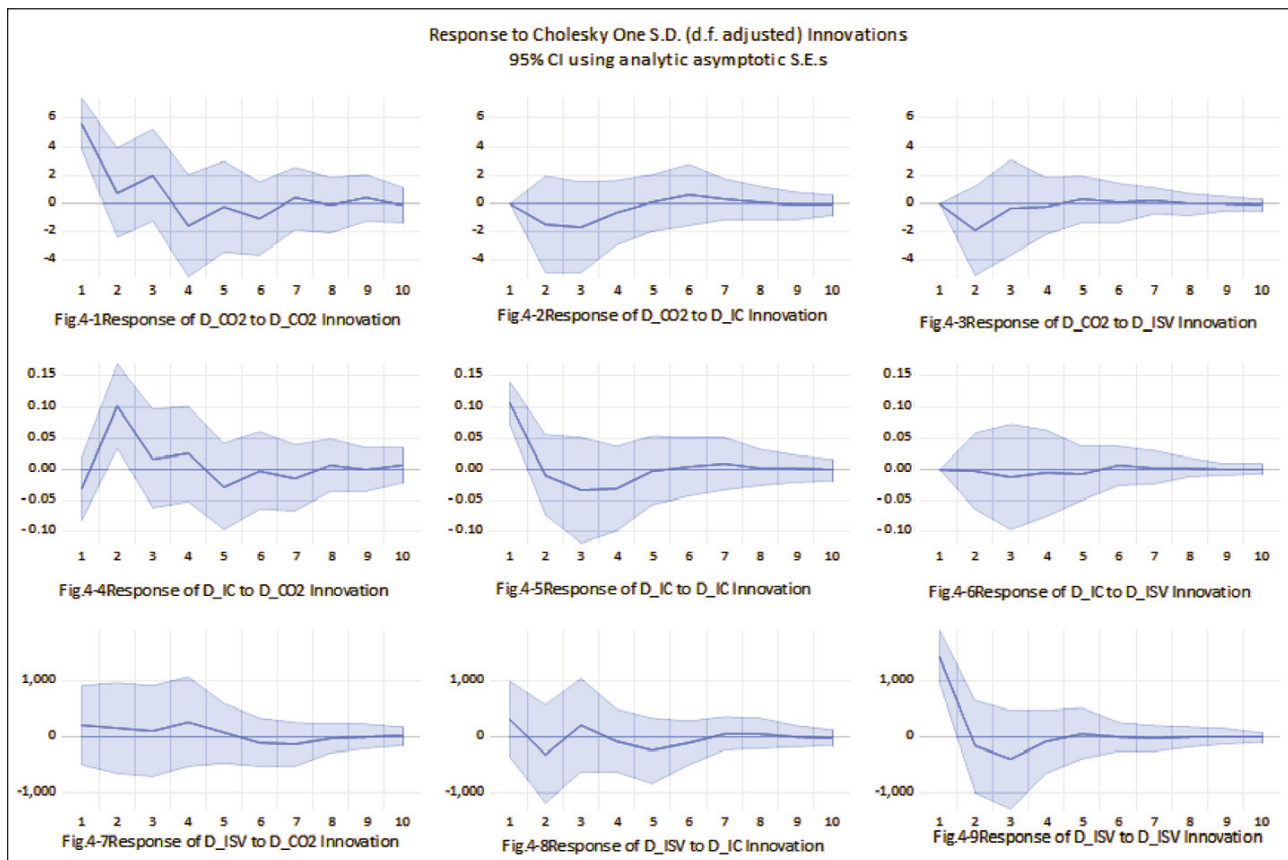


Fig. 4. Impulse response function distribution

reflected that D_{CO_2} exerted short-term positive transmission effects on D_{IC} , but demonstrated no sustained cumulative impact.

Figure 4-5 showed D_{IC} 's response to its own shocks. Under self-shocks, D_{IC} exhibited weak inertial characteristics (small fluctuations in periods 1–3), rapidly converging to zero, indicating that the D_{IC} series possessed low dynamic autocorrelation and brief memory effects from self-shocks.

Figure 4-6 represented D_{IC} 's response to D_{ISV} shocks. The impact of D_{ISV} shocks on D_{IC} was completely covered by confidence intervals (fluctuation amplitude approached zero), indicating extremely weak dynamic correlation between the two variables, with D_{ISV} shocks unable to effectively explain D_{IC} fluctuations.

Figure 4-7 depicts D_{ISV} 's response to D_{CO_2} shocks. D_{CO_2} shocks induced sustained medium-term fluctuations in D_{ISV} (significant deviations from steady state in periods 1–4), with convergence speed slower than other variables' responses to D_{CO_2} , indicating that D_{CO_2} exerted strong intertemporal transmission effects on D_{ISV} , with more persistent dynamic correlation between the two variables.

Figure 4-8 illustrates D_{ISV} 's response to D_{IC} shocks. D_{IC} shocks resulted in short-term negative adjustments in D_{ISV} (significantly negative in periods 1–2), followed by rapid convergence, reflecting that D_{IC} exerted instantaneous negative shocks on D_{ISV} , but demonstrated no long-term effects.

Figure 4-9 presents D_{ISV} 's response to its own shocks. Under self-shocks, D_{ISV} exhibited high volatility characteristics (large amplitude in periods 1–3), but still satisfied asymptotic convergence (returning to steady state after period 6), validating the stationarity of the differenced series whilst reflecting strong short-term dynamic volatility in D_{ISV} itself.

Variance decomposition

This study employed the Monte Carlo method to calculate standard errors, with results presented in tables 11, 12 and 13. The "Period" in the tables referred to the number of shock response periods, typically employed to measure the time span of dynamic influences between variables. The specific meaning requires a definition in conjunction with the data frequency employed in the research (such as annual, quarterly, or monthly). If the study utilised annual data, "Period 1" represented the first year following the shock occurrence, "Period 2" represented the second year, and so forth, with "Period 10" indicating the tenth year. If quarterly data were employed, "Period" represented quarters (such as Period 1 for the first quarter, Period 4 for the first year, and Period 10 for the second quarter of the second year).

Table 11 revealed that the variance decomposition of D_{CO_2} demonstrated self-shock dominance in long-term explanatory power. The variance decomposition results indicated that the forecast error variance of

D_{CO_2} across different periods was primarily explained by its own shocks, whilst the influences of other variables (D_{IC} and D_{ISV}) remained weak and gradually stabilised.

Short-term (Period 1): The forecast error variance of D_{CO_2} was 100% explained by its own shocks, with explanation proportions of D_{IC} and D_{ISV} equalling zero. This conformed to the short-term characteristics of variance decomposition—current period shocks originated solely from the variable itself.

Medium-term (Periods 2–5): As periods increased, D_{CO_2} 's own explanation proportion declined slowly from 84.71% in Period 2 to 80.73% in Period 5. D_{IC} 's explanation proportion increased from 5.63% to 11.20%, whilst D_{ISV} 's explanation proportion fluctuated modestly between 9.65% and 8.07%. This indicated that shocks from other variables began influencing D_{CO_2} , though their impact remained limited.

Long-term (Periods 6–10): The explanation proportions of all variables converged to stability: D_{CO_2} itself maintained 80.40% – 80.89%, D_{IC} stabilised around 11.20%, and D_{ISV} stabilised between 7.89% – 8.07%. The Monte Carlo simulation standard errors (lower values) demonstrated that the uncertainty of each estimate was relatively small (such as the Period 10 standard error for D_{CO_2} being 18.52% and D_{IC} being 16.44%), indicating robust results.

Overall, the dynamic changes in D_{CO_2} were primarily driven by its own shocks, whilst external shocks from D_{IC} and D_{ISV} demonstrated weak explanatory power for its forecast error, with long-term influences stabilising.

Table 12 revealed that the variance decomposition of D_{IC} demonstrated joint dominance by D_{CO_2} and its own shocks. The forecast error variance explanation of D_{IC} exhibited characteristics of "short-term self-dominance with significant medium-term D_{CO_2} shock intervention", whilst D_{ISV} 's influence remained consistently weak.

Short-term (Period 1): The forecast error variance of D_{IC} was 91.70% explained by its own shocks, with D_{CO_2} explaining 8.30% and D_{ISV} 's explanation proportion equalling zero, indicating that short-term fluctuations primarily originated from itself.

Medium-term (Periods 2–5): In Period 2, D_{CO_2} 's explanation proportion increased substantially to 49.75%, approaching D_{IC} 's own 50.18%.

Subsequently, D_{CO_2} 's explanation proportion stabilised between 47.06% – 48.59%, whilst D_{IC} 's own explanation proportion maintained 50.16% – 52.10%. D_{ISV} 's explanation proportion remained consistently below 1% (with the highest being 0.97% in Period 5). These results indicated that D_{CO_2} shocks exerted a significant influence on D_{IC} 's forecast error, with explanatory power comparable to D_{IC} 's own shocks.

Long-term (Periods 6–10): D_{CO_2} 's explanation proportion stabilised between 48.50% – 48.85%, D_{IC}

Table 11

D_CO ₂ VARIANCE DECOMPOSITION RESULTS				
Variance decomposition of D_CO ₂	S.E.	Impulse variable		
Period		D_CO ₂	D_IC	D_ISV
1	5.577149	100	0	0
		0	0	0
2	6.116735	84.71435	5.631571	9.654076
		(16.327)	(12.3785)	(12.7677)
3	6.660988	80.70884	10.97088	8.320283
		(18.8439)	(16.2497)	(12.9827)
4	6.866545	80.88623	11.21932	7.894451
		(19.9771)	(16.1148)	(12.5962)
5	6.876662	80.73444	11.1959	8.069658
		(20.3706)	(16.8598)	(12.4715)
6	6.985099	80.53912	11.63166	7.829221
		(20.3058)	(16.7992)	(12.2893)
7	7.005537	80.3954	11.73785	7.866752
		(20.7464)	(16.7673)	(12.7803)
8	7.006793	80.38305	11.74974	7.867208
		(21.518)	(17.4184)	(13.1568)
9	7.020052	80.42036	11.74195	7.837688
		(21.9271)	(17.528)	(13.7234)
10	7.021825	80.40224	11.74819	7.84957
		(22.6527)	(17.8485)	(13.9751)

Note: The "Period" column in the table refers to the number of periods of the shock response, based on annual data, with the corresponding time unit being years. It is used to measure the long-term impact path of shocks to various variables on fluctuations in carbon emissions (D_CO₂).

Table 12

D_IC VARIANCE DECOMPOSITION RESULTS				
Variance decomposition of D_IC	S.E.	Impulse variable		
Period		D_CO ₂	D_IC	D_ISV
1	0.110016	8.299040	91.70096	0.000000
		(14.3184)	(14.3184)	(0.00000)
2	0.149330	49.74821	50.18222	0.069576
		(20.1088)	(18.7221)	(6.68990)
3	0.154342	47.78397	51.49080	0.725224
		(18.3199)	(17.7881)	(10.8330)
4	0.159529	47.06336	52.10206	0.834575
		(19.0140)	(18.2415)	(12.4622)
5	0.162188	48.58652	50.43963	0.973847
		(20.0021)	(18.5880)	(11.9865)
6	0.162355	48.50112	50.41877	1.080115
		(20.7425)	(18.9032)	(12.3260)
7	0.163149	48.73675	50.16575	1.097506
		(20.8170)	(18.8475)	(12.2659)
8	0.163329	48.78757	50.08776	1.124661
		(21.4879)	(19.5020)	(12.5976)
9	0.163350	48.78574	50.08221	1.132046
		(22.1658)	(20.1215)	(12.8542)
10	0.163473	48.85127	50.01820	1.130523
		(22.1684)	(19.8518)	(13.4974)

Note: The "Period" column in the table refers to the number of periods of the shock response, based on annual data, with the corresponding time unit being years. It is used to measure the long-term impact path of shocks to various variables on fluctuations in carbon emissions (D_IC).

D_ISV VARIANCE DECOMPOSITION RESULTS				
Variance decomposition of D_ISV	S.E.	Impulse variable		
Period		D_CO ₂	D_IC	D_ISV
1	1493.128	2.136105	4.901384	92.96251
		(9.33651)	(10.5468)	(13.4570)
2	1540.186	3.248214	8.338625	88.41316
		(12.0231)	(13.8982)	(17.1046)
3	1610.899	3.531391	9.545294	86.92332
		(14.8295)	(14.1346)	(17.6680)
4	1638.745	6.437920	9.352284	84.20980
		(14.3905)	(13.7021)	(17.5514)
5	1658.238	6.510335	11.08701	82.40265
		(15.2935)	(13.6011)	(17.6320)
6	1663.681	6.786963	11.34843	81.86461
		(16.6154)	(14.9340)	(18.3993)
7	1669.947	7.284392	11.45047	81.26514
		(17.0572)	(15.6468)	(18.8581)
8	1671.848	7.285457	11.62085	81.09369
		(17.5922)	(15.4319)	(18.9874)
9	1672.150	7.293589	11.62562	81.08079
		(17.9480)	(15.8213)	(19.1523)
10	1672.394	7.315762	11.62709	81.05715
		(19.4131)	(16.3587)	(19.7653)

Note: The "Period" column in the table refers to the number of periods of the shock response, based on annual data, with the corresponding time unit being years. It is used to measure the long-term impact path of shocks to various variables on fluctuations in carbon emissions (D_ISV).

itself remained stable at 50.02% – 50.42%, whilst D_ISV remained below 1.13%. Monte Carlo standard errors demonstrated that the uncertainty of estimates was relatively small (such as the Period 10 standard error for D_CO₂ being 18.31%), further supporting the dominant role of both D_CO₂ and D_IC's own shocks in D_IC fluctuations.

Table 13 revealed that the variance decomposition of D_ISV demonstrated self-shock centrality with gradually emerging D_IC influence. The forecast error variance of D_ISV was primarily explained by its own shocks, whilst D_IC's influence strengthened gradually over time and stabilised, with D_CO₂'s influence remaining relatively weak.

Short-term (Period 1): D_ISV itself explained 92.96% of the forecast error variance, with D_IC explaining 4.90% and D_CO₂ explaining 2.14%, indicating that short-term fluctuations were dominated by self-shocks.

Medium-term (Periods 2–5): D_ISV's own explanation proportion declined from 88.41% in Period 2 to 82.40% in Period 5. D_IC's explanation proportion increased from 8.34% to 11.09%, whilst D_CO₂'s explanation proportion rose from 3.25% to 6.51%. This indicated that the impacts of D_IC and D_CO₂ shocks on D_ISV gradually emerged, with D_IC's influence being more significant.

Long-term (Periods 6–10): The explanation proportions of all variables converged to stability: D_ISV itself maintained 81.27% – 81.86%, D_IC stabilised

between 11.35% – 11.63%, and D_CO₂ stabilised between 6.79% – 7.32%. Monte Carlo standard errors demonstrated that the uncertainty of estimation results was relatively low (such as the Period 10 standard error for D_IC being 16.33%), validating the robustness of long-term dynamic relationships.

CONCLUSIONS, IMPLICATIONS AND OUTLOOK

Research conclusions

This study examined the relationships between economic growth, industrial concentration, and carbon emissions in the textile industry through Granger causality testing, VAR model lag determination, cointegration testing, VAR impulse response, and variance decomposition methods, yielding the following conclusions:

(1) VAR Granger Causality Test Results: At the 5% significance level, only the textile industry carbon emission change rate (D_CO₂) constituted a Granger cause of the industrial concentration change rate (D_IC) (Chi-sq = 11.426, P = 0.0033), whilst no significant Granger causal relationships existed among other variables. Specifically, D_IC and the economic growth change rate (D_ISV) did not constitute Granger causes of D_CO₂ (P-values of 0.3779 and 0.4841, respectively); D_ISV did not constitute a Granger cause of D_IC (P = 0.8222); and D_CO₂ and D_IC did not constitute Granger causes of D_ISV (P-values of 0.5691 and 0.6374, respectively).

Overall, Granger causal relationships between variables were weak, with only D_{CO_2} exerting a significant influence on D_{IC} .

(2) Unrestricted Cointegration Rank Test (Trace): At the 5% significance level, one cointegrating equation existed. Normalised cointegrating coefficients indicated that the long-term equilibrium relationship was: $D_{CO_2} + 23.61231D_{IC} - 0.001343D_{ISV} = 0$ (with standard errors of 20.2206 for D_{IC} and 0.00133 for D_{ISV}), demonstrating stable long-term associations among the three variables, with D_{IC} exhibiting relatively significant influence.

(3) Impulse Response Analysis: Variable shocks demonstrated differential impacts on various series. D_{CO_2} 's own shocks exhibited evident responses in early periods, whilst D_{IC} shocks had transient effects on it; D_{IC} demonstrated positive impulses to D_{CO_2} shocks, with weak self-shock influences; D_{ISV} exhibited sustained responses to D_{CO_2} shocks, with substantial self-shock volatility. Overall, dynamic interactions existed between variables, with D_{CO_2} playing a relatively prominent role in transmission mechanisms, providing foundations for understanding variable relationships and subsequent analysis.

(4) Variance Decomposition Analysis: D_{CO_2} shocks possessed significant explanatory power for D_{IC} (approximately 48.85% in the long term), whilst D_{IC} 's influence on D_{CO_2} remained weak (approximately 11.75% in the long term); D_{IC} 's influence on D_{ISV} (approximately 11.63% in the long term) exceeded D_{CO_2} 's influence on D_{ISV} (approximately 7.32% in the long term). Among the three variables, the forecast error variance of D_{CO_2} and D_{ISV} was primarily explained by their own shocks in the long term (approximately 80.40% and 81.06%, respectively), whilst D_{IC} was jointly dominated by its own shocks and D_{CO_2} shocks (approximately 50% each). The explanation proportions of all variables stabilised after Period 5, indicating that the system achieved long-term equilibrium, with dynamic influence relationships between variables converging to stable states.

Research implications

(1) Focus on Core Causality and Strengthen the Guiding Role of Carbon Emissions on Industrial Concentration. Given that only D_{CO_2} constituted a significant Granger cause of D_{IC} , the formulation of synergistic "carbon emission constraints – industrial concentration optimisation" policies was recommended. For high-carbon emission enterprises in the textile industry, measures such as dynamic carbon quota adjustments and green technology subsidies could compel enterprise mergers, reorganisations, or technological collaboration, promoting industrial concentration aligned with low-carbon development requirements. The establishment of dynamic monitoring mechanisms for carbon emissions and industrial

concentration was suggested to evaluate the transmission effects of D_{CO_2} shocks on D_{IC} in real-time and optimise policy tool combinations accordingly.

(2) Anchor Long-term Equilibrium and Construct Multi-variable Synergistic Regulatory Framework. Based on the cointegration test's revelation of "long-term stable associations among D_{CO_2} , D_{IC} , and D_{ISV} ," the construction of cross-variable synergistic regulatory systems was required. Using cointegrating equations as constraints, long-term adaptation targets for textile industry carbon emissions, industrial concentration, and economic growth (or scale variables) needed to be established. For variables deviating from equilibrium, differentiated policy interventions (such as implementing industry subsidies or production restrictions for D_{IC} deviations) could guide the system back to long-term stable states.

(3) Optimise Dynamic Interactions and Design Precise Short-term Shock Response Strategies. Combining the "differential characteristics of variable shocks" revealed by impulse response analysis, differentiated short-term regulatory measures should have been implemented. Targeting D_{CO_2} 's "strong early-period response" to its own shocks, carbon market emergency adjustment mechanisms (such as short-term carbon price fluctuations and reserve quota releases) needed to be established to smooth short-term violent carbon emission fluctuations. Utilising the "positive impulse effect" of D_{CO_2} on D_{IC} , industry integration policies (such as specialised merger and acquisition funds) could have been launched synchronously during carbon emission shock periods, accelerating industrial concentration optimisation through low-carbon constraints. Attention to D_{ISV} 's "high volatility characteristics" in self-shocks required counter-cyclical regulation of textile industry scale variables (such as output value and capacity) through measures like short-term credit support and capacity warnings to weaken system disturbances.

(4) Stabilise System Equilibrium and Establish Long-term Dynamic Monitoring and Adjustment Mechanisms. Based on the variance decomposition conclusion that "variable explanation proportions stabilised after Period 5", long-term equilibrium maintenance mechanisms needed to be constructed. Systematic assessments should have been conducted at 5-period intervals to monitor changes in variance explanation proportions of D_{CO_2} , D_{IC} , and D_{ISV} , with timely policy intensity adjustments (such as strengthening green technology R&D investment when D_{CO_2} 's self-explanation proportion remained persistently high, reducing carbon emission inertial dependence). Dynamic updating mechanisms for policy toolboxes needed to be established, flexibly switching between carbon taxes, industry subsidies, and scale controls based on variable equilibrium states to ensure long-term stable system convergence.

Through the aforementioned policy designs, the variable relationship characteristics revealed by research

could have been effectively connected, forming closed loops from short-term shock responses to long-term equilibrium maintenance, facilitating the textile industry's achievement of synergistic goals of "low-carbon development – industrial optimisation – economic stability."

Research outlook

This study, through systematic analysis, clarified the existence of dynamic associations between carbon emissions, industrial concentration, and economic growth in the textile industry, providing a foundational framework for understanding the intrinsic logic of industry development and low-carbon transformation. However, as the textile industry constituted a complex industry characterised by extensive industrial chains, significant regional differences, and strong policy sensitivity, numerous deeper patterns in the interactive mechanisms between variables remained to be explored. Future research could have been further deepened from three aspects to enhance the practical guidance value of the conclusions.

Firstly, focusing on industry subdivisions to thoroughly analyse heterogeneous characteristics of variable relationships. Current research predominantly employed the textile industry as a whole as the analytical unit, but spinning, weaving, dyeing, and garment processing subsectors demonstrated significant differences in energy consumption, carbon emission intensity, market concentration, and economic contribution. For example, the dyeing sector, as a high-energy consumption and high-emission core sector, might have exhibited entirely different relationships between carbon emissions and industrial concentration compared to the low-emission garment processing sector – the former might have achieved scale-based emission reduction effects through increased concentration, whilst the latter might have experienced dispersed emissions that were difficult to control due to small and medium enterprise clustering. Through disaggregating subsectors, unique association patterns among carbon emissions, concentration, and economic growth within each sector could have been precisely identified. For instance, the technology-intensive attributes of the spinning sector might have resulted in strong positive correlations between concentration increases and economic growth, with carbon emissions being more influenced by technological upgrades; the dyeing sector's strong policy constraints might have made the balance between carbon emissions and economic growth more dependent on pollution treatment facility sharing following concentration increases. Such subdivision research could have provided precise foundations for differentiated policy formulation, avoiding "one-size-fits-all" regulatory approaches and making policy interventions more aligned with the actual development needs of each sector.

Secondly, introducing cutting-edge analytical methods to explore non-linear and dynamic time-varying characteristics between variables. Existing research

predominantly constructed models based on linear assumptions, whilst during the textile industry's development process, relationships among carbon emissions, concentration, and economic growth might have exhibited non-linear characteristics following technological breakthroughs, policy shocks, and market structure changes. For example, when industrial concentration crossed certain thresholds, scale effects might have caused carbon emission intensity to demonstrate cliff-like declines rather than linear growth; economic growth's pulling elasticity on carbon emissions during different stages (such as high-speed expansion periods versus high-quality development periods) might also have exhibited structural breaks. Introducing machine learning methods (such as LASSO regression) could have precisely screened key moderating factors affecting relationships from high-dimensional variables (such as environmental technology investment and carbon trading policies), identifying turning points in non-linear relationships. Dynamic Bayesian VAR models could have captured evolutionary trajectories of inter-variable relationships over time, revealing changes in association strength during different periods (such as environmental policy tightening periods and industrial transfer peak periods), thereby improving model fitting precision to real-world scenarios. These methodological innovations could have not only enriched theoretical analytical frameworks but also provided more scientific tool support for predicting industry development trends and formulating dynamic adjustment policies.

Thirdly, expanding cross-regional research perspectives to analyse spatial transmission mechanisms and policy synergistic effects under industrial transfer backgrounds. Industrial transfer in the textile industry (such as migration from eastern to central and western regions) might have led to spatial redistribution of carbon emissions, whilst inter-regional economic associations (such as industrial chain supporting and trade exchanges) could have created spatial spillover effects in the influences of concentration and economic growth. For example, increased industrial concentration in eastern regions might have driven emission reductions in central and western regions through technological spillovers, whilst low environmental costs in central and western regions might have attracted high-emission capacity transfers, forming "pollution haven" effects.

Constructing spatial VAR models could have quantified such spatial transmission intensity, identifying interactive pathways of carbon emissions and concentration between regions. Combined with Dynamic Stochastic General Equilibrium (DSGE) models, the implementation effects of multiple policy combinations, such as carbon taxes, industry subsidies, and regional collaborative emission reductions, could have been simulated, evaluating costs and benefits of different policy tools in cross-regional coordination. Such cross-regional research could have not only filled current gaps in regional heterogeneity analysis but also provided theoretical support for formulating

collaborative policies that balanced regional equity with overall benefits, facilitating deep coordination between low-carbon development and high-quality growth in the textile industry nationwide.

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