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Moving to a Low-Carbon Economy in China: Decoupling and Decomposition Analysis of Emission and Economy from a Sector Perspective

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Abstract: Understanding decoupling China's emissions from the economy and identifying the drivers of emissions at a sector perspective can facilitate China's move to a low-carbon economy that makes economic growth compatible with carbon reduction. This study combined decoupling and decomposition econometric techniques to quantify both the decoupling effects and the driving elements of carbon emissions in China's six major sectors. The study found that the leading source of all carbon emissions in China come from the industrial sector, followed by the 'Other' sectors and the Transport sector. Further, the decoupling status in those sectors differed: Construction (weak decoupling), other (weak decoupling), Trade (weak decoupling), Industry (weak decoupling), Transport (expansive coupling) and Agriculture (expansive negative decoupling). Finally, the economic output effect becomes the major contributor for carbon emissions among these six sectors, followed by the energy intensity effect. However, the energy structure effect and carbon coefficient effect are both weak.

Keywords: decoupling status; decomposition; sector perspective; carbon emissions; China

1. Introduction

China currently faces dual problems of reducing carbon emissions and economic development. On the one hand, as the largest carbon emitter all over the world, China is under much pressure to address its carbon emissions. On the other hand, China, the world's largest developing country, has a great responsibility to alleviate poverty by developing its economy. In the 2015 Paris Climate conference, China specifically committed to decreasing its carbon intensity (carbon emission per unit gross domestic product (GDP)) by 60–65% from 2005 levels by 2030 [1]. At the 23rd UN Climate Change Conference in 2017, China actively promoted the process of negotiation on the implementation of the Paris Agreement and introduced a series of policy measures and actions that China has taken in response to climate change, showing China's determination to achieve its carbon reduction target. In addition, the Chinese government has committed to lifting more than 70 million people out of poverty by 2020—this is more people than in the total population of the United Kingdom or France [2].

The best strategy to address these dual needs is to transition to a low-carbon economy, which makes economic growth compatible with carbon reduction. This type of transition requires a better understanding of the decoupling status and effects of China's carbon emissions, at a sector level. To build this understanding, this paper calculates carbon emissions from every sector, quantifies decoupling status of carbon emissions from economic growth in each sector and investigates the key effects of carbon emissions.

This paper is organized as follows: Section 2 presents the literature review while Section 3 describes data collection and the method, including the Tapio decoupling model and the decomposition method of Logarithmic Mean Divisia Index (LMDI). Section 4 discusses the decoupling and decomposition results in different sectors. Finally, we present conclusions in Section 5.

2. Literature Review

The relationship between economic growth and carbon dioxide emissions has caused widespread concern among scholars [3–8]. Many studies have been completed, which focused on two aspects—the decoupling analysis of economic growth and CO₂ emissions—aimed at exploring driving factors of emissions.

In the “low carbon era,” the ideal goal of economic development is to have the economy grow, while also reducing carbon emissions. In this state, no interdependence exists between economy growth and carbon emissions [9]. In 1989, Von [10] presented the concept of ‘decoupling’ to reflect the non-synchronous changes between economic growth and CO₂ emissions. In 2002, the Organization for Economic Co-operation and Development (OECD) [11] applied the concept to develop a decoupling model. In 2005, Tapio [12] proposed a second model—the “Tapio decoupling model”—to study the decoupling between the two sides above.

Over time, international research on the decoupling problem has mainly adopted the above two models [4,13–15]. A lack of uniformity in decoupling indicators prevents us from determining the best method [16]. However, the “Tapio decoupling model” has been more widely adopted by many investigators because its decoupling index is complete, it is not subject to the impact of statistical dimensions and it does not require the selection of a base period [8,17–24].

For example, in order to study the decoupling of carbon dioxide emissions and economic growth of Brazil from 2004 to 2009, Freitas and Kaneko [25] constructed the Tapio decoupling model. Zhang et al. [26] made research on the decoupling relationship of economic growth and coal consumption. Zhou et al. [27] made an exploration on the extent of decoupling between economic growth and carbon emissions in eight primary areas in China between 1996 and 2012. Andreoni et al. [28] analyzed the degree of decoupling in Italy from 1998 to 2006 and concluded that the country did not achieve absolute decoupling between carbon dioxide emissions and the economy. Caneghem et al. [29] analyzed the decoupling relationship between economic growth and environmental impacts upon industrial sectors of the Flemish region from 1995 to 2006.

The rapid growth of China’s economy has brought about the continuous growth of carbon emissions. Many academics have adopted the Tapio decoupling method with the purpose of studying the decoupling relationship between economic growth and China’s CO₂ emissions at a national level [13,30] and a provincial-level [20,31]. Other academics have refined their studies to focus on a specific industry in China, such as Construction [17], Industry [14,32], or Transportation [33].

When exploring the factors that drive CO₂ emissions, the Logarithmic Mean Divisia Index (LMDI) approach is popular with academics because this approach uses the log mean weight function and there are no residual terms in the results of decomposition [3,7,31,34,35]. Lu et al. utilized the LMDI method and the Tapio decoupling model to evaluate CO₂ emissions from the industry in Jiangsu Province, China [36]. Lin and Moubarak [37] combined the LMDI framework to decompose CO₂ emissions from industry in Jiangsu Province, China into industrial activity, carbon intensity, energy intensity, and fossil fuel share on an industrial scale. Wang et al. [38] used the LMDI method to make a decomposition of industrial carbon emissions in Taiwan, finding that the energy intensity effect plays a leading role of facilitating decoupling; the effect of energy and industrial structure has a negative role and impact on decoupling. S. Ren et al. [39] used LMDI to analyze the degree of decoupling of carbon emissions in the manufacturing industries of China. Their results showed that the growth in output value had the greatest effect on CO₂ emissions growth. On the basis of a time series decomposition of LMDI, Liu et al. [40] analyzed differences in industrial carbon emissions in China from 1998 to

2005. With LMDI, Zhao et al. [41] decomposed the factors that drive industrial carbon emissions in Shanghai, China.

Some scholars divide the LMDI method into the additive decomposition form and the multiplicative decomposition form [4,7,8,42]. The additive decomposition is more popular than the multiplicative decomposition form, because it is easier to utilize and interpret. Because of it, in this paper we use the additive decomposition form.

China is the largest carbon emitter in the world, thus many studies have investigated decoupling and the factors influencing CO₂ emissions and economic growth in China. However, research has been mostly at the national level, regional level, or the entire industrial sector. This provides opportunities to further refine research within industrial structures. This study refined three basic industries into six types of industries, based on type of energy consumption. Based on carbon emission measurements, we explored the decoupling relation of carbon emissions and economic growth of each sector. Finally, the study applied the LMDI decomposition method to analyze the influence elements of carbon emissions among different sectors. We then propose policy recommendations to support future action.

3. Research Method and Data Collection

3.1. The Model of Calculating Sector's CO₂ Emission

Using the CO₂ emission calculation method proposed by IPCC, the CO₂ emissions related to energy consumption by different sectors is expressed as Equation (1):

$$C_i = \sum_{j=1}^{13} E_{ij} \times F_{ij} \quad (1)$$

In this expression, C_i is the total CO₂ emissions of the i th sector; E_{ij} is the consumption of the final energy type j in the i -th sector; and F_{ij} denotes the CO₂ emissions factor of energy type j in the i -th sector. The variable i denotes sector type; the sectors include: Agriculture (including Farming, Forestry, Animal Husbandry, Fishery and Water Conservancy), Industry, Construction, Transport (including Transport, Storage, Postal and Telecommunications Services), Trade (including Wholesale, Retail Trade and Catering Service) and Other (including Residential Consumption and other consumption). The variable j indicates energy type, including raw coal, cleaned coal, other washed coal, coke, crude oil, gasoline, kerosene, diesel oil, fuel oil, Liquefied Petroleum Gas (LPG), refinery gas, natural gas and electricity.

3.2. Decoupling Model

According to the Tapio decoupling model [12], which helps explore the relationship of CO₂ emissions (C_i) and gross domestic product (GDP_i) for the i th sector, the decoupling index can be expressed as follows:

$$e_{i(C,GDP)} = \frac{\Delta C_i / C_i}{\Delta GDP_i / GDP_i} \quad (2)$$

In this formula, e_i is the decoupling index of the i -th sector between CO₂ emissions and the gross domestic product; $\Delta C_i / C_i$ represents the rate of change of total carbon emissions in the i -th sector; $\Delta GDP_i / GDP_i$ represents the rate of change in the gross domestic product of the i -th sector.

Decoupling appears when the emission intensity declines while negative decoupling occurs when the emissions intensity increases. On the basis of the values of the decoupling index (e), we get eight logical possibilities [43]: strong decoupling, weak decoupling, expansive coupling, expansive negative decoupling, strong negative decoupling, weak negative decoupling, recessive coupling and recessive decoupling (Table 1).

Table 1. The framework for decoupling judgments.

Degree of Decoupling	ΔC	ΔGDP	e
Strong decoupling	<0	>0	<0
Weak decoupling	>0	>0	0.8 > > 0
Expansive coupling	>0	>0	1.2 > > 0.8
Expansive negative decoupling	>0	>0	>1.2
Strong negative decoupling	>0	<0	<0
Weak negative decoupling	<0	<0	0.8 > > 0
Recessive coupling	<0	<0	1.2 > > 0.8
Recessive decoupling	<0	<0	>1.2

3.3. Decomposition Technique

The total CO₂ emissions can be decomposed into several elements. The total CO₂ emissions can be expressed as the Kaya Identity, which is the most classical decomposition form when using the LMDI. The formula is as follows:

$$C_i = \sum_{j=1}^{13} \frac{C_{ij}}{E_{ij}} \cdot \frac{E_{ij}}{E_i} \cdot \frac{E_i}{Q_i} \cdot Q_i \quad (3)$$

$$= \sum_{j=1}^{13} F_{ij} S_{ij} I_i Q_i$$

In this expression, C_i is the total CO₂ emissions of the i th sector; C_{ij} is the CO₂ emissions of the j th energy type in the i -th sector; E_{ij} is the final consumption of the j -th energy type in the i -th sector; E_i is the total energy consumption of the i th sector; Q_i is the gross domestic product of the i -th sector; $F_{ij} = \frac{C_{ij}}{E_{ij}}$ illustrates the carbon coefficient of j -th energy type in the i th sector; $S_{ij} = \frac{E_{ij}}{E_i}$ illustrates the energy structure of j -th energy type in the i -th sector; $I_i = \frac{E_i}{Q_i}$ illustrates the energy intensity in the i -th sector.

Using the LMDI approach described by Ang [42,44], the divergence in CO₂ emissions from period a in base year 0 to period t in target year t , for the i -th sector (ΔC_i), can be decomposed into the following four driving factors. This study uses the additive form for the decomposition as denoted in Equation (4):

$$\Delta C_i = C_i^t - C_i^0 = \Delta C_{i,F} + \Delta C_{i,S} + \Delta C_{i,I} + \Delta C_{i,Q} \quad (4)$$

In this expression [17], ΔC_i is the total variation in carbon emissions of the i -th sector. Variables $\Delta C_{i,F}$, $\Delta C_{i,S}$, $\Delta C_{i,I}$ and $\Delta C_{i,Q}$ illustrate the CO₂ emission changes caused by carbon coefficient changes, energy structure changes, energy intensity changes and economic changes, respectively.

With the LMDI method, each effect on the right side of Equation (4) can be computed as:

$$\Delta C_{i,F} = \sum_{j=1}^{13} \left(\frac{C_{ij}^t - C_{ij}^0}{\ln C_{ij}^t - \ln C_{ij}^0} \cdot \ln \frac{F_{ij}^t}{F_{ij}^0} \right) \quad (5)$$

$$\Delta C_{i,S} = \sum_{j=1}^{13} \left(\frac{C_{ij}^t - C_{ij}^0}{\ln C_{ij}^t - \ln C_{ij}^0} \cdot \ln \frac{S_{ij}^t}{S_{ij}^0} \right) \quad (6)$$

$$\Delta C_{i,I} = \sum_{j=1}^{13} \left(\frac{C_{ij}^t - C_{ij}^0}{\ln C_{ij}^t - \ln C_{ij}^0} \cdot \ln \frac{I_i^t}{I_i^0} \right) \quad (7)$$

$$\Delta C_{i,Q} = \sum_{j=1}^{13} \left(\frac{C_{ij}^t - C_{ij}^0}{\ln C_{ij}^t - \ln C_{ij}^0} \cdot \ln \frac{Q_i^t}{Q_i^0} \right) \quad (8)$$

3.4. Data Collection

The time span of the study is from 2000 to 2014. Data about energy consumption in different sectors originated from China's Energy Statistical Yearbook for the researched years. Economic output data for different sectors was derived from the China Statistical Yearbook. In order to eliminate influences of inflation, we converted the GDP in every year into constant prices, regarding the GDP in 2000 as a standard. Table 2 shows the default carbon coefficient values for different energy types; these are from the GHG Protocol Tool for Energy Consumption in China [18].

Table 2. The carbon coefficients of different kinds of fuels.

	Fuel Source	Carbon Coefficient
1	raw coal	1.981
2	cleaned coal	2.405
3	other washed coal	0.955
4	coke	2.86
5	crude oil	3.02
6	gasoline	2.925
7	kerosene	3.033
8	diesel oil	3.096
9	fuel oil	3.17
10	LPG	3.101
11	refinery gas	3.012
12	natural gas	21.622
13	electricity	1.239

Notes: 1 t CO₂/1 t fuel, 1 t CO₂/10⁴ m³ natural gas or 1 t CO₂/10⁴ kw·h electricity.

4. Results and Discussion

4.1. The Output Values and CO₂ Emissions in Different Sectors

Figures 1 and 2 show the economic output values and CO₂ emissions from the different sectors from 2000 to 2014. Figure 1 shows that the economic output from all six sectors all grew from 2000 to 2014. The output from the Industry sector was much higher than in the other five sectors. In terms of the average annual growth rate, the top 3 sectors were Construction (11.78%), Trade (11.62%) and Industry (10.54%). With the rapid growth of output, CO₂ emissions across the six sectors also significantly increased.

Figure 2 shows that across the six sectors, the Industry sector produces the most CO₂ emissions, accounting for the total ones of approximately 70%. Emissions from the Industry sector grew rapidly, from 1321.25 million tons in 2000 to 3873.59 million tons in 2014, which reveals an annual increase rate of 7.99%. CO₂ emissions of the Industry sector increased more slowly from 2011 to 2014 and even slightly declined in 2014.

The second largest source of total CO₂ emissions was from the other sector, which includes Residential Consumption and other sectors. These emissions account for the total emissions of about 12%. The third largest source is the Transport sector, which experienced a CO₂ emissions increase of 443.28 million tons. The Transport sector also experienced the largest annual CO₂ emission growth rate, at 8.37%. Data shows that the output value from the Transport sector increased slowly, however, the CO₂ emissions increased rapidly. The remaining three sectors include Agriculture, Trade and Construction, which accounts for the whole CO₂ emissions of a small percentage, at 2.1%, 2.0% and 0.9%, respectively.

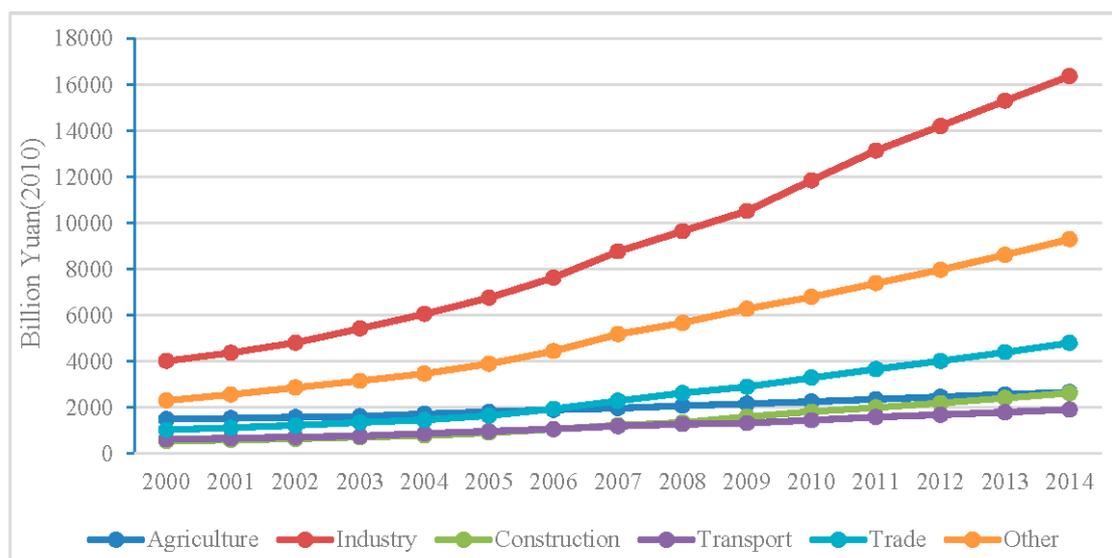


Figure 1. The economic output value of the different sectors.

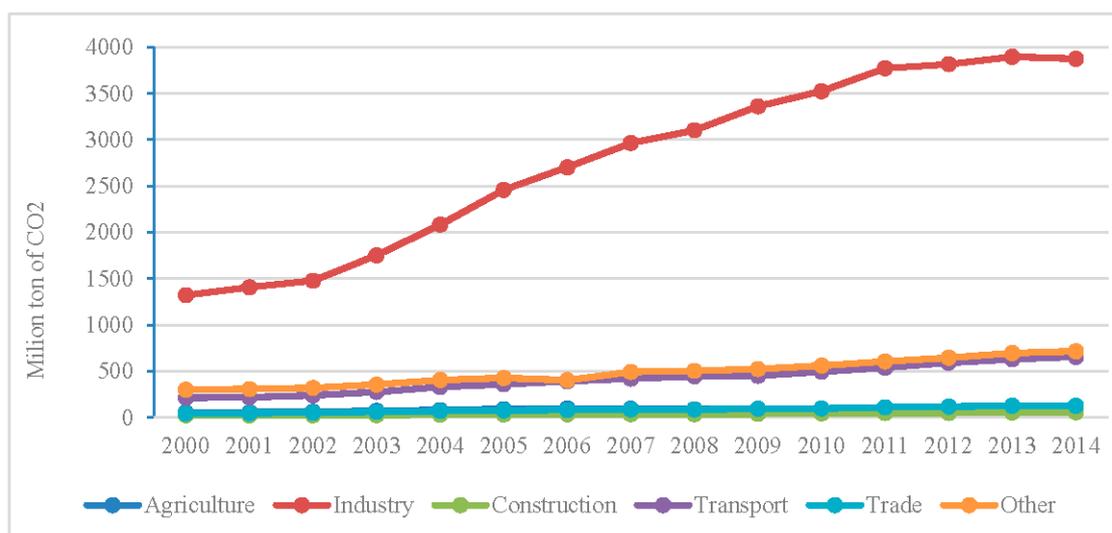


Figure 2. The CO₂ emissions from the different sectors.

4.2. Analysis on the Decoupling Effect in Different Sectors

According to the Tapio decoupling model and former studies [4,7,8,45–47] and using Equation (2), we calculated the value of the decoupling elasticity between CO₂ emissions and GDP from different sectors from 2000 to 2014 (see Table 3).

Table 3 shows that, overall, the CO₂ emissions and the economic output of all six sectors markedly increased from 2000 to 2014. The decoupling elasticity differs across sectors, with a wide range of numerical distribution. The decoupling elasticity of Construction is the smallest, at 0.361; the decoupling elasticity of Agriculture is the largest, which is 1.512.

Across the six sectors, the decoupling states of the Industry, Construction, Trade and Other sectors are the same; all are examples of weak decoupling. In these cases, the growth rate of GDP is higher than that of CO₂ emissions. The Transport sector shows an expansive coupling state, which means CO₂ emissions growth has risen at approximately the same rate as GDP growth. The Agriculture sector experienced expansive negative decoupling from 2000 to 2014, which means GDP grows with accelerating environment damage.

Therefore, the GDP growth, to some extent, reduced the pressure of environment in the Industry, Construction, Trade and Other sectors; however, these sectors did not achieve a real decoupling. The largest concern is with the Agriculture sector, because its carbon emissions increased with GDP growing but the CO₂ emission growth rate was higher than the that of economic growth. As a result, economic growth accelerates environment damage.

Table 3. Decoupling state between the CO₂ emission and the economic output in different sectors from 2000–2014.

	$\Delta C/C$	$\Delta GDP/GDP$	e	Decoupling State
Agriculture	1.189	0.786	1.512	Expansive negative decoupling
Industry	1.932	3.068	0.630	Weak decoupling
Construction	1.358	3.756	0.361	Weak decoupling
Transport	2.082	2.108	0.988	Expansive coupling
Trade	1.927	3.661	0.526	Weak decoupling
Other	1.377	3.030	0.455	Weak decoupling

4.3. Decomposition Analysis of the Different Sectors

4.3.1. Cumulative Effect of Carbon Emission Factors in Different Sectors

Using carbon emission calculations for different industries and earlier studies [4,7,8,42,48,49], Equations (3)–(8) were used to decompose the carbon emission factors into the carbon coefficient effect ($\Delta C_{i,F}$), energy structure effect ($\Delta C_{i,S}$), energy intensity effect ($\Delta C_{i,I}$) and economic effect ($\Delta C_{i,Q}$).

Figure 3 gives us information of the cumulative effect of carbon emission factors in different sectors. In terms of the figure, the cumulative economic effect ($\Delta C_{i,Q}$) is the primary factor contributing to growing carbon emissions for these 6 sectors, accounting for all of about 83%, 149%, 179%, 103%, 158% and 156% for the Agriculture, Industry, Construction, Transport, Trade and Other sector, respectively. The cumulative energy intensity effect ($\Delta C_{i,I}$) turns out to be the second largest contributor for changes of carbon emissions among six sectors. This cumulative energy intensity effect has promoted a lot in improving carbon emissions for Agriculture. In contrast, the effect has had a smaller role in carbon emission for the other sectors.

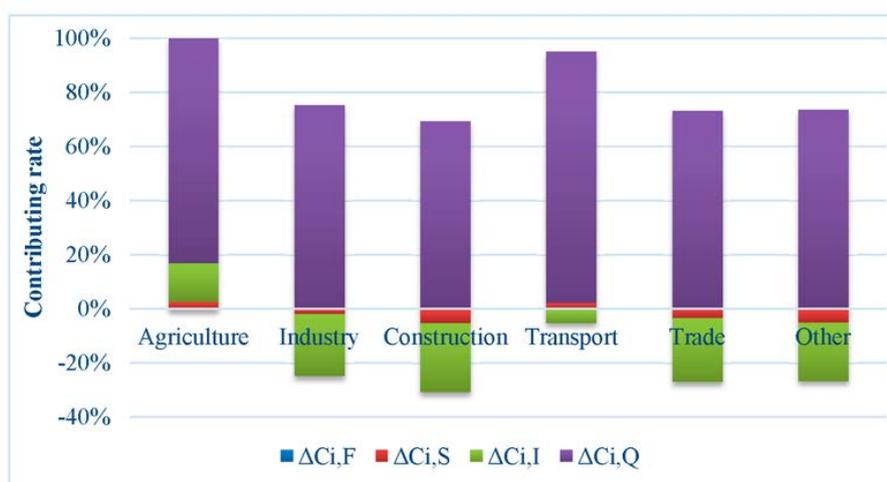


Figure 3. Cumulative effect of CO₂ emission factors in different sectors (unit: %).

The contribution from the cumulative energy structure effect ($\Delta C_{i,S}$) is not always positive for the six sectors. This has supported increased carbon emissions for the Agriculture and Transport sectors and has inhibited emissions for Industry, Construction, Trade and Other sectors. The cumulative carbon coefficient effect ($\Delta C_{i,F}$) is very small for the six sectors.

4.3.2. Analysis of Effects upon Different Sectors

This section analyzes directions and the extent of effects on different sectors (see Figure 4).

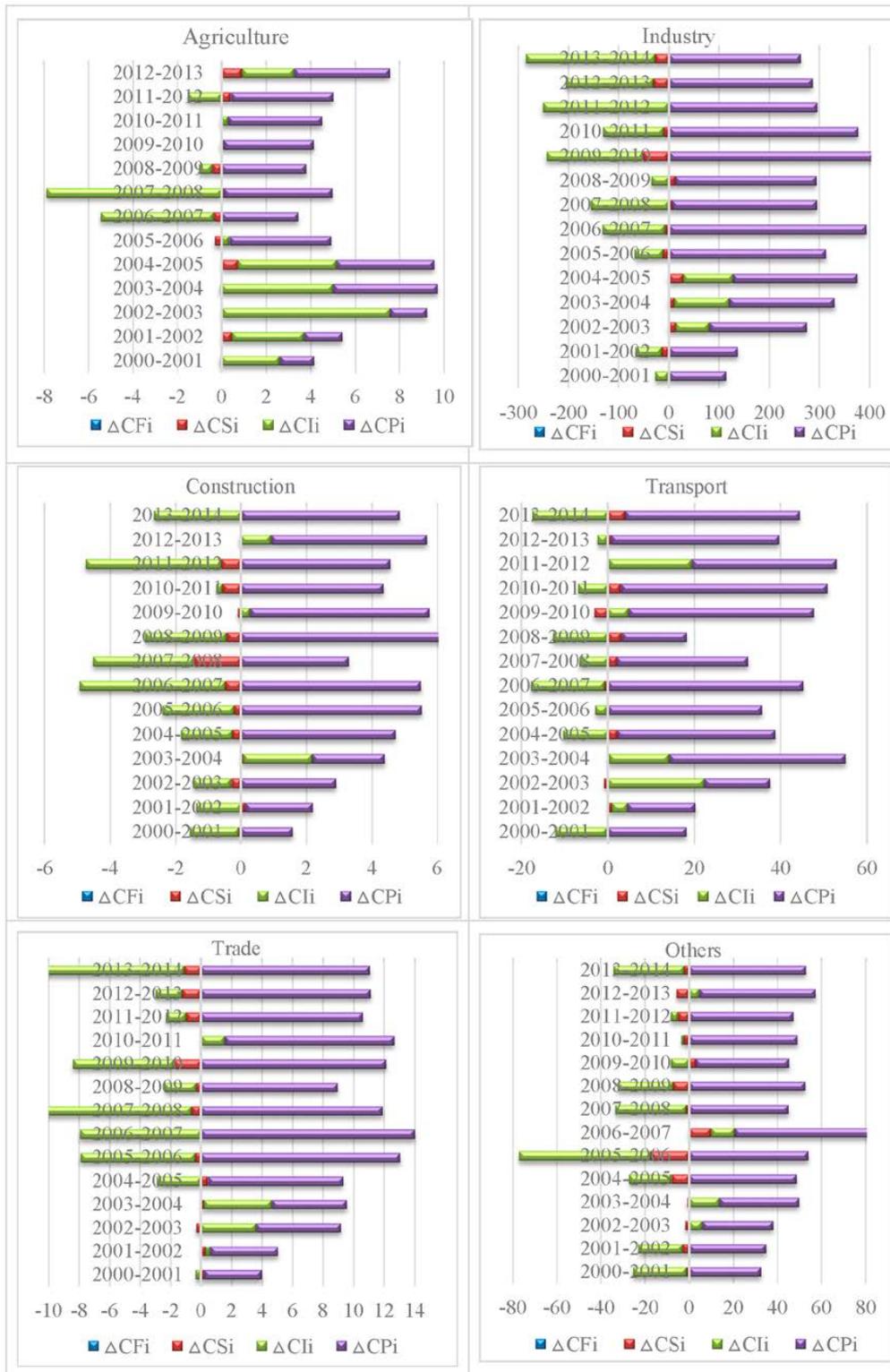


Figure 4. Decomposition of carbon emission in six sectors (unit: Million tons of CO₂).

Economic output from the Agriculture sector increased from 1494.36 billion Yuan in 2000 to 2669.31 billion Yuan in 2014. Such growth was associated with the accumulation of 63.63 million tons of carbon emissions from 2000 to 2014. Figure 4 shows that the economic effect is the major factor that drives changing CO₂ emissions from 2005 to 2006 and from 2008 to 2014; the energy intensity effect was the second highest driver. During other years, the energy intensity effect turned out to be the main reason of increased emissions, followed by the economic effect. The economic growth effect was always positive while the energy intensity effect varied more. From 2006 to 2008, the CO₂ emissions declined because the energy intensity effect played a negative role. This means that the energy intensity effect contributes by cancelling the growth in CO₂ emissions created by the economic effect.

The Industry sector experienced an increase in economic output of 12,351.88 billion Yuan during the study period; this was associated with 2552.34 million tons of CO₂ emissions growth from 2000 to 2014. The economic effect consistently promoted in increasing CO₂ emissions, which was also the largest factor that drive emissions from 2000 to 2013. In 2013–2014, the total CO₂ emissions declined by 226.79 million tons. This occurred because the inhibitory effect of energy intensity exceeded the positive industrial scale effect. The energy structure effect became the third greatest driving factor impacting the emissions.

Emissions from the Construction sector increased by 32.57 million tons with a GDP increase of 2078.34 billion Yuan. Figure 4 shows that the economic effect and the energy intensity effect were determinants of the CO₂ emission growth while the next element was energy structure effect. The carbon coefficient effect was marginal. The CO₂ emissions decreased during 2007–2008 and 2011–2012. This is because the energy intensity effect, the biggest driver of CO₂ emissions, played a negative role.

In the Transport sector, the number of CO₂ emissions in 2014, which was 656.17 million tons, was as 3.08 times as that in 2000. The economic output increased by 3.10 times, reaching 1914.94 billion Yuan. The total carbon emissions consistently remained in a state of growth, with no declines during the study period. This demonstrates that the inhibitory factor effects did not cancel the CO₂ emissions growth facilitated by the positive factors. The economic effect was the strongest driver of CO₂ emissions over this period, with an exception of 2002–2003. The energy intensity effect, which did not get that stable, was the second strongest element driving carbon emissions. The energy structure effect and carbon coefficient effect exerted a comparatively low positive effect.

In the Trade sector, the economic output and CO₂ emissions both significantly increased during the study period, increasing 3772.33 billion Yuan and 83.25 million tons, respectively. Figure 4 shows that the economic effect was a large driver of growing CO₂ emissions; the energy intensity effect was the most significant in decreasing CO₂ emissions, inhibiting emissions in most years. The impact of the energy structure effect on CO₂ emissions was unstable; it had a positive effect from 2001 to 2004, 2007–2008, 2010–2011 and 2013–2014 and a negative effect during the other years.

The economic output of the “Other” sector showed a significant increase, rising from 2307.61 billion Yuan in 2000 to 9298.81 billion Yuan in 2014. With the rapid increase in output, the CO₂ emissions significantly increased by 414.33 million tons. The economic effect had the largest active and most dominant effect on CO₂ emissions growth. However, CO₂ emissions declined by 230.95 million tons from 2005 to 2006. This decrease resulted from the influence of the energy intensity effect, making it a dominant factor cancelling the growth of the economic effect of CO₂ emissions. The energy structure effect and carbon coefficient effect only influenced CO₂ emissions a little.

5. Conclusions and Policy Implications

5.1. Conclusions

In this paper, we calculated CO₂ emissions produced by different sectors with data on final energy consumption and economic output from six different sectors from 2000 to 2014. Based on CO₂ emission measurements, we assessed the decoupling relation between CO₂ emissions and economic growth and

applied the LMDI decomposition method to decompose the factors that drive emissions from each sector. This study's key results are:

- (1) The economic output and carbon emissions of the six sectors all grew from 2000 to 2014. The Industry sector was the main source of total CO₂ emissions, accounting for the whole CO₂ emissions of around 70%. The Other and Transport sectors had the second and third highest emission levels. The other three sectors (Agriculture, Trade and Construction) accounted for the total number of emissions of a lower proportion.
- (2) From 2000 to 2014, the decoupling status of CO₂ emissions differed across different sectors in China. In terms of the ideal degree of low-carbon development, the six sectors were ranked as follows, from best to worst: Construction (weak decoupling), other (weak decoupling), Trade (weak decoupling), Industry (weak decoupling), Transport (expansive coupling) and Agriculture (expansive negative decoupling).
- (3) Different factors drive emissions across the six sectors differently, both in degree and direction. The economic effect is the primary driver of CO₂ emissions across the six sectors and plays a positive role of improving CO₂ emissions. According to contributions these factors provided, the next element was energy intensity effect, which advanced increasing CO₂ emissions for Agriculture but play a negative role in the other sectors. The energy structure effect contributes to emissions of the Agriculture and Transport sectors and inhibited the effect on the CO₂ emissions in other four sectors. Because single types of energy are used for each sector, the cumulative carbon coefficient effect was weak.

5.2. Policy Implications

This study found that as China's economy rapidly grows, the CO₂ emissions from the six analyzed sectors also increase. Therefore, China should adopt additional policies to curb these emissions. Three policy recommendations follow here.

- (1) Based on the total value of CO₂ emissions and decoupling states in different sectors, the Industry sector turns out to be the main origin of total carbon emissions, the annual growth rate of CO₂ emissions is largest for the Transport sector and the decoupling state of the Agriculture sector is expansive negative decoupling. These results indicate that the relevant departments should develop practical and feasible emission reduction targets and adopt differentiated industrial development policies.
- (2) For the Industry sector with the highest economic output and the most CO₂ emissions, it is necessary to develop technological innovations in green low-carbon industries and realize industrial production modes that achieve greater economic output through low CO₂ emissions.
- (3) The economic effect and energy intensity effect are determinants of CO₂ emissions from different sectors, followed by the energy structure effect. Increases in industrial scale will result in an increase in carbon emissions. As such, reducing energy intensity and optimizing energy structure are critical measures for the sake of achieving low carbon development goals of different sectors. Energy efficiency should improve in the future by promoting low-carbon technologies and promoting and applying energy efficient equipment. In addition, improving the usage frequency and scope of clean energy (natural gas, hydropower, solar energy and wind energy) could effectively inhibit the economic growth effect on CO₂ emissions.

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