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Research on the Decoupling Relationship and Driving Factors of Carbon Emissions in the Construction Industry of the East China Core Economic Zone

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Abstract: This study focuses on the core economic zone of East China, utilizing the decoupling model to investigate the relationship between carbon emissions and economic development in the construction industry. Furthermore, it analyzes the driving factors through the application of the logarithmic mean index method. The findings reveal that, firstly, Zhejiang and Jiangsu provinces exhibit higher total carbon emissions in the construction industry. Except for Fujian Province, the other regions exhibit a downward trend after 2019. Secondly, there is considerable spatial variability in carbon emissions in the construction industry within the core economic zone of East China, and it gradually decreases over the study period. While economically developed regions like Zhejiang and Jiangsu provinces tend to concentrate and consume more resources and energy, their impact on surrounding neighboring provinces or cities is relatively limited. Thirdly, carbon emissions from the construction industry in the core economic zone of East China show a development trend shifting from weak decoupling to strong decoupling, indicating a healthy growth in the construction industry. Specifically, different regions show different trends. Lastly, regarding influencing factors, the impact direction of carbon intensity on total carbon emissions shows instability. Energy intensity consistently exhibits inhibitory effects, and the economy and the population scale act as driving forces.

Keywords: building carbon emissions; decoupling model; spatiotemporal characteristics; LMDI

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1. Introduction

In the context of global warming, the international community has increasingly focused on greenhouse gas emissions. The Sixth Assessment Report by the IPCC emphasized that the global surface temperature from 2011 to 2020 was 1.1 °C higher than the period of 1850–1900, and human activities have significantly contributed to warming the atmosphere, oceans, and land. Consequently, there is a pressing need to integrate climate change adaptation measures with efforts to mitigate greenhouse gas emissions [1]. In 2019, sixty countries pledged to achieve net zero carbon emissions by 2050 [2,3]. Despite abundant resources, developing countries often face challenges due to a weak economic and technological base, resulting in elevated carbon emissions [4]. As the world's population and economy expand, there is an anticipated increase in the demand for energy, especially in developing countries [5]. Presently, carbon emissions in some developed countries have already peaked and stabilized, whereas a significant number of developing countries continue to experience growth alongside economic development [6,7].

The construction industry is vital to the national economy but concurrently contributes significantly to carbon dioxide emissions, thus exerting a notable environmental impact [8]. It stands as the primary contributor to both global energy consumption and carbon emissions [9]. Consequently, the effective control of carbon emissions within the construction industry holds paramount significance for global efforts to reduce overall carbon emissions.

In 2013, China's carbon emissions constituted 14.4% of the world's total [10]. By 2014, China's contribution to global greenhouse gas emissions had risen to 23.4%, surpassing the US and becoming the largest emitter [11]. The Global State of Building and Construction Report highlights that, in 2021, buildings accounted for around 37% of the world's total carbon emissions [12]. A 2022 Research Report on Energy Consumption and Carbon Emission in China's Buildings further highlights that the overall CO_2 emissions from China's buildings amounted to 5.08 billion tons in 2020, comprising 50.9% of the nation's total emissions [13]. Given these statistics, there is a pressing need to investigate pathways for lowering carbon emissions within the construction industry.

China's extensive land area results in an uneven development of the construction industry across regions, characterized by diverse natural conditions, economic development levels, population sizes, and industrial structures. Consequently, regional disparities in carbon emissions from the construction industry are evident. To develop efficient policies for emission reduction and allocate reduction tasks, it is crucial to consider the specific conditions of each region. Moreover, variations in data statistics among provinces introduce complexities when conducting national comparative analyses, potentially leading to interference factors. China can be categorized into seven major geographical regions based on its plates. Among them, East China covers only 8.7% of the country's land area. However, it houses more than 30% of the population and contributes to nearly 40% of the GDP. Clearly, East China has emerged as the most economically and culturally prosperous region in China. Jiangsu, Zhejiang, Anhui, Fujian, and Shanghai exhibit similar overall economic and cultural levels, encompassing a regional area of 474,000 square kilometers, representing 5% of China's land area. The population of the region stands at 260 million, constituting 1/5 of the country's total population and contributing to 1/3 of the total economic output, making it the core economic circle of East China.

Therefore, based on the imperative need to reduce carbon emissions, this paper takes the representative region of the core economic circle in East China as the research focus. Initially, it elaborates on the spatiotemporal distribution and evolutionary characteristics of carbon emissions in the construction industry from multiple perspectives. Then, it conducts trend and decoupling analyses in five provinces and cities, exploring the relationship between carbon emissions and economic development. Furthermore, it utilizes the logarithmic mean Divisia index (LMDI) model to analyze and study the driving factors, probing into the driving mechanism, and providing policy recommendations for the development of the regional construction industry. In today's context, inter-regional cooperation is paramount. This study investigates carbon emissions in the construction industry from a meso-level perspective, enriching the methodology and approaches for regional-level carbon emission research and addressing the gap in studies on inter-regional relationships in urban agglomerations' building carbon emissions. Through comparative analysis, it offers decision-making support for construction development.

Specifically, this paper contributes in the following ways: (1) Theoretically, current research on construction carbon emissions primarily focuses on individual countries or cities, often overlooking the meso dimension. To address this gap, this paper investigates carbon emissions from the construction industry in five regions of East China. By integrating considerations of spatial and temporal characteristics, decoupling effects, and driver analysis, this study enriches the content for subsequent regional-level carbon emissions research and expands the scope of theoretical exploration within the realm of carbon emission studies. (2) In terms of application, investigating the spatiotemporal variations in the driving factors and decoupling relationships of carbon emissions in five regions in East China reveals the development status of the construction industry and the impacts of various influencing factors on carbon emissions. This contributes to the timely achievement of carbon reduction goals in the construction industry. Additionally, this study offers valuable theoretical support for carbon emission reduction initiatives in East China and establishes a foundational basis for decision-making within the construction industry of each province and region. These insights are instrumental in formulating trans-regional construction development strategies tailored to local conditions.

2. Literature Review

As the world's largest emitter of carbon, China faces significant challenges in reducing carbon emissions from its key industry, the construction industry. Zhang et al. [14] have pointed out that China is confronted with significant challenges in reaching its goals of carbon peak and carbon neutrality. Li et al. [15] predict that China's construction industry will reach its carbon peak by 2045, with the possibility of achieving it as early as 2020 through technological breakthroughs. Chen et al. [16] suggest that China's carbon emissions far surpass those of the United States due to factors such as energy intensity and production structure effects. Du et al. [17] analyzed the carbon emissions from the construction industry in 30 provinces and regions of China and found that different influencing factors have varying effects across provinces and cities, indicating the need for tailored policies based on local conditions. In summary, China's construction industry faces significant challenges in carbon emissions reduction.

2.1. Carbon Emission Calculation Method

Countries, cities, enterprises, and communities demonstrate and exhibit distinct building emission characteristics, leading to variations in their carbon emission calculation methods. Currently, both domestic and international scholars predominantly employ the input–output method, the whole life cycle method, and the factor method.

The input–output method relies on input–output tables for collecting and calculating national statistical data [18]. In the early 1990s, Suzuki et al. [19] quantified energy consumption and CO_2 emissions in construction in Japan using the input–output analysis method. Since then, this method has gained widespread application. Li et al. [20] applied the input–output method to quantitatively evaluate the environmental impacts of construction activities. Li et al. [21] innovatively combined the process analysis method with the input–output method, providing a systematic quantification of greenhouse gas emissions and implied energy consumption for a specific construction project. While the input–output method proves effective in measuring carbon emissions by leveraging interconnections between various industries, the data within these tables often present challenges in terms of accessibility [8].

The whole life cycle assessment involves the calculation of carbon emissions across all stages of a project, spanning from its inception to its termination. Scholars such as Stephan [22] and Crawford [23] have proposed a hybrid life cycle assessment method based on LCA. Hu and Zheng [24] employed life cycle assessment (LCA) to compute the carbon emissions of residential buildings. It is crucial to note that the accuracy of LCA depends on the quality of data acquired from each stage [25]. Nevertheless, the manual and repetitive nature of conducting a complete LCA compromises its precision [26], rendering the method subject to certain limitations. Therefore, the use of LCA in process analysis may introduce significant biases into the conclusions [27].

The carbon emission factor (CEF) method, a widely employed approach for quantifying carbon emissions, involves estimating carbon emissions by multiplying the relevant CEF by the consumption of each carbon emission source and summing the total. Cheng et al. [28] used the CEF to establish a carbon emission accounting system, and identified the residential materialization stage as the main stage affecting carbon emissions. Zhao et al. [29] innovatively combined the carbon emission factor and energy value analysis methods, creating a carbon emission energy value factor (Em-CEF) accounting model. This model effectively addressed the challenge of incomplete databases of carbon emission factors. The majority of current research in this domain is centered around the six or nine main energy types used in the building industry for carbon emission calculations [8]. This study relies on data from the China Energy Statistics Yearbook (CESY) to utilize all available statistical energy sources as the foundation for calculations. This approach is expected to enhance the accuracy of the data analysis.

2.2. Carbon Decomposition Analysis

In the academic community, the most widely acknowledged methods for analyzing factors influencing carbon emissions include the IPAT models, index, and structural decomposition analysis methods.

To illuminate the environmental impacts of population growth, economic development, and technological progress, Ehrlich et al. introduced the IPAT model in 1971 [30]. This model has undergone evolution and is now widely recognized as a formula for understanding the drivers of environmental impacts [31]. The structural decomposition method, grounded in the input–output modeling framework, requires higher data requirements and more intricate calculations compared to the exponential decomposition analysis method [32]. In a study by José M et al. [33], enhanced structural decomposition analysis was employed to scrutinize the CO_2 emission changes in Spain. This analysis broke down changes into carbonation factors, energy intensity, technological factors, structural demand, consumption patterns, and scale factors. Additionally, Liang [34] applied structural decomposition analysis to both consumptions and supplies, quantifying the relative contribution of socioeconomic factors to changes in U.S. greenhouse gas emissions from 1995 to 2009.

The index decomposition methods include the Rasch index and the Diels index method [35]. The logarithmic mean Diels index (LMDI), due to its broad applicability, has been widely used. Ding and Li [36] examined the influence of diverse factors on CO_2 emissions across 30 provinces through the LMDI model. Additionally, Feng et al. [37] conducted a comprehensive analysis of the status, factors affecting, and trends in carbon emissions from rural buildings in a typical southern Chinese village, employing the CFE and the LMDI-LEAP model. The LMDI method, known for its strong applicability and clear analytical path, possesses advantages in handling zero values in the data and eliminating residual terms during the process of factor decomposition of the target variables [38]. This study, therefore, employs the LMDI method to analyze the drivers of construction industry carbon emissions.

In driver selection, numerous studies suggest that the Kaya model is an effective method for identifying factors driving carbon emissions in the construction sector. Tian et al. [39] applied the Kaya identity to decompose carbon intensity into four driving factors and conducted an analytical study. Lai et al. [40] investigated the relationship between carbon emissions in the Chinese construction sector and various driving factors based on an improved version of the Kaya model. Ma et al. [41] expanded and decomposed the Kaya identity using the LMDI method to study the driving factors of carbon emissions in commercial buildings in China. Therefore, this paper selects driving factors based on the Kaya identity equation.

2.3. Carbon Emissions and Economy

The analysis of the carbon emissions and economic relationship centers on the environmental Kuznets curve (EKC) and Tapio decoupling theory. While the EKC explores long-term trends, Tapio decoupling focuses on short-term trends.

Following Grossman and Krueger's proposal of the EKC to illustrate the link between economic factors and environmental pollution, a growing number of scholars have adopted this framework [42]. Ozturk et al. [43] explored the causal relationship among trade, economic growth, energy consumption, and carbon emissions in Turkey. The findings validated the EKC hypothesis in the Turkish economy. In a study by Liu [44], a Kuznets curve model was established to examine the inverted U-shaped relationship between CO_2 emissions and the regional economy, revealing the existence of a Kuznets curve between the two.

Decoupling theory, introduced by the OECD, stands as a fundamental theory and a vital tool for examining the interplay between economic and environmental pressures [45]. Wu et al. [46], Huo et al. [47], and Ma et al. [41] applied the model to assess the decoupling relationship between economic development and building carbon emissions in China. In this paper, we utilize the Tapio decoupling approach to investigate carbon emissions from construction in the central economic region of East China.

3. Data and Methodology

3.1. Data

The input–output method [21], the whole life cycle method [24], and the carbon emission factor method [28,29,38,48] are widely applied in calculating carbon dioxide emissions. Considering the research objective, this paper selects the emission factor method, currently the most extensively used, as the calculation method.

To provide a more objective and accurate reflection of CO_2 emissions, this paper chooses all energy sources as the basis for calculating direct carbon emissions. Specifically, this includes coal, coke, gasoline, diesel, thermal energy, electricity, and so on. With the exception of electricity and thermal energy, the rest can be calculated using the aforementioned methods. Indirect carbon emissions mainly originate from five major building materials: wood, steel, cement, glass, and aluminum.

The calculation model is shown below:

$$EF_{CO2,i} = HV_i \times C_i \times OX_i \times 44/12 \times 10^{-6} \tag{1}$$

$$C_{dir} = \sum_{i=1}^{9} C_i \times EF_i \tag{2}$$

where EF_i denotes the carbon emission factors of type i energy, C_i denotes the carbon content per unit calorific value of type i energy, OX_i denotes the oxidation rate of fuel type i, "44/12" denotes the molecular weight, C_{dir} denotes the total direct carbon emissions from the construction sector, C_i denotes the final consumption of type i energy.

$$C_{ind} = \sum_{i=1}^{5} C_j \times d_j \times (1 - \beta_j) \tag{3}$$

where C_{ind} denotes the total indirect carbon emissions, C_j denotes the consumption of type j building materials, d_j denotes the carbon emission factors for building materials, β_j denotes the recovery coefficient.

According to the document from the Chinese Ministry of Ecology and Environment, the calculation of carbon dioxide emissions from electricity uses the emission factor data released by the respective regional power grids. The default emission factor for heat is set at 0.11 t CO_2/GJ.

In this paper, the end-use consumption of energy (in physical terms) in "China Energy Statistical Yearbook (2007–2021)" is selected as the consumption of each type of energy (the current published data are only available until 2021). The discounted standard coal coefficients are taken from the "General Rules for Calculating Comprehensive Energy Consumption GBT2589-2020" [49] and the "Statistical System for Energy Resource Consumption in Public Organizations". Carbon content per unit calorific value is mainly from the "Guidelines for the Preparation of Provincial Greenhouse Gas Inventories (Trial)", and some unrelated data refer to the "2006 IPCC Guidelines for National Greenhouse Gas Inventories".

3.2. Decoupling Model

The decoupling model finds applications in various domains such as resources, environment, transportation, construction, and the economy. Its applications include the decoupling problem in energy consumption [50,51], agricultural resource utilization [52,53], and electricity consumption [54]. Carbon decoupling means a gradual reduction in energy consumption based on economic growth [55]. Building upon this concept, Vehmas et al. [56] established a framework. Utilizing this framework, Tapio [57] proposed eight states of decoupled relationships to further assess the decoupling dynamics of the study subject over a specific timeframe. The specific correspondences for decoupling states are detailed in Table 1. According to the calculation formula and corresponding data, the decoupling coefficient values are computed, with different values corresponding to different states. Based on these different decoupling states, the relationship between carbon emissions and local economic conditions can be assessed, thereby clarifying the developmental status of the construction sector in the area.

Table 1. Tapio's decoupling status.

T	ΔG	ΔC	Decoupling Status	
>1.2	>0	>0	Negative decoupling	Expansion
<0	<0	>0		Strong
0 < T < 0.8	<0	<0		Weak
0 < T < 0.8	>0	>0	Decoupling	Weak
<0	>0	<0		Strong
>1.2	<0	<0		Recessive
0.8 < T < 1.2	>0	>0	Coupling	Expansive
0.8 < T < 1.2	<0	<0		Recessive

This paper will use the Tapio decoupling model with the calculation formula as follows:

$$T = \frac{CP}{GP} = \frac{\Delta C/C}{\Delta G/G} \tag{4}$$

Here, T denotes the decoupling index, CP denotes the rate of change in carbon emissions from the construction sector, GP denotes the rate of change in GDP, ΔC denotes the change in carbon emissions from the construction sector in year n over year $n + 1$, C denotes the building carbon emissions in year n, ΔG denotes the value of the change in the gross value of construction output in year n over year $n + 1$, G denotes the gross regional product in year n.

0, 0.8, and 1.2 are three particular elasticity values specified by Tapio's decoupling theory, according to which a distinction can be made between the decoupling status of carbon emissions and economic growth. When the elasticity coefficient is greater than 1.2, the carbon emissions are expansion negative decoupling or recession decoupling. When the elasticity coefficient is less than 0, the carbon emissions are negative decoupling or strong decoupling.

3.3. The LMDI Method

The Kaya identity, first introduced during the 1989 IPCC workshop, is a correlation equation that gauges the impact of anthropogenic factors on the climate [58]. Widely acknowledged for its effectiveness in decomposing carbon emissions factors, the Kaya model employs a straightforward formula to break down carbon dioxide emissions into components like policy, population, and economy. In this study, the CO_2 emission influences are decomposed into four driving factors based on the Kaya identity equation. The specific representation is as follows:

$$C = \frac{C}{E} \times \frac{E}{G} \times \frac{G}{P} \times P = C_E \times E_G \times G_P \times P \tag{5}$$

Here, C denotes CO_2 emissions, E denotes energy consumption, G denotes GDP, P denotes population, C_E (C/E) denotes CO_2 emissions per unit of energy consumption, E_G (E/G) denotes energy intensity, and G_P (G/P) denotes GDP per capita.

The LMDI method, first proposed by Ang [59], allows for the decomposition of the target variable, exhibiting strong applicability and effectively avoiding residual problems [60]. With a clear analytical approach, it finds extensive application in identifying and analyzing factors that influence carbon emissions. To reflect the specific impact of each factor on carbon emissions, this study decomposes the changes in carbon emissions using factors derived from the Kaya model and employing the LMDI model.

According to the LMDI model, let the decomposition period be [0, T]. C_T represents the carbon emissions from the construction industry in period T, and C_0 represents the carbon emissions from the construction industry in the initial period. Employing the additive model for decomposition, the LMDI decomposition equation from the rolling base period year to period T is as follows:

$$\Delta C = C^T - C^0 = \Delta C_{CE} + \Delta C_{EG} + \Delta C_{GP} + \Delta C_P \tag{6}$$

where ΔC_{CE}, ΔC_{EG}, ΔC_{GP}, ΔC_P denote the carbon emission factor, the energy intensity factor, the economy factor, and the population factor, respectively. The formula for each factor is as follows:

$$\Delta C_{CE} = \ln\left(\frac{C_E^T}{C_E^0}\right) \times \frac{C^T - C^0}{\ln C^T - \ln C^0} \tag{7}$$

$$\Delta C_{EG} = \ln\left(\frac{E_G^T}{E_G^0}\right) \times \frac{C^T - C^0}{\ln C^T - \ln C^0} \tag{8}$$

$$\Delta C_{GP} = \ln\left(\frac{G_P^T}{G_P^0}\right) \times \frac{C^T - C^0}{\ln C^T - \ln C^0} \tag{9}$$

$$\Delta C_P = \ln\left(\frac{P^T}{P^0}\right) \times \frac{C^T - C^0}{\ln C^T - \ln C^0} \tag{10}$$

4. Results

4.1. Total Carbon Emissions in the Construction Industry

Utilizing the aforementioned calculation method, carbon emissions in the five regions were computed for the period spanning from 2007 to 2021. The outcomes are illustrated in Figure 1. The analysis reveals that the period from 2007 to 2021 can be delineated into three distinct phases: an ascending phase (2007–2012), a descending phase (2013–2015), and a stabilized phase (2016–2021). This is almost consistent with the analytical results obtained by Zhou et al. [60].

Throughout the study period, carbon emissions exhibited a continual increase starting in 2007, reaching a peak in 2012. The rapid development was propelled by social progress. In response to the global financial turmoil in 2008 and to stimulate domestic demand, China initiated the "Four Trillion Plan", aiming to construct a substantial amount of infrastructure within the construction sector. This initiative significantly contributed to the swift expansion of the construction industry. However, the construction industry was characterized by its predominantly crude nature in this period, with both emission reduction technology and environmental awareness at a nascent stage. Consequently, construction carbon emissions experienced substantial growth from 2007 to 2012.

Carbon emissions from the construction sector entered a declining phase from 2013 to 2015, reaching their lowest point in 2015. In 2013, the Chinese government introduced the "Green Building Action Program", advocating for the construction industry's development along the path of green, recycling, and low-carbon scientific principles. This program addressed various aspects, including concepts, standards, and measures, to foster a more environmentally sustainable trajectory for the construction industry.

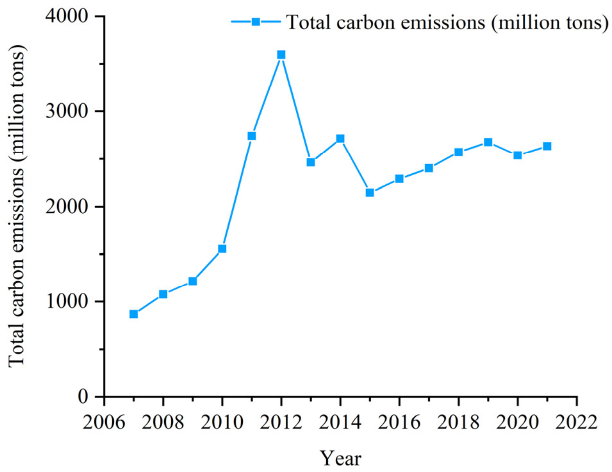


Figure 1. Trends during 2007–2021.

From 2016 onward, carbon emissions from the construction sector plateaued. The concept of "low-carbon development" gained increasing popularity, and there was a gradual formation of a green development path for the construction industry through policy guidance, technological advancements, and standard setting. As a result, carbon emissions have been more effectively controlled. The calculation of carbon emissions from the construction sector in the five regions of the core economic circle in East China is illustrated in Figure 2.

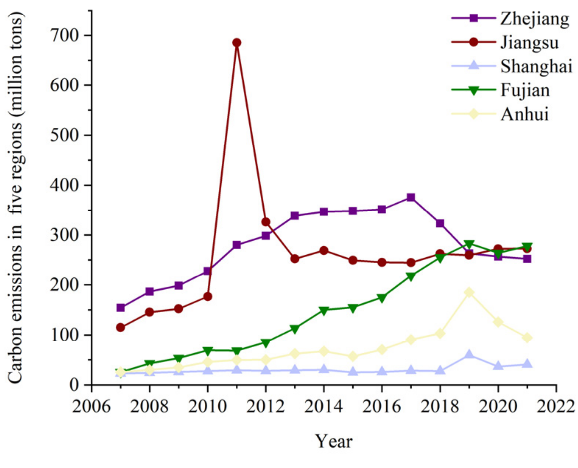


Figure 2. Carbon emissions in the five regions.

It is observed that the total carbon emissions in Zhejiang Province exhibit a pattern of growth followed by a decline, reaching its peak in 2017. This trend can be attributed to the recent implementation of stringent policy requirements in Zhejiang Province aimed at fostering green and sustainable development. The formulation of local construction standards and continuous efforts to drive the transformation of the construction sector have proven effective in mitigating the growth of carbon emissions.

Except for an abnormal spike in 2011, the overall trajectory of carbon emissions in Jiangsu Province has been ascending. Post-2013, carbon emissions in Jiangsu have stabilized, indicating a positive trend towards green development. The outlier in 2011 can be primarily attributed to an exceptionally high consumption of cement during that year, exceeding the previous year's consumption by four times. Cement constitutes a significant source of carbon emissions within the construction sector [61]. In 2011, cement prices in Jiangsu Province soared by as much as 44.90% due to supply shortages. Anticipating further price increases, some construction companies stockpiled large quantities of cement. Additionally, according to the list of key projects published by the Jiangsu Provincial Development and Reform Commission in 2011, a significant number of large-scale infrastructure or heavy industrial projects were initiated in Jiangsu Province, including roads, bridges, ports, and so on, which also consumed substantial amounts of cement. Therefore, an abnormal peak phenomenon occurred in 2011.

The overall carbon emissions in Shanghai have exhibited relative stability throughout the study period, with a slight upward trend. This trend can be attributed to the constraints imposed by Shanghai's administrative area and population size.

Carbon emissions in Fujian Province consistently increased from 2007 to 2021, with the highest relative increase compared to other regions. The construction sector plays a pivotal role in Fujian's economy. Despite the province's efforts to promote high-quality development and implement energy conservation measures in the construction industry, the efficiency of carbon emission remains in the mid-to-lower range nationally.

Carbon emissions in Anhui Province experienced a continuous increase from 2007 to 2019, reaching a peak in 2019, followed by a decline. In the course of advancing the construction sector, Anhui Province has proactively promoted the development of green buildings, aiming to ensure the sustainable and healthy growth of the construction industry. As a result of these efforts, carbon emissions in Anhui Province have been maintained at a relatively low level.

Overall, Anhui and Fujian provinces exhibit gaps in industrial scale, structural rationality, regulatory intensity, and the industrial modernization process when compared to the robust construction industry in Jiangsu and Zhejiang provinces. Therefore, there is an opportunity for them to learn from the experiences of more advanced provinces in reducing carbon emissions, thereby facilitating the transformation and upgrade of their construction industries.

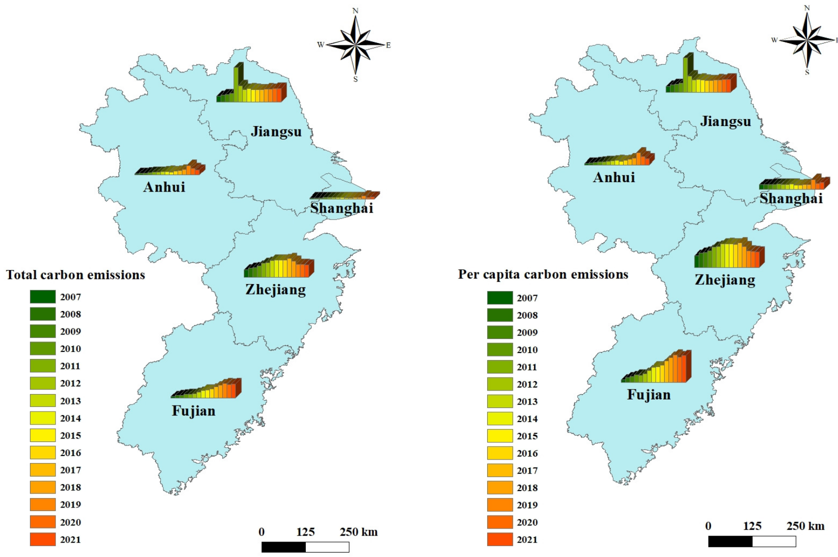
4.2. The Spatiotemporal Evolution Characteristics

4.2.1. Characteristics of Spatial Evolution

A graphical representation is created using the data on total and per capita carbon emissions in five regions from 2007 to 2021 as a foundation, with column heights indicating the respective emission levels.

As depicted in Figure 3a, the overall trend in the five regions of East China shows an upward trajectory from 2007 to 2021. The total emissions increased from 340 to 940 million tons, with an average annual growth of approximately 40 million tons. The distribution of carbon emissions in East China appears uneven, posing a significant challenge for future carbon emission reduction efforts. Except for Fujian Province, other provinces and cities exhibit a downward trend after around 2019. This decline can be attributed to proactive efforts in developing energy-saving industries, implementing green building initiatives, emphasizing environmental and ecological protection, and enhancing the overall levels of green construction and building management.

As depicted in Figure 3b, the overall trend of per capita carbon emissions shows an upward trajectory from 2007 to 2021. Anhui Province and Shanghai Municipality consistently maintain low per capita carbon emissions, generally not exceeding 2 tons per person. While Zhejiang Province consistently records high per capita carbon emissions, Fujian Province experiences a significant increase, surpassing Zhejiang Province in 2018 and becoming the highest among the five regions.



(**a**) (**b**)

Figure 3. Spatial and temporal variation. (**a**) Total carbon emissions; (**b**) carbon emissions per capita.

4.2.2. Spatial Correlation Characteristics of Carbon Emissions

The Moran's I index is categorized into global and local indexes. The global Moran's I index, developed by Patrick Alfred Pierce Moran [62], serves as a measure of spatial autocorrelation. In contrast, the local Moran's I index was introduced by Prof. Luc Anselin [63] in 1995.

The Moran's I index varies from [−1, 1]. Values larger than 0 indicate a positive correlation, with larger values indicating a stronger correlation. Conversely, values less than 0 signify a negative correlation, with smaller values indicating greater spatial disparity [64].

(1) **Global spatial autocorrelation features**

The global Moran's I index from 2007 to 2021 was calculated using GeoDa software (version 1.20.0.36), as illustrated in Figure 4. The Moran's I index for per capita carbon emissions was negative before 2017, indicating spatial variability among the five regions. However, it shifted to a positive value after 2017, suggesting a gradual reduction in spatial variability and the emergence of some correlation. After 2017, neighboring areas in the five regions exhibited similar characteristics or attributes in per capita carbon emissions, with fluctuating values between 0.066 and 0.158, indicating a moderate but slightly weaker correlation.

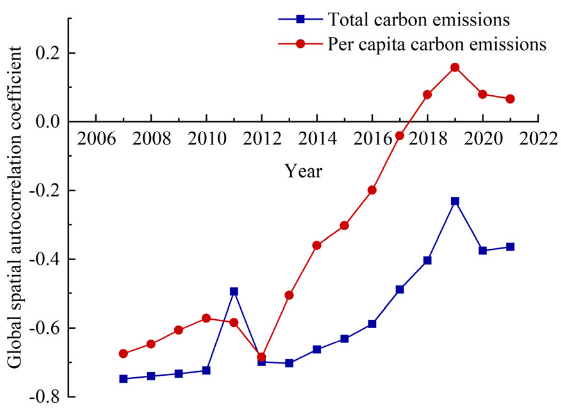


Figure 4. Autocorrelation coefficients of total and per capita carbon emissions.

The global Moran's I index for total carbon emissions consistently remains in negative territory, indicating significant spatial variability in carbon emissions within the East China region. As time progresses, the value gradually increases, signifying a reduction in spatial variability.

(2) **Local spatial autocorrelation features**

The local spatial autocorrelation analysis was conducted using GeoDa software to generate the respective LISA maps. The study spans from 2007 to 2021, with selected LISA maps for the years 2007, 2011, 2016, and 2021 chosen for representative analysis. Figures 5 and 6 depict the LISA aggregation maps for both total and per capita carbon emissions across the five regions of East China from 2007 to 2021.

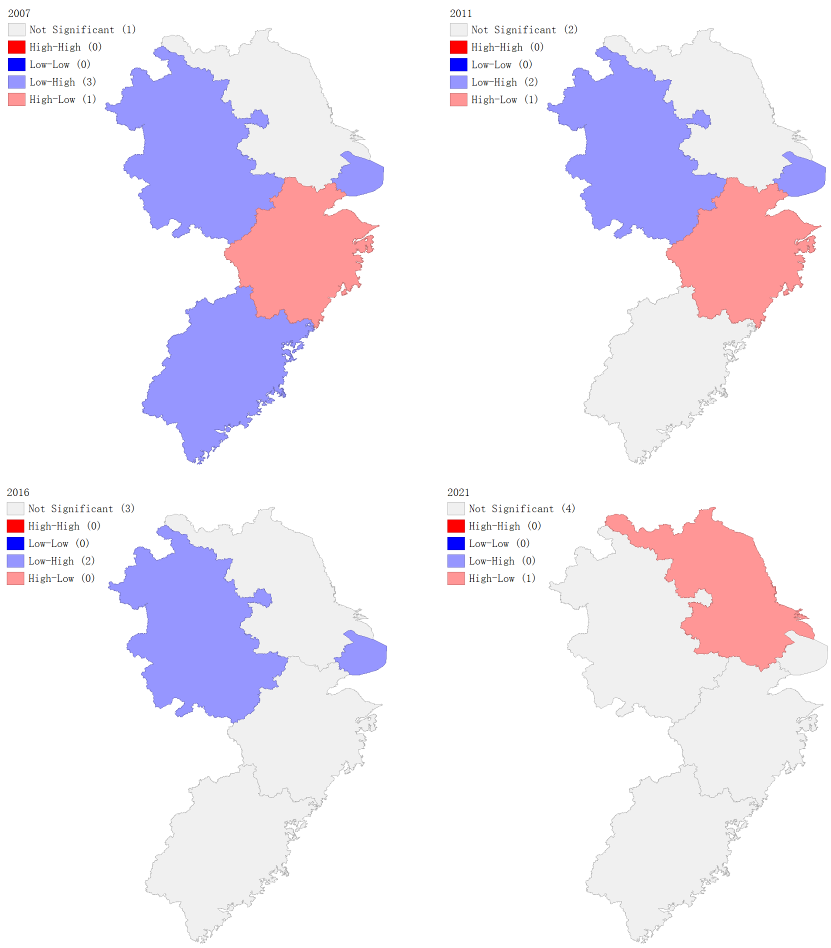


Figure 5. LISA aggregation of total carbon emissions.

Regarding the total carbon emissions, there were no significant high–high or low–low aggregations between 2007 and 2021. Instead, a consistent pattern of stable high–low aggregation was observed in Zhejiang Province, high–low aggregation in Jiangsu Province, low–high aggregation in Shanghai Municipality, and low–high aggregation in Anhui Province. This indicates that in the economically developed regions of Zhejiang and Jiangsu, there is an accumulation of greater resources and energy consumption. However, due to spatial negative correlation, the increase in construction industry carbon emissions within these provinces does not extend to neighboring provinces or cities.

In terms of per capita carbon emissions, there were no significant high–high or low–low aggregations in the five regions between 2007 and 2021, except for a low–low aggregation observed in Jiangsu Province in 2020. In other years, a more consistent high–low aggregation was noted in Zhejiang Province, low–high aggregation in Shanghai Municipality, low–high aggregation in Anhui Province, and low–high aggregation in Fujian Province. This pattern aligns closely with the earlier analysis of the Moran's I index. Zhejiang Province consistently exhibited a high–low aggregation, indicating its status as a hotspot region.

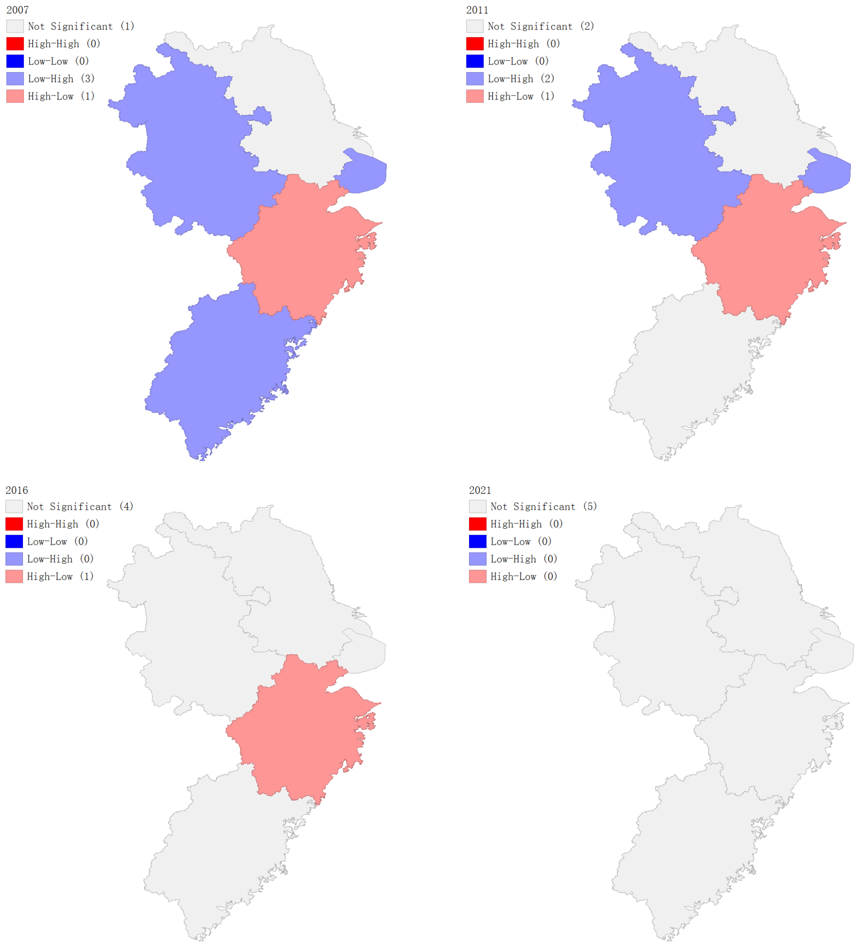


Figure 6. LISA aggregation of carbon emissions per capita.

4.3. Decoupling Analysis

4.3.1. Status of Economic Development in the Construction Industry

According to Figure 7, the overall trend in the five regions is on the rise. Jiangsu and Zhejiang provinces stand out with a high level of gross output value, while Anhui and Fujian provinces exhibit lower values. However, overall, all regions show a rapid and stable growth pattern. Jiangsu and Zhejiang provinces experience a significant increase in the gross output value of the construction industry, with Jiangsu consistently leading the charts. In contrast, Zhejiang Province witnessed a slight decrease in 2019. Additionally, due to factors such as geographical area, Shanghai's construction industry's gross output value has been gradually stabilizing with a slowing growth rate. Overall, the distribution of the construction industry's gross output value among the five regions in the East China region is uneven.

It is noteworthy that in 2011, carbon emissions in Jiangsu Province saw a significant increase, while the gross output value did not show a corresponding surge. This was primarily due to the sharp rise in cement prices during that year, prompting construction companies to stockpile cement, which significantly increased carbon emissions from construction activities, but this additional consumption did not immediately translate into economic output. Furthermore, in 2011, Jiangsu Province witnessed a significant increase in large-scale infrastructure and heavy industry projects. These types of projects typically require the substantial use of materials like cement, but their contribution to the overall output of the construction industry is relatively small.

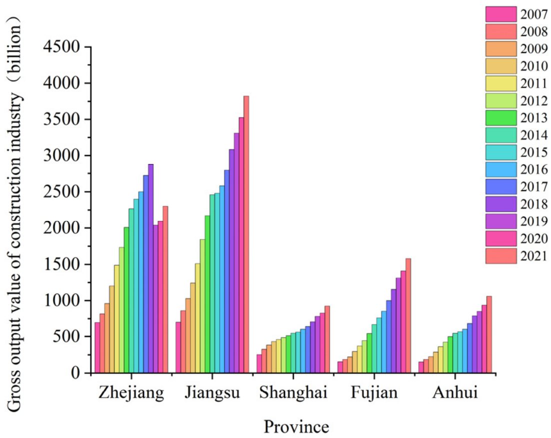


Figure 7. Gross output value of construction industry in the five regions.

4.3.2. Decoupling Result

The decoupling index of the five regions is calculated from 2007 to 2021, as shown in Figure 8. From the decomposition results, the carbon emissions in the five regions generally show a development trend from weak to strong decoupling. The development is relatively healthy and has stabilized in recent years. This is almost consistent with the findings of Zhou et al. [60]. Overall, Zhejiang, Jiangsu, and Shanghai are in a better state of development, and there is still room for optimization in Anhui and Fujian.

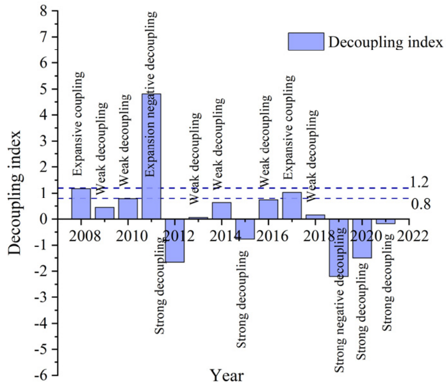


Figure 8. Decoupling index in five regions.

As shown in Figure 8, from 2007 to 2021, the construction industry exhibited an overall developmental trend in carbon emissions, transitioning from weak decoupling to strong decoupling. Initially dominated by a weak decoupling state, carbon emissions gradually stabilize in a strong decoupling state with the progression of time. While instances of strong negative decoupling and expansionary negative decoupling occasionally occur, their probability is extremely low and often attributed to incidental factors. Overall, the industry is making continuous strides towards green and low-carbon development, with recent years indicating a trend towards stability.

According to Figure 9, Zhejiang experienced seven instances of weak decoupling, making it the most frequently observed decoupling state. This state indicates that both the carbon emissions and gross output value of the construction industry in Zhejiang Province have shown growth. However, the carbon emissions are notably lower than the growth rate of the gross output value, presenting a relatively favorable developmental state. The overall trend of Zhejiang exhibits a transition from weak decoupling to strong decoupling. Although occasional occurrences of expansion negative decoupling and weak negative decoupling states have been observed, their likelihood is extremely low. On the whole, the development in Zhejiang appears relatively healthy, with a recent trend of maintaining stability.

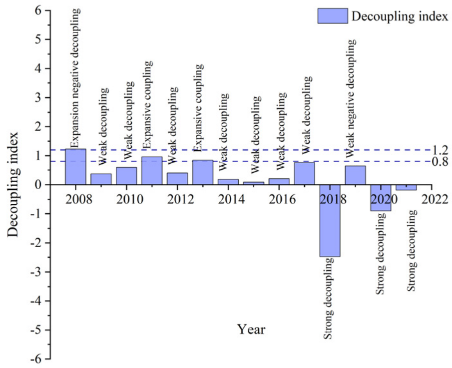


Figure 9. Decoupling index in Zhejiang Province.

According to Figure 10, spanning from 2007 to 2021, Jiangsu Province experienced occasional instances of expansive coupling and expansion negative decoupling. However, the likelihood of such occurrences is exceedingly low, with most incidents concentrated in the early part of the study period. Jiangsu Province is predominantly characterized by strong and weak decoupling states, each occurring six times, collectively accounting for 85.71% of the instances. This suggests that Jiangsu Province has exhibited a pattern of stable and healthy development throughout the study period.

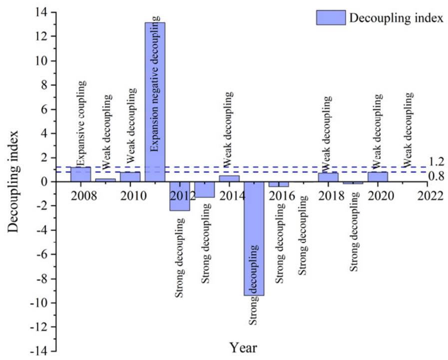


Figure 10. Decoupling index in Jiangsu Province.

According to Figure 11, Fujian Province witnessed six instances of negative decoupling expansions between 2007 and 2021, primarily concentrated in the early part of the study period. Through a series of measures, including the transformation of the construction industry and the adoption of efficient green technologies, it gradually transitioned towards a state of strong and weak decoupling. Over the study period, the probability of strong decoupling and weak decoupling is 35.7%. Notably, these two states, indicative of healthier development, were more prevalent in the period from 2019 to 2021. This suggests that the construction industry in Fujian Province is progressively moving towards a more desirable state, but achieving stability in this state will require concerted efforts from all stakeholders. In general, the construction industry in Fujian exhibits a slightly less favorable overall trend compared to Zhejiang and Jiangsu provinces. However, the development prospects of Fujian are relatively optimistic.

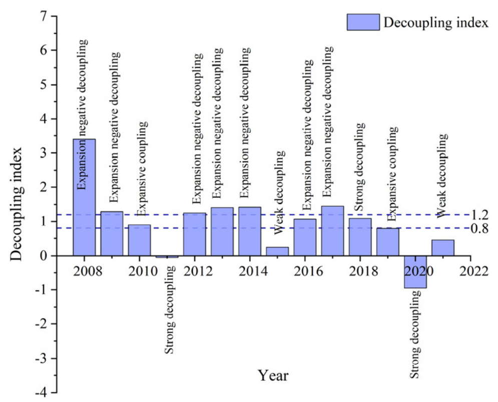


Figure 11. Decoupling index in Fujian Province.

According to Figure 12, Anhui Province was primarily characterized by strong and weak decoupling, gradually stabilizing in a strong decoupling state in the later stages. The proportion of occurrences of expansion negative decoupling and expansive coupling states was approximately 42.9%. Anhui Province experienced weak decoupling five times and strong decoupling three times, accounting for about 57.1% of the total. However, the occurrence of strong and weak decoupling states in Anhui Province is unstable. Continuous measures are required to promote healthy development and maintain a stable and favorable development trend. The overall development trend in Anhui Province appears moderate, with the states of strong and weak decoupling exhibiting instability. In comparison to Zhejiang and Jiangsu provinces, a discernible gap remains.

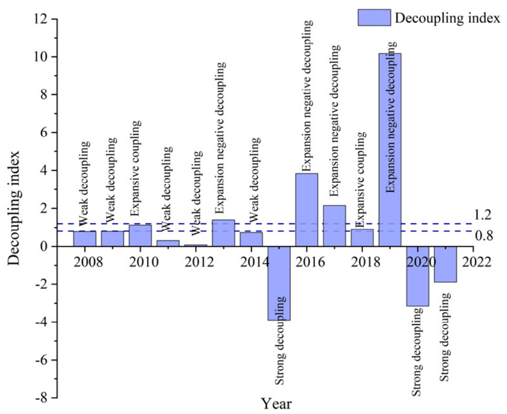


Figure 12. Decoupling index in Anhui Province.

According to Figure 13, Shanghai experienced two instances of expansion negative decoupling in 2016–2017 and 2018–2019, and two instances of expansive coupling in 2010–2011 and 2020–2021. The probability of these less desirable states was relatively low but predominantly occurred towards the end of the research period, indicating an unfavorable trend in decoupling states. Shanghai encountered weak decoupling six times and strong decoupling four times during the research period, collectively accounting for 71.5%. This suggests that the development of the construction industry in Shanghai presents an ideal state. Overall, the construction industry in Shanghai demonstrated relatively healthy development, but the decoupling states towards the end of the research period were less than ideal, emphasizing the need to enhance stability for sustained and healthy growth.

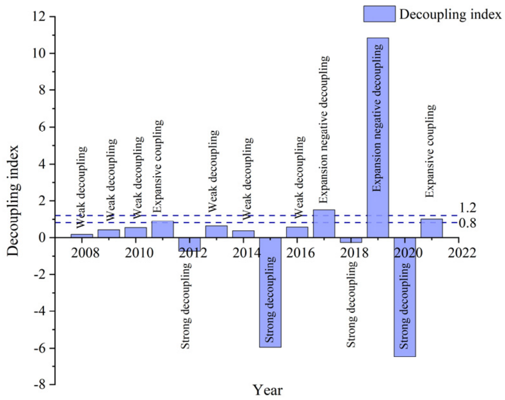


Figure 13. Decoupling index in Shanghai Province.

4.4. Results of Driver Analysis

The influencing factors are the basis for the differences in carbon emissions. In this section, the LMDI model is used to analyze the drivers of carbon emissions in Zhejiang, Jiangsu, Fujian, Anhui, and Shanghai provinces, respectively.

Observing Figure 14, in Zhejiang, it is evident that the economy is the primary factor contributing to the increase in carbon emissions, followed by the population. Li et al. [15] identified total GDP as the most critical driver of carbon emissions in the construction sector. This result is consistent with the findings of this study. In contrast, the decomposed values of energy intensity are mostly negative, indicating that this factor inhibits carbon emissions. Carbon intensity exhibits varying directional effects during different periods, with inconsistent impacts at different times.

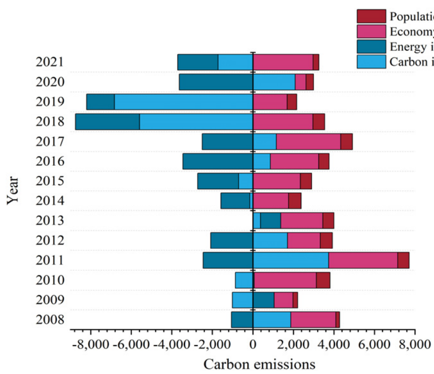


Figure 14. Decomposition values in Zhejiang.

The influence of carbon intensity varies significantly. The main reason for that is the lack of a clear pattern in the changes in the carbon emission intensity driving factor value, resulting in no discernible trend. Zhejiang Province witnessed a gradual reduction in energy intensity, a decrease in energy consumption per unit GDP, and an improvement in energy consumption efficiency. Particularly, from 2014 to 2018, the emission reduction effect of energy intensity was remarkably evident, providing momentum to curb carbon emissions. Therefore, optimizing the energy consumption structure and enhancing the technological level can effectively reduce carbon emissions in the construction industry. Population scale had a driving effect on carbon emissions during the research period, although slightly weaker compared to the economy. In recent years, Zhejiang Province has implemented various policies to attract talent, resulting in a continuous net influx of population, thereby increasing regional economic vitality to some extent and promoting industry development.

As shown in Figure 15, in Jiangsu, the economy is the primary reason for the increase in carbon emissions, followed by the population scale. Carbon intensity mostly contributes to the increase in most years, while energy intensity generally inhibits it. These two factors have not entirely consistent directional impacts. Except for the years 2010–2011 and 2018–2019, energy intensity has predominantly played a role in suppressing construction-related carbon emissions in other years. Overall, energy intensity is the key factor driving the reduction in carbon emissions. Particularly, the emission reduction effect of energy intensity was remarkably evident during 2019–2020. The economy consistently had a promoting effect on carbon emissions, contributing to an annual growth in carbon emissions exceeding 10 million tons.

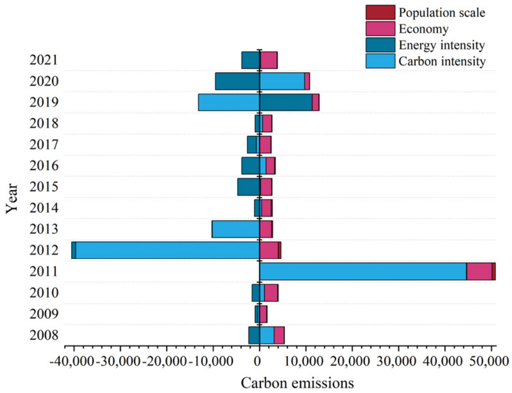


Figure 15. Decomposition values in Jiangsu.

As shown in Figure 16, the economy is a significant factor in the increase in carbon emissions. For Fujian Province, investigating how to achieve green, efficient, and energy-saving development in the construction industry is a crucial topic. Population scale has a driving effect during the research period, albeit a slightly weaker one. Fujian Province experienced a net increase in population, although the growth rate was lower compared to Zhejiang and Jiangsu provinces. The impact of population-induced carbon emissions growth is marginal, emphasizing the continued importance of attracting talent for urban development. Carbon intensity generally promotes carbon emissions in Fujian. The overall trend of the carbon intensity factor value in Fujian Province shows an increase during the research period. Therefore, focusing on developing the technological level of the construction and optimizing the energy industry structure becomes a crucial emphasis for controlling carbon emissions. Energy intensity, on the other hand, predominantly inhibits carbon emissions. The overall trend of the energy intensity driving factor value shows a decrease during the research period. The increase in the GDP generated by unit energy consumption has a positive impact, playing a good role in suppressing carbon emissions.

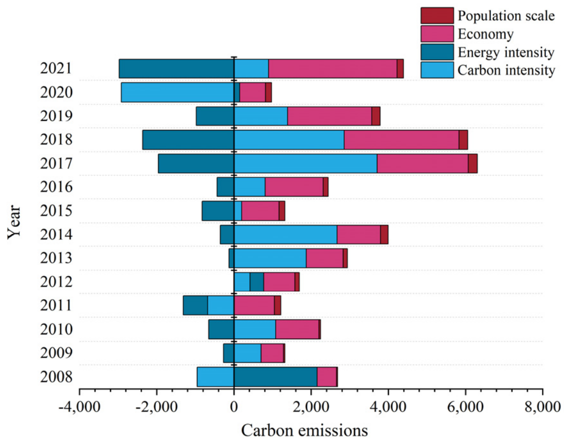


Figure 16. Decomposition values in Fujian.

As shown in Figure 17, in Anhui, the impact of carbon intensity exhibits significant variability. Unlike Jiangsu and Fujian provinces, where the promoting effect is more pronounced, Anhui Province shows a mixed trend, with seven years demonstrating a promoting effect and the remaining seven years showing a restraining effect. The overall impact of energy intensity on construction-related carbon emissions in Anhui Province tends to be inhibitory. The driving factor value of energy intensity shows a decreasing trend during the research period, indicating an overall improvement in energy consumption efficiency. The economy consistently plays a driving role in carbon emissions. Especially in recent years, its driving effect on the growth exceeds 10 million tons annually. The per capita construction GDP in Anhui Province has continued to increase over the years, reflecting a trend of rapid development. The inevitable choice is to follow the path of green and efficient development. Regarding population scale, it generally drives construction-related carbon emissions, except for the years 2008–2010, where a restraining effect is observed. However, the fluctuations in population inflow and outflow in Anhui Province are not substantial, resulting in a relatively weak impact on construction-related carbon emissions.

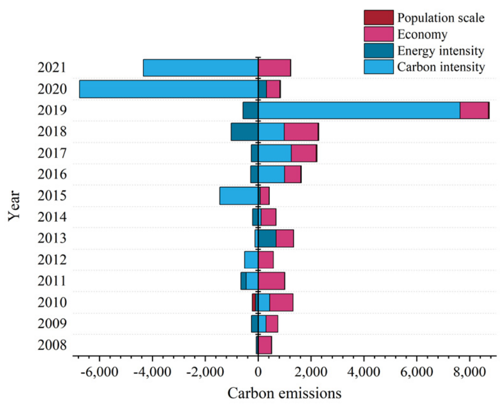


Figure 17. Decomposition values in Anhui.

Observing Figure 18, the driving factor of carbon intensity in Shanghai exhibits inconsistent directional fluctuations during the research period, resulting in an overall lack of apparent regularity in their impact on carbon emissions. Except for the period between 2019 and 2020, the impact of energy intensity acts as a constraint. The economy consistently promotes carbon emissions, highlighting its pivotal role in driving the increase in carbon emissions. Except for 2016–2017, the population scale factor in Shanghai positively drives construction-related carbon emissions. The negative value in 2016–2017 is attributed to a decrease in the total population in 2017 compared to 2016, leading to a reduction in the overall carbon emissions.

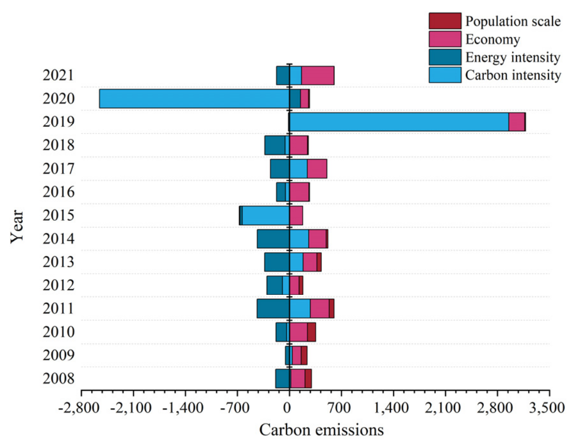


Figure 18. Decomposition values in Shanghai.

5. Conclusions and Policy Recommendations

5.1. Conclusions

This paper focuses on the five regions of East China, which serve as hubs for China's economic resources. It utilizes decoupling and LMDI models to analyze carbon emissions in the construction industry. On one hand, this study investigates the overall and individual development status and driving factors of carbon emissions in urban agglomerations, providing policy recommendations for the development of the construction industry in various provinces and urban clusters. On the other hand, it expands the theoretical research framework of carbon emissions in the construction industry at the meso level, laying the foundation for research applications on carbon emissions in other regions and future scenarios. The specific conclusions are as follows:

(1) Analyzing the evolutionary characteristics of carbon emissions from the construction industry in five regions of East China, this study reveals that Zhejiang and Jiangsu provinces exhibit large overall carbon emissions, while Anhui and Fujian provinces show relatively smaller emissions. Carbon emissions are to some extent linked to the level of regional development. Shanghai, due to its small area and population, has a comparatively lower total carbon emission. With the exception of Fujian Province, the other provinces and cities show a certain downward trend after around 2019. This trend contributed to the active pursuit of energy-saving initiatives and the enhancement of green construction and building management practices in these regions. However, Fujian Province still needs to step up its efforts to push for green development.

(2) Analyzing the spatial correlation characteristics of carbon emissions in the five regions of East China, this study reveals that the spatial difference is substantial. However, this difference gradually decreases over the study period. Per capita carbon emissions in the five East China regions were relatively high before 2017. In recent years, the spatial differences have gradually reduced, and a certain correlation has emerged. Additionally, the two more economically developed regions, Zhejiang and Jiangsu provinces, aggregate to consume more resources and energy, but their impact on neighboring provinces or cities is not significantly greater.

(3) Analyzing the decoupling of carbon emissions in the five regions of East China, this study reveals a general trend of development from weak decoupling to strong decoupling. The development is relatively healthy and has stabilized in recent years across the five regions. Specifically, the construction industry in Zhejiang, Jiangsu, and Shanghai is in a favorable state, while there is still room for optimization in Anhui and Fujian provinces. For the Anhui and Fujian provinces, strengthening low-carbon technology and facilitating information exchanges between regions can be effective strategies to expedite the transformation of the development mode.

(4) Analyzing carbon emission drivers in the five regions of East China, the research indicates that the directional impact of the carbon emission factor is unstable. This instability is primarily due to fluctuating values of the driving factor. The impact of energy intensity consistently has a suppressive effect, as the overall values of the driving factors for energy intensity show a declining trend. The economy drives the total carbon emissions. This is evident as the values of the economy in the construction industry have continuously increased throughout the study period, with Jiangsu and Zhejiang provinces experiencing the fastest growth rates. The population scale in the five regions also drives the total carbon emissions. With the exception of a significant decrease followed by an increase in the total population of Anhui Province, the populations in the other provinces and cities are experiencing positive growth trends.

The five regions of East China have always been at the forefront of China's reform. Conducting targeted research on them has established a theoretical framework for urban clusters in other regions of China. Furthermore, targeted recommendations based on the research results can reduce the total carbon emissions of the urban cluster's construction industry, and provide exemplary guidance for other provinces and municipalities, which can lead to an overall reduction in carbon emissions nationwide and facilitate China's early achievement of the "carbon neutrality" goal in turn. The research methods and logical framework used in this study can also offer insights into the carbon emissions from the construction industry in urban clusters of other countries, aiding in the formulation of tailored policy recommendations for respective localities.

5.2. Policy Recommendations

The Tapio decoupling results indicate that the overall trend of carbon emissions shows a development pattern from weak decoupling to strong decoupling. It suggests that the construction industry is gradually moving away from an industry development model overly reliant on energy consumption. Specifically, in Zhejiang, Jiangsu, and Shanghai, the construction industry has shown relatively healthy development, while there is still room for optimization in Anhui and Fujian. Therefore, Anhui and Fujian could learn from the government policies and business development paths of Jiangsu, Zhejiang, and Shanghai. Encouraging and supporting innovation in green building technologies is crucial. There should be increased investment in research and technological development to guide construction companies towards a low-carbon transformation. Efforts should be made to improve the production efficiency of the materials and enhance the recyclability of construction materials.

Regarding the carbon intensity factor, the values of the driving factor in the five regions of East China are all in a fluctuating state, leading to an unstable impact. Therefore, there is still room for improvement in the technological level of the construction industry. It is necessary to optimize the energy structure and control carbon emissions from construction activities.

Regarding the energy intensity factor, the five regions of East China consistently exhibit a suppressive effect on carbon emissions, and the suppression effect is relatively good. Therefore, each region needs to innovate development models, and alter the economic growth mode of the construction industry, progressively transitioning from an extensive to a refined development model.

Regarding the economy factor, the values of the economy in the construction industry have consistently risen, driving the total carbon emissions. The inevitable increase in the economic development and expansion of the construction industry will lead to a growth in carbon emissions. Striking a balance between industry development and carbon emission control is crucial. In the process of construction industry development, it is essential to pay attention to green development initiatives.

Regarding the population scale factor, the inevitable increase in urban population will lead to a rise in carbon emissions, but its overall promotional effect on carbon emissions is relatively weak. Population is a crucial driving force for urban development, and Jiangsu and Zhejiang provinces experienced rapid population growth due to their effective utilization of economic development opportunities. This was achieved by developing key industries in the urban areas and implementing policies to attract talent. Therefore, cities should focus on attracting skilled professionals to provide a continuous source of technical manpower support for the sustainable development of the construction industry.

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