Driving forces and mitigating strategies of CO_2 emissions in China: A decomposition analysis based on 38 industrial sub-sectors

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Abstract

Due to the substantial industry heterogeneity in China, CO_2 emissions and the major forces driving these emissions may vary in different sub-sectors. However, this topic has rarely been discussed at the industrial sub-sector level. To fill this gap, using an generalized Divisia index model (GDIM) incorporating investment factors, and considering 38 industrial sub-sectors, this study investigated the trajectories of China's industrial CO_2 emissions and their driving forces, both at the overall industrial sector and its sub-sector levels. The results showed, (1) during 2000–2017, 97.2% of the increases in China's total industrial CO_2 emissions was attributable to four sub-sectors. (2) Investment scale was the largest driver of increases in CO_2 emissions, followed by output scale and energy consumption. (3) Carbon intensity of investment, energy intensity, and investment efficiency were main drivers of reductions in CO_2 emissions, but their effects remained limited. (4) The roles of different drivers varied across sub-sectors, resulting in great heterogeneity in emission trajectories between different sub-sectors. The findings indicate the necessity of designing emission-reduction strategies at the sub-sector level, and more efforts should focus on the electricity, heat, metallurgy, mining, and chemical industries.

Key words: carbon emissions; driving factors; mitigation strategy; GDIM

1. Introduction

After a short period of decline during 2014–2016, global energy-related carbon dioxide (CO_2) emissions rebounded to the record level of 33.6 Mt in 2018[1]. Global collaborative efforts to reverse this undesirable situation are crucial. By the end of 2020, over half of countries had announced carbon neutrality targets. As the world's leading energy consumer and CO_2 emitter (Shan et al., 2020), China announced two ambitious goals to be achieved by 2030: reaching a peak CO_2 emissions level and lowering its carbon intensity by 60%–65% relative to the 2005 level (Zhang et al., 2017). Recently, the Chinese government further promised that China would aim to achieve its carbon neutrality by 2060 (China Daily, 2020). To predict future CO_2 emissions and design energy-saving and emission-reducing policies and thus meet these goals, it is crucial to determine the distribution of and factors driving historical CO_2 emissions (Wang and Liu, 2017; Zhang et al., 2020).

In the last four decades, China has transformed rapidly from an agricultural into an industrial economy, a process that has historically taken hundreds of years in developed countries. As shown in Fig.1, this can be verified by the changes in China's industrial structures, that is, the proportion of the added value of the primary industry in GDP decreased rapidly from 27.7% in 1978 to 7.7% in 2020. Another characteristic corresponding to the rapid industrialization is that China's GDP has maintained a miracle of high growth rate for many years, with an average growth rate of 9.3% during 1978–2020 (see Fig. 1). Large-scale investment is widely regarded as the major driver of China's rapid economic growth (Qin et al., 2006). Fig.1 shows, China's total fixed asset

[1] Source: International Energy Agency (IEA), Greenhouse Gas Emissions from Energy database. Available from https://www.iea.org/data-and-statistics/data-browser/?country=WORLD&fuel=CO2%20emissions&indicator=CO2BySource. Here, the world emissions are calculated from the annual data for 203 countries and 42 regional aggregates, from 1971 to 2019.

investment has increased rapidly since 2000, from 2.3 trillion CNY to 52.7 trillion CNY in 2020, with an average growth rate of 15.2%. Such an extensive growth model based on investment-driven and rapid industrialization inevitably leads to a large amount of energy consumption and CO_2 emissions. The national energy consumption in China increased by 2.4 times, from 1469.6 million tons of coal equivalent (Mtce) to 4980.0 Mtce during 2000–2020[2]. The shale of coal consumption in total energy consumption has always remained between 60% and 70% (see Fig. 1). Due to such heavily fossil fuels combustion, China became the world's largest CO_2 emitter in 2007 with an amount of 6473.3 Mt, accounting for 29.4% of global CO_2 emissions[3].

With respect to the industrial sector, as shown in Fig. 1, the energy consumption structure of China's industrial sector is highly similar to that of the whole country. This is because the industrial sector is responsible for 70% of China’s total energy consumption and 80% of its CO_2 emissions (Liu et al., 2015). Specifically, the industrial energy consumption increased by 1.9 times, form 1030.1 Mtce to 3023.1 Mtce during 2000–2017[4]. Accordingly, China’s industrial CO_2 emissions increased by 2.17 times, from 2452.3 Mt to 7768.2 Mt during the same period[5]. With the acceleration of energy transition, as shown in Fig.1, the shares of gas and oil both show an upward trend, but coal is absolutely the dominant energy source in China's industrial sector. Moreover, the industrial sector has consistently accounted for 38–48% of GDP over the past four decades. Thus, a study of energy, the environment, and climate change in China should initially focus on the industrial sector (Zhang and Da, 2015).

[2] Source: National Bureau of Statistics of China (NBSC). Available from https://data.stats.gov.cn.
[3] Source: IEA, Greenhouse Gas Emissions from Energy database. Available from https://www.iea.org/data-and-statistics/data-product/co2-emissions-from-fuel-combustion.
[4] Source: National Bureau of Statistics of China (NBSC). Available from https://data.stats.gov.cn.
[5] Source: China Emission Accounts and Datasets (CEADs). Available from https://www.ceads.net.

INSERT FIG.1 HERE

The objectives of this study were to uncover the factors driving China's industrial CO_2 emissions from the perspective of industry segmentation and to provide decision-making references for the design of feasible mitigation strategies for each industrial sub-sector. Specifically, using an extended GDIM decomposition model and considering 38 industrial sub-sectors, we investigated the trajectories of China's industrial CO_2 emissions and their driving forces during 2000–2017. Previous studies concluded economic scale was the largest driving force of increases in CO_2 emissions in China (e.g. Minx et al., 2011; Zhang et al., 2015; Vaninsky, 2014; Shao et al., 2016a; Fan et al., 2015; Li et al., 2017), but they overlooked an important fact that large-scale investment is the major driver of China's rapid economic growth (Qin et al., 2006). Given that the impacts of investment factors on CO_2 emissions have been ignored in traditional decomposition models (Zhao et al., 2016; Zhang et al., 2017, 2020), we considered not only the conventional factors but also three novel investment factors in our extended GDIM model, i.e., investment scale, carbon intensity of investment, and investment efficiency (see *Methodology and data* for their detailed definitions). Our results suggested a different conclusion, that is, both investment scale and carbon intensity of investment played an essential role in CO_2 emissions in all sub-sectors, especially their contributions exceeded those of economic activities.

This study makes three main contributions to previous literature. Regarding the first contribution, to the best of our knowledge, this study is the first to provide a relatively full sub-sectoral overview of forces driving CO_2 emissions in the Chinese context. Although China has an integrated industrial system, its industries vary in their resource endowments, technological levels, and economic contributions, leading to heterogeneity in both CO_2 emissions and the forces driving these emissions (Khan et al., 2020). For example, variations in technology level may lead to large differences in energy efficiency and carbon intensity of output (Luan et al., 2019). Furthermore, the investment efficiency of a capital-intensive industry differs from that of a labour-intensive industry (Qin and Song, 2009). It is both interesting and necessary to integrate different sub-sectoral analysis in the same decomposition framework – a gap that we help to fill in this article.

As our second contribution, we introduce three novel investment factors into the extended GDIM decomposition framework. Firstly, in terms of investment scale, this study examined the heterogeneous contribution to CO_2 emissions made by investment scale in each industrial sub-sector and thus analyzed the structural effect of the total investment. For example, CO_2 emissions may increase if heavily polluting industries increase their investment scale, while CO_2 emissions may decrease in the case of investment in green industries increases. Secondly, from the perspective of carbon intensity of investment, it reflects the impact (on CO_2 emissions) of changes in the low carbon level of fixed asset investment (Zhang et al., 2020). For example, an investment intended to renovate equipment to meet energy-saving and emission-reduction targets can certainly mitigate CO_2 emissions (Zhao et al., 2016; Zhang et al., 2017). However, an investment intended to expand production scale and improve capital productivity may also has a rebound effect, leading to increases in energy consumption and emissions (Shao et al., 2014; Baležentis et al., 2021; Khosroshahi and Sayadi, 2020). Thirdly, regarding investment efficiency, it reflects the impact of changes in capital productivity on CO_2 emissions (Zhang et al., 2020). Accordingly, the role of investment should be considered.

Regarding our third contribution, this article presents a relatively early discussion of how each industrial sub-sector in China can achieve its carbon peak target, in contrast with the usual discourses focused on the national (Ding et al., 2019) or province-level approaches (Fang et al., 2019; Zhang et al., 2020; Li et al., 2021). If CO_2 emissions in different sub-sectors are affected by different drivers, policymakers must consider sector-based mitigation strategies, such as a stratified pathway that distinguishes heavy industry from light industry. We sought to fill this gap by shifting the focus from the national or regional levels to the industrial sub-sector level.

The remainder of this article is organized as follows. Section 2 presents the literature review. Section 3 describes the extended GDIM method and data used in the study. Section 4 reveals the decomposition results. Section 5 discusses the emissions mitigating strategies. Section 6 draws research conclusions.

2. **Literature review**

The historical trajectories and driving forces of China's CO_2 emissions have been addressed extensively at the national and regional levels (Du and Lin, 2015; Du et al., 2017; Liao et al., 2019; Wen et al., 2019, 2020; Zhang et al., 2016, 2020). These macro-perspective analysis have enriched our understanding of the drivers of CO_2 emissions, but a sector-based perspective can offer the flexibility to mitigate emissions, which may be more feasible and manageable than a country-wide approach (Cai et al., 2007). Recently, increasing studies have shifted the focus into the sector level, but most of them have focused on emissions and diving forces in aggregated sectors (Erdoğan et al., 2020; Karakaya, et al., 2020; Zhang et al., 2017), or in specific industries such as the mining (Lin and Ouyang, 2014; Shao et al., 2016a; Feng et al., 2018; Wang and Feng, 2018), power and other energy sub-sectors (Zhang et al., 2013; Zhou et al., 2014; Morales-Lage, 2019), manufacturing (Shao et al., 2016a), transportation (Gambhir et al., 2015; Bai et al., 2020), and the agricultural sector (Lin and Xu, et al., 2018).

However, by analyzing the complementary or alternative relationship between energy and other inputs in Germany, Alataş (2020) found an opposite outcome was observed between some of energy-dominant industries and other industries in terms of both input substitution and its adjustment process. Aslan et al. (2018) found that inverted U-shaped EKC hypothesis was valid for total CO_2 emissions, industrial CO_2 emissions, electrical CO_2 emissions and residential CO_2 emissions, but the inverted U-shaped relationship between economic growth and CO_2 emission was not supported for commercial and transport sector. Khan et al. (2020) found that the impact of technological progress on CO_2 emissions varied among different economic sectors in Pakistan. These results clearly show us that the importance of conducting an empirical analysis at the dis-aggregated level and the necessity of implementing industry-oriented emissions mitigation policies. Similarly, there is a substantial industry heterogeneity in China. Strategies to mitigate CO_2 emissions should be designed at the sub-sector level based on the industry-specific needs and peculiarities. Unfortunately, this issue has not been paid enough attention in the Chinese context.

Regarding the drivers of CO_2 emissions, the factorial decomposition research has frequently considered the traditional socioeconomic factors such as energy intensity, energy structure, energy consumption, economic scale, economic structure, GDP per capital, and population (Mahony, 2013; Sadorsky, 2014; Cansino et al., 2015; Zhang and Da, 2015; Mi et al., 2018; Feng et al., 2018; Ghazali et al, 2019; Chong et al., 2019). For example, Chong et al. (2019) found that population, GDP per capital and end-use fuel-mix changes increased CO_2 emissions in Malaysia during 1978–2014, while energy intensity and electricity efficiency decreased CO_2 emissions. Cansino et al (2015) decomposed CO_2 emissions in Spain during 1995–2009 and demonstrated that improved performance in the carbon intensity and energy intensity exceeded the role of affluence and the effect of population as traditional drivers of CO_2 emissions, while the contribution of economic structure factor remained inconclusive. Diakoulaki and Mandaraka (2007) explained changes in industrial CO_2 emissions in 14 EU countries from 1990 to 2003 and concluded that the main influencing factors were output, energy intensity, structure, fuel mix and utility mix. Moutinho et al. (2015) analyzed the driving forces of energy-related CO_2 emissions in Europe and the results showed that CO_2 emissions were correlated with the energy consumption, which was determined by the change of population among the various countries. O'Mahony (2013) addressed the driving forces of CO_2 emissions in 11 final energy consuming sectors in Ireland from 1990 to 2010 and found that scale, structure and intensity were the three key factors. Mousavi et al. (2017) found economic activity was the largest driving force of increases in CO_2 emissions in Iran from 2003 to 2014. Bhattacharyya and Ussanarassamee (2004), Alves and Moutinho (2013) found that industrial structure, energy intensity and energy structure drove the changes in CO_2 emissions in Thailand and Portugal, respectively. In China, many studies concluded that economic growth appeared as the main driver of increases in CO_2 emissions (Zhang et al., 2015; Shao et al., 2016a; Fan et al., 2015; Vaninsky, 2014; Li et al., 2017), and the decrease of energy intensity played significant role in curbing CO_2 emissions (Zhang et al., 2016), but the reduction effect of inhibiting factors of CO_2 emissions was less than the driving effect of economic growth in most years (Zhang and Da, 2015).

In terms of the methods used in previous studies, as detailed by Feng et al. (2018), three primary categories of methods were broadly applied by researchers: the STIRPAT, IPAT and regression; the environmental Kuznets curve method; and decomposition analysis. Although each method has its advantages, decomposition analysis can not only identify the main driving forces of the variations in an aggregation but also show the clearly quantitative results of to what extent the driving forces affect the variations (Su and Ang, 2012).

Specifically, the decomposition analysis mainly includes three types of approaches (see Wang and Feng (2018) for details about the advantages and disadvantages of these three approaches). The first approach is structural decomposition analysis (SDA), which is based on input–output analysis (e.g., Rose and Casler, 1996; Guan et al., 2008; Su and Ang, 2012; Mi et al., 2016; Cansino et al., 2016). However, its use in the current study is limited by the lack of availability of an annual sub-sectoral input–output table. The second approach is production-theoretical decomposition analysis (PDA), which is based on production theory and the data envelopment analysis model (e.g., Kim and Kim, 2012; Li et al., 2017; Wang et al., 2018). The third approach is index decomposition analysis (IDA), which is based on index number theory (e.g., Zha et al., 2010; Wang and Feng, 2017, 2018). It is particularly well suited to our study due to its low data requirement and easy implementation (Ang and Zhang, 2000; Ang and Xu, 2013).

Among the various IDA models, the logarithmic mean Divisia index (LMDI) model is one of the popular method (e.g., Ang, 2005; Xu et al., 2012; Fernández-González et al., 2014; Moutinho et al., 2015; Lin and Long, 2016; Wang et al., 2017; Feng et al., 2018; Wang and Feng, 2018). In the LMDI model, the Divisia index has normally been used to decompose the target variable into several multiplicative factors. However, the effects of multiple quantitative and relative indicators on the resulting indicators cannot be simultaneously incorporated (Zhang et al., 2020). Besides, the decomposition results of LMDI strongly rely on the factors interdependence (Shao et al., 2016). Thus, the results of such factorial decomposition do not fully align with economic common sense because the structural factors are interconnected (Vaninsky, 2014). To this end, Vaninsky (2014) extended the Kaya identity and proposed a more general empirical decomposition framework, namely the GDIM method. Compared with the LMDI method, this approach includes these interconnected factors, and allows for the inclusion of any quantitative and relative indicators (Vaninsky, 2013, 2014).

In summary, the existing studies have shown that the key factors driving CO_2 emissions in countries at different historical stages or development levels are not completely consistent. Even in the same country, the roles of various factors are also volatile in different sectors. This indicates the necessity of our analysis from the perspective of the sub-sector level. Moreover, relatively few studies, particularly those using the GDIM method have considered investment factors. In this regard, Shao et al. (2016b) took the lead in introducing investment factors into the LMDI model. Zhao et al. (2016), and Zhang et al. (2017, 2020) found that investment scale was the dominant driver in promoting China's industrial CO_2 emissions. However, their investigations are limited to analyzing the role of investment at the overall industrial sector level, lacking of its sub-sectoral decomposition.

3. Methodology and data

3.1. GDIM decomposition approach

This study employed the GDIM method to decompose the drivers of changes in CO_2 emissions. As investment is the primary driver of rapid economic growth in China, this study expanded the basic GDIM model by adding three investment indicators. Under such circumstances, CO_2 emissions can be presented in one of four ways:

$$C = \sum_{i=1}^{n} C_i = \sum_{i=1}^{n} \frac{C_i}{Y_i} Y_i = \sum_{i=1}^{n} \frac{C_i}{E_i} E_i = \sum_{i=1}^{n} \frac{C_i}{I_i} I_i \qquad (1)$$

where the subscript i indicates the ith sub-sector; C is CO_2 emissions; E is energy consumption; G is economic output (industrial output value); and I is investment scale (fixed asset investment).

Let $ECI = C/E$ indicate the carbon intensity of energy; $GCI = C/Y$ the carbon intensity of output; $ICI = C/I$ the carbon intensity of investment; $EI = E/Y$ the energy intensity; and $IE = Y/I$ the investment efficiency. Using these newly defined variables, we can obtain the following equations:

$$EI_i = \frac{E_i}{Y_i} = \left(\frac{C_i}{Y_i}\right) \Big/ \left(\frac{C_i}{E_i}\right) = GCI_i / ECI_i \qquad (2)$$

$$IE_i = \frac{Y_i}{I_i} = \left(\frac{C_i}{I_i}\right) \Big/ \left(\frac{C_i}{Y_i}\right) = ICI_i / GCI_i \qquad (3)$$

According to the principle of the GDIM, we can then separate the above equations into a factor model and equations representing the interconnections between the factors:

$$C_i = Y_i \times GCI_i \qquad (4)$$

$$\varphi_1 = Y_i \times GCI_i - E_i \times ECI_i = 0 \qquad (5)$$

$$\varphi_2 = Y_i \times GCI_i - I_i \times ICI_i = 0 \qquad (6)$$

$$\varphi_3 = Y_i - I_i \times IEI_i = 0 \qquad (7)$$

$$\varphi_4 = E_i - Y_i \times EI_i = 0 \qquad (8)$$

Let $C_i(X)$ indicates the function of the contribution of factor X_i to CO_2 emissions. The Jacobian matrix Φ_x is the first-order derivative of φ ($\varphi = [\varphi_1, ..., \varphi_6]$). A gradient of the function $C_i(X)$ and the Jacobian matrix Φ_x are listed as follows:

$$\triangledown \ C_i = \langle GCI_i, Y_i, 0,0,0,0,0,0 \rangle^T \qquad (9)$$

$$\Phi_x = \begin{bmatrix} GCI_i & Y_i & -ECI_i & -E_i & 0 & 0 & 0 & 0 \\ GCI_i & Y_i & 0 & 0 & -ICI_i & -I_i & 0 & 0 \\ 1 & 0 & 0 & 0 & -IE_i & 0 & -I_i & 0 \\ -EI_i & 0 & 1 & 0 & 0 & 0 & 0 & -Y_i \end{bmatrix}^T \quad (10)$$

According to Vaninsky (1984), the factorial decomposition of changes in CO_2 emissions in the presence of the interconnections between factors can be expressed as follows:

$$\Delta C_i[X\|\mathbf{\Phi}] = \int_L \Delta C_i^T \left(\mathbf{I} - \Phi_X \Phi_X^+\right) dX \quad (11)$$

where L is time span; $\mathbf{I}$ is identity matrix; and the superscript + denotes the generalized inverse matrix. If the columns of the matrix Φ_x are linearly independent, then

$$\mathbf{\Phi_X^+} = \left(\mathbf{\Phi_X^T \Phi_X}\right)^{-1} \mathbf{\Phi_X^T} \quad (12)$$

See Albert (1972) for details. Hence, the changes in CO_2 emissions in each sub-sector (ΔC_i) can be decomposed into eight drivers in the following additive expression:

$$\Delta C_i = \sum_{j=1}^{8} \Delta C_i\left(X_j\right) \quad (13)$$

The eight drivers are the energy consumption effect (ΔC_E), output scale effect (ΔC_Y), investment scale effect (ΔC_I), carbon intensity of energy effect (ΔC_{ECI}), carbon intensity of output effect (ΔC_{GCI}), carbon intensity of investment effect (ΔC_{ICI}), energy intensity effect (ΔC_{EI}), and investment efficiency effect (ΔC_{IE}). As detailed in Zhang et al. (2020), ΔC_E , ΔC_Y , and ΔC_I reflect the impacts of changes in the absolute scale of energy consumption, industrial output, and fixed investment on emissions, respectively. Of the remaining relative indicators, ΔC_{GCI} reflects the impact of changes in the low carbon level of economic growth; ΔC_{ECI} reflects the impact of structural changes in energy consumption; ΔC_{ICI} reflects the impact of changes in the low carbon level of fixed asset investment; ΔC_{IE} reflects the impact of changes in capital productivity; and ΔC_{EI} reflects the impact of changes in economic dependence on energy use.

3.2. Definition of 38 sub-sectors

This study focused on the industrial sub-sectors. According to the latest revised National Standard of People's Republic of China (GB/T 4764–2017), the industrial sector includes 41 sub-sectors. As the classification of China's industrial sub-sectors has undergone four major adjustments during the entire study period, we strictly followed the suggestions from Chen (2009) and Shan et al. (2018) to maintain a consistent sample. For example, the "Logging and Transport of Wood and Bamboo" sub-sector has been integrated into the "Farming, Forestry, Animal Husbandry, Fishery and Water Conservancy" major-sector since 2003, we have dropped this sub-sector from our analysis. The "Rubber Products" sub-sector has been merged with the "Plastic Products" sub-sector since 2012, we have merged these two sub-sectors into one sub-sector, named the "Rubber and Plastic Products" sub-sector. The "Automobile Manufacturing" sub-sector has been separated from the "Transportation Equipment Manufacturing" sub-sector since 2012, but we still integrated the "Automobile Manufacturing" sub-sector into the "Transportation Equipment Manufacturing" sub-sector after 2012. Ultimately, our decomposition objects included 38 industrial sub-sectors. For simplicity, we here abbreviate the name of each sub-sector. The details are provided in Table A1 in the Appendix A.

3.3. Data

Based on the data availability, this study covered the 2000–2017 period. Firstly, the statistical standards and calibers of the industrial sub-sectors in the statistical yearbooks were adjusted in 1993 and 1998, respectively, making it difficult to match the data after the adjustment with the pre-adjusted data (Chen, 2009; Zhao et al., 2016). Chen (2009) provided a method to cope with the changes in statistical calibers after 1980, however, the data quality obtained by this operation has great uncertainty. Secondly, the CO_2 emissions dataset we used only provided the emissions data with the newly statistical caliber after 2000 (Shan et al., 2018, 2020). Therefore, in accordance with the general practice of many previous empirical studies focusing on China's industrial sector (e.g., Liu et al., 2007; Fujii et al., 2013; Yang et al., 2013; Luan et al., 2019), we have to limit the analysis to a certain range after 1998.

We constructed a panel data covering 38 industrial sub-sectors. The sub-sectoral output value, energy consumption, and fixed asset investment data were obtained from the *China Statistical Yearbook* (NBSC, 2001–2018), *China Industry Economy Statistical Yearbook* (NBSC, 2001–2012), *China Energy Statistical Yearbook* (NBSC, 2001–2018), and *China Fixed Asset Investment Statistical Yearbook* (NBSC, 2004–2018). The output value and investment data were deflated to 1990 prices. The energy consumption data included 17 types of fossil fuels, all of which were measured in standard coal equivalents.

For each sub-sector, the time series of CO_2 emissions were derived from CEADs (Available from https://www.ceads.net) issued by Shan et al. (2018; 2020). Because this dataset offers five advantages. Firstly, the dataset estimates CO_2 emissions in terms of the IPCC administrative territory-based accounting scope, which includes emissions from 17 fossil fuels combustion (energy-related emissions) and emissions from the cement production (process-related emissions). Secondly, to avoid duplication, the dataset does not include fossil fuels used as chemical raw materials, energy losses during transportation, or non-burning fossil fuel input during energy conversion processes. Thirdly, this dataset provides emissions in each industrial sub-sector using two different calculation methods, namely sectoral approach and reference approach. Our study used emissions data calculated by sectoral approach (see Shan et al. (2018) for details), because sectoral approach estimates are more accurate than reference approach estimates (Shan et al., 2018). Fourthly, the dataset uses updated emission factors, estimated based on a wide investigation of 4243 coal mine samples, and reports different oxygenation efficiencies for the fossil fuels used in different sectors, to represent differences in combustion technology levels. Most previous studies used the IPCC default value directly. However, the IPCC default emission factors are approximately 40% higher than the survey values in China (Shan et al., 2018). Fifthly, the dataset uses Monte Carlo simulations to propagate the uncertainties induced by both fossil fuel consumption and emission factors.

The mean value of each indicator is presented in Table 1. During 2000–2017, the average yearly CO_2 emissions of each sub-sector was about 153 Mt. In terms of the sub-sectors related to energy production, their carbon intensity of output, carbon intensity of investment, carbon intensity of energy, and energy intensity were much higher than those of other sub-sectors, but their average output scale was lower than that of other sub-sectors. This indicates the high emissions of energy-intensive sub-sectors did not result in correspondingly high economic output. In contrast, those sub-sectors with low-emissions and low-energy consumption (mainly concentrated in the high-tech and light manufacturing categories) exerted both high economic output and high investment efficiency.

INSERT Table 1 HERE

4. Results

This section analyzed the trajectories of China's CO_2 emissions and their driving forces, both at the overall industrial sector and its sub-sector levels. Firstly, we took the entire industrial sector as the decomposition object, thus the overall changes in industrial CO_2 emissions and the total contributions of the eight factors were investigated. Secondly, we shifted to the industrial sub-sectors, so CO_2 emissions and their driving forces of 38 sub-sectors were decomposed.

4.1. Overall decomposition results

Fig. 2 presents the yearly changes in total industrial CO_2 emissions and the overall contributions of the eight drivers. The detailed results are presented in Table A2. Overall, the total industrial CO_2 emissions in China increased by 2.17 times (5316.0 Mt) from 2000 to 2017, rising from 2452.3 Mt to 7768.2 Mt, respectively. However, the rate of growth decreased over time. As shown in Fig. 2 and Table A2, the changes in overall CO_2 emissions experienced four stages: high-speed growth stage (2000–2006), decreasing-speed growth stage (2007–2009), steady growth stage (2010–2012) and transition stage (2013–2017). This trend is in line with changes in China's national CO_2 emissions from 2000 to 2015 (Li et al., 2017). A short-term period of negative growth in CO_2 emissions occurred during 2014–2016, followed by a rapid increase in 2017, consistent with the trend of changes in global CO_2 emissions.

In terms of the sub-sectors' contributions to total industrial CO_2 emissions, as shown in Fig. 3, the top four sub-sectors were Production and Supply of Electric Power, Steam and Hot Water (PSESW), Smelting and Pressing of Ferrous Metals (SPFM), Nonmetal Mineral Products (NMP), and Raw Chemical Materials and Chemical Products (RCMC). The cumulative changes in CO_2 emissions of these four sub-sectors accounted for 97.2% (5164.8 Mt) of changes in total industrial CO_2 emissions during 2000–2017. Moreover, PSESW represented the most of changes in CO_2 emissions among 38 sub-sectors, followed by SPFM , NMP, and RCMC.

With regard to the quantitative indicators, as shown in Fig. 3, the output scale and energy consumption represented increases in CO_2 emissions of 1427.3 Mt and 1414.8 Mt, respectively, accounting for 26.9% and 26.6% of changes in total industrial CO_2 emissions, respectively. However, when we considered investment as the prerequisite of economic growth and incorporated it into the GDIM model, we found that the contribution of investment scale exceeded that of output scale and all other factors. This result is primarily due to the massive fixed asset investments attracted by the industrial sector, which are mainly used for capital construction rather than low-carbon technological innovation or equipment upgrading. The average nominal growth rate of fixed asset investments in China reached 21.0% during 2000–2015, exceeding the GDP growth rate, even though investment growth began to decline from the launch of the 13th Five-Year Plan (FYP). Ihe industrial sector, the scale of fixed asset investment increased by 10.4 times from 2042.7 billion CNY in 2003 to 23272.6 billion CNY in 2017, representing approximately 40% of the total fixed asset investments. During 2000–2017, the cumulative contribution of investment scale represented increases in CO_2 emissions of 5463.4 Mt (see in Fig. 3), accounting for 102.8% of changes in total industrial CO_2 emissions. However, as shown in Fig. 1, this trend yielded an inverted U-shaped curve, as the yearly contribution of investment scale to CO_2 emissions increased from 77.2 Mt at the beginning of the 10th FYP to 540.6 Mt at the end of the 11th FYP, but declined gradually after entering the 12th FYP to 16.43 Mt in 2017.

Among the other relative indicators, carbon intensity of investment, investment efficiency, and energy intensity all mitigated CO_2 emissions to varying degrees. Carbon intensity of investment was the largest driver of reductions in CO_2 emissions, yielding a cumulative reduction in CO_2 emissions of 3417.6 Mt. This mitigating effect increased across the 2000–2017 period due to increasing investments targeting green development and low-carbon technology innovation. For example, investments targeting environmental governance and industrial pollution control increased by 7.2 times and 3.0 times in China, respectively, during this period.

Investment efficiency counteracted increases in CO_2 emissions by contributing a decrease of 301.0 Mt. In China, over-investment over the long term in some industrial sub-sectors has led to a large amount of overcapacity, which in turn have resulted in diminishing marginal return on capital. During 2000–2017, investment efficiency (calculated at 1990 prices) decreased by 87.9%. Since the 12th FYP, China has implemented supply-side reforms, such as phasing out backward and redundant industrial production capacity and adjusting the industrial structure. Besides, the government has also paid more attention to green investment to accelerate energy conservation.

Energy intensity also counteracted increases in CO2 emissions. This observation supports the commitment made by the Chinese government at the Copenhagen Climate Conference in 2009; specifically, China pledged to reduce the CO_2 emissions per unit of GDP by 40–45% in 2020 relative to 2005. However, its mitigating effect is limited, as this factor was only responsible for a reduction in CO_2 emissions of 58.2 Mt during 2000–2017.

Carbon intensity of output did not yield the expected mitigating effect on CO_2 emissions except during specific periods, such as the global financial crisis from 2007 to 2010. This unexpected result is not only related to a long period of extensive economic growth in China, but also closely related to institutional factors. In China, for example, local government officials are generally appointed by the central government rather than by referendum due to the political centralization, leading to a widespread "political tournament" between local governments (Zhang and Zou, 1998; Jin et al., 2006). Meanwhile, since the fiscal decentralization reforms in 1990s, local governments have been required to choose between emission reduction and rapid economic growth. Generally, they have tended to sacrifice the environment in favour of the economy. This is exemplified by the approximate 17.0% increase in the carbon intensity of industrial output (at an average growth rate of 1.2%) during 2000–2017.

Carbon intensity of energy played a dual role in changes of CO_2 emissions throughout the study period, its cumulative contribution was a 373.6 Mt increase in CO_2 emissions. This factor played a mitigating role mainly in the early to middle stages of the 10th FYP and the later stage of the 12th FYP. This indicates the structural contradictions in China's energy transition. On the one hand, the proportion of non-fossil fuels contributing to the total energy consumption is increasing with the rapid development of clean and renewable energy. On the other hand, the production activities of some industrial sub-sectors still relies heavily on fossil fuels especially as coal, which remains the largest source of energy consumed in China (57.7% in 2019).

Overall, during 2000–2017, investment scale effect, output scale effect, and energy consumption effect were the primary drivers of increases in CO_2 emissions. Carbon intensity of investment effect, investment efficiency effect, and energy intensity effect were the main contributors to reductions in CO_2 emissions.

INSERT FIG. 2 HERE

INSERT FIG. 3 HERE

4.2. Sub-sectoral decomposition results

Since there are too many sub-sectors involved, we cannot compare the decomposition results of all sub-sectors one-by-one at the same time. Therefore, we followed the classification of Shan et al. (2018) to cluster these 38 sub-sectors into four categories. That is, energy production category (covered 9 sub-sectors), heavy manufacturing category (covered 11 sub-sectors), light manufacturing category (covered 13 sub-sectors), and high-tech industry category (covered 5 sub-sectors). Then, the decomposition results of each sub-sector were presented by category. This categorization makes each category includes limited sub-sectors, which enables us to compare the heterogeneity in contributions of various drivers across different sub-sectors. The contributions of eight indicators to changes in CO_2 emissions of 38 sub-sectors are presented in Fig. 4 to Fig. 7.

4.2.1. Energy production category

This category includes 9 sub-sectors related to energy production. During 2000-2017, CO_2 emissions of this category increased by 3035.5 Mt. Since the beginning of the current century, China has moved towards comprehensive urbanization and industrialization (Lin and Liu, 2010), leading to increasing demands for steel, cement, and electricity. As a result, most of these nine energy production related sub-sectors, such as PSESW, Petroleum Processing and Coking (PPC), Coal Mining and Dressing (CMD), Ferrous Metals Mining and Dressing (FMMD), Nonferrous Metals Mining and Dressing (NMMD), Non-metal Minerals Mining and Dressing (NMD), and Other Minerals Mining and Dressing (OMMD), experienced increases in CO_2 emissions during 2000–2017. However, some energy production sub-sectors, such as Production and Supply of Gas (PSG), Petroleum and Natural Gas Extraction (PNGE), yielded reductions in CO_2 emissions during 2000–2017. Especially after 2010, similar reductions were also observed in other sub-sectors, such as FMMD, NMMD, and NMD, although the cumulative changes in CO_2 emissions of all these three sub-sectors increased. This may be due to long-term over-investment in the mining field, which has led to a large excess capacity. Accordingly, the Chinese government has implemented supply-side reforms to reduce overcapacity in this field since the 12th FYP.

As shown in Fig. 4, the increases in CO_2 emissions of this category was mainly contributed by PSESW (2926.0 Mt), PPC (82.7 Mt), and CMD (24.9 Mt), so the driving forces of these three sub-sectors should be focused more attention. Specifically, in the PSESW sub-sector, energy consumption (4028.2 Mt) was the largest driver of increases in CO_2 emissions, followed by investment scale (1652.2 Mt), carbon intensity of energy (1019.8 Mt), carbon intensity of output (642.5 Mt), and output scale (547.7 Mt). Energy intensity (-4236.3 Mt) was the largest contributor to reductions in CO_2 emissions, followed by carbon intensity of investment (-511.3 Mt) and investment efficiency (-216.9 Mt). In the PPC sub-sector, investment scale (67.6 Mt), energy consumption (21.3 Mt), carbon intensity of output (19.2 Mt), output scale (15.0 Mt), and carbon intensity of energy (12.1 Mt) were dominant drivers of increases in CO_2 emissions. Carbon intensity of investment (-33.4 Mt), energy intensity (-11.2 Mt), and investment efficiency (-7.9 Mt) were major contributors to reductions in CO_2 emissions. In the CMD sub-sector, investment scale (45.9 Mt), output scale (22.2 Mt), energy consumption (9.4 Mt), and carbon intensity of energy (4.6 Mt) were dominant drivers of increases in CO_2 emissions. The remaining four factors all contributed to reductions in CO_2 emissions, but these contributions were mainly derived from the impacts of carbon intensity of investment (-33.13 Mt) and energy intensity (-12.9 Mt).

Due to the mitigating effects of carbon intensity of investment (-5.99 Mt) and carbon intensity of output (-4.79 Mt), PSG (-5.6 Mt) ranked third among 38 sub-sectors in terms of reductions in CO_2 emissions. In this sub-sector, only two factors, investment scale (4.64 Mt) and output scale (3.31 Mt), contributed to increases in CO_2 emissions. In the PNGE (-1.1 Mt) sub-sectors, in addition to the conventional reduction factors, such as carbon intensity of investment (-10.82 Mt), energy intensity (-5.16 Mt), investment efficiency (-3.53 Mt), and carbon intensity of energy (-2.26 Mt), output scale (-9.37 Mt) became the second largest contributor to reductions in CO_2 emission. However, carbon intensity of output (19.92 Mt) was the largest driver of increases in CO_2 emissions, exceeding the contributions of investment scale (12.11 Mt) and energy consumption (2.02 Mt).

In summary, energy consumption was the largest driver of increases in CO_2 emission in PSESW and NMMD, while investment scale was the largest driver in other sub-sectors related to energy production. Energy intensity, carbon intensity of energy, and carbon intensity of output were the major contributors to reductions in CO_2 emissions in PSESW, NMMD and OMMD, respectively. Besides, carbon intensity of energy led to reductions in CO_2 emissions in sub-sectors such as PNGE, PSG, and OMMD. Carbon intensity of output contributed to increases in CO_2 emissions in sub-sectors such as PNGE, PPC, and PSESW.

INSERT FIG. 4 HERE

4.2.2. Heavy manufacturing category

Heavy manufacturing is another important source of CO_2 emissions in China, which includes 11 sub-sectors in this study. Due to low labour costs, China has gradually become the ‘world’s manufacturing factory’ since joining the World Trade Organization in 2001, leading to huge demands for fossil fuels and petrochemical materials. As a consequence, CO_2 emissions of this category increased by 2267.6 Mt during 2000-2017, which was mainly contributed by five sub-sectors, namely SPFM, NMP, RCMC, Smelting and Pressing of Nonferrous Metals (SPNM), and Ordinary Machinery (OM). Especially the top three sub-sectors mentioned above accounted for 24.2% (1286.4 Mt), 15.0% (797.2 Mt), and 2.9% (155.2Mt) of changes in total industrial CO_2 emissions, respectively.

Meanwhile, increased environmental supervision by the Chinese government has led many equipment manufacturing and chemical industries to increase their investments in emission-reduction technologies and equipment. Therefore, the remaining six sub-sectors, such as Equipment for Special Purposes (ESP), Transportation Equipment (TE), Metal Products (MP), Chemical Fiber (CF), Rubber and Plastic Products (RPP), and Production and Supply of Tap Water (PSW), experienced reductions in CO_2 emissions in most years during 2000–2017, although the intensity of these reductions was limited.

As shown in Fig. 5, in the SPFM sub-sector, only investment efficiency (-54.1 Mt) and energy intensity (-51.9 Mt) showed mitigating but weak effects on CO_2 emissions. The other six factors all contributed to increases in CO_2 emissions, especially energy consumption (441.2 Mt), investment scale (407.5 Mt), and carbon intensity of output (333.7 Mt) were the top three drivers. In the RCMC sub-sector, only carbon intensity of investment (-110.0 Mt), energy intensity (-10.8 Mt), and investment efficiency (-10.0 Mt) presented mitigation effects on CO_2 emissions. The remaining five factors all exerted promoting effects on CO_2 emissions, especially investment scale (173.92 Mt), energy consumption (55.52 Mt), and output scale (54.48 Mt) were the major contributors. In the NMP sub-sector, in addition to investment scale (1104.08 Mt), output scale (330.42 Mt), and energy consumption (138.22 Mt), carbon intensity of energy (178.02 Mt) also exhibited a promoting effect on CO_2 emissions.

In summary, in this category, investment scale, output scale, and energy consumption all exerted promoting effects on CO_2 emissions. Carbon intensity of investment, energy intensity, investment efficiency, carbon intensity of output (except RCMC and SPFM), and carbon intensity of energy (except RCMC and SPFM) all exerted mitigating effects on CO_2 emissions. Investment scale (except SPFM and PSW) and carbon intensity of investment (except SPFM, ESP, and PSW) were the largest contributors to increases and decreases in CO_2 emissions of all sub-sectors, respectively.

INSERT FIG. 5 HERE

4.2.3. Light manufacturing category

In the early period of 1950s, China's light manufacturing industry was very backward, based primarily on family-owned workshops. In order to changes such a backward situation, China did not hesitate to sacrifice the environment to quickly establish a light industry system. However, by the 10th FYP, the environmental pollution and poor efficiency resulting from this model of extensive development had become increasingly conspicuous. Subsequently, the Chinese government pursued technological innovation, vigorously implemented a serious of energy-saving and emission-reduction policies, and gradually formed an environmentally friendly light manufacturing industry.

The light manufacturing category contains 13 sub-sectors, but the cumulative changes in CO_2 emissions only increased by 18.8 Mt during 2000–2017. The main reason for this result is that, on the one hand, unlike the sub-sectors related to energy production and heavy manufacturing, the sub-sectors in light manufacturing category generally have relatively limited demands for traditional fossil energy sources; on the other hand, due to a serious of environmental protection policies has been promulgated by the Chinese government in this field, forcing most of the sub-sectors to accelerate their industrial transformation and upgrading.

As shown in Fig. 6, the sub-sectors in this category all exhibited a trend of increasing first and subsequent decreasing in CO_2 emissions (i.e., an inverted U-shaped curve), except for the Tobacco Processing (TP) sub-sector. However, only the following five sub-sectors, such as TP, Textile Industry (TI), Garments and Other Fiber Products (GOFP), Timber Processing, Bamboo, Cane, Palm Fiber and Straw Products (TPBC), and Furniture Manufacturing (FM), exhibited varying degrees of decreases in CO_2 emissions. In other words, although the overall increase in CO_2 emissions of this category was not significant, there were still more than 60% of sub-sectors showing increases in CO_2 emissions.

The top three sub-sectors that contributed the most to emissions in this category were all related to food production, namely Agri-Food Processing (AFP), Food Production (FP), and Beverage Production (BP). CO_2 emissions in these three sub-sectors increased by 14.21Mt, 7.47 Mt, and 4.32 Mt, respectively. Although TI (-8.93 Mt) represented the largest reductions in CO_2 emissions among 38 sub-sectors, TP (-3.09 Mt) exhibited a consistent decrease in CO_2 emissions throughout the 2000–2017 period. Specifically, in the TP sub-sector, excluding output scale and investment scale, which drove increases in CO_2 emissions in this sub-sector, the other six indicators all showed obvious mitigating effects. In particular, the output scale and investment scale had also exerted mitigating effects from 2014 to 2017, and this effect is mainly related to China's strict enforcement of nationwide tobacco control campaigns in recent years.

In summary, investment scale, output scale, and energy consumption (except TP) were the main contributors to increases in CO_2 emissions in all sub-sectors of this category, while the remaining five relative indicators all had mitigating effects. Moreover, investment scale and carbon intensity of investment were the largest contributors to increases and reductions in CO_2 emissions in all sub-sectors, respectively. Output scale was the second contributor to increases in CO_2 emissions in all sub-sectors except TI, Cultural, Educational and Sports Articles (CESA), and Printing and Record Medium Reproduction (PRMR). Carbon intensity of output was the second contributor to reductions in CO_2 emissions in all sub-sectors except CESA.

INSERT FIG. 6 HERE

4.2.4. High-tech industry category

The high-tech industry category includes 5 sub-sectors. The total changes in CO_2 emissions of this category decreased by 8.9 Mt during 2000–2017. Obviously, compared to the above three categories, this category made the smallest contributions to changes in total industrial CO_2 emissions. Among these five sub-sectors, only the Scrap and Waste (SW) sub-sector exhibited a slight increase in CO_2 emissions (1.6 Mt), whereas the other sub-sectors, such as Electric Equipment and Machinery (EEM), Electronic and Telecommunications Equipment (ETE), Instruments, Meters, Cultural and Office Machinery (IMCM), and Other Manufacturing (OMs), all experienced reductions in CO_2 emissions during 2000–2017.

Regarding the driving factors, Fig. 7 clearly shows that, as in the light manufacturing category, investment scale, output scale, and energy consumption were the major contributors to increases in CO_2 emissions in all sub-sectors of this category, and the other relative indicators all had mitigation effects. Besides, the contributions of both investment scale and energy consumption to increases in CO_2 emissions exceeded that of output scale. Moreover, carbon intensity of investment had the strongest mitigating effect in all sub-sectors of this category. In particular, in the EEM sub-sector, the carbon intensity of investment led to CO_2 emissions decreased by 13.5 Mt, which is approximately 6.8 times greater than changes in CO_2 emissions of this sub-sector (-2.0 Mt). Carbon intensity of output was the second contributor to reduced emissions in the EEM and IMCM sub-sectors, whereas energy intensity and carbon intensity of energy were the second contributors to reduced emissions in the ETE and OMs sub-sectors, respectively.

INSERT FIG.7 HERE

5. Discussion

In this section, firstly, we summarized the contributions of various factors and compared our findings with the results of previous studies. Secondly, we presented a brief discussion on the future trends of the contributions of key driving forces, based on our historical decomposition results and the relevant industrial development plans and policies issued by the Chinese government. Finally, we discussed the mitigating pathways to achieve China's industrial carbon peak target by sub-sectoral efforts.

5.1. Summary of contributions of various factors

Our sub-sectoral decomposition results showed that the roles of eight driving factors on CO_2 emissions varied across sub-sectors. Here, we presented a detailed summary of the impact of each factor. The conclusions as shown in Fig. 8 to Fig. 15, and the details are presented in Table A3.

5.1.1. Investment scale effect

Investment scale played a negative role in mitigating CO_2 emissions in all sub-sectors. More importantly, in all sub-sectors except for PSESW and NMMD, the contribution of investment scale exceeded that of all other driving factors in promoting CO_2 emissions (see Table A3). This indicates that investment scale was the largest driver of increases in CO_2 emissions in China. Among 38 sub-sectors, as shown in Fig. 8, the investment scales of PSESW, NMP, SPFM, and RCMC represented the vast majority of contributions to increases in CO_2 emissions. This implies that reducing investments in these four sub-sectors is an important way to achieve the carbon peak target in China's industrial sector. This finding differs from many earlier studies, which identified economic scale as the most important contributor to increases in CO_2 emissions in China (e.g. Minx et al., 2011; Zhang et al., 2015; Vaninsky, 2014; Shao et al., 2016a; Fan et al., 2015; Li et al., 2017). However, our result is in line with those of recently studies considering investment factors (e.g., Zhao et al., 2016; Zhang et al., 2020). For example, Zhang (2020) proved that the impact of investment scale exceeded that of economic scale in promoting China's CO_2 emissions both at the national and provincial levels. Our study supplements the evidence of the important impact of investment scale at the sub-sector level.

INSERT FIG.8 HERE

5.1.2. Output scale effect

Output scale had an obvious promoting effect on CO_2 emissions in all sub-sectors except PNGE, but its impact decreased over time. As mentioned before, such a finding does not support the mainstream views of most previous studies that economic activity was the largest driving force of increases in CO_2 emissions. In terms of the contribution of output scale in different sub-sectors,

Fig. 9 shows PSESW was the largest contributor in this regard, followed by NMP, SPFM, RCMC, SPNM, and CMD. This means that intensifying efforts need to promote supply-side reforms to eliminate backward production capacity in above sub-sectors related to energy production and heavy manufacturing, which is a key measure to achieve China's industrial carbon peak target.

INSERT FIG.9 HERE

5.1.3. Energy consumption effect

Energy consumption also played a negative role in mitigating CO_2 emissions in all sub-sectors except OMMD, TP, and PSG. As shown in Fig. 10, this is mainly due to the huge scale of energy demand in the sub-sectors related to heavy manufacturing and energy production, such as SPFM (6719.4 Mtce), RCMC (3672.2 Mtce), NMP (3504.8 Mtce), SPNM (988.3 Mt), and PSESW (925.2 Mtce). The accumulative energy consumption of these sub-sectors reached 15809.9 Mtce, accounting for 69.7% of the total industrial energy consumption during 2000-2017. Especially the production activities of SPFM, RCMC, and NMP were strongly dependent on traditional fossil energy sources. Therefore, in China, speeding up the energy transformation of these sub-sectors and increasing the proportion of new energy, clean energy, and renewable energy in the final energy consumption are necessary measures in the future.

INSERT FIG.10 HERE

5.1.4. Carbon intensity of investment effect

Carbon intensity of investment played a positive role in mitigating CO_2 emissions in all sub-sectors except CESA and SPFM. More importantly, in most sub-sectors (except NMMD, OMMD, ESP, CESA, and SPFM), carbon intensity of investment was the largest contributor to reductions in CO_2 emissions among all factors. This finding is consistent with Zhang et al (2020) who also fond that carbon intensity of investment was the first driver on reducing national CO_2 emissions in China during 1995-2016. In this regard, as shown in Fig. 11, carbon intensity of investment of NMP had the largest impact, followed by PSESW and RCMC. This implies that continuing to increasing green investments of NMP, PSESW, and RCMC is an important pathway to help China's industrial sector reach its carbon peak target. However, carbon intensity of investment of SPFM contributed to increases in emissions by 56.52 Mt during the study period. Therefore, for SPFM, in addition to the strategy mentioned above that reducing its investment scale, it is more important to optimize its investment structure, such as increasing the proportion of investments in green technological innovation.

INSERT FIG.11 HERE

5.1.5. Investment efficiency effect

Investment efficiency was the second important factor in mitigating CO_2 emissions, however, as shown in Fig. 12, its mitigation effect varied greatly across sub-sectors. In this regard, the investment efficiency of PSESW, NMP and SPFM played a leading role. Generally speaking, investment activities can be categorized into two main types, one is to promote productivity and production scale (i.e., output and substitution effect), and the other is to promote energy-saving and emission-reducing (i.e., energy-saving and emission-reducing effects). So the impact of investment efficiency on CO_2 emissions depends on the relative magnitude of "output and substitution effect" and "energy saving and emission reduction effect" (Zhang et al., 2017). This means the main purpose of increasing green investment activities was to promote energy conservation and emission reduction, rather than expanding production scale, or that "energy-saving and emission-reducing effects" was more effective than "output and substitution effects", so that the decline of investment efficiency helped reduce CO_2 emissions. Available result from Zhang et al (2017) supported our speculation.

INSERT FIG.12 HERE

5.1.6. Energy intensity effect

Energy intensity was another contributor responsible for mitigating CO_2 emissions. As shown in Fig. 13, although energy intensity exerted a mitigating effect in all sub-sectors, its mitigation effect was rather limited except for PSESW. This means, in most sub-sectors, the emission reduction effect of energy intensity focused by the Chinese government was less than the expected. There are many reasons for this result. In addition to the aforementioned sub-sectors related to energy production and heavy manufacturing are still strongly dependent on fossil energy sources, the rebound effect of technological progress cannot be ignored (Shao et al., 2016b). This once again shows that accelerating the energy transition, and increasing the proportion of clean and renewable energy consumption should be regarded as the key emission-reduction policies for all sub-sectors. Nevertheless, the controversy still existed in the existing research on the direction (i.e., positive or negative) and degree (primary or secondary) of the impact of energy intensity on CO_2 emissions. Such as, earlier studies without considering investment factors generally concluded that energy intensity was the largest driving factor for reducing CO_2 emissions. Even though Zhao et al. (2016) and Zhang et al. (2017) incorporated investment factors into the LMDI model, the results still showed energy intensity was the leading contributor to the reduction of China's industrial CO_2 emissions. However, our finding was in line with Zhang et al. (2020) and Shao et al. (2016b) who also found that the mitigation effect of energy intensity was less than the expected.

INSERT FIG.13 HERE

5.1.7. Carbon intensity of output effect

Consistent with previous findings (e.g., Zhang et al., 2020), as shown in Fig. 14, carbon intensity of output exerted a mitigation effect on CO_2 emissions in most sub-sectors (except PSESW, SPFM, PPC, PNGE, and RCMC). Nevertheless, Fig. 14 also shows that carbon intensity of output of PSESW and SPFM led to an increase of 642.5 Mt and 333.7 Mt in CO_2 emissions, respectively. The huge impact of these two sub-sectors completely offset the emission-reduction effect of carbon intensity of output of other sub-sectors, resulting in an increase of 413.64 Mt in total industrial CO_2 emissions.

INSERT FIG.14 HERE

5.1.8. Carbon intensity of energy effect

Similar to carbon intensity of output, as shown in Fig. 15, carbon intensity of energy played a positive role in reducing CO_2 emissions in most sub-sectors. This indicates that most industrial sub-sectors are actively implementing the policies related to green and sustainable development put forward by the Chinese government, such as promoting clean and renewable energy transition, accelerating energy-related technological progress, and updating cleaner equipment. However, it should be noted that, there are nearly 30% of sub-sectors whose carbon intensity of energy exerted a promoting effect on CO_2 emissions. In particular, carbon intensity of energy of PSESW and NMP contributed to an increase of 1019.84 Mt and 178.02 Mt in CO_2 emissions, respectively.

INSERT FIG.15 HERE

5.2. Future trends of contributions of key drivers

The impacts of both investment scale and output scale on CO_2 emissions will decline, due to the slowdown of investment and economic growth and the rapid adjustment of the industrial structure in China. We have already observed this decreasing trend from our decomposition results in recent years. According to the data from NBSC (Available from https://data.stats.gov.cn), during 2003-2017, the growth rate of total fixed asset investment decreased continuously from 27.7% to 5.7%, especially in the industrial sector, from 40.0% to 2.1%; The growth rate of industrial added value decreased continuously from 15.9% to 12.1%; The proportion of industrial added value in GDP decreased continuously from 45.6% to 39.9%. Following this trend, we speculate that the contributions of investment scale and output scale to changes in CO_2 emissions will continue to decrease in the future. However, it should be noted that the industrial added value still maintains high growth, with an average growth rate of 12.9%. Meanwhile, economic growth remains China's top priority, especially in the industrial sector. Thus, the industrial output will maintain a relatively high growth rate in the future. Ultimately, we speculate that the impact of output scale on CO_2 emissions may not decline as much as expected.

The mitigation effect of carbon intensity of investment on CO_2 emissions will increase, with the increase of green investment. "Green development" has been listed by the Chinese government as an core part of the "14th FYP". It can be expected that green and high-quality development will be the main theme of China's economy. According to China's Green Finance Development Report released by the People's Bank of China (PBOC, 2020), by the end of 2019, the balance of green loans in China reached 10.2 trillion CNY; the scale of international green bonds reached 257.7 billion US dollars (about 1.8 trillion CNY), with an increase of 51.06% over the same period last year; Moreover, the scale of green bonds issued by China that in line with CBI international standards was second only to the United States. To this end, we speculate that the carbon intensity of investment will decrease over time, thereby its role in mitigating CO_2 emissions will continue to increase in the future.

The changes in the impacts of energy intensity and energy consumption on CO_2 emissions may not be clear. Energy-related emissions abatement mainly requires establishing incentive and constraint mechanisms for both energy saving and energy structural adjustment (Zhao et al., 2016). As mentioned before, economic growth remains China's top priority, which means that China still has a huge rigid demand for energy in the process of rapid industrialization and urbanization. Moreover, the energy structural adjustment in the industrial sector, including the promotion, applies, and research and develop of clean and renewable energy, largely depends on the degree of affordable costs (Zhao et al., 2016). Besides, although low-carbon technological progress, including production technologies that reduce the process-related carbon intensity and carbon capture and storage technologies, can curb industrial CO_2 emissions to some extent, the associated difficulties cannot be ignored. For example, on the one hand, the development of these new technologies or the improvement of existing technologies is confronted with high costs and technical bottlenecks; on the other hand, the improvement of energy efficiency or the decline of energy prices brought by technological progress will in turn promote energy consumption, so the benefits of technological progress will be offset by rebound effects.

5.3. Sub-sectoral emissions mitigating strategies

Based on the historical contributions of various factors during 2000-2017 and the future trends of contributions of key drivers discussed above, we recommend that policies intended to achieve China's industrial carbon peak target should focus on the following aspects.

- Strategies to mitigate China's CO_2 emissions should be designed at the sub-sector level based on the industry-specific needs and peculiarities. To date, most provinces in China have specified the time and pathway to achieve the provincial carbon peak target in the "14th FYP". Obviously, provincial emissions are composed of emissions from various industries, especially the industrial sector. Thus, the provincial carbon peak target should be further decomposed at the economic sector and its sub-sector levels. In view of our decomposition results show that the emission trajectories and their driving forces of different sub-sectors are not consistent, policymakers should consider setting a different peak target, peak time, and mitigation pathway for each sub-sector. For example, in the heavy manufacturing category, the peak targets of SPFM, NMP, RCMC, and SPNM should be different from the remaining seven sub-sectors in this category, because these four sub-sectors not only have a huge volume of emissions but also exhibit sustained trends of increasing emissions. Similarly, in energy production category, the peak targets of PSESW, CMD, and PPC should be different from the remaining six sub-sectors in this category.
- Efforts to reduce China's CO_2 emissions should focus more on PSESW, SPFM, NPM, and RCMC. Nearly half of the sub-sectors (n=17) experienced a negative growth in CO_2 emissions, and this downward trend was more obvious after 2010. Moreover, 97.2% of the

increases in China's industrial CO_2 emissions was mainly due to the outstanding contributions of four sub-sectors, namely PSESW, SPFM, NPM, and RCMC. Therefore, the achievement of the industrial carbon peak target or even the national carbon peak target in China will depend mainly on the degree of green transition of these major sub-sectors related to energy production and heavy manufacturing.

- Optimizing the investment structure and increasing green investment to strengthen the emission-reduction effects of investment factors. Investment scale and output scale were dominant drivers of increases in CO_2 emissions, especially investment scales and/or output scales of PSESW, NMP, SPFM, RCMC, SPNM, and CMD represented relatively large impacts. However, all countries including China will not sacrifice the economic development to reduce CO_2 emissions. Thus, it is a great challenge for China's industrial sector to balance CO_2 emissions mitigation and economic growth as well as investment (Zhao et al., 2016). In view of the fact that with the increases of green investment, carbon intensity of investment played a positive role in mitigating CO_2 emissions in all sub-sectors. Thus, if it is not feasible to reduce investment scale, we recommend that optimizing the investment structure and increasing green investment may be an alternative to reducing investment scale, which is at least suitable for the sub-sectors such as PSESW, NMP, SPFM, RCMC, SPNM, and CMD. Such as, increasing the proportion of investments in low-carbon technology innovation, including carbon capture and storage technologies and energy-saving equipment upgrading.
- Accelerating the conversion of clean and renewable energy should be the key points of supply-side reforms in energy-intensive sub-sectors such as SPFM, RCMC, NMP, SPNM, and PSESW. Energy consumption was an important contributor to increases in CO_2

emissions. Considering the energy demand of above five sub-sectors accounted for 69.7% of total industrial energy consumption during 2000-2017. Thus, accelerating the conversion of clean and renewable energy should be the key points of supply-side reforms in these five sub-sectors. In this regard, in addition to improving the efficiency of existing subside policies on clean and renewable energy and technologies, accelerating the market-oriented reform of energy prices, especially electricity prices, is a necessary measure for energy structural adjustment. Besides, given the fact that the production activities in SPFM, RCMC, and NMP are still strongly dependent on coal consumption, promoting the clean-utilization of coal in these three sub-sectors should be another alternative pathway.

- Business-as-usual emission-reduction strategies are appropriate for sub-sectors related to light manufacturing and high-tech industries. On the one hand, the historical emissions of these sub-sectors are rather small during the study period, indicating that these is a limited room for future emission-reduction. On the other hand, all these sub-sectors, except PPP, AFP and SW, have exhibited a trend of negative growth in CO_2 emissions for many years, indicating the current emission-reduction policies and strategies in these sub-sectors are effective.

6. Conclusions

In response to the Paris Agreement, China announced that it would aim to reach carbon peak in 2030. However, the literature has barely discussed strategies to achieve this ambitious target at the sub-sector level. To fill this research gap, using an extended GDIM model incorporating three investment factors, and considering 38 industrial sub-sectors, this study investigated the trajectories of China's industrial CO_2 emissions and their driving forces during 2000-2017.

The decomposition analysis yielded the following findings. Firstly, during the study period, 97.2% of the increases in China's total industrial CO_2 emissions were attributable to four sub-sectors related to energy production and heavy manufacturing, namely PSESW, SPFM, NPM, and RCMC. Secondly, different sub-sectors experienced different historical trajectories of CO_2 emissions, and the contributions of eight driving factors to CO_2 emissions varied across sub-sectors. Thirdly, investment scale was the most important driver of increases in CO_2 emissions during the study period; its contribution exceeded those of both output scale and energy consumption. On a positive note, the degree of the contribution of investment scale to CO_2 emissions has decreased gradually since the beginning of the 12th FYP. Fourthly, carbon intensity of investment, energy intensity, and investment efficiency were the main drivers of reductions in CO_2 emissions. Although the mitigating effects of these factors increased over time, the degree of their contribution remained limited.

In light of the above findings, we suggest that strategies to mitigate China's CO_2 emissions should be designed at the sub-sector level. Thus, policymakers should consider formulating a different peak target, peak time, and mitigation pathway for each sub-sector. In this regard, more efforts should focus on sub-sectors related to energy production and heavy manufacturing, such as PSESW, SPFM, NMP and RCMC. Compared to reducing investment scales of these sub-sectors, it is more important to optimize their investment structures through strategies such as increasing investment in low-carbon technology innovation and energy-saving equipment renovation. In addition, accelerating the conversion of clean and renewable energy should be the key points of supply-side reforms in energy-intensive sub-sectors.

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Table 1.

The mean value of indicators in each category during 2000–2017

Indicators	All sub-sectors	Energy production	Light manufacturing	Heavy manufacturing	High technology
	Mean	Mean	Mean	Mean	Mean
CO_2 emissions (Mt.)	152.89	343.65	14.56	247.99	4.54
Quantitative indicators					
Output scale (Billion CNY)	142.44	94.61	97.02	239.36	179.15
Investment scale (Billion CNY)	98.29	87.46	62.2	162.54	89.04
Energy consumption (Mtce)	33.31	20.12	10.63	91.12	5.49
Relative indicators					
Carbon intensity of output (Mt./Billion CNY)	1.26	4.10	0.15	0.85	0.06
Carbon intensity of investment (Mt./Billion CNY)	3.40	6.42	0.68	2.83	1.21
Carbon intensity of energy (Mt./Mtce)	2.55	9.27	1.52	1.92	0.29
Energy intensity (Mtce/Billion CNY)	0.56	1.75	0.11	0.33	0.07
Investment efficiency (CNY/CNY)	3.81	2.07	5.06	3.78	4.47

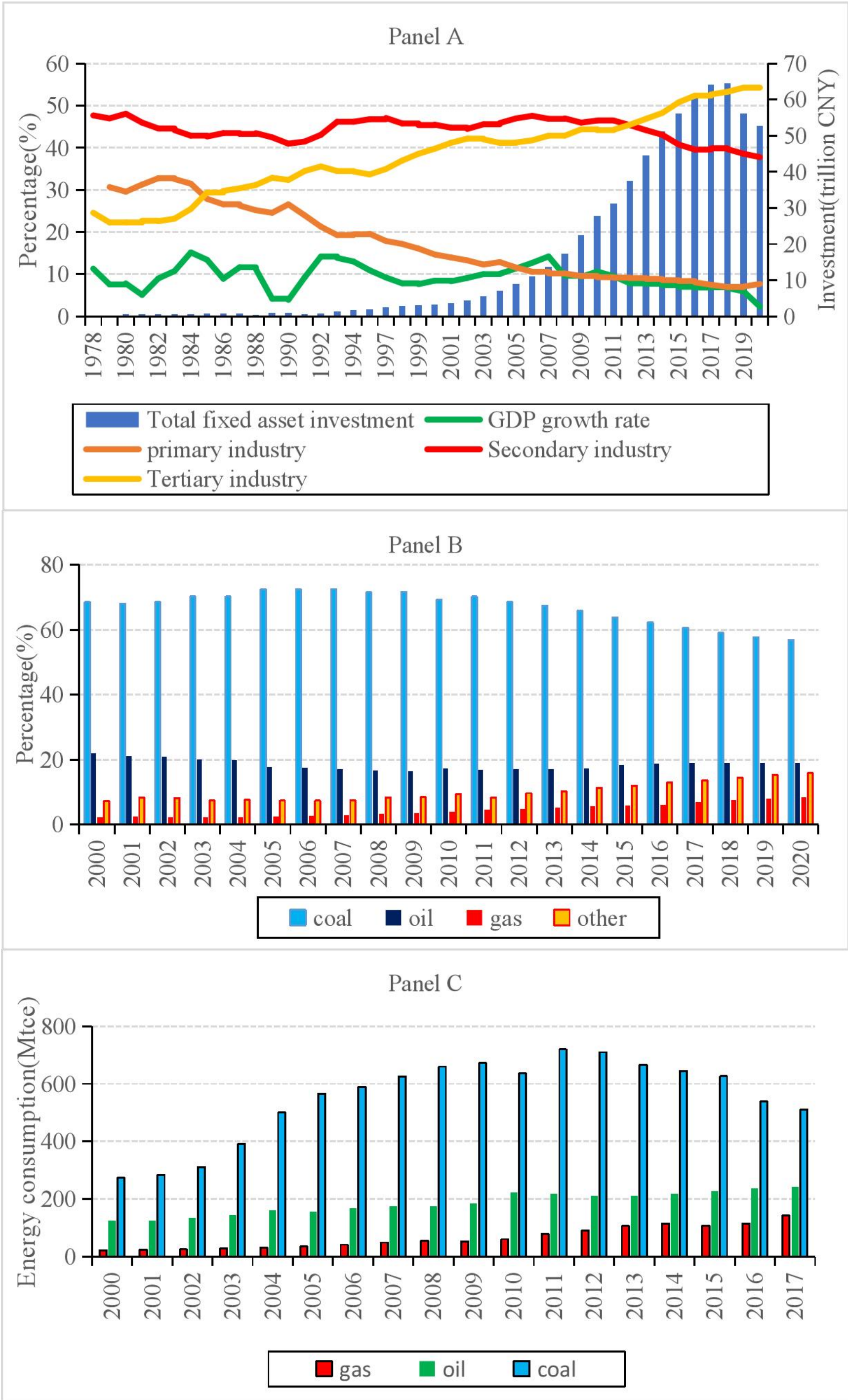

Fig.1. Trends of China's industrial structure adjustment, economic growth and total fixed asset investment (Panel A), Energy consumption structure in China (Panel B), and Three major energy consumption in China's industrial sector (Panel C). The original data of Panel A and Panel B were obtained from the website of NBSC (Available from https://data.stats.gov.cn). The original data of Panel C were obtained from the *China Energy Statistical Yearbook* (NBSC, 2001–2018)

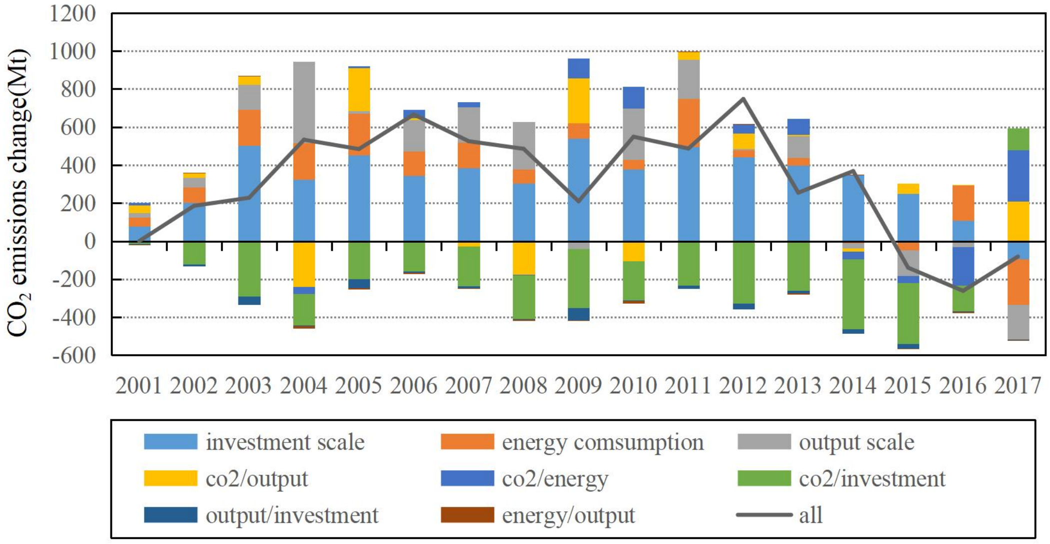

Fig.2. Yearly changes of total CO_2 emissions and factors' contributions during 2000–2017. The details are presented in Table A2 in the Appendix A.

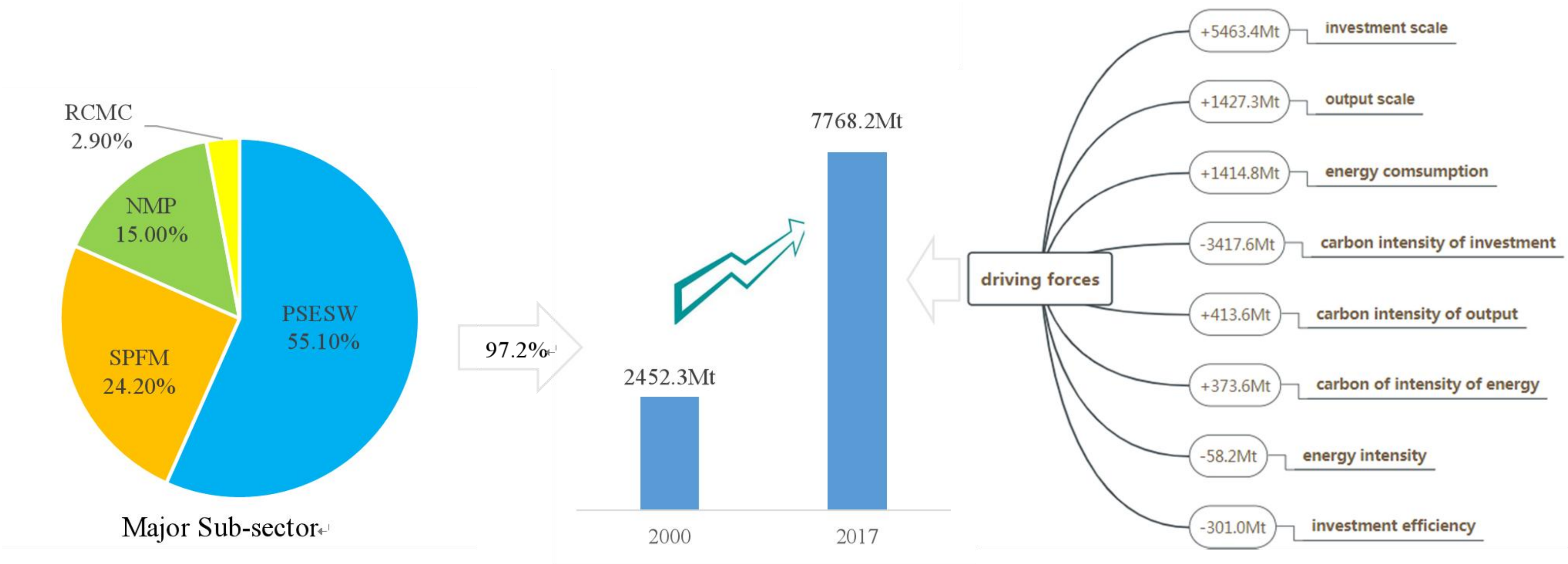

Fig.3. Cumulative contributions of major sub-sectors and driving factors to changes in total CO_2 emissions during the 2000–2017 period.

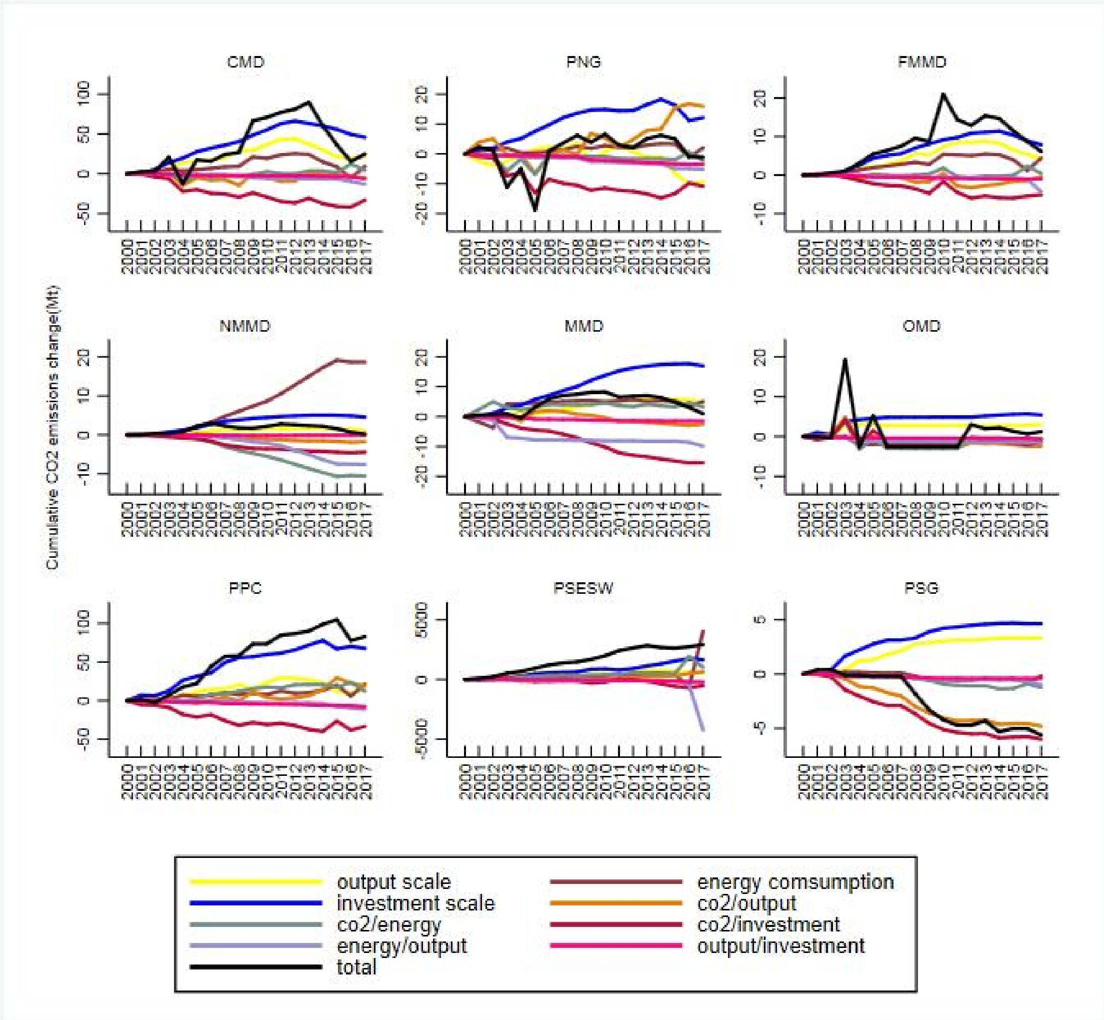

Fig.4. Energy production category: Contributions of eight factors to changes in CO_2 emissions during the 2000–2017 period. The baseline year is 2000. This category includes 9 sub-sectors: (1) Coal Mining and Dressing (CMD), (2) Petroleum and Natural Gas Extraction (PNGE), (3) Ferrous Metals Mining and Dressing (FMMD), (4) Nonferrous Metals Mining and Dressing (NMMD), (5) Non-metal Minerals Mining and Dressing (NMD), (6) Petroleum Processing and Coking (PPC), (7)Production and Supply of Electric Power, Steam and Hot Water (PSESW), (8) Production and Supply of Gas (PSG), and (9) Other Minerals Mining and Dressing (OMMD).

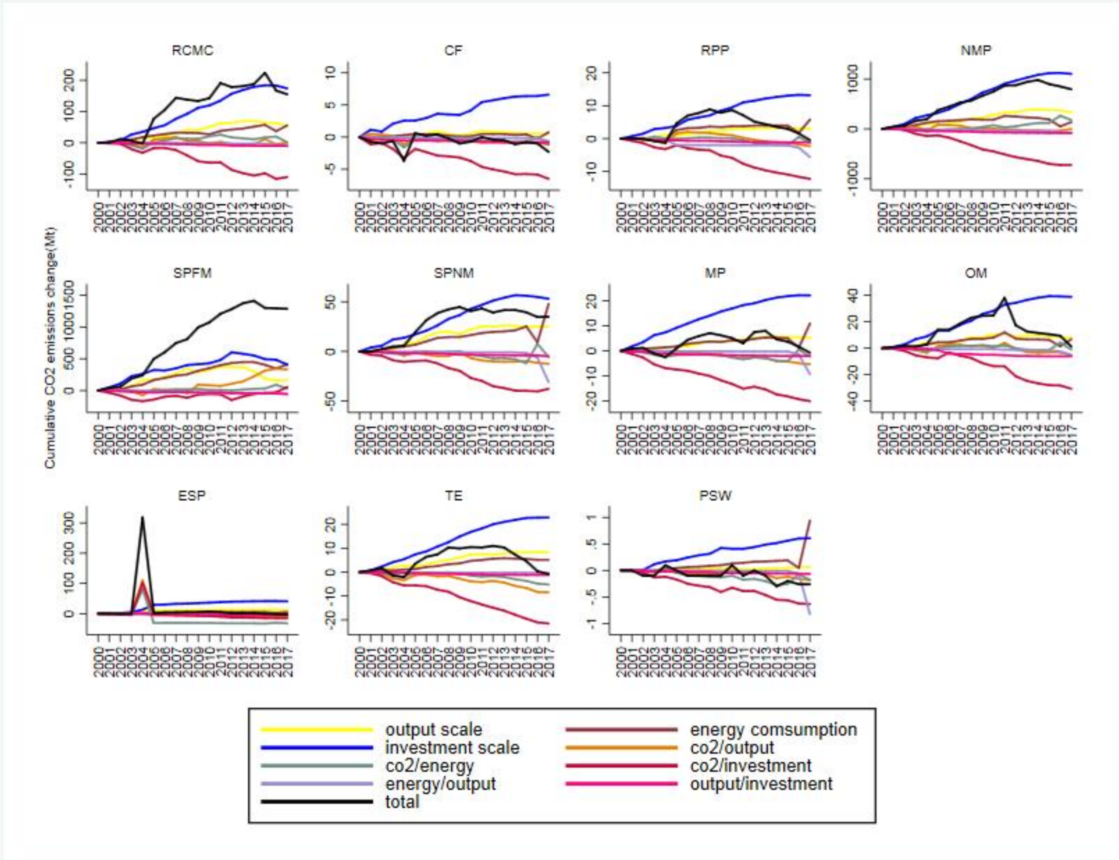

Fig.5. Heavy manufacturing category: Contributions of eight factors to CO_2 emission changes during the 2000–2017 period. The baseline year is 2000. This category includes 11 sub-sectors: (1) Raw Chemical Materials and Chemical Products (RCMC), (2) Chemical Fiber (CF), (3) Rubber & Plastic Products (RPP), (4) Nonmetal Mineral Products (NMP), (5) Smelting and Pressing of Ferrous Metals (SPFM), (6) Smelting and Pressing of Nonferrous Metals (SPNM), (7) Metal Products (MP), (8) Ordinary Machinery (OM), (9) Equipment for Special Purposes (ESP), (10) Transportation Equipment (TE), and (11) Production and Supply of Tap Water (PSW).

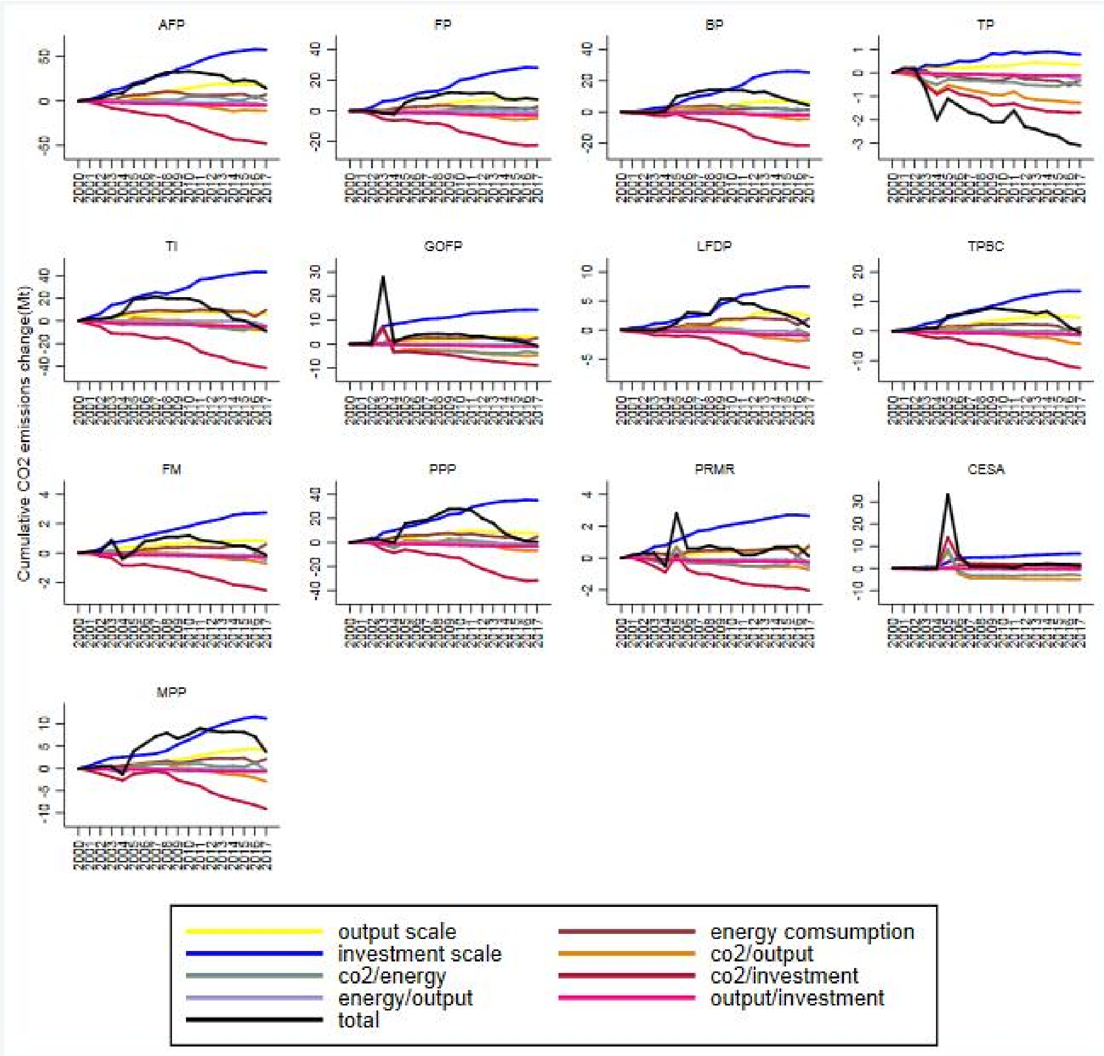

Fig.6. Light manufacturing category: Contributions of eight factors to changes in CO_2 emissions during the 2000–2017 period. The baseline year is 2000. This category includes 13 sub-sectors: (1) Agri-Food Processing (AFP), (2) Food Production (FP), (3) Beverage Production (BP), (4) Tobacco Processing (TP), (5) Textile Industry (TI), (6) Garments and Other Fiber Products (GOFP), (7) Leather, Furs, Down and Related Products (LFDP), (8) Timber Processing, Bamboo, Cane, Palm Fiber & Straw Products (TPBC), (9) Furniture Manufacturing (FM), (10) Papermaking and Paper Products (PPP), (11) Printing and Record Medium Reproduction (PRMR), (12) Cultural, Educational and Sports Articles (CESA), and (13) Medical and Pharmaceutical Products (MPP).

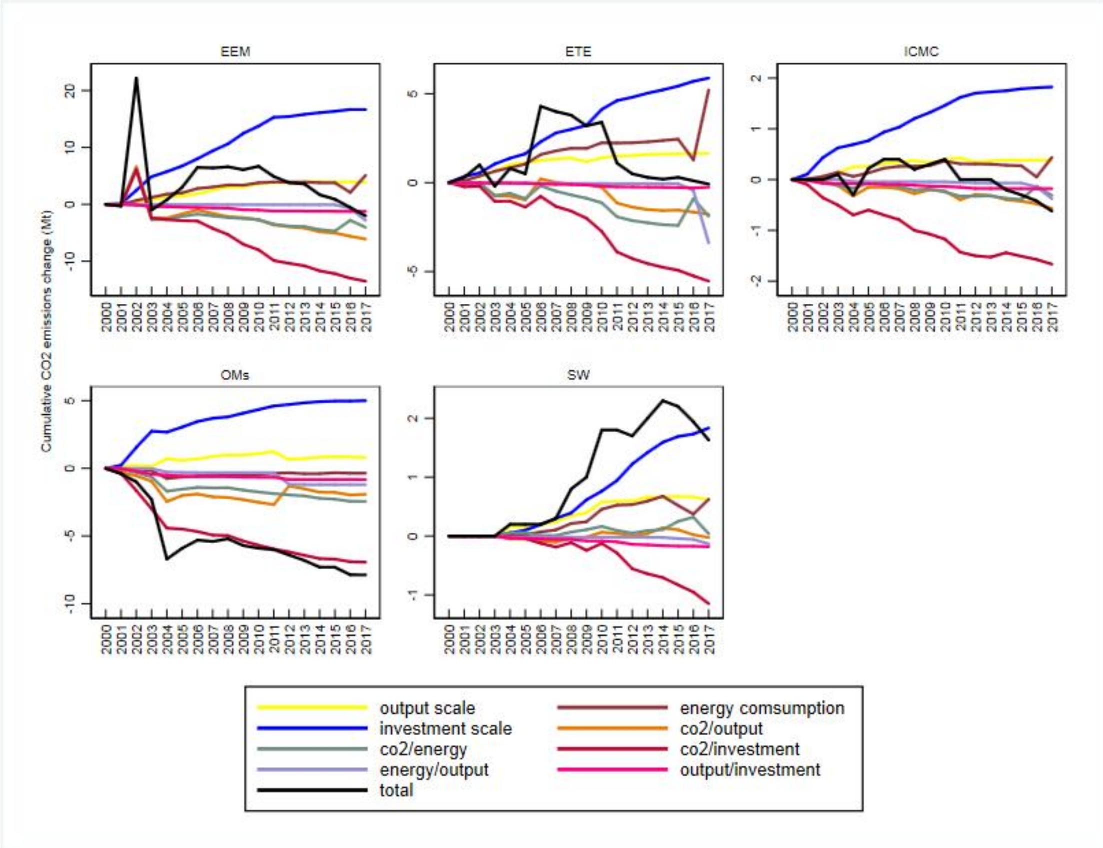

Fig.7. High-tech category: Contributions of eight factors to changes in CO_2 emissions during the 2000–2017 period. The baseline year is 2000. This category includes 5 sub-sectors: (1) Electric Equipment and Machinery (EEM), (2) Electronic and Telecommunications Equipment (ETE), (3) Instruments, Meters, Cultural and Office Machinery (IMCM), (4) Other Manufacturing (OMs), and (5) Scrap and Waste (SW).

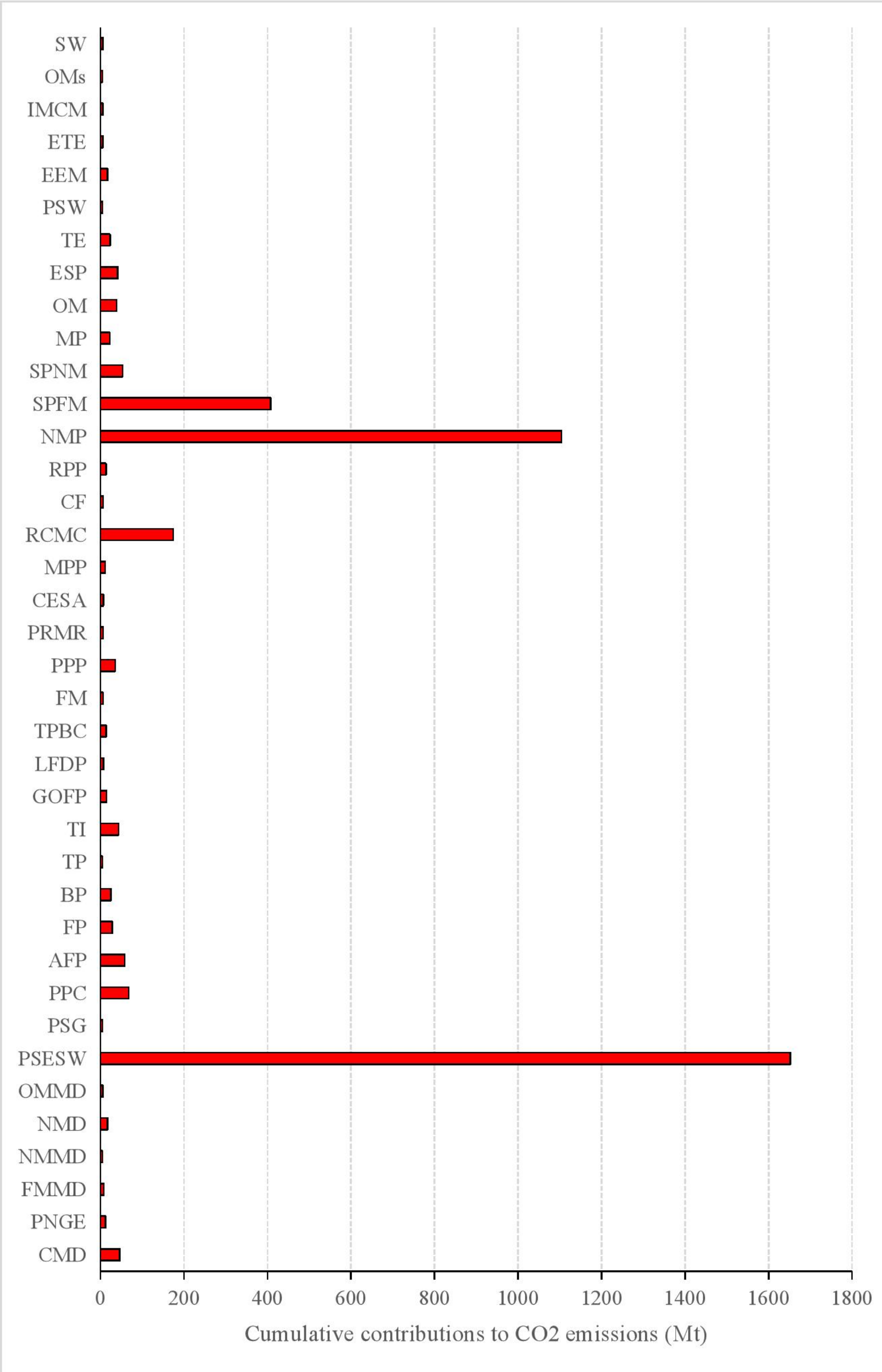

Fig.8. Investment scale effect

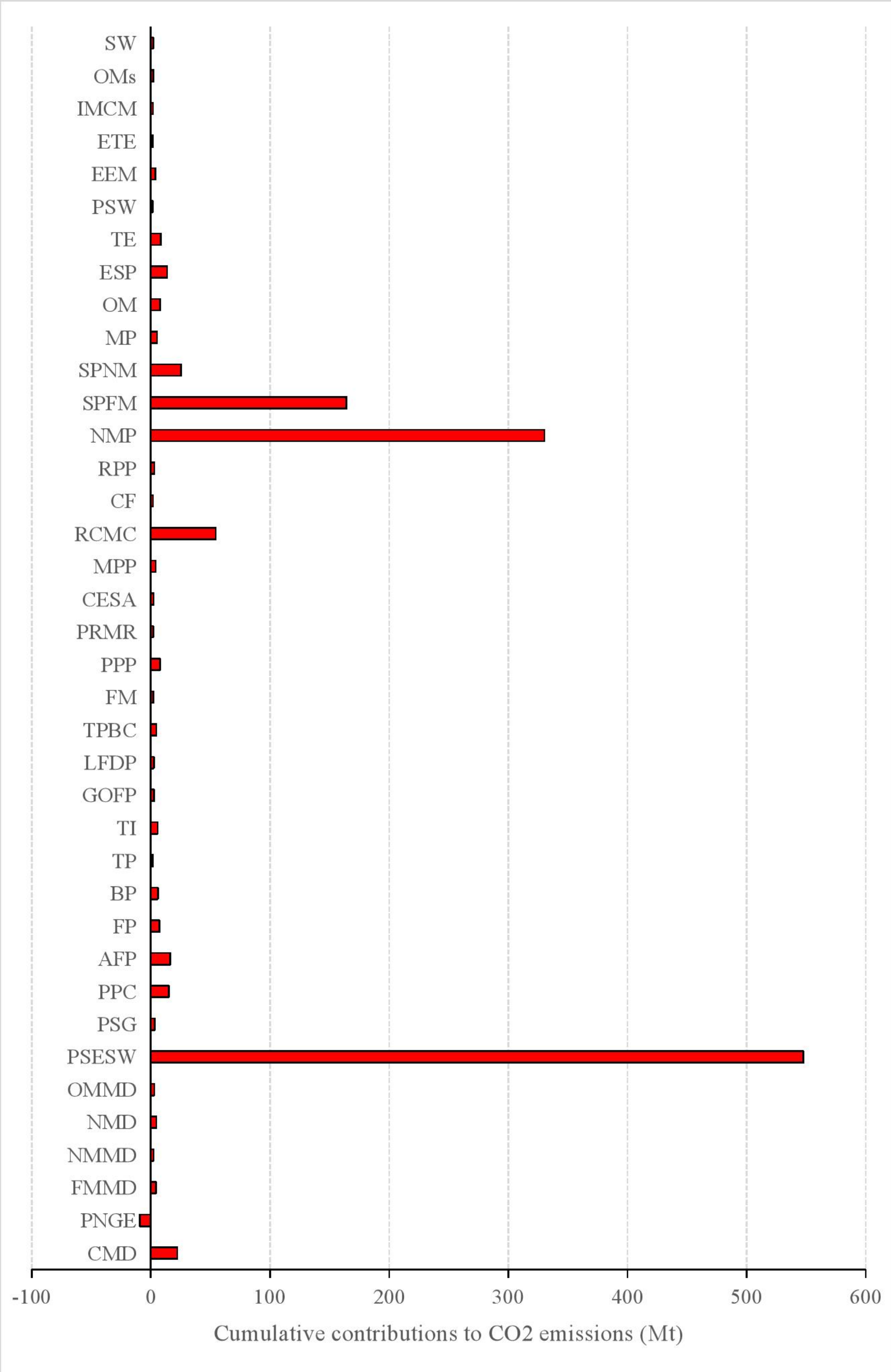

Fig.9. Output scale effect

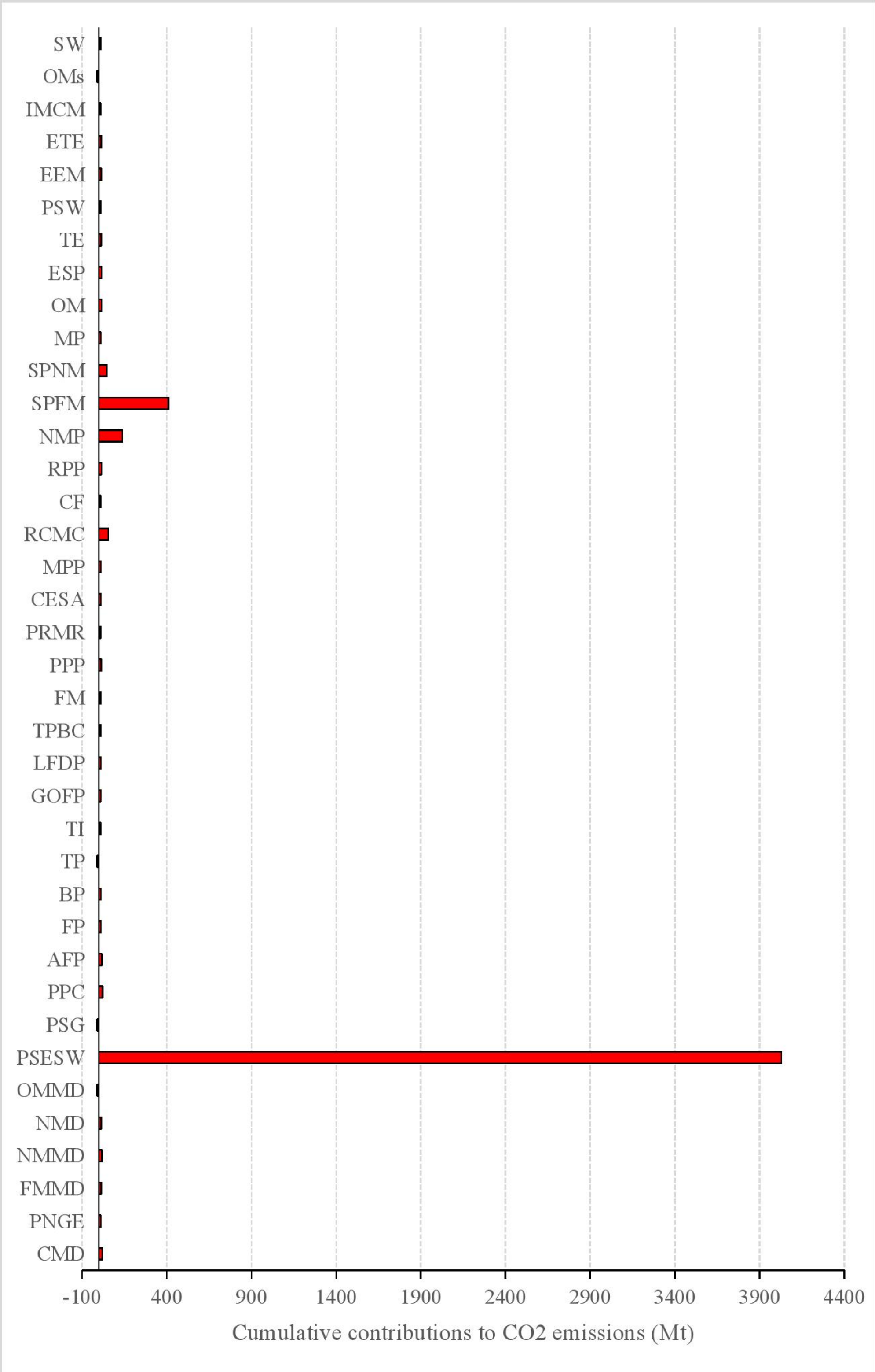

Fig.10. Energy consumption effect

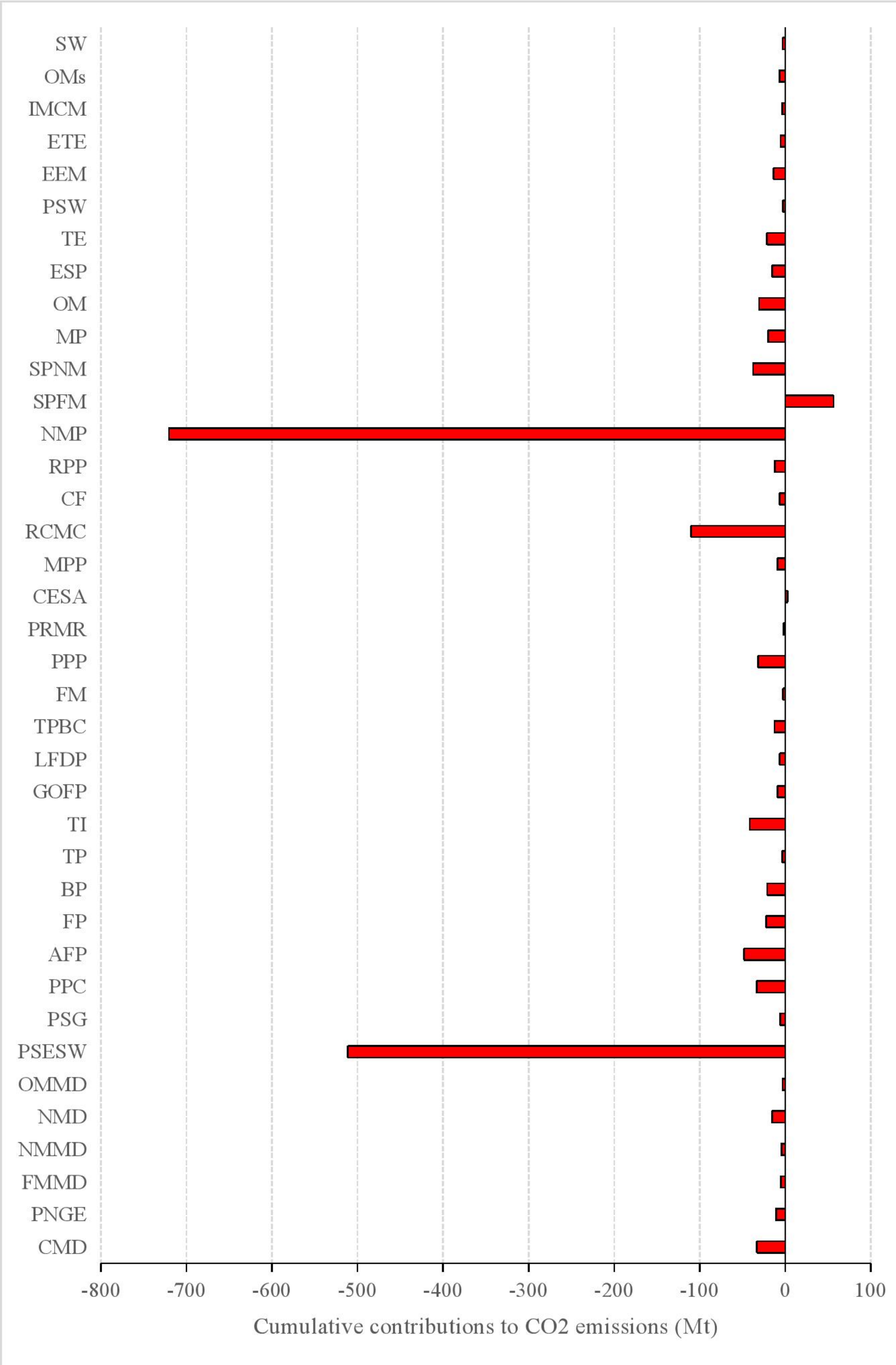

Fig.11. Carbon intensity of investment effect

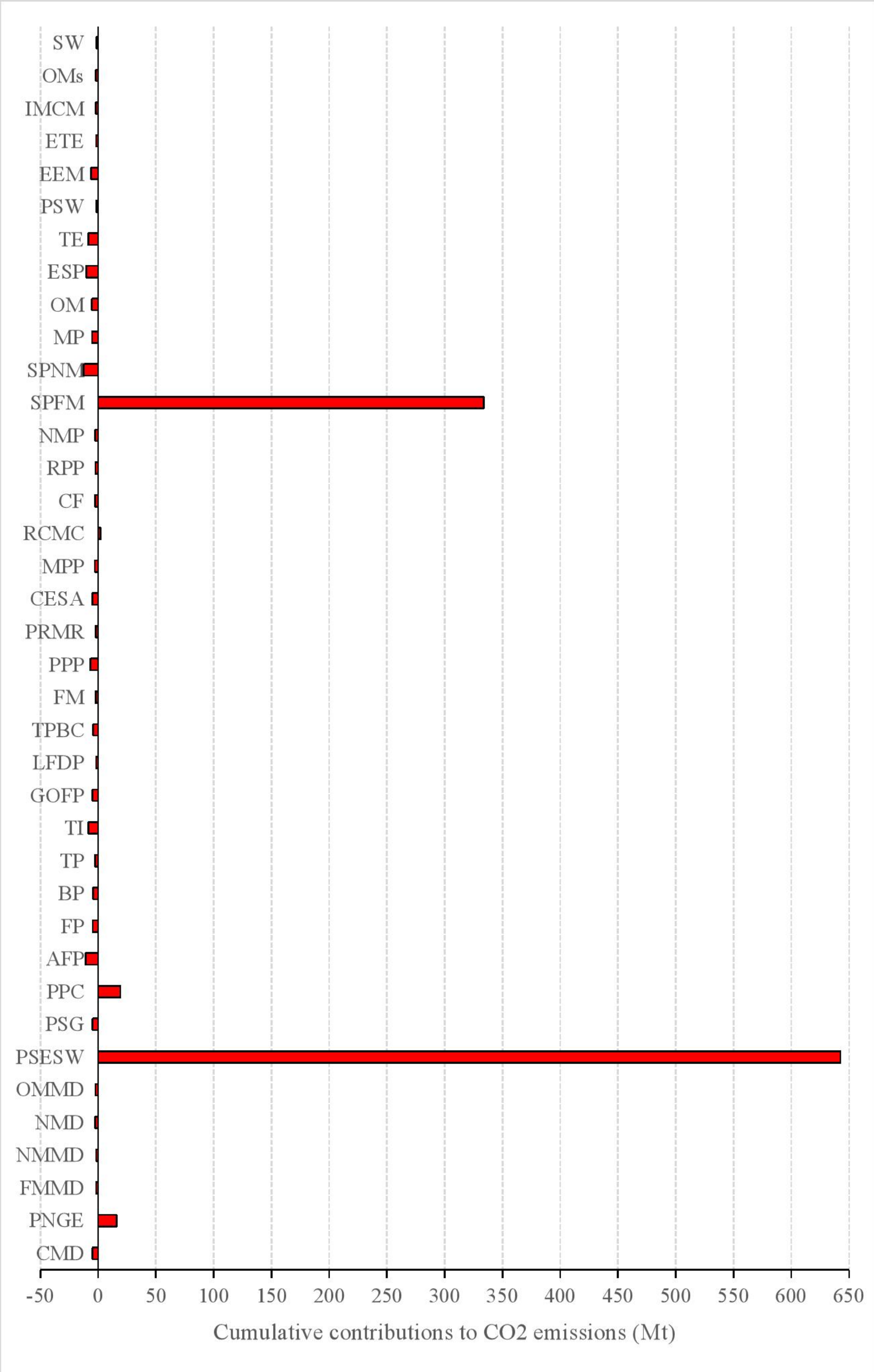

Fig.12. Carbon intensity of output effect

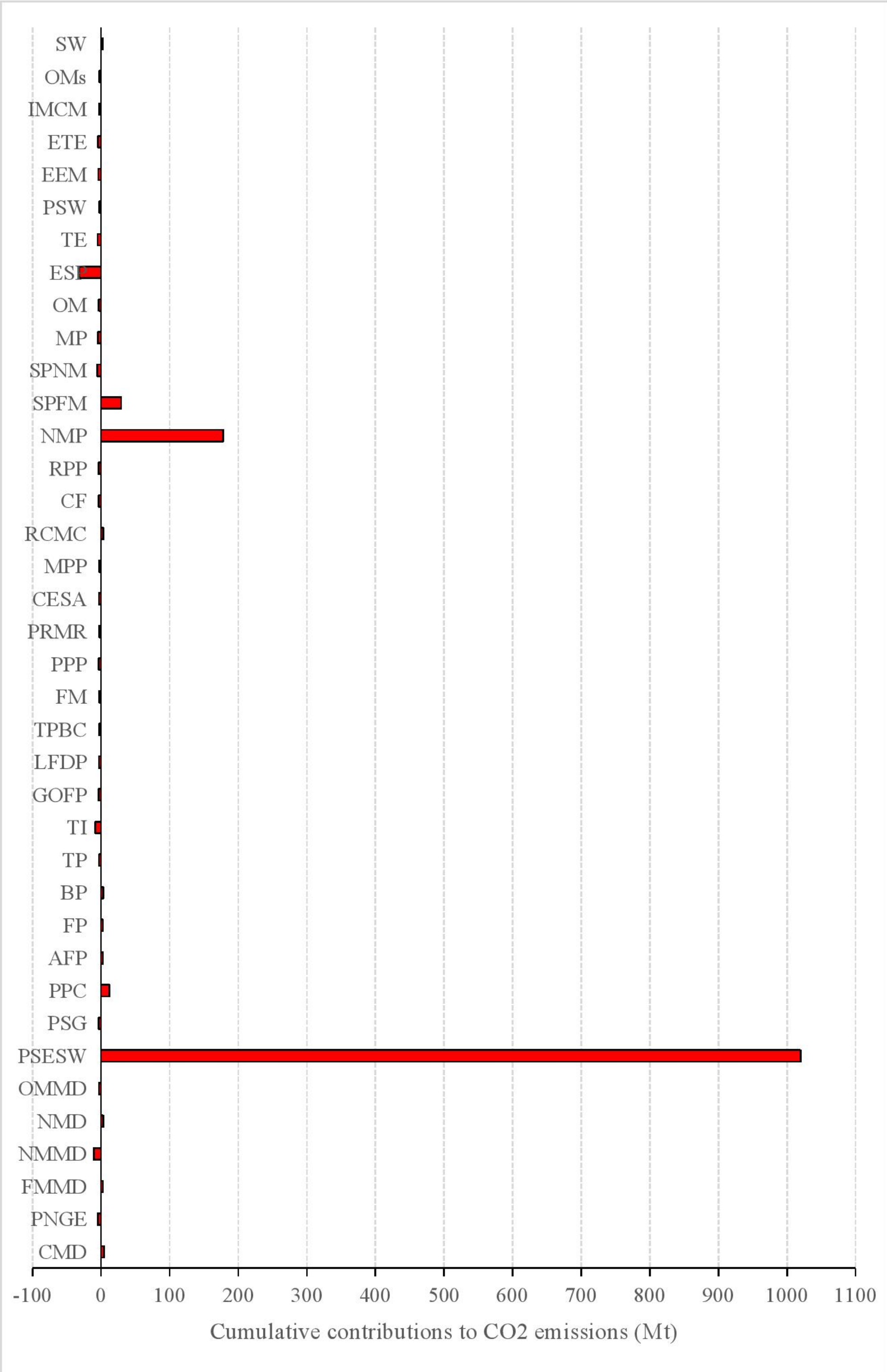

Fig.13. Carbon intensity of energy effect

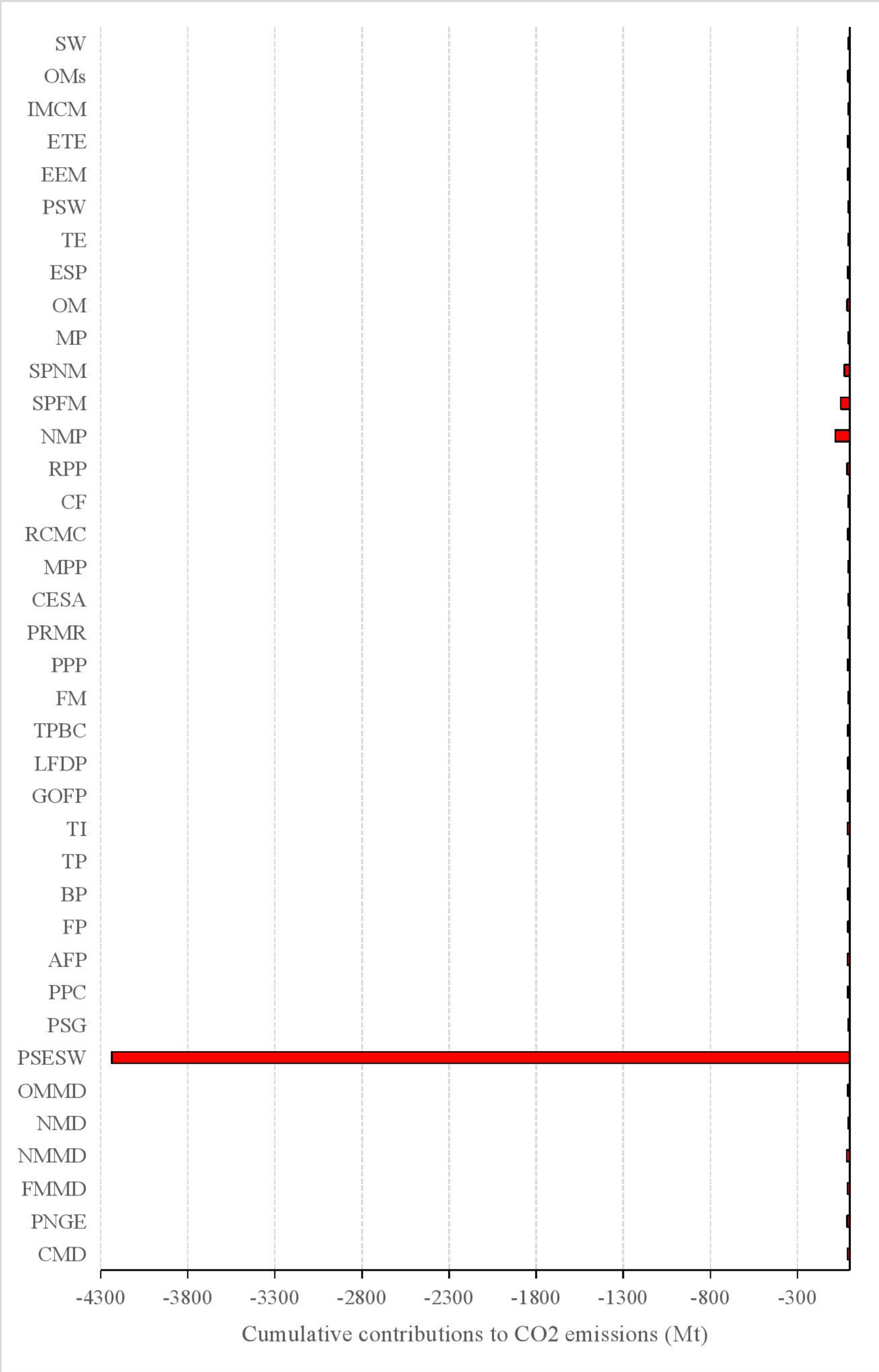

Fig.14. Energy intensity effect

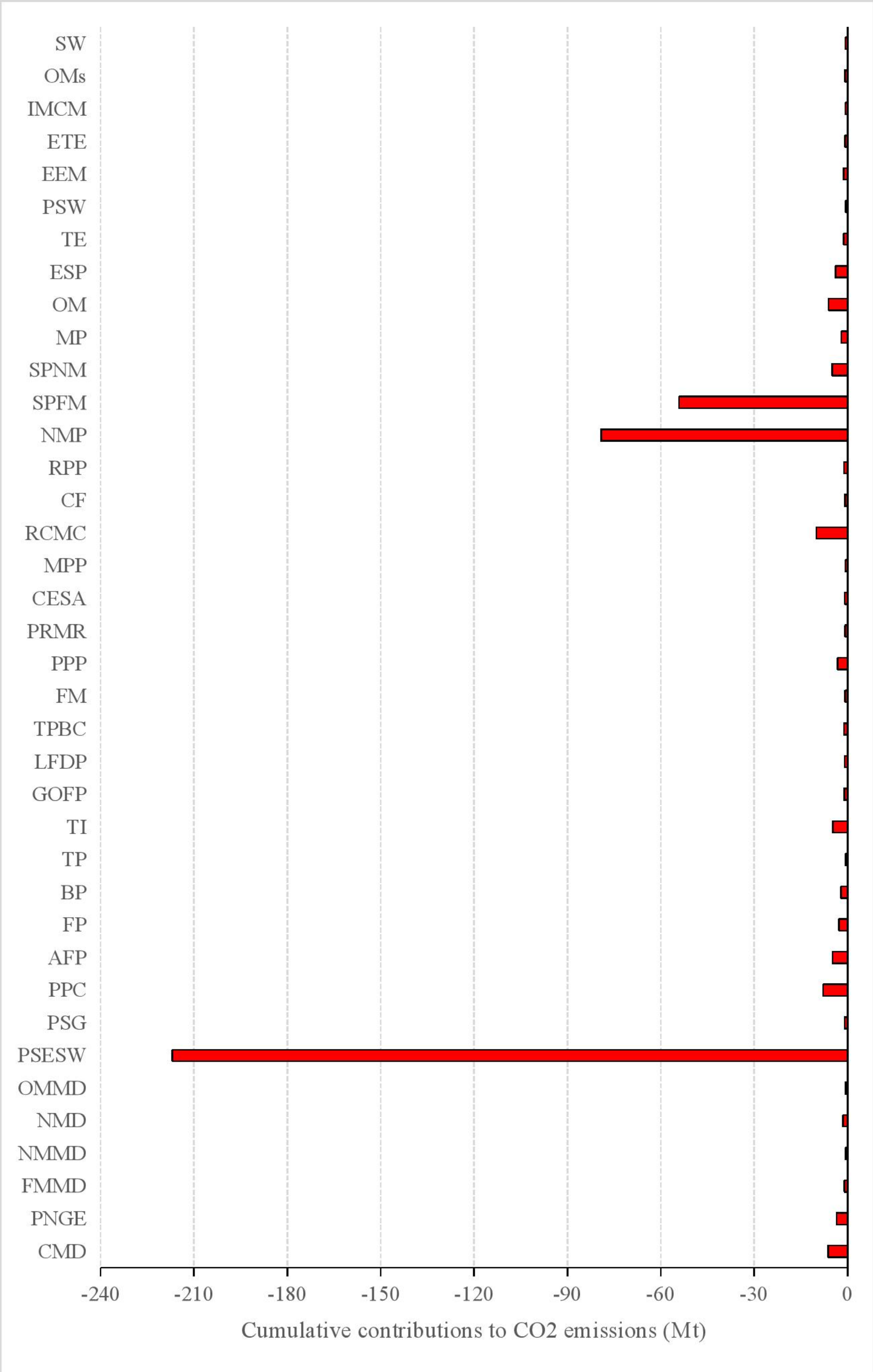

Fig.15. Investment efficiency effect