sustainability

Article

Decoupling for Carbon Neutrality: An Industrial Structure Perspective from Qinghai, China over 1990–2021

Niangjijia Nyangchak

Department of Economics, SOAS University of London, London WC1H 0XG, UK; j_niang@soas.ac.uk

Abstract: Carbon neutrality is urgent as rapidly emerging economies aggravate their share of global energy demand. In China, the energy structure is dominated by fossil fuels, but it varies significantly across provinces. As an indicator of carbon neutrality, previous studies of decoupling between carbon dioxide emissions and economic growth focused at the national and sector levels in China. However, they overlook the role of industrial structure in decoupling at the provincial level. In this light, the following paper focuses on Qinghai Province, analyzing decoupling and its influencing factors for achieving carbon neutrality from an industrial structure perspective over 1990–2021. It uses the Tapio decoupling model to evaluate decoupling states and the Logarithmic Mean Divisia Index decomposition to evaluate the influencing factors. A Data Envelopment Analysis model of super-efficiency Slacks-Based Measure is used to evaluate the decarbonization efficiency. The study finds that the overall trend shifted from weak to strong decoupling. Strong decoupling dominated the primary industry while weak decoupling dominated the secondary and tertiary industries. Economic growth negatively impacted overall decoupling, while population had a marginal effect. Energy structure and intensity generally promoted decoupling. Additionally, the overall mean efficiency of decarbonization was 0.95, led by the tertiary industry. The paper concludes by discussing policy implications.

Keywords: carbon neutrality; sustainable development; decoupling; economic growth; carbon emissions; industrial structure

check for updates

Citation: Nyangchak, N. Decoupling for Carbon Neutrality: An Industrial Structure Perspective from Qinghai, China over 1990–2021. *Sustainability* **2023**, *15*, 16488. https://doi.org/10.3390/su152316488

Academic Editor: Chengpeng Lu

Received: 5 October 2023
Revised: 28 November 2023
Accepted: 29 November 2023
Published: 1 December 2023

1. Introduction

Achieving carbon neutrality is vital for mitigating climate change. Carbon neutrality refers to balancing carbon dioxide emissions with their offset, aiming for a net zero impact. There has been a rise in research on the nexus between energy and sustainable development in support of the Paris Agreement to achieve carbon neutrality [1]. As a key player in this field, China has achieved unprecedented success in some of the Sustainable Development Goals (SDGs). It is shifting towards green growth by transforming its production and consumption practices [2,3]. A critical aspect of this transformation is the decoupling of economic growth from carbon emissions. This decoupling has become an urgent priority in the global race towards net zero by 2050 as countries set emission targets [4]. It has been widely used as a global, national, and regional policy goal and indicator of carbon neutrality [3]. A stronger decoupling signifies the likelihood of achieving carbon neutrality.

Decoupling is a prerequisite for achieving carbon neutrality. This is particularly so as emerging economies contribute significantly to global energy demand [5,6]. Affluent countries are seeing more absolute decoupling while developing countries are making progress toward relative decoupling [5,7,8]. The drivers of decoupling, such as clean technology, structural change, and economic growth patterns, are well recognized [5,8–11]. However, the sustainability and extent of decoupling efforts, particularly in affluent countries, remain areas of ongoing research. For instance, affluent countries have made notable advances in decoupling, but their consumption-based emissions continue to be a concern [12,13]. As absolute decoupling is not yet occurring at a global and regional scale [14,15], more research is needed. Stringent and coordinated policies of sustainable production and consumption must be explored at a large scale and speed for carbon neutrality.

China, the world's largest greenhouse gas emitter, plays a crucial role in global decarbonization. The country has been making progress in decoupling its economic growth from carbon emissions [16]. However, its energy structure, heavily reliant on fossil fuels, requires urgent optimization to mitigate climate risks [17,18]. China's decoupling has been driven by a range of policy interventions, including research and development (R&D), structural change, energy intensity, energy structure, and investment in clean technology [11,17,19–23].

While economy-wide decoupling at the national level has been researched extensively, there is less of an understanding of decoupling from an industrial structure perspective at the provincial level. Some provinces have more low-carbon energy sources than others. The heterogeneous emission trajectories of provinces make it a formidable task to determine whether China will meet its 2030 emissions peak and 2060 carbon neutrality [24]. Some provinces have already peaked emissions [25], offering valuable insights into the potentially effective policies for attaining absolute decoupling and carbon neutrality. In this light, this study will address the dynamics and understanding of achieving carbon neutrality through decoupling. It will focus on Qinghai, a northwestern province on the Qinghai-Tibet Plateau (QTP) in China, that had peaked carbon emissions in 2016.

The QTP, with its distinct trajectory of natural capital and economic growth, plays a significant role in the sustainable development and carbon neutrality goals. This region, known as China's ecological barrier, features the greatest tectonic landform and climate-sensitive glaciers. It has substantial potential for renewable energy sources like solar, wind, and hydropower. In recent years, national and provincial governments have made headway in safeguarding the delicate plateau resources and fostering renewable energy as pathways toward sustainable development. Particularly, Qinghai has laid the groundwork for sustainable development by establishing pilot industrial parks for renewable energy, a circular economy, green organic agriculture, and a destination for ecotourism. Local governments promote these green industries as though the region is destined to become a major sustainable development hub.

While the development of renewable energy is the leading factor in reducing global fossil fuels [15], Qinghai's approach to sustainable development and its contribution toward carbon neutrality may provide potential lessons that can be learned globally. Notably, carbon emissions in Qinghai peaked and began declining in 2016, despite national increases [26,27]. Several states of decoupling have been achieved due to a service-oriented economy, energy efficiency, energy structure, and low-carbon industries [28–30]. However, its potential for carbon neutrality through decoupling and driving factors remains underexplored. A systematic literature on decoupling and rising low-carbon industries in Qinghai is lacking. The region's sensitive plateau ecosystem, susceptible to climate change, underscores the need for further research to identify the drivers and barriers in achieving strong and absolute decoupling towards carbon neutrality.

In this light, this study analyzes carbon neutrality through the trends and influencing factors of decoupling between economic growth and energy-related carbon emissions from an industrial structure perspective in Qinghai over 1990–2021. The design of this research is predicated on the urgency of achieving carbon neutrality in the context of China's fast economic growth and its substantial reliance on fossil fuels for energy. Targeting a gap in decoupling literature on the QTP, the study chose Qinghai for its unique economic and ecological characteristics. It analyzes Qinghai as an ideal case for provincial-level analysis from an industrial structure perspective. The province's significant efforts toward renewable energy and sustainable practices further justify its selection for this study design.

The study integrates several models: the Tapio decoupling model is used to assess decoupling states, the Logarithmic Mean Divisia Index (LMDI) is used to identify influencing factors in decoupling, and a Data Envelopment Analysis (DEA) model of super-efficiency Slacks-Based Measure (SBM) is used to evaluate decarbonization efficiency. This multi-model approach is designed to provide a nuanced understanding of the interplay between economic development and carbon emissions in Qinghai. It offers insights for policy formulation towards sustainable development and carbon neutrality.

The research makes four contributions. First, it analyzed decoupling states between 1990 and 2021 in Qinghai for the first time to provide a longitudinal perspective on sustainable development trajectory. This perspective may help the province and country to understand the historical trends to guide sustainable development policies toward carbon neutrality, as well as to provide references for other countries. Second, it dissects economy-wide decoupling into three major industries, enhancing understanding of the drivers and barriers of decoupling from an industrial structure perspective. A breakdown of the carbon emissions by sector and source further elucidates the complex underlying composition of emissions. Third, a non-radial, non-oriented DEA model of super-efficiency SBM is added to the LMDI decomposition and the Tapio decoupling models. This combination enhances understanding of decarbonization efficiency and its influencing factors. Fourth, the study discusses policy implications for decarbonization.

2. Literature Review

2.1. Decoupling for Carbon Neutrality in China

As an eclectic approach, green growth fosters sustainable development with innovation in clean technology and substitution for achieving absolute decoupling between economic growth and resource use [31,32]. It embodies the rapid growth of green sectors and the 'de-growth' of inefficient sectors driven by green investment and high-speed green innovation [33]. The capacity of decoupling is a defining and intertwining characteristic of green growth for achieving carbon neutrality and sustainable development.

Decoupling literature in China can be grouped into economy-wide, sector-wide, and prospect studies. In the first strand, China exhibited a weak decoupling to an expansive coupling between 2000 and 2014, with the decoupling effect of the total energy consumption from the Gross Domestic Product (GDP) as a main driver [34]. However, some studies from the same period and 2000–2016 indicate a transition from expansive negative decoupling to strong decoupling, with the effect of economic growth increasing carbon emissions while the energy intensity decreases it [11,19].

Studies with different approaches provide diverse findings. From an industrial structure perspective, industrial restructuring has not increased carbon emissions, and decoupling shifted from a weak to strong decoupling from 2000–2001 to 2013–2016 [20]. It has a substantial effect on the primary industry, followed by tertiary and secondary industries [20]. In terms of the economic growth efficiency effect on decoupling, efficiency in carbon emissions reduction has marginally increased, consistent with China's strong negative decoupling [35]. Additionally, energy efficiency drove absolute decoupling in 22 provinces between 2006 and 2015 [17]. This has been accelerated by substituting natural gas and oil for coal, lowering industry share, and enhancing carbon sequestration [17].

Overall, China's decoupling from 1978 to 2020 was effectively driven by the relative energy price, an increased share of clean energy, government intervention, decreases in R&D investment, foreign trade, and the ratio of tertiary to secondary industries [22]. The literature demonstrates that industrial and energy structures can potentially further isolate economic growth from carbon emissions [11,21].

The second strand of literature focuses on specific sectors, such as mining, manufacturing, agriculture, and water [36–40]. China's industrial sector, for instance, experienced weak decoupling from 1993 to 2013, where the investment scale inhibited decoupling while the investment efficiency and energy intensity promoted it [41]. As an underlying sector for energy production, decoupling in China's mining has been a research hotspot [38]. The output scale effect and the potential energy intensity effect have driven weak decoupling followed by strong decoupling in the mining sector [38].

All Chinese provinces decarbonize toward carbon neutrality but with substantial variations [42]. The eastern region shows strong decoupling, the central region fluctuates considerably between decoupling states, and the western region shows mainly weak decoupling [21,25,34,35,38,42].

The third strand of literature focuses on forecasting prospective scenarios of decoupling. As China has pledged to peak its carbon emissions by 2030 and reach carbon neutrality by 2060, revealing the future of decoupling is vital [23,43]. China's carbon emissions may peak between 2025 and 2030 under baseline and green development scenarios [25]. However, others indicate that it may peak between 2028 and 2040, with 2030 being optimum [24]. Fourteen provinces have already peaked their emissions, while twenty-six of thirty provinces are highly likely to peak emissions on time despite perennial economic growth [24,25].

2.2. Decoupling for Carbon Neutrality on the Qinghai-Tibet Plateau

Decoupling in the provinces of the Qinghai-Tibet Plateau remains systematically understudied. Six of nine existing studies, summarized in Table A1, are from Chinese academic sources while the rest are from international periodicals. From 2006 to 2016, the plateau had a weak decoupling, hindered by the economic scale, investment intensity, and the industrial energy structure [28]. It is promoted by R&D efficiency, energy intensity, and R&D intensity [28].

In Qinghai, carbon emissions increased gradually, accelerated, and then fluctuated and declined from 1997 to 2017 [44]. Decoupling was primarily driven by the structural effect followed by the energy intensity effect, whereas economic growth and population increased carbon emissions [44]. From 2000 to 2019, Qinghai decoupled energy consumption and carbon emissions from economic growth, especially from 2016 [30]. This was attributed to the energy structure adjustment, with a fall in coal consumption and a rise in renewable energy consumption [30]. Others observe that decoupling was weak prior to 2013 and strong after 2013 [45]. The decoupling capacity in Qinghai has been expanding but is unstable owing to the negative effect of economic growth and investment [29]. The instability was also attributed to the positive effect of energy efficiency, urbanization, technological investment, and environmental regulation [29].

Other studies address decoupling from different perspectives. For example, one group of researchers observes decoupling between the regional resource-environment and the socio-economy systems in a prefecture in Qinghai using an indicator system [46]. Others approach decoupling greenhouse gas emissions from animal husbandry [47], transportation [48], and water consumption [49].

Overall, systematic literature on carbon neutrality through decoupling is scant for the QTP. Several studies indicate that Qinghai has achieved decoupling, but that it has been unstable and requires further investment in renewable energy sources, energy efficiency, and industrial structure. Further research is needed to identify effective strategies for maintaining a stable decoupling in Qinghai.

3. Materials and Methods

Decoupling and decomposition models have been widely used and replicated to explore driving mechanisms, such as energy structure, energy intensity, economic growth, population, industrial structure, technological progress, labor, and investment, for decoupling at global and national levels [5,19,22,34,42,50,51]. This study employs a DEA model of super-efficiency SBM method, in addition to Tapio decoupling and LMDI decomposition to evaluate efficiency of decarbonization.

3.1. Data

The decoupling and decomposition models of this study used data on carbon emissions, GDP per capita, population, and energy to be consistent with the literature. The super-efficiency SBM model used fixed asset investment, labor, and energy as inputs, GDP as desired output, and carbon emissions as undesirable output. All the data have been used at economy-wide level, and except for population, were used at the levels of primary, secondary, and tertiary industries.

1. Carbon emissions: CO_2 emissions in million metric tons (Mt) are calculated using mass balances based on IPCC guidelines [26]. As all the other data were available over 1990–2021, missing $\leq$25% of the total data for carbon emissions over 1990–1996 and 2021 were imputed using liner regression model. Visualizations of data on carbon emissions across sectors between 1997–2020 were provided without data imputation.
2. GDP: Gross domestic product at constant prices set in 1990 using GDP deflator.
3. Population: Total population in 10,000-person units without regard to industrial structures.
4. Energy: Total energy consumption converted into 10,000-ton standard coal equivalent.
5. Labor: Total persons employed in urban and rural units, private and state-owned enterprises, and self-employed citizens in 10,000-person units.
6. Capital: Calculated the price deflator index of investment data of three industries based on method literature [52,53] and deflator construction method [54]. The perpetual inventory method was used to obtain the capital stock data for the three industries based on the depreciation rate by [55] and the base year capital stock data by [53]. The method is written as: $(k_t = (1-\delta)k_{t-1} + I_t/P_t)$, wherein, I_t is the nominal value of gross fixed capital formation for the current year. P_t is the investment price index. 1990 is the baseline year. δ denotes the capital stock depreciation rate set at 10.96%. The data is in 100 million yuan. As the fixed asset investment price index was no longer available in the 2021–2022 Statistical Yearbook, the Consumer Price Index was used instead.

All the 1990–2021 data were obtained from the China Statistical Yearbook, Qinghai Statistical Yearbook, China Energy Statistical Yearbook, Historical Data of China's GDP Accounting 1952–2002, China Fixed Asset Investment Statistical Yearbook 2004–2017, and CEADs.

3.2. Decoupling Model

The essence of decoupling is measuring the ratio of change in resource consumption or pollutant emissions to the ratio of change in economic growth over a given period [56]. Decoupling Index (DI) in year t is calculated as follows:

$$\begin{aligned} \mathrm{DI} &= (\Delta R_t)/(\Delta G_t) \\ \Delta \mathrm{R}_t &= (R_t - R_{t-1})/(R_{t-1}) \\ \Delta \mathrm{G}_t &= (G_t - G_{t-1})/(G_{t-1}) \end{aligned} \quad (1)$$

wherein, ΔR_t denotes change in resource consumption in a target year and ΔG_t denotes economic growth in a target year. DI has one of the following scenarios: DI > 1 indicates a lack of decoupling, when resource consumption rate exceeds economic growth. DI = 1 indicates the turning point between absolute and relative decoupling. The higher the DI, the greater the economic growth's dependency on resources, and vice versa. 0 < DI < 1 indicates relative decoupling when resource consumption rate is less than that of economic growth. When DI ranges from 0 to 1, there is higher resource efficiency and lower resource dependency. DI = 0 indicates economic growth while resource consumption remains constant. DI < 0 indicates absolute decoupling, where resource consumption or pollutant emissions decrease as the economy expands.

Tapio [57] introduced decoupling elasticity and measured the incremental value sensitivity to enhance previous decoupling models [56,58,59]. Given its multi-states of decoupling, the Tapio decoupling model has been extensively used to evaluate the decoupling relationship between carbon emissions and economic growth [11,20,22,34,38]. The Tapio decoupling model is expressed as the below equation:

$$DI^t = \frac{\Delta C/C}{\Delta G/G} = \frac{(C^t - C^0/C_0)}{(G^t - G^0/G_0)} \tag{2}$$

wherein, DI^t is the decoupling index for a particular period; $\Delta C/C$ denotes the growth rate of carbon emissions; and $\Delta G/G$ denotes the growth rate of economic growth. The target and base years are t and 0, respectively. Decoupling is interpreted according to eight decoupling states [57], as shown in Table 1.

Table 1. Decoupling states.

Decoupling State	Sub-Categories	ΔC	ΔG	DI (*C*, *G*)
Negative	Expansive	>0	>0	D > 1.2
	Weak	<0	<0	0 < D < 0.8
	Strong	>0	<0	D < 0
Decoupling	Recessive	<0	<0	D > 1.2
	Weak	>0	>0	0 < D < 0.8
	Strong	<0	>0	D < 0
Coupling	Expansive	>0	>0	0.8 < D < 1.2
	Recessive	<0	<0	0.8 < D < 1.2

3.3. Decomposition Model

The Logarithmic Mean Divisia Index (LMDI) has been a dominant decomposition model for analyzing influencing factors of energy-related carbon emissions [60]. The LMDI method provides complete decomposition without residual errors, consistency of addition decomposition, and multiplication decomposition, and can handle zero values in data [40,61]. Based on prevalent literature on LMDI method [60–63], this study employs Kaya identity [64] and LMDI method [60] to evaluate the drivers and inhibitors influencing decoupling between carbon emissions and economic growth. It decomposes effect factors into energy intensity, energy structure, economic growth, and population scale. Based on Kaya identity, the decomposition factors of carbon emissions are calculated as:

$$\begin{aligned} C &= \sum\nolimits_i C_{i,t}/E_{i,t} \times E_{i,t}/G_{i,t} \times G_{i,t}/P_t \times P_t \\ &= \sum\nolimits_i c \times e \times g \times p \end{aligned} \tag{3}$$

wherein, i stands for industry $(i = 1, 2, 3)$. $C_{i,t}$ denotes carbon emissions in year t. $E_{i,t}$ denotes total energy consumption in year t. $G_{i,t}$ denotes GDP in year t. P_t denotes population in year t. c simplifies the sum of $C_{i,t}/E_{i,t}$ to denote energy structure factor or carbon intensity of energy. e simplifies the sum of $E_{i,t}/G_{i,t}$ to denote energy consumption intensity factor or energy intensity of GDP. g simplifies the sum of $G_{i,t}/P_t$ to denote economic growth factor or GDP per capita, and p simplifies P_t to denote population scale factor. Based on additive LMDI decomposition model, the change in carbon emissions from the base year (0) to the target year (t) is obtained as:

$$\Delta C = C_t - C_0 = \Delta C_c + \Delta C_e + \Delta C_g + \Delta C_p \tag{4}$$

wherein, ΔC is the change in total growth of carbon emissions. $\Delta C_c + \Delta C_e + \Delta C_g + \Delta C_p$ denotes the effect of energy structure intensity, energy consumption intensity, economic growth, and population on carbon emissions, respectively. The LMDI decomposition factors are expressed as:

$$
\begin{aligned}
\Delta C_c &= \sum_i \frac{C_{i,t}-C_{i,0}}{In\ C_{i,t}-In\ C_{i,0}} \times ln\frac{c_{i,t}}{c_{i,0}} \\
\Delta C_e &= \sum_i \frac{C_{i,t}-C_{i,0}}{In\ C_{i,t}-In\ C_{i,0}} \times ln\frac{e_{i,t}}{e_{i,0}} \\
\Delta C_g &= \sum_i \frac{C_{i,t}-C_{i,0}}{In\ C_{i,t}-In\ C_{i,0}} \times ln\frac{g_{i,t}}{g_{i,0}} \\
\Delta C_p &= \sum_i \frac{C_{i,t}-C_{i,0}}{In\ C_{i,t}-In\ C_{i,0}} \times ln\frac{p_{i,t}}{p_{i,0}} \\
&= \frac{C_{i,t}-C_{i,0}}{In\ C_{i,t}-In\ C_{i,0}} \left(ln\ \frac{c_t}{c_0} + ln\ \frac{e_t}{e_0} + ln\ \frac{g_t}{g_0} + ln\ \frac{p_t}{p_0}\right)
\end{aligned} \tag{5}
$$

Combined models of Tapio decoupling and LMDI decomposition can be expressed as:

$$
\begin{aligned}
DI &= \frac{\%\Delta C}{\%\Delta G} = \frac{\Delta C/C_0}{\Delta G/G_0} = \frac{(C_t-C_0)/C_0}{(G_t-G_0)/G_0} \\
&= \frac{\left(\Delta C_c+\Delta C_e+\Delta C_g+\Delta C_p\right)/C_0}{(G_t-G_0)/G_0} \\
&= \Delta C \times \frac{G_0}{\Delta G \times C_0} = \left(\Delta C_c + \Delta C_e + \Delta C_g + \Delta C_p\right) \times \frac{G_0}{\Delta G \times C_0} \\
&= D_c + D_e + D_g + D_p
\end{aligned} \tag{6}
$$

wherein, ΔC denotes the change in the growth of carbon emissions. ΔG denotes the change in GDP growth. D_c, D_e, D_g, and D_p denote decoupling index of each decomposition factor, calculated as:

$$
\begin{aligned}
D_c &= \frac{G_0}{\Delta G \times C_0} \times \sum_i \frac{C_{i,t}-C_{i,0}}{\mathrm{In}C_{i,t}-\mathrm{In}C_{i,0}} \times \ln\frac{c_{i,t}}{c_{i,0}} \\
D_e &= \frac{G_0}{\Delta G \times C_0} \times \sum_i \frac{C_{i,t}-C_{i,0}}{\mathrm{In}C_{i,t}-\mathrm{In}C_{i,0}} \times \ln\frac{e_{i,t}}{e_{i,0}} \\
D_g &= \frac{G_0}{\Delta G \times C_0} \times \sum_i \frac{C_{i,t}-C_{i,0}}{\mathrm{In}C_{i,t}-\mathrm{In}C_{i,0}} \times \ln\frac{g_{i,t}}{g_{i,0}} \\
D_p &= \frac{G_0}{\Delta G \times C_0} \times \sum_i \frac{C_{i,t}-C_{i,0}}{\mathrm{In}C_{i,t}-\mathrm{In}C_{i,0}} \times \ln\frac{p_{i,t}}{p_{i,0}}
\end{aligned} \tag{7}
$$

3.4. *Efficiency Model*

A few studies used DEA models to assess energy efficiency in addition to LMDI decompositions [34,35,65]. To further evaluate decoupling in terms of efficiency in decarbonization, this study employs a non-radial, non-oriented DEA model of SBM developed by Tone [66]. It has the additions of super-efficiency and undesirable output [67,68]. In this model, the study assessed fixed asset investment, labor, and energy as input, GDP as desired output, and carbon emissions as undesirable output. These factors play important roles in measuring efficiency of decarbonization in addition to LMDI decomposition factors.

In the super-SBM model, when there are n decision-making units (DMU) with input, desired output, and undesired output vectors: $X = (x_{ij}) \in R^{m\times n}, Y = \left(y_{kj}\right) \in R^{s_1\times n}$, $Z = \left(z_{lj}\right) \in R^{s_2\times n}$, let $X > 0, Y > 0, Z > 0$, then the production possibility set: $P = \{(x,y)|x \geq X\wedge, y \leq Y\wedge, z \geq Z\wedge, \wedge \geq 0\}$, where $\wedge = [\lambda_1, \lambda_2, \ldots, \lambda_n] \in R^n$ denotes the weight coefficient vector, and the two inequalities in the P function indicate that the actual input is greater than or equal to the frontier, the actual desired output is less than or equal to the frontier output, and the actual undesirable output is greater than or equal to the frontier. Thus, each DMU has input, desirable output, and undesirable output, denoted by X, Y, Z, respectively. $s^x \in R^m, s^z \in R^{s2}$ denote the excess of inputs and undesirable outputs, respectively, and $s^y \in R^{s1}$ denote the shortage of expected outputs [68].

As there is a lack of SBM model formulae with undesirable output by Tone [68], this study refers to the formula proposed by Cheng [69] to evaluate efficiency of DMUs (x_0, y_0, z_0). The super-SBM model with undesirable output is derived as follow:

$$
\begin{aligned}
\rho = \min & \frac{1+\frac{1}{m}\sum_{i=1}^{m}\frac{w_i^x s_i^x}{x_{i0}}}{1-\frac{1}{s_1+s_2}\left(\sum_{k=1}^{s_1}\frac{w_k^y s_k^y}{y_{k0}}+\sum_{l=1}^{s_2}\frac{w_l^z s_l^z}{z_{i0}}\right)} \\
& s.t. x_{i0} \geq \sum_{j=1,\neq 0}^{n}\lambda_j x_j - s_i^x, \forall i; \\
& y_{k0} \leq \sum_{j=1,\neq 0}^{n}\lambda_j y_j + s_k^y, \forall k; \\
& z_{l0} \geq \sum_{j=1,\neq 0}^{n}\lambda_j z_j - s_l^z, \forall l; \\
& 0 < 1 - \frac{1}{s_1+s_2}\left(\sum_{k=1}^{s_1}\frac{w_k^y s_k^y}{y_{k0}} + \sum_{l=1}^{s_2}\frac{w_l^z s_l^z}{z_{l0}}\right); \\
& s_i^x \geq 0, s_k^y \geq 0, s_l^z \geq 0, \lambda_j \geq 0, \forall i, j, k, l;
\end{aligned}
\tag{8}
$$

wherein, ρ denotes the efficiency value of the DMU, and m, s_1 and s_2 denote the number of variables for inputs, expected outputs, and undesired outputs. When ρ = 1, that is, $s^x = 0, s^y = 0, s^z = 0$, DMU is valid. When ρ < 1, DMU is non-valid and there is room for improvement. The model calculates an efficiency value as $\rho \geq 1$. Equal weighting is expressed as $w_i^x = 1, w_k^y = 1, w_l^z = 1$.

In contrast to super-efficiency models based on radial and directional DEA, the super-efficiency SBM model does not merely increase the condition of $j \neq 0$ [67]. It calculates efficient DMUs and returns 1 for inefficient DMUs. This study calculated super-efficiency SBM model results by synthesizing the non-super-efficiency model results and the super-efficiency model results. In other words, the efficient regions are calculated with the super-efficiency model and the inefficient regions with the non-super-efficiency model. The slack variables and Lambda coefficients are calculated using the coefficients from the non-super-efficiency model.

4. Results and Discussion

4.1. Carbon Emissions and Economic Growth

The relationship between carbon emissions and economic growth determines the decoupling for carbon neutrality. Figure 1 depicts the growth of carbon emissions and the GDP in overall, primary, secondary, and tertiary industries from 1990 to 2021. The overall carbon emissions have gradually increased, accelerated, and then fluctuated and declined, confirming the general trends observed by previous studies between 2000–2019 [10,29,30,45]. The growth of carbon emissions was mostly attributable to the secondary industry, followed by the tertiary industry, and then by the primary industry. The rise of carbon emissions from the secondary and tertiary industries was largely positive from 1990 to 2021, with some negative growth. For example, secondary industry experienced negative carbon emissions in 1997, 2000, 2010, and from 2016 to 2021. The tertiary industry had negative growth in 1997, 1998, 2001, 2012, and 2020. The rest of the years were growth positive. The secondary industry peaked carbon emissions in 2006 and the tertiary industry peaked carbon emissions in 2002. The primary industry had notable growth of carbon emissions in 2003, 2006, 2010, 2011, 2016, and 2020, while emissions were negative from 2001 to 2002, 2012 to 2015, 2017 to 2019, and 2021. They peaked in 2008.

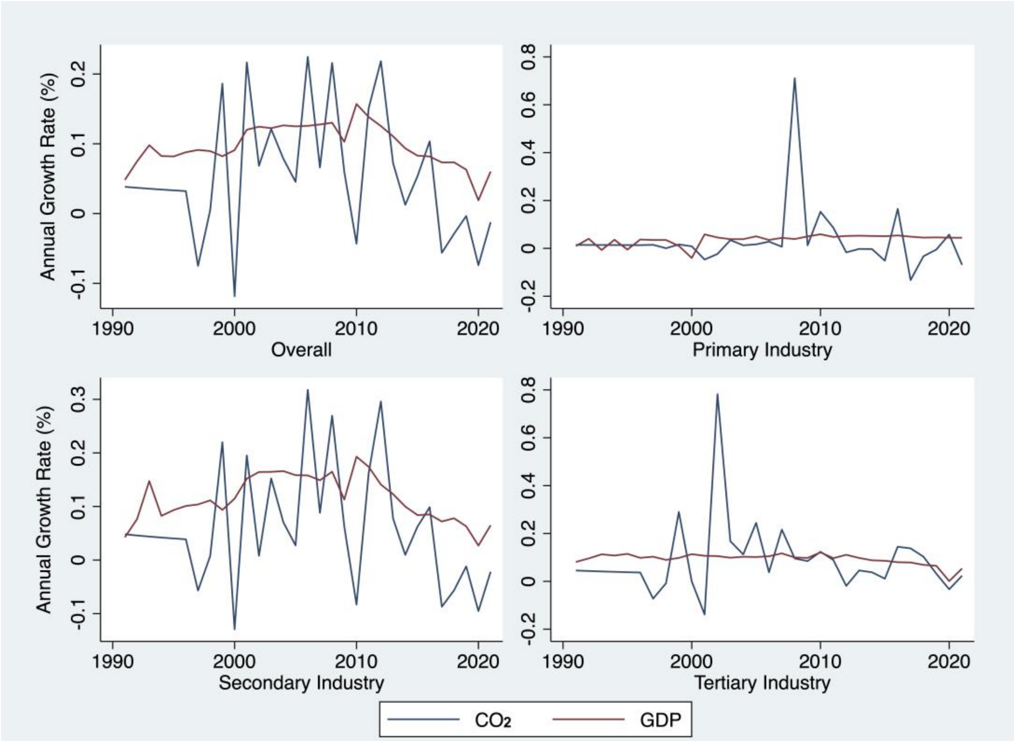

Figure 1. Annual growth of carbon emissions and GDP in overall and each industry.

Economic growth underlies decoupling or coupling in all sectors of the economy. Figure 1 indicates the economic growth in the primary, secondary, and tertiary industries from 1990 to 2021. The secondary and tertiary industries had positive growth throughout the study period, while the primary industry had negative growth in 1993, 1995, and 2000. The secondary industry led overall growth, followed by the tertiary industry and the primary industry. The primary industry grew almost constantly throughout the whole period, while the secondary industry peaked in 2010 and then gradually declined with a glitch due to the COVID-19 pandemic in 2020. The tertiary industry has grown almost constantly until its peak in 2010 and has since declined with a steep drop in 2020.

The divergent growth rates of the three industries are reflected in the structural changes and their respective output. In 1990, the GDP and its structural share were 17.67 (25%) in agriculture, 26.89 (38%) in manufacturing, and 25.38 (36%) in services [70]. In 2021, they were 352.65 (10%), 1332.61 (40%), and 1661.37 (50%), respectively [71]. While the output of the three industries have grown significantly from 1990 to 2021, their structures also shifted a great deal. The share of agriculture shrunk dramatically, while that of manufacturing expanded slightly, and the service industry increased significantly.

Sub-sectors and sources of carbon emissions shed light on the underlying composition of the emissions in the three industries. Figure 2 indicates the top 15 of 46 sectors contributing 97.41% of the cumulative carbon emissions in Qinghai, totaling 755.0616 Mt, from 1997 to 2020. With 56.6717 Mt, emissions peaked in 2016 almost simultaneously across the sectors and sources. Table A2 provides a complete sector-specific carbon emissions account. Figure 3 depicts the top 10 sources of carbon emissions in Qinghai. These sources account for 99.12% of the overall carbon emissions, totaling 768.2773 Mt, from 1997 to 2020. Table A3 provides a complete accounting of the carbon emissions by the top sources.

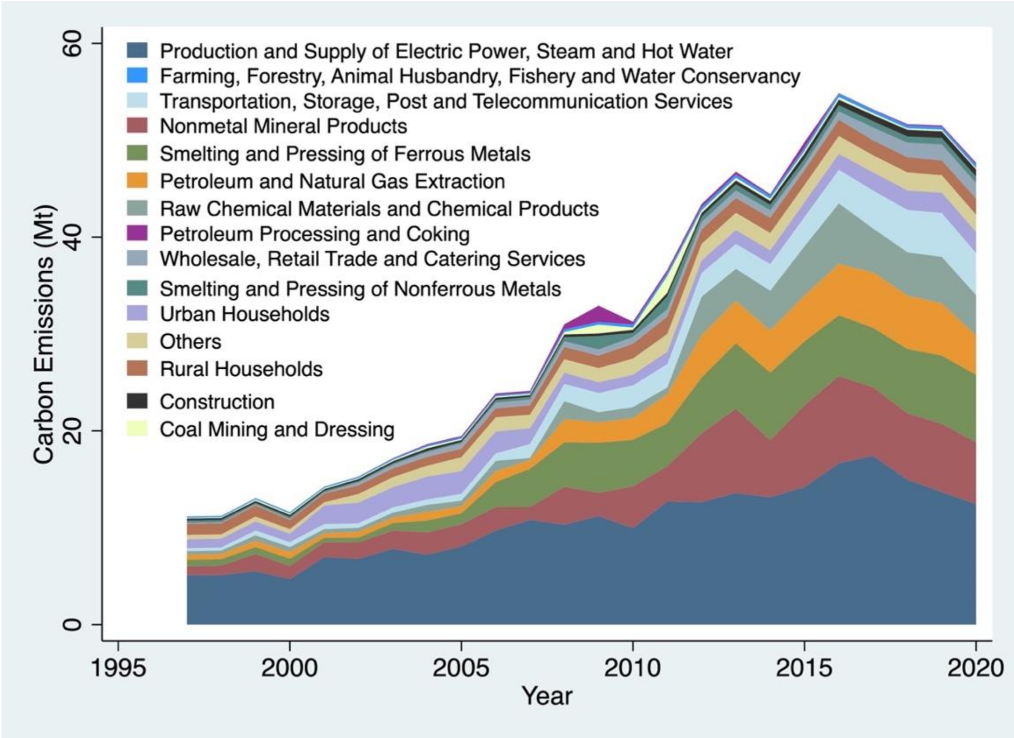

Figure 2. Top 15 sectors emitting carbon emissions.

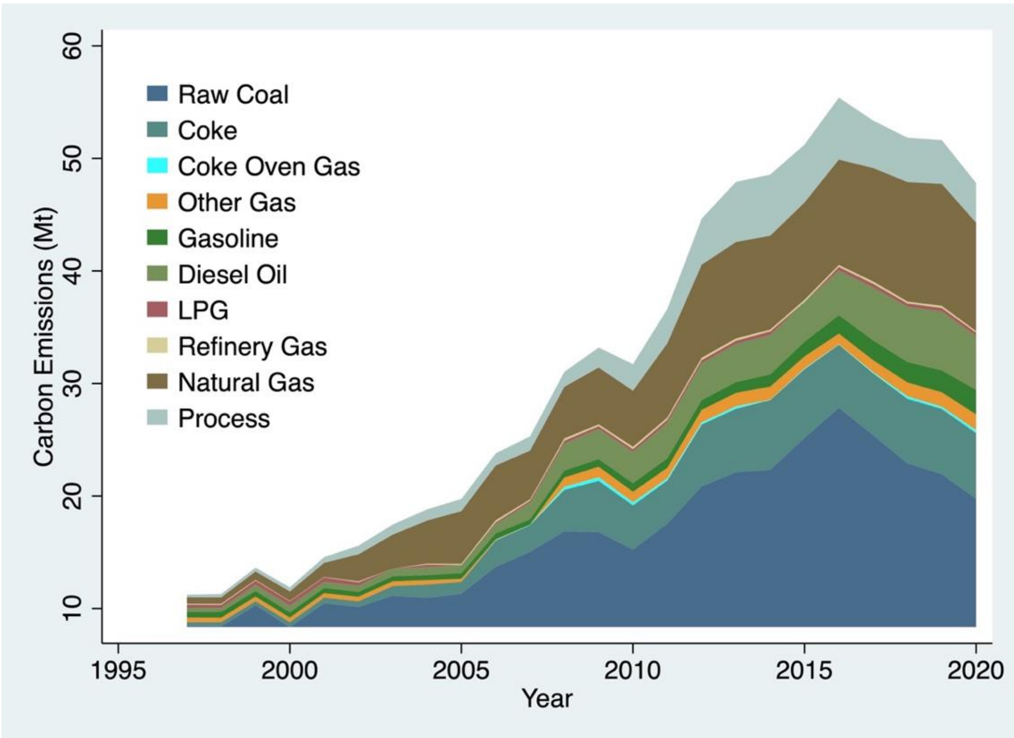

Figure 3. Top 10 sources of carbon emissions from 1997 to 2020.

4.2. Decoupling toward Carbon Neutrality

The overall trend from 1990 to 2021 was mostly weak decoupling, followed by strong decoupling, expansive negative decoupling, and expansive coupling, as shown in Figure 4 and Table A4. These trends confirm the general decoupling states observed in the previous studies between 2000–2019 [29,30,44,45]. Weak decoupling accounted for 15 years.

Expansive negative decoupling occurred in 1999, 2001, 2006, 2008, 2012, and 2016, while expansive coupling occurred in 2003 and 2011. Early strong decoupling occurred only in 1997, 2000, and 2010, while it was consistent from 2017 to 2021. The decoupling trend corresponds to the actual output of carbon emissions, which peaked in 2016 and have since gained traction in strong decoupling. The strongest decoupling state was in 2020 due to the low economic activity during the COVID-19 pandemic. It returned to pre-pandemic levels by 2021.

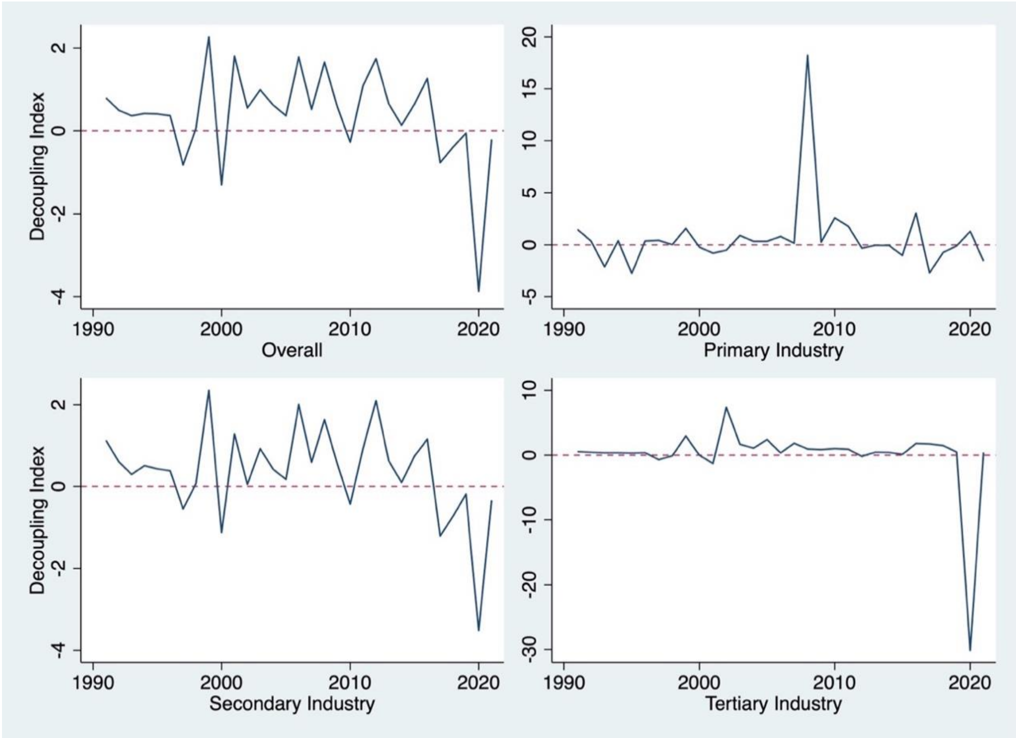

Figure 4. Decoupling index in overall, primary, secondary, and tertiary industries.

As shown in Figure 4 and Table A5, strong decoupling dominated the primary industry, followed by weak decoupling, expansive negative decoupling, strong negative decoupling, and expansive coupling. Strong decoupling occurred from 2000 to 2002, 2011 to 2015, 2016 to 2019, and from 2020 to 2021. Prior to 2009, weak decoupling occurred occasionally, and strong negative decoupling occurred in 1993, 1995, and 2000. Expansive coupling occurred in 2003 and 2006, while expansive negative decoupling occurred seven times throughout the study period.

The secondary industry was mostly weak decoupling, followed by strong decoupling, expansive negative decoupling, and expansive coupling, as shown in Figure 4 and Table A6. Strong decoupling has been more consistent from 2016 to 2021 than it was in 1997, 2000, and 2010. Expansive negative decoupling occurred in 1999, 2001, 2006, 2008, and 2012, while expansive coupling occurred in 1991, 2003, 2011, and 2016. The rest of the years were weak decoupling.

The tertiary industry was mostly weak decoupling, followed by expansive negative decoupling, strong decoupling, and expansive coupling, as illustrated in Figure 4 and Table A7. While most periods were weak decoupling, expansive negative decoupling occurred from 1998 to 1999, 2001 to 2003, 2004 to 2005, 2006 to 2007, and 2015 to 2018. In recent years, strong decoupling dominated the primary and secondary industries while the tertiary industry has seen few strong decoupling. Strong decoupling in the tertiary industry occurred from 1996 to 1998, 2000 to 2001, 2011 to 2012, and 2019 to 2020. The most recent index of strong decoupling was −30.1394, an outlier due to the COVID-19 pandemic. Expansive decoupling occurred from 2003 to 2004 and 2007 to 2011.

4.3. Factor Decomposition Analysis

The overall industry decomposition results for decoupling, as shown in Figure 5, indicate that economic growth (EG) was the single most negative factor on decoupling from 1990 to 2021. This is consistently followed by population (P), with a marginally negative decoupling effect throughout the whole period. The effect of economic growth peaked in 2013 and the effect of population peaked in 2016. Energy structure (ES) and energy intensity (EI) have both positive and negative effects on decoupling. From 1990 to 2021, energy structure had a negative effect on decoupling for fourteen years and a positive effect for seventeen years. Energy intensity had a negative effect on decoupling for eight years and a positive effect for twenty-three years. Notably, energy structure had the most negative effect on decoupling in 1993, 2001, 2008, 2012, and 2016, and similarly for energy intensity in 1994, 1999, and 2021. In contrast, energy structure had the most positive effect on decoupling in 1994, 2004, 2005, 2010, 2014, 2017, 2018, 2020, and 2021, and similarly for energy intensity in 1993, 2009, 2016, 2017, and 2019. Table A8 provides complete decomposition results.

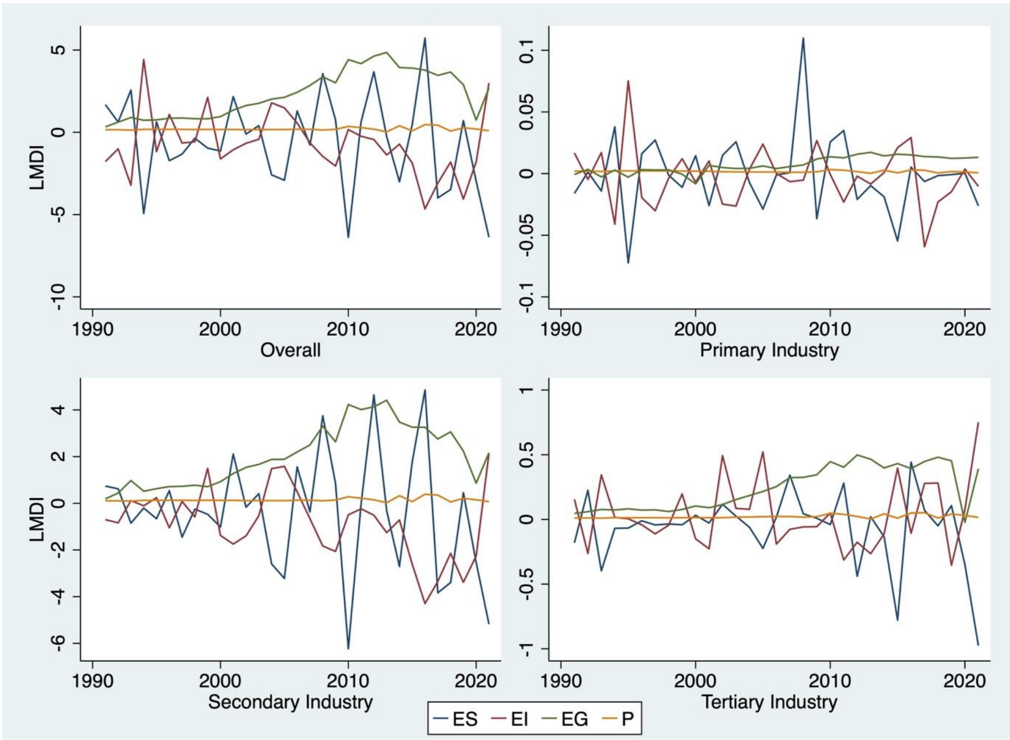

Figure 5. Decomposition results for overall, primary, secondary, and tertiary industries.

The decomposition results for the primary industry decoupling in Figure 5 show that economic growth and population mostly inhibited decoupling. Energy structure and energy intensity primarily promoted decoupling. Economic growth mostly inhibited decoupling, but it also promoted decoupling in 1991, 1993, 1995, 1999, and 2000. Population marginally inhibited decoupling over the whole period. Notably, energy structure had the most negative effect on decoupling in 2008, with an index of 0.1099. It had a positive effect in 1995 and 2015, with an index of −0.0725 and −0.0546, respectively. Energy intensity had the most negative effect on decoupling in 1995 with an index of 0.0752 and a positive effect in 2017 with an index of −0.0594. Table A9 provides complete decomposition results.

Figure 5 shows that economic growth and population had a negative effect on decoupling for the secondary industry from 1990 to 2021. Economic growth had the most significant effect from 2000 to 2019, peaking in 2013. It had a setback in 2020 due to the COVID-19 pandemic but swiftly rebounded by 2021. The effect of population has been less significant than that of economic growth and peaked in 2016. While energy structure and energy intensity mostly promoted decoupling, they also had a negative effect on decoupling. Notably, energy structure had the most negative effect on decoupling in 2001, 2008, 2012, and 2016. It had a significantly positive effect in 2004, 2005, 2010, 2014, 2017, 2018, 2020, and 2021. Energy intensity had the most negative effect in 2021, while it primarily promoted decoupling in 2009, and from 2015 to 2020. Table A10 provides complete decomposition results.

Figure 5 shows that for the tertiary industry, economic growth and population inhibited decoupling. Economic growth had briefly promoted decoupling during the COVID-19 pandemic. The economic growth effect on decoupling has been rising from 2000 to 2019 and in 2021, peaking in 2012 and 2018. The effect of population has been more marginal than that of economic growth, peaking in 2017. Throughout the period, energy structure and energy intensity had both positive and negative effects on decoupling. Notably, energy structure was most negative on decoupling in 1992, 2007, 2011, and 2016 and it was remarkably positive in 1993, 2005, 2012, 2015, 2020, and 2021. Energy intensity was most negative in 1993, 2002, 2005, 2015, 2017, 2018, and 2021 and it was notably positive in 1992, 2001, 2011, 2013, and 2019. Table A11 provides complete decomposition results.

4.4. Decomposition Analysis by Industries

As indicated in Figure 6, the energy structure effect in the primary, secondary, and tertiary industries mostly promoted decoupling from 1990 to 2021. They had both positive and negative effects on decoupling, dominated by the secondary industry, followed by the tertiary and primary industries. The energy intensity effect in all the industries had mostly promoted decoupling, dominated by the secondary industry followed by the tertiary and primary industries. The economic growth effect was largely negative to decoupling in all three industries, dominated by the secondary industry, followed by the tertiary industry. The effect in the secondary industry peaked in 2013, the tertiary industry in 2012, and the primary industry in 2013. Finally, the population effect in all industries showed a negative effect on decoupling throughout the study period. It has been dominated by the secondary industry followed by the tertiary industry. While the population effect in the secondary industry has constantly risen and peaked in 2016, the effect in 2013, 2015, and 2018 has been atypically low. Throughout the period, the population effect in the tertiary industry has been much lower than that of the secondary industry, but higher than that of the primary industry. The population effect in the tertiary industry peaked in 2017. In contrast, the population effect in the primary industry was negligible and peaked in 2010.

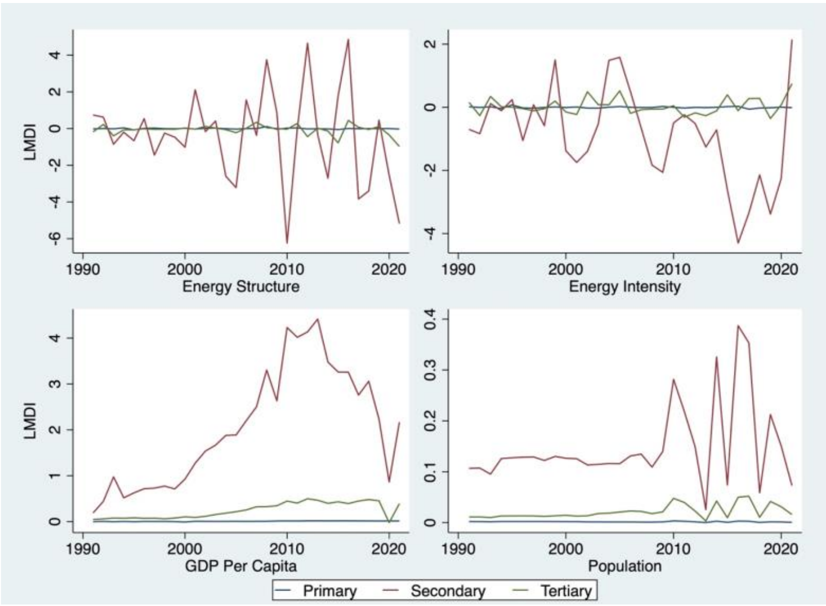

Figure 6. Decomposition results by industries.

4.5. Decarbonization Efficiency for Carbon Neutrality

Figure 7 depicts the efficiency of reducing carbon emissions as an undesirable output, the GDP as an output, and energy, capital, and labor as inputs from 1900 to 2021. In this period, the overall efficiency was high with a mean of 0.9518 and a standard deviation of 0.0677. Efficiency started from the lowest ρ value of 0.8071 in 1990 and to the highest ρ value of 1.0387 in 2021. Notably, the efficiency values where $\rho = 1 \geq$ occurred for 14 years, while a steep decline of efficiency values below 0.9500 occurred from 1990 to 1992, 1997, 1999, 2005 to 2006, and 2015 to 2019. The downturn in 1991, 1992, 1997, and 1999 was primarily driven by inefficiency in the secondary industry, followed by fluctuations in the primary and tertiary industries. The downturn from 2005 to 2006 was driven by a decline in the tertiary industry, followed by fluctuations in the secondary industry. The steep decline from 2015 to 2019 is mostly attributable to inefficiency in the primary industry, followed by a minor inefficiency in the secondary and tertiary industries. Table 2 summarizes the efficiency statistics and Table A12 provides the complete efficiency values for the overall and individual industries.

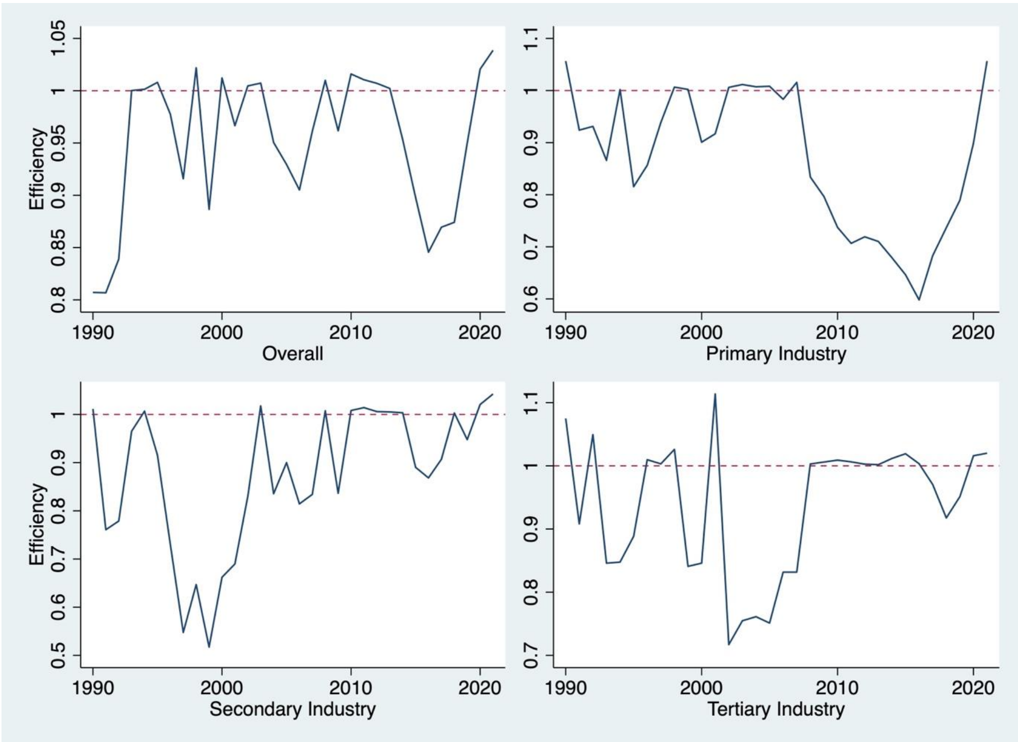

Figure 7. Efficiency of overall, primary, secondary, and tertiary industries from 1997 to 2020.

Table 2. Summary of efficiency in primary, secondary, and tertiary industries, 1990–2021.

Industry	Mean	Median	Standard Deviation	Minimum	Maximum
Overall	0.9518	0.9642	0.0677	0.8068	1.0387
Primary	0.8700	0.8999	0.1357	0.5981	1.0567
Secondary	0.8758	0.9035	0.1464	0.5173	1.0425
Tertiary	0.9388	1.0023	0.1056	0.7171	1.1138

From 1990 to 2021, Figure 7 shows a mean efficiency value of 0.8700 and a standard deviation of 0.1357 in the primary industry. The industry had efficiency values $\rho = 1 \geq$ for 10 years, with lower efficiency in 1993, 1995, and 1996, and a significant decline from 2008 to 2020. Its lowest efficiency value was 0.5981 in 2016. In recent years, efficiency has increased.

Figure 7 shows a mean efficiency value of 0.8758 and a standard deviation of 0.1464 for the secondary industry. It had 12 years of efficiency values where $\rho = 1 \geq$. In the early years, from 1991 to 1992 and 1996 to 2002, efficiency was notably low. In later years, efficiency was generally higher but with volatility.

Figure 7 shows a mean efficiency value of 0.9388 for the tertiary industry, the highest of all three industries with a standard deviation of 0.1056. The industry had 17 years of efficiency values where $\rho = 1 \geq$, outpacing the other two industries. It had also fluctuated, particularly before 2008. Efficiency declined in 1991, 1993 to 1995, 1999 to 2000, and most notably from 2002 to 2007. With an outlier efficiency value of 1.1138 in 2001, efficiency has been high and most consistent from 2008 to 2016.

5. Conclusions

This study analyzed carbon neutrality through decoupling in Qinghai from 1990 to 2021. It explored the relationship between carbon emissions and economic growth, and the trends and influencing factors of decoupling from an industrial structure perspective. The Tapio decoupling, Logarithmic Mean Divisia Index, and DEA model of super-efficiency Slacks-Based Measure were used. During the study period, carbon emissions in the overall, primary, secondary, and tertiary industries followed a trend of initial growth, acceleration, fluctuation, and decline. The secondary industry contributed most to carbon emissions, followed by the tertiary and primary industries. Economic growth showed a similar trend with the secondary and tertiary industries leading, while the primary industry experienced some negative growth. The GDP and structural share of these industries changed significantly over the years, reflecting a shift from agriculture to manufacturing and services. This study also examined the top sectors and sources contributing to carbon emissions in Qinghai, revealing that the top 15 of 46 sectors accounted for 97.41% of the cumulative emissions.

The decoupling trends between 1990 and 2021 varied across the industries. Overall, the trend shifted from weak to strong decoupling, with periods of expansive negative decoupling and expansive coupling. Each industry exhibited distinct decoupling patterns. The primary industry had mostly experienced strong decoupling. The secondary industry experienced a mix of weak and strong decoupling. The tertiary industry had predominantly experienced weak decoupling with periods of strong and expansive negative decoupling. The factor decomposition analysis revealed that economic growth negatively impacted decoupling across the industries, while the population had a marginal effect. Energy structure and intensity generally showed positive effects. In addition, the study revealed an overall high efficiency in decarbonization, with a mean of 0.9518 and variations across the industries. The tertiary industry showed the highest mean efficiency, while the primary and secondary industries had lower and more volatile efficiency levels.

The overall findings underscore the complexity of achieving carbon neutrality, highlighting the need for industry-specific, tailored strategies across the different industrial sectors, and the balanced promotion of economic growth alongside sustainable practices. Three essential policy implications are highlighted for enhancing decoupling and accelerating progress towards carbon neutrality:

Focus on Secondary Industry: The study revealed that the secondary industry, which includes manufacturing and processing, is a significant contributor to carbon emissions in Qinghai and exhibits weak decoupling. Policies should target this sector for greener growth, emphasizing efficiency improvements and reduced reliance on energy-intensive processes. Key sectors contributing over 70% of emissions, such as the production and supply of electric power, steam and hot water, nonmetal mineral products, the smelting and pressing of ferrous metals, petroleum and natural gas extraction, and raw chemical materials and chemical products, should be prioritized for sustained decoupling.

Optimize Energy Structure and Intensity: Strong decoupling also depends on optimizing the energy structure and intensity. Policies should focus on diversifying energy sources by increasing the use of sustainable alternatives and reducing dependency on fossil fuels, such as raw coal, natural gas, and diesel oil, which are major carbon emitters. The implementation of clean technologies and market-based incentives can further facilitate this transition. Ensuring energy efficiency in all processes, especially those contributing significantly to emissions, is crucial for sustainable development.

Strengthen and Sustain Decoupling Efforts: Qinghai has achieved a strong, though volatile, decoupling state since 2017. To maintain and strengthen this progress, policies should continue to support and expand renewable energy initiatives. An investment in clean technology and emerging low-carbon industries is essential. Coordination and integration with other provinces are necessary to leverage the shared resources, and advanced research and technologies. This collaborative approach can maximize the impact of sustainable policies and contribute to a more cohesive national strategy for carbon neutrality.

These policy directions are crucial for Qinghai's sustainable development trajectory. While the focus is on regional specifics, the lessons and strategies can be extrapolated to other regions and countries, particularly those with similar industrial structures and sustainability challenges. However, the study faces several limitations regarding the generalizability of its results, the use of imputed data for early carbon emissions, and the potential inadequacies in accounting for the full factors and their interconnections. These constraints necessitate a careful interpretation of the findings and highlight the need for further research across various geographical and industrial contexts, the acquisition of complete data and the application of robust imputation techniques, and the development of more extensive models to comprehensively understand the complexities involved in achieving carbon neutrality.

Funding: The APC was funded by Frank Yih.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are contained within the article.

Acknowledgments: This article is part of my doctoral dissertation at the Department of Economics, SOAS University of London, UK. I appreciate the feedback provided by Dic Lo and Risa Morimoto. In addition, I thank Frank Yih's longstanding support for my academic research.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Table A1. Key decoupling literature on the Qinghai-Tibet Plateau.

Authors	Methods	Variables	Periods
Fan et al., 2020 [28]	LMDI; Tapio	energy consumption, economic scale, investment intensity, energy structure, energy intensity, R&D efficiency, R&D intensity	2006–2016
Huang et al., 2021 [44]	LMDI; Tapio	energy-related carbon emissions, energy structure, energy intensity, economic growth, population	1997–2017
Bai et al., 2021 [47]	LMDI; Tapio; DEA	carbon emissions in animal husbandry, efficiency, structure, economy, labor force	1980–2015
Li et al., 2019 [48]	LMDI;	traffic carbon emissions, energy structure, energy intensity, economic output, population scale	2008–2017
Wang, Feng et al., 2021 [30]	LMDI;	energy consumption, carbon emission, energy structure, energy intensity, economic growth, industrial restructure, population scale	2000–2019
Hu et al., 2021 [45]	Tapio; GDIM	investment intensity, investment efficiency, output scale, output intensity, energy consumption, energy intensity, carbon emissions	2000–2019
Huang & Hu, 2021 [29]	Tapio; Entropy; OLS	economic, investment, industry structure, energy efficiency, urbanization, technical investment, environmental regulation	2000–2019
Wang, Wang et al., 2021 [46]	Tapio; CHDM; indicator system	resource and environmental level, resource and environmental pressure, resource and environmental system, social and economic system	2000–2018
Sun et al., 2020 [49]	LMDI	water intensity, urban and rural product export structure, trade volume	2012

Table A2. Cumulative sectoral carbon emissions from 1997 to 2020.

Industries	Sectors	Emissions	Share
Primary	Farming, Forestry, Animal Husbandry, Fishery and Water Conservancy	5.8518	0.75%
Secondary	Coal Mining and Dressing	6.3508	0.82%
	Petroleum and Natural Gas Extraction	61.1542	7.89%
	Ferrous Metals Mining and Dressing	0.4555	0.06%
	Nonferrous Metals Mining and Dressing	3.3651	0.43%
	Nonmetal Minerals Mining and Dressing	1.7715	0.23%
	Other Minerals Mining and Dressing	0.0298	0.00%
	Food Processing	1.5132	0.20%
	Food Production	0.9944	0.13%
	Beverage Production	0.7748	0.10%
	Tobacco Processing	0.2497	0.03%
	Textile Industry	0.1953	0.03%
	Garments and Other Fiber Products	0.4291	0.06%
	Leather, Furs, Down and Related Products	0.1511	0.02%
	Timber Processing, Bamboo, Cane, Palm Fiber & Straw Products	0.0294	0.00%
	Furniture Manufacturing	0.0707	0.01%
	Papermaking and Paper Products	0.0986	0.01%
	Printing and Record Medium Reproduction	0.3807	0.05%
	Cultural, Educational and Sports Articles	0.2176	0.03%
	Petroleum Processing and Coking	5.3422	0.69%
	Raw Chemical Materials and Chemical Products	51.2160	6.61%
	Medical and Pharmaceutical Products	1.9361	0.25%
	Chemical Fiber	0.0301	0.00%
	Rubber Products	0.1818	0.02%
	Plastic Products	3.2972	0.43%
	Nonmetal Mineral Products	98.9367	12.76%
	Smelting and Pressing of Ferrous Metals	91.8585	11.85%
	Smelting and Pressing of Nonferrous Metals	11.3457	1.46%
	Metal Products	0.6053	0.08%
	Ordinary Machinery	1.4187	0.18%
	Equipment for Special Purposes	0.3340	0.04%
	Transportation Equipment	0.0662	0.01%
	Electric Equipment and Machinery	0.5666	0.07%
	Electronic and Telecommunications Equipment	0.0524	0.01%
	Instruments, Meters, Cultural and Office Machinery	0.0498	0.01%
	Other Manufacturing Industry	0.2585	0.03%
	Scrap and waste	0.0556	0.01%
	Production and Supply of Electric Power, Steam and Hot Water	250.8114	32.36%
	Production and Supply of Gas	0.0454	0.01%
	Production and Supply of Tap Water	0.4187	0.05%
	Construction	8.5524	1.10%
Tertiary	Transportation, Storage, Post and Telecommunication Services	46.3851	5.98%
	Wholesale, Retail Trade and Catering Services	16.0040	2.06%
	Others	32.0116	4.13%
Households	Urban Households	38.5570	4.97%
	Rural Households	30.6842	3.96%
Total		775.1043	100.00%

Table A3. Top 15 sources of carbon emissions from 1997 to 2020.

Year	Raw Coal	Coke	Coke Oven Gas	Other Gas	Gasoline
1997	8.421359	0.373957	0.000000	0.396292	0.518619
1998	8.414337	0.373957	0.000000	0.396292	0.518619
1999	10.284698	0.368491	0.000000	0.398080	0.510132
2000	8.349702	0.448460	0.000000	0.391524	0.472669
2001	10.467052	0.501677	0.000000	0.394504	0.469743
2002	10.133567	0.514334	0.000000	0.400463	0.430232
2003	11.134053	0.870744	0.000000	0.415361	0.452475
2004	10.939949	1.186018	0.000000	0.399867	0.448085
2005	11.325319	1.053695	0.000000	0.264592	0.502230
2006	13.705366	2.343269	0.035742	0.064360	0.530619
2007	15.044180	2.370827	0.039201	0.000001	0.479401
2008	16.861240	3.684619	0.264561	0.826891	0.624632
2009	16.792529	4.553481	0.321921	0.932501	0.677363
2010	15.235584	3.929936	0.274188	0.933675	0.766281
2011	17.542671	3.829402	0.200617	0.921900	0.847293
2012	20.858538	5.488425	0.189929	1.104385	0.875255
2013	22.097378	5.650227	0.219064	1.192451	0.961143
2014	22.318013	6.214628	0.030208	1.154467	1.087318
2015	25.153242	6.116293	0.079555	1.052408	1.314987
2016	27.841790	5.606478	0.041899	0.937698	1.639057
2017	25.397793	5.502949	0.106811	1.054243	1.757508
2018	22.912774	5.721400	0.223676	1.227611	1.816924
2019	21.940058	5.793556	0.202923	1.275881	1.954774
2020	19.754889	5.831709	0.270948	1.388511	2.188328
Total	392.926080	78.328532	2.501242	17.523960	21.843687
Year	Diesel Oil	LPG	Refinery Gas	Natural Gas	Process
1997	0.337536	0.286474	0.091553	0.579075	0.229719
1998	0.337536	0.286474	0.091553	0.579075	0.294407
1999	0.552556	0.366624	0.059476	0.749773	0.339276
2000	0.594323	0.379460	0.041098	0.844845	0.359501
2001	0.542965	0.388540	0.036086	1.257544	0.511834
2002	0.544512	0.315591	0.080860	2.402731	0.765731
2003	0.663006	0.000000	0.000000	3.035824	0.892142
2004	0.703225	0.226361	0.082865	3.833133	0.996206
2005	0.719622	0.000000	0.104918	4.687799	1.077022
2006	0.835022	0.146211	0.183105	4.870283	1.079056
2007	1.483796	0.167501	0.111935	4.335416	1.269486
2008	2.408835	0.246868	0.197206	4.589057	1.330222
2009	2.686534	0.248478	0.155248	5.052963	1.775537
2010	2.777343	0.245425	0.207497	4.986617	2.357028
2011	3.156933	0.274576	0.189788	6.605205	3.045750
2012	3.282792	0.273957	0.203497	8.268698	4.096065
2013	3.388660	0.290231	0.197473	8.576071	5.340385
2014	3.507745	0.308675	0.167371	8.347137	5.432970
2015	3.532523	0.000626	0.187449	8.651415	5.137488
2016	3.982200	0.308786	0.171026	9.369542	5.508091
2017	4.705965	0.335672	0.201523	10.086252	4.213700
2018	4.924432	0.284595	0.170742	10.621105	3.937223
2019	5.229174	0.315904	0.180098	10.845276	3.894040
2020	4.770051	0.313086	0.135658	9.636942	3.533696
Total	55.667286	6.010115	3.248025	132.811778	57.416574

Table A4. The overall decoupling state of three industries from 1990 to 2021.

Year	ΔC	ΔG	DI	Decoupling State
1990–1991	0.0384	0.0483	0.7945	weak decoupling
1991–1992	0.0369	0.0749	0.4935	weak decoupling
1992–1993	0.0356	0.0980	0.3636	weak decoupling
1993–1994	0.0344	0.0825	0.4172	weak decoupling
1994–1995	0.0333	0.0818	0.4063	weak decoupling
1995–1996	0.0322	0.0879	0.3662	weak decoupling
1996–1997	−0.0749	0.0912	−0.8216	strong decoupling
1997–1998	0.0050	0.0895	0.0559	weak decoupling
1998–1999	0.1863	0.0821	2.2684	expansive negative decoupling
1999–2000	−0.1185	0.0910	−1.3029	strong decoupling
2000–2001	0.2166	0.1201	1.8028	expansive negative decoupling
2001–2002	0.0686	0.1245	0.5506	weak decoupling
2002–2003	0.1211	0.1224	0.9897	expansive coupling
2003–2004	0.0786	0.1264	0.6219	weak decoupling
2004–2005	0.0455	0.1250	0.3636	weak decoupling
2005–2006	0.2246	0.1258	1.7858	expansive negative decoupling
2006–2007	0.0662	0.1277	0.5181	weak decoupling
2007–2008	0.2158	0.1302	1.6578	expansive negative decoupling
2008–2009	0.0596	0.1028	0.5796	weak decoupling
2009–2010	−0.0432	0.1571	−0.2751	strong decoupling
2010–2011	0.1513	0.1384	1.0934	expansive coupling
2011–2012	0.2185	0.1254	1.7419	expansive negative decoupling
2012–2013	0.0722	0.1107	0.6523	weak decoupling
2013–2014	0.0125	0.0935	0.1342	weak decoupling
2014–2015	0.0534	0.0830	0.6431	weak decoupling
2015–2016	0.1035	0.0818	1.2649	expansive negative decoupling
2016–2017	−0.0562	0.0733	−0.7671	strong decoupling
2017–2018	−0.0289	0.0734	−0.3941	strong decoupling
2018–2019	−0.0036	0.0629	−0.0568	strong decoupling
2019–2020	−0.0739	0.0191	−3.8722	strong decoupling
2020–2021	−0.0124	0.0602	−0.2055	strong decoupling

Table A5. The decoupling state of primary industry from 1990 to 2021.

Year	ΔC	ΔG	DI	Decoupling State
1990–1991	0.0146	0.0098	1.4870	expansive negative decoupling
1991–1992	0.0144	0.0401	0.3580	weak decoupling
1992–1993	0.0142	−0.0067	−2.1124	strong negative decoupling
1993–1994	0.0140	0.0360	0.3877	weak decoupling
1994–1995	0.0138	−0.0050	−2.7541	strong negative decoupling
1995–1996	0.0136	0.0370	0.3669	weak decoupling
1996–1997	0.0148	0.0350	0.4232	weak decoupling
1997–1998	0.0007	0.0350	0.0190	weak decoupling
1998–1999	0.0165	0.0104	1.5888	expansive negative decoupling
1999–2000	0.0087	−0.0400	−0.2181	strong negative decoupling
2000–2001	−0.0466	0.0585	−0.7963	strong decoupling
2001–2002	−0.0232	0.0455	−0.5101	strong decoupling
2002–2003	0.0346	0.0385	0.8977	expansive coupling
2003–2004	0.0129	0.0385	0.3356	weak decoupling
2004–2005	0.0169	0.0505	0.3350	weak decoupling
2005–2006	0.0281	0.0350	0.8033	expansive coupling
2006–2007	0.0069	0.0440	0.1565	weak decoupling
2007–2008	0.7105	0.0390	18.2185	expansive negative decoupling
2008–2009	0.0130	0.0500	0.2597	weak decoupling
2009–2010	0.1530	0.0590	2.5927	expansive negative decoupling
2010–2011	0.0863	0.0480	1.7985	expansive negative decoupling
2011–2012	−0.0167	0.0520	−0.3204	strong decoupling
2012–2013	−0.0022	0.0530	−0.0415	strong decoupling
2013–2014	−0.0028	0.0520	−0.0542	strong decoupling
2014–2015	−0.0513	0.0510	−1.0065	strong decoupling
2015–2016	0.1647	0.0540	3.0505	expansive negative decoupling
2016–2017	−0.1323	0.0490	−2.6992	strong decoupling
2017–2018	−0.0330	0.0450	−0.7334	strong decoupling
2018–2019	−0.0047	0.0460	−0.1029	strong decoupling
2019–2020	0.0578	0.0446	1.2954	expansive negative decoupling
2020–2021	−0.0690	0.0445	−1.5492	strong decoupling

Table A6. The decoupling state of secondary industry from 1990 to 2021.

Year	ΔC	ΔG	DI	Decoupling State
1990–1991	0.0481	0.0426	1.1294	expansive coupling
1991–1992	0.0459	0.0764	0.6008	weak decoupling
1992–1993	0.0439	0.1474	0.2977	weak decoupling
1993–1994	0.0420	0.0826	0.5090	weak decoupling
1994–1995	0.0403	0.0933	0.4324	weak decoupling
1995–1996	0.0388	0.1010	0.3840	weak decoupling
1996–1997	−0.0568	0.1038	−0.5472	strong decoupling
1997–1998	0.0077	0.1115	0.0687	weak decoupling
1998–1999	0.2200	0.0937	2.3481	expansive negative decoupling
1999–2000	−0.1291	0.1147	−1.1260	strong decoupling
2000–2001	0.1952	0.1520	1.2840	expansive negative decoupling
2001–2002	0.0081	0.1644	0.0492	weak decoupling
2002–2003	0.1524	0.1646	0.9256	expansive coupling
2003–2004	0.0706	0.1661	0.4249	weak decoupling
2004–2005	0.0273	0.1585	0.1725	weak decoupling
2005–2006	0.3177	0.1580	2.0107	expansive negative decoupling
2006–2007	0.0883	0.1490	0.5925	weak decoupling
2007–2008	0.2695	0.1650	1.6333	expansive negative decoupling
2008–2009	0.0624	0.1130	0.5522	weak decoupling
2009–2010	−0.0831	0.1930	−0.4306	strong decoupling
2010–2011	0.1623	0.1740	0.9330	expansive coupling
2011–2012	0.2960	0.1410	2.0991	expansive negative decoupling
2012–2013	0.0776	0.1230	0.6307	weak decoupling
2013–2014	0.0097	0.1000	0.0966	weak decoupling
2014–2015	0.0624	0.0840	0.7428	weak decoupling
2015–2016	0.0985	0.0850	1.1594	expansive coupling
2016–2017	−0.0870	0.0720	−1.2082	strong decoupling
2017–2018	−0.0566	0.0780	−0.7261	strong decoupling
2018–2019	−0.0118	0.0630	−0.1878	strong decoupling
2019–2020	−0.0951	0.0271	−3.5095	strong decoupling
2020–2021	−0.0219	0.0649	−0.3374	strong decoupling

Table A7. The decoupling state of tertiary industry from 1990 to 2021.

Year	ΔC	ΔG	DI	Decoupling State
1990–1991	0.0453	0.0811	0.5585	weak decoupling
1991–1992	0.0433	0.0959	0.4518	weak decoupling
1992–1993	0.0415	0.1130	0.3675	weak decoupling
1993–1994	0.0399	0.1079	0.3696	weak decoupling
1994–1995	0.0383	0.1150	0.3334	weak decoupling
1995–1996	0.0369	0.0983	0.3757	weak decoupling
1996–1997	−0.0721	0.1031	−0.6989	strong decoupling
1997–1998	−0.0082	0.0899	−0.0912	strong decoupling
1998–1999	0.2899	0.0981	2.9550	expansive negative decoupling
1999–2000	0.0000	0.1136	0.0001	weak decoupling
2000–2001	−0.1383	0.1068	−1.2953	strong decoupling
2001–2002	0.7820	0.1057	7.3979	expansive negative decoupling
2002–2003	0.1675	0.0989	1.6938	expansive negative decoupling
2003–2004	0.1125	0.1029	1.0934	expansive coupling
2004–2005	0.2445	0.1018	2.4014	expansive negative decoupling
2005–2006	0.0382	0.1050	0.3634	weak decoupling
2006–2007	0.2162	0.1170	1.8475	expansive negative decoupling
2007–2008	0.0956	0.1000	0.9561	expansive coupling
2008–2009	0.0847	0.0980	0.8643	expansive coupling
2009–2010	0.1237	0.1210	1.0222	expansive coupling
2010–2011	0.0893	0.0970	0.9209	expansive coupling
2011–2012	−0.0189	0.1110	−0.1706	strong decoupling
2012–2013	0.0457	0.0980	0.4668	weak decoupling
2013–2014	0.0380	0.0880	0.4318	weak decoupling
2014–2015	0.0112	0.0860	0.1301	weak decoupling
2015–2016	0.1448	0.0800	1.8097	expansive negative decoupling
2016–2017	0.1378	0.0790	1.7446	expansive negative decoupling
2017–2018	0.1031	0.0690	1.4938	expansive negative decoupling
2018–2019	0.0320	0.0650	0.4922	weak decoupling
2019–2020	−0.0332	0.0011	−30.1394	strong decoupling
2020–2021	0.0237	0.0536	0.4425	weak decoupling

Table A8. The overall decomposition effect of decoupling in three industries from 1990 to 2021.

Year	ΔC_c	ΔC_e	ΔC_g	ΔC_p
1990–1991	1.6806	−1.7787	0.3315	0.1548
1991–1992	0.6214	−1.0058	0.6185	0.1541
1992–1993	2.5659	−3.2144	0.9008	0.1358
1993–1994	−4.9392	4.4179	0.7313	0.1781
1994–1995	0.6288	−1.1741	0.7546	0.1789
1995–1996	−1.7262	1.0821	0.8529	0.1795
1996–1997	−1.3254	−0.6531	0.8678	0.1777
1997–1998	−0.3570	−0.5753	0.8235	0.1665
1998–1999	−0.9613	2.1212	0.8216	0.1745
1999–2000	−1.1351	−1.6154	0.9547	0.1684
2000–2001	2.1675	−1.0633	1.3470	0.1698
2001–2002	−0.1089	−0.6681	1.6271	0.1592
2002–2003	0.4029	−0.4216	1.7615	0.1632
2003–2004	−2.5862	1.7916	2.0176	0.1640
2004–2005	−2.9120	1.4851	2.1261	0.1655
2005–2006	1.2898	0.5654	2.4298	0.1819
2006–2007	−0.7740	−0.6377	2.8446	0.1785
2007–2008	3.5598	−1.4650	3.3702	0.1400
2008–2009	0.7530	−2.0529	3.0068	0.1755
2009–2010	−6.3848	0.1649	4.4141	0.3604
2010–2011	0.6289	−0.2408	4.1711	0.2843
2011–2012	3.6777	−0.4402	4.6280	0.1875
2012–2013	−0.2639	−1.3758	4.8502	0.0310
2013–2014	−3.0049	−0.7208	3.9341	0.3954
2014–2015	0.4785	−1.8671	3.9025	0.0894
2015–2016	5.7230	−4.6524	3.7770	0.4676
2016–2017	−3.9885	−3.0910	3.4594	0.4345
2017–2018	−3.4776	−1.8061	3.6610	0.0745
2018–2019	0.7083	−4.0573	2.8887	0.2747
2019–2020	−2.9752	−1.7928	0.7442	0.1979
2020–2021	−6.3741	2.9957	2.6882	0.0971

Table A9. The decomposition effect of decoupling in primary industry from 1990 to 2021.

Year	ΔC_c	ΔC_e	ΔC_g	ΔC_p
1990–1991	−0.0161	0.0167	−0.0007	0.0021
1991–1992	0.0013	−0.0047	0.0035	0.0020
1992–1993	−0.0141	0.0171	−0.0027	0.0017
1993–1994	0.0379	−0.0410	0.0028	0.0022
1994–1995	−0.0725	0.0752	−0.0029	0.0022
1995–1996	0.0161	−0.0195	0.0032	0.0022
1996–1997	0.0272	−0.0301	0.0029	0.0022
1997–1998	−0.0013	−0.0038	0.0030	0.0022
1998–1999	−0.0111	0.0120	−0.0005	0.0021
1999–2000	0.0145	−0.0069	−0.0083	0.0020
2000–2001	−0.0260	0.0102	0.0067	0.0019
2001–2002	0.0148	−0.0247	0.0049	0.0015
2002–2003	0.0258	−0.0264	0.0041	0.0014
2003–2004	−0.0073	0.0035	0.0043	0.0013
2004–2005	−0.0289	0.0239	0.0062	0.0013
2005–2006	−0.0011	0.0001	0.0041	0.0013
2006–2007	0.0008	−0.0065	0.0057	0.0011
2007–2008	0.1099	−0.0053	0.0070	0.0010
2008–2009	−0.0365	0.0267	0.0118	0.0015
2009–2010	0.0257	−0.0006	0.0137	0.0033
2010–2011	0.0350	−0.0231	0.0127	0.0027
2011–2012	−0.0209	−0.0021	0.0157	0.0016
2012–2013	−0.0097	−0.0085	0.0172	0.0002
2013–2014	−0.0189	0.0008	0.0143	0.0028
2014–2015	−0.0546	0.0210	0.0157	0.0006
2015–2016	0.0052	0.0292	0.0152	0.0030
2016–2017	−0.0064	−0.0594	0.0139	0.0027
2017–2018	−0.0016	−0.0230	0.0135	0.0004
2018–2019	−0.0008	−0.0147	0.0124	0.0016
2019–2020	0.0003	0.0037	0.0127	0.0013
2020–2021	−0.0262	−0.0103	0.0132	0.0006

Table A10. The decomposition effect of decoupling in secondary industry from 1990 to 2021.

Year	ΔC_c	ΔC_e	ΔC_g	ΔC_p
1990–1991	0.7376	−0.7001	0.1899	0.1067
1991–1992	0.6219	−0.8359	0.4409	0.1072
1992–1993	−0.8526	0.1171	0.9744	0.0953
1993–1994	−0.2028	−0.1070	0.5180	0.1259
1994–1995	−0.6611	0.2417	0.6262	0.1274
1995–1996	0.5412	−1.0520	0.7163	0.1286
1996–1997	−1.4460	0.0792	0.7295	0.1290
1997–1998	−0.2485	−0.5825	0.7735	0.1222
1998–1999	−0.4695	1.4981	0.7128	0.1301
1999–2000	−1.0151	−1.3776	0.9259	0.1265
2000–2001	2.1105	−1.7465	1.2742	0.1256
2001–2002	−0.1678	−1.3955	1.5372	0.1134
2002–2003	0.4120	−0.5356	1.6680	0.1145
2003–2004	−2.5960	1.4862	1.8791	0.1162
2004–2005	−3.2193	1.5834	1.8874	0.1158
2005–2006	1.5596	0.4935	2.2001	0.1311
2006–2007	−0.3697	−0.6605	2.5010	0.1346
2007–2008	3.7497	−1.8297	3.3043	0.1091
2008–2009	0.8559	−2.0609	2.6330	0.1398
2009–2010	−6.2347	−0.4951	4.2302	0.2815
2010–2011	−0.0281	−0.2356	4.0181	0.2184
2011–2012	4.6466	−0.5107	4.1341	0.1494
2012–2013	−0.3234	−1.2572	4.4148	0.0255
2013–2014	−2.7051	−0.7157	3.4787	0.3257
2014–2015	1.7789	−2.6115	3.2611	0.0739
2015–2016	4.8531	−4.2986	3.2577	0.3871
2016–2017	−3.8366	−3.3465	2.7578	0.3531
2017–2018	−3.3950	−2.1436	3.0595	0.0587
2018–2019	0.4575	−3.3831	2.2363	0.2123
2019–2020	−2.5468	−2.2561	0.8632	0.1506
2020–2021	−5.1780	2.1485	2.1678	0.0727

Table A11. The decomposition effect of decoupling in tertiary industry from 1990 to 2021.

Year	ΔC_c	ΔC_e	ΔC_g	ΔC_p
1990–1991	−0.1805	0.1555	0.0467	0.0111
1991–1992	0.2250	−0.2631	0.0598	0.0112
1992–1993	−0.3975	0.3439	0.0766	0.0099
1993–1994	−0.0688	0.0155	0.0731	0.0131
1994–1995	−0.0669	0.0046	0.0820	0.0132
1995–1996	−0.0106	−0.0415	0.0717	0.0133
1996–1997	−0.0428	−0.1110	0.0741	0.0132
1997–1998	−0.0353	−0.0452	0.0611	0.0123
1998–1999	−0.0415	0.1973	0.0772	0.0134
1999–2000	0.0317	−0.1496	0.1036	0.0143
2000–2001	−0.0280	−0.2270	0.0904	0.0129
2001–2002	0.1173	0.4928	0.1151	0.0134
2002–2003	0.0250	0.0853	0.1539	0.0178
2003–2004	−0.0601	0.0781	0.1845	0.0186
2004–2005	−0.2243	0.5218	0.2161	0.0208
2005–2006	0.0176	−0.1906	0.2539	0.0229
2006–2007	0.3420	−0.0767	0.3230	0.0221
2007–2008	0.0434	−0.0578	0.3252	0.0176
2008–2009	0.0086	−0.0563	0.3453	0.0212
2009–2010	−0.0396	0.0499	0.4468	0.0477
2010–2011	0.2802	−0.3138	0.4037	0.0396
2011–2012	−0.4395	−0.1760	0.4981	0.0228
2012–2013	0.0204	−0.2649	0.4653	0.0033
2013–2014	−0.1341	−0.1116	0.3979	0.0426
2014–2015	−0.7781	0.3962	0.4319	0.0096
2015–2016	0.4424	−0.1069	0.3934	0.0499
2016–2017	0.0701	0.2789	0.4480	0.0519
2017–2018	−0.0500	0.2810	0.4809	0.0104
2018–2019	0.1065	−0.3538	0.4530	0.0416
2019–2020	−0.3497	0.0766	−0.0225	0.0312
2020–2021	−0.9758	0.7510	0.3919	0.0159

Table A12. Efficiency values in overall, primary, secondary, and tertiary industries from 1990 to 2021.

Year	Overall	Primary	Secondary	Tertiary
1990	0.8071	1.0566	1.0116	1.0752
1991	0.8068	0.9240	0.7608	0.9082
1992	0.8390	0.9312	0.7788	1.0494
1993	1.0002	0.8659	0.9652	0.8460
1994	1.0014	1.0018	1.0068	0.8477
1995	1.0080	0.8155	0.9157	0.8885
1996	0.9775	0.8565	0.7298	1.0098
1997	0.9159	0.9386	0.5478	1.0032
1998	1.0219	1.0066	0.6469	1.0261
1999	0.8865	1.0021	0.5173	0.8409
2000	1.0122	0.9008	0.6622	0.8460
2001	0.9666	0.9170	0.6897	1.1138
2002	1.0046	1.0061	0.8299	0.7171
2003	1.0073	1.0116	1.0176	0.7548
2004	0.9505	1.0072	0.8356	0.7613
2005	0.9295	1.0082	0.9000	0.7512
2006	0.9052	0.9832	0.8145	0.8318
2007	0.9613	1.0157	0.8342	0.8318
2008	1.0099	0.8339	1.0076	1.0030
2009	0.9617	0.7965	0.8365	1.0061
2010	1.0160	0.7373	1.0082	1.0091
2011	1.0105	0.7066	1.0142	1.0064
2012	1.0071	0.7192	1.0059	1.0027
2013	1.0022	0.7103	1.0052	1.0019
2014	0.9533	0.6791	1.0035	1.0117
2015	0.8979	0.6464	0.8903	1.0192
2016	0.8456	0.5981	0.8683	1.0034
2017	0.8695	0.6830	0.9070	0.9705
2018	0.8742	0.7367	1.0030	0.9176
2019	0.9499	0.7894	0.9478	0.9513
2020	1.0207	0.8989	1.0207	1.0160
2021	1.0387	1.0567	1.0425	1.0201
Mean	0.9518	0.8700	0.8758	0.9388

References

1. Pan, X.; Shao, T.; Zheng, X.; Zhang, Y.; Ma, X.; Zhang, Q. Energy and sustainable development nexus: A review. *Energy Strat. Rev.* **2023**, *47*, 101078. [CrossRef]
2. Jiang, Y.; Tian, S.; Xu, Z.; Gao, L.; Xiao, L.; Chen, S.; Xu, K.; Chang, J.; Luo, Z.; Shi, Z. Decoupling environmental impact from economic growth to achieve Sustainable Development Goals in China. *J. Environ. Manag.* **2022**, *312*, 114978. [CrossRef]
3. Xin, M.; Guo, H.; Li, S.; Chen, L. Can China achieve ecological sustainability? An LMDI analysis of ecological footprint and economic development decoupling. *Ecol. Indic.* **2023**, *151*, 110313. [CrossRef]
4. Makondo, C.C. Green growth, sustainability, and decoupling carbon emissions from industrial activities in emerging economies: A focus on Zambia's energy sector. *Extr. Ind. Soc.* **2023**, *14*, 101271. [CrossRef]
5. Wu, Y.; Zhu, Q.; Zhu, B. Comparisons of decoupling trends of global economic growth and energy consumption between developed and developing countries. *Energy Policy* **2018**, *116*, 30–38. [CrossRef]
6. Herman, K.S. Green growth and innovation in the Global South: A systematic literature review. *Innov. Dev.* **2023**, *13*, 43–69. [CrossRef]
7. González-Álvarez, M.A.; Montañés, A. CO_2 emissions, energy consumption, and economic growth: Determining the stability of the 3E relationship. *Econ. Model.* **2023**, *121*, 106195. [CrossRef]
8. Lundquist, S. Explaining events of strong decoupling from CO_2 and NOx emissions in the OECD 1994–2016. *Sci. Total Environ.* **2021**, *793*, 148390. [CrossRef]
9. Jia, H.; Li, T.; Wang, A.; Liu, G.; Guo, X. Decoupling analysis of economic growth and mineral resources consumption in China from 1992 to 2017: A comparison between tonnage and exergy perspective. *Resour. Policy* **2021**, *74*, 102448. [CrossRef]
10. Huang, S.-W.; Chung, Y.-F.; Wu, T.-H. Analyzing the relationship between energy security performance and decoupling of economic growth from CO_2 emissions for OECD countries. *Renew. Sustain. Energy Rev.* **2021**, *152*, 111633. [CrossRef]
11. Wang, X.; Yan, L. Driving factors and decoupling analysis of fossil fuel related-carbon dioxide emissions in China. *Fuel* **2022**, *314*, 122869. [CrossRef]
12. Diakoulaki, D.; Mandaraka, M. Decomposition analysis for assessing the progress in decoupling industrial growth from CO_2 emissions in the EU manufacturing sector. *Energy Econ.* **2007**, *29*, 636–664. [CrossRef]
13. Papież, M.; Śmiech, S.; Frodyma, K. Does the European Union energy policy support progress in decoupling economic growth from emissions? *Energy Policy* **2022**, *170*, 113247. [CrossRef]

14. Vadén, T.; Lähde, V.; Majava, A.; Järvensivu, P.; Toivanen, T.; Hakala, E.; Eronen, J.T. Decoupling for ecological sustainability: A categorisation and review of research literature. *Environ. Sci. Policy* **2020**, *112*, 236–244. [CrossRef] [PubMed]
15. Papież, M.; Śmiech, S.; Frodyma, K.; Borowiec, J. Decoupling is not enough—Evidence from fossil fuel use in over 130 countries. *J. Clean. Prod.* **2022**, *379*, 134856. [CrossRef]
16. Cohen, G.; Jalles, J.T.; Loungani, P.; Marto, R.; Wang, G. Decoupling of emissions and GDP: Evidence from aggregate and provincial Chinese data. *Energy Econ.* **2019**, *77*, 105–118. [CrossRef]
17. Liang, D.; Lu, H.; Guan, Y.; Feng, L. Drivers for decoupling carbon footprint pressure from economic growth in China's provinces. *Geogr. Sustain.* **2022**, *3*, 258–267. [CrossRef]
18. Zhu, J.; Lin, N.; Zhu, H.; Liu, X. Role of sharing economy in energy transition and sustainable economic development in China. *J. Innov. Knowl.* **2023**, *8*, 100314. [CrossRef]
19. Wang, Q.; Jiang, R. Is China's economic growth decoupled from carbon emissions? *J. Clean. Prod.* **2019**, *225*, 1194–1208. [CrossRef]
20. Du, Y.; Liu, Y.; Hossain, A.; Chen, S. The decoupling relationship between China's economic growth and carbon emissions from the perspective of industrial structure. *Chin. J. Popul. Resour. Environ.* **2022**, *20*, 49–58. [CrossRef]
21. Liu, X.; Zhong, S.; Yang, M. Study on the decoupling relationship of energy-related CO_2 emissions and economic growth in China: Using the new two-dimensional decoupling model. *Ecol. Indic.* **2022**, *143*, 109405. [CrossRef]
22. Xie, P.; Gong, N.; Sun, F.; Li, P.; Pan, X. What factors contribute to the extent of decoupling economic growth and energy carbon emissions in China? *Energy Policy* **2023**, *173*, 113416. [CrossRef]
23. Ding, S.; Zhang, H. Forecasting Chinese provincial CO_2 emissions: A universal and robust new-information-based grey model. *Energy Econ.* **2023**, *121*, 106685. [CrossRef]
24. Fang, K.; Tang, Y.; Zhang, Q.; Song, J.; Wen, Q.; Sun, H.; Ji, C.; Xu, A. Will China peak its energy-related carbon emissions by 2030? Lessons from 30 Chinese provinces. *Appl. Energy* **2019**, *255*, 113852. [CrossRef]
25. Zhu, B.; Zhang, Y.; Zhang, M.; He, K.; Wang, P. Exploring the driving forces and scenario analysis for China's provincial peaks of CO_2 emissions. *J. Clean. Prod.* **2022**, *378*, 134464. [CrossRef]
26. Shan, Y.; Huang, Q.; Guang, D.; Hubacek, K. China CO_2 Emission Accounts 2016–2017. *Sci. Data* **2020**, *7*, 54. Available online: https://www.nature.com/articles/s41597-020-0393-y (accessed on 28 November 2023). [CrossRef] [PubMed]
27. Zhang, T. Scientific Research Indicates Qinghai's Net Carbon Emissions Have Peaked and Net Zero Emissions are Expected in 2037. 2022. Available online: https://news.sciencenet.cn/htmlnews/2022/11/489210.shtm (accessed on 7 August 2023).
28. Fan, W.; Meng, M.; Lu, J.; Varbanov, P.S.; Fan, W.; Wang, X.; Zhang, Q. Decoupling Elasticity and Driving Factors of Energy Consumption and Economic Development in the Qinghai-Tibet Plateau. *Sustainability* **2020**, *12*, 1326. [CrossRef]
29. Huang, L.; Hu, X.W. Research on carbon decoupling between economic growth and energy production. *Econ. Financ.* **2021**, *11*, 10–16. (In Chinese)
30. Wang, M.; Feng, X.Z.; An, Q.; Zhou, Y.; Zhao, M.X.; Du, X.L.; Wang, P. Study on green and low-carbon development in Qinghai province based on decoupling index and LMDI. *Clim. Change Res.* **2021**, *17*, 598–607. (In Chinese) [CrossRef]
31. Hickel, J.; Kallis, G. Is Green Growth Possible? *New Political Econ.* **2020**, *25*, 469–486. [CrossRef]
32. Belmonte-Ureña, L.J.; Plaza-Úbeda, J.A.; Vazquez-Brust, D.; Yakovleva, N. Circular economy, degrowth and green growth as pathways for research on sustainable development goals: A global analysis and future agenda. *Ecol. Econ.* **2021**, *185*, 107050. [CrossRef]
33. Jänicke, M. "Green growth": From a growing eco-industry to economic sustainability. *Energy Policy* **2012**, *48*, 13–21. [CrossRef]
34. Dong, F.; Li, J.; Wang, Y.; Zhang, X.; Zhang, S.; Zhang, S. Drivers of the decoupling indicator between the economic growth and energy-related CO_2 in China: A revisit from the perspectives of decomposition and spatiotemporal heterogeneity. *Sci. Total Environ.* **2019**, *685*, 631–658. [CrossRef] [PubMed]
35. Sheng, P.; Li, J.; Zhai, M.; Majeed, M.U. Economic growth efficiency and carbon reduction efficiency in China: Coupling or decoupling. *Energy Rep.* **2021**, *7*, 289–299. [CrossRef]
36. Chen, W.; Yan, S. The decoupling relationship between CO_2 emissions and economic growth in the Chinese mining industry under the context of carbon neutrality. *J. Clean. Prod.* **2022**, *379*, 134692. [CrossRef]
37. Xu, Y.; Man, X.; Fu, Q.; Li, M.; Li, H.; Li, T. A decoupling analysis framework for agricultural sustainability and economic development based on virtual water flow in grain exporting. *Ecol. Indic.* **2022**, *141*, 109083. [CrossRef]
38. Li, Y.; Zuo, Z.; Cheng, Y.; Cheng, J.; Xu, D. Towards a decoupling between regional economic growth and CO_2 emissions in China's mining industry: A comprehensive decomposition framework. *Resour. Policy* **2023**, *80*, 103271. [CrossRef]
39. Hu, J.; Chi, L.; Xing, L.; Meng, H.; Zhu, M.; Zhang, J.; Wu, J. Decomposing the decoupling relationship between energy consumption and economic growth in China's agricultural sector. *Sci. Total Environ.* **2023**, *873*, 162323. [CrossRef]
40. Wang, Q.; Wang, X. Moving to economic growth without water demand growth—A decomposition analysis of decoupling from economic growth and water use in 31 provinces of China. *Sci. Total Environ.* **2020**, *726*, 138362. [CrossRef]
41. Zhao, X.; Zhang, X.; Shao, S. Decoupling CO_2 emissions and industrial growth in China over 1993–2013: The role of investment. *Energy Econ.* **2016**, *60*, 275–292. [CrossRef]
42. Gao, C.; Ge, H.; Lu, Y.; Wang, W.; Zhang, Y. Decoupling of provincial energy-related CO_2 emissions from economic growth in China and its convergence from 1995 to 2017. *J. Clean. Prod.* **2021**, *297*, 126627. [CrossRef]
43. Zhu, S.; Zhang, D.; Zhang, L.; Luo, L.; Li, M. The Assessment and Forecasting of Carbon Emission for Gansu-Qinghai-Shaanxi of China. *Environ. Sci. Pollut. Res.* **2023**, 1–15. [CrossRef] [PubMed]

44. Huang, C.; Zhou, Y.-J.; Cheng, J.-H. Research on Energy-Related CO_2 Emissions Characteristics, Decoupling Relationship and LMDI Factor Decomposition in Qinghai. *Front. Energy Res.* **2021**, *9*, 700385. [CrossRef]
45. Hu, X.; Huang, L.; Li, Y. Carbon decoupling level measurement and carbon peaking path selection on the Qinghai-Tibet Plateau under climate change, a case study of Qinghai Province. *Qinghai Soc. Sci.* **2021**, *5*, 43–54. (In Chinese) [CrossRef]
46. Wang, L.Q.; Wang, X.P.; Fang, H.J.; Liang, T.; Pei, Z.H. Coupling relationship between resource environment and social economy development in typical regions of Qinghai-Tibet Plateau. *Acta Geogr. Sin.* **2021**, *41*, 2510–2518. (In Chinese) [CrossRef]
47. Bai, Y.; Guo, C.; Li, S.; Degen, A.A.; Ahmad, A.A.; Wang, W.; Zhang, T.; Huang, M.; Shang, Z. Instability of decoupling livestock greenhouse gas emissions from economic growth in livestock products in the Tibetan highland. *J. Environ. Manag.* **2021**, *287*, 112334. [CrossRef] [PubMed]
48. Li, X.; Ji, M.G. Analysis of Influencing Factors of Transportation Carbon Emission in Sanjiangyuan Area Based on LMDI Model. *STM* **2019**, *20*, 246–250. (In Chinese) [CrossRef]
49. Sun, S.; Wang, J.; Qi, W. Urban-and-rural virtual water trade of Qinghai-Tibet Plateau: Patterns and influencing factors. *Acta Geogr. Sin.* **2020**, *75*, 1346–1358. (In Chinese) [CrossRef]
50. Chen, C.; Lu, Y.; He, G. Driving mechanisms for decoupling CO_2 emissions from economic development in the ten largest emission countries. *Ecosyst. Health Sustain.* **2022**, *8*, 2059016. [CrossRef]
51. Li, D.; Shen, T.; Wei, X.; Li, J. Decomposition and Decoupling Analysis between HDI and Carbon Emissions. *Atmosphere* **2022**, *13*, 584. [CrossRef]
52. Zhang, J.; Wu, G.; Zhang, J. The estimation of China's provincial capital stock: 1952–2000. *Econ. Res.* **2004**, *10*, 35–44. (In Chinese)
53. Shan, H. Re-estimation of China's physical capital stock K: 1952–2006. *J. Quant. Tech. Econ.* **2008**, *10*, 17–31. (In Chinese)
54. Xu, X.; Zhou, J.; Shu, Y. Estimation of the capital stock of three industries in China's provinces and regions. *Stat. Res.* **2007**, *24*, 6–13. (In Chinese)
55. Zong, Z.; Liu, Z. Re-estimation of China's interprovincial tertiary industrial capital stock: 1978–2011. *J. GUFE* **2014**, *3*, 8–16. (In Chinese)
56. UNEP. Decoupling Natural Resource Use and Environmental Impacts from Economic Growth, A Report of the Working Group on Decoupling to the International Resource Panel. 2011. Available online: https://www.unep.org/resources/report/decoupling-natural-resource-use-and-environmental-impacts-economic-growth (accessed on 7 August 2023).
57. Tapio, P. Towards a theory of decoupling: Degrees of decoupling in the EU and the case of road traffic in Finland between 1970 and 2001. *Transp. Policy* **2005**, *12*, 137–151. [CrossRef]
58. OECD. Indicators to Measure Decoupling of Environmental Pressures for Economic Growth. OECD, Paris. 2002. Available online: https://www.oecd.org/env/indicators-modelling-outlooks/indicatorstomeasuredecouplingofenvironmentalpressurefromeconomicgrowth.htm (accessed on 7 August 2023).
59. OECD. *Decoupling: A Conceptual Overview*; OECD Papers; OECD: Paris, France, 2006; Volume 5/11. [CrossRef]
60. Ang, B.W. LMDI decomposition approach: A guide for implementation. *Energy Policy* **2015**, *86*, 233–238. [CrossRef]
61. Ang, B.W.; Zhang, F.Q.; Choi, K.-H. Factorizing changes in energy and environmental indicators through decomposition. *Energy* **1998**, *23*, 489–495. [CrossRef]
62. Ang, B.W. Decomposition analysis for policymaking in energy: Which is the preferred method? *Energy Policy* **2004**, *32*, 1131–1139. [CrossRef]
63. Ang, B.W. The LMDI approach to decomposition analysis: A practical guide. *Energy Policy* **2005**, *33*, 867–871. [CrossRef]
64. Kaya, Y. *Impact of Carbon Dioxide Emission Control on GNP Growth: Interpretation of Proposed Scenarios*; IPCC Energy and Industry Subgroup, Response Strategies Working Group: Paris, France, 1990.
65. Andrei, J.V.; Avram, S.; Băncescu, I.; Deac, I.I.G.; Gheorghe, C.A.; Diaconu, A.I. Decoupling of CO_2, CH_4, and N_2O agriculture emissions in the EU. *Front. Environ. Sci.* **2022**, *10*, 920458. [CrossRef]
66. Tone, K. A slacks-based measure of efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2001**, *130*, 498–509. [CrossRef]
67. Tone, K. A slacks-based measure of super-efficiency in data envelopment analysis. *Eur. J. Oper. Res.* **2002**, *143*, 32–41. [CrossRef]
68. Tone, K. Dealing with Undesirable Outputs in DEA: A Slacks-based Measure (SBM) Approach. GRIPS Research Report Series I-2003-2005. Tokyo: National Graduate Institute for Policy Studies. 2003. I:2003-0005. 2003. Available online: https://www.researchgate.net/publication/284047010_Dealing_with_undesirable_outputs_in_DEA_a_Slacks-Based_Measure_SBM_approach (accessed on 28 November 2023).
69. Cheng, G. *Data Envelopment Analysis: Methods and MaxDEA Software*; Intellectual Property Publishing House: Beijing, China, 2014. (In Chinese)
70. Qinghai Statistics Bureau (QSB). *Qinghai Statistical Yearbook*; China Statistics Press: Beijing, China, 1991.
71. Qinghai Statistics Bureau (QSB). *Qinghai Statistical Yearbook*; China Statistics Press: Beijing, China, 2022.