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Toward the Construction of a Sustainable Society: Assessing the Temporal Variations and Two-Dimensional Decoupling of Carbon Dioxide Emissions in Anhui Province, China

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Abstract: This study comprehensively assessed carbon dioxide emissions over a span of two decades, from 2000 to 2020, with the decomposition and decoupling analyses considering multiple influence factors across both short-term and long-term dimensions. The results revealed great fluctuations in the decoupling analysis index (DAI) for subjected sectors such as natural resource processing, electricity, gas, water, textiles, machinery, and electronics manufacturing. Of note, significantly changed sectoral DAIs were observed in urban traffic and transportation, logistics warehousing, and the postal industry within Anhui Province. In contrast, the DAIs of other sectors and social services exhibited a weak decoupling state in Anhui Province. The industrial sectors responsible for mining and textiles and the energy structure encompassing electricity, gas, and water emerged as the primary contributors to carbon dioxide emissions. Additionally, the efficiency of the socio-economic development (EDE) was identified as the principal driver of carbon dioxide emissions during the observed period, while the energy consumption intensity (ECI) served as the putative crucial inhibiting factor. The two-dimensional decoupling of carbon dioxide emissions attributable to the EDE demonstrated a gradual transition from industrial sectors to buildings and tertiary industries from 2000 to 2020. In the future, the interaction between urban carbon dioxide emissions and the socio-economic landscape should be optimized to foster integrated social sustainable development in Anhui Province.

Keywords: industrial economy; carbon dioxide emissions; Logarithmic Mean Divisia Index; attribution analysis; Tapio model; decoupling analysis index

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Citation: Zhang, K.; Jiang, L.; Liu, W. Toward the Construction of a Sustainable Society: Assessing the Temporal Variations and Two-Dimensional Decoupling of Carbon Dioxide Emissions in Anhui Province, China. *Sustainability* **2024**, *16*, 9923. https://doi.org/10.3390/su16229923

Received: 28 August 2024
Revised: 21 October 2024
Accepted: 12 November 2024
Published: 14 November 2024

1. Introduction

In response to the warming of the Earth's atmosphere, governments have implemented a range of regulatory measures aimed at mitigating carbon dioxide emissions, which pose significant threats to all living organisms globally [1–3]. Currently, anthropogenic activities are the primary contributors to the pressing challenges of global climate change and environmental degradation, largely stemming from increased carbon dioxide emissions associated with the consumption of fossil fuels such as coal and oil [4–8]. Both developed and developing nations are grappling with the physicochemical and biochemical repercussions of global warming and environmental decline driven by carbon dioxide emissions [7–14]. The future challenges regarding human living conditions are expected to be even more pronounced in developing countries.

China stands as a prominent developing nation characterized by its substantial fossil energy consumption. This extensive reliance on fossil fuels typically results in a rapid escalation of carbon dioxide emissions, which, in turn, exert serious impacts on global climate change and environmental degradation in key cities across the nation [7,13,14].

Consequently, the Chinese government has enacted national “dual carbon” strategies and corresponding measures aimed at curbing carbon dioxide emissions at their source [15,16]. On 22 September 2020, and again on 21 September 2021, President Xi Jinping articulated the national “dual carbon” reduction strategy during the 75th and 76th United Nations General Assemblies [17], targeting carbon neutrality and peak emissions in China. The introduction of the “dual carbon goal” has intensified the resource and environmental constraints encountered by industrial development. In this context, it is imperative to decouple carbon dioxide emissions from socio-economic development, particularly in light of the sluggish international economic environment and increasingly fierce domestic industrial competition, to foster a sustainable eco-society [18–20]. Anhui Province, recognized as one of the significant manufacturing hubs and a recipient of industrial transfers, traditionally exhibits high energy consumption levels [21]. Addressing the intricate relationship between industrial socio-economic development and carbon dioxide emissions is crucial for Anhui Province to meet the national “dual carbon” reduction objectives [20–28].

With the push for national integrated development, Anhui Province has gradually become part of the expansive eco-society of the Yangtze River Delta (YRD). However, due to its relatively brief integration period and underdeveloped foundation, Anhui lags behind other more developed regions within the YRD [18,29–31]. The integrated development of the YRD has progressively shifted secondary industries to surrounding cities with less stringent environmental regulations and outdated technology [19–21,24,29–32]. As a vital receptor area for industrial transfers within the YRD, Anhui Province is also endowed with rich mineral resources. Particularly, prefecture-level cities such as Huainan, Huaibei, Ma’anshan, and Tongling are principal resource-based cities, collectively accounting for one-fourth of Anhui’s total area. This has resulted in traditional high-carbon dioxide-emitting industries occupying a disproportionately large share within the industrial sector structure (ISS) of Anhui Province amid regional integration development [21,32].

In recent years, a variety of methods have been employed to decouple the increasing consumption of resources and energy from different perspectives within socio-economic development. Currently, three primary types of decoupling analysis indexes (DAIs) are commonly utilized in research. The first is the widely recognized DAI approach established by the OECD in 2002 [33], which is based on the growth of the emission intensity. The second is Tapio’s elastic index (TEI), typically used to delineate the potential decoupling of resources and energy [34]. The third is a newly emerged combined DAI approach recently introduced by scholars [26,35,36].

Since 2005, the concepts of elasticity and the elastic index were integrated into various models of decoupling analysis, such as the popular TEI model, along with related criteria for decoupling classification. Subsequently, it was determined that the DAI represents a long-term or adaptive process necessitating a certain duration and cost for effective “decoupling” [37]. Building on this understanding, an enhanced TEI model was proposed [37–40]. The improved TEI model was then employed to examine the environmental pressures from discharged waters and to decouple industrial water resource consumption from regional socio-economic development in the Yangtze River Delta (YRD) from 2000 to 2017 [41]. The findings indicated a trend of increasing decoupling strength across the YRD, albeit with significant regional variations [30,41–44]. During the period from 2007 to 2017, carbon dioxide emissions from tourism in developing areas along the international “Belt and Road” initiative surged by approximately 0.84 times [42]. Notably, regions with elevated carbon dioxide emissions were predominantly located in southeastern and northeastern China [42]. It was also observed that the decoupling of carbon dioxide emissions from regional socio-economic factors is not a short-term phenomenon but rather an adaptive process requiring a substantial historical timeframe and associated costs [42–44]. Given that many decoupling analysis methods fall short in evaluating macrosocial and macroeconomic driving factors, numerous scholars have employed Structural Decomposition Analysis (SDA) and Index Decomposition Analysis (IDA) to delve deeper into the potential influencing factors [45–49]. Compared to SDA and other decomposition methodologies, IDA is more prevalently applied in the decoupling analyses of carbon dioxide emissions due to its flexibility in data handling [50,51]. At the same time, the Logarithmic Mean Divisia Index (LMDI) decomposition approach, characterized by comprehensive decomposition and zero residual error, has gained widespread acceptance in combined research reports on carbon dioxide emissions [52–58]. For instance, the combined index model of Tapio and the LMDI have frequently been utilized to assess multi-sector decoupling efforts aimed at reducing carbon dioxide emissions in China [52–55]. These studies have revealed a shift in the decoupling state of the carbon dioxide emissions from weak to strong, with the energy intensity, technological innovation, and the economic structure identified as the key drivers in emissions reduction [52–55]. Subsequently, combined index models such as Tapio+STRIPAT+LMDI and Kaya+LMDI have been employed to compute and estimate the decoupling relationship between economic growth and carbon dioxide emissions, as well as to predict the carbon peak timeline in Chengdu, China [56,57]. Recently, the comprehensive index model of Tapio+Kaya+LMDI was used to evaluate the decoupling relationship between economic growth and waste emissions in the construction sectors of the European Union and China [58]. The findings indicated that from 1991 to 2022, most E.U. countries' construction sectors remained in a state of weak or negative decoupling, while China's sector primarily exhibited weak decoupling [58].

Nevertheless, due to the shifting inhibitory effects of recent socio-economic structural factors, natural resources are depleting, and the potential for reducing carbon dioxide emissions is diminishing in China too. In light of these analyses, this study focused on Anhui Province, a representative central province, to conduct a decoupling analysis aimed at providing effective recommendations for the evolution of low-carbon policies in Central China. By integrating various computation models of the DAI with diverse decomposition methods, such as SDA and IDA, the decoupling status of carbon dioxide emissions and relevant influencing factors can be accurately assessed. For example, utilizing extended approaches of the Kaya identity and LMDI decomposition with energy consumption data, the size of the consumer population and the level of socio-economic output were identified as critical factors contributing to the increase in carbon dioxide emissions in Xinjiang from 1952 to 2010 [59]. From the perspectives of energy consumption and carbon dioxide emissions, social changes and the potential influencing factors were also explored and evaluated using a two-stage approach of LMDI decomposition in Sichuan Province from 2000 to 2018 [60]. It was found that Jiangsu Province significantly contributed to emission reductions and exhibited high energy efficiency [60]. Later, the novel approach of attribution analysis (AA) was further integrated to measure and evaluate the contribution rates of different sectors based on the LMDI decomposition approach [40,61,62]. Through the AA method, factors such as the energy consumption intensity (ECI) and industrial sector structure (ISS) were comprehensively assessed from the perspectives of targeted intensity and carbon dioxide emission volumes [63]. It was determined that the ECI and industry category were the primary factors driving the regional decline in carbon dioxide emissions and other greenhouse gases [63]. By combining the TEI and AA approaches, a study investigated the decoupling status and potential influencing factors of carbon dioxide emissions in BRICS countries, revealing a general transition trend from negative to initially weak and subsequently to strong decoupling [40].

Industries, particularly the manufacturing sector, are typically viewed as the primary contributors to regional carbon dioxide emissions. Consequently, the estimation and assessment of carbon dioxide emissions, along with potential pollutants from industrial production and their influencing factors, have consistently been focal points of research [24,27,64–69]. With the rise of the tertiary sector, carbon dioxide emissions stemming from transportation have also garnered increasing scholarly attention [70–73]. Therefore, conducting simultaneous analyses across multiple national economic sectors can yield a more comprehensive understanding of the level and intensity of the carbon dioxide emissions within each industry, facilitating the exploration of how various production factors influence industrial emissions [32,74–76].

In addition, distinct regions exhibit unique developmental characteristics, often shaped by the dominant countries, areas, and representative provinces or big cities [19,77–81]. The factors influencing carbon dioxide emissions have gradually transitioned from traditional metrics—such as the carbon productivity (CP), energy consumption intensity (ECI), industrial sector structure (ISS), and energy structure (ES)—to encompass aspects like public expenditure, the research and development intensity, the energy technology efficiency, renewable energy innovation, and private debt [23,28,66–86]. However, the existing literature predominantly focuses on the industrial sectors, especially manufacturing, leaving a notable gap in the research pertaining to other national sectors. When examining individual industrial sectors, there is a scarcity of in-depth analyses regarding the impact of various national economic sectors and production changes on carbon dioxide emissions. In terms of the methodologies, the research is largely confined to Logarithmic Mean Divisia Index (LMDI) analyses, with few diverse combined studies, leading to inconclusive findings [87–90]. Future research should prioritize combinatorial analyses, and more comprehensive studies are needed. At present, the prefecture-level cities within Anhui Province currently face a myriad of challenges related to energy consumption, including an unsuitable energy structure, excessive consumption, and a complex composition of energy use. Accordingly, this study sought to explore and evaluate the regional economies of resource-based areas by categorizing them into five industrial sectors in Anhui Province, utilizing the combined analyses of the LMDI decomposition approach [24,38,40,52–96] and Tapio decoupling models [37–40,97].

Previous research has emphasized the pressing need for carbon reduction in China, underscoring the significance of decomposition methods in such investigations. In this study, combined analytical methods based on the widely accepted five national economic sectors were employed, with the further subdivision of the industrial sectors facilitating a deeper understanding of the impacts of the various national economic sectors on carbon dioxide emissions. To comprehensively evaluate the actual effects of governmental strategies and measures, this study systematically analyzed the relationship between carbon dioxide emissions and the economic benefits of the five national sectors, considering six influencing factors. The research is divided into four distinct temporal stages: 2001–2005, 2006–2010, 2011–2015, and 2016–2020, with a detailed analysis of the changing characteristics of the industrial DAI and the primary influencing factors of the carbon dioxide emissions in each stage. This study sought to address several pertinent questions: (1) To what extent has the economic growth in various industrial sectors decoupled carbon dioxide emissions from energy consumption in Anhui Province? (2) If decoupling effects emerged, what were the key driving factors? (3) What impact did each industrial sector have on the driving forces behind the decoupling of carbon dioxide emissions from economic growth? Ultimately, this research aspired to conduct multi-factor decomposition and decoupling analyses of regional carbon dioxide emissions, contributing to the construction of a sustainable eco-society in Anhui Province. Additionally, it aims to provide a valuable reference for research in similarly industrially dominated regions facing the dual constraints of resources and environmental challenges, akin to those in Anhui Province.

2. Materials and Methods

2.1. Research Area

The research area encompassed Anhui Province, situated in the eastern part of mainland China, which serves as a vital component of the broader Yangtze River Delta (YRD) region. This province occupies a strategic position within the YRD, acting as an important intermediary zone among the several major domestic economic hubs critical to the national socio-economic development. The economy and culture of Anhui Province share significant historical and natural ties with other regions within the YRD. Geographically, this study encompassed the entirety of Anhui Province, which currently comprises 16 cities (see Figure 1).

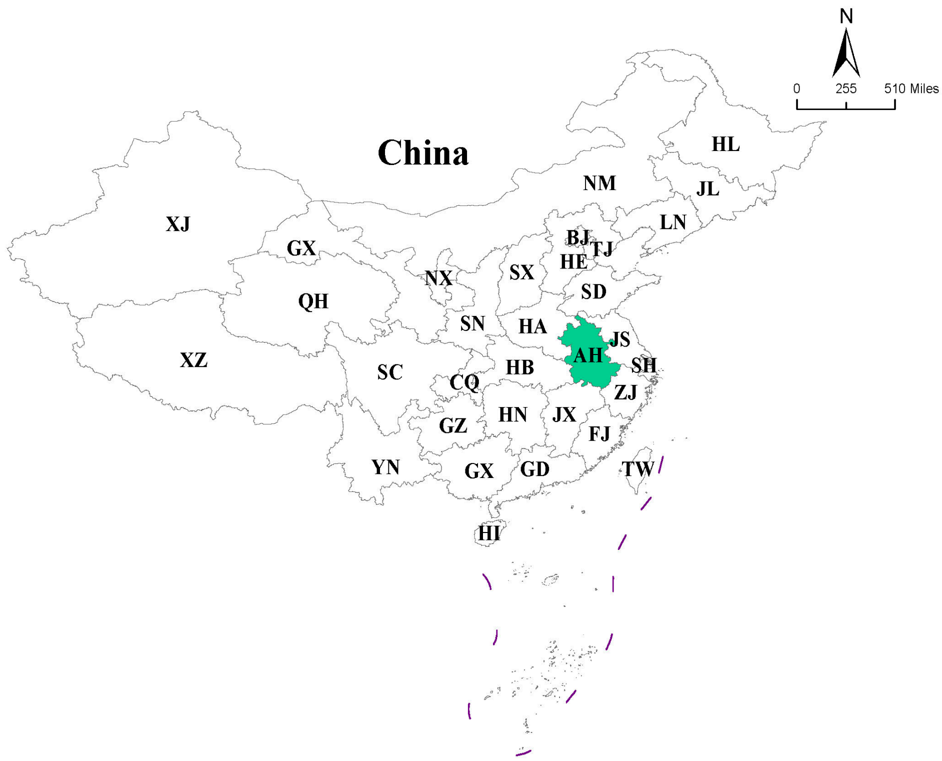

Figure 1. Map of research area (Anhui Province, AH in abbreviation).

2.2. Research Datasets

Acknowledging the significance and diversity of the industrial levels [98], this study categorized the overall economic industries of Anhui Province into five principal socio-economic sectors: construction, industry, transportation, agriculture, and trade. In alignment with the International Standard Industrial Classification (ISIC), the industrial sectors were further delineated into mining, textiles, resource processing, ME (machinery and electronics manufacturing), and EGW (electricity, gas, and water) [98]. The research datasets were sourced from the Annual China Energy Statistical Yearbooks, accessible via the China National Knowledge Infrastructure (CNKI) website (URL: https://oversea.cnki.net/ (accessed on 2 January 2023)). The types of consumed energy were subsequently classified into three categories: coal, oil, and electricity. Due to the absence of industrial output data for Anhui Province from 2017 to 2020, this study utilized the "Main Business Revenue" figures from the Anhui Statistical Yearbook and employed the interpolation method to estimate the missing industrial output values. The interpolation method is usually adopted to address the issue of missing data based on statistical sampling methods [99]. As interpolation is a widely accepted data imputation technique adept at addressing gaps in datasets, this study specifically applied linear interpolation to establish the linear relationships among the available data points, thereby effectively filling in the gaps [99].

2.3. Research Methods

2.3.1. The Measuring Method of Carbon Dioxide Emissions

The refined model proposed by the IPCC was employed to calculate and measure the volumes of carbon dioxide emissions in Anhui Province, specified in Equation (1) [79]:

$$CO_2 = \sum_{i=1}^{n} \mathrm{Q_i} \times \mathrm{NCV_i} \times \mathrm{EK_i} \times \mathrm{COF_i} \times 44/12 \tag{1}$$

Herein, $\mathrm{Q_i}$ means the consumption amount of the ith kind of energy, and $\mathrm{NCV_i}$ stands for the average low calorific value of the ith kind of energy. Moreover, $\mathrm{EK_i}$ denotes the carbon content per unit calorific value of the ith kind of fuel, and COF_i means the carbon oxidation rate of the ith kind of fuel.

In addition, the carbon dioxide emission coefficient was calculated and estimated with the method previously reported [100], specified in Equations (2)–(4):

$$EEV_m = \frac{\sum_i (FC_{i,m} \times u_i)}{EG_m} \tag{2}$$

$$K_m = \frac{EEV_m - ECV}{EEV_m} \tag{3}$$

$$EF_m = \frac{\sum_i (FC_{i,m} \times EF_{co_2,i})}{EC_m} \tag{4}$$

EEV_m represents the energy equivalent value of electricity in the mth year (kgce/kW·h), while ECV denotes the corresponding energy calorific value of electricity (kgce/kW·h). Similarly, $FC_{i,m}$ is the consumption of the ith kind of fuel in electricity production in year m (kg or m^3), and ui means the coal conversion coefficient of the ith kind of fuel (kgce/kg or kgce/m^3). EG_m expresses the provincial regional power production in the mth year (108 kW·h), whereas Km stands for the ratio of the provincial regional power production in the mth year. EF_m means the carbon dioxide emission index of electricity in the mth year (tco2/104 kW·h), and $EF_{co_2,i}$ indicates the carbon dioxide emission index of the ith kind of fuel (kgco2/kg). EC_m reveals the electricity consumption of the provincial regional consumer in the mth year (108 kW·h), while i indicates the ith kind of fossil fuel consumed in the electricity production of a certain provincial region in the mth year.

Especially, the specific electric calorific value of China's energy was 0.1229 (kgce/kW·h), released and published by the official sectors. Table 1 shows the indicators for the carbon dioxide emission factors of each energy source that were derived from the compiled guidelines for the provincial greenhouse gas inventories in China [101].

Table 1. Carbon dioxide emission correlation coefficients of energy varieties.

Energy Type	EF (kg C/Gj)	COF %	NCV (kcal/kg or kcal/m^3)	EF $kgco_2$/kg or $kgco_2/m^3$
Raw Coal	26.4	0.94	5000	1.9027
Cleaned Coal	25.4	0.93	6300	2.2855
Other Washed Coal	25.4	0.93	2497	0.9059
Briquettes	33.6	0.9	4200	1.9498
Coke	29.5	0.93	6800	2.864
Crude Oil	20.1	0.98	10,000	3.024
Gasoline	18.9	0.98	10,300	2.9827
Kerosene	19.6	0.98	10,300	3.0372
Diesel Oil	20.2	0.98	10,200	3.0998
Fuel Oil	21.1	0.98	10,000	3.1744
LPG	17.2	0.98	12,000	3.1052

2.3.2. Computation of Decoupling Analysis Index (DAI)

Decoupling analysis is primarily employed in the realms of resources and environmental studies to assess and illustrate the diminishing correlation between socio-economic development and carbon dioxide emissions [25]. Given that economic fluctuations are susceptible to external shocks and business cycles in the short term, the decoupling analysis index (DAI), when expressed as a chain ratio, may not accurately reflect the long-term developmental trajectory. Additionally, variations in carbon dioxide emissions are influenced by factors such as the energy consumption intensity (ECI), industrial structure shift (ISS), economic output, and technological advancement. Considering the characteristics of China's industrial development phase, particularly within the framework of the five-year plan, provincial and municipal economic sectors are endowed with more specific developmental objectives and coherent strategic plans. Thus, measuring the DAI within this five-year planning context proves to be more applicable [22]. In calculating the long-term DAI, with the year 2000 designated as the base period, this study further examined the dynamic changes in each short-term DAI. Consequently, this approach facilitated a comprehensive assessment of the evolving patterns of industrial carbon dioxide emissions. The specified estimation formula of the elastic DAI (denoted as the K value) is shown in Equation (5):

$$K = \frac{C^T - C^0}{C^0} / \frac{G^T - G^0}{G^0} = \frac{C^T - C^0}{G^T - G^0} \times \frac{G^0}{C^0} \quad (5)$$

Herein, C^T denotes the total carbon dioxide emissions at the conclusion of the period, while C^0 signifies the total carbon dioxide emissions at the outset. G^T represents the final gross domestic product, and G^0 indicates the initial gross domestic product. The study period was segmented into four principal intervals: 2001–2005, 2006–2010, 2011–2015, and 2016–2020. The final year of each interval was selected as the reference base period for calculating the elastic decoupling analysis index (DAI) for each respective period (Table 2). According to the Tapio decoupling model, the decoupling states were divided into eight types with the corresponding classification criteria, shown in Table 2.

Table 2. The partition standard of decoupled states.

Type of Decoupling	Remark	%GDP	%C	k
Decoupling	Strong decoupling	>0	<0	k < 0
	Weak decoupling	>0	>0	0 < k < 0.8
	Recessive decoupling	<0	<0	k > 1.2
Coupling	Expansive coupling	>0	>0	0 < k < 0.8
	Recessive coupling	<0	<0	0 < k < 0.8
Negative decoupling	Weak negative decoupling	<0	<0	0 < k < 0.8
	Expansive negative decoupling	>0	>0	k > 1.2
	Strong negative decoupling	<0	>0	k < 0

2.3.3. The Exponential Decomposition of the LMDI Model

The integration of the decoupling analysis method with the Logarithmic Mean Divisia Index (LMDI) model enhances the examination of the putative drivers behind fluctuations in carbon dioxide emissions [23,45–49,65–102]. The results derived from both the additive and multiplicative decompositions of the LMDI model and indicators were found to be consistent. Utilizing the LMDI indicators alongside the multiplicative decomposition technique, this study disaggregated the presumed influencing factors into the carbon emission efficiency (CEE), energy structure (ES), energy consumption intensity (ECI), industrial structure shift (ISS), socio-economic development efficiency (EDE), and carbon productivity (CP).

Next, employing the LMDI multiplicative decomposition method, the alterations in the carbon dioxide emissions and the contribution of each influencing factor to these changes were systematically investigated and assessed from the standpoint of change ratios. The specified formula is shown in Equation (6):

$$CO_2 = \sum_{i=1}^{I} \sum_{j=1}^{J} \frac{C_{ij}}{E_{ij}} \times \frac{E_{ij}}{E_j} \times \frac{E_j}{Q_j} \times \frac{Q_j}{Q} \times \frac{Q}{P} \times P = \sum_{i=1}^{I} \sum_{j=1}^{J} ED_{ij} \times ES_{ij} \times EI_j \times IS_j \times G \times P \quad (6)$$

C_{ij} represents the carbon dioxide emissions of the ith-type energy in the jth industry, E_{ij} is ith-type energy consumption in the jth industry, and E_j denotes the energy consumption in the jth industry. Similarly, Q_j means the production value of the jth industry, Q is the value of the total industry production, and P represents the number of total employees in the industry. ED_{ij} and ES_{ij} are the values of the carbon dioxide emission efficiency (CEE) and ES belonging to the ith-type energy in the jth industry, while EI_j and IS_j indicate the values of the ECI and ISS in the jth industry, respectively. Moreover, G stands for the value of the EDE, and P means the total engaged population.

With the LMDI decomposition approach, the influencing factors of the carbon dioxide emissions across various national economic sectors and sub-industries in Anhui Province were calculated, utilizing the conclusion of each period as the reference point. The estimation formulas of the six ED_{ij}, ES_{ij}, EI_j, IS_j, G, and P factors are shown in (7a)–(7f). Referring to the Sato–Vartia method, we calculated the weight (Wij) of the energy (i) of the industry (j). The estimation equations are shown in Formulas (7g) and (7h):

$$D_{ED} = \exp(\sum_{i=1}^{I}\sum_{j=1}^{J} w_{ij} \ln \frac{ED_{ij,t}}{ED_{ij,t_0}}) \tag{7a}$$

$$D_{ES} = \exp(\sum_{i=1}^{I}\sum_{j=1}^{J} w_{ij} \ln \frac{ES_{ij,t}}{ES_{ij,t_0}}) \tag{7b}$$

$$D_{EI} = \exp(\sum_{i=1}^{I}\sum_{j=1}^{J} w_{ij} \ln \frac{EI_{j,t}}{EI_{j,t_0}}) \tag{7c}$$

$$D_{IS} = \exp(\sum_{i=1}^{I}\sum_{j=1}^{J} w_{ij} \ln \frac{IS_{j,t}}{IS_{j,t_0}}) \tag{7d}$$

$$D_{G} = \exp(\sum_{i=1}^{I}\sum_{j=1}^{J} w_{ij} \ln \frac{G_{t}}{G_{t_0}}) \tag{7e}$$

$$D_{P} = \exp(\sum_{i=1}^{I}\sum_{i=1}^{J} w_{ij} \ln \frac{P_{t}}{P_{t_0}}) \tag{7f}$$

$$w_{ij} = \frac{L(C_{ij,t}/C_t, C_{ij,t_0}/C_{t_0})}{\sum\limits_{i=1}^{I}\sum\limits_{j=1}^{J} L(C_{ij,t}/C_t, C_{ij,t_0}/C_{t_0})} \tag{7g}$$

$$L(a,b) = \frac{a-b}{\ln a - \ln b},\ a \neq b \tag{7h}$$

2.3.4. The Computation of Attribution Analysis (AA)

The AA approach was utilized to quantify the contributions of the terminal sub-industries or industrial sectors to the levels of carbon dioxide emissions [38]. This method further facilitated the identification of the primary sources or influencing factors of the carbon dioxide emissions, such as the energy structure (ES) and energy intensity (EI). This study adopted a five-year cycle, using the conclusion of each period as the reference point to calculate the single-period attribution of the six influencing factors. Taking the EI as an example, the specific estimation formula is shown in Equations (8) and (9):

$$\frac{EI_t}{EI_{t_0}} - 1 = \sum_{i=1}^{I}\sum_{j=1}^{J} r_{ij}(\frac{EI_{j,t}}{EI_{j,t_0}} - 1) \tag{8}$$

$$r_{ij} = \frac{\dfrac{w_{ij}EI_{j,t_0}}{L(EI_{j,t}, EI_{j,t_0}EI_t/EI_{t_0})}}{\sum\limits_{i=1}^{I}\sum\limits_{j=1}^{J}\dfrac{w_{ij}EI_{j,t_0}}{L(EI_{j,t}, EI_{j,t_0}EI_t/EI_{t_0})}} \tag{9}$$

$$\sum_{i=1}^{I} r_{ij}\left(\frac{EI_{j,t}}{EI_{j,t_0}} - 1\right) \quad (10)$$

The expression of the variables in Equation (10) represents the contribution rate of the industry (j) to the change in the EI index, and the variable r_{ij} expresses the weight of the ith-type energy in the jth industry. Through the estimation of Equation (8), the contribution ratio of the terminal sub-industries or the industrial sectors to the decomposition index in each period could be quantified. EI_t means the energy intensity at time (t), while EI_0 denotes the energy intensity during the base period. The ratio EI_t/EI_0 reflects the relative change in the energy intensity at time (t) compared to that in the same base period.

3. Results and Discussion

This study comprehensively assessed carbon dioxide emissions over a span of twenty years, from 2000 to 2020, while exploring the corresponding multiple influencing factors from both the short-term and long-term perspectives. The findings from the decomposition and decoupling analyses are presented as follows.

3.1. Decoupling Analysis

The DAI can be effectively integrated with the change rates of carbon dioxide emissions and production values to categorize the decoupling status [59,81]. Utilizing the Tapio index model, the DAIs and their variations were computed and classified into five national economic sectors and five industrial sectors within Anhui Province, respectively [34]. To more accurately depict the fluctuations in the DAI of each industry, this study substituted values of the DAI exceeding 1.5 and those below −1.5 with 1.5 and −1.5, respectively.

3.1.1. Analysis of the Long-Term Decoupling Analysis Indexes

With the exception of the traffic and transportation sector, the DAIs of all other industrial sectors exhibited a downward trend (Figure 2), indicating that the relationship between their economic benefits and carbon dioxide emissions gradually diminished in Anhui Province from 2000 to 2019. The long-term DAI for traffic and transportation has remained in a state of expansive negative decoupling for an extended period. Between 2000 and 2019, the urban carbon dioxide emissions increased at an annual rate of 15%, while the economic benefits grew at a rate of 10% (Figure 2). Obviously, the annual growth rate of the economic benefits lagged behind that of the carbon dioxide emissions. Agriculture experienced expansive negative decoupling twice, in 2001 and 2003. Following significant decoupling in 2005 and 2006, the DAI stabilized at 0.35 in subsequent years. The DAIs for trade and construction were characterized by strong decoupling prior to 2012 and 2013, after which they transitioned into a state of weak decoupling, tending towards stabilization. The industrial sector exhibited weak decoupling, with the DAI continuing to decline. This clearly indicates a diminishing relationship between the industrial socio-economic development and carbon dioxide emissions. From the perspective of the DAI, the sectors can be ranked as follows: traffic and transportation > agriculture > industry > trade > construction. This finding is partially corroborated by previous studies [25,28,65,79,87,102–104].

The DAIs of various sectors underwent continuous changes from 2000 to 2020 in Anhui Province (Figure 3). With the exception of the mining sector, the DAIs of all other sectors experienced a persistent decline and began to stabilize, indicating a gradual weakening of the relationship between the economic benefits and carbon dioxide emissions within these sectors. The long-term DAI of the mining sector rose from 0.41 in 2000 to 0.75 in 2020, with the annual carbon dioxide emissions and economic benefits growing at rates of 8.4% and 9.7%, respectively. This suggests a close correlation between the growth of the social economy and carbon dioxide emissions. The sectors of resource processing, EGW, textiles, and ME exhibited significant fluctuations in their DAIs during the period from 2000 to 2005, alternating between states of differentiated expansive negative decoupling and coupling. However, post-2005, with the exception of the traffic and transportation, logistics warehousing, and postal sectors, the DAIs settled into a state of weak decoupling, with the range of changes gradually stabilizing.

Figure 2. Trends of decoupling index changes for five national economic sectors in Anhui Province from 2000 to 2019.

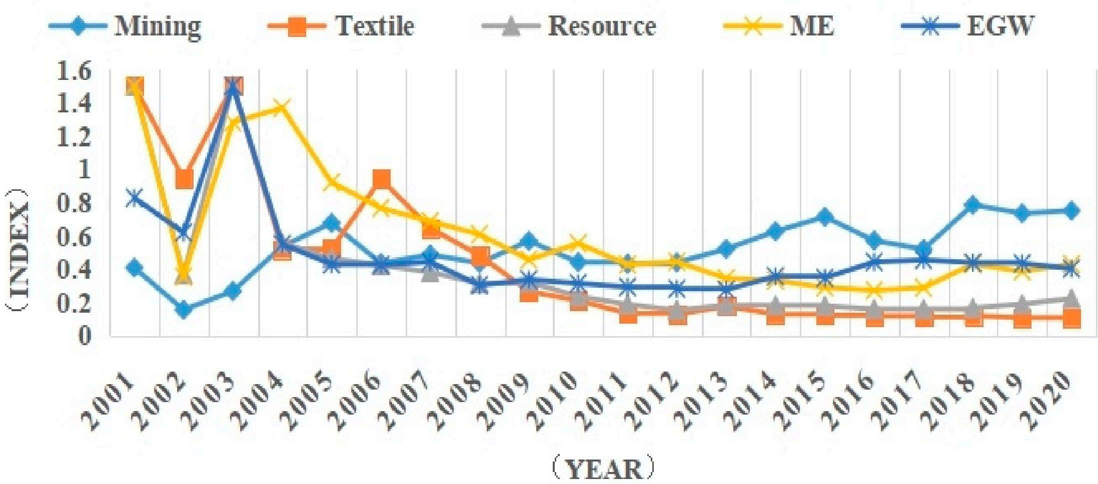

Figure 3. Trends of decoupling index changes for five industrial sectors in Anhui Province from 2000 to 2020.

3.1.2. Analysis of the Short-Term Decoupling Analysis Indexes

During the years 2001–2005, the industrial DAIs predominantly exhibited strong decoupling, comprising 44%, primarily concentrated in the construction and trade sectors. Weak decoupling and expansive negative decoupling accounted for 28%, mainly emerging from the industrial and traffic and transportation sectors. The DAIs of these sectors were largely characterized by weak decoupling, which represented 56%, particularly notable in 2002, 2004, and 2005. Concurrently, the expanding negative decoupling of these sectors accounted for 32%, predominantly observed in 2001 and 2003. During this period, the industrial sector most closely associated with economic benefits and carbon dioxide emissions in Anhui Province was traffic and transportation. The DAIs of numerous industrial sectors were significantly aligned with the statistical trends of these years. Moreover, they collectively exhibited a tendency towards expansive negative decoupling in 2001 and 2003 (Figures 4 and 5).

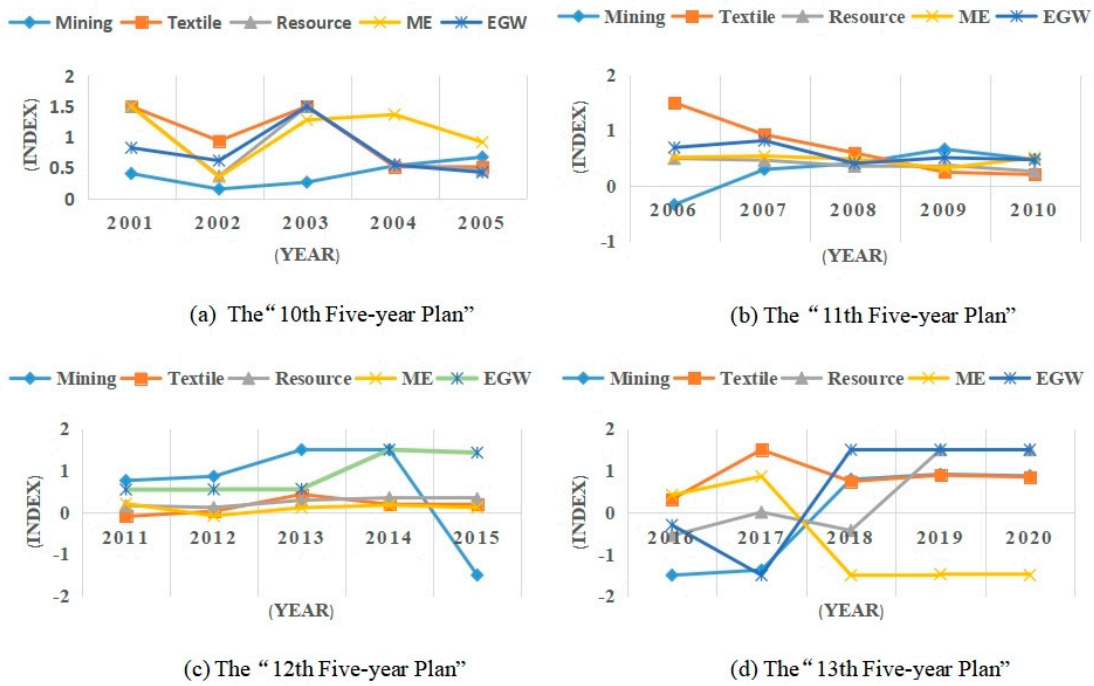

Figure 4. Trends of DAIs of five national economic sectors in each period.

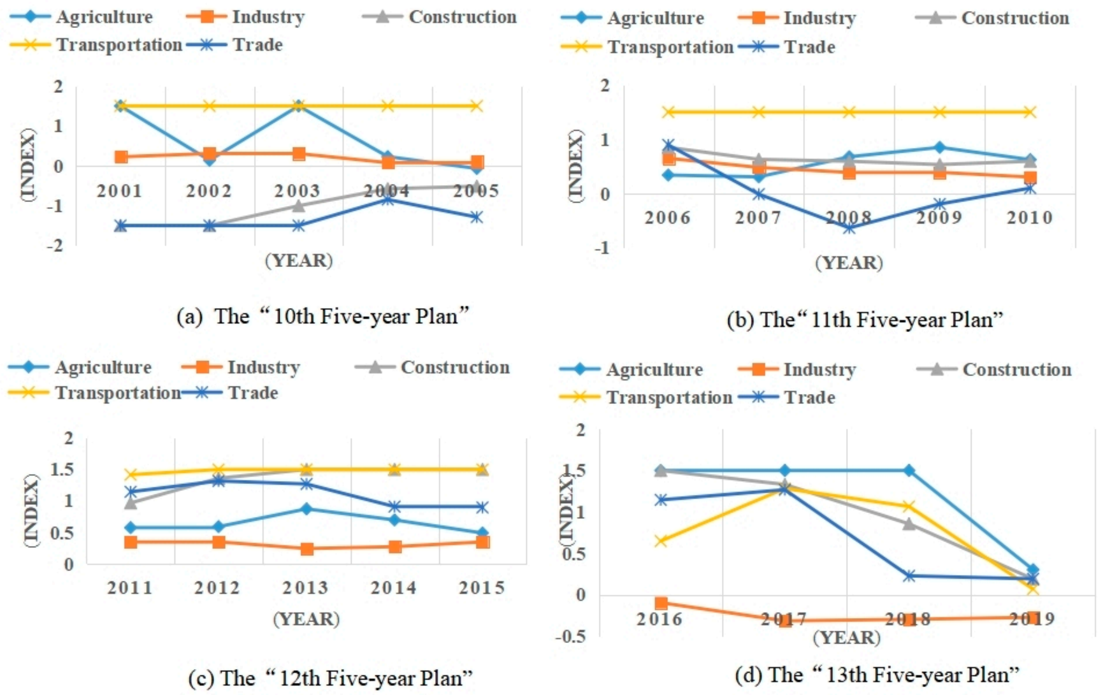

Figure 5. Trends of DAIs of the five industrial sectors in each period.

From 2006 to 2010, the industrial DAIs were predominantly characterized by weak decoupling, comprising 56%, primarily concentrated in the agriculture, industry, and construction sectors. Expansive negative decoupling accounted for 20%. During this period, the trade and commerce sector experienced remarkable socio-economic growth, with an annual rate of 14.7%, leading to a shift in the short-term DAI from strong decoupling to weak decoupling. The DAIs of these sectors were largely defined by weak decoupling, accounting for 84%, reflecting an increase from the previously observed period. Although the short-term DAI of traffic and transportation remained in a state of expansive negative decoupling, its value continued to decline. Overall, this trend indicated a gradual decrease in the correlation between economic benefits and carbon dioxide emissions in Anhui Province (Figures 4 and 5).

During the years 2011–2015, the industrial DAIs were predominantly characterized by expansive negative decoupling, comprising 44%, primarily concentrated in the construction, traffic and transportation, and trade sectors. Weak decoupling accounted for 36%, mainly concentrated in agriculture and industry. The DAIs of these sectors were largely defined by weak decoupling, which represented 72%, indicating a slight decline. Throughout this observed period, both the mining and EGW sectors experienced expansive negative decoupling on two occasions, with fluctuations in economic benefits serving as the primary catalyst for these changes (Figures 4 and 5).

From 2016 to 2020, industrial DAIs continued to be predominantly characterized by expansive negative decoupling, comprising 35%, primarily arising from the construction, traffic and transportation, and trade sectors. Weak decoupling accounted for 30%, notably emerging in the observed year of 2019. The DAIs of these sectors were largely defined by recessive coupling, which constituted 24%, primarily emanating from the mining and textile sectors. Expansive negative decoupling accounted for 20%, chiefly originating from the resource processing and EGW sectors (Figures 4 and 5).

Through these analyses, it was revealed that expansive negative decoupling progressively transitioned from the industrial sectors to construction, traffic and transportation, and trade. Meanwhile, the short-term DAI of the industry underwent three distinct phases: expansive negative decoupling, weak decoupling, and recessive coupling (Figures 4 and 5). This indicates that carbon dioxide emissions surged rapidly alongside the growth of the tertiary industry in Anhui Province. Concurrently, the industrial sector exhibited sluggish growth, gradually entering a new state of equilibrium. These findings align with previous research conducted by other scholars [25,79,103,104].

3.1.3. LMDI Decomposition Analysis

Utilizing the LMDI decomposition approach, the ongoing variations in the carbon dioxide emissions across the national economic sectors in Anhui Province were dissected into six key factors: the CEE, ES, ECI, ISS, EDE, and CP. Subsequently, we examined and assessed the potential influence of each factor on the carbon dioxide emissions during the various observed periods. Accordingly, the Tapio decoupling model was employed to investigate and evaluate the relationship between the carbon dioxide emissions and socio-economic development. The analytical results of the specified models are illustrated in Figures 6 and 7.

During the years 2001–2005, the EDE experienced substantial growth, with annual rates of 6.6% in the national economic sectors and 17.9% in specific sectors. This underscored the EDE as the primary driver of carbon dioxide emissions, while the ECI emerged as the principal inhibitory factor during the observed periods across the relevant economic sectors. The ECI declined from 0.88 and 1.01 in 2001 to 0.58 and 0.66 in 2005, reflecting average annual reduction rates of 7.8% and 8.2%, respectively, as its inhibitory effect continued to strengthen (Figures 6 and 7). Conversely, the changes in the ISS, ES, CEE, and CP were relatively minor, exerting minimal influence on the carbon dioxide emissions.

From 2006 to 2010, the EDE continued to rise rapidly. The EDE for national economic sectors increased from 1.12 and 1.2 in 2006 to 1.96 and 2.1 in 2010, while socio-economic development advanced by 11.9% and 11.8%, respectively, establishing them as the main drivers of carbon emissions during this period. The ECI for the national economic sectors and sectors fell from 0.96 and 0.89 in 2006 to 0.61 and 0.56 in 2010, with average annual reduction rates of 8.7% and 8.9%, respectively. The values for the ES, ISS, CP, and CEE fluctuated around 1, indicating their limited impact on the carbon dioxide emissions (Figures 6 and 7).

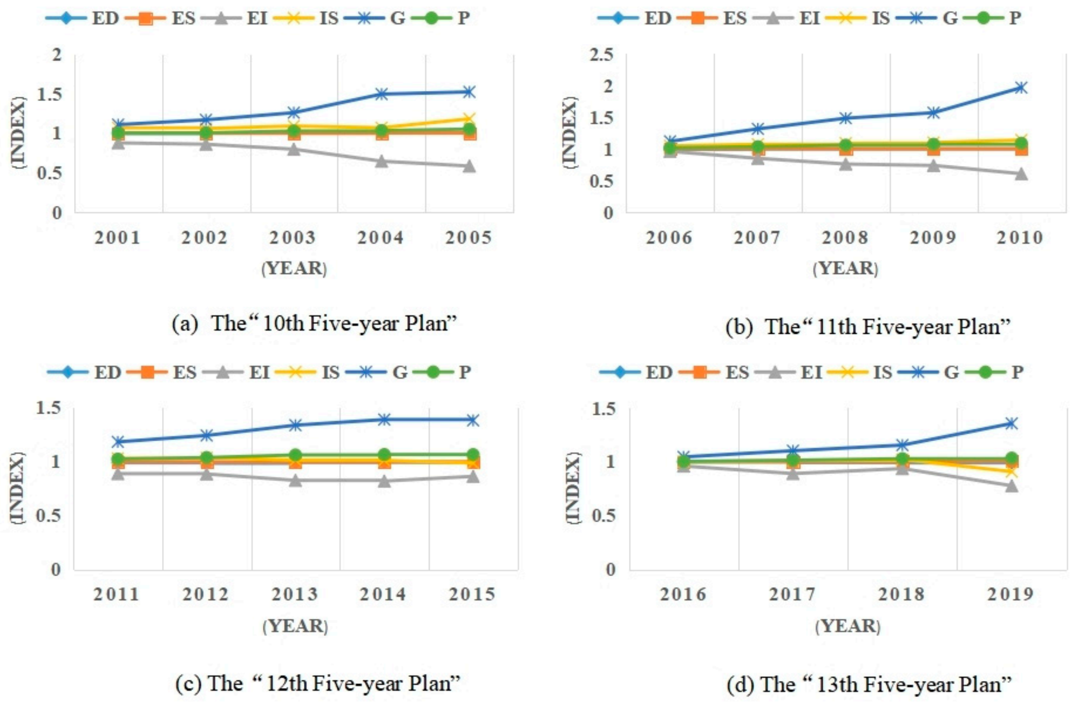

Figure 6. Decomposition trends of the LMDI of the five national economic sectors in each period.

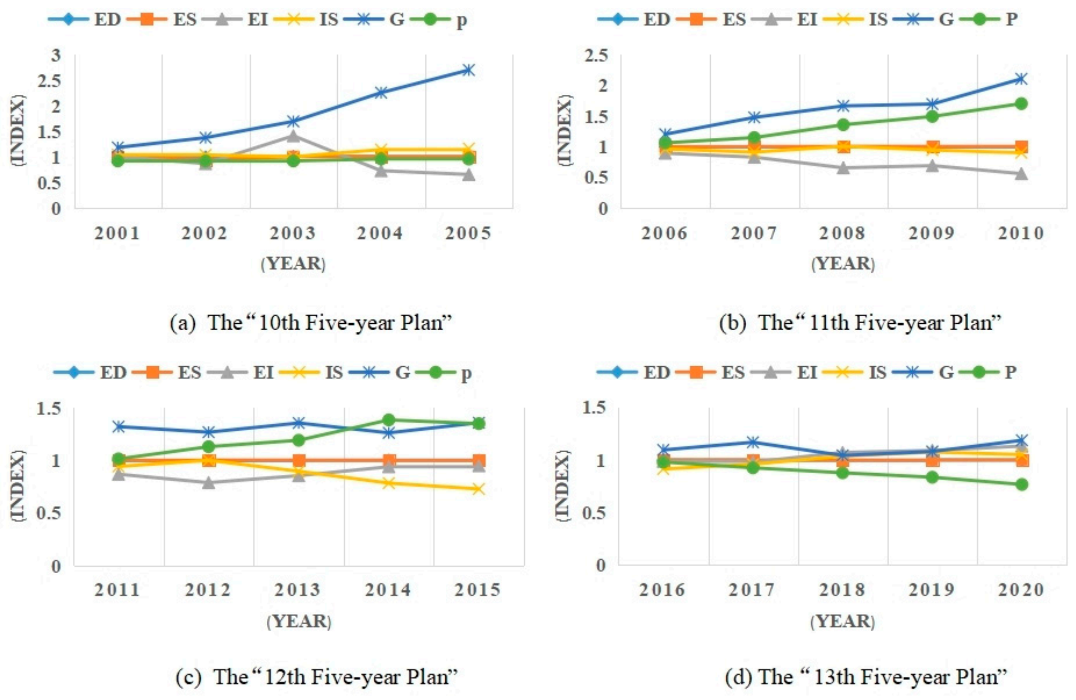

Figure 7. LMDI decomposition trends of the five industrial sectors in each period.

During the years 2011–2015, the EDE remained the predominant driver of industrial carbon dioxide emissions. However, compared to the preceding "11th Five-Year Plan" period, the growth rates of the national economic sectors were relatively modest, at only 3.2% and 0.56%. Notably, the annual rates of the ECI registered at −0.57% and 1.8%, respectively, although its inhibitory effect gradually diminished. The acceleration of carbon dioxide emission inhibition decelerated, with the average annual decline rate dropping from 8.7% in the previous period to 0.57%. The values for the CEE and ES hovered around 1, signifying a negligible impact on the carbon dioxide emissions. In all sectors, the annual rate for the sectoral architecture (SA) was recorded at −5%, establishing it as the primary inhibitor of carbon dioxide emissions during the observed period (Figures 6 and 7).

During the years 2016–2020, the EDE and ECI continued to serve as the principal drivers and inhibitors of industrial carbon dioxide emissions, exhibiting annual rates of 6.7% and −5.1%, respectively. The inhibitory influence of the ISS on carbon dioxide emissions was bolstered, with a yearly rate of −2.4%. Concurrently, the ECI, SA, and EDE contributed to the rise in carbon dioxide emissions, with annual rates of 2.8%, 2.8%, and 1.6%, respectively. Notably, during this period, the CP emerged as the primary inhibitor of carbon dioxide emissions, achieving an average annual reduction rate of 4.8%. The number of industrial employees declined from 3,509,384 in 2016 to 2,741,585 in 2020, reflecting an average annual decrease of 5.2%. Meanwhile, employment in the mining, EGW, and textile sectors fell by 22%, 12%, and 6.4%, respectively (Figures 6 and 7), marking them as the principal sources of employment decline. During this timeframe, the workforce in the resource processing industry decreased by 2.2% per year, while employment in the ME industry saw a modest increase of 0.8% annually. It is evident that the judicious reallocation of industrial employees during this period played a significant role in mitigating industrial carbon dioxide emissions. These findings align with those of previously reported studies [22,86,105].

3.2. Attribution Analysis

Due to the fact that the LMDI decomposition approach could not further quantify the contribution of the terminal industry to each factor in the observed periods, this study employed attribution analysis to calculate the contribution rate of the terminal industry for each period using Equations (8) and (9). The specific results pertaining to the main factors are presented in Tables 3–7. The contribution values of each terminal industry were aggregated to derive the overall contribution of the national economic sectors to factors such as the ECI, EDE, and ISS across different periods. Table 3 illustrates that the EDE and ECI were the primary influencing and inhibitory factors of carbon dioxide emissions within the national economic sectors, with their respective contributions diminishing over time. The ECI exhibited a relatively pronounced inhibitory effect on the carbon dioxide emissions across various sectors during the initial two periods but shifted to a rising trend during the "13th Five-Year Plan". These findings are consistent with the majority of the previously reported estimations [22,24,84–86,93,105].

In the attribution analysis of the EDE, the industrial sector emerged as the predominant contributor to changes in the national economic sectors' EDEs, with contribution rates of 0.51, 0.83, 0.12, and 0.08 across the four periods, respectively. It was evident that the industry's contribution to the EDE was primarily concentrated in the initial two periods. Conversely, the contributions from construction, transportation, and trade to the EDE exhibited an upward trend, suggesting that the changes in industrial carbon dioxide emissions driven by the EDE were gradually transitioning from the industrial sector to buildings and the tertiary industry. This finding aligned with the results of the aforementioned industry decoupling analysis. The mining, resource processing, and EGW sectors were the main contributors to the changes in the EDEs within these sectors. Notably, their contribution rates declined significantly from 0.41, 1.08, and 0.97 during the "10th Five-Year Plan" period to 0.18, 0.06, and 0.33 in the "13th Five-Year Plan" period, reflecting a substantial reduction (Tables 3–6). This shift can be attributed to the rapid industrial development experienced in Anhui Province during the first two periods, which resulted in substantial carbon dioxide emissions. However, with advancements in technology and the government's ongoing promotion of high-quality industrial development, the enhancement of industrial economic benefits no longer came at the expense of significant carbon dioxide emissions, thereby gradually diminishing the role of economic benefits in driving industrial carbon dioxide emissions. This observation was consistent with the changing trend of the long-term industrial DAI evaluated in Anhui Province (Tables 4 and 6).

Table 3. Single-period attribution of Anhui's national economic sectors and sectors (unit %).

	National Economic Sectors				Sectors			
	2001–2005	**2006–2010**	**2011–2015**	**2016–2019**	**2001–2005**	**2006–2010**	**2011–2015**	**2016–2020**
ED	0.01	0.004	−0.007	−0.011	0.012	−0.001	−0.001	0.002
ES	0.024	0.001	−0.009	−0.011	−0.003	−0.001	−0.002	0.001
EI	−0.419	−0.392	−0.147	−0.218	−0.344	−0.441	−0.055	0.133
IS	0.18	0.139	−0.008	−0.085	0.164	−0.099	−0.372	0.052
G	0.533	0.877	0.101	0.219	2.519	1.332	−0.144	0.572
P	0.231	0.297	0.329	0.06	−0.145	0.394	0.571	−0.39

Table 4. Attribution analysis of ECIs and EDEs of Anhui's national economic sectors (unit %).

	2000–2005		2006–2010		2011–2015		2016–2019	
	EI	**G**	**EI**	**G**	**EI**	**G**	**EI**	**G**
Agriculture	−0.004	0.012	−0.003	0.022	−0.003	0.010	−0.001	0.003
Industry	−0.399	0.514	−0.388	0.831	−0.182	0.120	−0.132	0.080
Construction	−0.033	0.010	−0.002	0.010	0.005	0.005	−0.011	0.019
Traffic and Transportation	0.026	0.004	0.009	0.008	0.034	−0.046	−0.079	0.101
Trade	−0.010	−0.007	−0.008	0.006	0.000	0.013	0.005	0.016

Table 5. Attribution analysis of ISSs and CPs of Anhui's national economic sectors (unit %).

	2000–2005		2006–2010		2011–2015		2016–2019	
	IS	**P**	**IS**	**P**	**IS**	**P**	**IS**	**P**
Agriculture	−0.009	−0.004	−0.009	−0.004	−0.004	−0.004	−0.005	0.000
Industry	0.191	0.201	0.179	0.272	0.003	0.253	−0.151	0.051
Construction	0.008	0.011	0.000	0.004	−0.001	0.002	0.009	0.001
Traffic and Transportation	−0.003	0.011	−0.031	0.017	−0.011	0.078	0.055	0.007
Trade	−0.007	0.012	−0.001	0.008	0.005	0.000	0.007	0.001

Table 6. Attribution analysis of ECIs and EDEs of Anhui's sectors (unit %).

	2000–2005		2006–2010		2011–2015		2016–2020	
	EI	**G**	**EI**	**G**	**EI**	**G**	**EI**	**G**
Mining	−0.039	0.410	−0.071	0.351	0.084	−0.111	0.012	0.183
Textiles	−0.006	0.040	−0.019	0.033	−0.016	0.014	0.002	−0.001
Resources	−0.165	1.079	−0.239	0.447	−0.134	0.149	0.073	0.064
ME	0.000	0.016	−0.004	0.010	−0.006	0.005	0.005	−0.001
EGW	−0.133	0.974	−0.108	0.491	0.018	−0.201	0.041	0.326

In the results of the attribution analysis of the ECI, it was determined that the ECI served as the primary inhibitor of the reduction in energy-related carbon dioxide emissions in the national economic sectors of Anhui Province. Simultaneously, the industrial sector emerged as the principal contributor to the decline in the ECI. The estimated contribution rates of the industrial sector to the ECI across the four five-year periods were −0.40, −0.39, −0.18, and −0.13, respectively, indicating that all the contribution rates were negative and exhibited a decreasing trend. The resource processing industrial sectors and EGW were identified as the main contributors to the decline in the ECI, with their contributions predominantly concentrated in the initial two periods. In the subsequent two periods, their contributions to the ECI gradually transitioned from a restraining effect to a promoting one (Tables 4 and 6).

Table 7. Attribution analysis of SAs and CPs of Anhui's economic sectors (unit %).

	2000–2005		2006–2010		2011–2015		2016–2020	
	IS	**P**	**IS**	**P**	**IS**	**P**	**IS**	**P**
Mining	0.040	0.010	−0.017	0.032	−0.174	0.133	−0.057	−0.172
Textiles	−0.011	−0.003	0.001	0.018	0.006	0.009	−0.006	−0.006
Resources	0.020	−0.077	−0.045	0.265	−0.039	0.081	0.044	−0.038
ME	0.001	0.001	0.002	0.012	0.002	0.004	0.001	0.000
EGW	0.114	−0.077	−0.039	0.066	−0.166	0.344	0.070	−0.174

Through the analysis of the economic benefits and energy consumption across the sectors during the "13th Five-Year Plan" period, it was revealed that the economic benefits experienced a decline to varying degrees, with the reduction in economic benefits surpassing that of energy consumption. This disparity resulted in an increase in the ECI, leading to a period characterized by recessive coupling in the DAI. Examining the trends in the ECI, it became apparent that economic benefits significantly outweighed energy consumption in the nascent stages of industrial development. During this period, the continuous enhancement of industrial technology and energy efficiency led to a substantial decline in the ECI. However, as industrial development progressed in Anhui Province, the economic benefits generated by the industry began to diminish, while the advancements in energy efficiency driven by technological progress gradually approached a bottleneck. Consequently, the inhibitory effect of the ECI on carbon dioxide emissions was continuously diminished. Given that the technology and energy efficiency remained relatively stable, the ECI became increasingly determined by the economic benefits of the industry. Thus, fostering steady growth in industrial economic benefits could more effectively harness the carbon dioxide emission reduction potential of the ECI (Tables 4 and 6).

The results of the attribution analysis of the ISS revealed that its impact on carbon dioxide emissions could be delineated into two distinct stages. In the initial observed period, the ISS functioned to promote carbon dioxide emissions, whereas in the subsequent observed period, it served to inhibit them. The industrial sector emerged as the principal contributor to the fluctuations in the ISS, with the mining and EGW sectors being the key drivers of the change in the SA. For instance, the industrial sector's share escalated from 0.38 in 2000 to 0.56 in 2010, contributing a cumulative rate of 0.37 to the changes in the ISS within Anhui Province. However, following this period, as the ISS underwent continuous adjustments, the proportion of the industrial sector began to decline. During the "13th Five-Year Plan" period, its contribution to the ISS turned negative. The shares of the mining and EGW sectors fell from 0.07 and 0.08 in 2010 to 0.03 and 0.05 in 2015, reflecting significant decreases in Anhui Province. Concurrently, their cumulative contribution to the changes in the ISS was −0.34, marking them as the primary inhibitors of industrial carbon dioxide emissions during the "12th Five-Year Plan" period. During the "13th Five-Year Plan" period, the proportion of the ME sector experienced an annual growth rate of 2.3%; however, its contribution rate to the changes in the SA was merely 0.005. From this analysis, it is evident that to enhance the inhibitory effect of ISS adjustments on carbon dioxide emissions, it is imperative to continuously reduce the proportion of industry while promoting the SA to decrease the shares of mining and EGW, alongside increasing the proportion of ME (Tables 5 and 7).

The attribution analysis of the CP indicated that it played a relatively modest role in promoting industrial carbon dioxide emissions, as evidenced by the LMDI decomposition results. The industrial sector was the primary contributor to changes in the CP, with contributions of 0.2, 0.27, and 0.25 in the initial three periods, which subsequently declined to 0.05 during the "13th Five-Year Plan" period. The annual growth rates of industrial employment in each period were 4%, 6%, 5%, and 2%, respectively, demonstrating a consistent correlation between the growth rate of the industrial CP and its contribution rate. From 2000 to 2019, the annual growth rate of trade employment was 4.9%, surpassing the 4.3% rate of the industrial sector; however, its contribution rate remained significantly lower than that of industry. The resource processing industry, EGW, and mining emerged as the principal contributors to changes in the CP across the sectors. During the period from 2000 to 2020, the annual rates of the employed CP in mining, textiles, resource processing, ME, and EGW were −2.8%, 1.9%, 1.9%, 7%, and 0.5%, respectively. The corresponding contribution rates to the sectoral CP were 0, 0.02, 0.23, 0.02, and 0.16, respectively, indicating that the changes in the CP within EGW, mining, and resource processing had a more significant impact on the sectoral CP, while the employment CP of textiles and ME exerted a lesser influence. Based on this analysis (Tables 5 and 7), three strategic missions could be identified to effectively reduce industrial carbon dioxide emissions. These missions involve controlling the number of industrial employees, particularly by decreasing the workforce in mining, EGW, and resource processing, while simultaneously directing personnel towards the ME industry and tertiary sector. These measures are crucial for enhancing the role of CP in mitigating carbon dioxide emissions.

The attribution analysis of the ES revealed that it exerted a minimal impact on the carbon dioxide emissions of the national economic sectors in Anhui Province. From the "10th Five-Year Plan" to the "13th Five-Year Plan" period, the contribution of the ES to carbon dioxide emissions gradually diminished, eventually turning negative. Notably, the industrial sector emerged as the primary contributor to changes in the ES, with the contributions from the construction industry as well as traffic and transportation also increasing, albeit their contribution rates eventually shifted to negative values.

The adjustment of the ES had a limited inhibitory effect on the carbon dioxide emissions across the sectors, with resource processing identified as the main contributor. This analysis indicates that the ES had little influence on the industrial carbon dioxide emissions, a situation closely tied to Anhui Province's reliance on coal and oil as predominant energy sources.

While different industries depend on various specific energy sources, industrial sectors primarily consume coal and oil resources. Among these, mining, resource processing and EGW were the chief consumers of coal and oil, whereas the ME and textile sectors gradually reduced their dependence on these resources, increasingly relying on electricity instead.

In the traffic and transportation sector, oil was the primary energy source, while electricity dominated in trade. Thus, it becomes evident that further reducing the coal consumption in resource processing, textiles, and ME, along with enhancing the energy utilization efficiency in mining and EGW, would foster the development of the sectoral ES towards a reduction in carbon dioxide emissions. These findings align well with those of previously reported studies [61,93,96].

3.3. Confirmatory Analysis

In order to avoid the potential biases in research results caused by the use of a single research method, this study further employed traditional regression econometric models to validate the aforementioned analysis results, thereby enhancing the credibility of the research findings. This study adopted the logarithm of energy consumption from different types of industries and industrial enterprises as the dependent variable, while the carbon emission rate (ED), energy structure (ES), energy intensity (EI), industrial structure (IS), economic efficiency (G), and population (P) were employed as the independent variables to construct a two-way fixed-effects panel regression model, with the corresponding results and data shown in Tables 8 and 9.

Table 8, column (1), shows that the ES, EI, IS, and P all had significant impacts on the energy consumption of the national economy sectors. In Column (2), the logarithm of energy consumption in the dependent variable is replaced with the logarithm of carbon dioxide emissions, and the results indicate that the significance of the variables remained unchanged. Column (3) shortened the sample time period, analyzing data from 2010 to 2019, and it was found that the significance of most variables remained unchanged, while the significance of the carbon emission rate increased. In Table 8, the results of the two-way fixed-effects panel regression model indirectly reflect that different factors had varying impacts on the carbon emissions in the national economy sectors over the different time periods, confirming the rationality of the above segmented analyses conducted according to the five-year plan.

Table 8. Regression results of the carbon emission influencing factors in Anhui's economic sectors.

Variable	(1)	(2)	(3)
	Energy Consumption	**Carbon Emissions**	**Energy Consumption**
ED	−0.062	0.364	−1.288 ***
	(0.527)	(0.530)	(0.356)
ES	−1.108 ***	−1.113 ***	0.075
	(0.397)	(0.399)	(0.412)
EI	1.029 ***	1.027 ***	1.100 ***
	(0.113)	(0.113)	(0.071)
IS	5.638 ***	5.613 ***	5.529 ***
	(0.819)	(0.817)	(0.712)
G	0.020	0.020	0.093 ***
	(0.049)	(0.049)	(0.032)
P	−0.220 *	−0.217 *	−0.110
	(0.112)	(0.112)	(0.081)
_cons	4.808 ***	4.646 ***	6.743 ***
	(1.313)	(1.317)	(1.080)
Year	Yes	Yes	Yes
Sector	Yes	Yes	Yes
Adj.R2	0.957	0.959	0.977

Note: * and *** indicate significance at the levels of 10% and 1%, respectively.

Table 9. Regression results of the carbon emission influencing factors in Anhui's industrial sectors.

Variable	(1)	(2)	(3)
	Energy Consumption	**Carbon Emissions**	**Energy Consumption**
ED	−10.274 ***	−9.869 ***	−10.042 ***
	(0.675)	(0.669)	(0.539)
ES	5.411 ***	5.414 ***	4.343 ***
	(0.323)	(0.324)	(0.270)
EI	0.349 ***	0.350 ***	0.442 ***
	(0.054)	(0.054)	(0.067)
IS	5.924 ***	5.934 ***	5.713 ***
	(0.499)	(0.499)	(1.489)
G	0.006 ***	0.006 ***	0.005
	(0.002)	(0.002)	(0.004)
P	0.244 *	0.244 *	0.014
	(0.127)	(0.127)	(0.397)
_cons	32.159 ***	32.055 ***	37.490 ***
	(2.447)	(2.432)	(5.366)
Year	Yes	Yes	Yes
Industry	Yes	Yes	Yes
Adj.R2	0.942	0.942	0.981

Note: * and *** indicate significance at the levels of 10% and 1%, respectively.

Similarly, the relevant results of the panel regression model in the five industrial sectors are shown in Table 9, with the analyzing process and results being similar to those of the analyses above. In Table 9, through the analysis of the panel regression model, it was verified that the impact of the aforementioned factors on the carbon emissions was significant using a two-way fixed-effects panel regression model. Then, it was further verified to ensure the robustness of the regression modeling results by adopting the substitute variables and adjusting the sample time.

4. Conclusions

The development strategies of national urban integration and regional integration have presented significant opportunities for Anhui Province, enabling it to attract industrial transfers from surrounding developed provinces. Given the natural constraints of resources and the environment, the focus of this study was to explore how to achieve low-carbon development in resource-based regions. This research employed the Tapio decoupling model to examine the relationship between the carbon dioxide emissions and economic benefits across five national economic sectors and five industrial sectors in Anhui Province. Utilizing the LMDI multiplicative decomposition model, this study investigated the primary driving and inhibitory factors influencing the carbon dioxide emissions over five-year intervals, considering six key factors: the CEE, ES, ECI, ISS, EDE, and CP. Furthermore, through attribution analysis, the contribution values of these six influencing factors to various industries across different periods were determined. The corresponding summarized conclusions were drawn as follows.

In Anhui Province, there were notable sectoral decoupling adjustment indices (DAIs) observed in urban traffic and transportation, logistics warehousing, and the postal industry. In contrast, the DAIs for other sectors and social services remained in a state of weak decoupling. The industrial sectors associated with mining, textiles, and EGW within the energy system (ES) were identified as the primary contributors to carbon dioxide emissions. In addition to the traffic and transportation sector, the DAIs of the remaining four national economic sectors also exhibited weak decoupling, with a continuing decline evident in Anhui Province. This trend suggests a gradual weakening of the relationship between industrial economic benefits and carbon dioxide emissions.

The DAIs experienced a decline following a period of negative decoupling during the "Tenth Five-Year Plan", yet they remained in a weak decoupling state for an extended duration. Through LMDI decomposition analysis, it was determined that the energy demand efficiency (EDE) was the principal influencing factor on the carbon dioxide emissions across the national economic sectors, with its driving effect diminishing over time. The EDE emerged as the primary driver of carbon dioxide emissions throughout the observed period, while the energy consumption intensity (ECI) acted as the principal potential inhibitor. In the estimation and evaluation, the ECI was confirmed as the key inhibitory factor for industrial carbon dioxide emissions, exerting a substantial inhibitory effect on the decline of emissions in the national economic sectors during the early stages. However, its inhibitory influence weakened in the later stages, at times even contributing to an increase in emissions. The industrial structure shift (ISS) initially promoted carbon dioxide emissions in the first two periods but subsequently inhibited emissions in the latter two periods.

The attribution analysis revealed that the industrial sector was the foremost contributor to carbon dioxide emissions, with mining, EGW, and resource processing identified as the primary sources of emissions within the sectors.

5. Policy Implications and Suggestions

This study comprehensively assessed twenty years of carbon dioxide emissions utilizing official energy statistics from 2000 to 2020, and it also examined the corresponding influencing factors from both the short-term and long-term perspectives. Employing Tapio's index model, the research calculated and categorized the decoupling adjustment indices (DAIs) and their variations across five national economic sectors and five industrial sectors in Anhui Province. The results from the decomposition and decoupling analyses revealed substantial fluctuations in the DAIs for natural resource processing, electricity, gas, water, textiles, and machinery and electronics manufacturing. Notably, significant sectoral DAIs were observed in urban traffic and transportation, logistics warehousing, and the postal industry within Anhui Province. In contrast, the DAIs for other sectors and social services remained in a state of weak decoupling. In the near future, it will be imperative to optimize the interaction between urban carbon dioxide emissions and the socio-economic landscape to foster integrated sustainable development.

First and foremost, it is essential to augment the sectoral share of the tertiary industry while diminishing the sectoral representation of mining and energy generation and water (EGW). A substantial industrial sector proportion hampers efforts to reduce carbon dioxide emissions; thus, decreasing its share will facilitate a shift in the industrial structure (ISS) towards a more favorable trajectory for emissions reduction. Elevating the sectoral contributions of the machinery and electronics (ME) industry, alongside the tertiary sector, particularly in traffic and transportation, will enhance the efficacy of ISS adjustments in curbing industrial carbon dioxide emissions, ultimately fostering the continuous optimization of Anhui's ISS.

Secondly, there is an urgent need to optimize the distribution of industrial personnel and encourage the migration of the workforce towards low-carbon industries. The industrial sector significantly influences demographic changes, with mining, EGW, and resource processing being the primary contributors to sectoral carbon footprints. During the "13th Five-Year Plan" period, the inhibitory effect on carbon dioxide emissions was largely attributed to a decline in the carbon footprint of the mining sector and EGW. Directing employment towards the tertiary sector and ME, while enhancing automation in high-carbon dioxide-emitting industries, can more effectively harness the potential of carbon footprints in mitigating emissions.

Lastly, it is imperative to reduce the reliance on coal within resource processing, the ME industry, and the tertiary sector while simultaneously improving the energy utilization efficiency in mining and EGW. Given the unique characteristics of mining and EGW, altering their energy structures, which are predominantly coal-based, poses significant challenges, resulting in minimal impact on industrial carbon dioxide emissions. Strategically optimizing the energy structure of resource processing, the ME industry, and other sectors can more effectively contribute to the reduction in carbon dioxide emissions.

Furthermore, it is imperative to persistently cultivate new strategic industries to guarantee the sustained enhancement and sustainable development of industrial sectors. The inhibitory effects of the Economic Complexity Index (ECI) on carbon dioxide emissions, coupled with a decline in industrial benefits, suggest that regional industrial development in Anhui Province has reached a bottleneck. In light of the current challenges, including the lack of breakthroughs in novel low-carbon technologies and the diminishing advantages of traditional industries, the government must continuously recalibrate the industrial structure shift (ISS) and foster the emergence of industries characterized by lower carbon dioxide emissions and greater economic returns.

Additionally, the government should progressively elevate the proportion of high-tech industries within the resource processing and machinery and electronics (ME) sectors. This approach will not only optimize the industrial configuration and reduce the prevalence of traditional industries but also ensure the economic development efficiency (EDE) of the sector, thereby enabling the ECI to more effectively contribute to emissions reduction.

In comparison to the existing research reports, this study presents two significant theoretical contributions. Firstly, while previous studies predominantly concentrated on national development levels or economically advanced cities, they largely overlooked provincial development levels. Anhui Province, as an integral part of the modern Yangtze River Delta, serves as a quintessential representative of central provinces in Central China. Thus, evaluating the decoupling status of the carbon dioxide emissions in Anhui Province constitutes a meaningful endeavor. Given that Anhui is a vital component of the Yangtze River Delta and a pivotal region for the industrial transition from the developed coastal zones, this study may offer a promising exploration of how resource-rich yet economically disadvantaged regions can achieve low-carbon development amidst the dual challenges of resource limitations and environmental concerns during extensive regional integration. The insights gleaned from this study are invaluable for similar regions that primarily depend on industrial sectors. Secondly, fostering provincial low-carbon development can enhance and expand the industrial transfer responsibilities within the Yangtze River Delta. Consequently, this will further facilitate industrial upgrading in Jiangsu Province and

Zhejiang Province, bolstered by the strengthened provincial markets of the entire Yangtze River Delta.

6. Limitations and Future Research

Through full analyses and discussions, several potential limitations were identified in this study that warrant further investigation. Firstly, although the research broadens its scope to encompass five major sectors in Anhui Province—namely, agriculture, forestry, animal husbandry, fisheries, and industry—it neglects to consider other subdivided sectors, such as construction, transportation, storage, postal services, as well as wholesale, retail, accommodation, and catering. Consequently, this study does not examine the provincial decoupling performance of economic growth and carbon dioxide emissions across the 16 prefecture-level cities in Anhui Province, primarily due to spatial constraints. Secondly, while the study employs a combined Logarithmic Mean Divisia Index (LMDI) model to assess the impacts of various factors on the provincial carbon dioxide emissions, it only integrates technological advancements and social policies within the LMDI variations and lacks a comprehensive elaboration due to length limitations. Furthermore, the model construction does not adequately account for technological changes and production efficiencies. These aspects should be explored in greater detail in subsequent investigations, and future research will endeavor to address these gaps.

Author Contributions: Conceptualization, K.Z., L.J. and W.L.; methodology, L.J. and K.Z.; software, L.J.; validation, L.J., K.Z. and W.L.; formal analysis, L.J., K.Z. and W.L.; investigation, L.J. and K.Z.; resources, L.J. and K.Z.; data curation, L.J. and K.Z.; writing—original draft preparation, K.Z. and W.L.; writing—review and editing, L.J., K.Z. and W.L.; visualization, W.L.; supervision, K.Z. and W.L.; project administration, K.Z. and W.L.; funding acquisition, K.Z. and W.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the projects of the Anhui Provincial Educational Commission Foundation of China (grant numbers 2023AH040060 and gxgnfx2021005), the Anhui Provincial Projects of College Student Innovation and Entrepreneurship Training Program (No. S02310371008), and the Biological and Medical Sciences of Applied Summit Nurturing Disciplines in Anhui Province (Anhui Provincial Education Secretary Department [2023]13).

Informed Consent Statement: Not applicable.

Data Availability Statement: The literature sources of the data that came from the literature and official released statistics, the data generated in management practices, and all the remaining data are indicated in the study.

Acknowledgments: The authors thank the referees for their constructive comments. All individuals included have consented to the acknowledgement.

Conflicts of Interest: The authors declare no conflicts of interest.

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