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Research on the Carbon Reduction Effects of Industrial Structure Upgrading in the Context of a Unified National Market

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Abstract

Facilitating industrial restructuring and modernization plays a pivotal role in realizing China's dual-carbon objectives (carbon peaking and carbon neutrality) and advancing sustainable socioeconomic progress. Leveraging panel data from 30 provincial-level administrative units (2005–2022) and adopting the Spatial Durbin Model, this research investigates how industrial structure upgrading influences carbon emission intensity within the framework of a unified national market, while elucidating its operational mechanisms. The key findings include the following: (1) Provincial carbon emission intensity demonstrates pronounced "high-high" and "low-low" spatial agglomeration during the study period. Industrial restructuring exhibits marked carbon abatement effects, accompanied by discernible cross-regional spillover benefits. (2) Industrial structure upgrading can reduce carbon emission levels by promoting the technology diffusion effect, while the competitive demonstration effect of digitalization has not yet manifested. (3) The establishment of an integrated national market enhances the capacity of industrial upgrading to suppress carbon emission intensity. (4) The emission-reducing impacts of industrial restructuring manifest heterogeneous patterns across regions and temporal phases: In Eastern China, industrial upgrading paradoxically elevates emission intensity. Central-western regions experience significant emission reductions. Temporally, the relationship follows an inverted U-shaped trajectory. These insights underscore the necessity for policymakers to refine industrial modernization strategies, expedite nationwide market integration mechanisms, and cultivate region-specific green transition roadmaps.

Keywords: unified national market; market integration; industrial structure upgrading; carbon emission reduction

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1. Introduction

The development of a unified national market stands as a cornerstone strategy for propelling China toward a high-caliber economic paradigm. As outlined in the Guidelines on Accelerating the Formation of a Unified National Market, this initiative mandates the creation of cohesive institutional frameworks to eliminate regional protectionist practices, dismantle market segmentation barriers, and ensure the unimpeded circulation of commodities and production factors across jurisdictions. Concurrently, it aims to catalyze industrial modernization, bolster technological innovation, and nurture emerging sectors. Within this transformative agenda, industrial structure upgrading serves as a pivotal mechanism for economic revitalization, not only elevating the global competitiveness of domestic industries but also streamlining resource allocation efficiency, curbing carbon emissions, and anchoring sustainable development trajectories. Nevertheless, the

relentless pace of global economic growth has intensified resource scarcity, ecosystem destabilization, and carbon emission surges, underscoring the imperative for coordinated international mitigation efforts [1]. In response to mounting climate crises, decarbonization has emerged as a universal priority. In December 2019, the European Commission unveiled the "European Green Deal", a comprehensive strategy addressing climate change and promoting sustainable development. This initiative aims to achieve carbon neutrality in Europe by 2050 through enhanced resource efficiency, adoption of clean energy, climate change mitigation, pollution reduction, and other measures to ensure sustainable economic growth [2,3]. Subsequently, the 28th United Nations Climate Change Conference (COP28) was successfully convened, focusing on advancing ambitious climate objectives. Key priorities included limiting global temperature rise to 1.5 °C above pre-industrial levels, scaling up climate financing for developing nations, and urgently expanding investments in climate adaptation measures [4]. As the foremost developing nation, China has embraced a development model synergizing equilibrium, innovation, and ecological accountability. By formally adopting the "dual-carbon" objectives (carbon peaking by 2030 and carbon neutrality by 2060), China underscores its commitment to aligning industrial evolution with climate imperatives. Within this context, advancing industrial structure upgrading becomes indispensable for harmonizing emission abatement, dual-carbon target attainment, and sustained socioeconomic progress.

Against this backdrop, scholarly investigations into the relationship between industrial structure upgrading and carbon emissions have proliferated, centering on two principal dimensions. First, methodologies have been devised for carbon emission quantification [5,6]: For example, Tian and Yin [7] quantified China's agricultural carbon emissions (2005–2019) by integrating energy consumption and agricultural input factors, identifying fluctuating declines in both total emissions and emission intensity. Cheng et al. [8] utilized the STIRPAT model to assess provincial-level carbon emission performance, revealing a gradual improvement trend with spatially diminishing efficiency from eastern to western regions. Xu et al. [9] examined the spatiotemporal dynamics of urban carbon emissions (2001–2021) through Mann–Kendall trend analysis and Hurst exponent calculations, documenting persistent emission growth in most cities, with over 40% experiencing doubled total emissions.

Second, analyses of industrial structure upgrading's emission impacts have been carried out [10]: The transition toward high-value-added industries, coupled with the phasing out of polluting and energy-intensive sectors, drives technological innovation and operational efficiency gains, thereby suppressing carbon outputs [11]. Beyond direct emission curtailment, industrial structure upgrading indirectly moderates emission intensity via economic spillovers and technology diffusion mechanisms [12]. Yang and Deng [13] demonstrated that industrial structure rationalization consistently reduces emissions, whereas industrial structure advancement follows an inverted V-shaped trajectory, initially elevating emissions before inducing reductions. Through input–output modeling, Yang et al. [14] evaluated emission reduction potentials from industrial restructuring and clean energy adoption, finding that sectoral adjustments—particularly constraints on economically marginal high-carbon industries—achieved a 7.47% emission reduction. A study by OYE Queen Esther (2025) demonstrates that green industrialization can stimulate economic output while reducing carbon emissions, offering Africa a viable pathway to reconcile economic prosperity with environmental preservation [15]. Nevertheless, skepticism persists regarding the efficacy of industrial structure upgrading, with some scholars arguing that such structural transformations exert negligible impacts on carbon emissions or might paradoxically elevate emission levels. Employing the LMDI method and Tapio decoupling model, Du et al. (2022) analyzed the decoupling relationship between CO_2 emissions and economic growth in China, concluding that industrial restructuring did

not induce a significant increase in CO_2 emissions [16]. Earlier decomposition analysis by Stephen D. Casler and Adam Rose (1998) identified intra-sectoral efficiency improvements and energy substitution effects within the U.S. energy sector as primary drivers of CO_2 emission reductions [17]. Conversely, Yuan and Zhou (2021) observed that advanced industrial restructuring—specifically, the transition from lower-tier to higher-tier industries—could temporarily exacerbate carbon emissions [18]. While the impact of industrial structure upgrading on carbon emissions varies significantly contingent on factors such as developmental stages and regional disparities, the majority of studies concur that it ultimately exerts a net decarbonizing effect from a long-term perspective.

While existing scholarship extensively examines the carbon abatement effects of industrial structure upgrading, most studies confine their analyses to conventional analytical frameworks, overlooking the transformative role of unified national market development—a pivotal national strategy—in reshaping this relationship. Critical gaps persist in holistically integrating market integration, industrial restructuring, and emission dynamics into a unified paradigm. Furthermore, scant attention has been paid to phase-specific variations in upgrading impacts or the spatial diffusion mechanisms of emission mitigation. Addressing these lacunae, this study innovatively investigates the carbon reduction mechanisms of industrial structure upgrading within the strategic context of unified national market advancement through a spatial spillover lens. The contributions of this research are tripartite: (1) It investigates the spatial clustering characteristics of carbon emissions and evaluates the impact of industrial structure upgrading on emissions at the provincial level, including its spatial spillover effects. (2) It explores the moderating role of unified national market development in enhancing the carbon reduction effects of industrial structure upgrading. (3) It examines the heterogeneous impacts of industrial structure upgrading on carbon emissions across regions and over time. These advancements substantially broaden the theoretical frontier encompassing industrial modernization, market integration, and climate governance while offering empirically grounded insights for regional low-carbon policymaking.

The remainder of this paper is structured as follows: Section 2 analyzes the theoretical mechanisms and proposes the primary research hypotheses. Section 3 introduces the data sources and research methodology. Section 4 presents the empirical findings and discusses their implications, followed by Section 5, which formulates policy recommendations grounded in the empirical results.

2. Theoretical Analysis and Research Hypotheses

2.1. Industrial Structure Upgrading and Carbon Emissions

Industrial structure reflects the complex relationships among different industrial sectors. The essence of industrial structure upgrading lies in the dynamic adjustment of inter-sectoral relationships, representing a transformation from low-level, resource- and labor-intensive industries to capital- and technology-intensive industries [19]. This process plays a pivotal role in achieving high-quality economic development [20].

On the one hand, industrial structure upgrading directly attenuates carbon emissions through productivity-enhancing structural dividends. Strategic elimination of obsolete production capacities, coupled with targeted development of emerging industries and optimized factor reallocation, unlocks these dividends [21]. Such restructuring propels the real economy toward intelligent manufacturing ecosystems and green industrial clusters, simultaneously curbing pollutant outputs and establishing foundations for sustainable development. Notably, these transitions mitigate the carbon intensity of economic expansion while reinforcing long-term competitiveness [22]. As low-end industries transition to high-end sectors, energy-intensive and polluting industries are gradually phased out,

while the industrial structure shifts toward service industries, high-tech sectors, and clean energy industries. These structural changes directly influence carbon emission levels [23].

On the other hand, industrial structure upgrading indirectly reduces carbon emissions by optimizing energy structures and enhancing regional collaboration. Industrial upgrading promotes energy structure optimization [24], as energy consumption patterns evolve during this process, demand for traditional high-energy resources declines, while clean energy adoption increases, collectively lowering carbon emissions. Additionally, industrial structure upgrading elevates enterprises' positions in global value chains, enabling them to absorb green technologies from developed regions and prioritize sustainable production practices, thereby reducing emissions. Moreover, the inhibitory effect of industrial structure upgrading on carbon emissions exhibits spatial spillover effects. Adjustments in one region's industrial input–output structure may trigger changes in neighboring regions' industrial sectors, creating interregional industrial linkages [25]. These linkages, combined with technology diffusion and learning effects, further suppress carbon emissions [26]. Based on the above analysis, the first hypothesis is proposed:

H1. *Industrial structure upgrading reduces carbon emission intensity and generates spatial spillover effects.*

Industrial structure upgrading facilitates carbon emission reduction through technological advancement and digital transformation. The continuous optimization of industrial structures drives technological progress, which in turn enhances resource allocation efficiency. This process improves the rational utilization of human capital, technological assets, and financial resources, fostering innovation in clean energy extraction and utilization while diminishing reliance on conventional energy sources like coal and petroleum [1,27]. During industrial restructuring, green technologies diffuse across regions through interprovincial knowledge exchange and talent mobility [28], catalyzing the development of novel techniques and production processes that collectively reduce carbon emissions.

Furthermore, industrial structure upgrading typically concentrates resources in high-value-added sectors with intensified demand for digital technologies. As the service sector expands, requirements for digital services such as cloud computing and artificial intelligence grow substantially. This structural evolution stimulates nationwide improvements in digital infrastructure, accelerating the deployment of IoT technologies and intelligent transportation systems. Enhanced digital infrastructure establishes a robust hardware foundation for innovation capacity building, thereby supporting comprehensive digital development [29]. Crucially, such upgrading generates digital competitive-demonstration effects among neighboring regions [30], where competitive pressures compel adjacent provinces to elevate their digital capabilities, ultimately lowering carbon emission intensity. Based on this analytical framework, we propose the following hypotheses:

H2. *Industrial structure upgrading generates spatial spillover effects on carbon reduction through technological diffusion mechanisms.*

H3. *Industrial structure upgrading generates spatial spillover effects on carbon reduction via digital competitive-demonstration mechanisms.*

2.2. Industrial Structure Upgrading, Unified National Market, and Carbon Emissions

The core objective of unified national market development is to dismantle regional barriers, optimize resource allocation, and facilitate the free flow of production factors. The

reinforcement of industrial structure upgrading's carbon reduction effects through unified market development manifests in two key dimensions:

First, the unified national market optimizes regional industrial layouts through factor integration [31]. By eliminating administrative barriers between regions, it promotes the circulation of production factors, enhances comparative advantages, and fosters interregional specialization and collaboration. This accelerates industrial structure upgrading through technological progress and environmental efficiency improvements [32]. Furthermore, market integration facilitates trade liberalization and streamlines supply-demand relationships across production sectors, strengthening interregional industrial linkages and synergies, thereby driving structural upgrading [33].

Second, the unified national market reduces carbon emissions by intensifying market competition, improving resource allocation efficiency, and deepening collaborative governance. Market integration heightens competition, incentivizing firms to reduce emissions through technological innovation, energy efficiency gains, and carbon productivity improvements. Regions with stronger innovation capabilities and stricter emission regulations exhibit more pronounced carbon reduction effects [34]. Studies based on spatial synergy theory, such as that of Wang and Wang [35], demonstrate that market integration enhances regional collaborative emission reduction, with technology spillovers, economic spillovers, and environmental governance spillovers serving as key mechanisms. Digital empowerment—through digital economy integration, technological applications, and management systems—further amplifies these effects. As regional integration spurs rapid economic growth, demand for high-quality environments intensifies, making environmental governance a critical theme in regional cooperation. Cities increasingly align environmental regulations and policies, while developed regions assist less developed areas through fiscal transfers to reduce pollution and carbon emissions [36]. Based on this analysis, the second hypothesis is proposed:

H4. *Unified national market development moderates the carbon reduction effect of industrial structure upgrading, meaning market integration strengthens the emission-reducing impact of industrial upgrading.*

The hypothesized mechanism is illustrated in Figure 1. This study employs a Spatial Durbin Model (SDM) to assess the direct effects and spatial spillover impacts of industrial structure upgrading on carbon emissions. Subsequently, empirical validation is conducted to examine the mediating roles of technological diffusion mechanisms and digital competitive-demonstration mechanisms. Additionally, the moderating role of unified national market development in this chain is systematically analyzed.

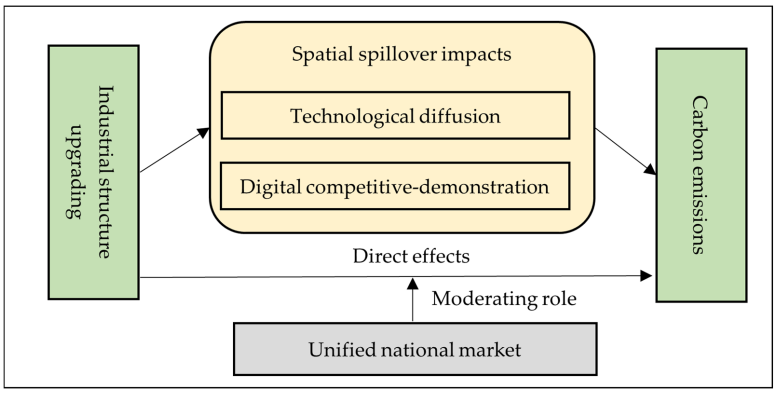


Figure 1. Hypothesized mechanism.

3. Research Design

3.1. Spatial Weight Matrix

The decarbonization outcomes of industrial structure upgrading are shaped not merely by geographical adjacency but also by cross-regional economic interdependencies. To precisely capture the intensity of provincial economic interactions, this study employs an economic distance spatial weight matrix, a metric that quantifies connectivity through the inverse of absolute disparities in mean regional GDP over the sample period. Formally, the spatial weight W between regions i and j is mathematically formulated as follows:

$$W = \frac{1}{\left| gdp_i - gdp_j \right|} \tag{1}$$

3.2. Spatial Econometric Model

Spatial analytical frameworks offer methodological tools to dissect territorial interdependencies, elucidating both immediate impacts and interregional spillover dynamics [37]. To rigorously assess the localized and spatially diffused effects of industrial structure upgrading on carbon emissions, we formulate the following spatial econometric specification (Equation (2)):

$$\begin{aligned} lncei_{it} = \alpha_0 + \rho W lncei_{it} + \alpha_1 isu_{it} + \theta_1 W isu_{it} + \sum \alpha_j X_{it} + \sum \theta_j W X_{it} \\ + \gamma_i + \mu_t + \varepsilon_{it} \end{aligned} \tag{2}$$

In Equation (2), the subscript i and t index regions and years, respectively. α_0 represents the constant term. $lncei_{it}$ represents the logarithm of carbon emission intensity; isu_{it} indicates the level of industrial structure upgrading; and X_{it} denotes the control variables. W is the spatial weight matrix, ρ is the spatial autocorrelation coefficient, θ represents the parameters of spatial lag terms, γ_i and μ_t denote regional fixed effects and time fixed effects, respectively, and ε_{it} is the random error term. α_1 and α_j denote parameters to be estimated.

3.3. Variable Selection and Data Sources

3.3.1. Dependent Variable

Carbon emission intensity (*lncei*) is defined as the natural logarithm of the ratio between total carbon dioxide (CO_2) emissions and regional GDP. Following the IPCC guidelines, total CO_2 emissions are quantified using fossil fuel-specific emission coefficients, adopting the methodology proposed by Wang and Wang [38]. The computational formula is formalized as follows:

$$CE = \sum_{i=1}^{9} E_i \times NCV_i \times CEF_i \tag{3}$$

In Equation (3), CE denotes total CO_2 emissions; i represents nine energy types (e.g., coal, coke); E_i is the consumption of the i-th energy type; NCV_i is the average net calorific value; and CEF_i is the carbon emission factor for the i-th energy type.

3.3.2. Explanatory Variable

Industrial structure upgrading (*isu*) is derived through the analytical framework proposed by Jiao et al. [39], operationalized mathematically as follows:

$$isu = \sum_{k}^{3} y_k \times k \tag{4}$$

In Equation (4), y_k denotes the proportion of the k-th industry (primary, secondary, tertiary) in regional GDP. Elevated index values correlate with advanced stages of industrial

structure upgrading, reflecting progressive shifts toward technology- and service-oriented economic configurations.

3.3.3. Mediating Variables

Technological advancement (*tech*) is operationalized following Su et al. [40], measured by R&D expenditure input intensity. Digitalization (*lndig*) is quantified adopting the methodology of Sun [41], proxied by the logarithm of the number of invention patents granted in the digital economy sector.

3.3.4. Mechanism Variable

The market integration index (*mii*) quantifies the progress of unified national market development, constructed via the price index methodology outlined in Parsley and Wei [42] and Lei and Lang [43]. Grounded in the iceberg cost model, this approach evaluates market segmentation by analyzing interregional price differentials: integrated markets exhibit negligible arbitrage opportunities, with relative prices stabilizing within a defined bandwidth.

First, calculate the absolute value of relative price fluctuations ($\left|\Delta Q_{ijt}^{k}\right|$). Let p denote the retail price index, k represent commodity categories (e.g., grains, beverages/tobacco/alcohol, clothing/footwear/hats, and five others), i and j denote provinces, and t denote the year:

$$\left|\Delta Q_{ijt}^{k}\right| = \left|\ln\left(\frac{p_{it}^{k}}{p_{it-1}^{k}}\right) - \ln\left(\frac{p_{jt}^{k}}{p_{jt-1}^{k}}\right)\right| \tag{5}$$

Second, apply a demeaning process to eliminate commodity-specific idiosyncratic effects unrelated to market segmentation:

$$q_{ijt}^{k} = \left|\Delta Q_{ijt}^{k}\right| - \left|\Delta \overline{Q_{t}^{k}}\right| \tag{6}$$

Finally, the market integration index is derived from the variance of relative price fluctuations across eight commodity categories between each pair of regions, calculated as follows:

$$mii_{it} = \sqrt{\frac{1}{\sum_{i \neq j} var\left(q_{ijt}\right)}} \tag{7}$$

3.3.5. Control Variables

Economic development level (*lnpgdp*): Derived from the natural logarithm of regional GDP per capita. Green innovation level (*lngil*): quantified as the logarithmic transformation of annual green patent filings. Openness (*ope*): computed as the ratio of total merchandise trade (imports + exports) to regional GDP. Urbanization level (*ul*): expressed as the proportion of urban residents to the total population. Transportation infrastructure (*lntil*): captured through the logarithm of cumulative highway network length.

Based on data availability, this study employs panel data from 30 provincial-level regions in China (excluding Tibet, Hong Kong, Macao, and Taiwan) spanning 2005 to 2022. The primary data sources include the China Energy Statistical Yearbook, National Bureau of Statistics, China National Research Data Service Platform (CNRDS), China Statistical Yearbook, China Science and Technology Statistical Yearbook and China National Intellectual Property Administration. Missing values are addressed through interpolation. Descriptive statistics for all variables are summarized in Table 1.

Table 1. Descriptive statistics.

Variable	Obs	Mean	Std. Dev	Min	Max
lncei	540	0.802	0.761	−1.496	2.631
isu	540	2.366	0.131	2.085	2.835
tech	540	0.016	0.011	0.001	0.068
lndig	540	7.574	2.026	1.099	12.195
mii	540	56.08	15.55	17.79	106.6
lnpgdp	540	10.54	0.674	8.560	12.15
lngil	540	7.349	1.698	2.197	10.94
ope	540	0.304	0.348	0.00763	1.711
ul	540	0.563	0.140	0.269	0.896
lntil	540	11.58	0.871	9.001	12.91

4. Results

4.1. Spatial Autocorrelation Test

4.1.1. Global Autocorrelation

Prior to investigating the spatial spillover effects of industrial structure upgrading on decarbonization, we assess the spatial interdependence of carbon emission intensity. The Moran's I index—a robust metric for evaluating territorial agglomeration patterns—quantifies latent cross-regional spillovers [44]. The Moran's I index is calculated based on the spatial weight matrix as follows:

$$Moran's\ I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(lncei_i - \overline{lncei}\right)\left(lncei_j - \overline{lncei}\right)}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \quad (8)$$

In Equation (8), w_{ij} is the spatial weight, *lncei* and $\overline{lncei}$ are carbon emission intensity and its mean, n is the number of regions, and S^2 is the sample variance.

Table 2 presents the global Moran's I test results. Global Moran's I indices achieve statistical significance at the 10% and 5% thresholds for 2005 and 2006, respectively, and at the 1% level for 2007–2022. This persistent positive spatial autocorrelation validates the necessity of spatial econometric modeling.

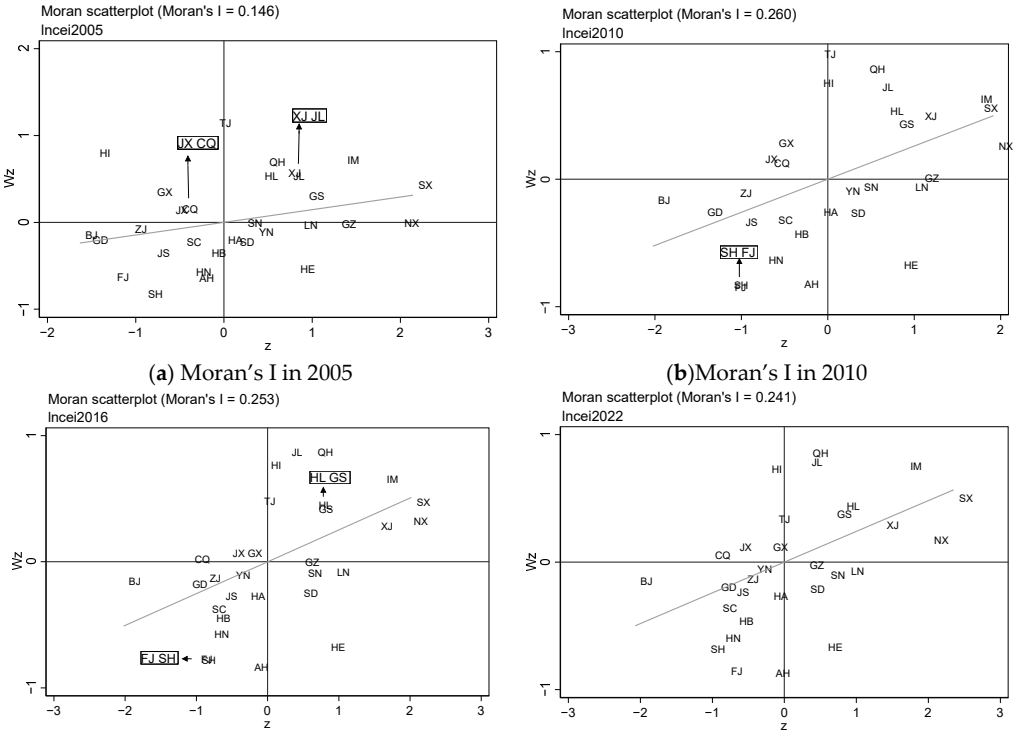
Table 2. Global Moran's I index of carbon emission intensity.

Year	Moran's I	Z-Value
2005	0.146 *	1.895
2006	0.205 **	2.522
2007	0.259 ***	3.083
2008	0.248 ***	2.957
2009	0.250 ***	2.981
2010	0.260 ***	3.087
2011	0.267 ***	3.176
2012	0.275 ***	3.260
2013	0.261 ***	3.112
2014	0.263 ***	3.130
2015	0.245 ***	2.949
2016	0.253 ***	3.022
2017	0.247 ***	2.962
2018	0.251 ***	3.009
2019	0.247 ***	2.972
2020	0.238 ***	2.884
2021	0.246 ***	2.974
2022	0.241 ***	2.928

Note: ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

4.1.2. Local Autocorrelation

While the global Moran's I index captures macro-level geographical agglomeration trends, local Moran's I scatterplots provide granular insights into provincial spatial autocorrelation patterns. Figure 2a–d illustrate these scatterplots for carbon emission intensity across four benchmark years (2005, 2010, 2016, 2022). A predominant concentration of provinces within the first and third quadrants reveals distinct "high-high" and "low-low" clustering behaviors, reinforcing the prevalence of positive spatial autocorrelation. This signifies the following: High-emission clusters: Provinces with elevated carbon intensity exhibit interdependencies with neighboring high-emission regions, likely driven by industrial symbiosis or shared energy infrastructure. Low-emission clusters: Provinces with reduced emissions demonstrate spatial linkages to adjacent low-emission areas, potentially reflecting coordinated environmental governance or technology spillovers. According to the First Law of Geography and externality theory, tighter interregional linkages amplify spillover effects. Carbon reduction in one region can lower emissions in neighboring areas, whereas increased emissions in one region may elevate emissions in adjacent regions. Specifically, economically developed regions such as Beijing, Shanghai, and Zhejiang cluster in the "low-low" quadrant (third quadrant). With a high proportion of tertiary industries, these regions exhibit lower carbon emission intensity. Through industrial chain specialization facilitated by unified regional market development, they diffuse low-carbon technologies to neighboring provinces, forming low-carbon development clusters (e.g., the Yangtze River Delta region). Provinces like Shanxi and Inner Mongolia, reliant on coal, steel, and other high-carbon industries, lag behind in terms of clean energy transition and maintain persistently high carbon emission intensity.



(**a**) Moran's I in 2005 (**b**)Moran's I in 2010

(**c**) Moran's I in 2016 (**d**) Moran's I in 2022

Figure 2. Local Moran's I scatter plots of carbon emission intensity (2005, 2010, 2016, 2022). **Note:** The abbreviations represent: BJ: Beijing, TJ: Tianjin, HE: Hebei, SX: Shanxi, IM: Inner Mongolia, LN: Liaoning, JL: Jilin, HL: Heilongjiang, SH: Shanghai, JS: Jiangsu, ZJ: Zhejiang, AH: Anhui, FJ: Fujian, JX: Jiangxi, SD: Shandong, HA: Henan, HB: Hubei, HN: Hunan, GD: Guangdong, GX: Guangxi, HI: Hainan, CQ: Chongqing, SC: Sichuan, GZ: Guizhou, YN: Yunnan, SN: Shaanxi, GS: Gansu, QH: Qinghai, NX: Ningxia, XJ: Xinjiang.

4.2. Spatial Econometric Model Test

Before proceeding with spatial econometric estimations, preliminary diagnostic evaluations are essential to identify the optimal model specification. This study utilizes the Lagrange Multiplier (LM) test, Hausman test, and Wald test for comparative model selection. Diagnostic outcomes, consolidated in Table 3, reveal that the Spatial Durbin Model incorporating fixed effects demonstrates superior explanatory power relative to conventional standalone frameworks such as the Spatial Error Model (SEM) or Spatial Lag Model (SAR).

Table 3. Spatial econometric model test results.

Test	Statistic	*p*-Value
LM spatial error	0.330	0.566
Robust LM spatial error	2.979	0.084
LM spatial lag	8.672	0.003
Robust LM spatial lag	11.321	0.001
Hausman test	158.97	0.0000
Wald spatial error	77.61	0.0000
Wald spatial lag	77.26	0.0000
LR spatial error	72.56	0.0000
LR spatial lag	72.30	0.0000

4.3. Baseline Regression and Effect Decomposition

Empirical estimations via the Spatial Durbin Model are reported in Table 4. The spatial autoregressive coefficient ρ attains a value of 0.175 with 1% statistical significance, confirming pronounced spatial autocorrelation in carbon emission intensity (*lncei*). This indicates that a region's emission levels are positively influenced by neighboring regions' emissions, corroborating prior spatial dependence diagnostics and underscoring the indispensability of spatial considerations in analyzing industrial structure upgrading's decarbonization effects.

Table 4. Baseline regression and effect decomposition.

Variable	Main	Wx	Direct Effect	Indirect Effect	Total Effect
isu	−0.638 ***	−4.712 ***	−0.774 ***	−5.671 ***	−6.444 ***
	(0.216)	(0.639)	(0.223)	(0.880)	(0.948)
lnpgdp	−1.111 ***	−0.563 **	−1.136 ***	−0.890 ***	−2.026 ***
	(0.085)	(0.246)	(0.083)	(0.257)	(0.281)
lngil	0.100 ***	−0.332 ***	0.093 ***	−0.366 ***	−0.272 ***
	(0.028)	(0.076)	(0.028)	(0.093)	(0.100)
ope	0.196 ***	0.588 ***	0.216 ***	0.741 ***	0.957 ***
	(0.073)	(0.172)	(0.071)	(0.197)	(0.198)
ul	1.457 ***	−2.560 ***	1.381 ***	−2.784 **	−1.403
	(0.403)	(0.984)	(0.387)	(1.209)	(1.369)
lntil	−0.027	0.515 ***	−0.009	0.614 ***	0.605 **
	(0.071)	(0.186)	(0.073)	(0.235)	(0.270)
Time FE	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes
ρ			0.175 **		
			(0.076)		
R^2			0.332		
N			540		

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

For the focal explanatory variable, industrial structure upgrading (*isu*), the regression coefficient is −0.638 (1% significance level), evidencing its substantial direct carbon

abatement effect locally. The mechanism lies in the advancement of industrial structure, which enhances technological capabilities and management efficiency. The adoption of high-tech solutions reduces energy consumption and operational costs, thereby lowering carbon emissions. Additionally, industrial structure upgrading compels firms to prioritize green development, adopt environmentally friendly equipment, and further drive emission reductions.

Regarding the control variables, economic development level *(lnpgdp*) exhibits negative significance, indicating that higher economic development reduces regional carbon emission intensity. The promotion of clean energy has played a positive role in coordinating economic and environmental development [45], aligning with the pattern revealed by the environmental Kuznets curve. Green technology innovation (*lngil*) shows positive significance. While green innovation facilitates long-term carbon reduction, it presents a "green innovation paradox" in the short term. Green innovation introduces new environmental risks, increases investment costs for technological upgrades [46], and activities such as R&D investment and new equipment procurement may consume substantial energy, leading to short-term increases in carbon emissions. Openness to the external world (*ope*) is positively significant, as expanded openness may trigger more trade activities. Trade scale expansion accompanies increased goods transportation, production, and processing, all of which elevate energy consumption and carbon emissions. Urbanization level (*ul*) is positively significant, suggesting that population agglomeration, infrastructure construction, and lifestyle changes during urbanization collectively increase energy demand, thereby raising carbon emissions.

To comprehensively assess the indirect (spatial spillover) and total effects of industrial structure upgrading on carbon reduction, we decompose the Spatial Durbin Model estimates using partial derivative analysis. The indirect effect coefficient of industrial structure upgrading remains statistically negative and significant. This dual negativity confirms that industrial restructuring not only curtails local carbon emission intensity but also generates cross-regional decarbonization synergies. Specifically, advanced industrial practices in one region stimulate inter-jurisdictional industrial collaboration, enabling knowledge spillovers, green technology transfer, and adoption of sustainable business frameworks in neighboring areas. Such synergies accelerate structural optimization and emission abatement across spatially linked economies. The total effect coefficient underscores the compounded efficacy of industrial structure upgrading, combining direct local reductions and spatially propagated benefits. This dual-channel impact validates its role as a multiscalar decarbonization lever, simultaneously advancing emission mitigation at local and regional tiers. In conclusion, Research Hypothesis 1 is validated.

4.4. Robustness and Endogeneity Tests

To validate the robustness of the regression outcomes, this study employs two modifications: altering the core explanatory variable and adjusting the spatial weight matrix. Following the approach of Yu and Jin [47], industrial structure upgrading is redefined as the ratio of tertiary industry output to secondary industry output, and the Spatial Durbin Model is recomputed. Additionally, the spatial distance weight matrix replaces the economic distance matrix, defined as follows:

$$W = \begin{cases} \frac{1}{d_{ij}} & , \quad i \neq j \\ 0 & , \quad i = j \end{cases} \tag{9}$$

In Equation (9), i and j represent different regions, and d_{ij} denotes the distance between regions i and j. As shown in Table 5, the re-estimated results confirm that the direct and spatial spillover effects of industrial structure upgrading on carbon emission intensity

remain negative and statistically significant, aligning with the baseline findings. This consistency reinforces the robustness of the empirical conclusions.

Table 5. Robustness and endogeneity tests.

Variable	Variable Replacement		Matrix Replacement		DSDM	
	Direct Effect	Indirect Effect	Direct Effect	Indirect Effect	Direct Effect	Indirect Effect
isu_a	−0.280 ***	−0.708 ***				
	(0.042)	(0.139)				
isu			−0.651 ***	−2.181 *	−0.133	−0.658 **
			(0.228)	(1.208)	(0.107)	(0.275)
lncei_lag					0.841 ***	0.110 **
					(0.022)	(0.048)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes
ρ	0.106		−0.241		−0.225 ***	
	(0.079)		(0.182)		(0.083)	
R^2	0.323		0.159		0.863	
N	540		540		510	

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

To address potential endogeneity arising from bidirectional causality between industrial structure upgrading and carbon emissions, as well as omitted variable biases in model specification, this study employs a Dynamic Spatial Durbin Model (DSDM) to mitigate these concerns. While the conventional Spatial Durbin Model incorporates spatial lag terms to partially alleviate endogeneity, its limitations persist. The DSDM further resolves these issues by integrating a one-period temporal lag of the dependent variable into the SDM framework [48]. The endogeneity tests presented in Table 5 confirm that industrial structure upgrading retains its statistically significant decarbonizing effect, thereby validating the robustness of the baseline regression results.

4.5. Channel Test

Building on prior findings, industrial structure upgrading demonstrably reduces carbon emissions while exhibiting spatial spillover effects. To disentangle the mediating roles of technological diffusion mechanisms and digital competitive-demonstration effects—proposed as key pathways—this study establishes a mediation analysis framework based on Equation (2), employing a stepwise regression approach [49]. Given the established impact of industrial structure upgrading on emission reduction, the analysis focuses on the second and third steps of the mediation model, formalized as follows:

$$M_{it} = \alpha_0 + \rho WM_{it} + \alpha_1 isu_{it} + \theta_1 Wisu_{it} + \sum \alpha_j X_{it} + \sum \theta_j WX_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (10)$$

$$lncei_{it} = \alpha_0 + \rho Wlncei_{it} + \alpha_1 isu_{it} + \alpha_2 M_{it} + \theta_1 Wisu_{it} + \theta_2 WM_{it} \sum \alpha_j X_{it} + \sum \theta_j WX_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (11)$$

where M_{it} denotes the mediators: *tech* and *lndig*. Other variables retain their original definitions.

As shown in Table 6, Model (1) replicates the baseline regression. Models (2) and (3) evaluate the mediating role of technological advancement. In Model (2), the coefficient for technological advancement is significantly positive, indicating that industrial structure upgrading stimulates regional technological progress. Model (3) incorporates both industrial structure upgrading and technological advancement, revealing a significantly negative coefficient for industrial structure upgrading, with its absolute magnitude decreasing by 2.654 compared to the baseline. Concurrently, technological advancement exhibits a significantly

negative coefficient, supporting mediation. The Sobel test further confirms the mediation effect. These results validate the transmission pathway "industrial structure upgrading → technological advancement → carbon reduction", demonstrating that technological progress not only drives local decarbonization but also generates spatial spillovers through technology diffusion, catalyzing emission reductions in neighboring regions. Hypothesis H2 is thus empirically substantiated.

Table 6. Channel test.

	(1)	(2)	(3)	(4)	(5)
Variable	***lncei***	***tech***	***lncei***	***lndig***	***lncei***
isu	−5.671 ***	0.061 ***	−3.017 ***	0.108	−5.259 ***
	(0.880)	(0.013)	(0.696)	(1.153)	(0.791)
tech			−14.742 ***		
			(5.015)		
lndig					−0.292 ***
					(0.070)
lnpgdp	−0.890 ***	0.024 ***	−0.368 *	−0.127	−0.857 ***
	(0.257)	(0.004)	(0.221)	(0.375)	(0.251)
lngil	−0.366 ***	0.001	−0.235 ***	0.131	−0.220 **
	(0.093)	(0.001)	(0.077)	(0.131)	(0.090)
ope	0.741 ***	−0.005	0.450 **	−0.366	0.775 ***
	(0.197)	(0.003)	(0.175)	(0.302)	(0.195)
ul	−2.784 **	−0.056 ***	−3.429 ***	−2.093	−1.826 *
	(1.209)	(0.020)	(0.956)	(1.726)	(1.100)
lntil	0.614 ***	−0.011 ***	0.310	−0.120	0.494 **
	(0.235)	(0.004)	(0.191)	(0.336)	(0.219)
Time FE	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes
ρ	0.175 **	0.203 ***	0.021	−0.158 **	0.131 *
	(0.076)	(0.063)	(0.080)	(0.079)	(0.077)
R^2	0.332	0.049	0.387	0.887	0.372
Sobel-Z			−2.47 **		−0.094
N	540	540	540	540	540

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

Models (4) and (5) examine the mediating role of digitalization. In Model (4), the coefficient for digitalization is statistically insignificant, and the Sobel test fails to reject the null hypothesis, suggesting that while digitalization mitigates carbon emissions, it does not act as a significant mediator between industrial structure upgrading and emission reduction. This implies that the digital competitive-demonstration mechanism remains underdeveloped across regions, with insufficient spillover benefits from digitalization yet to be fully realized [50]. The digital sector remains exploratory, characterized by limited industrial scale and R&D capacity. There is a shortage of talent with digital technology skills, and an excessive talent competition effect exists among regions. Digital development, heavily reliant on internet infrastructure, has led to concentrated growth in tech hubs, exacerbating regional digital divides and uneven development patterns [51].

4.6. Mechanism Test

To evaluate the regulatory influence of market integration on the carbon reduction efficacy of industrial structure upgrading, this study augments Equation (2) by incorporating

the market integration index (mii_{it}) and its interaction with the core explanatory variable. The extended model is formalized as follows:

$$lncei_{it} = \alpha_0 + \rho Wlncei_{it} + \alpha_1 isu_{it} + \alpha_2 mii_{it} + \alpha_3 isu_{it} \times mii_{it} + \theta_1 Wisu_{it} + \theta_2 Wmii_{it} + \theta_3 Wisu_{it} \times mii_{it} + \sum \alpha_j X_{it} + \sum \theta_j WX_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad (12)$$

In Equation (12), mii_{it} denotes the market integration index, reflecting the level of unified regional market development. The interaction term $isu_{it} \times mii_{it}$ captures the moderating effect of market integration on the carbon reduction impact of industrial structure upgrading. The definitions of other variables remain unchanged. The empirical results are presented in Table 7.

Table 7. Mechanism test.

			Mature Urban Clusters		Less-Developed Clusters	
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	Direct Effect	Indirect Effect	Direct Effect	Indirect Effect	Direct Effect	Indirect Effect
isu	−0.240	−5.763 ***	1.134 ***	−1.432 **	−0.969 ***	−3.865 ***
	(0.265)	(0.888)	(0.422)	(0.713)	(0.230)	(0.739)
mii	0.029 ***	0.011				
	(0.007)	(0.019)				
isu×*mii*	−0.013 ***	−0.008				
	(0.003)	(0.008)				
lnpgdp	−1.126 ***	−0.771 ***	−0.735 ***	0.567 **	−1.160 ***	0.846 ***
	(0.081)	(0.258)	(0.084)	(0.235)	(0.103)	(0.297)
lngil	0.077 ***	−0.387 ***	0.047	−0.118	0.182 ***	−0.084
	(0.027)	(0.087)	(0.039)	(0.072)	(0.029)	(0.072)
ope	0.140 **	0.566 ***	−0.122 *	−0.730 ***	0.234	1.055 **
	(0.070)	(0.197)	(0.072)	(0.153)	(0.233)	(0.489)
ul	1.468 ***	−2.234 *	1.441 ***	−1.082 *	−1.368 **	−10.997 ***
	(0.408)	(1.142)	(0.395)	(0.650)	(0.544)	(1.605)
lntil	−0.035	0.516 **	−0.043	−0.088	−0.113	0.257
	(0.066)	(0.212)	(0.087)	(0.205)	(0.080)	(0.235)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes
ρ	0.121		−0.497 ***		−0.394 ***	
	(0.076)		(0.111)		(0.108)	
R^2	0.348		0.004		0.100	
N	540		198		342	

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

Both direct and total effects of the interaction term exhibit statistically negative coefficients, confirming that market integration significantly amplifies the carbon reduction utility of industrial structure upgrading. Unified market development dismantles interregional trade barriers and factor mobility constraints, enabling firms to optimize resource allocation during industrial restructuring. Enhanced market integration facilitates the adoption of advanced low-carbon technologies and sustainable management practices, magnifying emission abatement. Regions with higher integration levels exhibit greater alignment in environmental regulations, reinforcing emission control through standardized green policies.

As a pivotal component of regional integration and unified national market development, China's National-level Urban Agglomeration Planning aims to strengthen intercity economic linkages through coordinated planning and intercity specialization, thereby reducing institutional disparities and advancing market integration [52]. While China's factor market integration has fostered highly integrated urban clusters (e.g., Yangtze River Delta, Pearl River Delta), central and western clusters exhibit comparatively fragmented markets.

To empirically test market integration's moderating role in the decarbonization effects of industrial structure upgrading, this study adopts Zhou et al.'s [53] methodology, categorizing the sample into mature urban clusters (Beijing, Tianjin, Hebei, Shanghai, Jiangsu, Zhejiang, Guangdong, Fujian, Hubei, Chongqing, Sichuan) and less developed clusters based on developmental stages. The results in Table 7 (Models 3–6) reveal consistently significant negative coefficients for industrial structure upgrading across the subsamples, with smaller absolute coefficients in mature clusters, indicating stronger decarbonization effects of industrial structure upgrading in less developed clusters. This divergence stems from lower market integration levels in less developed clusters due to persistent local protectionism, administrative monopolies, and institutional fragmentation. In these regions, industrial restructuring acts as a catalyst to dismantle market barriers and enhance systemic integration, amplifying its emission reduction efficacy. Consequently, Hypothesis H4 is empirically validated.

4.7. Heterogeneity Analysis

4.7.1. Regional Heterogeneity

Given pronounced variations in developmental stages, industrial configurations, and resource endowments across Chinese regions, industrial structure upgrading exerts geographically divergent impacts on carbon emission intensity. To dissect this spatial heterogeneity, the sample is bifurcated into the eastern and central-western regions. Empirical outcomes are detailed in Table 8.

Table 8. Regional heterogeneity.

	Eastern Region			Central-Western Regions		
Variable	**Direct Effect**	**Indirect Effect**	**Total Effect**	**Direct Effect**	**Indirect Effect**	**Total Effect**
isu	2.990 ***	1.311 *	4.301 ***	−1.039 ***	−4.168 ***	−5.207 ***
	(0.411)	(0.748)	(0.796)	(0.245)	(0.589)	(0.579)
lnpgdp	−0.141	0.100	−0.041	−1.298 ***	−0.126	−1.424 ***
	(0.136)	(0.214)	(0.287)	(0.095)	(0.243)	(0.245)
lngil	−0.094 **	−0.004	−0.097	0.188 ***	−0.097	0.091
	(0.041)	(0.078)	(0.089)	(0.027)	(0.076)	(0.077)
ope	0.098	−0.629 ***	−0.531 **	0.112	1.141 ***	1.253 ***
	(0.071)	(0.195)	(0.213)	(0.191)	(0.405)	(0.414)
ul	1.614 ***	1.076 *	2.690 ***	−1.078 **	−9.624 ***	−10.702 ***
	(0.359)	(0.586)	(0.604)	(0.518)	(1.426)	(1.570)
lntil	−0.190 **	−0.293	−0.483 ***	−0.064	0.048	−0.016
	(0.077)	(0.202)	(0.179)	(0.079)	(0.241)	(0.250)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes
ρ		−0.368 ***			−0.396 ***	
		(0.113)			(0.103)	
R^2		0.301			0.184	
N		180			360	

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

Regional heterogeneity is evident. In the eastern region, the direct, indirect, and total effects of industrial structure upgrading are statistically positive and significant, revealing a paradoxical short-term emission surge during structural transitions. While transitioning toward service-dominated, high-value-added economic structures, emerging sectors—such as digital services and tech-intensive industries—exhibit elevated energy demands due to data infrastructure expansion and R&D intensity, temporarily offsetting efficiency gains. Specifically, the development of emerging industries relies on robust new infrastructure systems, yet the construction of digital infrastructure and related facilities entails substantial energy consumption, which may transiently escalate carbon emissions [54,55]. In Eastern

China, where high-tech and light industries dominate the economic structure, firms in technology-intensive sectors prioritize R&D investments to strengthen cutting-edge innovation and production efficiency strategies aimed at consolidating competitive advantages rather than emission mitigation. Consequently, the "output expansion effect" induced by R&D intensification outweighs its "energy-saving effect," resulting in net upward pressure on emissions [56]. Furthermore, the relatively high factor allocation efficiency in eastern regions diminishes the marginal decarbonization returns of industrial structure upgrading. Concurrently, the prevalence of mature light industries may inadvertently perpetuate lax energy consumption regulations, fostering extensive energy use patterns that counteract decarbonization efforts [18].

In contrast, the central-western regions exhibit negative and statistically significant effects, demonstrating that industrial structure upgrading reduces carbon emission intensity while generating spatial spillover effects. The central-western regions still rely heavily on traditional manufacturing industries. Industrial structure upgrading significantly optimizes resource allocation, reduces the proportion of energy-intensive industries, and thereby lowers carbon emission intensity. Furthermore, these regions benefit from late-mover advantages, allowing them to directly adopt mature green technologies and management models from the eastern region, avoiding repetition of high-carbon development pathways. This enables them to achieve low-carbon development during industrial upgrading.

4.7.2. Temporal Heterogeneity

China's economic landscape underwent a pivotal transformation in 2012, when the tertiary sector's output value exceeded that of the secondary sector for the first time, as documented by the National Bureau of Statistics [57]. This milestone highlights the ascendancy of modern service industries as the primary driver of economic expansion, displacing traditional manufacturing and signaling a new phase in industrial structure upgrading. Notably, prior to 2012, despite accelerated shifts in China's economic development paradigm and the rapid emergence of circular economy practices, the growth model remained entrenched in an extensive phase. Manufacturing sectors were large-scale but technologically weak, service industries accounted for a disproportionately low share compared to developed countries, and severe overcapacity plagued multiple sectors. A structural mismatch persisted between escalating demand for high-quality products and lagging low-end supply chains. The 2013 Decision on Major Issues Concerning Comprehensively Deepening Reforms marked a turning point by redefining state–market relations, emphasizing market-determined resource allocation to reinvigorate economic vitality. Subsequent policy frameworks prioritized industrial restructuring and high-quality development, catalyzing sustained transitions toward service-oriented economies [58]. To empirically validate 2012 as a structural breakpoint, a Chow test was conducted, confirming its statistical significance. To capture the temporal heterogeneity of industrial structure development, the sample period is divided into two phases using 2012 as the breakpoint: the early period (2005–2011) and the later period (2012–2022). The regression results, detailed in Table 9, reveal distinct temporal heterogeneities in decarbonization trajectories.

Significant temporal heterogeneity is observed in the relationship between industrial structure upgrading and carbon emission intensity, which follows an inverted U-shaped trajectory. Specifically, carbon emission intensity initially increases before declining. During the initial phase, the direct effect of industrial structure upgrading on carbon emission intensity is positive and statistically significant, indicating that upgrading efforts failed to curb emissions and instead contributed to their rise. Conversely, in the later phase, the direct, indirect, and total effects of industrial structure upgrading become negative and significant, demonstrating its effectiveness in reducing carbon

emission intensity. In the early stage, China's industrial upgrading progressed sluggishly, with manufacturing remaining dominated by labor-intensive sectors. The six major energy-intensive industries accounted for approximately 70% of industrial energy consumption, exacerbating resource constraints. At this stage, structural transformation primarily manifested as the substitution of primary industries by emission-heavy secondary industries. The rising share of secondary sectors exerted a net positive impact on carbon intensity [59], thereby demonstrating that industrial structure upgrading prior to 2012 paradoxically amplified carbon emissions. The adoption of clean production technologies lagged, and the integration of industrial restructuring with green innovation was insufficient. Consequently, the scale effect of industrial expansion overshadowed efficiency gains, leading to increased carbon emissions. However, as industrial structure upgrading advanced—particularly after 2012, when the tertiary sector's output surpassed that of the secondary sector and continued to expand—services became the primary driver of economic growth. During this period, industrial structure upgrading reduced carbon emission intensity by promoting green innovation, optimizing energy structures, and improving production efficiency. This evolution underscores the shifting role of industrial restructuring in fostering low-carbon development.

Table 9. Temporal heterogeneity.

	Early Period (2005–2011)			Later Period (2012–2022)		
Variable	**Direct Effect**	**Indirect Effect**	**Total Effect**	**Direct Effect**	**Indirect Effect**	**Total Effect**
isu	0.742 **	−1.000	−0.259	−0.818 ***	−4.863 ***	−5.681 ***
	(0.332)	(0.954)	(0.999)	(0.302)	(0.712)	(0.720)
lnpgdp	−0.320 ***	0.767 ***	0.447	−0.925 ***	−0.724 **	−1.649 ***
	(0.122)	(0.287)	(0.328)	(0.129)	(0.298)	(0.287)
lngil	0.054	−0.334 ***	−0.280 ***	0.000	0.119	0.119
	(0.036)	(0.089)	(0.095)	(0.029)	(0.081)	(0.082)
ope	0.092	0.025	0.117	0.408 ***	1.010 ***	1.418 ***
	(0.076)	(0.141)	(0.152)	(0.112)	(0.315)	(0.332)
ul	0.910	−5.126 ***	−4.216 **	−0.448	−5.023 ***	−5.471 ***
	(0.618)	(1.705)	(1.830)	(0.534)	(1.343)	(1.581)
lntil	−0.211 ***	−0.130	−0.341 **	−0.363 ***	0.599 *	0.236
	(0.053)	(0.144)	(0.166)	(0.108)	(0.343)	(0.349)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Regional FE	Yes	Yes	Yes	Yes	Yes	Yes
ρ		−0.102			−0.057	
		(0.128)			(0.104)	
R^2		0.015			0.115	
N		210			330	

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

5. Conclusions and Policy Recommendations

5.1. Research Conclusions

This study employs a Spatial Durbin Model to analyze the carbon emission reduction effects of industrial structure upgrading under the framework of a unified national market, using panel data from 30 Chinese provincial-level regions between 2005 and 2022. The key findings are summarized as follows:

First, provincial carbon emission intensity exhibits significant "high-high" and "low-low" spatial agglomeration patterns. Industrial structure upgrading significantly reduces regional carbon emission intensity, demonstrating a pronounced carbon reduction effect, while generating positive spatial spillovers to neighboring areas. Higher economic development levels contribute to lower emissions, whereas rapid urbanization may inadvertently increase carbon intensity. Second, the decarbonization impact operates

through technology diffusion mechanisms, whereas the hypothesized digital competitive-demonstration mechanisms remain empirically unsubstantiated. Third, the construction of a unified national market positively moderates the carbon reduction effect of industrial structure upgrading. Fourth, the carbon reduction effects of industrial structure upgrading exhibit significant regional and temporal heterogeneity. In Eastern China, industrial structure upgrading initially exhibits positive direct, indirect, and spillover effects on carbon emissions. Conversely, central and western regions benefit from late-mover advantages, resulting in significant negative effects. The impact of industrial structure upgrading on carbon emission intensity follows an inverted U-shaped trajectory.

Addressing climate change and reducing carbon emissions have emerged as a global imperative. Industrial structure upgrading serves as a critical pathway to achieve sustainable economic development and decarbonization. This study empirically demonstrates the enhancing role of market integration in amplifying the carbon reduction effects of industrial structure upgrading, providing policymakers with evidence for strategic interventions. Notably, the decarbonization efficacy of industrial structure upgrading exhibits regional heterogeneity, where local economic characteristics, geographical conditions, and institutional contexts significantly moderate policy effectiveness. Consequently, policy design must systematically account for regional disparities to optimize outcomes.

Beyond informing China's policy landscape, these findings hold implications for other emerging economies undergoing similar industrial transitions—particularly those experiencing rapid tertiary sector expansion and gradual supersession of secondary industries. By adopting context-sensitive strategies to accelerate industrial restructuring, these nations can leverage analogous mechanisms to mitigate emissions while fostering sustainable growth.

5.2. Policy Recommendations

First, the green transformation of industrial development should be sustainably deepened to unlock the carbon reduction potential of structural upgrading. Policy support should be strengthened to continuously guide and promote industrial structure upgrading. Assistance for manufacturing transformation and modernization should be enhanced and manufacturing should be steered toward green, high-end, and intelligent development. We should continue supporting the growth of service industries, accelerate their digital transformation, and increase the proportion of service sectors in the economy.

Second, we should accelerate technological innovation and narrow regional digital divides to harness digital dividends. Energy efficiency improvements in digital development should be prioritized, low-power chip research and applications should be incentivized, and excessive emissions from communication infrastructure and data centers should be mitigated.

Third, institutional, trade, and factor mobility barriers across regions should be dismantled to facilitate cross-regional exchanges of technology, talent, and capital. We should strengthen the national carbon market and implement market-driven pricing and trading mechanisms for carbon emission allowances, internalizing the spatial externalities of regional carbon emissions through rigorous cap-and-trade systems. We should integrate environmental governance metrics into official performance evaluations to align bureaucratic incentives with decarbonization goals, while minimizing nonessential fiscal interventions in market operations.

Fourth, regionally differentiated support strategies should be implemented to foster green development tailored to local conditions. Eastern regions should incentivize enterprises to augment resource allocation toward low-carbon technology R&D and application. Industries exhibiting accelerated decarbonization trajectories—particularly those achieving

rapid reductions in carbon emission intensity—should be prioritized for additional carbon emission allowances and green subsidies. Central-western regions should prioritize green technology adoption and scale effects, and capitalize on late-mover advantages by proactively introducing advanced green technologies and management models. In addition, they should enhance educational standards and workforce competence, strengthen vocational skills training, and improve infrastructure development to create favorable conditions for the transfer and upgrading of industries from eastern regions.

5.3. Research Limitations and Future Directions

While this study provides a detailed analysis, several limitations remain, offering avenues for future research: First, the analysis relies exclusively on provincial-level data from China. Future research could expand the scope by incorporating cross-country datasets to explore whether the carbon reduction effects of industrial structure upgrading exhibit heterogeneity across different national contexts. Second, this study focuses on carbon emission intensity. Broader perspectives, such as total carbon emissions and carbon emission performance, could provide a more comprehensive understanding of the relationship between industrial restructuring and environmental outcomes. Third, the current study is confined to macro-level provincial data, lacking granular insights from enterprise-level operations. Future work could utilize firm-specific datasets to investigate how industrial structure upgrading influences carbon emissions at the organizational level, enhancing the practical relevance of policy recommendations.

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